ASSET PRICING WITH EMPIRICAL, ZERO-BETA, MACRO AND STATE VARIABLES IN INTERNATIONAL EQUITY MARKETS

MUHAMMAD ABDULLAH

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

at the

SALFORD BUSINESS SCHOOL

UNIVERSITY OF SALFORD

2018

Declaration

I hereby declare that the research work contained in this thesis is contributed, written and composed by me except where explicitly stated. All errors are my own.

Muhammad Abdullah

Table of Contents

TABLE OF TABLES

TABLES OF FIGURES

Terminology

APT	Arbitrage Pricing Theory
ARDL	Autoregressive Distributed Lags
CAPM	Capital Asset Pricing Model
CCAPM	Consumption Capital Asset Pricing Model
CMA	Conservative Minus Aggressive
CPI	Consumer Price Index
DEF	Default Spread
DY	Dividend Yield
EMH	Efficient Market Hypothesis
FFR	Federal Fund Rate
FOMC	Federal Open Market Committee
G-CAPM	Gold Capital Asset Pricing Model
GLS	Generalised Least Square
GRS	Gibbon, Ross, and Shanken (1989) Test
GMM	Generalised Method of Moments
HML	High Minus Low
ICAPM	Intertemporal Capital Asset Pricing Model
MS	Money Supply
NYSE	New York Stock Exchange
NASDAQ	National Association of Securities Dealers Automated Quotations
OLS	Ordinary Least Square
PE	Price Earnings Ratio
PRIYR	Previous I –Year
RF	Risk Free Rate

RMW	Robust Minus weak
S&P	Standard and Poor's
SMB	Small Minus Big
SVAR	Stock Variance
U.K.	United Kingdom
U.S.	United States
VAR	Vector Autoregressive Model
VECM	Vector Error Correction Model
VS	Value Spread

Acknowledgements

I am grateful to Almighty Allah who blessed me with the knowledge, courage and strength to complete this work. Credit must be given to my parents who always supported and prayed through all my life and encouraged me to work hard and complete PhD in asset pricing. I am also thankful to my wife who has remained a source of support and motivation during this journey.

I am hugely indebted to my first supervisor Dr Rasol Eskandari who always supported me during my PhD with his knowledgeable feedback and experience. He pushed me to become an active researcher in asset pricing. His thoughtful and insightful feedback allowed me to develop four research papers from my PhD thesis. With his timely feedback and support, I have presented these papers at the reputed national and international conferences. I am also thankful to my co-supervisor Professor Ghulam Sorwar for his valuable guidance, feedback and support during this journey.

I would also like to convey my deepest gratitude to Professor Hassan Yazdifar for his guidance and support. His leadership and guidance motivated me to work hard with commitment and devotion. He always provided timely guidance in improving structure, methodology and quality of my research work. I am also thankful to other teaching staff for sharing useful information and providing useful econometric training of the STATA and other econometric software packages.

I am also thankful to my colleagues who shared valuable time with me. Particularly, I would like to thank David Dunne, Dr Babafemi, Dr Ashraful, Salam Al-Abdullah and Abdul Rahman and other colleagues who always motivated and encouraged me during this journey. I am also grateful to researchers from other universities who collaborated with me in international conferences that immensely helped me in developing econometric research methodology in this work. Finally, I am also thankful to my other friends that I cannot name and hope to share joys in both work and life in near future.

Dedication

Muhammad Ameer my father, Jameela Khatoon my mother, Insha Tahir my wife, to you, I dedicate this work.

Presentations at Conferences

- ‘A horserace of empirical factor models in international equity markets’, 9th-12th of April 2018, *British Accounting and Finance Association*, Annual Conference, Central Hall Westminister, London

- ‘Application of Gold return as risk-free rate in asset pricing: The case of Empirical factor models’, 12th & 13th of June, 2017, *Young Finance Scholars Conference*, University of Sussex.

- ‘Assessing application of gold return to improve asset pricing in developed markets’, 10-12th of April 2017, *British Accounting and Finance Association*, Annual Conference, Herriot Watt University, Edinburgh.

- ‘Investigating applicability of gold as a proxy of risk free rate in asset pricing’, 14th of June, 2016. *Salford Postgraduate Annual Research Conference*, Salford Business School, the University of Salford, Manchester. *“Won the Best Presentation Award”*

- ‘Whether gold can be used to improve asset pricing in developed markets’, 6th & 7th May, 2016, *2nd International Conference in Applied Theory, Macro and Empirical Finance,* The University of Macedonia, Greece.

- ‘Gold Capital Asset Pricing Model: Whether Gold can be used to predict market boom or crisis’ 8th & 9th June, 2015, *5th Annual International Conference on Accounting and Finance*, Singapore.

Abstract

This study aims to improve asset pricing by using empirical, zero-beta, macro and state variables. Firstly, we improve asset pricing with empirical factors as we find the gap that the five-factor model augmented with momentum factor, is yet to be examined in international equity markets. We use the time-series and cross-sectional tests to assess the performance of this six-factor model and compare the performance with other traditional asset pricing models. Findings suggest that the five-factor model improves with the addition of momentum factor. Secondly, we attempt to improve asset pricing by using the gold return as a proxy of the zero-beta rate in global regions. We find that the gold beta is insignificantly different from zero in the U.S. and U.K. equity markets. We confirm the efficiency of gold markets with a battery of efficiency tests and find the position of gold at the minimum variance frontier. When we perform empirical tests by using gold as a zero-beta asset in empirical factor models, we find a convincing evidence in those equity markets as we obtain higher R-squared values, lower Sharpe ratios of alphas and fewer significant pricing errors. Thirdly, we examine the role of gold as a hedging factor in the Intertemporal Capital Asset Pricing Model (ICAPM) in the U.S. and global asset pricing. We perform multivariate and Generalised Method of Moments (GMM) to assess the joint significance of the market and gold price factors. We find that the gold is not a useless factor both in the U.S. and the global asset pricing. Fourthly, we employ empirical, macroeconomic, and state variables to improve asset pricing. We assess the performance of the 23 asset pricing models with the Merton (1973) criteria of multifactor models. We also explore the innovative role of inflation and industrial production with ICAPM and empirical multifactor models. We employ single and multiple predictive regressions to assess forecasting criteria and utilise first-stage GMM to assess the cross-sectional criteria of multifactor models. Results on the multifactor models confirm earlier findings that the applicability of gold return as a proxy of the zero-beta rate improves the model performance of not only empirical factor model but also ICAPM models. This research has many useful applications for investors, policy makers and regulatory bodies. The alternative zero-beta models are useful to obtain better estimates of expected returns during the market crisis and improve pricing of small and risky stocks.

Chapter One

Introduction

1.1 Introduction

The trade-off between risk and return is one of the primary concepts in finance. Capital Asset Pricing Model (CAPM) was developed by Sharpe (1964), (Lintner, 1965a, 1965b) and Mossin (1966) as an alternative to Markowitz (1959) mean-variance theory. Markowitz (1952) considers the total risk and return on portfolios and emphases on risk-reduction that is achieved through diversification. In contrast, the CAPM emphasises on the systematic risk that cannot be diversified. Due to its concise expression of the risk and return trade-off, the CAPM has received worldwide recognition among financial community as it provides a simple solution to the tedious financial problems faced by corporate managers and investors. The CAPM theory states that the asset returns are only determined by the market risk which is estimated by the beta (β). The assets with the higher beta earn the higher returns under the CAPM theory. If the estimated beta is high, then the asset would have a higher risk that would be compensated with the higher expected return. The CAPM has been considered a reasonable risk estimation method for more than two decades as it was able to explain higher returns of assets in the financial market. Merton (1973) has developed the alternative Intertemporal CAPM (ICAPM) model that includes state variables in addition to the market factor. Merton (1973) argues that the investors hedge against a shortfall of consumption and future investment opportunities and the market cannot be the only priced factor. Merton (1993) emphasises that the investors form portfolios to hedge against uncertainties. After a few years, Roll (1977) proposes Arbitrage Pricing Theory (APT) as a substitute for the CAPM that includes the macroeconomic factors with the market price factor. Roll (1977) highlights that eliminating arbitrage opportunities make the market efficient and, in an equilibrium, the expected returns are linearly related to the macroeconomic factors. It relaxes the CAPM's restrict assumptions of the existence of the market portfolio and homogenous expectations of market returns. The CAPM, the ICAPM and the APT theories have resulted in the development of various multifactor models, but each model shows empirical weakness on different sets of test portfolios. Due to empirical limitations of multifactor models, empirical research continues to improve asset pricing.

1.2 Problem statement

Apart from APT and ICAPM models, the extended versions of the CAPM also have been developed. This is because the Sharpe's (1964) CAPM implies that investors are only concerned about exposure to the market risk premium in making investment decisions, however, subsequent empirical evidence suggests that the investors consider other security specific factors as well. For instance, Banz (1981) finds that small capitalization stocks provide higher returns than large capitalization stocks, while Reinganum (1981) further investigates size and value factors and shows the inability of the CAPM in predicting realized returns. Fama and French (1993) study the joint roles of size and the book-to-market effect and find that the explanatory power of the CAPM significantly increases with the addition of these factors. Jegadeesh and Titman (1993) reveal that the stock returns also show momentum effect: stocks which have performed particularly well or particularly badly, tend to continue doing so in the subsequent six months to one year. Carhart (1997) further develops this and proposes a four-factor model which augments the Fama and

French (1993) three-factor model with a momentum factor. More recently, Fama and French (2015) propose a five-factor model which includes investment and operating profitability as additional factors, but which excludes momentum. Testing this five-factor model in the U.S. equity market on test portfolios of size, value, operating profitability and investment, they find evidence of significant investment and profitability premia. However, the five-factor model augmented with momentum factor needs to be assessed in global markets. Further, the five-factor model has a limitation in pricing small stocks. Hence, there is also a room for improvement in this new extended multifactor model.

Further, Fama-French models are criticised to perform on their own set of mimicking portfolios, for instance, Fama and French (1996) have admitted that their model performs only on size and book-to-market portfolios. Further, small stock pricing has remained an unsolved puzzle even with the advancement of these multifactor models. These empirical multifactor factors need to be re-examined and re-developed to make them more robust so that they are able to work on an extended set of test portfolios with least pricing errors. This could also help in pricing small and risky stocks.

Apart from the improvement in empirical factor models, the proxy of risk-free rate also needs to be reconsidered. The return on the risk-free asset is one of the most critical variables in financial equilibrium models, yet its choice and value have not been without controversy. In the U.S. equity market, Mehra and Prescott (1985) link the problem of an equity premium with the risk-free rate. They question the low risk-free rate when equity premium has remained so high. Further, it is revealed that the equity premium is related to the risk-free rate puzzle (Weil, 1989). Conventionally, the risk-free rate has been proxied by the return on a Treasury bill, but the choice of the tenor of Treasury bill rate again has been debated. Treasury bills are presumed to constitute risk-free investments since their issuing governments are viewed as ‘default free’ entities that offer guaranteed investments.

If governments default or the possibility of default arises, then their obligations do not remain guaranteed. The creditworthiness of U.S. Treasury Bills has raised concerns among investors after Standard & Poor's downgrades its debt ranking rate from AAA to AA+ in mid-2011 for the first time in the history (Appelbaum & Dash, 2011). Cenesizoglu & Reeves (2012) report the inclusion of the default risk premium in Treasury securities after the global financial crisis of 2008. Even for the United States, Nippani and Smith (2010) reveal that the Treasury securities are not default-free, as they observe the non-zero Credit Default Swap premia during the financial crisis. The same is doubly true of Treasury securities of less creditworthy states such as Mexico, Greece, Spain, and Italy.

Researchers have employed Treasury securities of different maturities to seek to improve asset pricing models. For instance, Mehra and Prescott (1985) utilise a one-year rate and Albuquerque, Eichenbaum, Luo, & Rebelo (2016) examine the applicability of 1, 5, and 2 -year rates. Barberis, Greenwood, Jin, & Shleifer (2015) develop the assumption that risk-free rate is constant over long periods, whereas Fama and French (1993, 2015) have used a 1-month T-bill rate. If the nature of the of the asset used to derive this short-term rate, does not satisfy restrictions of general equilibrium models (Weil, 1989), then the nature of the asset should be reexamined. Further, there is a need to replace risk-free aseet with zero-beta asset or portfolio as it can be useful in improving estimation of expected returns (Black, 1995).

Risk-free rate provides the foundation for estimating the cost of equity and the expected returns on assets or portfolios. If Treasury bills do not remain risk-free investments, then the application of the return on Treasury bills may not be the appropriate proxy for the risk-free rate. Therefore, there is a need to investigate the applicability of using return on an alternative investment that may provide better estimation of expected results than risk free rate. Hence, in spirit of Black, Jensen and Scholes (1972), we assess applicability of using a proxy of a zero-beta rate rather than risk free rate to improve estimation of expected returns. In this study, we estimate the models in absence of risk-free rate as return on Treasury bills (risk-free rate) is ex-ante because investors are already aware of the return on Treasury bills in 1-month time.

1.3 Role of gold as a zero beta and a hedging factor

Contrary to Treasury securities, gold has received significant attention in financial markets due to its remarkable performance during the global financial crisis. Contrary to equity markets, there was no impact of the global financial crisis of 2008 on the efficiency of the gold market. Instead, gold prices considerably increased and gold market gained further efficiency (Wang, Wei, & Wu, 2011). The financial press and many researchers have documented safe haven properties of gold during the financial crisis (Baur & Lucey, 2010). Gold has a centuries-old history of serving as a financial security and has long served as a monetary currency in the nineteenth and twentieth century in various countries.

The significant impact of gold on stock returns have been emphasised by various researchers. For instance, McCown & Zimmerman (2006) research on the U.S. data concludes that the gold plays a significant role to determine the value of U.S. dollar, real interest rate, exchange rate, and expected inflation. Baur & McDermott (2010) find that gold act as a stabilising force for the financial system and was a safe haven during the financial crisis in the developed markets. Chua, Sick, & Woodward (1990) examine the stock-gold relationship by focusing on betas and report that gold beta is insignificantly different from zero. Smith (2002) investigates the role of gold on stock returns and provides empirical evidence of the significant influence of the gold price on stock prices in the U.S. and U.K. equity markets. His findings report gold as a safe haven during abrupt market conditions. Recently, Barro & Misra (2016) reveal that the real change of monthly price of gold is very close to the monthly return on Treasury bills in the United States which is used as a proxy of risk-free rate in financial models. Findings of this research open opportunities for in depth research on the applicability of gold as an alternative to return on Treasury bills in financial modelling.

1.4 Gaps of research

This study attempts to improve asset pricing by using, empirical, zero-beta, macro and state variables in global developed markets and explore the following gaps in asset pricing literature:

1.4.1 Five-factor augmented model

Initially, we explore the usability of momentum factor with the new Fama and French (2015) five-factor model and intends to improve asset pricing by using empirical factors in global regions. This study addresses three notable gaps in Fama and French (2015). The first of these gaps concerns their omission of a momentum factor in their five-factor model, which they justify on the basis that this and the Pástor and Stambaugh (2003) liquidity "have regression slopes close to zero and so produce trivial changes in model performance." (Fama and French, 2015, p.8), though they do not report the results which underlie this assertion. However, they do admit that the momentum factor is significant when test assets are sorted on momentum: "except when the LHS portfolios are formed on momentum, in which case including a momentum factor is crucial". (ibid., p.8). In the event, Fama and French (2015) do not employ any test assets sorted on momentum, and they also do not report the results which underlie this second assertion. By contrast, this study will include a rigorous set of asset pricing tests will necessarily include test assets of portfolios sorted on momentum, as indeed do Fama and French (1996), Fama and French (2007), Fama and French (2008), and Fama and French (2012). This study would address this gap by adding a momentum factor to the five-factor model, as Fama and French (2015) did in their unreported results, and also, testing all models against test assets sorted on momentum, which is not performed in Fama and French (2015), in order to assess how it survives this challenging test as their three-factor model has a poor record on test portfolios sorted on momentum or other portfolios (Fama and French, 1996)

The second of these gaps concerns the test of the six-factor model in global regions as is stressed by Fama and French (2017) that it would be interesting to test the six-factor model in international markets. Fama and French (2017) test the five-factor model on portfolios of Global, North American, European, Japanese and Asia Pacific equities, we test the six-factor model in global regions. Further, in spirit of Fama and French (2012, 2017), we employ both global and locally-derived Fama-French and momentum factors to compare the performance of the five-factor and six-factor models in global markets.

The third gap in Fama and French (2015) concerns the nature of the analyses used: Fama and French (1992), Fama and French (1993), and Fama and French (1996) perform both time-series and cross-sectional regressions as part of their Fama-MacBeth (1973) analyses, and so are able to extract cross-sectional prices of factor risk. In a similar vein, Gregory, Tharyan, and Christidis (2013) perform both time-series and cross-sectional regressions for the three- and four-factor models in the U.K. context, and are able to show that they seldom give economically plausible or significant cross-sectional prices of factor risk. By contrast, Fama and French (2012) and Fama and French (2015) employ only time-series regressions and omit second-stage, cross-sectional regressions, leaving us unable to observe whether their factors models yield economically plausible or significant cross-sectional prices of factor risk. This study seeks to remedy this by performing both time-series and cross-sectional regressions, and using both first- and second-stage regression results to judge the comparative success of the competing asset pricing models in this study. This study also follows Ferguson and Shockley (2003) in adding graphical illustrations of the relative success of the different asset pricing models, using plots of actual-versus-predicted average returns.

1.4.2 Gold as a zero-beta asset

After exploring gap of the usability of a momentum factor in the five-factor model, this study explores the gap of finding the correct proxy for the risk-free rate in asset pricing. The use of a correct proxy for the risk-free rate has remained a topic of debate among academicians and practitioners. In contrast to the return on debt issued by governments, gold has a centuries-old history of serving as a financial security and has long served as a form of currency in various countries. Gold has received significant attention in financial markets in more recent times due to its remarkable performance during the global financial crisis of 2008, and researchers have labeled it a safe-haven asset since it acts as a stabilizing force for financial systems in developed markets (Baur & Lucey, 2010b; Baur & McDermott, 2010). The safe-haven, currency hedging and diversification benefits of gold during the global financial crisis (2008) also have been re-assessed and reaffirmed in recent studies (Hoang, Lean, & Wong, 2015; O'Connor, Lucey, Batten, & Baur, 2015). Evidence has also emerged that there is a close relationship between the gold return and the return on Treasury bills: Barro and Misra ((2016) examine the returns on gold and U.S. Treasury bills from 1836 to 2011 and reveal that the real price change of gold is close to the real return on Treasury bills. It also has been found that gold prices react swiftly to changes in federal fund rates (MacDonald, & Saggu, 2013).

Despite gold being recognised as a safe-haven and a hedging instrument, it is surprising that researchers have never yet assessed the application of the return on gold as a zero-beta rate in the asset pricing literature. This study attempts to fill this gap through providing a thorough investigation of the applicability of gold as an alternative proxy for the zero-beta rate. This study uses the gold return in the spirit of Black, Jensen, and Scholes (1972) as the return on a zero-beta asset. Several studies find gold to have a zero beta with respect to the market (J. F. Jaffe, 1989; Chua, Sick, & Woodward, 1990; McCown & Zimmerman, 2006). Regarding efficiency, Wang, Wei, and Wu (2011) and Ntim, English, Nwachukwu, & Wang (2015) report weak-form efficiency in the U.S. gold market. This feature makes the gold return a better candidate to satisfy (Constantinides & Duffie, 1996) Arrow-Debreu conditions than the return on Treasury bills. However, gold is not risk-free ex-ante unlike return on Treasury bills as gold return is not determinined in advance and hence, we do not attempt to replace gold return with a risk-free asset. Instead, we attempt to improve asset pricing by using gold return as an alternative proxy of the zero-beta rate.

1.4.3 Gold as a hedging factor

In addition to exploring applicability of gold return as a zero-beta rate, this study also explores its usability as a hedging factor. This study examines its application in the Merton (1973) Intertemporal Capital Asset Pricing Model (ICAPM). Merton (1973) assumes that the investors construct portfolios to hedge against uncertainties. Gold plays a crucial role in the financial economics of global markets. Portfolio diversification, hedging and safe haven characteristics of gold are widely documented (Chan & Faff, 1998; Baur & Lucey, 2010; Ciner, Gurdgiev, & Lucey, 2013). However, very limited literature explores gold as a potential hedging factor in the Merton’s (1973) ICAPM despite its significant relation with macro and state variables. In a previous study, Davidson, Faff, and Hillier (2003) examine the gold factor exposure on global industries from 1975 to 1994, and find a significant evidence of the gold factor exposure in global asset pricing. This study extends their study and examine gold factor exposure from 1995 to 2015.They utilise a sample of 34 global industries and this study advances on them to include 40 global industries to provide a fresh evidence of gold factor exposure in global asset pricing. Further, I find a gap of research as the extra-market sensitivity of the gold price factor has not been recently assessed in the U.S. equity market. In the U.S. equity market, a number of studies agree that the gold functions as a strong safe haven asset (Baur & McDermott, 2010; Bredin, Conlon, & Potì, 2015; Constantinides & Duffie, 1996; O'Connor, Lucey, Batten, & Baur, 2015). It is surprising that gold is not explored as a potential hedging factor in the U.S. asset pricing. I differentiate this study from the previous studies as this study specifically explores prospects of using gold as a Merton (1973) hedging factor who emphasises that a potential hedging factor should be negatively correlated with a market beta and should forecast aggregate market returns.

I examine gold as a hedging factor in the U.S. equity market as gold has a unique status in the U.S. economy. The U.S. is the only country with the largest gold holding in the world. The gold position of central banks reflects economic strength of the country, and intensity of gold holding is associated with global power (Aizenman & Inoue, 2013). Further, due to the sheer size of its economy, and the supplier of the international currency (US Dollar), the assessment of gold as a hedging factor is important to determine the role of gold in the U.S. asset pricing.

In addition to the two-factor model, I also assess the role of gold in multifactor Arbitrage Pricing Theory (APT) multifactor model by adding a set of macroeconomic and state variables and examine its ability to influence stock market returns in the presence of other variables.

1.4.4 Asset pricing with state and macro variables

Finally, this study finds the gap of the improvement of multifactor models and explores the applicability of macro factors in the multifactor ICAPM models. For instance, this study finds a gap as inflation and industrial production factors have not yet been examined with the empirical factors in the multifactor models. This study develops new asset pricing models by augmenting these factors with Fama and French (1993) and Petkova (2006) multifactor models. However, inflation and industrial production have been examined in the APT models (Chen, Roll and Ross, 1986; French, 2017), but their usability in the ICAPM models is innovative that I explore in this study. Including these two alternative models, this study assesses the performance of the twelve multifactor models with the strict Merton (1973) criteria of the multifactor models i.e. the state variables must forecast aggregate market returns or volatility; the state variables must produce the same sign in cross-section, the sign they show in time-series predictive regressions; and lastly the ICAPM should produce positive and economically meaningful estimate of the price of the market risk. Further, there is a gap as ICAPM multifactor models have not been examined by using gold return as an alternative proxy of a zero-beta rate. This study compares twenty-three models with the strict ICAPM criteria by using time series and cross-sectional tests to achieve conclusive results.

First is the two-factor ICAPM that utilises gold as a hedging factor. Second is the Hahn and Lee (2006) model that uses market, term and default spread. The third is the Petkova (2006) that utilises market, term default spread, dividend yield, and Treasury bill rate. Fourth is the alternative Petkova model (P*) augmented model with inflation and industrial production. The fifth model is the Campbell and Vuolteenaho (2004) that uses market, term, price earnings ratio and value spread. Sixth is the Fama and French (1993) three-factor model. Seventh is the Fama and French (1993) ICAPM model that uses market, size, and value with the term-structure and default spread. Eighth is the alternative Fama and French (1993) ICAPM that uses inflation and industrial production*)* with Fama and French (1993) factors. Ninth is the Carhart (1997) four-factor model that uses momentum with Fama and French (1993) factors, the tenth is the Pástor and Stambaugh (2003) model that uses liquidity price factor with the Fama and French (1993) factors. Eleventh is the Fama and French (2015) five-factor model, and twelfth is the Fama and French (2015) augmented model with the momentum price factor. Further, this study also compares these models with their gold zero-beta analogues. Hence, this study examines twenty-three asset pricing models in total.

In time series, single and multiple predictive regressions are performed, whereas in cross-section, first-stage GMM estimates are obtained for each model to assess these criteria. Like Brennan, Wang, & Xia (2004), the asset pricing models are assessed on the 25 size and book-to-market and 30 industry portfolios in the U.S. equity market.

1.5 Aim, objectives and research questions

The aim of this research is to improve asset pricing by using empirical, zero-beta, macro and state variables in international equity markets. Firstly, this study assesses the performance of the traditional empirical factor models in global regions. Then, I assess the applicability of gold as a zero-beta asset in empirical factor models in international equity markets. I further examine the extra-market sensitivity of the gold price factor on the global industries. Lastly, I identify the key state and macroeconomic variables and examine the performance of a wide range multifactor models with the strict testable implications of asset pricing theory.

1.5.1 Objectives

1) To compare empirical performance of a five-factor augmented model with momentum factor with the three-factor, four-factor and five-factor models in international equity markets
2) To assess the applicability of gold as a zero-beta asset with the theoretical and empirical perspective in the traditional empirical factor models in international equity markets.
3) To examine the applicability of gold as a hedging factor in the Intertemporal Capital Asset Pricing Model (ICAPM) framework to assess its empirical application in the global and U.S. equity markets.
4) To assess the performance of empirical, zero-beta, macro and state variables in multifactor models according to the testable implications of asset pricing theory.

1.5.2 Research questions

1) Whether five-factor augmented model with the momentum factor outperforms single-factor, three-factor, and four-factor models in international equity markets with time-series and cross-sectional asset pricing tests?
2) Whether gold return can be used as a zero-beta rate in the empirical factor models and whether it helps to improve the performance of empirical factor models?
3) Whether gold price factor can be used as a risk factor in the U.S. and global equity markets and which industry equity portfolios exhibit exposure to the gold price factor and whether the exposure is significant in different sub-periods?
4) What are the main empirical, macro and state factors that influence stock market returns and whether the models that employ empirical, zero-beta, macro and state variables meet the testable implications of asset pricing theory?

1.6 Contributions of research

This study documents the following contributions in asset pricing literature:

1.6.1 Five-Factor augmented model in International Markets

The first contribution of this research is the thorough assessment of traditional empirical factor models in the US, European, Asian, U.K. and the Global markets. This study contributes to the asset pricing literature in the following ways: firstly, in time-series results, findings reveal that the five-factor model augmented with momentum outperforms all other asset pricing models on test portfolios sorted on size and value, and size and momentum: it produces higher time-series R-squared values on both sets of test portfolios than either the five-factor, the four-factor or the three-factor model.

Further, it produces the lowest GRS values for the North American, Japanese, and Asia Pacific regions on portfolios sorted on size and value. This study confirms the comments made by Fama and French (2015) about the essential nature of the momentum factor in pricing portfolios sorted on momentum: for the test assets sorted on size and momentum, the five-factor model augmented with a momentum factor surpasses the models in terms of producing the lowest GRS values for the North America, Europe and the Asia Pacific regions.

Secondly, I demonstrate that the five-factor model augmented with the momentum factor provides economically more plausible and significant cross-sectional pricing of market risk premium than the competing models. Specifically, in the North American region, significant size, value, momentum, investment, and profitability premia are obtained in cross-section. In the European region, significant value and profitability premia are reported, whereas the five-factor models performs as good as five-factor augmented with momentum. In the Asia Pacific, findings show the weak evidence in favour of the five-factor and six-factor models and convincing evidence is only obtained in sub-periods rather than the whole sample.

1.6.2 Applicability of gold as a zero-beta asset in asset pricing

The second contribution of this study is the application of gold return as a zero-beta rate in international equity markets. This study finds that gold meets the conditions of the zero-beta rate as it is efficient and is located on the minimum variance frontier as is required in asset pricing theory. This study contributes to the literature by employing for the first time, gold return as a zero-beta rate in equity asset pricing models, in place of the more traditional use of the yield on a 1-month T-bill as a risk-free rate. This study shows that this is preferable on several practical levels, and that that yield on a 1-month T-Bill has serious theoretical shortcomings in terms of suitability as a risk-free return. This study further shows that the return on gold notably lacks these shortcomings, and so is preferable on theoretical grounds. Findings also show that asset pricing models which use gold return as a zero-beta rate in place of the traditional T-Bill rate have better performance on a wide range of test assets, both in terms of time-series and cross-sectional performance.

This study provides a comprehensive comparison of the traditional Fama and French (1992, 2015) and Carhart (1997) models with those that employ gold as a zero-beta asset on an extensive range of test assets. For robustness and ease of comparison with Fama and French (2015), the performance of these asset pricing models is assessed with and without small stocks and demonstrate an improved pricing of small stocks. Ang, Hodrick, Xing, & Zhang (2006) use a volatility factor to improve the performance of the Fama-French (1993) three-factor model on portfolios sorted on cash-flow volatility, and in a similar vein, I examine gold as a zero-beta asset to price portfolios sorted on variance. Black, Jensen, and Scholes (1972) relax the CAPM assumption that investors can borrow and lend freely to an unlimited extent at the risk-free rate, and examine the CAPM with limited borrowing, permitting investors to lend but not borrow at the zero-beta rate. Similarly, I also restrict investors to investing, but not borrowing at the gold return rate. I employ extended dataset over 35 years and perform time-series and cross-sectional asset pricing tests. In order to assess empirical performance before, during and financial crisis, I also assess the performance in three sub-periods.

Regarding results, in time-series, higher R-squared values, lower Sharpe ratios of alphas and fewer significant pricing errors are obtained, when gold is used as a zero-beta asset. We find that such models are better able to price portfolios of small stocks, where traditional models struggle. In cross-section, we find fewer cross-sectional pricing errors, and we find economically plausible values of the market risk premium appearing, for test assets where traditional models generate implausible (negative) estimates of market risk price. We show that the CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model and the Fama-French (2015) five-factor model are all improved in terms of asset pricing performance using gold as a zero-beta asset. Finally, this study shows that there is information in the return on gold above and beyond those in the Carhart (1997) factors: a gold return factor constructed to be orthogonal to these remains significant in cross-section when added to the Carhart (1997) model, showing that it explains additional variance not encompassed by the four factors.

1.6.3 Gold factor exposures

The third contribution of this study is the usability of gold as a hedging factor in the U.S. and global asset pricing. Findings show that gold meets the ICAPM criteria for a state variable as it significantly predicts aggregate market return in the global market and predicts market volatility in the U.S. market despite being a zero-beta asset. This study documents a detailed evidence of the gold factor exposure in the U.S. and international asset pricing. Initially, this study identifies industries showing significant exposure to a gold price factor in the full-period analysis. Then, I assess whether this exposure is significant in sub-periods and test the stability of a gold price in three non-overlapping periods. It would allow to assess the gold factor exposure before, during, and after the financial crisis. I also categorise industries into groups and perform asset pricing tests utilising multivariate regressions, generalised method of moments (GMM), and Fama and Macbeth (1973) tests to achieve confidence in the results of this study.

Findings from this contribute to the literature in the following ways: firstly, I confirm that gold is not a useless factor as many U.S. and global industries show a significant exposure to this commodity. I find a stronger gold factor exposure with the positive real gold premium in the second sub-period that covers the period of the financial crisis (2008). Secondly, I find an evidence that the gold price factor varies over time as this exposure becomes negative with the declining gold price in the third sub-period that covers a period of the post-financial crisis. Thirdly, when I make industry groups and test the significance of the market and gold price factors, I find overall evidence in favour of a two-factor model. However, results also suggest that gold factor exposure is industry specific as the null hypothesis of joint significance is not rejected over each industry group. Fourthly, Merton (1973) theory of negative correlation between a market beta and a gold price factor is comparatively better satisfied with the U.S. industries as compared to the global industries. I find similar evidence from cross-sectional tests. Further, I find that the gold price factor is significantly positive in global industries in the first and second sub-periods that cover the periods of Asian and global financial crises. Among global industries, it is significantly negative in the sub-period of post-financial crisis showing a stronger hedging role of gold in the U.S. asset pricing. Finally, when I use gold in the APT models with the term-structure, default spread, inflation, exchange rate and money supply variables, then the gold price factor is produced significant in the cross-section which confirms that gold is a crucial factor in the U.S. asset pricing.

1.6.4 Assessment of multifactor models

Finally, I contribute to the asset pricing literature by exploring new role of macro variables and comparing a range of multifactor models that have not been examined in existing literature. I perform single predictive regressions on each state variable to assess its forecasting ability. I propose two new multifactor models by using inflation and industrial production with Fama and French (1993) and Petkova (2006) models. These macro factors satisfy the forecasting criteria with the single and multiple predictive regressions. When these alternative models are tested in cross-section, significantly negative priced factors are produced However, these findings are limited to size and book-to-market portfolios as Petkova (2006) and Fama and French (1993) perform reasonably well on industry portfolios and the addition of these factors do not make difference in the model performance.

In addition to exploring new role of macro variables, this study contributes to the asset pricing literature by examining twenty-three multifactor models with the Merton (1973) criteria and that is the main contribution from this study. This study examines eleven multifactor models by using 1-month Treasury bill rate as a proxy of risk-free rate and also by using gold return as a proxy of the zero-beta rate. With the multifactor ICAPM models, further empirical evidence is obtained in favour of the applicability of gold return as a proxy of a zero-beta rate. Like empirical factor models, ICAPM models also produce higher R-squared and economically more meaningful estimates of the relative risk aversion (RRA), when the gold return is employed as a proxy of a zero-beta rate. Particularly, the performance of Pástor and Stambaugh (2003) four-factor model and Petkova (2006) five-factor model significantly improve as they produce insignificant cross-sectional alpha as compared to their traditional versions where they produce significant pricing errors.

This study also implements robustness checks proposed by Clare, Priestley, & Thomas

(1997) by adding APT variants in the Fama and French (1993, 2015) and Carhart (1997) models that is an additional contribution to the research.

1.7 Overview of research methods

I adopt the realism research philosophy and the positivist paradigm of research. My approach is objective and I employ quantitative financial econometric techniques to achieve the objectives in this study. I develop models and hypotheses and test those models with time series and cross-sectional asset pricing tests.

Among time series tests, I employ Gibbons, Ross, and Shanken (1989, GRS test) that has been widely used in asset pricing literature (Fama and French, 1993, 2012, 2015). In the GRS test, I estimate time-series alphas, Sharpe ratio of alphas and R-squared to examine the model performance. Significant alphas show pricing errors and lower Sharpe ratio of alphas are desirable for the adequate performance of the model. R-squared is the coefficient of determination and hence, higher R-squared value is desirable for the model performance. In cross-section, I adopt traditional Fama and MacBeth (1973) methodology, employ Shanken (1992) correction. I also plot the actual and predicted returns from each model on all test portfolios to show the model performance.

I examine gold return as a proxy of a zero-beta rate under the Black, Jensen, and Scholes (1972) criteria for a zero-beta portfolio which is an efficient and minimum variance portfolio. Therefore, firstly, I perform a range of market efficiency tests including variance ratio tests of Lo and Mackinlay (1988), Wright (2000), multiple variance ratio tests of Whang and Kim (2003), Automatic Portmanteau test of Escanciano and Lobato (2009) to find whether the gold markets are efficient in the global developed markets. Secondly, I determine the position of gold on minimum variance frontier by plotting gold against different sets of test portfolios to verify the position of gold on the minimum variance frontier. After satisfying main conditions of a zero-beta rate, I assess its application in global regions and international equity markets.

After examining the gold return as a proxy of a zero-beta portfolio, I examine the extra market sensitivity of the gold price factor on the global and U.S. industries. Finally, I employ empirical, zero-beta, macro and state variables to develop new multifactor models. I compare the performance of new multifactor models with the traditional multifactor models. I compare twenty-three asset pricing models with the Merton (1973) criteria of multifactor models. I perform predictive regression and first-stage Generalised Method of Moments (GMM) tests employed by Maio and Santa-Clara (2012) and Lutzenberger (2015). Insignificant cross-sectional alpha and economically plausible (positive) estimate of the market price is desirable for the model performance.

1.8 Summary of chapter

Asset pricing with empirical, zero-beta, macro and state variables in global markets

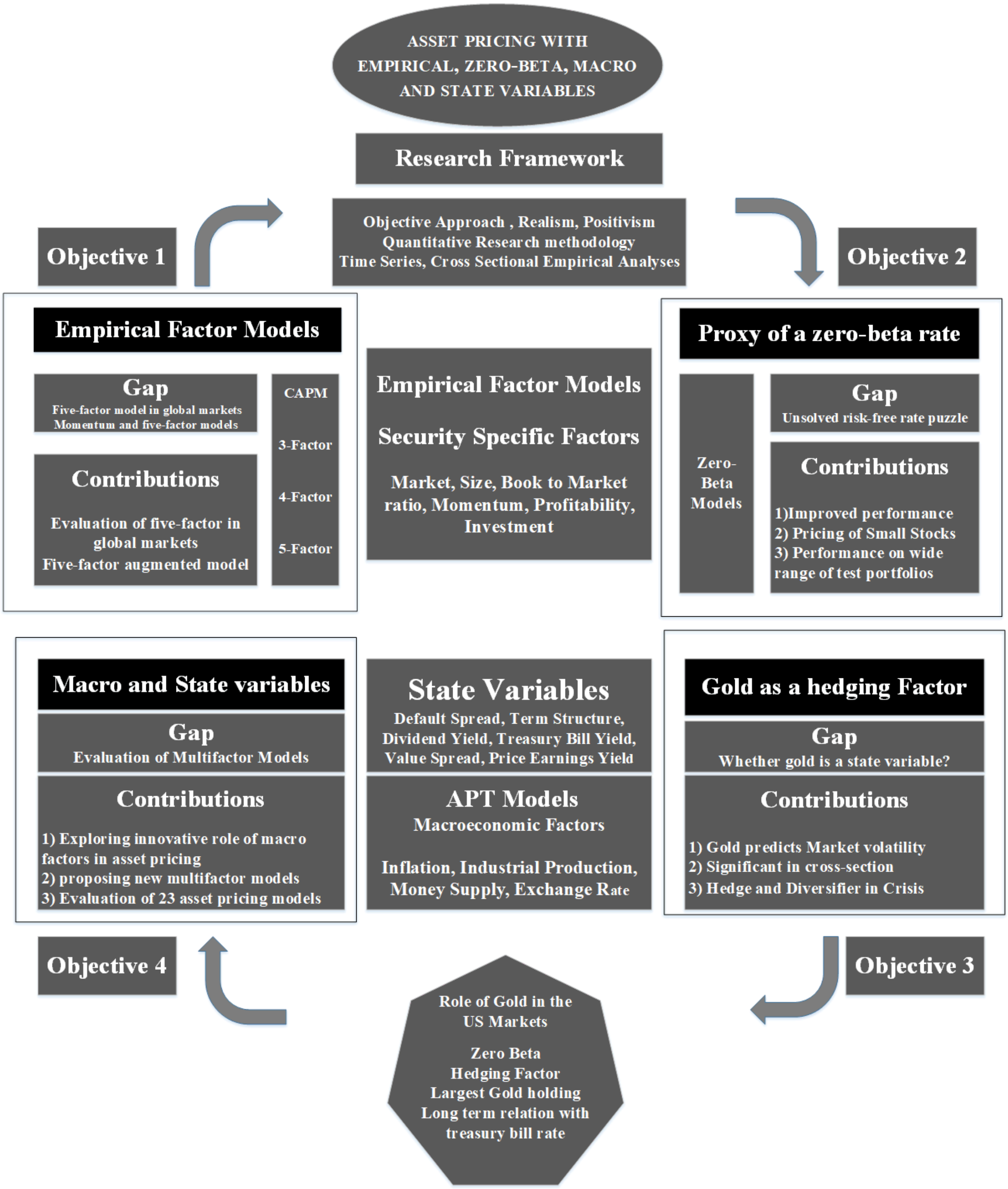


Figure 1: Framework of research shows objectives, gaps, and contributions

Source: Author's own

Figure (1) shows gaps and contributions from this study and concludes this chapter. To achieve the first objective, I examine the applicability of momentum factor in the five-factor models to improve the five-factor model in global regions. To achieve the second objective, I explore innovative proxy of a zero-beta rate and examine the gold return as a proxy of the zero-beta rate in empirical asset pricing in global equity markets. I contribute to asset pricing literature by improving the performance of asset pricing models on an extended range of test portfolios and improving pricing of small stock pricing. To achieve the third objective, I examine the applicability of gold as a hedging factor in global markets in the two-factor and the APT multifactor models and find the significant gold factor exposure on the global and the U.S. industries. Finally, to achieve the fourth objective, I explore the innovative role of macroeconomic and state variables in multifactor models. I develop new models by using inflation and industrial production with the traditional multifactor models. I compare twenty-three models by using empirical, macro and state variables and assess these models according to the strict testable implications of asset pricing theory. I find a diverse role of gold in asset pricing. Results suggest that gold is a zero-beta asset, however, this zero-beta asset predicts market volatility and hence, satisfies the main forecasting condition of a Merton (1973) state variable. Findings also reveal that inflation, and industrial production factors play a competitive role like other state variables and can be used with the empirical and the ICAPM models.

Chapter Two

Literature Review

2.1 Overview of global developed markets

The equity markets in North America, Europe, Australia, New Zealand, Singapore and Japan are efficient and stable than developing and emerging markets, and, often referred as the developed markets. In this study, I attempt to improve asset pricing in the developed markets and hence, I evaluate the asset pricing literature in those markets. The developed markets have a lower political risk than emerging markets due to relatively stable political and economic environment (Diamonte, Liew, & Stevens, 1996). Researchers have established that the efficient markets are crucial to promote financial and economic growth (Arestis, Demetriades, & Luintel, 2001). Efficient markets are important to build investor confidence to bring local and foreign capital in the stock markets. Fama and French (2012) categorise developed markets into four regions, North America, Europe, Japan, and the Asia Pacific.

2.1.1 U.S. and U.K. equity markets

Cheung & Mak (1992) mark the U.S. stock market as a 'global factor' that influences stock returns of most of the emerging markets in Asian-Pacific region as well. The U.K. equity market also occupies a prominent position in the global developed markets. After NYSE, NASDAQ, and Toronoto, London stock exchange is the fourth largest stock exchange in the world with the market capitalisation of over $3.6 trillion

The stock markets in the U.S. and U.K. are considered more efficient and stable than other developed markets. Historically, there is a close relationship between the U.S. and U.K. stock markets. Various researchers in the past have done research to explain their relationship. Research suggests that there is co-movement between these two developed markets. Blanchard, Shiller, and Siegel (1993) determine that the co-movement of U.S. and U.K. stock markets can be explained in terms of a simple present value model. Conversely, Engsted and Tanggaard (2004) interpret this co-movement as the result of stock return news. They find a high positive correlation between U.S. and U.K. stock markets from 1918 to 1999. Their research reveals that the news factor is the most significant determinant of stock return volatility in both countries and stock returns news is highly correlated across U.S. and U.K. stock markets. Sornette (2009) has presented evidence on the nature of co-movement in the monthly U.S. and U.K. stock returns by examining time-varying correlations since 1980. He reports that correlations not only increase over time but further increases in periods of high volatility.

The stock markets in the U.S. are governed by the U.S. Security and Exchange Commission (SEC). The SEC is responsible for proposing rules, regulations and enforcing securities-related legislation (Bernstein, 2015). It also administers enforcement of Sarbanes-Oxley Act of 2002 that publishes rules on compliance requirement and sets deadlines. In the UK, corporate governance is administered through independent regulator Financial Reporting Council (FRC) who has set guideline through the U.K. Corporate Governance Code and the U.K. Steward Code to promote high-quality governance practices (Council, 2012).

Regardless of political and economic strength and rigorous regulatory framework than developing and emerging markets, the developed markets are also susceptible to uncertainty and financial crisis. The U.S. financial crisis severely hit stock markets as they experienced the worst decline during 2007-08 after Great Depression of the 1930s.

2.1.2 Overview of asset pricing models

The CAPM has been under criticism since the 1980s when researchers find different patterns for stock portfolio returns that were not addressed by Sharpe's classic CAPM. The main criticism arises from the use of a single market factor to estimate stock returns (Black, Jensen, & Scholes, 1972), and dominant effect of market portfolio (Roll, 1977; Ross, 1977). Roll's critique stimulates the debate whether CAPM can be testable. The Sharpe's CAPM implies that the investors are only concerned about the market risk premium for making investment decisions but the evidence is found in the subsequent periods in which researchers report that the investors consider other factors as well. The small capitalization stock is reported to provide higher returns than large capitalization stocks and this size factor is not considered in the Sharpe's CAPM (Banz, 1981). The size stimulates the debate for re-examining the security's systematic risk (Reinganum, 1981). Later, it is found that the low price to earnings ratio (P/E) stocks provide higher returns than high P/E stocks (Basu, 1983). These explanatory factors are not explained by the single factor CAPM and usually labelled as the CAPM's anomalies as researchers find that the market's risk factor is not the only factor to estimate stock returns. In the early 1990s, the joint roles of size, book to mark and market effect is tested in the landmark studies of Fama and French (1992, 1993), as they find that the explanatory power of the CAPM significantly increases with the addition of these factors. Later, Carhart (1997) further develops this research and find that the momentum factor (winners minus losers) is another risk factor which should be accounted in the Fama-French three-factor model. Recently, Fama and French (2015) have proposed five-factor model as they find investment and operating profitability as additional factors that contribute to improve the explanatory power of the three-factor model in the U.S. market. However, Fama and French (2015) have not employed momentum factor with their five-factor model. Further, empirical performance of the five-factor augmented model (six-factor model) with the momentum factor is yet to be tested in international markets. In addition, the cross-sectional performance of the five-factor and the six-factor model also needs to be examined. Further, Fama and French (2015) highlight the limitations of five-factor model in pricing small stocks and identify this gap in their study. We attempt to fill this gap in this studies through critical assessment of asset pricing models. Before evaluating the performance of asset pricing models, I must explain theoretical framework of asset pricing. It is crucial to understand portfolio theory which is the foundation of modern asset pricing. After explaining portfolio theory, I evaluate CAPM, its extended multi beta, inflation and consumption CAPM models. Then, I shed light on the developmental process of Fama-French models, evaluate their empirical performance, applications and limitations with the critical assessment. After explaining Fama-French models. I explain the importance of momentum factor in asset pricing and shed light on its empirical performance in global markets. Then I explore the applicability of gold as a zero-beta asset in empirical asset pricing. I also examine its applicability as a hedging factor in the two-factor model. Finally, I assess a range of multifactor models by empirical, macro and state with the ICAPM criteria and propose robust asset pricing models. The structure of literature review is shown in Figure (2).

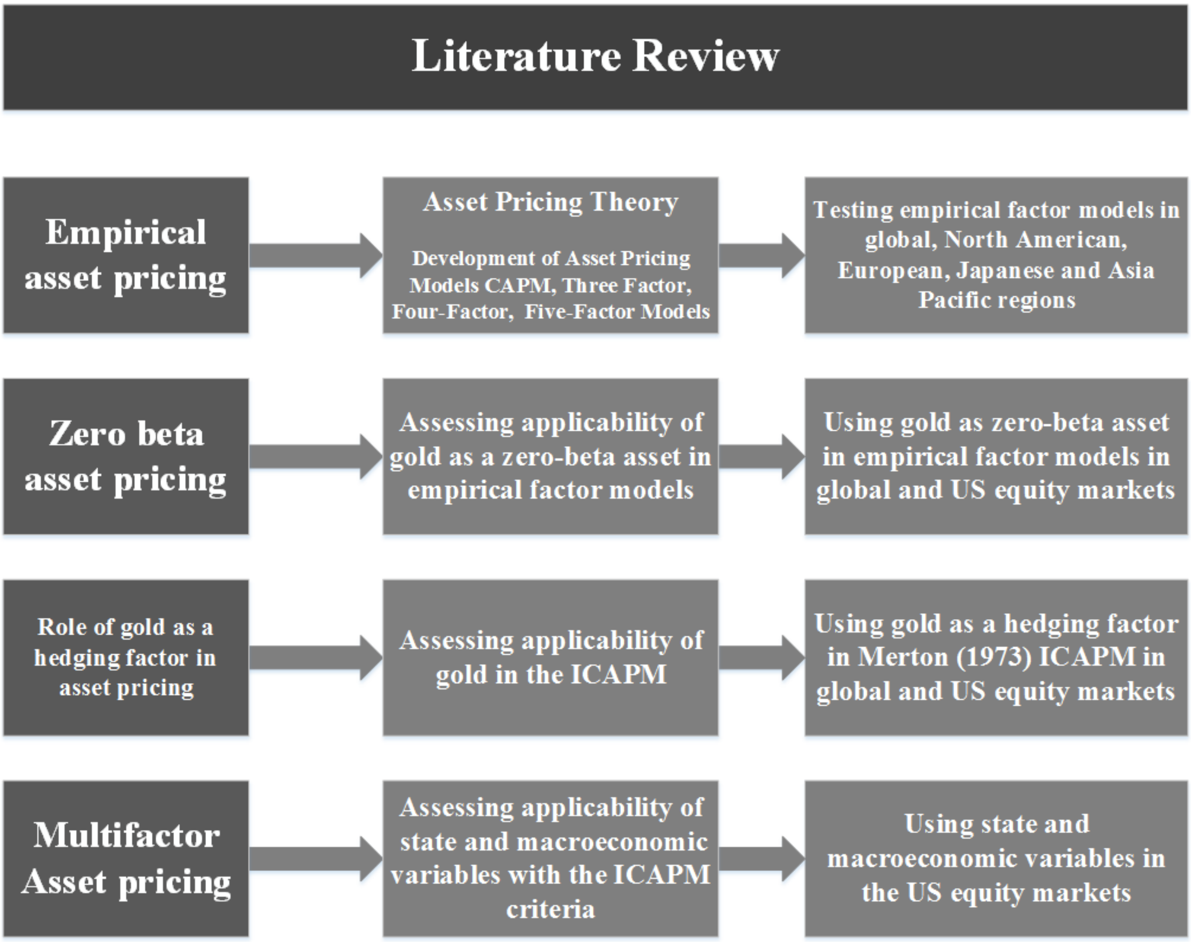


Figure 2: Structure of Literature review

Source: Author's own

2.1.3 Theoretical framework of asset pricing

2.1.3.1 Portfolio Theory

Markowitz (1952) has laid the foundation of asset pricing models in his popular study "portfolio selection" in which he explains the two-stage process of portfolio selection. The first stage involves observation and experience of available securities' performance which results in forming beliefs about their future performance. The second stage begins with those beliefs and ends with the portfolio selection. Markowitz was the first to develop a precise measure to derive portfolio's expected return and risk of a portfolio. He finds that if returns of risky assets in a portfolio are not perfectly positively correlated, then the standard deviation of the risky portfolio is less than the sum of standard deviation (risk) of all individual risky securities forming that portfolio. Portfolio selection theory formalised the investor's portfolio formation and securities' selection process whereas idea was general as every investor would consider expected return as favourable whereas variance or standard deviation (risk) as unfavourable or undesirable. There is a probability for any stock price to rise or fall in the market. Therefore, inclusion or exclusion of such securities should not affect the portfolio. But, when such securities move in opposite directions and are included in the portfolio, they reduce the volatility of the portfolio and thus reduces its overall risk.

His proposed model produces efficient frontier with a set of portfolios where investors are expected to select appropriate efficient portfolios according to their risk appetite. Markowitz's theory is based on the assumptions such as portfolio returns are normally distributed. Constant or fixed correlation exist among stocks over a period of time; investors seek maximization of economic utility; market players are risk averse and rational; information is freely available to all market players; there are no taxes and transaction costs; and actions of investors i.e. buying or selling of securities do not affect their prices. In other words, investors are price takers. Markowitz model postulates that a portfolio chosen in time t will give a random return r at time t. The main assumption of the model is that investors are risk averse and they are only concerned with the mean and variance of a portfolio for their investment during the specific time period. Therefore, only mean-variance efficient portfolios are chosen which maximize expected return at a given variance level.

Tobin (1958) extends Markowitz work and proposes a course of action for identification of suitable portfolios in the efficient portfolio set. He demonstrates how investment opportunities, transaction costs and liquidity (cash) factors may influence the investors in choosing appropriate portfolio.

Later, Markowitz (1959) explained relationship of expected returns, variance and covariance of risky assets in a portfolio which can be algebraically expressed as

Expected Return: $E[R_t] = \sum_{i=1}^{n}[R_i \, P_i]$ (2.1)

Variance: $Var\,(R) = \sum_{i=1}^{n}(R_i - E[R_i])^2$ (2.2)

Covariance: Cov $(R_i - R_j) - Corr(R_i - R_j) \times Var(R_i) \times (R_j)$ (2.3)

where *Ri* and *Rj* are risky assets or securities in a portfolio *Pi*. Covariance is the deviation from the mean returns which measures the level of direction to which returns of *Ri* and *Rj* move in a portfolio. In the case of the positive covariance, securities move in the same direction while negative covariance means the securities move in opposite directions. If covariance is zero, it means that securities' returns are independent of each other. Markowitz suggests that the knowledge of this econometric relationship enables the investors to choose set of risky assets to form an optimal portfolio. In order to make Markowitz' optimal portfolio, the investors are likely to pick securities with negative covariance as the downfall of returns of one security will be compensated by the rise in the returns of another security. Tobin (1958) has extended Markowitz's portfolio selection theory (PST) by including utility theory. Tobin (1958) marks that when investors encounter uncertain conditions, then their choices are based on the assumptions of maximizing their own utility functions. Thus, Tobin's utility theory and Markowitz's mean-variance theory provide a solution to the portfolio selection puzzle, as risk-averse investors may find it easier to choose portfolios that maximize their utility functions. Markowitz' theory formalizes portfolio diversification in corporate finance but it was nevertheless centuries' old idea. Friend and Blume (1970) note that the English translation of Spanish novel *Don Quixote* provides insight about diversification concept where Sancho Panza (a fictional character) advises his master, "It is the part of a wise man to…not venture all eggs in one basket". Friend and Blume (1970) also cite Lintner (1965b) who point out that the proverb "Do not keep all your eggs in one basket" is far too old as it was even mentioned by Torriano's (1666): *Common Place of Italian Proverbs.* However, Markowitz provides a risk reduction method but computation with this theory remains a tedious exercise for investment managers. Sharpe (1964) eased this computation difficulty through developing an efficient single index model which is computationally more efficient than Markowitz's model where the return of each security is related to the common index (Galagedera & Galagedera, 2007).

2.1.3.2 Development of Capital Asset Pricing Model

The credit for the development of Capital Asset Pricing model goes to Markowitz (1952, 1959), Tobin (1958), Sharpe (1963;1964) and Lintner (1965). However, most of the literature recognises Sharpe (1964) and Lintner (1965) for the development of CAPM. Treynor is another prominent financial economist who has worked with Williams Sharpe for the original development of CAPM (Cochrane, 2005; Elton, Gruber, Brown, & Goetzmann, 2009), but his manuscripts were not published. He provides the basic framework of the CAPM through emphasising on risk premium concept. He marks that risk premiums implicit in share prices are associated with portfolio decisions of investors. Sharpe (1963) uses a computer program for initial practical applications of Markowitz portfolio analysis technique. He has used CAPM to test 2000 securities and has reported this model simple, low cost and efficient with minimum sacrifice of information for portfolio analysis. Markowitz portfolio analysis technique was considered as complex and time-consuming exercise as it was tedious to compute mean return, variance and covariance of all securities for choosing optimal portfolios. Later, Sharpe (1964) provides a detailed explanation of his market equilibrium model through econometric modelling and diagrammatical presentation of the capital market line for choosing optimal portfolios. In his paper, he has presented a conceptual framework of the CAPM with the Capital Market Line distinguished from the pure interest rate. For his ground-breaking contribution in asset pricing, he was awarded Nobel Prize in 1990. Lintner (1965a, 1965b) further extends Sharp's work and formalised the term "excess return" in asset pricing. Other researchers have also independently published similar market models based on Markowitz portfolio and diversification. Mossin (1966) outlines a theory of market risk premiums and shows that general equilibrium specifies the existence of *market line* and shows the concept of risk in terms of the slop of capital market line. Friend, Landskroner, and Losq (1976) assess market equilibrium models proposed by Sharpe (1964) and Lintner (1965) and document clarification comments on their models. He finds that there was no conflict between these models. Sharpe and Lintner were able to quantify the risk-return relationship of risky assets in a portfolio through a simplified model. The CAPM equation can be expressed as

$$E(\tilde{R}j) = R_f + \beta_i[E(\tilde{R}_m) - R_f] \quad (2.4)$$

where $\tilde{R}j$ is the return on asset *j*, whereas $\tilde{R}m$ is the market return or portfolio of all assets taken together. The first component of the right side of the equation is risk-free rate (R_f). Sharpe (1964) marks it as riskless rate having zero variance (risk) and regard it as pure interest rate. R_f is the certain and fixed return the investor will get for delaying the current consumption for potential future consumption and investors are aware of this rate before making investments. After risk-free rate (R_f), the second component of the CAPM equation is β_i (beta) which is calculated by the slope of the regression line relating $\tilde{R}j$ and $\tilde{R}m$. Jensen (1968) defines market sensitivity of security *j* with allegorical representation as:

$$\beta_j = \frac{Cov(\tilde{R}_j, \tilde{R}_m)}{\sigma^2\,(\tilde{R}_m)} \quad (2.5)$$

where β_j is regarded as the measure of security risk or systematic risk. It is deemed crucial in asset pricing models to determine prices of securities. It can also be described as the amount of risk times the market price of risk. Investors are rewarded with the risk premium for taking risk and investing in the market. The risk arises due to variations in the market. The CAPM stipulates that increasing investment in the market portfolio increases both risk and market risk premium, therefore, specifies linear relationship between expected return and returns on risk-free and risky investments.

The CAPM converts Markowitz model's algebraic statements into an efficient testable model. According to Galagedera and Galagedera (2007), the CAPM relates expected return of a security as a measure of its systematic risk. The CAPM reflects the view that securities are priced in a way that their expected risks are rewarded by their expected returns. CAPM conveys two basic relationships, Capital Market Line (CML) and Security Market Line. The Capital Market Line (CML) specifies expected return for an individual investor on a portfolio. There is a linear relationship between risk and return on efficient portfolios which can be written as:

$$E(Rp) = R_f + \sigma_p \left(\frac{E(R_m) - R_f}{\sigma_p}\right) \tag{2.6}$$

where Rp is the return on a portfolio; R_f is the risk-free rate; Rm is the return on market whereas σ is the standard deviation (risk) on the portfolio. On the other hand, Security Market Line expresses the return for the individual investor and is expressed in terms of risk-free rate and risk of security or portfolio as is shown in equation (4.1). Black, Jensen, and Scholes (1972) highlight the four assumptions of the Sharpe's (1964) CAPM; 1) Risk-averse investors choose portfolios on the grounds of mean and variance; (2) There are no taxes and transactions costs; (3) Investors have homogeneous views on joint probability distribution of security returns; and (4) all investors can borrow and lend at a given riskless rate of interest.

The CAPM is usually expressed in expected returns. Expected returns are computed from the difference of future and current prices divided by current prices. Therefore, it would be useful to express the CAPM in price to obtain the valuation in the required currency. Elton, Gruber, Brown, & Goetzmann (2009) express the CAPM in price as:

$$P_i = \frac{1}{r_F}\left[\bar{Y}_i - (\bar{Y}_M - r_F P_M)\frac{cov\,(Y_i Y_M)}{Var\,(Y_M)}\right] \qquad (2.7)$$

where, r_F is the risk-free rate which is computed as (r_F +1), Pi is the present price of asset i and P_M is the present price of all assets in portfolio. Yi is the market value of an asset i including dividends and Y_M is the market value of all assets in portfolio including dividends. Eq. (2.7) considers expected dollar return next year $\bar{Y}_{i,}$ minus payment for compensation for risk taking and then taking the present value of net amount. The CAPM expressed in prices is used for the valuation of new stocks in the stock markets.

Fama and French (2004) clarify that the Sharp-Lintner CAPM added two assumptions to the mean-variance efficient portfolio theory. According to their assessment, the first assumption is about the complete agreement among investors on the joint distribution of returns whereas the second assumption is about borrowing and lending at the risk-free rate. The risk-free rate does not change regardless of the amount lent or borrow and riskless borrowing opportunities are available for all investors. There is no covariance between riskless asset and market portfolio and riskless asset does not move with or against a market index or portfolio (Sharpe, (1964).

2.1.3.3 Testable Implications for Sharpe's CAPM

There are three main testable implications for the Sharpe's CAPM. 1) Expected returns on assets are linearly related to their betas which means that higher beta securities have higher expected return than lower beta securities. Beta is a risk of an asset, so it can be stated that there is a linear relationship between risk and expected risk. In the Sharpe's CAPM, beta is a complete measure of risk for an asset; 2) The beta premium should be positive which underlines that the market portfolio's return should be higher than those assets whose returns were uncorrelated with the market; 3) The returns of uncorrelated assets should be equal to the risk-free rate while risk premium is the difference between expected return on the market and the risk-free rate. Cross section and time series methods are conventionally used to test these assumptions. The existence of perfect market conditions is an important underlying assumption of the CAPM.

Earlier, simple tests were performed to test CAPM's theory and confirming the risk-return relationship. Sharpe (1965) examines the empirical performance of 34 mutual funds and explained risk-return relationship through plotting expected returns and standard deviation. He reports highly significant relationship when he regressed the expected returns over the standard deviation and also when he regressed the standard deviation over the expected returns. He points that the true relationship should exist between the two lines. Later, Sharpe and Cooper (1972) further investigate the risk-return association. They construct the stock portfolios based on six months earlier estimated betas to find out whether the high risk is associated with the high returns of portfolios and whether the regression (slope) is linear and significant. Later on, application tests are performed to test the validity of the CAPM by using the market model to evaluate the empirical performance of portfolios and mutual funds. Sharpe (1966) considers the average return and risk to evaluate the mutual fund performance to determine whether high average returns are obtained through holding risky portfolios. His results are in line with CAPM in which he points that the managers spend more time in diversification than finding incorrectly priced securities. Jensen (1968) further investigates the mutual fund performance through the CAPM and marks that the managers are not able to outperform by opting buy and hold policy and confirms the CAPM's assertion that the capital markets are efficient and finds little evidence where individual funds could perform better than what one could expect due to a random chance. However, the research of Friend and Blume (1970) challenge the CAPM's validity in which they examine the performance of 200 portfolios and come up with the evidence that the CAPM does not hold. They document a significant negative relationship which is in contradiction with the Sharpe (1964) theory. The negative risk-return relationship reflects lower risk in the market that arise during market recovery or market boom periods.

2.1.4 Initial tests of the CAPM

Lintner (1965b) performs direct tests by using market model and performs first pass regression to estimate beta coefficients for a sample of 301 stocks. This is followed by the cross-sectional regression to estimate the regression coefficients.

$$\bar{R}_i = \gamma_0 + \gamma_1 b_i + \gamma_2 S_{ei}^2 + \eta_1 \tag{2.8}$$

where γ_0 is the cross-sectional pricing error, $\gamma_1 b_i$ is the price of the market risk and $\gamma_2 S_{ei}^2$ is the price of the residual risk. For the CAPM's validity, γ_0 = 0; whereas γ_1 = $\overline{\mathrm{R_m - R_f}}$.; $\gamma_2 = 0$. In the Lintner CAPM's results, γ_0 was greater than R_f, γ_1 was less than market premium (R_m- R_f) whereas the residual risk (γ_2) was significant and positive. The results show that the CAPM does not hold. Blume (1970) accounts errors in the variables that improves methodology for the CAPM testing.

2.1.4.1 Black, Jensen, and Scholes (1972)

Black, Jensen, and Scholes (1972) have used extensively in-depth CAPM tests which allow reviewing CAPM's assumptions. They highlight the empirical contradiction of the classic Sharpe's CAPM through their empirical tests. The CAPM is developed on the portfolio and capital market theories and those theories are themselves based on some extreme assumptions. For instance, it will be unfair to mark the only assumption that investors are only concerned with the mean and variance of single period portfolio return. It can also be fair to assume that investors are concerned with co-variance of their portfolio returns with wealth, income and investment opportunities. If investors are concerned about other factors as well while selecting their portfolios, then the single market beta factor may not be enough to explain the risk of an asset. This empirical contradiction stimulated for the search of a better and appropriate asset pricing model. They proposed two-factor model based on the information available on the aggregate portfolios. They constructed the second variable called a zero-beta portfolio to explain asset's risk. The equation for expected return on security J under Black, Jensen, and Scholes two factor CAPM can be mathematically expressed as

$$\tilde{R}_J = \tilde{R}_z\left[1 - \beta_J\right] + \tilde{R}_M\beta_J + \tilde{w}_J \tag{2.9}$$

Where $\tilde{R}_z$ is the return on the zero beta portfolio whose return is not correlated to the market beta whereas $\tilde{R}_M\beta_J$ is the stochastic market return. Black, Jensen and Scholes (1972) construct portfolios in the subsequent periods to reduce loss of information and employ two pass regression technique to first estimate stock betas and then estimate sensitivity of portfolios to the average market returns. Their findings are in line with findings of the zero beta CAPM of Black (1972) and are not consistent with the standard CAPM.

2.1.4.2 Fama and MacBeth (1973) Methodology

Fama and MacBeth (1973) teste CAPM in the NYSE (New York Stock Exchange) by using value-weighted portfolios to find out whether the market portfolio is efficient. The methodology adopted by Fama and MacBeth (1973) is recognized as a most comprehensive CAPM testing methodology. Following analogues approach to Black, Jensen, and Scholes (1972), they construct twenty portfolios in three different sub-periods. In the first period, individual stock betas are estimated while in the second period, portfolio betas are estimated. The third period is used to re-estimate portfolio betas to bring robustness and stability in CAPM testing methodology. The returns are then used in the cross-sectional regression. The variables included are; 1) Squared market beta to test the implication that there is a linear relationship between the market beta and the portfolio expected return, 2) Residual variance of portfolio returns are used to test whether market beta was the only factor of risk explaining expected returns. The estimated variables for portfolios can be represented in the following cross-sectional testable model

$$R_{jt} = \tilde{\gamma}_{0t} + \tilde{\gamma}_{1t}\beta_j + \tilde{\gamma}_{2t}\beta_j^2 + \tilde{\gamma}_{3t}S_j + \tilde{\eta}_{j_t} \tag{2.10}$$

where β_j^2 is the squared market beta which is added to find out whether portfolio expected return of portfolio j is linearly related to the market beta. While S_j is the residual variance which is obtained after the regression of portfolio returns with market and it is used to find out whether the market beta is the only risk factor influencing expected return of portfolio j. Residual variance S_j measures that risk of security j which is not related to market beta. These variables could not provide explanatory power to the average returns explained by a market beta. The results of Fama and MacBeth (1973) study is consistent with the findings of Black, Jensen and Scholes (1972). They find that overall, there is a positive relationship between risk and return and this suggests the efficient market portfolio for the NYSE value weighted index. The cross sectional results of Fama and MacBeth (1973) reinforce efficiency of the market value weighted portfolio and it lies on the minimum variance frontier. It is also found that the beta (systematic risk) influences average returns while coefficient and residuals from the regressions underpin efficient capital market which is the main underlying assertion of CAPM. The coefficients of the CAPM are estimated via regression and if estimates are statistically significant (i.e. p value <0.05), then the null hypothesis(H_0=0), is rejected; and estimates are compared with CAPM's recommended estimates ($\alpha = 0, \beta = \overline{R_m - R_f}$).

2.1.5 Assessment of the CAPM

The CAPM provides simple and powerful predictions for risk and return that makes it a powerful and attractive expected return model, but unluckily, its empirical record is not good enough to validate its application. The anomalies in the CAPM has stimulated wide-ranging research efforts to improve asset pricing since long as is noted by Merton (1987) who marks that the CAPM model is based on frictionless market, optimistic investor behaviour and complete information, and can be adequate to capture the complexity of rationality in action (Merton, 1987). Therefore, he recommends using adequate state or country factors as factor loadings to improve asset pricing.

The poor empirical record of the CAPM reflects its theoretical weakness, flaws in underlying assumptions and difficulty in the valid testing of the model (Fama & French, 2004). However, having some empirical support during the periods of economic stability, the anomalies lead to the empirical failure of the CAPM during abrupt market conditions. Dempsey (2013) criticises the CAPM for its failure during the financial crisis and declares it as dead. His research also expresses doubt on the viability of CAPM's extended models as they are based on the CAPM's beta. Bornholt (2013) supports this argument by highlighting beta anomalies in the CAPM and expresses concern on the long-term viability of Fama-French three-factor model. Moosa (2011, 2013) criticises and invalidates financial models by arguing that the global financial crisis is the empirical failure of asset pricing models. The weakness in the framework of Efficient Market Hypothesis (EMH) and the CAPM can be identified from the CAPM's theory. The theory states that the risky assets should outperform less risky assets in diversified optimal portfolios in the efficient markets as expected return on assets are linearly related to their betas. Thus, the investors tend to focus on the 'beta' and overlook variable economic factors while choosing their investment portfolios (Moosa, 2013). Avramov & Chordia (2006) also attribute the failure of the CAPM to its static nature and point out that the asset pricing models are not able to capture the market anomalies with constant beta and suggest that the beta should vary according to the changing macroeconomic variables. Abbas, Ayub, Sargana, and Saeed (2011) support this view by arguing that beta derived from the past prices may make errors in valuation, therefore, beta should be time-varying and sensitive to the economic factors. Due to its reliance on the single beta factor and inability to address micro and macroeconomic factors, multifactor models were proposed. Fama and French (2004) point out the empirical failure of the CAPM by arguing that "the empirical record of the CAPM is poor enough to invalidate the way it is used in applications as the beta alone cannot explain the cross-sectional differences in stock returns. William Sharpe defends single factor CAPM by pointing out that *"anyone who believes markets are so screwy that returns are not related to the risk of having a bad time, which is what beta represents, must have a very harsh view of reality"* (Burton, 1998).

2.1.6 Extensions of the CAPM

2.1.6.1 CAPM with multi periods

One of the underlying assumptions of CAPM is that the investors make portfolio decisions for a single time period. Jensen (1968) and Fama (1970) show that under the general set of assumptions for consumer behaviour in multi-period and perfect market context, individuals act as single period expected utility maximisers. Therefore, the CAPM can be used for different time periods as well. However, it will be desirable to predict different or multi-period investments with the multi-period or multi beta CAPM models. The prominent multi-period models are the Consumption-based CAPM (CCAPM) and Intertemporal CAPM (ICAPM).

2.1.6.2 Consumption CAPM

Rubinstein (1976) develops a formula for the valuation of uncertain income streams for securities and options and put insight on asset pricing in multi- periods. Mankiw and Shapiro (1984) define the framework of Consumption CAPM by giving credit to Breeden (1979) who derives a concise expression related to asset returns and aggregate consumption. Breeden (1979) derives multi-good single beta asset pricing model for the continuous time period with uncertain consumption-goods-prices and uncertain investment opportunities. He marks that when no riskless asset is used, zero-beta CAPM is derived. He finds that the random changes in consumption are linearly related to the random changes in wealth and state variables. The relationship between the asset returns and consumption growth rate can be written in the equation form as:

$$R_i = a_0 + a_2\beta_{Ci} + u_i \qquad (2.11)$$

where R_i is the realised return on asset i at time t whereas Ci represents growth in aggregate consumption and u_i represents the error term.

$$a_0 = [E_t(S_t)]^{-1} - 1 \tag{2.12}$$

where S_t is the marginal rate of substitution for consumption at time t. Consumption beta (β_{Ci}) can be calculated as:

$$\beta_{Ci} = Cov(R_{it,}C_{t+1}/\, C_t\,)/\, Cov(R_{MT,}C_{t+1}/C_t) \tag{2.13}$$

In the CCAPM, the measured beta of an asset i (β_{Ci}) is like that of the standard CAPM, i.e. it is covariance of asset's returns with the consumption growth ($C_{t+1}/\, C_t$). The investors tend to hold assets so that they can shift purchasing power from one to another period to enable them fund consumption in those time periods when their level of income would be low. It is accomplished from the research of Lucas (1978) and Breeden (1979) that the estimation of systematic risk obtained from the covariance of asset's returns with the consumption growth is better than the covariance of returns with market portfolio. Their results provide residuals having zero mean. Further, the residuals between asset returns and growth in aggregate consumption are also uncorrelated which is desirable for the validity of the model. Literature suggests that several financial econometric researchers have performed CCAPM tests to improve estimation of systematic risk that could be explained with the covariance of security returns with the growth on aggregate consumption but concrete evidence is not found. Shapiro and Mankiw (1985) compare the performance of the CAPM and CCAPM with the cross sectional data of 464 U.S. companies and find that the CAPM outperformes CCAPM as consumption betas are not statistically significant. On the other hand, CAPM betas are statistically significant and provide a better estimation of systematic risk. Later on, Breeden, Gibbons and Litzenberger (1989) perform extensive CCAPM tests in which they adjust measurement problems associated with the consumption data and test

CCAPM by using consumption and portfolio having maximum correlation with the consumption. They find highly significant and positive market price of the risk with estimate of real interest rate close to zero which was desirable. However, the results from traditional CAPM were also similar and they are unable to prove that CCAPM outperforms the traditional CAPM through their empirical analysis. Later studies also support traditional CAPM models and do not find convincing evidence in favour of the consumption based models. For instance, Campbell and Cochrane (2000) highlight the poor performance of the consumption CAPM and prove from their empirical tests that the CAPM and its extended models could provide better estimates of systematic risk than the Consumption based models. They argue that the CCAPM produces expected returns which are time varying which can be tracked by the divided price ratio. The traditional CAPM models are based on portfolios and they can capture some of the variations in state variables which state-independent consumption functional is unlikely to capture. Therefore, portfolio based models (CAPM models) are better than the consumption based models (Cochrane, 2005).

2.1.7 Factor models

There are a number of factor models that are used for investment analysis, but the most prominent academic models are those developed by Fama and French (1993) and Carhart (1997). In their ground-breaking research, Fama and French (1992, 1993) jointly examine market beta, firm size and book-to-market values in the cross-sectional analysis of NYSE, AMEX and NASDAQ stock indices. Their research challenged market beta as the sole measure of security risk and proposed a multifactor model with size and book-to-market value as additional security-specific factors. Earlier, various researchers have highlighted the influence of security-specific factors in determining security returns. For instance, Banz (1981) examines empirical relationship between stock returns and total market value of

NYSE common stocks. He reports that the smaller firms had higher risk-adjusted returns than larger firms and this size factor exists for more than forty years and therefore, CAPM is miss-specified. In the same year, Reinganum (1981) also points out CAPM's empirical anomalies and documents size and value anomalies. He constructs portfolios on the basis of earning per price (E/P) and firm size. He finds that the computed average returns were different from the CAPM model. Later, Basu (1983) confirms that stocks with the high E/P (earning per price) earn high risk-adjusted returns than the stock with the lower earning per price (E/P) ratios. These results document empirical anomalies in the single factor model as size and value factors are not explained by the single factor model. These findings challenge the explanatory power of the single market beta as other security specific factors also play role in explaining returns of stocks. Chan, Hamao, and Lakonishok (1991) report a significant effect of the book-to-market equity ratio on stock returns in Japanese markets and their results were consistent with previous research (Basu, 1983).

2.1.7.1 Three-factor model

Fama and French (1992) recommend a multifactor model which was later known as a three-factor model. This model shows that the investors are not just concerned about macroeconomic market risk which is explained in the Sharpe-Lintner CAPM but also, they are concerned about microeconomic risk, therefore, size (market capitalisation) and book-to-market ratio (value) should also be included as additional factors in the CAPM model. In their next papers, Fama and French (1993, 1996) provide further detailed evidence to support their recommended three-factor model in which they point out that the anomalies of single factor CAPM are addressed in the three-factor CAPM. Fama French three-factor model can be mathematically expressed as:

$$E\,(\tilde{R}_{i,t}) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + e_{i,t} \qquad (2.14)$$

where, $E(R_{i,t})$: expected return on asset or security *i* at time *t*;

$E(R_{m,t}) - R_{F,t}$: excess return over risk-free rate on market index or portfolio at time *t*;

SMB_t: the difference between return on portfolios with smaller and larger market capitalisation at time *t*

HML_t: the difference of portfolio returns on high BE/ME and low BE/ME stocks at time *t*

We refer to this model hereafter as the Three-Factor model.

The underlying concept behind size and book-to-market value the construction of portfolios which is a two-step process. In the first step, securities are ranked into two groups according to their size, small and big relating to their market equity. Size is defined each year as the total market value of equity (number of shares times price). Then securities are ranked into three groups sorted on the book-to-market equity ratio (BE/ME). Each year, the two-way categorization is used to make six portfolios. The first portfolio contains all stocks with small size and low book-to-market category whereas the last one contains stock with the biggest market value and book-to-market categories. The value-weighted portfolio returns are estimated for each of the portfolio.

In the second step, the actual indexes are defined. The size variable is defined as small minus big (SMB) – the difference between two portfolios. The second portfolio is defined as the high minus low (HML) - the difference between high BE/ME portfolios and low BE/ME portfolios. This construction of two portfolios is done to make size factor free of the book-to-market effects and book-to-market factor free of the size effect. The third and last variable is the market excess return over Treasury bill rate. The formulated variables are reported to have 0.08 correlation with the zero net investment which has implications for equilibrium

CAPM tests. Fama and French (1993) find that the explanatory power (R-squared) of the model is considerably increased when size and book-to-market value variables are added in the CAPM. In the U.S. market, the size and expected returns relations are reported to be strongly negative that highlights the higher returns for smaller firms. On the other hand, the relationship between returns and book-to-market equity ratio is strongly positive that shows higher returns of value stocks over growth stocks (Fama & French, 1992, 1993, 1996). However, the predictive power of three-factor model has been reported comparatively weak in the U.K. market (Pástor & Stambaugh, 2000).

2.1.7.2 Assessment of the three-factor model

The size factor is derived from companies' relative prospects to economic environments. During the financial crisis, due to uncertain economic conditions, the earning capacity of small companies is more sensitive than the larger companies. Regarding size, asymmetric information also has a different impact on the smaller and larger firms. Larger firms distribute information to a greater level than smaller firms, thus larger firms have less information asymmetry than smaller firms. The investors consider this as a risk factors and hence, demand the extra return for investing in smaller firms.

Regarding the book-to-market (value) factor, Lakonishok, Shleifer, & Vishny (1994) highlight the value anomaly by arguing that the value strategies are not fundamentally riskier instead sub-optimal behaviour of investors cause them to yield higher returns. They explain that most investors and institutional money managers have shorter time horizons and they prefer to invest in glamorous stocks rather than value stocks in an attempt to make abnormal returns. They highlight that the money managers have shorter time horizons and may perceive value strategy as riskier as it takes 3 to 5 years to pay off and therefore, may end up making judgemental errors in their investment decisions. Highlighting underperformance of pension funds relative to market index, Lakonishok, Shleifer, & Vishny (1992) mark that if portfolios of money managers are investigated, overinvestment in glamorous stocks and underinvestment in value stocks can easily be identified resulting in the underperformance of funds than market index. Daniel, Titman, & Wei (2001) reject three-factor model in the Japanese markets and Gregory, Tharyan, and Christidis (2013) find poor performance of the three-factor model in the U.K. equity market that raises questions on its empirical performance on other markets as well.

These arguments provide the basis for criticism on the three-factor model as the primary motivation for its development was not to identify factors which estimate security prices but explaining average returns (Black, 1995). Thus, it can be summarised that the size factor is more specific to smaller firms than larger firms whereas the value effect is useful in the long run rather than short run. Therefore, the performance of three-factor model remains debatable.

2.1.7.3 Four-factor model

The extension of the three-factor CAPM is the four-factor CAPM in which Carhart (1997) proposes momentum as another risk factor for stock returns after Jegadeesh & Titman (1993) document evidence that stock returns can be predicted from momentum. The four-factor model can be mathematically expressed as:

$$E\,(\tilde{R}_{i,t}) = R_{F,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{F,t}\big] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,m}[E(MOM_t)] + e_{i,t} \qquad (2.15)$$

where MOM_t is the Carhart (1997) momentum factor, being the difference in the return between a portfolio of stocks with highest decile returns over the previous year, and a portfolio of stocks with lowest decile returns over the previous year. We refer to this model hereafter as the Four-Factor model. In this way, previous year's momentum effect is captured to address security's risk as it is reported to significantly affect its returns. The measure of performance is the Carhart's alpha. It is considered the extension of Jensen's alpha. Positive and statistically significant Carhart's alpha shows higher returns after adjusting for the four risk factors. Theoretically, Carhart's alpha should be close to zero for appropriate predictive performance of an asset pricing model.

2.1.7.4 Momentum and international equity returns

Carhart (1997), Fletcher and Forbes (2002), Fama and French (2012) and others report the superior performance of this model over single and three-factor models in global markets. Maio and Santa-Clara (2012) compare the performance of the eight multifactor models and report superior performance of the four-factor models in the U.S. equity market. In a similar vein, Lutzenberger (2015) compares the performance of empirical and ICAPM models in the European equity market and find that the four-factor model outperforms competing asset pricing models. In the U.K. equity market, Gregory, Tharyan, and Christidis (2013) also confirm that the four-factor model performs better than the three-factor model. They, however, admit that the four-factor model explains cross-sectional returns of large firms without extreme momentum effects. Their research leaves room for researchers to improve asset pricing in the U.K. equity market.

Asness, Moskowitz, and Pedersen (2013) find that the momentum factor effectively explains returns in the most equity markets, but it is less prominent in collectivistic cultures. For instance, Chui, Titman, and Wei (2010) find the strong positive relation between individualism and momentum profits and find that momentum factor dominates in those countries and cultures where individualism is highly valued. Fama and French (2012) confirms this evidence and find that momentum factor is significant in the developed regions of North America, Europe, and the Asia Pacific that value individualism but it struggles to explain returns in Japanese region that is based on collectivistic culture and value collectivism more than individualism.

2.1.7.5 Application of factor models

Ang and Kjaer (2012) among others mark that factor investing can be seen as a useful tool for long-run investment strategy especially for those institutions who are not vulnerable to poor returns in occasional periods. However, little evidence is found for their applications for smaller firms particularly for U.K. market (Gregory, Tharyan, & Christidis, 2013). The proponents of modern finance argue that the additional factors tend to increase risk premium. It allows investors to demand an extra return for their risk exposure for size, book-to-market value and momentum (Strong & Xu, 1997; Fama & French, 1998). Factor investing has been recommended for sovereign Norwegian investment fund where government invests for future generations (Ang, 2009). The data from the Ken French website reveal that the four-factors (market, size, book-to-market ratio and momentum) have remained significantly positive from 1927 to 2012 in the U.S. market but their response is different during the global financial crisis of 2008. The momentum factor experiences a sharp downward trend during this financial crisis than size and book-to-market value. These factor models are extensively used in the performance evaluation at the firm or sector level. For instance, Iqbal, Akbar, and Shiwakoti (2013) have used the Fama-French three-factor and the Carhart (1997) four-factor models to evaluate the long run performance of the British firms that make multiple rights issues. Coakley, Dotsis, Liu, & Zhai (2014) have employed those models in option pricing and make a noteworthy contribution in explaining long-short run strategies with the three-factor model.

2.1.7.6 Five-factor model

Fama and French (2015) develop the five-factor model through incorporating profitability and investment factors in the three-factor model (Fama and French, 1992). They highlight that five-factor model performs better than the three-factor model in capturing stock returns, but still struggles to address small stocks with low average returns. Earlier, Fama and French (2006) have reported the effect of profitability and investment on stock returns in their asset pricing tests and conclude that high profitability leads to higher returns. Various other researchers have also reported statistically significant evidence of investment- expected returns relationship (Haugen & Baker, 1996; Titman, Wei, & Xie, 2004).

Novy-Marx (2013) documents further evidence of strong relation of expected profitability with expected returns. He marks that profitability which is measured by gross profits to assets has the similar effect on cross-sectional returns as a book-to-market prediction. It is reported that the performance of value strategies is increased after controlling for profitability particularly among larger liquid stocks. The profitability factor addresses earning and unrelated profitable trading strategies.

The testable five-factor Fama and French (2015) model can be expressed as:

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,C}[E(CMA_t)] + \beta_{i,r}[E(RMW_t)] + e_{i,t} \quad (2.16)$$

where CMA_t and RMW_t are the additional Fama and French investment and operating profitability factors, at time *t*. We refer to this model hereafter as the five-factor model. Five-factor model is an extension of the three-factor model and primarily serves to improve its performance for larger and liquid stocks.

2.1.7.7 Assessment of factor models

However, the development of three, four and five-factor models considerably increased the explanatory power of the model, but these models experience criticism as well (Chopra, Lakonishok, & Ritter, 1992). The critics argue that the addition of these risk factors have resulted in extra returns than they are really perceived as extra risk elements. For, instance Chan, Jegadeesh, and Lakonishok (1996) criticise Fama French factors by highlighting that market risk, size, book-to-market effects do not explain the changes in stock returns as the market responds only gradually to new information. After the global financial crisis, the academic financial model including equilibrium asset pricing models was heavily criticised as they were not able to predict any unforeseen collapse of financial markets (Colander et al., 2009).

Despite the development of multifactor CAPM models, their empirical performance remains questionable during times of uncertainty. In order to understand the poor performance in depth, DeMiguel, Garlappi, and Uppal (2009) have compared the performance of 14 asset allocation models by using different empirical and simulated datasets. They reveal that several extensions to the mean-variance models have been proposed to deal with the estimation error problem but they fail to outperform. They conclude that more research should be done to improve the estimation of stock returns by focusing not only on statistical methods, but also other relevant information should be taken into account for reliable asset pricing.

Similarly, Subrahmanyam (2010) also stresses for more research to improve asset pricing. He performs empirical tests on various risk-return models and finds that the overall picture for asset pricing models remains murky and suggests to take into account the correlation structure amongst variables and develop a comprehensive set of controls to improve asset pricing. His research concludes that it is hard to interpret the existing literature on the predictors of stock market returns as various models use different controls that yield different results. These arguments provide the basis for criticism on factor models as the primary motivation for their development is not to improve estimation of expected returns as is emphasised in Black (1995), but instead they focus only to explain average returns.

However, researchers have made attempts to improve predictability of stock returns through improving predictive regression (Zhou, 2010), and recommending sophisticated CAPM tests (Guermat, 2014). But the question of improving CAPM's predictability to predict financial crisis remain unanswered. Recently, Fama and French (2015) propose the five-factor model to improve their three-factor model but it has also received criticism as it has limitations. For instance, Fama and French (2015) admit the empirical weakness of their five-factor model in capturing average returns of small stocks. Furthermore, the five-factor model is limited in capturing the risk of profitable firms with high leverage and vulnerable to financial distress and bankruptcy. Therefore, research is required to improve the five-factor model in particular, and asset pricing in general.

2.1.7.8 Cross-sectional performance of the five-factor model

Further, they leave another gap as the cross-sectional performance of the five-factor model is not reported in their Fama and French (2015) study. In other studies, they have also emphasised on cross-sectional tests in addition to time series tests. For instance, Fama and French (1993, 1996, 2008) view cross-sectional performance as the main testable implication of an asset pricing model. Fama and French (1993) perform Fama and MacBeth (1973) tests, Fama and French (1996) provide cross-sectional evidence that their model explains cross-sectional variation of average returns on portfolios formed on size and book-to-market and highlight limitation of their model on other test portfolios, and particularly it does not much explain variation on portfolios sorted on momentum. Other researchers Maio and Santa-

Clara (2012), Kan, Robotti, and Shanken (2013) perform cross-sectional tests to compare the performance of the competing empirical and ICAPM multifactor models. In a similar vein, we attempt to address this gap and follow Fama and French (1993) and adopt traditional Fama and MacBeth (1973) methodology. Further, we follow Kan, Robotti, and employ Ordinary Least Square (OLS) and Generalised Least Square (GLS) estimation methods to produce the precise estimates in cross-section. In this way, we test the five-factor and other competing empirical factor models in different global regions and compare their cross-sectional performance.

2.1.7.9 Five-factor model augmented with momentum

It is surprising that Fama and French (2015) have not tested their model on momentum portfolios, however, they state that "*when the LHS portfolios are formed on momentum, in which case including a momentum factor is crucial".* Further, they also admit in Fama and French (1996) that their three-factor model is unable to explain cross-sectional variation on the portfolios sorted on momentum portfolios. In other related work, they utilise momentum factor with their three-factor model even when left-hand-side (LHS) portfolios are sorted on size and book-to-market (Fama & French, 2007, 2008, 2010, 2012). In Fama and French (2015) study, they employ the LHS portfolios sorted on the five factors i.e. size, value, investment, and profitability. Hence, there is a gap of research as the five-factor model needs to be assessed on portfolios sorted on momentum and in that case, the inclusion of momentum as six factor would be crucial. As we also utilise size and momentum portfolios as LHS test portfolios in addition to size and book-to-market portfolios, hence, we include Carhart (1997) momentum factor with the five-factor model. In this way, we develop the six-factor model which is the five-factor augmented model with the momentum factor. The first working hypothesis can be expressed as:

Hypothesis H_1 : *The performance of five-factor model will improve with the addition of* *momentum factor*.

The testable five-factor Fama and French (2015) augmented model with momentum can be expressed as:

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,m}[E(MOM_t)] + \beta_{i,C}[E(CMA_t)] + \beta_{i,r}[E(RMW_t)] + e_{i,t} \tag{2.17}$$

Fama and French (2017) provide evidence of the empirical performance of the five-factor model in international equity markets. However, six-factor model is yet to be tested on different global regions. In this way, they leave this gap of research that needs to be addressed. This study attempts to fill this gap as it assesses the performance of the six-factor model in the global market and then also in different global regions. We test this six-factor model on different global regions as Griffin (2002) marks that Fama-French factors are country-specific, therefore, it is crucial to examine this six-factor model on other global regions as well. Griffin (2002) also reveals that the pricing errors arise when global factors are used for the Fama-French three-factor model. In this study, we test for the six-factor model that whether the addition of the momentum factor improves the performance of the five-factor model when global factors are used. For this purpose, we test this model with both local and global factors in each region.

We test this six-factor model on two sets of LHS test portfolios, size and book to market and size and momentum in the global market and also in other global regions of North America, Europe, Asia Pacific, and Japan.. Further, we compare the performance with other traditional models such as Sharpe (1964) single factor CAPM, Fama and French (1993) three-factor, Carhart (1997) four-factor, and Fama and French (2015) five-factor models. We compare the performance of competing asset pricing models in international markets with time series and cross-sectional tests.

2.2 Gold as a zero-beta asset in asset pricing

After examining the applicability of the momentum factor in the Fama and French (2015) five-factor model, we explore an alternative proxy of the zero-beta rate to improve asset pricing. The researchers in the past have challenged the empirical nature of risk-free lending and highlighted the fact it may also be negative (Brennan, 1971). The return on risk-free asset is linked with its certain return over a period of time and uncertainty always exists (Cochrane, 2009). Some argue that there is no "free lunch" in financial markets and risk always remain with even safe havens (Agarwal & Naik, 2004). In this section, we aim to assess the empirical application of gold as a zero-beta asset in the asset pricing models. The motivation of this research is Black, Jensen, and Scholes (1972) zero-beta CAPM in which risk-free rate is replaced with the return on a zero-beta portfolio.

2.2.1 Zero-beta CAPM

A principal assumption of the Sharpe's CAPM is that investors may lend or borrow to an unlimited extent at the riskless interest rate. Brennan (1971) relaxes the strict assumption of the availability of borrowing and lending at the risk-free rate to estimate expected returns with an equilibrium asset pricing model in which investors face different lending and borrowing rates and the risk-free rate is not available to every investor. Black, Jensen, and Scholes (1972) relax the CAPM's assumption that investors can borrow and lend freely and to an unlimited extent at the risk-free rate. They estimate the CAPM in the absence of a risk-free rate. Black (1972) provides theoretical evidence in support of the Black, Jensen, and Scholes (1972) findings and reveals that, in the absence of riskless borrowing, a zero-beta portfolio of risky assets replaces the risk-free rate and demonstrates a linear risk-return relationship. Black, Jensen, and Scholes (1972) define this zero-beta portfolio as an efficient portfolio which is uncorrelated with the market and which possesses minimum variance. Black (1995) further argues that the zero-beta portfolio is well-grounded theoretically, and helps in estimating expected returns. In his view, the Fama and French (1993) size and book-to-market factors tend to explain average returns rather than estimating expected returns, and he argues that estimating expected returns is different from explaining average returns or explaining variance, as estimating expected returns is more challenging and requires a theoretical rather than a pragmatic foundation. This study aims to develop zero-beta models and hence, it would focus on estimating expected returns that just explaining average returns.

Black (1972) also identifies this assumption as unrealistic for all investors, and further documents empirical support in support of the use of zero-beta portfolios, while criticising the traditional CAPM after comparing the linear risk and return relationship.

Black, Jensen, and Scholes (1972) argue that a two-factor model better explains the risk and return relationship than Sharpe's single-factor CAPM. We may define the conventional CAPM as:

$$E\,(\tilde{R}_{i,t}) = R_{F,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{F,t}\big] + e_{i,t} \tag{2.18}$$

where $E\,(\tilde{R}_{i,t})$ is the expected return on asset *i* at time *t*, R_{Ft} is the risk-free rate as proxied by the return on a 1-month Treasury Bill at time *t*, $E\big(\tilde{R}_{m,t}\big)$ is the expected return on the market portfolio at time *t*, and $e_{i,t}$ is an error term.

By contrast. Black, Jensen, and Scholes (1972) express their two-factor model as:

$$E\,(\tilde{R}_{i,t}) = a_i + b_i\tilde{R}_{m,t} + (1 - b_i)\tilde{R}_{z,t} + e_{i,t} \tag{2.19}$$

where $\tilde{R}_{z,t}$ is the return on a zero-beta portfolio at time *t*. This represents the first use of the zero-beta concept in the literature, which they formally define as an efficient, minimum variance portfolio which is uncorrelated with the market. In expected return form, equation (2.19) can be rewritten as:

$$E\left(\tilde{R}_{i,t}\right) = E\left(\tilde{R}_{z,t}\right) + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - E\left(\tilde{R}_{z,t}\right)\right] + e_{i,t} \tag{2.20}$$

where $\tilde{R}_{Z,t}$ is the return on the zero-beta portfolio for time *t*. This expression is analogous to the CAPM expression, but with the return on the zero-beta asset replacing the risk-free rate. Therefore, the relationship between expected return and asset *i* remains the same in the presence or absence of a risk-free rate. The expected return of a security (*i*) remains a linear function of β_i in the absence or presence of a riskless asset (Black, 1972).

In excess returns form, equation (2.20) can be expressed as:

$$E\left(\tilde{R}_i\right) = \gamma_0 + \beta_i \gamma_1 \tag{2.21}$$

where γ_0 is the expected return on the zero-beta portfolio and γ_1 is the price of market risk or the estimate of relative risk aversion (RRA). Black, Jensen and Scholes (1972) find evidence against the implications of Sharpe's CAPM which requires that γ_0= 0 and γ_1 = $E\left(\tilde{R}_m\right)$, and suggest by contrast that γ_0= $E\left(\tilde{R}_Z\right)$ and that γ_1 = $E\left(\tilde{R}_m\right)$ - $E\left(\tilde{R}_z\right)$.

Black, Jensen, and Scholes (1972) find significant negative time-series CAPM alphas for high beta securities and positive alphas for low beta securities, contrary to the predictions of the CAPM, and that in cross-section regressions, the coefficient on the excess market return varies significantly across different sub-periods, again inconsistent with the CAPM. Conversely, they find that their zero-beta model performs better than the CAPM in explaining the returns of equity portfolios.

This study attempts to develop the gold zero-beta models by using the gold return instead of risk-free rate in empirical asset pricing models. Black, Jensen, and Scholes (1972) examine the CAPM with limited borrowing, in that they permit investors to lend at the zero-beta rate but cannot borrow at that rate. Similarly, we also restrict investors that they may invest, but not borrow at the gold return rate. The construction of the zero-beta portfolio itself involves constraints of optimisation procedures (Banz, 1981) as Black (1972), Fama and MaxcBeth (1973) develop their own assumptions to choose weights of the risky assets and various studies such as Shanken (1985), Davidson, Hillier and Faff (2003) have not estimated the zero-beta portfolios while estimating asset pricing models.

2.2.2 Undermining of theoretical foundations of CAPM

The CAPM is founded theoretically on the Arrow-Debreu model market (Arrow and Debreu, 1954), which states the conditions required for the existence of equilibrium for a competitive market, which includes perfect competition, demand independence, and information efficiency. This is consistent with the Efficient Market Hypothesis (EMH) of Fama (1991).

When satisfied, these conditions guarantee market efficiency (Rubinstein, 1975), and prices will adjust in such a way that aggregate supply equals aggregate demand for each commodity in the economy. However, following empirical evidence indicates that the Arrow-Debreu conditions are not satisfied in reality, and therefore the traditional CAPM loses its theoretical foundation in practice. Firstly, the Arrow-Debreu requires Treasury securities or default-free bonds exist in zero net supply. However, Constantinides and Duffie (1996) show that this does not hold in reality, since government bonds and Treasury bills are not in zero net supply, and ought to be included in the list of "securities" rather than constituting an asset in zero net supply. Notably, recent times have seen the extremely large issuance of debt by governments of all major economies; in this way, government bonds and Treasury bills do not satisfy the Arrow-Debreu conditions of a risk-free asset. Secondly, Mehra and Prescott (1985) show that application of the Arrow-Debreu model fails to simultaneously explain higher average equity returns and a low average risk-free rate.

Mehra and Prescott (1985) also find that the general equilibrium models strongly violate their restrictions when estimating average returns in the U.S. market and raise the issue of the 'equity premium puzzle' for the 1889 -1978 period. They identify the model misspecification and measurement problems of equilibrium models and ask why average equity returns have remained so high when the risk-free rate has remained so low since a risk-free rate close to zero would indicate that investors are risk neutral. However, a high equity risk premium conversely indicates that investors are strongly risk-averse. Continuing this vein of the investigation, Weil (1989) attempts to explain the equity premium puzzle through his Kreps-Porteus non-expected utility preferences[1] which relax the testable implications for the CAPM.

He admits that the separation of relative risk aversion and intertemporal substitution does not help in resolving the equity premium puzzle, but instead magnifies the risk-free rate puzzle. In this way, evidence has accumulated against the Arrow-Debreu in practice, and thereby against the CAPM. Further, it is apparent that government bonds and Treasury bills, in reality, do not fulfill the conditions of a risk-free asset in CAPM framework. By contrast, the relative increase in the global quantity of gold from year to year is small when compared with the global increase in the number of government bonds, and hence gold is much closer to fulfilling the Arrow-Debreu conditions for a risk-free asset than they are.

2.2.3 Gold as a zero-beta asset and its relationship with T- Bills

Historically, gold has been viewed as a zero-beta asset as gold returns have tended to remain uncorrelated with the market. Chua, Sick, and Woodward (1990) estimate the market beta of gold bullion from 1971 to 1988 and find to be it insignificantly different from zero, arguing that gold bullion is a useful hedge to reduce the systematic risk of equity portfolios. McCown and Zimmerman (2006) extend this research and provide empirical evidence that gold does not reflect systematic risk and behaves as a zero-beta asset. Their findings

[1] Weil (1990) expands the Kreps-Porteus nonexpected utility preferences (Kreps and Porteus, 1978) by separating relative risk aversion and intertemporal substitution.

document a close relationship between gold, the real interest rate and exchange rates in the US, concluding that gold acts as a currency and that it reflects the value of U.S. dollar and its monetary policy. Kolev (2013) reveals that gold is a risk-free asset and it does not correlate with the market factor or Fama-French risk factors. He also marks that the gold has shown comparative performance with the market factor and it is surprising that it does not show correlation with the traditional risk factors that are used in asset pricing models.

A close relationship between gold and interest rates is further documented by the study of Sarno & Thornton (2003). They find that the federal funds rate influences the T-Bill rate and there are clear linkages between the federal funds rate and the gold return, for instance, Barro and Misra (2016) find a close relationship between gold and Treasury bills over an extended period. They compare the real change in the price of gold with the U.S. T-Bill yield from 1836 to 2011, and establish that the real expected rate of return of gold is close to the return on Treasury bills, estimated to be around one percent.

2.2.4 Research on the proxy of a risk-free rate

Various researchers have worked in the past to get a correct proxy for the risk-free rate to be used in asset pricing models. After, Mehra & Prescott (1985) and Weil (1989), Cenesizoglu & Reeves (2012) report equity premium with risk-free rate problems in consumption-based asset pricing models. They use Vector ARCH model to include the pricing kernel and equity return to investigate the implications on equity premium and risk-free rate in consumption-based asset pricing model. Findings reveal that the model fails in the short term but in the long term, it captures time variations of equity premium and matches the observed risk-free rate. Their research concludes that risk-free rate may be the primary reason for the failure of consumption-based asset pricing model in the short run. Flannery & Protopapadakis (2002) assess an impact of macroeconomic factors on stock returns. They indirectly examine the application of return on Treasury bills as risk-free rate. They reject the presumption that risk-free rate can easily be obtained. They criticise the approach to estimate risk parameters of individual firms without having a correct proxy of the risk-free rate. Their findings identify the errors in valuation as a consequence of incorrect risk-free rate in valuation models. They also attempt to develop a framework for risk-free rate if risk-free rate is not available or there is default risk premium on Treasury bonds. Bjørnland & Leitemo (2009) highlight that there is a significant synchronised interaction between interest rate setting and stock prices. As monetary policy is important to determine stock prices, the real shock in stock prices also plays role in determining interest rates and monetary policy. His research provides a hint to derive interest rate from changes in stock returns. The use of risk-free rate in asset pricing models has remained a debatable topic among academicians and practitioners. However, the focus on the debate has remained more on using short-term or long-term return on Treasury bills. Nevertheless, little research has been done to investigate the applicability of alternative proxy for the risk-free rate in asset pricing models.

Before we deeply examine the role of gold as a zero-beta asset, it is important to understand the main determinants which influence return on Treasury Bills. In the US, Federal Reserve plays a key role in determining federal fund rate which then plays a key role in adjusting return on Treasury bills.

2.2.5 Role of Federal Reserve in Financial Crisis

Taylor (2009) point out that some of the effects of the financial crisis may have been avoided if Federal Reserve would come out with less aggressive interest rates cuts to overcome the crisis. His research examines the Federal Reserve policy decisions from 2000 to 2006 during which interest rates were dropped in 2003 and then steadily raised until

2006. Taylor's research shows that the changes in interest rate would have been different if Federal Reserve followed the historical policy during periods of Great Moderation from 1980 to 2000. Earlier, Taylor (1993) has documented monetary policy guidelines and recommended rules to decide federal fund rates on the basis of the state of the economy. These rules attracted a lot of attention from financial analysts and policymakers. These rules recommend to increase federal fund rates in the wake of high inflation and lowering rates when recession appears to be an apparent threat (Kozicki, 1999). However, Cecchetti (2009) supports Federal Reserve policy by highlighting that when traditional central banking tools fail to overcome the crisis, then Federal Reserve engineer effective solutions to restore financial system to its normal status.

2.2.6 Relationship between interest rate and Treasury-bill yield

Federal Fund and Treasury bill rate are the short-term interest rates having significant importance in the U.S. financial system. The Federal Reserve device monetary policy through Federal Fund Rate while Treasury bill rate is the most widely used default risk-free rate in the U.S. market. Sarno & Thornton (2003) have examined the dynamic relationship between three-month Treasury bills and overnight federal fund rates (FF) from 1947 to 1999. They report a remarkable stable long-term relationship as the empirical evidence reveals the strong co-integrating relationship between these two U.S. money market interest rates. They have determined that most of the adjustments toward long-term equilibrium arise from changes in federal fund rates. It implies that rates for Treasury bills which are used as a proxy for risk-free rates are determined by federal fund rates. It is also reported in the findings that federal fund rate adjusts swiftly than T-Bill rate toward the long run equilibrium joining these rates. This research provides empirical support to the conventional perspective of monetary policy where Federal Reserve control federal fund rate whereas Treasury Bill rate and other short-term rates are anchored by federal fund rate. Federal Reserve adopted aggressive monetary easing policy and sharply cut interest rates in the response to the financial contagion. Mishkin (2009) defends Fed's aggressive monetary policy easing by arguing that the view of ineffective monetary policy during the financial crisis is wrong as it may bring policy inaction in the wake of severe crunch. He supports the policy by pointing out that it will serve risk management to encounter contraction during the financial crisis and it will be more influential and inertial to recover from the existing crisis than it may serve in other normal times.

In the UK, monetary policy is implemented by the Monitory Policy Committee (MPC) of the Bank of England. Like Federal Reserve in the U.S, the Bank of England also adopted monetary policy easing after global financial crisis to promote demand in order to overcome the crisis. In March 2009, the Bank rate reached ½% which was effectively the lowest level at that time (Joyce, Tong, & Woods, 2011). Some of the researchers have criticized excessive interest rates cuts as it delayed the recovery process. Joyce, Miles, Scott, & Vayanos (2012) find that even if quantitative easing is effective for boosting the economy in the short run, but in the long run, it has failed to solve the issue of sluggish recovery. This may be the reason that historic lowest interest rate in the U.K. has not yet been raised since March 2009. For asset pricing perspective, the return on T-Bill rates is used as a proxy for the risk-free rate. In the aftermath of financial crisis, these rates were significantly lowered which not only affected the empirical performance of asset pricing models but also questioned risk-free nature of Treasury bills. The aggressive easing monetary policy was also the result of excessive foreign lending. As a result, the U.S. has reached several times legal binding limits of the debt ceiling. After the financial crisis, a sharp decline in T-Bill rates coupled with excess foreign lending raise issues of default risk of U.S. Treasury securities (Liu, Shao, & Yeager, 2009).

2.2.7 Federal fund rates and relationship with gold during the financial crisis

Kontonikas, MacDonald, & Saggu (2013) mark gold and three-month Treasury bills as safe haven assets in their recent research in which they find highly significant structural shifts between gold and federal funds rates during the financial crisis. The price of both safe-haven assets significantly increased during financial crisis between 2007 and 2009 in the U.S. They point out that gold returns promptly respond to federal fund rates' shock during the financial crisis. They further elaborate that the hypothetical 1% expansionary shock during the financial crisis is reflected by 6% rise in gold returns. They indicate this response in line with a flight to safety reading of the market which has been seen as good news for safe havens and bad news for risky assets. When they use gold as a dependent variable, they find the relationship strong and positive, particularly during market turmoil. This highly significant relationship between FFR and gold can be utilised to improve asset pricing during the financial crisis. These findings are consistent with the findings of Baur & Lucey (2010) who mark that gold is a safe-haven for most developed markets. The financial crisis had a positive impact on the gold market as it raised the gold price and its importance both in the market and in the literature. During abrupt market conditions, the gold price is not simply determined by the demand and supply of gold but due to its comprehensive features as commodity, currency, and hedging investment instrument.

2.2.8 Role of gold in the U.S. market: Past and present perspective

2.2.8.1 Gold Standard

Historically, gold has been recognised for its value preserving properties. The gold has played a dominant role in the U.S. and U.K. financial system. The U.S. and U.K. maintain

Gold Standard[2] in their financial system during the 19th and 20th centuries. Bordo (1981) mark that the gold has desirable properties of money as it is durable, storable, portable, easily recognizable, divisible and easily standardized. Gold has maintained a commodity money standard for its long-run price stability. He elaborates that there are very limited possibilities of changes in its stock with its high cost of production which makes it difficult for governments to manipulate the level of stock. In case of strict Gold Standard, the financial system could work without Central Banks as government ruling is required to maintain fixed currency price of gold by freely selling and buying gold. Before World War I, the countries on Gold Standard did not have Central banks as these evolved from large commercial banks into Central Banks after the end of Gold Standard. For instance, the Bank of England was the commercial bank. It was founded in 1667 and later evolved into the *lender of the last resort* for the banking sector in England.

2.2.8.2 After Gold Standard

After the end of the gold standard, Herbst (1983) finds that the role of gold has evolved in the U.S. economy and its role is more dominant in the portfolio investment management rather than an inflation hedge. However, gold's historical hedging capabilities are observed in the aftermath of Asian and global financial crisis (Baur and Lucey, 2010; Davidson, Faff, and Hillier, 2003). The price of gold has experienced a boom during the period of the financial crisis over the period 2008 to 2009. Since, October 2008, following the collapse of Lehman Brothers, the price of gold has surged to give a positive response to the intensification of the financial crisis. The gold price has retained upward trajectory till mid-2011 until stability started to prevail in stock markets. In contrast to other assets, gold price reacts positively to negative stock market shocks. The oil crisis in the 1970s resulted in

[2] The Gold Standard was a commitment of participating countries to fix the price of their currencies with specified gold amount. For instance, from 1834-1914, Great Britain maintained a fixed price of gold at £3, 17s whereas United States maintained at $20.67 from 1834-1933 excluding Greenback era (Bordo, 1981).

rampant inflation in 1980 which has resulted in a record increase in the price of gold in 1980. The similar pattern of increase in gold prices has been recorded when the worst financial crisis hit the stock markets in 2008 in the United States and various countries in the European Union.

During recent times, the opposite movements of gold and U.S. dollar have been widely recognised in the literature of financial economics. The disjointed movements can be seen as prospects of portfolio diversification and currency hedging in the U.S. market. Reboredo & Rivera-Castro (2014) examine the use of gold for downside risk and currency hedging benefits. They find that the inclusion of gold in the currency portfolio provide risk diversification benefits provided negative correlation between gold and U.S. dollar. It is highlighted that the extreme depreciation of the U.S. dollar during extreme market conditions, can be counterbalanced with gold, as the value of gold remains unchanged during such conditions. His findings are consistent with the previous papers where researchers agree that gold function as a currency hedge (Capie, Mills, & Wood, 2005; Joy, 2011; Reboredo, 2013). Pukthuanthong & Roll (2011) confirms the even closer relationship of gold with British Pound and Euro. They find that the world gold market is dominated by the European currency bloc as two-thirds of gold market power is enjoyed by the member countries of the European Union. The appreciation and depreciation of GBP and Euro have direct impact on the rise or fall of gold prices in other currencies. Central Banks maintain reserves of gold which provides them attractive hedging benefits in the case of unforeseen depreciation of U.S. Dollar. Bampinas and Panagiotidis (2015) also verify inflation hedging ability of gold in the U.S. market and also confirm that it is higher in the U.S. as compared to the UK.

2.2.8.3 Role in Financial Crisis

Since 2000, gold has become a good add-on to a portfolio for hedging purpose. In the U.S. market, the gold occupies a dominant position among other commodities when it comes to hedging and safe have benefits during the financial crisis. Baur & McDermott (2010) mark that gold was a strong safe-haven during the peak of the U.S. financial crisis. They also confirm that gold is a much stronger safe-haven asset in the U.S. market than Australian, Canadian, Japanese and BRIC emerging markets. They show that investors show a reluctance for stock trading during uncertain market conditions, as uncertainty adds ambiguity to asset values, but in such conditions, trading of gold actually increases due to its hedging ability. Baur and Lucey (2010) also document similar evidence that gold acts as a strong hedge in the wake of extreme market shock in the U.S. market. They also confirm gold as an effective hedge for stocks and a safe-haven asset in the European markets. However, gold is not a safe haven for bonds in any market (Baur & Lucey, 2010).

2.2.9 Dominant role of U.S. in global gold holdings

Gold has a dominant role in the U.S. economy and maintains a unique position in the Federal Reserve’s portfolios. Aizenman and Inoue (2013) provide evidence from 22 developed countries and reveal the tendency of central banks to report international reserves valuation excluding gold stocks that are held more passively. Further, gold reserves are reported at historical valuation. They show that the central banks maintain passive sizeable gold stocks regardless of positive or negative trends in gold prices. They also reveal that the gold retains the stature of a strong safe-haven asset in the U.S. economy. Their findings support views that gold position of the central bank reflects economic strength of the country, and intensity of gold holding is associated with the global power. The under-reporting is consistent with central banks’ policy of loss aversion and avoid criticism in declining times of real gold prices.

The U.S. owns the largest gold reserves (8,133.5 tons out of 33,604.1 world gold) in the world that constitute 74.9 percent of its total reserves (World Gold Council, 2017). Further, the U.S. is also the supplier of the international currency (US Dollar), therefore, it is crucial to examine the extra market sensitivity of the gold price factor on the U.S. industries in addition to global industries to deeply examine the hedging role of gold in asset pricing.

2.2.10 Efficiency of gold market

The Gold market has been found to be highly efficient in developed markets in recent years, compared to Treasury security markets. The gold price is determined by the participants of the market whereas government policies influence more on adjusting return on Treasury bills.

After the great financial crisis of 2008, gold has come under increased investigation and has gained more importance in financial economics. Ho (1985), Wang, Wei, and Wu (2011), Ntim, English, Nwachukwu, & Wang (2015) and Pierdzioch, Risse, and Rohloff (2014) examine the efficiency of gold markets from the perspective of U.S. investors and they could not find any evidence of non-normality and conclude in favour of market efficiency. Ho (1985) report a weak-form efficiency of London gold market. Wang, Wei, and Wu (2011) assess the efficiency of COMEX gold market on the basis of multifractal detrended fluctuation analysis and conclude that gold markets have become more and more efficient since 2001 and efficiency is further improved during upward periods in developed markets. Pierdzioch, Risse, and Rohloff (2014) re-affirm weak-form efficiency of London gold market and state it is informationally efficient. Ntim, English, Nwachukwu, & Wang (2015) compares the efficiency of gold markets in developed and emerging markets and find that gold markets are more efficient in developed markets than emerging markets. They utilise strict random walk (RWS) and relatively relaxed martingale difference sequence (MDS) tests.

We also test the market efficiency of gold markets in this study to find that whether gold prices follow strict random walks (RWS) with independently and identically distributed (iid) restrictions or martingale difference sequence (MDS). The efficiency of the gold market is important for the applicability of gold as a zero-beta asset in asset pricing and it must be located on the efficient minimum variance frontier as is emphasised in Black, Jensen, Scholes (1972).to compare the performance of competing asset pricing models in international markets.

Hence, the first hypothesis can be defined in the following way:

$H_{2.1}$: Gold prices follow a random walk.

The martingale difference sequence (MDS) is a relatively relaxed test of market efficiency as it relaxes the strict independently and identically distributed (iid) restrictions. Hence, the second hypothesis can be defined as:

$H_{2.2}$: Gold prices follow a martingale difference sequence (MDS).

The third hypothesis is related to the position of the gold on minimum variance frontier as Black, Jensen, and Scholes mark that "In fact, there is an infinite number of such zero portfolios. Of all such portfolios, however, r_z is the return on the one with minimum variance". Hence, we develop the hypothesis ($H_{2.3}$) that gold return can only meet Black, Jensen and Scholes (1972) requirements of a minimum variance zero beta portfolio when it is also located on the minimum variance frontier.

2.2.11 Gold as an alternative numeraire

An alternative approach to the discussion of zero-beta assets is the perspective of the numeraire, an approach more familiar to the domain of financial derivatives. A numeraire is an asset which, when used as a denominator, allows the expression of the price of one asset in terms of units of another asset. Familiar examples from elementary derivatives classes are the pricing of binomial options, where the terminal value of the option can be expressed in terms of units of the underlying stock as a numeraire, and the dynamics of the forward price of a bond, where the role of numeraire is played by a zero-coupon bond maturing at the forward date (Wiersema, 2008, pp. 179–201).

A similar line of analysis can be used in asset pricing: using a 1-month T-bill as a risk-free rate is equivalent to converting all raw asset prices into numbers of units of a zero-coupon bond maturing in 1 month's time, and then performing all return calculations in terms of prices expressed in this numeraire. That is, instead of subtracting the "risk-free rate" derived from the return on a 1-month T-Bill and then working in terms of excess returns above the T-Bill rate, one would get the exactly same results if one converted the price of all assets into units of a 1-month zero-coupon bond at each point in time, and then worked in terms of these transformed prices.

The specific choice of a 1-month T-Bill as effective numeraire is standard, but is not obligatory; all it accomplishes is the measurement of values today in terms of a known value in 1-month's time. One could equally well choose another asset which will have a nonzero value in one month's time, just as one chooses to measure the binomial option in terms of units of the underlying stock in the example cited above.

By a similar analogy, one can pick another asset to be a numeraire: instead of a 1-month T-Bill, one could elect to use the price of a fixed weight of gold. One could then transform all asset prices into units of a fixed weight of gold at each time point, and then work in terms of these gold-transformed prices. Rather than quoting prices in units of T-Bills, one would quote prices in terms of ounces of gold. Equivalently, one could use the return on gold as a substitute zero-beta- rate, and express all asset returns in terms of excess returns above this return on gold.

2.2.12 The influence of Central bank decisions on the T-Bill rate

Financial theory demands that the risk-free rate be set by frictionless price discovery processes between market participants, but in reality, one could observe that T-bill rates are strongly influenced by central bank rate-setting decisions. In the case of the US, the Federal Open Market Committee (FOMC) sets the target range for the overnight Fed Funds Rate; the 1-month T-bill rate, though not directly controlled by the FOMC, will be strongly influenced by the overnight Fed Funds Rate, being so close to it terms of tenor on the bond yield curve. In this way, the 1-month T-Bill rate can scarcely be described as being set by unimpeded price discovery processes, but rather, is closely tethered to an administratively-set figure. The infrequent changes in the Fed Funds Rate lead to the 1-month T-Bill rate being artificially smoothed across time, and does not the marked shifts which might be expected during periods of increased risk aversion. This is another key aspect in which the 1-month T-Bill yield fails the Arrow-Debreu conditions for a risk-free rate.

By contrast, the gold price is set by price-discovery processes in a highly liquid, global market, without being tethered to an administratively-set rate. Although Central Banks trade in size in the global gold market and some have gold retention targets, they do so as standard market participants rather than controlling entities and do not seek to influence its price range in the same way that the Fed Funds Rate strongly influences the 1-month T-Bill rate.

2.2.13 Hypothesis development for the applicability of gold as a zero-beta asset in empirical factor models

Our fourth working hypothesis ($H_{2.4}$) is that: Asset pricing models which use this gold return will function better than models which employ the 1-month T-bill rate as a risk-free rate.

The above literature review prove that the gold market is efficient, particularly in the U.S. economy, and also suggests that gold is a hedge for equity portfolios, so I may dispense with concerns that the gold return is inefficient. I have also established that the beta of the return on gold is equivalent to zero with respect to the U.S. market. Therefore, the use of gold return is worthy of detailed examination in the U.S. equity market. Further, I have identified that the use of the T-bill rate gives rise to the conundrums of a low risk-free rate and a high equity market premium, leading Mehra and Prescott (1985) and Weil (1989) to conclude that the application of the return on Treasury bills violates the restrictions of general equilibrium models. This study has also established that T-bills and bonds are not in zero net supply (Constantinides & Duffie, 1996), as required by the Arrow- Debreu model (Weil, 1989), and the 1-month T-Bill yield is strongly influenced by and tethered to the Fed Funds Rate set by the FOMC. These are the fundamental assumptions which traditional equilibrium models fail to meet when the Treasury bill yield is used as a risk-free rate.

However, gold is much closer to satisfying these conditions: its return has a zero market beta, it is effectively in zero net supply, with negligible extra supply coming to the market compared to the existing stock, and unlike T-bills, has a short-term yield that is not directly influenced and artificially smoothed by Central Bank decisions. In this way, the return on gold should be expected to function as a more reliable zero-beta rate than the risk-free rate derived from the T-Bill yield. Therefore, I here investigate the applicability of the gold return in empirical factor models in an attempt to improve model fit.

The application of gold as a zero-beta asset is also consistent with Black, Jensen, and Scholes (1972) zero-beta CAPM's framework. In their formulation of a minimum variance portfolio, they use a portfolio of risky equities, in which each stock's contribution to portfolio variance becomes smaller as the number of stocks increases. By contrast, I employ the return on gold bullion as a zero-beta asset, and consider that this has advantages over the their portfolio of risky stocks: gold itself is a hedge against equity market variations and is regarded as a safe-haven even in market uncertainty and times of financial crisis (Baur & Lucey, 2010b; Kontonikas, MacDonald, and Saggu, 2013), and has a much better claim to be a secure store of value than a portfolio of risky stocks. I, therefore, use the return on gold rather than forming a zero-beta portfolio of equities.

2.3 Gold as a hedging factor

After assessing the applicability of gold as a zero-beta asset, I assess its application as a hedging factor in the framework of Intertemporal Capital Asset Pricing Model (ICAPM). Gold plays a diverse role in the financial economics of global markets. In the wake of financial crisis, gold has become a prominent commodity in financial markets given its portfolio diversification, hedging, and safe haven characteristics. An extensive range of studies highlight these properties. However, very limited literature explores gold as a potential hedging factor in the Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). For instance, Rubio (1989) has used gold in the Spanish market, and Chan and Faff (1998) have used gold in Australian market where they find significant evidence of the role of gold as a hedging factor. Davidson, Faff, and Hillier (2003) find an evidence of extra market sensitivity in world industries, but further research is required to provide a fresh evidence on international markets before and after the financial crisis.

2.3.1 Merton (1973) Theory of ICAPM

Merton (1973) ICAPM is based on the assumption that investors can construct portfolios to hedge against uncertainties (Merton, 1973). Merton (1973) emphasises a negative correlation between a market beta and a potential hedging factor. In view of Davidson, Hillier, & Faff (2003), if interest rates, and exchanges rate can be used in the ICAPM setting, then it is surprising that little work includes gold in ICAPM's analysis despite its widely documented hedging propoerties. Davidson, Faff, and Hillier (2003) do not find a convincing evidence of this negative correlation in a sample of world industries. Researchers (Baur and Lucey, 2010; Ciner, Gurdgiev, and Lucey, 2013; Bredin, Conlon, and Potì, 2015) present an extensive evidence of hedging and safe-haven properties of gold in the U.S. market, it motivates me to assess extra market sensitivity of a gold price factor in the Merton (1973)

ICAPM framework, in the U.S. asset pricing.

2.3.2 Financial economics of gold

After the great financial crisis of 2008, gold has come under increased investigation and has gained more importance in financial economics. Firstly, it is important to identify the focus of past research. Gold is recognised as a portfolio diversifier, hedging instrument, and a safe-haven asset. Baur and Lucey (2010) distinguish between hedge, diversifier, and a safe-haven asset. The hedge is an asset which is uncorrelated with another asset; diversifier is not perfectly correlated with another asset; whereas safe-haven is an asset which is negatively correlated with another asset during times of market uncertainty or extreme stock market shocks. The distinction between a safe-haven and a hedge is the length of their effect. Further, the distinction between a weak and strong hedge is also vital for investors. A strong safe-haven provides positive returns when other assets suffer losses in times of financial stress; whereas it is not achieved in case of a weak hedge or a weak safe-haven. To assess the role of gold in asset pricing, these diversification, safe-haven and hedging properties needs to be deeply examined.

2.3.3 Benefits of diversifying

Secondly, it is important to evaluate diversying benefits with gold. Jaffe (1989), Chua, Sick, & Woodward (1990), Chan and Faff (1998), Hillier, Draper, and Faff (2006), Belousova and Dorfleitner (2012), Dee, Li, & Zheng (2013), Hoang, Lean, and Wong (2015), have examined diversification benefits with gold stocks. Jaffe's (1989) research covers the data from 1971 to 1987 (after the U.S. government ended convertibility of gold to dollars) and concludes that the addition of gold reduces standard deviation and increases average returns. Jaffe (1989) distinguishes gold bullion from gold stocks by estimating their betas and find that gold bullion beta remains insignificantly different from zero in the 1970s and 1980s whereas betas of gold stocks remain double in the estimated time periods. Hence, he underlines gold bullion as a meaningful investment for diversification, both in short and longer investment horizons. Chua, Sick, and Woodward (1990) find that however, gold stocks can be used for risk-reduction but after 1971, gold bullion offers better diversification benefits than gold stocks. Chan and Faff (1998) reveal that gold may serve as a proxy for GDP in estimating multifactor models in the Australian market. They propose that instead of holding diversified portfolios, investors might hold gold assets as a hedge against market uncertainties. Hillier, Draper, and Faff (2006) mark that gold with other precious metals such as platinum and silver offer diversification benefits to broad investment portfolios. Financial portfolios which comprise precious metals perform significantly better than traditional equity portfolios. Furthermore, they also reveal hedging capabilities of gold against abnormal equity market shocks.

Belousova and Dorfleitner (2012) examine diversification benefits of precious metals from the perspective of euro investors and document commodities as attractive investments for both aggressive and conservative investors. They recommend that diversification benefits can be enhanced with effective risk-management strategy through price movements in the equity markets. They reveal that gold has greater diversification power in reducing portfolio risk than platinum in bear markets. Gold has a strategic value in portfolio investment during uncertain market conditions (Dee, Li, & Zheng, 2013). Hoang, Lean, and Wong (2015) examine the role of gold in the diversification of French portfolios from 1949 – 2012 by using stochastic dominance approach. Their results show that stock portfolios are comprising gold stochastically dominate standard equity portfolios at second and third orders which implies that including gold in the portfolio increases expected utility for risk-averse investors. The results are particularly stable during times of equity market crisis. They find similar results for gold quoted in Paris and London. Their findings also confirm that gold does not help in diversification of bond portfolios. Recently, Mensi, Hammoudeh, Al-Jarrah, Sensoy, and Kang, (2017) provide further evidence that gold offers better portfolio diversification benefits and downside risk reductions than oil.

2.3.4 Safe-haven during crisis

Thirdly, it is crucial to assess literature on safe-haven abilities in detail in global markets. Hillier, Draper, and Faff (2006) report the hedging ability of gold and silver during times of market volatility or uncertainty while Kat and Oomen (2006) report on the effectiveness of gold as a hedging instrument during times of financial distress. After financial, crisis, various researchers such as, Harris and Shen (2017), Baur and Lucey (2010), Baur and McDermott (2010), Reboredo (2013), Hood and Malik (2013), Bredin, Conlon, and Potì (2015), Low, Yao and Faff (2016), and Bris and Rezaee (2017) have confirmed gold as a safe-haven asset during financial crisis. Baur and Lucey (2010) study constant and dynamic relationships between stock and gold returns in the U.S., U.K., and Germany to examine whether gold is a hedge or a safe-haven. Their findings conclude that gold is a typical hedge against stocks and a safe-haven in extreme stock market shocks. However, their findings also mark that gold is not a safe-haven for bonds in any market. Gold serves as a safe-haven for stocks only during extreme market conditions, and this safe-haven property lasts for a limited period. Baur and McDermott (2010) also report similar evidence in developed markets of US, UK, and Eurozone markets of Germany, France, Italy, and Switzerland. They conclude that gold acts as a stabilising force for financial systems and provide stability to prevent extreme losses in the aftermath of financial crisis. Baur and McDermott (2010) also find that investors react to extreme short-lived shocks by investing in the safe-haven asset. They added that gold has served as a strong safe-haven asset during periods of financial crisis in 1987 and 2008. However, they also document that gold is not a safe-haven asset for Australia, Canada, Japan and largest emerging markets, e.g., BRIC (Brazil, Russia, India, China) countries. Reboredo (2013) examine the role of gold in currency portfolios and assess its role as a hedge or a safe haven against the U.S. dollar. He confirms hedging role of gold against the U.S. Dollar and finds it as an effective safe-haven against extreme movements. Moreover, diversification benefits of gold in currency portfolios are also noticed.

Hood and Malik (2013) assess the role of gold with precious metals and VIX (Volatility Index) concerning hedging and safe-haven benefits in a portfolio analysis. They also find gold a better hedge than precious metals, but VIX index outperforms in extremely low or high market volatility. Low, Yao and Faff (2016) further provide evidence through comparing the safe-haven and hedging properties of precious metals with diamonds. They report the superior performance of gold and silver over diamonds during extreme market conditions in developed markets of US, France, Germany, and Australia. For the U.S. and European markets, gold act as a stabilising cushion to protect the financial system from the meltdown in the wake of strong negative market shocks. Bris and Rezaee (2017) examine the dynamic correlations between stocks and bonds in the absence of inflation in the French market during the Gold Standard. They report higher correlations during the Gold standard as they find considerably fewer periods of financial crisis during the Gold standard. They conclude that financial crises reduce stock-bond correlation, as investors prefer safe havens in market uncertainties. Wu and Chiu (2017) implement asset allocation strategy containing price range information and asymmetric dependence to assess the economic relationship of gold, stocks, and bonds. They document significant evidence of asymmetric dependence across stock, gold and bond markets as they find the striking explanatory power of gold to explain volatility structures. Their out of sample results suggest that information related to asymmetric dependence can earn profits from 35 to 517 annualised basis points whereas information on volatility structures can produce additional profits from 90 to 1111 basis points each year. The asymmetric dependence and price range information is economically more valuable during the financial crisis and is profitable for relative less risk-averse investors.

2.3.5 Hedging Exposure on gold mining firms

Fourthly, Blose and Shieh (1995), Tufano (1996, 1998), Callahan (2002), Dionne and Garand (2003), Faff and Hillier (2004), Baur (2014) and Basher and Sadorsky (2016) mark hedging role of gold on gold mining industry portfolios. Blose and Shieh (1995) examine data of 23 publically listed gold mining companies in the United States from 1981 – 1990. The elasticity of the gold price is reported to be more than one which shows the significant exposure of gold to gold mining stocks. Tufano (1996) uses data of the 48 gold mining firms to examine risk management practices in North America. However, his research is focussed on managerial risk management, but indirectly, he also underlines the role of gold in hedging as he states that if the firms' managers hold more stock, then they keep more gold to manage risk; whereas if they hold more options, then they hold less gold. Tufano (1998) further elaborates hedging exposures on gold mining companies by finding that the average gold mining stocks move by 2 percent in response to 1 percent change in the price of gold.

The exposure is found significantly negative to firms' hedging and positive to firms' leverage activities. He also admits that the exposure varies across firms and considerably changes over time. On the other hand, Callahan (2002) argues against hedging in the gold mining firms. His assessment of the five years data for twenty gold mining companies in the North America suggests that hedging might be of limited value to those investors who are primarily interested in value maximization. The firms that are not involved in the gold mining business can be less strongly associated with gold price, but they can be indirectly linked to changes in gold price. However, limited research has been done on gold factor exposure on industries other than gold mining companies. In view of Davidson, Faff, and Hillier (2003), it is possible that the gold factor exposure on other industries is negative unlike gold mining companies that shows positive exposure. For instance, if companies' managers use gold as a hedging instrument, then downfall in the financial, banking, tobacco, energy, may lead to increase in gold prices. Changes in gold price can also have subsidiary effects on other industries that are involved in retail, production or supply of commodity-related metals whose suppliers or customers are affected by changes in gold prices, for instance, materials, electricity and utilities industries which can be indirectly affected by gold prices. Dionne and Garand (2003) have also assessed hedging factors for North American gold mining companies, and find that the companies with more financial stress are more likely to hedge the price of gold than firms with gold financial health.

Faff and Hillier (2004) extends Tufano's (1998) research to the other countries outside of North America. They find that the gold factor exposure differs in Australian and South African gold mining industry as compared to North American companies. The volatility of gold bullion's return, however, shows negative association gold price does not have a significant effect to explain conditional betas in South African and Australian gold mining industry. However, the research of Baur (2014) finds contradictory results in the Australian mining industry. They examine all gold mining companies of S&P/ASX[3] (ASX: Australian Stock Exchange) over the period 1980 to 2010. They document gold factor exposure to gold mining companies as exposure increases with favourable changes in gold prices and decreases with adverse gold price changes. The average gold beta is estimated to be one which varies with price changes of gold over time. Basher and Sadorsky (2016) estimate dynamic conditional correlations between emerging equity markets and gold price. They

[3] S&P/ASX All Ordinaries Gold Index (AUD) comprises a wide range of firms in the gold sub-industry, and hence, functions as an ideal broad market index in the Australian gold industry.

report much higher correlation (0.28 expressed in the U.S. Dollars) between emerging market stock prices and gold prices from 2001-2012 than the correlation between gold and developed markets (0.11). They also document the evidence that over half of the consumer demand for gold has originated from China and India in that period.

2.3.6 Hedging Exposure to macroeconomic factors

Fifthly, gold hedging exposures are also documented on macroeconomic factors. For instance, Salant and Henderson (1978), Sjaastad and Scacciavillani (1996), Taylor (1998), Worthington and Pahlavani (2007), examine the influence of gold on macroeconomic factors. Salant and Henderson (1978) state that gold price efficiently anticipates to the government announcements. However, the announcement of possible future government gold auction reduces the price, but the government still maintains the price-ceiling as sales from its stockpile causes the price to rise at a higher rate due to possible sudden attack from speculators. Sjaastad and Scacciavillani (1996) assess gold price and exchange rates over the period 1982 to 1990 and find that floating exchange rates cause instability in the gold markets. Taylor (1998) examines the relationship between gold prices and inflation from 1914 to 1937 (during World War I and II) and oil crisis from 1968 to 1996. His findings mark gold as a hedge against inflation during periods of socioeconomic crises. Worthington and Pahlavani (2007) examine the long-term relationship between inflation and gold price from 1945 to 2006 and then from 1973 – 2006 in the United States. They employ unit root test and considers the timing of structural breaks in their analysis and report cointegration between gold and inflation since the early 1970s. Furthermore, they also document evidence of gold as an inflationary hedge in the United States.

In a similar vein, Ciner, Gurdgiev, and Lucey (2013) prove that gold provides a currency hedge against exchange rate fluctuations in both the U.K. and the US, while Białkowski, Bohl, Stephan, & Wisniewski (2015) confirm gold as an inflation hedge, dollar hedge, safe-haven and portfolio diversifier. Likewise, Bampinas and Panagiotidis (2015) have examined inflation hedging ability of gold over the long term dataset from 1791 to 2010 in the U.S. and the UK. They perform time-invariant and time-varying cointegration tests and find that gold serves as a strong inflation hedge in the U.S. over the long-term period whereas this inflation hedging ability is weaker in the UK. On the other hand, silver serves as a weak inflation hedge in the U.S. it serves as a better hedge over a long-term period in the UK. For the U.S. dataset, Francis, Hasan, & Hunter (2008) find that the gold industry has higher exposure of currency risk as compared to entertainment (fun), consumer goods, household, clothing industries which have relatively less exposure of currency risk. They also find that mining industries including metallic and non-metallic mining, shipbuilding and railroad equipment industries also have higher exposure to currency risk. As gold offers a hedge against currency risk (Worthington and Pahlvani, 2007; Reboredo, 2013 and others), therefore, industries with higher exposure of currency risk (gold mining, shipbuilding, and rail road equipment industries) may hedge against currency risk with gold investments. Van Hoang, Lahiani, & Heller (2016) study gold as an inflation hedge in UK, USA, China, France and India. They have used autoregressive distributed lags (ARDL) approach in their study. They have used local gold prices and have shown that gold is not an inflation hedge in the long run in these countries. However, their findings prove that in short run, gold is a strong hedge against inflation in UK, USA and India.

2.3.7 Gold factor exposures to industry portfolios

Finally, it is important to examine the role of gold on industry portfolios. Research suggests that gold has played an important role as a hedging factor on global and country industry portfolios (Chan and Faff, 1998; Davidson, Hillier and Faff, 2003). Chan and Faff (1998) examine gold factor exposure to Australian industrial equity returns from 1975 to 1994 and document a widespread extra market sensitivity to gold price factor. In their results, the sensitivity is found to be a negative sign for industrials sector and positive for resource and mining industries. Later, Davidson, Hillier, and Faff (2003) assess 34 world industry portfolios and report evidence of gold factor exposure to 16 world industry portfolios and report negative premium on gold. Both Chan and Faff (1998) and Davidson, Hillier, and Faff (2003) point out that gold factor exposure changes over time as is reflected from their sub-period analysis. Recent studies of Oglend and Selland Kleppe (2016) and Todorova's (2017) have highlighted the trend pattern in gold prices. Oglend and Selland Kleppe (2016) explain trend as the equal frequency of positive and negative movements, but movements are found to be larger for up movements. Todorova's (2017) findings on high-frequency data from 2nd of January 2003 to 6th of June, 2016, explain asymmetric gold price volatility as multifaceted and complex and it is mainly due to the projection of positive and negative trend pattern in gold prices. Trend patterns in gold prices suggest that gold premium can be positive as well as negative in different sub-periods.

2.4 Asset pricing with macroeconomic and state variables

Apart from gold, it is also important to assess the role of macro and state variables on asset pricing. The macroeconomic and state variables have a significant role in asset pricing. Therefore, it is important to assess the academic literature on the empirical application of these models. Ross (1976, 1977) proposes a multifactor model to explain asset pricing. He used the new and different approach in determining asset returns which is based on the law of one price i.e. two same items cannot be sold at different prices. APT's description of equilibrium is more general than provided by the CAPM. This model replaces CAPM's assumption of using the mean-variance framework with the process of generating security returns, thus it is able to address Roll's critique.

2.4.1 Roll's critique

Roll (1977) highlights ambiguities and marks unfeasibility in testing asset pricing models. Roll's critique is considered as a significant contribution to the CAPM's testing methodology as it stimulated researchers to work on improving CAPM's testing techniques. It was a challenge to the asset pricing researchers to come up with those tests having the power to test mean-variance efficiency- which is the main underlying theory of CAPM. He explains inference errors and ambiguities resulting from incomplete asset pricing tests. In his paper, he questions the validity of CAPM's tests by pointing out that the CAPM's tests used up-to-date has done little in testing CAPM's mean-variance theory. The complete information on the true market portfolio is not considered while performing CAPM tests. He marks that the complete knowledge of the true market portfolio is vital for testing asset pricing models and if it is known with certainty, then CAPM may not be testable. Roll's critique outlines two implications of CAPM tests. 1) Mean-variance tautology which implies that testing CAPM is equivalent to testing mean-variance efficiency of the portfolio; 2) the market portfolio is unobservable.

Practically, the market portfolio should include all assets including precious metals, real estate, gold, jewellery, stamp collections and other assets of any value. The returns of all these possible investments are unobservable. The validity of the model is subject to mean-variance efficiency in relation to all investment opportunities. Without considering returns of all investment opportunities, it is not feasible to test whether the portfolio is mean-variance efficient. In this way, it is impossible to test CAPM. Later, researchers attempted to address Roll critique by extending the market portfolio through including human capital and extending asset pricing model to consumption and investment opportunities (Elton, Gruber, Brown, & Goetzmann, 2009).

2.4.2 Arbitrage pricing theory

Risk-free rate or Treasury bill rate used in the CAPM is not the only macroeconomic factor that influences stock returns. However, it is argued that changes in Macroeconomic variables also influence stock returns. Roll (1977) 's Arbitrage Pricing Theory (APT) postulates that stock returns are determined by macroeconomic factors with idiosyncratic risk. Idiosyncratic risk is the volatility related to the individual securities. According to Arbitrage pricing theory, two identical assets cannot be sold on the arbitrage argument (Ross, 1976), as the arbitrage opportunities should not exist in the efficient markets. The rational arbitragers attempt to bring to bring the prices to the equilibrium in case the arbitrage opportunities exist. This research is using gold which is a macroeconomic factor and is recognized in the literature to provide hedging benefits to the investors. The use of gold in the asset pricing setting can be helpful to improve asset pricing.

Arbitrage Pricing Theory (APT) utilise macroeconomic variables whereas Merton (1973) emphasises to use innovations in state variables in the ICAPM. It is also important to clarify the testable implications of ICAPM and APT models as there is a close relationship between ICAPM and APT. The main difference between ICAPM and APT is that the APT is multi-index model whereas ICAPM is multi beta CAPM. There is also a close relationship between CAPM and APT as well. In the CAPM, the returns are generated by single Index whereas in APT, the returns are generated by the multi-index model (Elton, Gruber, Brown, & Goetzmann, 2009).

In addition to the gold return, this study is using different macroeconomic and state variables. The list of variables and data source is available in the data source part of the methodology. The framework of APT requires that the asset returns should be linearly related to a set of indexes. Mathematically, it can be expressed as:

$$R_i = a_i + b_{iI}I_I + b_{i2}I_2 + \cdots + b_{ij}I_j + e_i \tag{2.22}$$

where, a_i: the expected return of asset *i* if all indexes have zero value

I_J: value of the *jth* index which affects *ith* asset's return

b_{ij}: the sensitivity of the *ith* asset's return to the *jth* index

e_i: the error term with mean equal to zero and variance equal to σ_{ei}^2

The main strength of APT framework is that it is developed on the no-arbitrage basis. As no-arbitrage assumption should hold for a subset of securities, therefore, it is not essential to identify all risky assets or *market portfolio* to test this model. Therefore, it is able to escape from Roll's critique about the inclusiveness of market portfolio. However, this multi-index model is extremely general which can be characterised its weakness or strength. Arbitrage pricing theory provides no evidence of the appropriateness of specific multi-index model.

However, it is emphasized that at least three indexes should be included to get better results from the APT model (Elton, Gruber, Brown, & Goetzmann, 2009). The main feature of this multifactor model that it is not inconsistent with Sharpe-Lintner-Mossin's CAPM and the CAPM's testing methodologies can be used to test this model. These multi-index models can be based on industry, macroeconomic, security-specific factors. Cochrane (1999) notices that this multifactor risk model is completely natural as financial markets do not function in isolation. Investors choices are based on macroeconomic cycles as they confront inflation, political and liquidity risks at the same time. These factors influence investors' decisions and finally determine security prices. Arbitrage pricing model has the flexibility to incorporate a different set of factors which are linearly related to asset's return to price its risk. As there are so many factors in the economy interacting with one another and influencing asset prices, so it is highly unlikely that any multifactor model is unique in its factors. The main testable implications for the models are that the factors have positive risk premium and they signify predominant recognizable risk for which investors expect compensation in the form of positive returns in excess of riskless rate. Malkiel & Xu (2002) reveal from cross-sectional results of the U.S. stock market that idiosyncratic affect stock returns as every investor is not able to hold market portfolio. Pontiff (2006) provides evidence from his empirical research and criticises CAPM diversification theories which postulate that idiosyncratic risk does not much matter in computing stock returns as it can be diversified. Instead, his research mark idiosyncratic risk the single most impediment factor to market efficiency. He concludes that idiosyncratic risk is an arbitrage cost and arbitrageurs are not able to hedge idiosyncratic risk. Therefore, arbitrageurs have to trade-off between the position of making a profit and the position of being exposed to idiosyncratic risk. Arbitrage pricing model accounting for macroeconomic factors with idiosyncratic risk may help to address CAPM's anomalies.

2.4.3 Macroeconomic factors

2.4.3.1 Money Supply

There are a number of macroeconomic factors that influence stock returns in developed markets. Among those variables, exchange rate, money supply and interest rate have been described by many researchers as most influencing determinants of stock returns both in developed and emerging markets. Urich & Wachtel (1981) explain the relationship between money supply and stock returns by highlighting that fluctuations in money supply influence stock market as change in money supply cause inflation uncertainty which in turn influence stock returns. Schwert (1989) has examined the relationship of s tock returns real and nominal macroeconomic factors, stock trading activity and financial leverage from 1857 to 1987 to extend research of Officer (1973) on stock volatility during great depression in the U.S. Aggregate leverage is found to be correlated with aggregate stock volatility but they are not able to explain many fluctuations in stock volatility particularly during Great Depression.

Humpe and Macmillan (2009) report the insignificant but positive impact of money supply on the U.S. returns while examining the influence of macroeconomic variables on stock returns in U.S. and Japan. Bjørnland and Leitemo (2009) implement Structural Vector Autoregressive Model to determine interdependence between U.S. monetary policy and S&P 500 stock index. They propose a solution to the problem of recognizing simultaneity shock of monetary and stock prices shock by using a combination of long run and short restrictions which maintain qualitative properties of a monetary supply shock.

Flannery and Protopapadakis (2002) examine the influence of a series of 17 macroeconomic announcements and report that stock returns are significantly correlated with inflation and money growth. They implement GARCH model of daily stock returns where their volatility and realised returns depend on a series of 17 macroeconomic announcements. Their findings report three nominal variables including *Monetary Aggregates, PPI* (Producer Price Index) and *CPI* (Consumer Price Index) while *Employment, Housing* starts and *Balance of Trade* as real factors influencing stock market returns.

2.4.3.2 Interest rate and Inflation

Fama and Schwert (1977) examine the extent to which the assets were hedged against the expected and unexpected rates of inflation from 1953- 1971-time period. Due to their surprise, they find an anomalous negative relationship between inflation and stock returns in the U.S. market. They also document evidence that private real estate was a comprehensive hedge against inflation in addition to Government bonds, Treasury bills and debt instruments. Fama (1981) extends his argument by highlighting that the negative inflation- stock relationship in the post-1953 period is the result of the proxy effects. The relevant real variables determine stock returns and the negative inflation-stock returns is stimulated by the negative relation between real activity and inflation during this specific period. This was the time period when researchers were focussed on looking at real macroeconomic variables to explain asset returns. The results of Lee (1992) provide empirical support to Fama's (1981) findings in which he reports that the relationship between stock returns and inflation is due to the changes in the real activity. Later, Gultekin (1983) extends this research to twenty-six countries for the post-war period and examines the relationship between expected inflation and stock returns in those countries. He finally rejects Fisher Hypothesis which stresses that nominal returns on the stock are directly proportional to variations in the expected inflation. He documents substantial evidence of the lack of positive relationship between inflation and stock returns in most of the countries. The influence of inflation on stock returns is also documented in the literature in other developed and emerging markets. For instance, Altay (2003) implements two-step APT test procedure of Fama and MacBeth (1973) in the German and Turkish stock markets. Altay (2003) finds that asset prices response to macroeconomic factors while unexpected fluctuations in macroeconomic factors are anticipated in stock markets. He uses factor analytic technique (Principle components and Maximum Likelihood Factor Analysis) to derive four factors from German and three factors from Turkish market by using the same economic indicators. He reports that the unexpected change in interest rate and inflation influence stock returns in German stock market. However, this research does not report any significant influence of any macroeconomic factor on Turkish stock market. The influence of macroeconomic factors in emerging markets is more prominent than developed markets. Maio and Philip (2013) examine 107 macroeconomic factors to shortlist the most significant risk factors for pricing the cross-section of stock returns. They show that models that are based on the interest rate or inflation outperform other APT models. They have tested three extensions of the standard CAPM: a two-beta CAPM where another beta is related to the macro factor in addition to the market beta; a two-beta conditional CAPM where each of the macro variables is a conditioning variable and drives a time-varying or dynamic beta. Their findings demonstrate that the conditional CAPM that utilises macro factor as a conditioning variable provides more or less explanatory power for average portfolio returns than the two-beta model. In the other related work, Maio (2013) proposes a conditional CAPM that utilises interaction of cash flow news with inflation (CPI) and shows that it outperforms traditional Campbell and Vuolteenaho (2004) ICAPM model.

2.4.3.3 Industrial Production

Chen, Roll, and Ross (1986) find inflation and industrial production as significant priced factors in the first stage of Fama and MacBeth (1973) regression. However, these variables are not found significant in the cross-sectional second stage regression. Their views suggest that these variables are not the appropriate state variables for asset pricing but this will stimulate further research for recognition of appropriate state variables to improve asset pricing. Asprem (1989) examine five variables for the economic activity including industrial production, real gross national product, gross capital formation, employment and exports. Their findings suggest that the industrial production is the most promising variable that influences stock market returns. Liu and Zhang (2008) find that growth in industrial production is useful in explain momentum effect. Ji, Martin and Yao re-examine Chen, Roll, and Ross (1986) model on three sets of test portfolios and compare its performance with a q-factor model of Hou, Xue, & Zhang (2015) that utilises market factor, a size factor, an investment factor, and a profitability factor. They find that q-factor outperforms Chen, Roll, and Ross (1986) model. Their findings suggest that the profitability factor covaries with the momentum returns for the whole years and hence, explains momentum returns better than industrial production.

2.4.3.4 Consumption

Lettau and Ludvigson (2001) give insight about the role of consumption-wealth ratio in determining stock market returns in the U.S. Their findings reveal that consumption-wealth ratio is the strong predictor of real and excess stock returns over Treasury bills in the U.S. He claims that consumption-wealth ratio provides a reliable and better forecasts for short and intermediate time periods than dividend payout ratio, dividend yield and other factors. They argue that the consumer behaviour models for optimal behaviour signify consumption-wealth as the sum of human capital and aggregate asset holdings ratio. The main drawback of this model is that they make assumptions to estimate consumption-wealth ratio as they admit that this "ratio is not observable” which highlights the limitations of this model. However, the contradictory evidence on the performance of the consumption-based models is documented in the literature (Campbell & Cochrane, 2000). Later, Lettau and Ludvigson (2003) come up with further evidence to prove consumption-wealth and asset returns relationship through arguing that the macro models which do not account for transitory changes in wealth are often misleading and misstated.

2.4.3.5 GDP

Hou and Robinson (2006) find evidence of the influence of GDP growth in the U.S. market. They note that higher stock premiums in the case of economic contraction when the short term and forecast of GDP growth is low. It implies that the investors raise the required rate of return in the wake of weaker economic conditions in the near future. In addition to examining inflation, T-Bill rate, they also include future and current GDP growth rates to assess the relation of stock premiums with economic activity. They document highly significant relations between stock returns and future GDP growth for the next year. Their results are in line with findings of Fama (1990) and Kothari and Shanken (1992) who assert that the short period stock returns carry forward-looking information about the economic conditions of the market for many future periods. The evidence of the influence of GDP and oil is also documented in other developed markets. For instance, Chaudhuri and Smiles (2004) have

used Johnsen's multivariate cointegration methodology to explain the relationship betwee n macroeconomic variables and stock returns in the developed market of Australia. Their findings report the long-run relationship between real stock prices and real economic activity measured by the real money supply, the real GDP, and the real price of oil.

2.4.3.6 Oil Prices

Regarding the influence of oil price on stock returns, Jones and Kaul (1996) examine an impact of the oil price shocks in the U.S., Canadian, Japanese and U.K. stock markets. He finds that the influence on stock price in response to oil price shocks is more accounted to the changes in cash flow whereas, in the U.K. and Japanese markets, volatility in oil prices significantly explain variations in stock returns. On the other hand, Sadorsky (1999) argues that oil price and oil price volatility both affect stock returns in the U.S. He marks that after 1986, the movement in oil prices explain variations in stock returns more than interest rates. Park and Ratti (2008) reveal that oil price shocks not only significantly influence real stock returns in the U.S. but also other 13 European countries. He uses the data from 1983 to 2005 and marks that the contribution of oil price volatility to stock returns variability in the U.S. and other European countries is greater than the influence of interest rate on stock returns. Kilian & Park (2009) explain the relationship of U.S. stock returns with reference to change in oil price. This study report that the supply and demand shocks which drive the overall global oil market and may cause 22% long-run variation in the stock returns of the U.S. market. There are mixed arguments regarding the impact of oil price on stock prices in the literature. Jones and Kaul (1996) find a negative relationship between oil and stock prices while Wei (2003) report that the fall in the U.S. stock prices in 1974 was not due to the 1973-1974 increase in oil prices.

2.4.3.7 Exchange Rate

Jaffe and Westerfield (1985) examine daily stock returns in the U.S., UK, Canadian and Australian markets. They document weekend effect in each country and report that foreign investors face this effect independent of the weekend effect in the U.S. market. They attempt to find whether the integration of foreign currency markets can be used to determine the day of the week effects which can be used by the U.S. stock investors to counterbalance the effect. Their results reveal that the seasonal changes on the foreign exchange do not counterbalance seasonal changes in the stock markets. Giovannini and Jorion (1989) examine CAPM under different assumptions and use return on a portfolio which is composed of developed market currencies such as Dollar, Sterling, Deutsche mark and Swiss Franck asset and includes the US. Stock market return. The results show that the computed conditional variance does not explain time variations of risk premium. His research suggests the developed of reliable asset pricing require the inclusion of more assets with modern computational techniques to estimate a large set of variables. Jorion (1991) also finds an insignificant relationship between stock returns and exchange rate. He assesses the impact of exchange rate risk on the stock returns in the U.S. market. Their empirical evidence reveals that the relationship between stock returns and U.S. Dollar varies across industries. He concludes that the exchange risk is not priced in the U.S. market as he finds the insignificant premium for exchange risk. He criticises financial hedging policies as they do not reduce the cost of capital. Exchange rate influence more in developed markets as compared to emerging and developing markets as Rad (2011) reports a weak relationship between stock prices and exchange rate while investigating the impact of macroeconomic variables in emerging market of Iran. Richards, Simpson, and Evans (2009) have examined the relationship between exchange rate and stock prices in Australia. Their study reports the strong positive relationship between these two variables. They find positive co-integration with Granger causality running from stock prices to exchange rate during their sample period of 2003 to 2006.

2.4.4 Intertemporal CAPM

Intertemporal Capital Asset Pricing Model is an alternative and extended version of single factor CAPM model. The ICAPM model includes empirical as well as macro or state factors. It is a multifactor modelwhich assumes that risk can be explained by the multi beta factors. Fama and French (1996) highlight that there is a scope of including macro or state variables in their three-factor model to improve its empirical performance. Researchers have even included Fama and French's three-factor model among the category of ICAPM models (Petkova, 2006; Maio and Santa-Clara, 2012). Merton (1973) derives ICAPM from the arbitrary behaviour of investors in portfolio selection who tend to maximize the expected utility of life lasting consumption to trade in multi-period continuously in time. He derives explicit demand functions of assets and argues that as compared to single period CAPM model, current demands of assets are influenced by uncertain changes in future investment prospects. After deriving demand functions, he derives equilibrium relationships among assets and reveals that the expected returns on risky assets were different from risk-free rate even when the systematic risk does not exist. In this way, he derives a generalised ICAPM in which a number of state factors are priced to explain the expected return of an asset. The idea behind that model is that the uncertainty does exist in the expected returns and also in the factors which affect security expected returns. These factors can be future investment opportunities, prices of consumption goods in future, income inflation rate and other state factors. Fama (1996) derives Merton's ICAM that can be expressed by the following equation as:

$$E(R_i) = R_f + [E(R_m) - R_f]\beta_{iM} + \sum_{s=1}^{S}[E(R_s) - R_f]\,\beta_{is}, \tag{2.23}$$

$$i = 1, \dots, N, \mathrm{s} = 1, .., \mathrm{S}$$

In this equation, $E(R_s)$ represents mimicking portfolios for state variables s whereas β_{is} shows state variable *s* beta for asset *i*. In simple words, ICAPM signifies that market beta is not sufficient to explain expected returns because market portfolio is not mean variance efficient instead it is multifactor efficient. Fama (1991) criticises the ICAPM's theory and label it as an empiricist's dream by marking it as off-the-shelf theory which can be used to test cross-sectional relations between expected returns and factor loadings which are correlated with returns. Fama (1996) attempts to explain ICAPM's theory and highlights that market and state variable risk premiums can be positive or negative in the ICAPM model. The positive or negative premiums for state variables rely on the investors' choices for different set of future consumption and investment opportunities. The risk aversion mind set of investors results positive premium from the return variance of multifactor efficient portfolio which however, remains unexplained by state variables. The market portfolio is multifactor efficient, therefore, its residual return variance produces positive premium. Fama (1996) argues that the positive premium should be offset as market portfolio hedge against risks associated with state variables. Fama (1998) marks about ICAPM that it does not specify state variables that are of hedging concern for investment. Cochrane (2009) emphasises that only those factors should be included in the factor loadings for ICAPM which significantly predict future investment opportunities. Elton, Gruber, Brown, & Goetzmann (2009) highlight inflation model as the simplest multi beta model where expected return of a security is expressed as a function of two sensitivities.

$$\bar{R}_i - R_F = \beta_{iM}(\bar{R}_M - R_F) + \beta_{iI}\,(\bar{R}_I - R_F) \tag{2.24}$$

The new term in this expression is the product of newly introduced beta which is the sensitivity of security to the securities' portfolio which is held to hedge inflation risk and is referred as the price of inflation risk. The ICAPM shows that the security's expected return is related to a set of sensitivities as it is influenced by a number of influencing state variables. It can be mathematically expressed as:

$$\bar{R}_i - R_F = \beta_{iM}(\bar{R}_M - R_F) + \beta_{iI1}\,(\bar{R}_{I1} - R_F) + \beta_{iI2}\,(\bar{R}_{I2} - R_F) + \cdots \tag{2.25}$$

This expression allows expected return of a security to hedge against a set of risks with which it is exposed.

2.4.5 State variables

2.4.5.1 Term Structure

The term structure of interest rates is also referred as yield curve which represents the relationship between interest rate and maturity time period of different financial instruments such as government bills and bonds. Given the current market conditions, it measures the future interest rate expectations in the market and provides the investor insight into the possible future outlook of the economy.

Ho and Lee (1986) develop AR[4] model to explain the stochastic[5] movement of term structure in such a way to make it arbitrage free. Chen, Roll, and Ross (1986) mark the term structure of interest rates as an important factor to influence stock returns. They point out that the difference of interest rate between short-term and long-term maturity government bonds influence stock returns when they use it as an additional variable in the asset pricing tests. Campbell (1987) supports these findings and reports that the term structure predicts not only excess returns of stock but also predicts excess returns on bonds and bills. His research uses simple asset pricing models and uses the data set from 1959-1979. He finds that the relationship between the conditional variance and excess returns is positive despite the fact that the conditional variance of excess returns varies over time. Burmeister and McElroy (1988) provide further empirical support through their empirical cross-sectional tests. They highlight that term structure including default risk significantly explain variations of stock returns in the U.S. market. Fama and French (1993), Hahn and Lee (2006) and Petkova (2006) have used the term-structure in their ICAPM models and find it significant in the time series and cross-sectional tests.

[4] AR Model: Arbitrage Free Interest Rate Model
[5] Stochastic term is usually used to explain momentum or price movements of financial instruments in technical financial analysis.

2.4.5.2 Default Spread

Like term-structure, default spread is also an important state variable that also has been used as a crucial factor in the ICAPM in many studies. For instance, Burmeister and McElroy (1988) ,Chen, Roll, and Ross (1986), Fama and French (1993), Hahn and Lee (2006) and Petkova (2006) use this factor in their multifactor ICAPM models. Default spread is the difference between long-term government and long-term corporate bond yields. Maio and Philip (2013) provide evidence in support of state factors that are based on bond yield factors. They show that the conditional CAPM and ICAPM models that based on bond yield or interest rate factors outperform the multifactor APT models.

2.4.5.3 Liquidity

The liquidity is also reported to influence stock returns. Pastor & Stambaugh (2001) report that the expected returns exhibit cross-sectional relation with aggregate liquidity. They conclude that the market-wide liquidity is a state variable which shows statistically significant influence on stock returns. That state variable can be sued in the Intertemporal Capital Asset Pricing model. They have used this variable with size, book-to-market and momentum risk factors and highlight that the stock returns that exhibit higher sensitivity to aggregate liquidity provide higher returns. Findings show liquidity should be considered as another factor in asset pricing. Some of the researchers mark insufficient liquidity and illiquid assets on the balance sheet of global banks as the main cause of financial crisis (Cornett, McNutt, Strahan, & Tehranian, 2011). Liu (2006) also stresses that liquidity is an important source of the priced risk. He proposes the modified two-factor liquidity augmented model. He provides empirical evidence from cross-sectional tests that their liquidity augmented model perform better than Fama-French three-factor model.

Back, Li, & Ljungqvist (2013) argue that the higher liquidity can be harmful to governance as higher liquidity increases the likelihood of trading in blocks on private information. They implement exogenous variation in empirical tests from three distinct sources and reveal that the variation in liquidity decrease activism among block holders.

2.4.5.4 Volatility Factor

Bakshi and Kapadia (2003) highlight the impact of volatility factor on stock returns through pointing that the investors are usually averse to the periods of high volatility and they are willing to pay a premium to hedge against the possible loss during volatility period. The pricing of options is more influenced by volatility than stocks as out-of-the-money options are traded at a premium than at-the-money options (Coval & Shumway, 2001). The empirical evidence of influence on stock returns is also documented (Ang, Hodrick, Xing, & Zhang, 2006). Later, Ang (2009) further reports that stocks with low volatility have higher returns than stocks with low volatility in the global stock market as well. It is argued that the options are not the only financial instruments which are influenced by volatility instead stocks are also influenced likewise (Blitz & Van Vliet, 2007). When global equities are sorted into portfolios on historical volatility, the stocks with long low volatility provide high premium than stock with short high volatility. However, this is inconsistent with the economic logic that low volatility stocks provide higher returns but this seems consistent with leverage aversion (Asness, Frazzini, & Pedersen, 2012). This argument can be related to the hedging with gold as investors heavily invested in gold during financial crisis despite the fact that the consistent increase of gold prices to hedge their possible losses in the stock market (Wang, Wei, & Wu, 2011). Bollerslev, Tauchen, & Zhou (2009) support these findings and report that the volatility premia developed from implied volatility provide high future returns to low volatility stocks.

2.4.6 Testable Implications of ICAPM models

Maio and Santa-Clara (2012) have highlighted the time series and cross-sectional implications for multifactor CAPM and ICAPM models. They have detailed the restrictions imposed on multifactor asset pricing models. In case of assets (n), the instantaneous return of asset (i) is given as:

$$\frac{dP_i}{Pi} = \mu_i(s,t)dt + \sigma_i(s,t)d\xi_i \quad i = 1, \ldots, N, \tag{2.26}$$

where P_i shows the price of security $i; d\xi_i$ is Weiner process[6] whereas $\sigma_{ij}\, dt$ is the covariance between two risky securities. The investment opportunities vary over time as both mean ($\mu_{i)}$ and volatility (σ_i) are functions of an individual state variable (s) which emerges as a diffusion process that can be expressed as:

$$ds = a(s,t)dt + b(s,t)d\zeta, \tag{2.27}$$

where, $d\zeta$ signifies again Weiner process whereas the covariance of risky security's return with state variable should be equal to $\sigma_{is}\, dt$. The ICAPM of Merton (1973) does not directly specify state variables. Instead, the model imposes restrictions on the models that the state variables forecast stock returns' initial two moments. If *N + 1th* asset is a riskless security, then its instantaneous return is given as:

$$\frac{dP_i}{P_I} = r_f\, dt \tag{2.28}$$

Cochrane (2005) assumes that utility lasts forever and utility function can be expressed as:

$$U = E_t \sum_{i=0}^{\infty} \beta_i\, u(C_{i+i}) \tag{2.29}$$

On the other hand, the dynamics of wealth can be expressed as:

[6] Weiner Process: Wiener process is a continuous stochastic process and is named after Norbert Wiener. This is often referred as standard Brownian motion because of its historical link with physical process called as Brownian motion which was originally observed by Robert Brown.

$$dW = \sum_{i=1}^{N} \omega_i \,(\mu_i - r_t^W) W\, dt + (r_t^W - C) dt + \sum_{i=1}^{N} \omega_i \, W \sigma_i d\xi_i \qquad (2.30)$$

As investors have to begin with wealth (W_0) which earns instantaneous return r_w and they do not have other sources of income. If, interest rate is constant and returns on security are independent and identically distributed (*i.i.d.*) over time, then investors tend to maximise their utility and the value function *V(W)* can be expressed as:

$$V(W, s, t) = \max_{C,\omega_i} E_t \sum_{i=0}^{\infty} \beta_i \, u(C_{t+i}) \qquad (2.31)$$

The investors are also limited to budget constraints, therefore

$$W_{t+1} = r_{t+1}^W (W_{t+1} - C_t); r_t^W = w_t' r_t;\; w_t' 1 = 1 \qquad (2.32)$$

In this equation, ω_i signifies portfolio weight for asset *i* whereas *C* denotes Consumption. The equilibrium relation of risk and expected return in the ICAPM model is given as:

$$\mu_i - r = \gamma \sigma_{im} + \gamma_s \sigma_{is} \qquad (2.33)$$

where $\gamma \equiv -W V_{WW}(W, s, t) / V_W(W, s, t)$ shows the parameter of relative risk aversion. In equation (2.33), σ_{im} represents the covariance between the return on security *i* and market *m* whereas σ_{is} denotes the covariance between security *i* and state variable *s*.

where $\gamma_s \equiv -\frac{V_{ws}(W,s,t)}{V_w(W,s,t)}$ (2.34)

where $V_w(.)$ shows marginal value for wealth; $V_{ww}(.)$ denotes growth in marginal value; and $V_{ws}(.)$ signifies a cross derivative in relation to state variable *(s)* and wealth *(w)*. Taking guidelines from Cochrane (2005) and Maio and Santa-Clara (2012); the above equation can be expressed into pricing equation in discrete time as:

$$E_t(R_{i,t+1}) - R_{f,t+1} = \gamma Cov_t(R_{i,t+1}, R_{m,t+1}) + \gamma_s Cov_t(R_{i,t+1}, \mathbf{\Delta s}_{t+1}) \qquad (2.35)$$

where $R_{i,t+1}$ is the return on security *i* from time *t* to *t +1 ;* $R_{f,t+1}$is the return on the risk-free rate which is identified at time t; $R_{m,t+1}$ is the return on the market, and $\mathbf{\Delta s}_{t+1}$ is an innovation in state variable *s*. If the price of the risk related to the state variable is equal to zero i.e. $\gamma_s = V_{s(.)} = 0$. If such is the case, then it will be equivalent to the static CAPM. This pricing equation reflects theory the behind multifactor asset pricing models and for this reason, ICAPM is stated as fishing licence (Fama, 1991). The unconditional ICAPM can b e expressed as:

$$E_t(R_{i,t+1} - R_{f,t+1}) = \gamma Cov\left(R_{i,t+1}, R_{m,t+1}\right) + \gamma_s Cov(R_{i,t+1}, \mathbf{\Delta s}_{t+1}) \qquad (2.36)$$

In the above equation, risk premiums are explained by a couple of sources. The first one is explained by the market risk premium and is also related to the static CAPM, $\gamma Cov\left(R_{i,t+1}, R_{m,t+1}\right)$; It denotes that a security which covaries positively with the market, gets a positive risk premium above risk-free rate. The reason is that an investor tends to hold this security only if it provides premium over risk-free rate as this security is unable to offer hedge against unexpected changes in aggregate wealth *(W)*. Maio and Santa-Clara (2012) cite Mehra and Prescott (1985) who emphasise that the estimate of relative risk aversion (RRA) should be positive from one to ten.

The second source of risk is explained by the term state variable, $\gamma_s Cov(R_{i,t+1}, \mathbf{\Delta s}_{t+1})$, which forecasts positive market premium. In case of positive premium for state variable γ_s, a security with a positive covariance with a state variable earns a positive premium. The main underlying reason behind this positive premium is that a security does not provide a hedge against unexpected negative changes in aggregate wealth as it provides lower returns in case of expected low returns of aggregate wealth. Thus, a risk averse investor tends to hold such security only if it provides premium over return of riskless asset. The economic insight of ICAPM places restriction on the coefficient's sign (γ_s) of a state variable in the cross-sectional results. For instance, if a state variable positively covaries positively with expected market return:

$$Cov_t(R_{m,t+2}, S_{t+1}) = Cov_t[E_{t+1}(R_{m,t+2}), S_{t+1}] \quad (2.37)$$

$$= Cov_t\left[E_{t+1}\left(R_{m,t+2}\right), \Delta S_{t+1}\right] > 0$$

Likewise, given the above assumption, also suppose if return on security *i* also positively correlates with a change in state variable,

$$Cov_t(R_{i,t+1,} s_{t+1}) = Cov_t\left(R_{i,t+1}, \mathbf{\Delta s}_{t+1}\right) > 0 \quad (2.38)$$

In this case, the intertemporal risk premium is positive. Therefore, it is implied from the above two conditions that the return on security *i* positively correlates with future aggregate market return.

$$Cov_t(R_{i,t+1}, R_{mt+2}) = Cov_t[(R_{i,t+1,} E_{t+1}(R_{m,t+2})] > 0 \quad (2.39)$$

This final condition has an important economic implication as security *i* does not hedge against negative change in the market return and earns a higher risk premium than a security with $Cov(R_{i,t+1}, R_{mt+2}) = 0$, then it will result, $\gamma_s Cov(R_{i,t+1}, \Delta S_{t+1})$>0. It is also implied that γ_s> 0, given the above mentioned condition, $Cov_t\left(R_{i,t+1}, \mathbf{\Delta s}_{t+1}\right) > 0$.

Furthermore, the state variables which predict expected market variance, are also considered in this research. Moreover, the corresponding cross-sectional signs of state variables (γ_s) are also re-examined. Maio and Clara (2012) report that the sign of intertemporal risk premium is negative if state variables have positive correlation with future volatility of market returns.

On the other hand, if a security *i* negatively covaries with a state variable *(s)*, then it will earn a negative risk premium. The main implication of the above-mentioned conditions is that if a state variable forecasts positive expected return, its risk premium should also get the correct sign in the cross-section[7].

[7] It is not sufficient that a set of state variables forecast positive or negative future aggregate returns, but their

$$Cov_t(R^2_{m,t+2}, S_{t+1}) = Cov_t[E_{t+1}(R^2_{m,t+2}), S_{t+1}] \tag{2.40}$$

$$= Cov_t\left[E_{t+1}\left(R^2_{m,t+2}\right), \Delta S_{t+1}\right] > 0$$

Without losing generality, assume if the return on security *i* is positively correlated with innovation in the state variable, then it is also positively correlated with expected market volatility.

$$Cov_t(R_{i,t+1}, R^2_{m,t+2},) = Cov_t[R_{i,t+1}, E_{t+1}(R^2_{m,t+2})] > 0 \tag{2.41}$$

The economic inference of this condition suggests that such security offers reinvestment hedge against expected market volatility as it provides a higher return in case of higher market volatility. Therefore, such security will get lower risk premium as compared to the security with $Cov_t\left[R_{i,t+1}, R^2_{m,t+2}\right] = 0$, therefore, $\gamma_s Cov(R_{i,t+1}, \Delta S_{t+1}) < 0$, considering the assumption as discussed above $Cov_t\left(R_{i,t+1}, \Delta \mathbf{s}_{t+1}\right) > 0$. In case, a state variable predicts negative market volatility, then risk premium will be positive. The underlying reason is that when covariance of a security is negative with future market volatility, then it does not offer a hedge for risk aversion, therefore, investors only prefer to hold those securities which offer a premium for uncertainty in their future wealth. These results are opposite as compared to the expected returns. In the cross-sectional result, the risk price should get a correct if a state variable forecasts positive or negative market volatility. If we use return on riskless asset R_f[8], then we can express the above-mentioned relations into a single equation as, $Cov_t(R_{f,t+1}, R_{mt+1}) = Cov_t\left(R_{f,t+1}, \Delta \mathbf{s}_{t+1}\right) = 0$, which finally to the pricing equation as:

$$E\left(R_{i,t+1} - R_{f,t+1}\right) = \gamma Cov\left(R_{i,t+1} - R_{f,t+1}, R_{m,t+1}\right) + \gamma_s Cov\left(R_{i,t+1} - R_{f,t+1}, \Delta \mathbf{s}_{t+1}\right) \tag{2.42}$$

risk prices should also receive that sign in the cross sectional test to validate application of a multifactor model in estimating expected returns (see also Lutzenberger (2015), Cooper and Maio (2016) and others. In the asset pricing literature, most predictive variables forecast positive expected returns for equity markets. For instance, ratios such as book-to-market dividend-to-price or earning-to-yield ratio, term structure and default spread.

[8] The risk-free rate ($R_{f,t+1}$) is given at the start of the period.

2.4.7 Generalised Method of Moments (GMM)

For empirical tests of CAPM, Generalised method of moments (GMM) has been recommended as the robust and sophisticated method as it takes into account heteroscedasticity of returns (Brooks, 2014). This method of estimation has been put forward by Hansen (1982) and has been recognised as the modern estimation method in financial econometrics. This is the generalisation of other estimation procedures such as least squares, instrumental variables and maximum likelihood and therefore, it is less likely that it can be miss-specified (Chaussé, 2010). GMM is more flexible estimation methods because it only needs some assumptions for moment conditions. For instance, stock returns data are characterised by heavy-tailed and skewed distributions and GMM does not apply any restriction on the distribution of data. Cochrane and Orcutt (1949) recommend correction for serial correlation which is termed as Cochrane Orcutt. This correction for heteroscedasticity and serial correlation is not required under this method. The main drawback of GMM is that it may not perform with small samples. Chaussé (2010) cite Campbell, Lo, & MacKinlay (1997) in explaining a procedure for estimating a system of CAPM's equations with Generalised Method of Moments who have demonstrated GMM application in the CAPM tests. According to them, the CAPM can be expressed as : $\mu_i - R_f = \beta_i(\mu_m - R_f)\forall_i$. In this CAPM's equation, μ_i is the expected return for stock ***i***, R_f is the risk-free rate and μ_m is the expected market return. The testable equation is given by:

$$(R_t - R_f) = \alpha + \beta\left(R_{mt} - R_f\right) + \epsilon_t \tag{2.43}$$

where R_t is the *Nx1* observed vector of stock returns whereas R_{mt} is the observed proxy for market return. R_f is the risk-free rate on and $\epsilon_t$is the error term having covariance matrix $(\sum_t)$. When this error term is estimated by least square (LS) or maximum likelihood (ML), it is assumed to be fixed. The main advantage of GMM is that it allows this error term to be serially correlated and constantly changing with robust characteristics of heteroscedasticity. The CAPM implies that the α should be zero and this can be tested by estimating above model $(R_{mt} - R_f)$ by using Fama French factors as instruments and null hypothesis can be tested as $H_0,\ \alpha = 0$. Earlier, Jagannathan, Skoulakis, and Wang (2002) have presented some applications of GMM in Finance in which one of the prominent is the representation of the CAPM in the form of stochastic discount factor (SDF). The CAPM theory denotes that $E(m_t R_{it}) = 1$ for all assets *i*, in which m_t is the SDF-*Stochastic Discount Factor* and R_{it} is the gross return (1+r_{it}). The CAPM is valid if $m_t = \theta_0 - \theta_1 R_{mt}$ which means the following moment conditions:

$$E[R_{it}(\theta_0 - \theta_1 R_{mt}) - 1] = 0\ ,\ i=1\ldots\ldots,N \qquad (2.44)$$

Cochrane (2005, Chapter 12) has recommended using GMM for empirical tests of asset pricing models. Various researchers have used GMM to assess empirical performance of asset pricing models (Bodurtha & Mark, 1991; Davidson, Faff, & Hillier, 2003; Maio & Santa-Clara, 2012; Maio & Philip, 2013 and many others). Maio and Santa-Clara (2012), Maio & Philip (2013) and Lutzenberger (2015) have used first stage GMM to examine the consistency of multifactor models. First stage GMM is theoretically equivalent to OLS (Ordinarily Least Square) cross-sectional regression in which average excess returns are regressed against factor covariance They assess various multifactor models in the criteria of ICAPM and deeply examine theoretical restrictions on the risk factors of multifactor models explained above. They also include market return within testing assets in an attempt to combine cross-sectional literature of ICAPM with time series aggregate trade-off of risk and return which is mostly reported in time series literature. In first stage GMM, the models are estimated in expected return covariance form rather than expected return-beta to obtain estimates of factor risk prices and then each model is assessed according to the criteria of

ICAPM. The main formulas of GMM are explained below. The covariance of excess return (r) and factor (f) can be expressed as:

$$E(r) = Cov\ [(r\ (f')]b \tag{2.45}$$

In spirit of Cochrane (2005), the weighting matrix of GMM system can be expressed as:

$$W = \begin{bmatrix} W^* & 0 \\ 0 & I_{K+1} \end{bmatrix} \tag{2.46}$$

W^* signifies an NxN weighting matrix, 0 shows a conformable matrix of zeros whereas I_{K+1} represents a $K+1$ identity dimensional matrix. In this expression, the weighting matrix (W^*) is related to the first N moment conditions and corresponds to the pricing errors of N testing securities (assets). On the other hand, I_{K+1} denotes the weighting matrix for the last $K+1$ moment conditions which enable to compute factor means. We implement first step GMM to estimate multifactor models which is conceptually similar to Ordinary Least Square (OLS) cross-sectional regression of excess returns over covariance of returns and factors, hence, in first stage GMM, W^* will be related to the identity matrix, $W^* = I_N$. The estimate of risk price (b) in the first stage GMM can be expressed as:

$$\hat{b} = [C'C]^{-1}C'E_t(r) \tag{2.47}$$

$$\bar{f} = E_t(f) \tag{2.48}$$

In this estimation, $E_t(.)$ represents mean of the testing security (asset) whereas $C \equiv E(r(\tilde{f}')$ denotes variance and covariance matrix of excess returns and factors i.e. $\hat{f} = f - \bar{f}$.

We also use second stage GMM for robustness checks. The second stage GMM is equivalent to cross-sectional Generalised Least Square (GLS) estimation. In case of second stage GMM, the weighting matrix of W^* is inverse of the first NxN portion of the spectral density matrix[9] $W^* = S_N^{-1}$. The variance-covariance formula for risk price ($\hat{b}$) and factor *($\bar{f}$)* can be expressed as:

$$Var(\hat{b}, \bar{f}\,) = \frac{1}{T}(d'Wd)^{-1}d'W\hat{S}Wd(d'Wd)^{-1} \tag{2.49}$$

In this formula, *d* denotes the matrix of moments in relation to the parameters (*b)* and factors (*f)*:

$$d = \begin{bmatrix} C & E(r)b' \\ 0 & I_{K+1} \end{bmatrix} \tag{2.50}$$

In the above formula, $\hat{S}$ denotes spectral density matrix of S, which is formed with estimation of White (1980) or heteroscedastic robust standard errors with absence of lags of moment functions in estimation of $\hat{S}$ as recommended by Cochrane (2005). He marks that asset pricing model is true if moments defining pricing errors are orthogonal to the past information, that is, past information forecast pricing errors and factors.

$$\hat{S} = \begin{bmatrix} E(u_t u_t') & E(u_t \hat{f}_t') \\ E(\hat{f}_t u_t') & E(\hat{f}_t \hat{f}_t') \end{bmatrix} \tag{2.51}$$

In the above matrix, u_t shows the pricing errors, $u_t \equiv r_t(1 - \hat{f}_t{}'b)$. The statistical significance of the estimate of each risk price can be tested with the null hypothesis that the price of *i*th factor is equal to zero (Cochrane, 2005, Chapter 10):

$$\frac{\hat{b}_i}{\sqrt{Var(\hat{b})ii}} \sim N(0,1) \tag{2.52}$$

[9] Spectral density matrix is the spectrum of covariance exhibiting periodicities in a matrix. The spectral density enables to detect periodicities in financial data.

2.5 Evaluation of Multifactor Models

Literature suggests that the researchers have used a number of state variables to perform time series and cross-sectional tests to assess empirical validity of Merton's ICAPM. Brennan, Wang, & Xia (2004) develop and estimate ICAPM for time-varying investment opportunities. Their model assumes that investment opportunities are described by real interest rate and Sharpe ratio. They test their model through cross-sectional Fama and MacBeth (1973) methodology to find whether their proposed model is consistent with Merton's ICAPM. They use a combined sample of 55 portfolios, 25 size and book-to-market value portfolios and 30 industry portfolios in estimating and testing their model. They use Kalman filter to estimate parameters of state variables. The F-test proposed by Gibbons, Ross, and Shanken (1989) is implemented to test join significance of α's in OLS regression estimates of portfolios' excess returns over market excess returns. For empirical tests of ICAPM, Lo and MacKinlay (1990) have recommended not to use returns on portfolios which are constructed on the basis of association with returns. Brennan, Wang, & Xia (2004) mention that since size and book-to-market value meet this criteria, therefore, it will be better to use industry portfolios as well in the testing process of ICAPM tests. In their findings, the pricing restrictions for their models were rejected. They conclude that the empirical implementation of ICAPM should be paid careful attention for selection of state variables as ICAPM is not just another factor model, the state variables must be limited to those responsible to predict future investment opportunities. Petkova (2006) finds that HML (high minus low) and SMB (small minus big) are significantly correlated with innovations in state variables that forecast excess market returns and its variance. He finds HML as a proxy for a term spread while SMB proxies for default spread surprise factor. He attempts to establish a significant link between of time series and cross-sectional returns predictability. He recommends the ICAPM model which is based on dividend yield, term spread, default spread and short-term T-Bill rate for cross-section of expected return than Fama-French models. Bali and Engle (2010) extend time-series tests of ICAPM to many risky assets. They estimate ICAPM using dynamic conditional correlation (DCC) model of Engle (2002). They use the mean-reverting DCC model to estimate portfolio (stock)'s conditional covariance for market and test whether conditional covariance forecasts time variation in the portfolio (stock)'s expected returns. They estimated daily intertemporal relationship between expected returns and risk for 30 stocks in the Dow Jones Industrial Average and various equity portfolios. They find cross-sectional consistency in the intertemporal relationships and additional statistical power in their results which is reported to be obtained through pooling multiple cross-sectional time series for joint estimation of slope coefficients. They did not price SMB and MOM factors in the ICAPM and report Investment to assets (IA), the return on investment (ROA) and book-to-market value (HML) as priced factors which could be viewed as proxy for investment opportunities. Citing prediction of Merton (1980) that expected returns must be related to conditional variance, they emphasise that it should apply not only to the market portfolio but to individual securities as well. Maio & Santa-Clara (2012) apply the ICAPM to eight popular multifactor models and their findings show that most of the models do not satisfy ICAPM's restrictions. They conclude that Fama and French (1993) and Carhart (1997) models perform consistently better in meeting ICAPM's restrictions. His other models could explain size, value and momentum anomalies but are inconsistent in satisying the ICAPM conditions.

2.6 Summary of Literature Review

The Capital Asset Pricing Model (CAPM) is the foundational model in asset pricing. The CAPM and its extended versions are used in estimating the cost of equity and expected returns. In the literature review, we examine in detail the developmental process of the

CAPM, its extended Fama-French, Consumption, ICAPM, and APT versions and critically evaluate the empirical performance in international equity markets.

Markowitz (1952, 1959) proposes the mean-variance theory for portfolio analyses and then Sharpe (1964) develops the CAPM that simplifies the risk and return relationship. Banz (1981) reports that the smaller firms had higher risk-adjusted returns than larger firms and highlights CAPM's failure in explaining size effect in the U.S. equity market. Reinganum (1981), Basu (1983) further underline size and value anomalies until Fama and French (1993) test three-factor model by including market, size and value anomalies in the U.S. equity market. Their three-factor model shows superior performance than traditional CAPM in both time series and cross-sectional asset pricing tests.

Jegadeesh and Titman (1993) mark that the stock returns also show momentum, i.e. stocks which have performed particularly well or particularly badly, tend to continue doing so in the subsequent six months to one year. Carhart (1997) further develops this and proposes a four-factor model which augments the Fama and French (1993) three-factor model with a momentum factor. Fama and French (2006) highlight the role of value, investment and profitability on stock returns. They find that high value and profitability are related to high returns, whereas high investment is related to low returns. Novy-Marx (2013) documents further evidence of strong relation of expected profitability with expected returns. Fama and French (1993) three-factor model struggle on other markets and portfolios (Fama and French, 2012; Gregory, Tharyan, and Christidis, 2013). Four-factor model performs better than the three-factor model on other markets but it also struggles in pricing small stocks. Fama and French (2015) develop their five-factor by including investment and operating profitability factors with their three-factor model. However, they leave the gap of testing five-factor model on momentum portfolios where they consider inclusion of momentum is ‘crucial’. We develop the first hypothesis that empirical performance should improve with the addition of momentum in global regions.

Similar to three-factor and four-factor models, Fama and French (2015) also admit empirical limitation of their five-factor model in explaining average returns of small stocks. Despite the development of these empirical multifactor models, pricing of small stocks remains an unsolved puzzle in empirical finance. Further, Fama-French models are criticized to perform only on mimicking sets of test portfolios.

The proxy of a risk-free rate could be the underlying reason for empirical weaknesses of empirical factor models. Three-factor, four-factor and five-factor models are extensions of the CAPM. One of the main assumptions of CAPM allows investors to borrow and lend to an unlimited extent at the risk-free rate. Black, Jensen, and Scholes (1972) criticize this assumption and mark unrealistic as the risk-free rate is unavailable to all investors. They relax this assumption and examine the CAPM with limited borrowing. They propose an alternative model that replaces risk-free rate with a zero-beta rate and examine the CAPM with the assumption that allows the investors to lend but not borrow at the zero-beta rate. Shanken (1985), Davidson, Hillier and Faff (2003) estimate zero-beta models in absence of risk-free rate. However, they do not employ return on zero-beta portfolio due to difficulty in identifying and estimating the return on a zero-beta portfolio. Mehra and Prescott (1985) raise the concern of higher equity premium puzzle in the U.S. equity market and relate this puzzle with the lower risk-free rate in the U.S. equity market. They argue that the lower risk-free rate with higher equity premium violate the restrictions of general equilibrium models. Weil (1989) extend their research and raise the concern of risk-free rate puzzle. Constantinides and Duffie (1996) find that the Treasury bonds are not in zero-net supply and hence, violate restrictions of Arrow- Debreu models conditions as well. on which CAPM is theoretically developed. These views are also consistent with the efficient market hypothesis of Fama (1991) that solely focusses on the efficiency of financial markets.

Contrary to government securities, gold is recognised as a zero-beta (Chua, Sick and Woodward, 1990) and risk-free asset (McCown and Zimmerman, 2006). Gold has received attention due to its prominent role as a hedging and safe-haven asset in global markets during the financial crisis (Baur and Lucey (2010; Baur and McDermott, 2010). In the United States, the gold return is equivalent to the Treasury bill rate from 1836 to 2011 (Barro and Misra, 2016). Wang, Wei, and Wu (2011), Pierdzioch, Risse, and Rohloff (2014), Ntim, English, Nwachukwu, & Wang (2015) find weak-form efficiency in the U.S. and U.K. gold markets. The efficient nature of gold makes it suitable to be used as a proxy of a zero-beta rate. We develop the hypothesis that the applicability of gold return as a proxy of a zero-beta rate could improve empirical performance of empirical factor models.

After examining the role of gold as a zero-beta asset, we also examine the literature on the extra-market sensitivity of the gold price on equity markets. Chan and Faff (1998) find the significant extra market sensitivity of gold in the Australian market, Davidson, Hillier, and Faff (2003) provide evidence of gold factor exposures on global industries from 1975 to 1994. We extend this study from 1995 to 2015 in the global and U.S. industries to provide an updated and fresh evidence in three different sub-periods. We include U.S. industries in this studies as the U.S. owns the largest gold reserves in the world that constitute 74.9 percent of its total reserves (World Gold Council, 2017). We critically review safe-haven, hedging and diversification benefits before financial crisis (Davidson, Hillier and Faff, 2003; Faff and Hillier, 2004; Hillier, Draper, and Faff; 2006), during financial crisis (Baur and McDermott, 2010) and after financial crisis (Hood and Malik, 2013; Baur, 2014; Bredin, Conlon, and Potì, 2015; Low, Yao and Faff, 2016; Bris and Rezaee, 2017).

Finally, we review the influence of macro and state variables on stock returns by using Merton (1973) Intertemporal CAPM theory and Arbitrage Pricing Theory (APT) theory of Roll (1976) and Ross (1977). We review the influence of macro variables such as money supply, interest rate, inflation, consumption, GDP, industrial production, oil prices and exchange rate in asset pricing. Among state variables, we examine the term-structure, default spread, liquidity and volatility. Moreover, we review the performance of the multifactor ICAPM and APT models.

We also critically review the criteria for the validity of multifactor asset pricing models from the perspective of asset pricing theory. Majority of the models have been developed in response to the CAPM's failure to price portfolios sorted on stock specific or state variables. Fama and French (1993, 2015), and Carhart (1997) have attempted to explain dispersion in the cross-section of stock returns to price portfolios sorted on size, book-to-market, momentum, profitability, investment and other stock specific factors. Petkova (2006), Hahn and Lee (2006) have proposed alternative ICAPM models. The multifactor ICAPM models may include all those variables in addition to the market return which influence stock returns. We find that most of the ICAPM models are unable to satisfy the ICAPM's criteria and the empirical factor models outperform these ICAPM models.

In addition, we also discuss asset pricing tests such as Lintner (1965), Black, Jensen and Scholes (1972), Fama and MacBeth (1973), Gibbon, Ross and Shanken (1989) tests. Further, we discuss the Generalised Method of Moments (GMM) methodology as is explained in Cochrane (2005) and employed by Maio and Clara (2012) and Lutzenburger (2015).

Chapter Three

Research Methodology

3.1 Research philosophy

From an ontological perspective, there are two main perceptions of reality, realism and relativism. Realism is the ontological perspective within the positivist or quantitative paradigm of research that is looking for the facts or truth about reality that can be revealed observed and measured, therefore, the epistemology within positivism is objective in nature. This objectivity implies that the researchers take appropriate measures to prevent any influence on results to ensure fairness and credibility of the research.

Burrell and Morgan (1979) detail the guideline about choosing research methodology. They outline that if the researcher has a deterministic approach for human nature and believes that reality is not socially constructed, then nomothetic methods should be used: the focus of which is to obtain objectivity through scientific techniques.

Hence, this research adopts an objective approach that is based on a realistic view of positivistic epistemology. Realists believe in the “truth” which is static, objective and measurable. Realism is based on cause and effect laws and context-free generalisations.

The philosophical approach of positivism is based on the deterministic view of nature and focuses on the quantitative data analysis. Deterministic and positivistic approaches are categorised under the umbrella of realism. Positivism and determinism are mostly common in natural science research that is based on experimental analyses (Neuman, 2005). Burnell and Morgan (1979) mark that the social science researchers may adopt an intermediate approach that allows the influence of voluntary and situational factors to account for the activities of human beings.

The methodology in the positivistic paradigm is, therefore, experimental in which hypotheses are tested, control measures are implemented and quantitative techniques are regarded as superior. As the aim of this research is to improve asset pricing models, therefore, the positivistic approach is used and quantitative methodology is implemented. This study tests different models, develop different hypotheses and experiment different models with different data to come up with reliable models by using quantitative financial econometric research methods. Neuman (2005) marks that PSS[10] prefer to produce quantitative data which is subject to statistical analysis. Stuart Mill-the founder of positivistic approach emphasizes that the statistical analysis enables to derive a system of logic to reach results and make rational decisions (Mill, 1843). This study intends to enable investors to make rational investment choices in their portfolio investment decisions. After determining research approach, this study attempts to improve asset pricing with the empirical, zero-beta, macro and state variables. Empirical analyses are performed to compare the performance of proposed models with existing asset pricing models to achieve the objectives of this research. The research design is shown in Figure (3).

[10] PSS: Positivist Social Science which is widely used as positivism and most commonly approach of natural science (Neuman, 2005). Multiple versions of positivism exist and is developed by British philosophers David Hume in "*A Treasure OF Human Nature* (1739-1740)" and John Stuart Mill in a "*A System of Logic*" published in 1843.

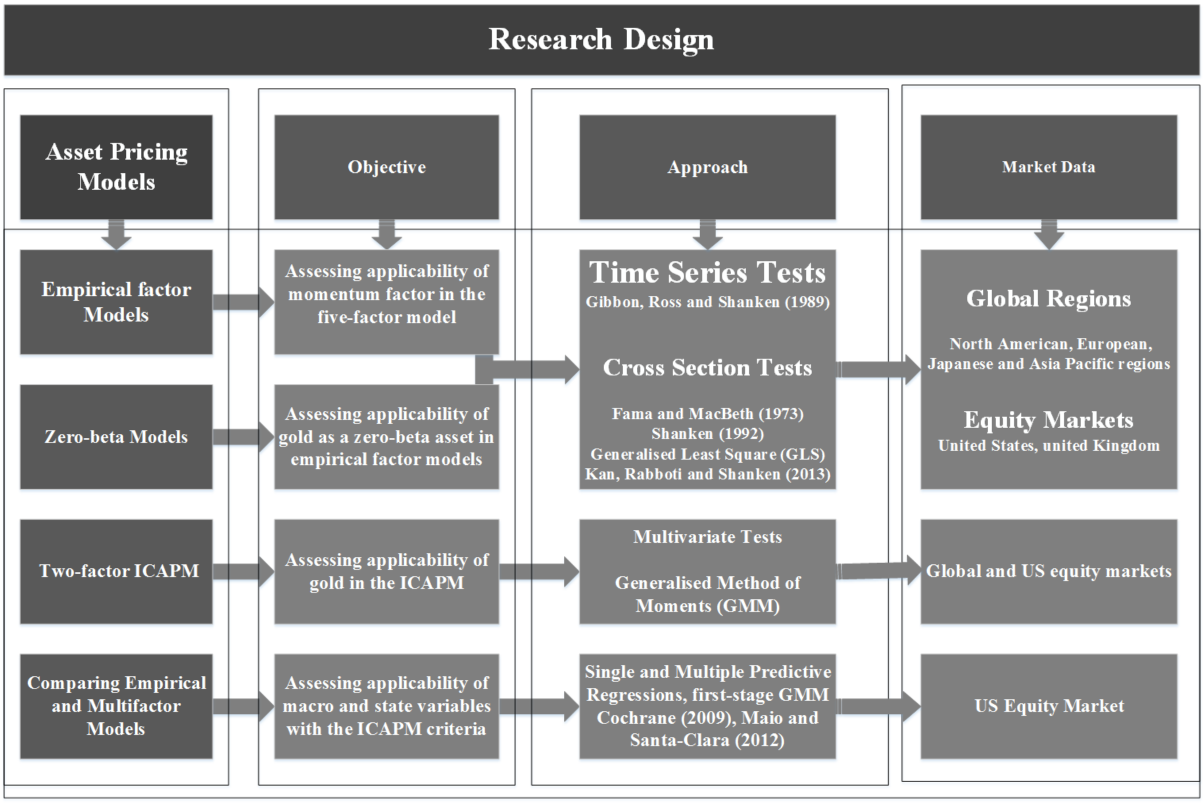


Figure 3: Research design shows the strategy of the research to improve asset pricing by using empirical, zero-beta, macro and state variables in global markets.

3.1.1 Assessment of empirical factor models

Firstly, the empirical performance of single factor, Fama and French (1993) three-factor, Carhart (1997) four-factor, Fama and French (2015) five-factor, and six-factor models are evaluated with time-series and cross-sectional tests. In expected return form, these models can be expressed in Eq. (3.1) - (3.5) as follows:

$$E\,(\tilde{R}_{i,t}) = R_{F,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{F,t}\big] + e_{i,t} \tag{3.1}$$

$$E\,(\tilde{R}_{i,t}) = R_{F,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{F,t}\big] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + e_{i,t} \tag{3.2}$$

$$E\,(\tilde{R}_{i,t}) = R_{F,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{F,t}\big] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] +$$

$$\beta_{i,m}[E(MOM_t)] + e_{i,t} \tag{3.3}$$

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,C}[E(CMA_t)] + \beta_{i,r}[E(RMW_t)] + e_{i,t} \tag{3.4}$$

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,m}[E(MOM_t)] + \beta_{i,C}[E(CMA_t)] + \beta_{i,r}[E(RMW_t)] + e_{i,t} \tag{3.5}$$

3.1.2 Global and Local Factors

Griffin (2002) examines Fama-French factors and examines their performance by using global and local factors. Empirical evidence from findings suggests that local factors explain more variation in time series and produce less pricing errors than global factors. He also finds that when local factors are decomposed with foreign factors, then these factors produce in-sampling or out-of-sampling pricing errors. Further, he adds that country-specific factors are more suitable for performance evaluation. I further extend this study to examine the local or global nature of Carhart (1997) and Fama and French (2015) factors in international markets to gain robust and conclusive findings.

3.1.3 Asset pricing tests

3.1.3.1 Time Series Test

3.1.3.1.1 Gibbons, Ross and Shanken (1989) Test

In time-series, Gibbons, Ross and Shanken (1989, GRS) tests are performed on the first-stage regression results. The GRS statistic tests the null hypothesis that intercepts (hereafter, alphas) from the first-stage time-series regressions are jointly equal to zero.

The null hypothesis for a system of N time-series equations can be expressed as:

H_0: $\alpha_i = 0 \quad i = 1, \ldots, N,$

The closer the alphas to zero, the better the performance of the asset pricing model. The econometric interpretation of the GRS test in the case of a single-factor model can be expressed as follows:

$$GRS = \frac{(T-N-1)}{N}\left(\left[\frac{\sqrt{1+\hat{\delta}_q^2}}{\sqrt{1+\hat{\delta}_p^2}}\right]^2 - 1\right) \tag{3.6}$$

where $\hat{\delta}_p$ is the Sharpe ratio of R_p and $\hat{\delta}_q$ is the Sharpe ratio of the ex-post efficient portfolio, which is the frontier portfolio comprising all assets. The GRS test captures the relative variations and deviations of R_P from the ex-post efficient portfolio, calculated using the ex-post sample means and covariance matrix. A lower GRS value determines that the portfolio R_P differs less from the ex-post efficient portfolio and implies a better performance of the asset pricing model.

The Sharpe ratio of the first-stage alphas is computed and the number of significant first-stage alphas are also reported. The Sharpe ratio of alphas *SR(a)* represents the core of the GRS test (Lewellen, Nagel, and Shanken, 2010; Fama and French, 2012), and is defined as:

$$SR(a) = (\boldsymbol{a}'\boldsymbol{S}^{-1}\boldsymbol{a})^{\frac{1}{2}} \tag{3.7}$$

where ***a*** denotes the vector of alphas of all test portfolios and ***S*** is the covariance matrix of residuals obtained from all first-stage regressions. In these, a lower value of *SR(a)*, and fewer significant alphas indicate a better asset pricing model.

Fama and French (2012) further shed light on the methodology of the Gibbons, Ross, and Shanken (1989) that estimates Sharpe ratio of alphas $SR(a)^2$. Sharpe ratio of alphas is the crucial output of the GRS test and lower value is desirable for the adequate performance of the model. It is the difference between. 1) the square of the maximum Sharpe ratio of the portfolios that can be formed from the left-hand side (LHS) and right-hand side (RHS) assets in a time series regression and 2) the square of the maximum Sharpe ratio of the portfolios that can be formed from only right-hand side (RHS) assets. In other words, Sharpe ratio of alphas *SR(a)* is the maximum Sharpe ratio of the excess portfolio returns formed from the left-hand side (LHS) assets having a zero slope on the right-hand side (RHS) portfolio returns. Sharpe ratio of alphas *SR(a)* provides the information about unexplained average returns in a model. The key benefit of the Sharpe ratio of alphas *SR(a)* is that it combines the intercepts from regression with the covariance matrix of residuals, which is the main determinant of the precision and accuracy of alphas. It can be regarded advantage as *SR(a)* combines information regarding both magnitude of alphas and their precision, hence, it is beneficial to have more information provided by the average absolute intercept, the average R-squared, and the average standard error of alphas.

3.1.3.2 Cross-Sectional Test

3.1.3.2.1 Fama and Macbeth (1973) Methodology

After the time-series tests, the cross-sectional tests are performed by using Fama-MacBeth (1973) regressions. This study follows the methodology that detailed in Cochrane (2009) and also employed by Gregory, Tharyan, and Christidis (2013) and Blackburn & Cakici (2017).

In the Fama-MacBeth (1973) regressions, firstly, a vector of factor loadings is estimated in time series regressions of excess returns on each portfolio of the test assets on the vectors of risk factors, as

$$R_{i,t} - R_{f,t} = \alpha_i + \boldsymbol{\beta_i f_t} + e_{i,t} \tag{3.8}$$

where $R_{i,t}$ is the return on portfolio *i* at time *t*, $R_{f,t}$ is $R_{F,t}$ for the conventional models and $R_{G,t}$ in the case of their gold analogues, $\boldsymbol{\beta_i}$ is a vector of coefficients, and $\boldsymbol{f_t}$ is a vector of factors from the model being tested.

In the second pass, the rolling cross-sectional regressions are run on each month as

$$R_i - R_f = \gamma_0 + \boldsymbol{\gamma}\widehat{\boldsymbol{\beta}}_{\boldsymbol{i}} + \varepsilon_i \qquad (3.9)$$

where $\widehat{\boldsymbol{\beta}}$ is the estimated vector of factor loadings from the first-pass regression and $\boldsymbol{\gamma}$ is a vector of cross sectional regression coefficients. The time-series average of all $\boldsymbol{\gamma}$ coefficients is estimated over all months in the sample (420 months in this study).

The CAPM implies that the cross-sectional coefficients are equal to the mean of the factors, and so the market coefficient ought to be equal to the market risk premium, $R_m - R_F$.

The use of estimated coefficients from the first stage regressions as independent variables in the second stage regressions, introducing an error-in-variables bias in the standard errors owing to time series correlation in the residuals.

3.1.3.2.2 Addressing Errors-in-variables (EIV)

In the traditional two-pass Fama-MacBeth (1973) regression system, the independent variables in the second-pass regression represent the time-series coefficients from the first-pass regressions. The coefficients in the second pass regressions are subject to the errors-in-variables (EIV) problem, which makes it biased in the case of small samples and can be inconsistent as the number of assets increases in the sample. Shanken (1992) proposes the modified estimator which makes a correction to provide standard errors corrected for the errors-in-variables (EIV) effects. All the variables excluding one in the cross-sectional regressions of the present analysis represent firm characteristics and are measured without error, and therefore, should not much face error-in-variables problems. The one exemption is the firm’s market beta. Since this beta is estimated from a first-pass regression, the market beta may face error-in-variable effect (Shanken, 1992). As all other independent variables except market beta are measured without error, therefore various researchers have used the

OLS estimator and have not reported the modified estimator which addresses the error-in-variables problem (Moskowitz & Grinblatt, 1999; Fama & French, 2012; Blackburn & Cakici, 2017). In the present study, though, the Shanken (1992) correction is implemented to estimate the standard errors for the alphas and the cross-sectional coefficients of market beta and other risk factors for the sake of robustness and completeness.

Shanken (1992) demonstrates a traditional two-pass cross-sectional regression system comprising k_1 general factors subject to the error-in-variable problems, k_2 additional factors which are held to be priced by the cross-sectional regression, and k_3 additional variables which are measured exactly and, therefore are not subject to error-in-variable considerations. In most studies, $k_2 = 0$, and the system resembles the conventional Fama-Macbeth (1973) cross-sectional regression system. He presents an asymptotic covariance matrix for the pricing of risk factors. The covariance matrix is formed by a second-pass cross-sectional regression which is T-consistent and converges to the true value as the number of time points T tends to infinity, is given by:

$$(1+\hat{c})\left[W-\hat{\sum}_F^*\right]+\hat{\sum}_F^* \tag{3.10}$$

where $\hat{c} = \hat{\Gamma}'_{25}\hat{\sum}_F^{-1}\hat{\Gamma}_{25}$

W is the sample covariance matrix of the second-pass regression system, $\hat{\Sigma}_F^*$ is an autocorrelation – consistent estimator for Σ_F^*, which itself is a “bordered” variance-covariance matrix of the general factors. The k_1 x k_1 variance-covariance matrix Σ_F of the k_1 general factors, is subject to error-in-variables problems in the centre, and k_3 rows of zeros at the left and the bottom; and $\hat{\Gamma}_{25}$ is a vector comprising the coefficient estimates of the ex-post estimates of risk factors for the k_1 general factors that face error-in-variables problems and the k_2 additional factors.

In the case of only one variable, $k_2 = 0$, $k_1 = 1$, namely, the market beta, which may subject to the error-in-variable problem, and the remaining exactly-measured variables in each cross-sectional regression form the other k_3 variables. $\hat{\Gamma}_{25}$ then comprises only the coefficient estimate for the estimate of the market beta, and Σ_F comprises only the variance of the excess market return.

The adjusted variance for the cross-sectional regression intercept is then:

$$\mathrm{Var}\left[\hat{\alpha}_{Shanken}\right] = \left(1+\hat{c}\right) \times \mathrm{Var}\left[\hat{\alpha}_{OLS}\right] \tag{3.11}$$

where $\hat{c} = \dfrac{\overline{\gamma}^2_{RmRf}}{\sigma^2_{RmRf}}$,

$Var\left[\hat{\alpha}_{OLS}\right]$ is the unadjusted OLS variance of the estimated value of the intercept,

$\overline{\gamma}_{\beta RmRf}$ is the expected value of the ex-post cross-sectional pricing of the market beta, and

σ^2_{RmRf} is the time-series variance of the excess market return.

The adjusted variance for the cross-sectional market beta is:

$$\mathrm{Var}\left[\hat{\beta}_{Shanken}\right] = \left(1+\hat{c}\right) \times \mathrm{Var}\left[\hat{\beta}_{OLS}\right] + \sigma^2_{RmRf} \tag{3.12}$$

where $\mathrm{Var}\left[\hat{\beta}_{OLS}\right]$ is the unadjusted OLS variance of the estimated value of the cross-sectional pricing of market beta,

In this way, the Shanken (1992) correction is applied to correct the error-in-variables bias to adjust the standard errors produced from the Fama-MacBeth procedure. However, Jagannathan and Wang (1998) find that if the error term is heteroscedastic, then the Fama-MacBeth procedure does not necessarily estimate smaller standard errors for the cross-sectional coefficients. Therefore, following Petkova (2006), the cross-sectional t-statistics are estimated from both unadjusted and adjusted procedures. We employ Shanken (1992) correction to compare the performance of the empirical factor models in international equity markets. Further, we use the Shanken (1992) correction to compare the performance of the traditional empirical factor models and gold zero-beta models.

3.2 Research methodology for applicability of gold as a zero-beta asset

Apart from empirical factors, there is a scope for improving a proxy of a zero-beta rate. Gold is widely recognised as a zero-beta asset. This study examines its application as a proxy of a zero-beta rate in asset pricing. Firstly, the market efficiency tests are performed in global gold markets to find the efficiency level of the gold markets. Further, the position of gold is established by plotting minimum variance frontier. A zero-beta portfolios of Black, Jensen, and Scholes (1972) is found on the efficient minimum variance frontier; hence it is important to confirm that gold is an efficient asset and lie on the minimum variance frontier.

3.2.1 Market efficiency tests

This study follows Ntim, English, Nwachukwu, & Wang (2015) in assessing the market efficiency and perform strict random walks (RWS) and relaxed martingale difference sequence (MDS) tests. Hence, these tests are implemented to assess the weak form efficiency of global gold markets. The weak form efficiency shows that the future prices cannot be predicted from past prices. Campbell, Lo and MacKinlay (1997) and Ntim, English, Nwachukwu, & Wang (2015) show that the random walk hypothesis (RWS) tests the assumption that price series of a financial asset follow a random walk, if:

$$P_t = \mu + P_{t-1} + \varepsilon_{t,} \varepsilon_t \sim IDD\ N(0, \partial^2)$$

where (P_t) shows the log of the asset's return series (P_t) , daily spot gold price series at time *t*; μ is a drift parameter, and $\varepsilon_{t,} \varepsilon_t \sim IDD\ N\left(0, \partial^2\right)$ is an error term that is independent and identically distributed (iid) with a zero mean and a unit variance (∂^2). In this way, this study tests a strict random walks (RWS) test (H_{01}).

Conversely, the price series (P_t) of a financial asset follows a martingale difference sequence (MDS) if the following condition is satisfied: $E[P_{t+1} - P_t | P_t, P_{t-1}, \ \ldots] = 0$, where P_t

refers to the log of the spot daily gold price at time *t.* This shows equal probability of the increase or decrease in gold prices at time *t*, hence, price series of a financial asset is difficult to be predicted under the MDS restrictions. The MDS is a relaxed test of market efficiency as it relaxes the strict assumptions of *iid* and allows the possible presence of the dynamic volatilities in gold prices, for instance conditional heteroscedasticity, that, however, restrict consistent residual changes to be independent, but does not expect it to be identically distributed.

The parametric and non-parametric variance ratio tests are performed to test the strict random walks ($H_{2.1}$) and relaxed MDS ($H_{2.2}$) hypotheses. The parametric variance-ratio test is developed by Lo and MacKinlay (1988), whereas its non-parametric form is suggested by Wright (2000). The variance ratio test is based on the assumption that the log of price series of a financial asset follows a random walk. Ntim, English, Nwachukwu, & Wang (2015) adopt Lo and MacKinlay (1988, hereafter, LM test) and Wright (2002) approach in implementing variance ratio tests. Likewise, we follow this approach in testing a weak form efficiency of gold prices.

Firstly, I discuss the parametric LM test. Suppose, P_t represents a price series of T observations, $p_1, p_2, \ldots, p_T$ of a financial asset, then, the variance ratio of qth difference, *VR(q)* is expressed as

$$VR(q) = \frac{\partial^2(q)}{\partial^2(1)} \tag{3.13}$$

where $VR(q)$ denotes the variance ratio of the qth difference of a gold price series, q shows the number of observations, the days or week in this study, q=15, 20, 25, and 30.

$\partial^2(q)$ denotes the unbiased estimators of 1/q variance of the qth difference, and

$\partial^2(1)$ show an unbiased variance estimator of first difference of a gold price series,

$\partial^2(q)$ is computed as:

$$\partial^2(q) = \frac{1}{Tq}\sum_{t=q}^{T}(p_t + \cdots + p_{t-q+1} - q\hat{\mu})^2 \tag{3.14}$$

where $\hat{\mu}$ is an arbitrary drift and is estimated as

$$\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T} p_t \tag{3.15}$$

The unbiased variance estimator, $\partial^2(q)$, is estimated as

$$\partial^2(1) = \frac{1}{T}\sum_{t=1}^{T}(p_t - \hat{\mu})^2 \tag{3.16}$$

The estimated *VR (q)* would be equivalent to the unity under the null hypothesis if the gold price series follow a random walk.

The LM test implements the test statistics in two specifications. The initial test statistic tests the strict hypothesis of random walks (RWS) and is denoted by $M1(q)$ and is estimated as

$$M_1(q) = \frac{VR(q)-1}{\phi(q)^{1/2}} \tag{3.17}$$

$M_1(q)$ represents a homoscedastic-consistent test statistic as it tests a price series under the assumptions of the homoscedasticity ,i.e. a series is normally distributed, having a zero mean and a unit variance, $\phi(q)$ denotes a homoscedastic consistent asymptotic variance of estimated variance ratio, $\phi(q)$ is computed as

$$\phi(q) = \frac{2(2q-1)(q-1)}{3qT} \tag{3.18}$$

On the other hand, the second test statistic of LM test $M_2(q)$, is a heteroscedastic-consistent test statistic and is employed to test the MDS hypothesis and is given expressed as

$$M_2(q) = \frac{VR(q)-1}{\phi^*(q)^{1/2}} \tag{3.19}$$

$M_2(q)$ test statistic is a heteroscedastic robust statistic and $\phi^*(q)$ shows its heteroscedasticity-consistent variance and is expressed as

$$\phi^*(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q}\right]^2 \delta\,(j) \tag{3.20}$$

where $\delta(j) = \frac{\sum_{t=j+1}^{T}(p_t-\hat{\mu})^2(p_{t-j}-\hat{\mu})^2}{\left[\sum_{t=1}^{T}(p_t-\hat{\mu})^2\right]^2}$

Wright (2000) redevelops LM (1988) parametric test to a non-parametric test. In Wright (2000) non-parametric test, the test statistic replaces the differences in returns of price series (p_t) with ranks and signs. For instance, p_t is replaced with ranks series, R_1 and R_2 that test RWS hypothesis, and sign series s_1 that test MDS hypothesis. Ranks R_1, R_2 , and signs s_1, s_2 are expressed as

$$R_1 = \left(\frac{\frac{1}{Tq}\sum_{t=q}^{T}(r_{1t}+\cdots+r_{1t-k+1})^2}{\frac{1}{T}\sum_{t=1}^{T}{r_{1t}}^2} - 1\right) \times \phi(q)^{-1/2} \tag{3.21}$$

$$R_2 = \left(\frac{\frac{1}{Tq}\sum_{t=q}^{T}(r_{2t}+\cdots+r_{2t-k+1})^2}{\frac{1}{T}\sum_{t=1}^{T}{r_{2t}}^2} - 1\right) \times \phi(q)^{-1/2} \tag{3.22}$$

where $\phi(q)$ is homoscedastic-consistent and is shown in Eq. (3.18).

$$s_1 = \left(\frac{\frac{1}{Tq}\sum_{t=q}^{T}(s_t+\cdots+s_{t-k+1})^2}{\frac{1}{T}\sum_{t=1}^{T}s_t{}^2} - 1\right) \times \phi^*(q)^{-1/2} \tag{3.23}$$

$$s_2 = \left(\frac{\frac{1}{Tq}\sum_{t=q}^{T}(s_t(\bar{\mu})+\cdots+s_{t-k+1}(\bar{\mu}))^2}{\frac{1}{T}\sum_{t=1}^{T}s_t(\bar{\mu})^2} - 1\right) \times \phi^*(q)^{-1/2} \tag{3.24}$$

where $\phi^*(q)$ is a heteroscedastic-consistent and is defined in Eq. (3.20). The test s_1 defines a series $s_t = 2\mu(p_t, 0)$ whereas, s_2 considers defining a series $s_t(\bar{\mu}) = 2\mu(p_t, \bar{\mu})$ and if $\bar{\mu} = \mu$, then $s_t(\bar{\mu}) = 2\mu(p_t, 0)$, hence, distribution of $S(\bar{\mu})$ becomes identical of the distribution of S_1. Wright (2000) implements various Monte-Carlo tests to confirm that the ranks (R_1, R_2) are homoscedastic robust and signs (s_1, s_2) are heteroscedastic robust, and hence, can be effectively employed for testing RWS and MDS hypotheses respectively. Wright (2000) marks that s_2 test produces a relatively lower power, therefore, this study only estimates R_1, R_2, and s_1 in this study. Lugar (2003) reveals that non-parametric tests are even robust in non-normalities.

In addition to the above tests, this study also performs an Automatic Portmanteau test for robustness (Escanciano & Lobato, 2009; Charles, Darné, & Kim, 2011). Escanciano and Lobato (2009) propose this test as an alternative to LM (1988) and Wright (2000) tests. Charles and Kim (2011) find the Portmanteau test as a robust test for assessing market efficiency in small samples. They implement this to test the MDS hypothesis. This test is implemented over the full sample 1981-2015 and the sub-samples from 1991-2015 and 2000 to 2015. In order to obtain robust evidence in sub-samples, the multiple variance ratio test of Whang and Kim (2003) is performed by using subsampling of different lengths. This test is implement to gain deeper insight into the level of market efficiency. This study uses observations N∈(4174, 6524, 9132) and considered holding periods of 15, 20, 25, 30 and 35 days in the similar fashion of conducting LM (1988) and Write (2000) tests. This research considers six different subsamples (denoted *b1,…, b6)* in performing sub-sample tests. N∈(4174, 6524, 9132) are chosen to test the market efficiency from 1981 to 2015, 1990 to 2015 and 2000 to 2015.

3.2.2 Position of gold on efficient frontier

This research also determines the position of gold on efficient frontier to establish the efficient nature of gold and its applicability as a zero-beta asset in asset pricing. Literature review shows that use of the T-bill rate as a risk-free rate violates restrictions of general equilibrium models (Mehra and Prescott, 1985). It gives rise to the problems of a low risk-free rate and a high equity market premium (Mehra and Prescott, 1985; Weil, 1989). Further Treasury bill rate is strongly influenced by federal fund rate set by FOMC where gold market is weak form and informationally efficient (Wang, Wei, and Wu, 2011; Ntim, English, Nwachukwu, & Wang, 2015 ; Pierdzioch, Risse, and Rohloff, 2014). This is the fundamental assumption that traditional equilibrium models fail to meet when the Treasury bill yield is used as a risk-free rate. The applicability of gold as an efficient zero-beta asset may help in improving estimation of expected returns. Further, it can be used as an additional measure to estimate expected returns and help in improving pricing of small risky stocks.

This study is similar in nature to the Black, Jensen, and Scholes (1972) study who employ a zero-beta portfolio of risky assets. The zero-beta asset is located at the minimum variance frontier as is shown in Figure (4).

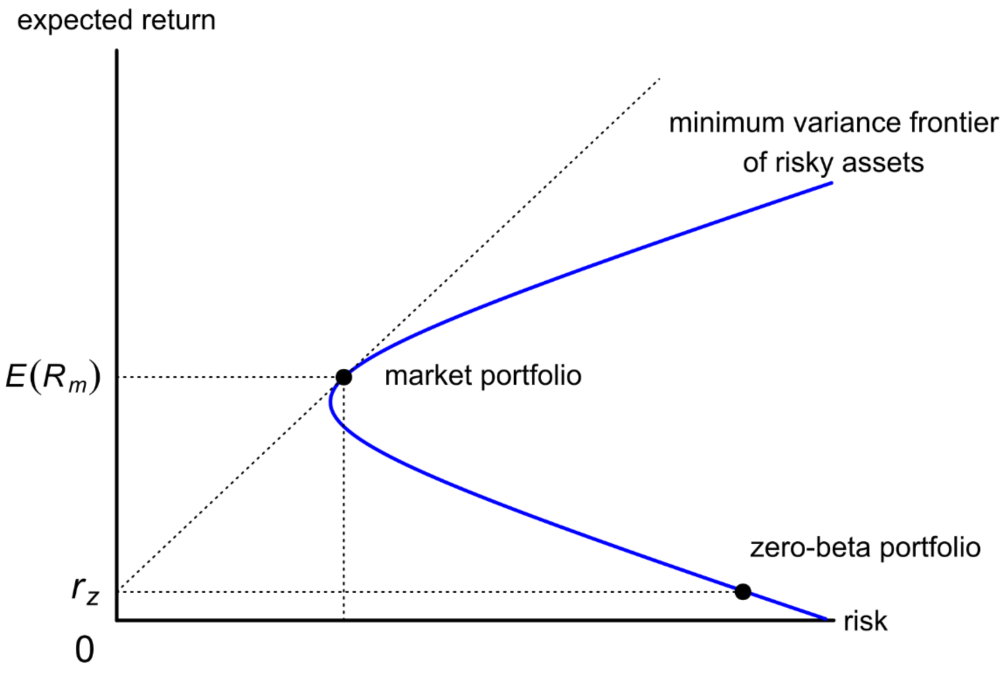


Figure 4: Minimum variance frontier of risky assets

Source: Author’s own

The efficient frontier is the set of minimum-variance (MV) portfolios of risky assets with all possible expected returns. This research takes guidance from Clarke De Silva, and Thorley (2006) and Kan and Smith (2008) in plotting the minimum variance efficient frontier. In a portfolio of *n* asset, efficient frontier can be estimated by using variance-covariance matrix (Σ) of returns, a vector of expected returns (μ_i), a colums vector of portfolios weights (ω_i), and a unit column vector (u).

Firstly, we estimate inverse of the variance-covariance matrix (Σ^{-1}) and then a, b, c, and d are calculated in the following way:

$$a = u'\Sigma^{-1}u \tag{3.25}$$

$$b = \mu'\Sigma^{-1}u \tag{3.26}$$

$$c = \mu'\Sigma^{-1}\,\mu \tag{3.27}$$

$$d = ac - b^2 \tag{3.28}$$

Finally, the minimum variance efficient frontier is plotted by using the following equation

$$\sigma p^2 = (\,a\,\mu p^2 - 2b\,\mu p + c)\,/d \tag{3.29}$$

Hence, this study tests the third hypothesis ($H_{2.3}$) that gold return can only satisfy Black, Jensen and Scholes (1972) restriction of a minimum variance portfolio if it is located on the minimum variance frontier of risky assets.

3.2.3 Application of gold as a zero-beta asset in empirical factor models

To evaluate the hypothesis that asset pricing models which use gold return will function better than models which employ the 1-month T-bill rate as a risk-free rate, this study performs the empirical tests using gold return as a zero-beta rate in pricing U.S. equities, so that the role played by the T-bill rate in the above equations is replaced by the 1-month return on gold. This study, therefore, denotes a CAPM model which utilises the return on gold in place of the T-Bill yield as a risk-free rate, as the G-CAPM:

$$E\ (\tilde{R}_{i,t}) = R_{G,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{G,t}\big] + e_{i,t} \tag{3.30}$$

where $R_{G,t}$ is the 1-month return on gold, and all other variables are defined as above.

In similar fashion, for brevity, this study denotes a Fama-French (1993) model which utilises the return on gold in place of the T-Bill yield as a risk-free rate, as a G-Three-Factor Model:

$$E\ (\tilde{R}_{i,t}) = R_{G,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{G,t}\big] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + e_{i,t} \tag{3.31}$$

Likewise, this study denotes a Carhart (1997) model which utilises the return on gold in place of the T-Bill yield as a risk-free rate, as a G-Four-Factor Model:

$$E\ (\tilde{R}_{i,t}) = R_{G,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{G,t}\big] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,m}[E(MOM_t)] + e_{i,t} \tag{3.32}$$

This study also denotes a Fama-French (2015) Five-Factor model which utilises the return on gold in place of the T-Bill yield as a risk-free rate, as a G-Five-Factor Model:

$$E\ \big(\tilde{R}_{i,t}\big) = R_{G,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{G,t}\big] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,C}[E(CMA_t)] + \beta_{i,r}[E(RMW_t)] + e_{i,t} \tag{3.33}$$

Finally, this study defines the G-Six-Factor model as the zero-beta gold analogue of the six-factor model:

$$E\ \big(\tilde{R}_{i,t}\big) = R_{G,t} + \beta_i\big[E\big(\tilde{R}_{m,t}\big) - R_{G,t}\big] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,m}[E(MOM_t)] + \beta_{i,C}[E(CMA_t)] + \beta_{i,r}[E(RMW_t)] + e_{i,t} \tag{3.34}$$

As a robustness test, this study adopts the Ferguson and Shockley (2003) methodology to derive residual factor, $R_t^{G\perp}$, constructed to be orthogonal to the Rm-Rf, SMB, HML and MOM factors. This study derives this factor from the time-series regression:

$$R_t^{Gold} = a_0 + a_1 R_t^{Mkt-R_F} + a_2 R_t^{SMB} + a_3 R_t^{HML} + a_4 R_t^{MOM} + e_{i,t} \tag{3.35}$$

$R_t^{G\perp}$ is then calculated as $a_0 + e_{i,t}$, that is, adding the intercept and residual from equation (18). $R_t^{G\perp}$ contains all information present in R_t^{Gold} which is not contained in the four independent variables, and its inclusion as an independent variable test for the null hypothesis that it explains no extra variance.

3.2.4 Small stock pricing

Similar to Fama and French (2012), this study estimates asset pricing models with and without small stocks . This is done to establish whether gold zero-beta asset pricing models help to improve pricing of small stocks. Recent studies by Fama and French (2012, 2015, 2017) have evaluated that it is challenging to price small stocks in the U.S. market. I attempt to address this main problem of asset pricing with gold zero-beta models. It is also important to explicitly define small stocks to get deeper understanding of the contribution from this study. Small stocks are viewed as the risky stocks in the asset pricing due to small market capitalisation as compared to the large stocks. Small caps are those stocks that have market capitalization less than $2 billion, whereas large caps are those stocks that have market capitalization more than $10 billion. On the other hand, nano caps are those stocks that have market capitalization less than $50 million. This study estimates and compares the performance of traditional and gold zero-beta asset pricing models with and without small caps. The traditional asset pricing models struggle to explain average returns when small stocks are included in the RHS test portfolios (Fama and French, 2012).

3.3 Research Methodology for the two-factor ICAPM

After assessing application of gold return as a zero-beta rate, this thesis examines its application as a hedging factor in the global and U.S. equity markets. This study starts analyses by estimating the two-factor model[11] for each global and U.S. industry portfolio. The two-factor model can be expressed as:

$$R_{i,t} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{goldt} + e_{it} \tag{3.36}$$

where R_{it} is the return on an industry portfolio *i* in month *t*, $R_{m,t}$ is the return on the market portfolio in month *t*, and R_{goldt} is the return on gold in month *t*.

In Eq. (3.36), the signs of gamma (γ_i) depend on the positive or negative exposure of the gold price factor to an industry portfolio *(i)*, hence, it is industry dependent. Findings from the Merton's (1973) ICAPM and Macdonald and Solnik's (1977) two factor model shows that a hedging factor is negatively correlated with the market returns. If the market beta is high (low), the price of the hedging exposure should be negative (positive). Therefore, high risk industries should show a negative exposure to the hedging factor whereas low risk industries should exhibit a positive exposure. When gold is used as a hedging factor, a negative exposure is expected to be obtained. However, it is important to establish a distinction for gold industry portfolios themselves as gold prices are expected to have positive exposure on gold industry portfolio due to strong effect of gold prices on their returns. In the absence of extra-market sensitivity or hedging, gamma coefficient would be zero (γ_i= 0).

[11] A similar two-factor model has been used by McDonald and Solnik, Chan and Faff (1998), and Davidson, Faff and Hillier (2003).

3.3.1 Stability tests of gold factor exposures

The results for the full period present a relative weak gold factor exposure in the world industries if the results are compared with the results of the Davidson, Faff, and Hillier (2003) study. The stability of the significance of the gold factor is also required to be considered. Apart from the stability tests, it is also important to examine the gold factor exposure to the world and the U.S. industry portfolios before and after the financial crisis. Therefore, three non-overlapping sub-periods are used in addition to the full-time period to further analyse the gold factor exposure to the U.S. and world industry portfolios. The three chosen sub-periods are : (1) January 1995 - December 2001; (2) January 2002 – December 2008; and (3) January 2009 - December 2015.

This study follows Davidson, Faff, & Hillier (2003) and re-specify the two-factor model of Eq. (3.36) by using correctly defined dummy variables.

$$R_{i,t} = \sum_{j=1}^{3} \alpha_{j,i} D_j + \sum_{j=1}^{3} \beta_{j,i} \left[D_j R_{m,t}\right] + \sum_{j=1}^{3} \gamma_{j,i} \left[D_j R_{gold,t}\right] + e_{i,t} \qquad (3.37)$$

D_j represents dummy variables for three sub-periods, 1995-2001, 2003-2008, and 2009-2015 respectively. All other variables have been defined in Eq (1).

For each industry portfolio, the equality of the gold factor is tested with the following hypothesis:

$$H_{3.1}: \gamma_{i1} = \gamma_{i2} = \gamma_{i3}$$

$$H_{3.2}: \gamma_{i1} = \gamma_{i2}$$

$$H_{3.3}: \gamma_{i2} = \gamma_{i3} \qquad (3.37a)$$

3.3.2 Asset pricing tests

In performing asset pricing tests of the two-factor model, we make an assumption that the factor producing process is appropriately explained by the market and gold price factors with the following specification:

$$R_{i,t} = E(R_i) + b_i\left[R_{m,t} - E(R_m)\right] + \delta_i[R_{gold,t} - ER_{gold})] + e_{i,t} \quad (3.38)$$

where $R_{i,t}$ is the return on the *ith* industry portfolio in month *t*, $R_{m,t}$ is the market portfolio which is $R_{w,t}$ (value-weighted world index), for world industries and, $R_{US,t}$ (value-weighted U.S. index) in case of U.S. industries, $R_{gold,t}$ is the gold return in month *t*, and all returns are expressed in the same currency (US Dollars).

This study assumes that a risk-free rate does not exist, then the two-factor model[12] can be expressed as:

$$E(R_i) = \gamma_0 + b_i[E(R_m) - \gamma_0] + \delta_i\left[E\left(R_{gold}\right) - \gamma_0\right] \quad (3.39)$$

where R_i denotes return on industry portfolios, $i = 1,2,\ldots, N$.

To test risk premiums, the Eq. (3.39) is parametrised as follows:

$$\phi_m = E(R_m) - \gamma_0 \quad (3.40)$$

$$\phi_{gold} = E\left(R_{gold}\right) - \gamma_0 \quad (3.41)$$

Eq. (3.40) and (3.41) are substituted into Eq. (3.39) as follows:

$$E(R_i) = \gamma_0 + b_i\phi_m + \delta_i\phi_{gold} \quad (3.42)$$

Now, Eq. (3.42) is substituted into Eq. (3.38)

$$R_{i,t} = [\gamma_0 + b_i\phi_m + \delta_i\phi_{gold}] + b_i\left[R_{m,t} - E(R_m)\right] + \delta_i\left[R_{gold,t} - E\left(R_{gold}\right)\right] + e_{i,t} \quad (3.43)$$

Additionally, Eq. (3.40) and (3.41) are solved in terms of $E(R_m)$ and $E\left(R_{gold}\right)$ respectively, and substitute in Eq. (3.43) as follows:

$$R_{i,t} = [\gamma_0 + b_i\phi_m + \delta_i\phi_{gold}] + b_i\left[R_{m,t} - (\phi_m + \gamma_0)\right] + \delta_i\left[R_{gold,t} - \right. \quad (3.44)$$

[12] Alternative to the ICAPM, this model can also be interpreted as the two-factor version of the Arbitrage Pricing Theory (APT) model, where gold is a hedging factor

$$(\phi_{gold} + \gamma_0)\big] + e_{i,t}$$

Hence, the market and the gold returns can be modelled as follows:

$$R_{m,t} = (\phi_m + \gamma_0) + \xi_t \tag{3.45}$$

$$R_{gold,t} = \left(\phi_{gold} + \gamma_0\right) + \nu_t \tag{3.46}$$

In order to obtain confidence in the results, like Davidson, Faff, and Hillier (2003), this study randomly sort world and U.S. industries into four groups respectively. World industries are randomly categorised into four groups, group I, group II,group III and group IV, each group having 10 industries. Similarly, U.S. industries are categorised into four groups, group I, group II, and group III, each group having 12 industries. The joint significance of the market and the gold price factor is examined over the full sample of industries and each group. For this purpose, the following three hypotheses are derived from a system of equations for the global industries (3.44) – (3.46):

$H_{3.1a}: b_1 = b_2 \ldots = b_{40}$

$H_{3.2a}: \delta_1 = \delta_2 \ldots = \delta_{40}$

$H_{3.3a}: \delta_1 = \delta_2 \ldots = \delta_{40} = 0$

Similarly, the following three hypotheses are derived from a system of equations for the U.S. industries.

$H_{3.1b}: b_1 = b_2 \ldots = b_{48}$

$H_{3.2b}: \delta_1 = \delta_2 \ldots = \delta_{48}$

$H_{3.3a}: \delta_1 = \delta_2 \ldots = \delta_{48} = 0$

3.3.2.1 Multivariate tests

Initially, the multivariate tests are employed over the full sample of industries and for each industry group to find whether the gold price factor is not a ‘useless’ factor. Kan and Zhang (1999) raise the concern of ‘useless’ factors in their study of two-pass tests of asset pricing models. In their argument, they highlight that if the hypothesis of joint equality to zero, is not rejected, then a factor under investigation can be ‘useless’. However, this study tests the null hypothesis that both market and the gold price factors are significant. In the previous study, Petkova (2006) performs cross-sectional tests to confirm that the proposed factors are not ‘useless’. If the null hypothesis is rejected, then it implies that a gold price factor which is under scrutiny in this study is a ‘useless’ factor.

3.3.2.2 GMM Test

For robustness, the generalised method of moments (GMM) test is also performed on each group of world and U.S. industries to assess the joint significance of a market beta and a gold price factor. GMM test is proposed by Hansen (1982), and after then, it is extensively used in asset pricing literature by various researchers. For instance, MacKinlay & Richardson (1991) implement the GMM procedure, and they prove that the results obtained from GMM tests are more robust than traditionally employed tests. They further show that the conclusions drawn from the mean-variance efficiency of market indexes could be sensitive to the estimation methods of asset pricing tests. Cochrane (1996) utilises GMM framework to compare the performance of investment-based asset pricing models, and later, confirms it a superior method of estimation (Cochrane, 2009, Chapter 13).

Like multivariate analysis, the GMM procedure is implemented to test the null hypothesis imposed by the two-factor augmented model in Eq. (3.42) on a system of equations (3.44) – (3.46). In the GMM system, each equation utilises its own regressors as instrumental variables. In this empirical system, there are ($3N$ + 2) moment equations, having ($2N$ + 3) unknown parameters that have to be estimated (i.e. b_1, b_2, . . ., b_N, $\delta_{1,}\delta_2$, . . ., $\gamma_0, \phi_m, \phi_{gold}$). Consequently, ($N$ - 1) overidentifying restrictions arise, and are tested with the GMM system[13] as follows:

$$GMM = (T - N - 1) * g_T(\hat{\delta})' S_T^{-1} g_T(\hat{\delta}) \qquad (3.47)$$

where T denotes time series observations, t =1, . . ., T , N denotes assets, i=1, . . .,N,

$g_T(\hat{\delta}) = 1/T \sum_{t=1}^{T} f_t(\hat{\delta})$, is the moment vector, $\hat{\delta}$ is the GMM parameter estimator, and, $g_T(\hat{\delta})' S_T^{-1} g_T(\hat{\delta})$ is a variance-covariance matrix.

Hansen (1982) shows that the GMM parameter estimator $\hat{\delta}$ exhibits asymptotic normal distribution with mean δ, and asymptotic variance covariance matrix $\left[g_T(\hat{\delta})' S_T^{-1} g_T(\hat{\delta})\right]$. The GMM estimator produces a chi-squared statistic, χ^2 , having *N-1* degrees of freedom.

First stage GMM

This study also estimates the gold price factor using the first stage GMM procedure of Cochrane (2005). The first-stage GMM is essentially equivalent to the OLS cross-sectional regression. In first stage GMM, equally weighted moments are estimated. It has advantages over OLS as it provides a solution for statistical problems of regression models such as heteroscedasticity or serial correlation (Chaussé, 2010). The GMM system comprises N+K+1 moment conditions. The initial moments are the pricing errors of the testing (N) portfolio whereas the later (K+1) moments are used for mean estimation of the factors (K) which also includes the market factor. Expected return model can be expressed as:

$$g_T(\theta) = \frac{1}{T} \sum_{t=1}^{T} \begin{cases} R_{i,t+1} - \gamma_0(R_{i,t+1})(RM_{t+1} - \mu_M) - \gamma_1(R_{i,t+1})(R_{gold,t+1} - \mu_1) \\ RM_{t+1} - \mu_M \\ R_{gold,t+1} - \mu_{gold} \end{cases} = 0 \qquad (3.48)$$

In this system, $R_{gold,t+1}$ represents gold factor, γ shows covariance risk price which is an estimate of a hedging factor and μ is the unconditional mean of a factor.

In the case of two factor model, there is a single parameter to estimate, $R_{gold,t+1 \equiv Gold_{t+1}}$.

[13] This GMM system represents small-sample adjusted form of Mackinlay and Richardson (1991).

The estimated covariance risk price from this system take into account the estimation errors arising from the factor means.

3.3.2.3 Fama-MacBeth regressions

In addition to GMM tests, the Fama-MacBeth cross-sectional regressions are also performed for robustness. The methodology is detailed in section (1).

3.4 Multifactor APT and ICAPM asset pricing models

After examining empirical factor models and role of gold in asset pricing, the impact of macroeconomic and country factors on stock markets is also examined in detail. Time-series and cross-sectional tests are performed to compare the performance of multifactor models.

3.4.1 Time series analysis

Time-series analyses are performed to assess the impact of macroeconomic and country factors on stock markets to identify the main stock influencing variables.

3.4.1.1 Stationarity

Kwiatkowski, Phillips, Schmidt, & Shin (1992) state that the economic time series data should be stationary. Nevertheless, time series data can be non-stationary and this may cause the problem of a spurious regression. Ferson, Sarkissian, & Simin (2003) have investigated the spurious regression problems in regressing models and report the presence of the spurious bias in the predictive regression for stock returns. They have marked that if the expected returns remain persistent, then there is a high risk of the spurious relation between the return and high auto-correlated lagged individual variables. Earlier, classic studies of Yule (1926), and Granger & Newbold (1974) also reveal problems of the spurious regression. In the recent study, Geda (2015) reveals if economic series show steady upward or downward patterns then the risk of spurious correlation may arise. Therefore, the assumption is developed in order to obtain valid statistical results. So, it is assumed that the economic series exhibit covariance of stationarity. The economic series is stationary if its mean and variance do not vary over time. If time series is not stationary, the results of econometric modelling are economically not valid and spurious regression results may be obtained.

3.4.1.2 Stationarity Tests of Economic Time Series Data

The typical regression model considers dependent and independent variables to be stationary. The main characteristics of a stationary variable are that its mean, variance and autocorrelation must remain constant over time. Dickey & Pantula (1987) and Evans (1991) have recommended to the difference a series repeatedly until it becomes stationary to address spurious regression problems. Before differencing economic time series, one needs to ascertain the stationarity of time series through stationarity tests. DeFusco, McLeavey, Pinto, & Runkle (2007) have employed Augmented Dicky Fuller Test[14] (ADF) to determine whether time series variables are non-stationary. This study also uses ADF test to determine whether time series variables have a unit root or not. If they have a unit root, then they are not stationary and if the unit root is not found, then time series variables are stationary. Hence, it desirable unit root is not found in a time series variable.

This study tests the null hypothesis that variables have a unit root (not stationary) in counter to an alternative hypothesis that there is no unit root (stationary). Im, Pesaran, & Shin (2003) have provided detailed explanation of detail Dicky Fuller regression and provided

[14] Augmented Dicky Fuller Test (ADF) is named after Dickey & Fuller (1979) who developed this test. In ADF test, the null hypothesis for the presence of a unit root is tested in the autoregressive model.

a guideline to choose ADF test. The ADF test is implemented with the intercept and linear time trends to examine the unit root in variables. The equation is given as:

$$\Delta X_{it} = \alpha_i + \beta_i t + \sum_{i=1}^{k} \psi \, \Delta X_{(t-j)} + \varepsilon_{it} \qquad (3.49)$$

Augmented Dicky Fuller tests whether ΔX =0 or ΔX ≠0. Here Δ is the first difference, α_i is an intercept, β_i is linear trend and j is the number of first difference lagged terms.

3.4.1.3 Co-integration and Vector Error Correction model

After performing stationarity, co-integration tests are performed to assess the long-term and short association of macroeconomic series with stock returns. The research suggests that Granger (1986) considerably contributes to the tests of co-integration. He redevelops econometric models through improving the model specification. He has proposed the error correction models by included "error equilibrium" factor while developing a model for macroeconomic series. Engle & Granger (1987) propose the two-step procedure for testing co-integration through ordinary least square (OLS) method. In the first step, the regression is estimated to extract residuals. In the second step, these residuals are tested for a unit root. If the residuals are found stationary, the null hypothesis (H_0) for no cointegration can be rejected. This methodology is criticised as there is the possibility of errors which can be transferred from first step regression to the second step from the error term. Later, Johansen (1988) and Johansen & Juselius (1990) develop the Vector Error Correction Model (VECM) by using sophisticated maximum likelihood method for estimating co-integrating vectors.

For instance, Y_t is a vector of *n* stock indexes which are of the same order I (0) integrated and individually non- stationary. The VAR model can be expressed as

$$Y_t = \mu + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots .. A_k Y_{t-k} + \varepsilon_t \qquad (3.50)$$

In the above equation, Y_t is a 4x1 vector $\begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix}$ of the order I(1), whereas A_k is *4* x *4* coefficient matrix and ε_t is the error term for t= 1,2,3…N. The VECM model can be expressed as

$$\Delta Y_t = \mu + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \cdots .. \Gamma_{k-1} \Delta Y_{t-k} + \Pi Y_{t-k} + \varepsilon_t \qquad (3.51)$$

where Δ represents operator for the first difference, whereas Γ is the short term coefficient (*N* x *N*) matrix, whereas Π is the long-term coefficient (*N* x *N*) matrix. When Π is greater than zero but less than a number of variables, then co-integrating vectors are found with the stochastic trends. The number of vectors determine the level to which equity markets are integrated. Π can be expressed into α and β matrices (p x r) where the β matrix contains co-integrating vectors whereas the αr is the adjustment matrix containing adjustment vectors. Johansen (1991) estimates con-integrating vectors through trace statistics (λ_{trace}) and maximum eigenvalues (λ_{max}). The trace (λ_{trace}) statistic is a test for the null hypothesis that the number of co-integrated vectors are equal or less than *r* against the alternative hypothesis that the number is greater than *r*. On the other hand, the maximum eigenvalue (λ_{max}) is a separate test for the null hypothesis that the number of co-integrating vectors are equal to *r* against hypothesis that *r+1* relationship exists.

The guideline from Lütkepohl (2004) has been considered for model selection and testing. In the beginning, Johnson Co-integration test will be done to determine whether there is co-integration between market returns and macroeconomic factors. If there is a long run association between variables, then Vector Error Correction Model (VECM) will be implemented. If the variables are not integrated with one another, then unrestricted Vector Autoregressive (VAR) model will be used.

3.4.1.4 Diagnostic Tests

Diagnostic tests will also be used for APT and VECM models. Diagnostic tests for serial correlation and distribution of residuals will be performed. It is recommended for the correct specification of the model that residuals should be normally distributed and there should be no serial correlation among residuals. Breusch-Godfrey LM Test will be implemented to examine the existence of the serial correlation while Jarque Berra test will be used to investigate the distribution of residuals. The null hypothesis for the Breusch-Godfrey LM Test and Jarque Berra statistics signify that there is no serial correlation between residuals and they are normally distributed. Therefore, the rejection of null hypothesis is not desirable for the statistical adequacy of the models. The results of the VECM model are reported in Appendix (C.3).

3.4.2 Econometric modelling of the ICAPM Models

This study tests multi beta Intertemporal CAPM and choose only those factors that have been recognised as determinants of stock market returns. This study compares twelve ICAPM models. First is the two-factor ICAPM where we gold return is used as a hedging factor.

$$E\ (\tilde{R}_{i,t}) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - \ R_{F,t}\right] + \beta_{i,g}[E(GOLD_t)] + \ e_{i,t} \tag{3.52}$$

Second is the Hahn and Lee (2006) model that uses market (*MKT*), term-structure (*Term*) and default risk (*DEF*) as factor loadings.

$$E\ (\tilde{R}_{i,t}) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - \ R_{F,t}\right] + \beta_{i,t}[E(TERM_t)] + \tag{3.53}$$

$$\beta_{i,def}[(DEF_t)]\ + e_{it}$$

Third is the Petkova (2006) ICAPM that employs market (*MKT*), the term (*Term*) default risk (*DEF*), dividend yield *(DY)*, and Treasury bill yield *(RF)*.

$$E\ (\tilde{R}_{i,t}) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,t}[E(TERM_t)] + \beta_{i,def}[(DEF_t)] + \beta_{i,dy}[(DY_t)] + \beta_{i,rf}[(RF_t)] + e_{it} \quad (3.54)$$

Fourth is the alternative Petkova model (P*) augmented model with inflation and industrial production.

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,t}[E(TERM_t)] + \beta_{i,def}[(DEF_t)] + \beta_{i,dy}[(DY_t)] + \beta_{i,rf}[(RF_t)] + \beta_{i,cpi}[(CPI_t)] + \beta_{i,ind}[(IND_t)] + e_{it} \quad (3.55)$$

The fifth model is the Campbell and Vuolteenaho (2004) that uses market (*MKT*), term (*Term*), price earnings ratio *(PE)* ratio and value spread *(VS)*.

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,t}[E(TERM_t)] + \beta_{i,p}[(PE_t)] + \beta_{i,v}[(VS_t)] + e_{it} \quad (3.56)$$

Brennan, Wang, & Xia (2004) emphasize that Fama and French (1993) factors are consistent with Merton's ICAPM and hence, sixth is the Fama and French (1993) three-factor model that is already shown in Eq. (3.2). Seventh is the Fama and French (1993) ICAPM model that uses market, size, and value with the term-structure and default risk.

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] + \beta_{i,t}[E(TERM_t)] + \beta_{i,def}[(DEF_t)] + e_{it} \quad (3.57)$$

Eighth is the alternative Fama and French (1993) ICAPM (FF ICAPM*) that uses inflation (*CPI)* and industrial production (*IND)* with Fama and French (1993) factors.

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \beta_{i,h}[E(HML_t)] +$$

$$\beta_{i,cpi}[E(CPI_t)] + \beta_{i,ind}[(IND_t)] \ +e_{it} \qquad (3.58)$$

Ninth is the Carhart (1997) four-factor model that uses momentum with Fama and French (1993) factors. This is shown in Eq. (3.3). The tenth is the Pástor and Stambaugh (2003) four-factor model that uses liquidity price factor (LIQ) in addition to Fama and French (1993) factors.

$$E\left(\tilde{R}_{i,t}\right) = R_{F,t} + \beta_i\left[E\left(\tilde{R}_{m,t}\right) - \ R_{F,t}\right] + \beta_{i,s}[E(SMB_t)] + \ \beta_{i,h}[E(HML_t)] +$$

$$\beta_{i,l}[E(LIQ)]{+}e_{it} \qquad (3.59)$$

Eleventh is the Fama and French (2015) five-factor model and twelfth is the Fama and French (2015) augmented model with the momentum price factor. These models are already shown in Eq. (3.4) and (3.5).

Further, gold return is utilised as a zero-beta rate in all those above-mentioned models except the two-factor model in Eq. (3.52) where the gold price is included as a hedging factor. Hence, we evaluate the performance of the 23 models. In the twelve models, we utilise the 1-month Treasury bill rate as a proxy of risk-free rate whereas in other eleven models we use gold return as a proxy of the zero-beta rate. This would help to assess whether gold return as a proxy of a zero-beta rate improves the performance of the ICAPM models as it improves the performance of the empirical factor models.

3.4.2.1 Criteria of ICAPM's Model Selection

The performance of the above-mentioned multifactor models is examined with the strict testable implications of asset pricing theory. Fama (1991) interprets ICAPM as the "fishing license" which allows to include ad hoc[15] factors in the model to price portfolios. However,

[15] Fama (1991) views ICAPM as a 'fishing license' that allows those factors to be included in the model which forecast future aggregate returns. His views highlight that Merton (1973) has not specified state variables that can be used in the model and therefore, any state variable, which influence stock, portfolio or

the argument has been put forward by Cochrane (2005, Chapter 9) that, however, ICAPM does not specify the state variables or risk factors but the model needs to meet certain restrictions or satisfy ICAPM's criteria. He interprets Merton's (1973) ICAPM as a model in which state variables are related to the changes in investment opportunities and therefore, they should forecast expected aggregate market returns. Moreover, changes (innovations) in the state variables must be reported as priced factors in cross-section. Fama and French (1993) and Carhart (1997) can be regarded as extended applications of Merton's (1973) ICAPM as on the basis of its theoretical background, Maio and Clara (2012) have examined the restrictions associated with ICAPM in the U.S. market through cross-sectional tests of eight multifactor models. Most recently, Lutzenberger (2015) has investigated those restrictions in the European market on the multifactor CAPM and ICAPM models. They have defined three main testable implications of ICAPM. They are of the view that these implications prevent a multifactor model to be recognised as a 'fishing license' in explaining cross-section of average stock returns. The empirical application of an ICAPM is only justified if the model is able to meet this criterion.

3.4.2.2 Criterion 1

The first criterion or testable implication of the ICAPM is that the estimate of the market covariance or market risk price must be economically plausible[16] and its value should be between 0 and 10. In other words, the coefficient from the cross-sectional test should be an estimate of relative risk aversion (RRA) for the respective investor. This criterion is a reflection of CAPM's theory which is based on the postulation that covariance of a security

market returns, can be included in the model. Therefore, a state variable can be replaced by another variable over time depending on their influence on market returns.

[16] Economically plausible coefficient of market risk premium refers to the relative risk aversion (RRA) of the representative investor as investor will invest in the stock only if it provides premium for bearing risk for unexpected changes in the aggregate stock returns. Maio and Clara (2012) and Lutzenberger (2015) cite Mehra and Prescot (1985) that coefficient of RRA should be positive and its value should be between 0 and 10.

with the market is positive as it should get a risk premium over return on riskless (asset or) security (Jagannathan, Skoulakis, & Wang, 2002). This is because rational investors would expect a premium for holding a security that does not provide a hedge against unexpected changes in aggregate wealth. In pricing equation of ICAPM, the first source of risk is explained by the risk premium of the market, $\gamma Cov\left(R_{i,t+1}, R_{m,t+1}\right)$, in where γ is the coefficient of RRA.

3.4.2.3 Criterion 2

The second criterion requires the candidates for state variables to forecast future market returns and market volatility. Forecasting power of the testing model can be assessed by using long horizon time series regressions (see also Maio, 2017). The candidates for state variables must forecast distribution of future returns, i.e., first or second moment of aggregate returns.

3.4.2.4 Criterion 3

The third criterion is related to the second risk factor of ICAPM which is explained by the coefficient (γ_s) of state variable (s), $\gamma_s Cov(R_{i,t+1}, \Delta s_{i,t+1})$. The third implication can be further subdivided into 3 (a) and 3 (b).

Criterion 3 (a)

If a candidate for a state variable forecasts positive (negative) future aggregate market returns in time series regression, then its risk factor (γ_s) should earn a positive (negative) estimate of risk price in the cross-sectional result. An asset or security which covaries positively with aggregate market return, does not offer reinvestment hedge and thus, will not be preferred by risk averse investor as it will offer low returns in the case of lower expected market return. Therefore, the rule of risk aversion requires a rational investor to demand higher risk premium for holding this security than a security having no correlation with market return.

Criterion 3 (b)

If covariance of the candidate for a state variable (s) is positive (negative) with expected market volatility, then its risk price should earn a negative (positive) sign in the cross-section. In other words, intertemporal risk price (γ_s) will be negative if a state variable positively covaries with expected market volatility and will be positive for negative covariance. Intertemporal risk factors receive opposite signs for covariance with market volatility. This is because an asset or security which covaries positively with market volatility, provides hedge against market volatility and the risk averse investor would like to invest in this security as it will provide higher returns during higher market volatility. Therefore, an investor would expect lower risk premium for holding this security than a security which has no correlation with expected market volatility.

The criteria of the ICAPM imply that the candidate state variables must not only forecast aggregate market returns and volatility but also their risk factors should also be priced with the correct signs in the cross-sectional tests. Maio and Clara (2012) and Lutzenberger (2015) investigate at least eight multifactor models in the U.S. and European markets respectively. Both of these studies agree that at least the four-factor model satisfies the ICAPM's criteria.

3.4.3 Asset Pricing Tests

Time-series and cross-sectional tests are performed to assess the above-mentioned criteria of multifactor asset pricing models. In time-series, the predictive regressions are run to assess the second and third criteria of the ICAPM. In sprit of Maio and Santa-Clara (2012), I assess whether the state variables are able to forecast the first or second moment of the market returns or market volatility. Single predictive regressions are performed over each state variable to assess the predictive ability of a potential state variable. In addition, multiple predictive regressions are performed over each multifactor models to find the predictive power of each model. In cross-section, this study employs the first-stage GMM recommended by Cochrane (2009, Chapter 12) to assess the first criteria of the multifactor models to find whether the tested model produces the plausible estimate of the market risk. This study takes guidance from Lo and MacKinlay (1990), Brennan, Wang, & Xia (2004), Petkova (2006), Maio and Santa-Clata (2012) and Lutzenberger (2015) in implementing cross-sectional methodology.

3.4.3.1 First-stage GMM

The first stage GMM method of Hensen (1982) is used to estimate each multifactor model. In the first stage GMM, the equally weighted moments[17] are estimated. This procedure is better than the OLS cross-sectional regression as it provides a solution for statistical problems of regression models such as heteroscedasticity and serial correlation (Cochrane, 2005, chapter 12). The GMM system comprises N+K+1 moment conditions. The initial moments are the pricing errors of the testing (N) securities or portfolios whereas the later (K+1) moments are used for mean estimation of the factors (K) which also include market factor. Expected return model can be expressed as:

[17] In statistics or econometrics, the word is used for expectational equation. In CAPM test, a system of expectational equations is estimated (see also Campbell, Lo, and MacKinlay (1997), Cochrane (2005), Chausse, 2015 and many others)

$$g_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\left\{\begin{array}{c} (R_{i,t+1} - R_{f,t+1}) \; - \gamma(R_{i,t+1} - R_{f,t+1})(RM_{t+1} - \mu_M) - \gamma_1(R_{i,t+1} - R_{f,t+1})(F_{1,t+1} - \mu_1) \\ -\gamma_2\big(R_{i,t+1} - R_{f,t+1}\big)\big(F_{2,t+1} - \mu_2\big) \ldots\ldots \gamma_k\big(R_{i,t+1} - R_{f,t+1}\big)\big(F_{k,t+1} - \mu_K\big) \\ RM_{t+1} - \mu_M \\ F_{1,t+1} - \mu_1 \\ . \\ . \\ . \\ F_{k,t+1} - \mu_K \end{array}\right. = 0 \tag{3.60}$$

where K represents number of factors, (θ) is a (K+1) x1 vector of parameters and F denotes factors, γ shows covariance risk price which is an estimate of a hedging factor and μ is the unconditional mean of a factor. The first moments of the system enable to estimate the covariance estimates of the risk prices of the (K+1) factors. For instance, in the case of Carhart (1997) four factor model, there are three parameters to estimate (K=3) with $F_{1,t+1\equiv SMB_{t+1}}, F_{2,t+1\equiv HML_{t+2}}, F_{3,t+1\equiv UMD_{t+1}}$. These estimated covariance risk prices from this system take into account the estimation errors arising from the factor means (Cochrane, 2005, Chapter 13). The final K+1 moment conditions of the above system helps to estimate factor means.

In the spirit of Cochrane (2009) and Maio and Santa-Clara (2012), this study uses two measures to assess goodness of fit of the models. Firstly, I use cross-sectional pricing error and then estimate the cross-sectional R-squared that can be expressed as:

$$\mathrm{R}^2_{\mathrm{OLS}} = 1 - \frac{\mathrm{Var}_{\widehat{\alpha}_\mathrm{i}}}{\mathrm{Var}_\mathrm{N}(\overline{\mathrm{R}_\mathrm{i}})} \tag{3.61}$$

where $\overline{R_\iota} = \left(\frac{1}{T}\right)\sum_{t=0}^{T-1}(R_{i,t+1} - R_{f,t-1})$ represents the average excess returns for asset *i* whereas Var_N shows cross sectional variance. R^2_{OLS} denotes the fractional cross sectional variance in average excess returns explained by multifactor models.

3.5 Data Sources

This study uses Thomson Reuters DataStream (DS) to collect data on macroeconomic variables, industry factors and stock indices, as it is a reliable source than other data sources. Thomson Reuters DataStream is widely known for providing accurate and timely data for empirical finance research. DataStream is traditionally known to make error corrections in historical data which ensures high quality of data.

3.5.1 Data source of International equity markets

The Ken French website is used to collect portfolio data sets on international equity markets. Fama and French (2012) categorise global developed markets into 23 countries. These markets can be listed as:

1. Australia
2. Austria
3. Belgium
4. Canada
5. Switzerland
6. Germany
7. Denmark
8. Spain
9. Finland
10. France
11. Great Britain
12. Greece
13. Hong Kong
14. Ireland
15. Italy
16. Japan
17. Netherlands
18. Norway
19. New Zealand
20. Portugal
21. Sweden
22. Singapore
23. United States

These 23 markets are further categorised into North American, European, Japanese, and Asia Pacific regions. Ken French website provides freely accessible equity data for the North American, European, Japanese, Asian, and Global equity markets.

The North American region includes the equity markets in the United States and Canada. The North American region occupies the dominant position in global developed markets due to the presence of the world largest U.S. equity market with the market capitalization of more than $16 trillion. There are two main stock exchanges in the US, the New York Stock Exchange (NYSE) and NASDAQ (National Association of Securities Dealers Automated Quotations). NYSE is the world largest stock exchange with the market capitalisation of $13.4 trillion, whereas NASDAQ is the second largest stock exchange with the market capitalisation of $3.9 trillion (Forbes, 2018). After NYSE and NASDAQ, Toronto stock exchange is the third largest stock exchange in North America with the market capitalisation of $2.2 trillion.

Europe is the second largest region and out of 23 developed markets, 16 are located in the Europe that includes the equity markets in Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal and Sweden. Euronext is the fifth largest stock exchange in Europe with the market capitalisation of $2.9 trillion. Japanese stock exchange is the third largest stock exchange after NYSE and NASDAQ with the market capitalisation of $3.8 trillion and maintains the dominant position in global developed markets. The Asia Pacific includes stock markets in Australia, Hong Kong, New Zealand and Singapore. Fama and French (2012) find that empirical factor models particularly, three-factor and four-factor models struggle to explain portfolio returns in Asia Pacific region. However, it is also reported that these factor models offer comparatively better performance in Japanese, North American and European regions.

This study uses the 25 portfolios sorted on size and book-to-market ratios, and the 25 portfolios sorted on size and momentum as test portfolio datasets to assess the performance of empirical factor models in international markets. The return on 1-month Treasury Bills and monthly returns on SMB, HML, RMW, CMA and MOM, being the size, book-to-market, operating profitability, investment and momentum factors respectively, are used for each market.

3.5.2 Data source for the application of gold as a zero-beta asset

3.5.2.1 Data to assess gold market efficiency

This study uses two types of data to test the market efficiency of gold markets. Firstly, this study uses the daily spot gold prices from United States, United Kingdom, Europe, Japan and Canada from January 1981 to December 2015. All spot prices are quoted in the related currencies. Hence, the return series cover over 35 years of data. The data is collected from Datastream and World Gold Council website. This research chooses this time period because this time period is suitable to examine the efficiency of gold markets. The dissolution of Bretton Woods gold standard system[18] had completed between 1968 and 1973. From 1973 to 1980, the gold markets had well established and gold prices were freely set by markets.

3.5.2.2 US Equity Data

Secondly, this research uses the U.S. equity data to compare performance of the zero-beta

[18] Under gold standard system, a standard unit of exchange was priced by a specific quantity of gold, initially pegged at GBP 12.5 or $35 to a quantity of an ounce of gold.

models with traditional models. Ferson, Nallareddy, & Xie (2013) have shown that the CAPM and other asset pricing models are the long run risk models and they should be assessed over the longer time period. The U.S. equity data cover the value-weight returns of all U.S. firms listed on the New York Stock Exchange (NYSE), American stock exchange (AMEX), and NASDAQ (National Association of Securities Dealers Automated Quotations). This research uses the Ken French website to obtain this data that utlises CRSP[19] database to construct portfolios and empirical factors.

To assess the performance of gold as a zero-beta asset, this research compares the relative performance of the various traditional asset pricing models against their analogues in which the risk-free rate as proxied by the Treasury bill yield is replaced by the return on gold. This study employs 35 years (420 months) of data from January 1981 to December 2015 to achieve confidence in the results. In a similar study, Gregory, Tharyan and Christidis (2013) have used 30 years of data from 1980 to 2010 to compare the performance of asset pricing models. For robustness, this research also uses sub-period analysis before (2003 – 2007), during (2007 – 2011), and after the financial crisis (2011- 2015). According to financial press[20], financial crisis started in 2007 and continued until 2011. Monthly data is used and all returns are measured in U.S. Dollars. The return on gold is calculated by using the log returns of the end of month London Bullion price, denominated in U.S. Dollars, and obtained from Datastream.

This study also obtains data on the returns of a number of test asset portfolios from the Ken French website, namely, the 25 portfolios sorted on size and book-to-market, the 25 portfolios sorted on size and momentum, the 25 portfolios sorted on size and investment,

---

[19] The Center for Research in Security Prices (CRSP) provides historical data for the U.S. equity market. This center is associated with the Booth School of Business, University of Chicago.
[20] Guardian. (2011). Global financial crisis: five key stages 2007-2011.

and the 25 portfolios sorted on size and operating profitability. Furthermore, this study also uses the 32 portfolios sorted simultaneously on size, book-to-market and operating profitability, the 32 portfolios sorted simultaneously on size, book-to-market and investment, and the 32 portfolios sorted simultaneously on size, operating profitability and investment.

In addition to the above-mentioned portfolios, this study also makes comparisons using test asset portfolios which are not sorted on Fama - French factors: this research employs the 35 portfolios sorted on size and net share issues, the 49 industry portfolios, the 25 portfolios sorted on size and accruals, the 25 portfolios sorted on size and variance, the 25 portfolios sorted on size and residual variance, and the 25 portfolios sorted on size and market beta.

For the U.K. market, this research uses the data source from the Exeter Business School. This research also utilises the equity market data from global, North American, European, and Asia Pacific regions in this section. Further, this research also assesses the applicability of gold return as a zero-beta rate in the global regions and this study utilises 25 years of data from 1991 to 2015.

3.5.3 Data source for the two-factor Intertemporal CAPM

This study uses Datastream and Morgan Stanley database to extract 40 world industry indices. The value-weighted world market index is used for the proxy of the market portfolio. The gold price is the London Bullion end of month's gold price sourced from Datastream. The data covers the time-period from January 1995 to December 2015 over 252 months. Monthly returns are used and all returns are measured in U.S. Dollars. For the U.S. equity market, this study uses 48 industries sourced from the Ken French website. Three-non-overlapping sub-periods are used, each comprising seven years. Sub-periods of seven years are consistent with earlier study of Davidson, Hillier and Faff (2003).

3.5.4 Data source for the multifactor ICAPM and APT models

Datastream, Bloomberg, Ken French, Robert Shiller, Chicago Booth, and Goyal and Welch (2008) databases are used. Monthly returns are used and all returns are expressed in percentage. The U.S. equity data is used. The 25 size and book to market portfolios and the 30 industry portfolios are used. The industrial classifications are defined in the Ken French website. Each NYSE, AMEX, and NASDAQ stock is assigned to an industry portfolio at the end of year *t* (June) on the basis of its four-digit *SIC* code. (Compustat *SIC* codes were used for year end *t-1*). Where Compustat SIC codes were not available, CRSP SIC codes were used for June of year *t*.) Then returns are computed from July of *t* to June of *t+1*. Monthly change in the state and macroeconomic variables is used by estimating log returns to account for innovation (unexpected change) in macroeconomic and state variables.

3.5.4.1 Data sources for macroeconomic variables

Foreign exchange, money supply, inflation, and commodity prices are widely used in the literature of Arbitrage pricing theory (Chen, Roll, and Ross, 1986; Clare & Thomas, 1994; Antoniou, Garrett, & Priestley, 1998). Among commodities, this study uses the oil and gold prices as they are most widely used commodities in asset pricing literature (Chen, Roll, and Ross, 1986; Faff & Chan, 1998; Jones & Kaul, 1996).

Index Returns: The market index has been obtained from the Robert Shiller website[21]. All returns are expressed in percentage. Monthly log normal returns are used. Returns are calculated as:

$SP500_{(t)} = \log SP500_{(t)} - \log SP500_{(t-1)}$.

1) **Foreign Exchange**: The unanticipated monthly change in the foreign exchange is used and

[21] S&P Composite index has been used from Robert Shiller website: http://www.econ.yale.edu/~shiller/data.htm

is computed by using this formula

$FX_{(t)} = log\ FX_{(t)} – log\ FX_{(t-1)}.$

Monthly data on Foreign Exchange Reserves[22] has been used from Datastream.

2) **Money Supply:** This study uses the money supply (M1) in this study. It has been used by various researchers in the past (Pearce & Roley, 1983; Kandir, 2008). MI U.S[23] has been collected from the Datastream.

$MS_{(t)} = log\ MS_{(t)} – log\ MS_{(t-1)}.$

3) **Consumer Price index:** This study converts CPI data into monthly changes to account for unexpected innovation by using the formula

$ACPI_{(t)} = log\ CPI_{(t)} – log\ CPI_{(t-1)}$

CPI for *All Urban Items* is used in this study.

4) **Gold Prices:** The end of month's London Gold price is used. The monthly change in the gold price is computed by using the following formula:

$AG\ (t) = log\ AG_{(t)} – log\ AG_{(t-1)}.$

5) **Oil Prices:** This study uses the crude oil price in this study. Monthly change in the crude oil price[24] is computed by using the following formula:

$AOP\ (t) = log\ AOP_{(t)} – log\ AOP_{(t-1)}.$

3.5.4.2 Data sources for State variables

The list of variables used in multifactor models are given as:

1) **Term Structure:** The term structured is calculated by the return on long-term government

[22] DataStream Code: USFOREXR

[23] M1 US consists of (1) currency outside the U.S. Treasury, Federal Reserve Banks, and the vaults of depository institutions; (2) traveller's checks of nonbank issuers; (3) demand deposits at commercial banks less cash items in the process of collection and Federal Reserve float; and (4) other checkable deposits (OCDs), consisting of negotiable order of withdrawal (NOW) and automatic transfer service (ATS) accounts at depository institutions, credit union share draft accounts, and demand deposits at thrift institutions (DataStream, 2016).

[24] Monthly crude oil spot price is used (Datastream code: HWWICG)

bonds (10-year) minus short-term (1-month) Treasury bill rate (Chen, Roll, and Ross, 1986; Burmeister & Wall, 1986). The one-month Treasury bill rate is collected from the Ken French website. DataStream is used for 10-year long-term government bonds[25] data.

$$\Delta TERSTR = \ln(LGB_t - SRB_t) - \ln(LGB_{t-1} - SRB_{t-1})$$

where LGB_t is the long-term government bond in month t and SRB_t is the yield on short-term Treasury bill at the end of the month.

2) **Risk-free Rate:** Fama and Schwert (1977), Campbell (1991), Hodrick (1992) and others have used 1-month Treasury bill yield in their multifactor asset pricing models. In a similar way, this research uses the one-month Treasury bill rate that is obtained from the Ken French website.

3) **Default Risk:** The default risk is estimated by the long-term government bonds' return minus the long-term corporate bonds' return (Burnmeister and Wall, 1986). The return on 10-year government and corporate bonds have been used.

4) **Dividend Yield:** In the spirit of Fama and French (1988, 1989), and Campbell and Shiller (1988), this research uses the dividend to price ratio (dividend yield). The dividend yield is estimated by the log ratio of the annual dividend to the level of the Standard and Poors 500 index.

5) **Price Earning:** Campbell and Shiller (1988) and Campbell and Vuolteenaho (2004) use the price-earnings ratio as a factor loading in their multifactor models. In a similar vein, this research uses price-earnings (*PE*) ratio and is computed as the log ratio of the index price to the ten years moving an average of earnings[26].

6) **Value Spread:** Campbell and Vuolteenaho (2004) employ value spread in their studies and

[25] 10 year Government Bond yields have been used (USA DataStream code: USOIR061R)

[26] Data for dividend, index, and earnings are obtained from Rober Shiller website. Standard and Poors 500 index is used.

this research follows their procedure in constructing value spread factor. This study uses six portfolios sorted on the size and book-to-market ratios from the Ken French website. Then the difference of the monthly log book-to-market ratios of small value and small growth portfolios is estimated to compute the value spread in the U.S. equity market.

7) **Stock Market Variance:** Guo (2006), Goyal and Welch (2008), Maio and Santa-Clara (2012) use the stock market variance (*SVAR*) to assess the predictive ability of state variables. In a similar vein, this study also uses the stock variance to examine the predictive performance of macro and state variables. *SVAR* is estimated by the sum of squared daily returns of the market index.

$$SVAR_{t,t+q} = SVAR_{t+1} + \cdots + SVAR_{t+q}$$

8) **Liquidity:** Pastor & Stambaugh (2001) introduce liquidity factor as an additional empirical factor. This study uses this variable as a state factor. The data on liquidity factor is available on the website[27] of Chicago Booth University.

3.5.4.3 Alternative Proxies

After constructing size, value, investment and operating profitability factors from the above-mentioned methodology, the cumulative sum of last 60 months is used to construct alternative state variables for size, value, investment, operating profitability, momentum, liquidity and gold price factors. For instance, alternative state variable for size is constructed as:

$$CSMB_t = \sum_{s=t-59}^{t} SMB_s$$

Cumulative sum is obtained to maintain the stationarity of a time series state variable (Maio and Santa-Clara, 2012)

[27] http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2015.txt

3.6 Software packages

Standard econometric software packages STATA, MATLAB, and R software packages are used for testing financial econometric models. These software packages are popular for the efficient data management, statistical analysis and custom programming. Therefore, they are used for the time series and cross-sectional asset pricing tests.

3.7 Summary of Research methodology

The realism research philosophy is adopted to achieve the objectives in this study.

Realism is the positivist paradigm of research that is looking for the facts or truth about reality. Positivists believe in objectivity which implies that the researchers take appropriate measures to prevent any influence on results to ensure fairness and credibility of research. Positivist approach emphasises on using quantitate research methodology. Quantitative financial econometric techniques are used as they are specialised for examining asset pricing models. This study develops models and hypotheses, and test those models with time series and cross-sectional tests on an extensive range of data sets to achieve the objectives of this study.

This research employs the first-stage (time series) and second stage (cross-sectional) asset pricing tests to achieve objectives of this study. In the first stage, Gibbons, Ross and Shanken (1989, GRS) test is used that has been widely used in asset pricing literature (Fama and French, 1993, 2012, 2015). In GRS test, the time-series alphas are estimated with their associated t-statistics, and R-squared value is computed to deeply examine the model performance. Significant alphas denote pricing errors and higher R-squared is desirable for the model performance. GRS summary presents GRS test statistic, average R-squared and Sharpe ratio of alphas. Lower values of GRS and lower Sharpe ratio of alphas are desirable for the adequate performance of the tested model. This study also plots the actual and predicted returns from each model on all test portfolios to show the model performance.

In the second stage, traditional Fama and MacBeth (1973) methodology is adopted which is extensively used in asset pricing literature (Fama and French, 1993, 1996; Gregory, Tharyan and Christidis; 2013; Blackburn & Cakici, 2017). This study follows Kan, Robotti, & Shanken (2013) and perform Fama-MacBeth tests with both OLS and GLS estimation methods to compare the performance of asset pricing models. GLS is recommended when residuals are autocorrelated Cochrane (2009, Chapter 12). Further, Shanken (1992) correction is implemented to overcome errors in variables (EIV) bias that usually arises in the second stage regression. In Shanken (1992) correction, the modified estimator makes a correction to provide robust standard errors that corrected for the errors-in-variables (EIV) effects. This study utilises data from global regions (North America, Europe, Japan, Asia Pacific) to achieve the first objective of this study in which the applicability of the six-factor model is examined in global regions.

To achieve the second objective, this study assesses the applicability of gold return as a proxy of the zero-beta rate. This study utilises data from the U.S. and U.K. equity markets in addition to the global data. Black, Jensen and Scholes (1972) theory suggest that the potential zero-beta portfolio should be an efficient and minimum variance portfolio. Hence, gold must be the efficient asset and must be located on a minimum variance frontier. Therefore, firstly, the efficiency of global gold markets is examined with a battery of market efficiency tests. This study performs a variance ratio parametric test of Lo and MacKinlay (1988) and also perform its non-parametric version proposed by Wright (2000). Further, this study performs multiple variance ratio test of Whang and Kim (2003) by using subsampling of different lengths. Additionally, Automatic Portmanteau test of Escanciano and Lobato (2009) is performed in different sub-periods to confirm the level of efficiency in global gold markets. Secondly, this study determines the position of gold on minimum variance frontier by plotting gold against different sets of test portfolios. This study follows Clarke De Silva, and

Thorley (2006) and Kan and Smith (2008) in plotting minimum variance frontier. After examining characteristics of a zero-beta rate, the performance of traditional with above mentioned time series and cross-sectional tests.

To achieve the third objective, this study utilises global and U.S. industries data to examine gold factor exposure. Finally, this study employs only the U.S. data to evaluate the performance of a wide range multifactor models that utilise empirical, zero-beta, macro and state variables.

In the final section, this study evaluates the performance of the twenty-three asset pricing models including empirical factor models, ICAPM multifactor models and their gold zero-beta analogues. This study assesses these models according to the strict criteria of Merton (1973) Intertemporal CAPM theory that requires that the state variables of a multifactor model must forecast first or second moment of future aggregate returns or market volatility, and the tested model should produce an economically plausible estimate for the price of the market risk. Single predictive regressions are performed over each state variable to assess the predictive ability of a state variable. Further, multiple predictive regressions are performed for each model to examine the predictive power of the tested model. The cross-sectional estimates are obtained by using first-stage Generalised Method of Moments (GMM) methodology that is recommended in Cochrane (2009, Chapter 12) and is used by Maio and Clara (2012) and Lutzenberger (2015).

Chapter Four

Empirical Results and Discussions

4.1 Assessment of empirical factor models

Firstly, this study assesses the empirical performance of the single factor, three-factor, four-factor, five-factor and six-factor models in international markets. This assessment will enable to provide an updated evidence on the performance of empirical factor models. It also enables to compare the performance of the five-factor model with Carhart (1997) four-factor and six-factor model. In the six-factor model, I include the momentum factor with the Fama and French (2015) model. Before assessing performance with asset pricing tests, the descriptive analysis is performed for the Carhart (1997) momentum, and Fama and French (2015) size, book-to-market, investment, and operating profitability factors in Global, North American, European, Japanese, and Asian markets. Descriptive results for international markets are shown in Table (1) – (5).

Market premiums[28] ($R_m - R_f$) are larger in Asia Pacific market 0.77% per month, followed by North American (0.67% per month), European (0.52% per month) and Global market (0.48% per month). Market premium in Japan remains lowest with 0.07% per month.

The size premium is insignificantly different from zero. Fama and French (2012), Asness, Moskowitz, and Pedersen (2013) find significantly strong value and momentum returns. This study also finds similar results. The value premium is significant in all regions which ranges

[28] The difference between average monthly value weighted market return and average 1-month U.S. Treasury Bill yield.

from 0.33% (t=2.48) per month for global to 0.62% (t=3.48) for Asia Pacific market. Likewise, momentum is also significant and remain above 0.60% for all regions except Japan. Regarding operating profitability, it is significant at the 5% level in global, North American, and European market where it is insignificantly different from zero in Asia Pacific and Japanese markets. The investment premium is significant in the global and Asia Pacific at the 5% level whereas it is insignificant in other regions.

Table 1: Summary statistics for the Fama-French and Carhart (Momentum) factors in the Global market, January 1991-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), and Panel B reports correlations among the factor returns. All returns are expressed in percentage.

			Global				
Panel A	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
Mean	0.48	0.23	0.14	0.33	0.66	0.34	0.24
Std	4.28	0.18	1.97	2.31	3.97	1.47	1.92
Kurtosis	1.74	-1.54	1.85	5.52	7.19	2.22	4.04
Skewness	-0.69	0.00	-0.19	0.56	-1.05	-0.03	0.69
t-mean	1.96	21.77	1.21	2.48	2.86	4.06	2.19
Obs.	300	300	300	300	300	300	300
Panel B: Correlations							
	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
$R_m - R_F$	1.00						
R_f	-0.04	1.00					
SMB	-0.08	-0.11	1.00				
HML	-0.15	0.10	0.03	1.00			
MOM	-0.23	0.04	0.14	-0.24	1.00		
RMW	-0.46	0.08	-0.23	0.23	0.15	1.00	
CMA	-0.39	0.03	-0.02	0.73	-0.05	0.20	1.00

Table 2: Summary statistics for the Fama-French and Carhart (Momentum) factors in the North American market, January 1991-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), and Panel B reports correlations among the factor returns. All returns are expressed in percentage.

North America							
Panel A	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
Mean	0.67	0.23	0.21	0.23	0.65	0.33	0.28
Std	4.27	0.18	2.81	3.28	4.91	2.47	2.69
Kurtosis	1.66	-1.54	4.83	4.86	8.43	9.39	4.96
Skewness	-0.72	0.00	0.33	0.57	-0.19	0.14	0.99
t-mean	2.72	21.77	1.26	1.21	2.29	2.34	1.80
Obs.	300	300	300	300	300	300	300
Panel B: Correlations							
	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
$R_m - R_F$	1.00						
R_f	0.00	1.00					
SMB	0.18	-0.04	1.00				
HML	-0.24	0.06	-0.13	1.00			
MOM	-0.14	0.06	0.18	-0.25	1.00		
RMW	-0.39	0.06	-0.41	0.43	-0.05	1.00	
CMA	-0.43	0.04	-0.16	0.79	-0.09	0.38	1.00

Table 3: Summary statistics for the Fama-French and Carhart (Momentum) factors in the European market, January 1991-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), and Panel B reports correlations among the factor returns. All returns are expressed in percentage.

Europe							
Panel A	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
Mean	0.52	0.23	0.06	0.33	0.95	0.41	0.19
Std	4.95	0.18	2.24	2.45	4.07	1.51	1.87
Kurtosis	1.73	-1.54	0.79	3.00	7.57	0.68	3.42
Skewness	-0.58	0.00	-0.04	0.37	-1.31	-0.26	0.42
t-mean	1.83	21.77	0.44	2.37	4.04	4.74	1.71
Obs.	300	300	300	300	300	300	300
Panel B: Correlations							
	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
$R_m - R_F$	1.00						
R_f	-0.01	1.00					
SMB	-0.18	-0.14	1.00				
HML	0.20	0.10	0.01	1.00			
MOM	-0.32	0.01	0.09	-0.29	1.00		
RMW	-0.30	0.03	-0.03	-0.52	0.43	1.00	
CMA	-0.28	0.01	0.03	0.55	0.03	-0.16	1.00

Table 4: Summary statistics for the Fama-French and Carhart (Momentum) factors in the Japanese market, January 1991-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), and Panel B reports correlations among the factor returns. All returns are expressed in percentage.

			Japan				
Panel A	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
Mean	0.07	0.23	0.12	0.38	0.14	0.10	0.09
Std	5.63	0.18	3.32	2.86	4.48	2.20	2.46
Kurtosis	0.42	-1.54	1.75	2.65	2.87	1.88	4.18
Skewness	0.29	0.00	0.14	-0.21	-0.46	0.04	-0.79
t-mean	0.21	21.77	0.63	2.29	0.56	0.79	0.61
Obs.	300	300	300	300	300	300	300
Panel B: Correlations							
	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
$R_m - R_F$	1.00						
R_f	-0.12	1.00					
SMB	0.08	-0.15	1.00				
HML	-0.18	0.07	0.14	1.00			
MOM	-0.17	0.03	-0.14	-0.24	1.00		
RMW	-0.25	0.01	-0.20	-0.36	0.31	1.00	
CMA	-0.01	-0.03	0.23	0.59	-0.27	-0.69	1.00

Table 5: Summary statistics for the Fama-French and Carhart (Momentum) factors in the Asia Pacific market, January 1991-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), and Panel B reports correlations among the factor returns. All returns are expressed in percentage.

			Asia				
Panel A	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
Mean	0.77	0.23	-0.06	0.62	0.90	0.17	0.38
Std	6.02	0.18	3.01	3.08	4.55	2.81	2.53
Kurtosis	2.39	-1.54	2.49	10.59	18.36	2.72	1.57
Skewness	-0.38	0.00	0.41	1.47	-2.89	-0.35	0.02
t-mean	2.21	21.77	-0.34	3.48	3.41	1.05	2.59
Obs.	300	300	300	300	300	300	300
Panel B: Correlations							
	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
$R_m - R_F$	1.00						
R_f	-0.04	1.00					
SMB	0.01	-0.09	1.00				
HML	0.11	0.04	0.09	1.00			
MOM	-0.23	-0.01	0.01	-0.30	1.00		
RMW	-0.40	0.04	-0.23	-0.61	0.25	1.00	
CMA	-0.50	0.06	-0.08	0.17	0.18	0.18	1.00

4.1.1 Asset Pricing Tests

After descriptive analysis, the performance of single-, three-factor, four-factor, five-factor, and six-factor models is assessed by using asset pricing tests. Initially, the first-stage (time-series) tests are performed that are followed by the Fama and Macbeth (1973) cross-sectional tests.

4.1.2 Time Series Results

In time-series analysis, the GRS test is performed. The GRS test is named after Gibbon, Ross, Shanken (1989) approach to test the performance of asset pricing models. In order to obtain confidence from results, the alphas, t-statistics, and R-squared for each model are reported in addition to the summary of GRS results. The 25 SBM[29] and 25 SM[30] portfolios are utilised for global and each region to assess the performance of asset pricing models. Fama and French (2012) report alphas and t-statistics which identify the pricing errors with each model on test portfolios. This study advances on this to report R-squared which is the coefficient of determination and explains the variance. Hence, a comprehensive comparison is conducted for each model under scrutiny on the above mentioned test portfolios and regions for reliability and consistency in the results.

4.1.2.1 Testable Implication in Time Series Test

This study considers the number of pricing errors to assess the performance of asset pricing models. Pricing errors are referred to significant alphas in time-series regression (Gregory, Tharyan, and Christidis, 2013). To identify pricing errors, the associated t-statistics of alphas are reported. The t-statistic (t-stat > 2) above 2 signifies a pricing error in an asset pricing model. Further, the R-squared values are reported that are used to rank the performance of asset pricing models.

4.1.2.2 Results and Discussion of time-series tests

Results of time series tests are reported in Tables (6) - (17). Firstly, the performance of asset pricing models is assessed in the global market on the 25 SBM and the 25 SM portfolios that are reported in Tables (6) and (7). The single-factor CAPM produces less pricing errors (4) as compared to the three-factor model (6), but we find relative much higher R-squared with the three-factor model. This result is consistent with the findings of Fama and French (1993, 2012) as they find much higher R-squared with the three-factor model as compared to the single-factor model. However, one argue that R-squared is improved with the additional

[29] 25 SBM denotes 25 portfolios sorted on *Size and Book-to-market* ratios.
[30] 25 SM denotes 25 portfolios sorted on *Size and Momentum*.

factors. Further, more pricing errors are produced with the CAPM and the three-factor model on the 25 SM portfolios as compared to the 25 SBM portfolios.

Regarding the comparison of the four-factor and five-factor models, four-factor model outperforms five-factor model in the global region on both sets of test portfolios. For instance, we find four pricing errors as compared to the ten with the five-factor model on the 25 SBM portfolios. Likewise, we obtain seven pricing errors as compared to the thirteen pricing errors on the 25 SM portfolios. Regarding six-factor model, we find eight pricing errors on the 25 SBM and nine pricing errors on the 25 SM portfolios. Further, we find that the five-factor model produces lower R-squared on the 25 SM portfolios than the four-factor, and six-factor models.

After assessing the performance in the global region, the performance of empirical factor models is assessed in the North American region on the 25 SBM and the 25 SM portfolios that are reported in Tables (8) and (9). Findings show that three pricing errors are produced with the CAPM as compared to five pricing errors with the three-factor model whereas higher R-squared is produced with the three-factor model. Regarding the comparison of four-factor, five-factor, and six-factor models, five pricing errors are produced with the four-factor and six-factor models as compared to the seven pricing errors with the five-factor model. However, a notable difference in R-squared values is not found for the four-factor, five-factor, and six-factor models. Regarding comparison on the 25 SM portfolios, I find higher R-squared with the three-factor model than CAPM but it produces twelve pricing errors as compared to the CAPM that produces eleven pricing errors.

Regarding the comparison of the four-factor, five-factor, and six-factor models, I find the superior performance of the six-factor model than other models. Four-factor model produces six pricing errors, five-factor model produces seven, whereas six-factor model produces five pricing errors. Similar to the global region, the R-squared of the five-factor model remains much lower than the four-factor, and six-factor models on the 25 SM portfolios in the North American region.

Results for the European region are reported in Tables (10) and (11) on the 25 *SBM* and 25 *SM* portfolios. In the European region, two pricing errors are produced with the single-factor CAPM, whereas five pricing errors are produced with the three-factor model on the 25 SBM portfolios. On the other hand, CAPM produces thirteen pricing errors as compared to seventeen pricing errors with the three-factor model on the 25 SM portfolios. Though, three-factor model produces higher R-squared than the single-factor CAPM both on 25 SBM and 25 SM portfolios. It implies that the addition of factors raises the R-squared value. On the other hand, two pricing errors are produced with the four-factor, and five-factor models and one pricing error is produced with the six-factor model. Findings do not suggest a prominent difference in R-squared values of these models. Regarding results on the 25 SM portfolios, eight pricing errors are produced with the four-factor model whereas nine pricing errors are produced with the six-factor model and find a slight improvement in the R-squared with the six-factor model. Conversely, more pricing errors are produced (thirteen) with the five-factor model as compared to the four-factor and six-factor models. These findings are consistent with the global and North-American region and imply poor performance of the five-factor model on momentum portfolios.

Results for the Japanese region are reported in Tables (12) and (13) on the 25 *SBM* and 25 *SM* portfolios. In Japanese region, the superior performance of asset pricing models is reported on the 25 SBM portfolios. Findings show only one pricing error with the CAPM, and two pricing errors with three-factor, and four-factor models and do not find any pricing error with five-factor, and six-factor models on the 25 SBM portfolios. Interestingly, findings do not report a notable differences in R-squared values with the three-factor, four-factor, five-factor, and six-factor models and it remains less than 0.90 with all modes. Similar to Fama and French (2012), findings do not report momentum patterns in Japanese portfolio returns. Regarding time-series results on 25 SM portfolios, findings show similar results as single pricing error is produced with the CAPM, two pricing errors with the three-factor, and four-factor models, three pricing errors with the five-factor model, and four pricing errors are produced with the six-factor model. Four-factor model outperforms five-factor model as it produces higher R-squared values on the 25 SM portfolios. Three-factor, and five-factor models produce similar R-squared values. Findings also show similarity in R-squared values of the four-factor, and six-factor models.

Results for the Asia Pacific region are reported in Tables (14) and (15) on the 25 *SBM* and 25 *SM* portfolios. In Asia Pacific region four pricing errors are produced with the CAPM whereas, seven pricing errors are produced with the three-factor model on the 25 SBM portfolios. On the other hand, four pricing errors are produced with the four-factor model, whereas, three pricing errors are produced with the five-factor, and six-factor models. Results show that the R-squared value is marginally improved with the five-factor, and six-factor models on the 25 SBM portfolios. Regarding results on the 25 SM portfolios, nine pricing errors are produced with the single factor model, whereas thirteen pricing errors with the three-factor model, ten pricing errors with the four-factor model and eleven pricing errors with the five-factor model and eight pricing with the six-factor model. Results show that the four-factor model produces higher R-squared as compared to the five-factor model. Findings do not show a difference in R-squared values of the four-factor and six-factor models.

Table 6: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 Global *Size and Book-to-market* portfolios, January 1991- December 2015. The table reports Alphas (*a*), t-statistics t (*a*) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
CAPM															
Small	-0.35	-0.07	0.22	0.29	0.61	-1.77	-0.40	1.46	2.18	4.38	0.65	0.71	0.73	0.74	0.68
2	-0.34	-0.08	0.09	0.20	0.29	-1.98	-0.62	0.85	1.91	2.24	0.73	0.82	0.82	0.83	0.75
3	-0.26	-0.08	0.06	0.12	0.26	-1.80	-0.69	0.61	1.26	2.25	0.80	0.84	0.88	0.85	0.80
4	-0.09	0.00	0.04	0.17	0.18	-0.72	0.02	0.55	1.87	1.64	0.83	0.91	0.92	0.87	0.84
Big	-0.06	-0.01	0.02	0.04	-0.03	-0.61	-0.26	0.29	0.51	-0.24	0.86	0.95	0.95	0.92	0.86
Three-Factor															
Small	-0.30	-0.10	0.12	0.10	0.34	-3.14	-1.29	1.72	1.74	5.39	0.92	0.93	0.94	0.95	0.94
2	-0.26	-0.12	-0.03	-0.02	-0.03	-4.10	-2.06	-0.63	-0.50	-0.72	0.96	0.97	0.97	0.97	0.97
3	-0.12	-0.10	-0.08	-0.11	-0.04	-1.89	-1.64	-1.34	-1.87	-0.79	0.96	0.96	0.95	0.95	0.96
4	0.07	-0.06	-0.10	-0.04	-0.11	1.06	-0.95	-1.74	-0.57	-1.99	0.95	0.95	0.96	0.94	0.96
Big	0.20	0.04	-0.05	-0.09	-0.23	3.84	0.75	-1.00	-1.87	-3.14	0.96	0.96	0.97	0.96	0.94
Four-Factor															
Small	-0.32	-0.08	0.11	0.10	0.31	-3.31	-1.01	1.57	1.65	4.84	0.92	0.93	0.94	0.95	0.94
2	-0.20	-0.07	-0.02	0.00	-0.02	-3.18	-1.19	-0.34	0.00	-0.47	0.97	0.97	0.97	0.97	0.97
3	-0.08	-0.10	-0.05	-0.06	-0.03	-1.22	-1.57	-0.77	-0.97	-0.45	0.96	0.96	0.95	0.95	0.96
4	0.07	-0.01	-0.08	0.01	-0.07	0.93	-0.23	-1.34	0.17	-1.21	0.95	0.95	0.96	0.94	0.96
Big	0.22	0.01	-0.04	-0.08	-0.14	4.24	0.20	-0.90	-1.54	-1.97	0.96	0.96	0.97	0.96	0.95
Five-Factor															
Small	-0.13	0.00	0.19	0.13	0.34	-1.38	0.02	2.58	2.15	5.11	0.93	0.94	0.95	0.95	0.94
2	-0.14	0.00	0.00	-0.05	-0.04	-2.16	0.09	0.00	-1.04	-0.87	0.97	0.97	0.97	0.97	0.97
3	0.05	-0.04	-0.13	-0.16	-0.10	0.76	-0.68	-1.93	-2.74	-1.78	0.97	0.96	0.95	0.95	0.96
4	0.23	-0.07	-0.14	-0.15	-0.16	3.32	-1.02	-2.36	-2.40	-2.76	0.96	0.95	0.96	0.95	0.96
Big	0.15	-0.03	-0.08	-0.08	-0.03	2.74	-0.62	-1.66	-1.48	-0.46	0.96	0.97	0.97	0.96	0.96
Six-Factor															
Small	-0.17	0.00	0.17	0.13	0.32	-1.71	0.05	2.37	2.03	4.77	0.93	0.94	0.95	0.95	0.94
2	-0.11	0.03	0.01	-0.03	-0.03	-1.67	0.48	0.14	-0.64	-0.66	0.97	0.97	0.97	0.97	0.97
3	0.06	-0.05	-0.10	-0.12	-0.08	0.97	-0.73	-1.50	-2.08	-1.40	0.97	0.96	0.95	0.96	0.96
4	0.21	-0.04	-0.12	-0.11	-0.12	3.03	-0.53	-2.01	-1.73	-2.16	0.96	0.95	0.96	0.95	0.96
Big	0.17	-0.04	-0.08	-0.07	0.01	3.15	-0.83	-1.54	-1.31	0.14	0.96	0.97	0.97	0.96	0.96

Table 7: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 Global *Size and Momentum* portfolios, January 1991- December 2015. The table reports Alphas (a), t-statistics t (a) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
CAPM															
Small	-0.52	0.22	0.45	0.74	1.01	-2.63	1.78	3.83	5.88	5.42	0.69	0.74	0.72	0.70	0.63
2	-0.52	0.04	0.23	0.42	0.62	-2.67	0.36	2.16	3.76	3.53	0.74	0.80	0.80	0.78	0.67
3	-0.41	0.01	0.16	0.21	0.39	-2.30	0.06	1.73	2.20	2.33	0.78	0.83	0.85	0.84	0.70
4	-0.43	-0.01	0.17	0.18	0.39	-2.37	-0.07	2.18	2.24	2.40	0.77	0.86	0.89	0.88	0.70
Big	-0.49	-0.11	0.04	0.18	0.18	-2.84	-1.16	0.57	2.16	1.09	0.76	0.88	0.91	0.88	0.68
Three-Factor															
Small	-0.73	-0.02	0.23	0.57	0.92	-4.75	-0.22	3.59	8.27	7.17	0.82	0.92	0.92	0.91	0.83
2	-0.72	-0.18	0.02	0.27	0.59	-4.38	-2.51	0.39	4.24	5.34	0.81	0.93	0.94	0.93	0.88
3	-0.60	-0.22	-0.03	0.06	0.39	-3.66	-2.62	-0.54	0.94	3.12	0.82	0.91	0.93	0.92	0.84
4	-0.59	-0.18	0.02	0.08	0.44	-3.31	-2.22	0.28	1.18	3.25	0.78	0.91	0.94	0.91	0.80
Big	-0.50	-0.17	-0.01	0.18	0.34	-2.89	-2.09	-0.14	2.21	2.19	0.77	0.90	0.94	0.89	0.73
Four-Factor															
Small	-0.20	0.13	0.23	0.44	0.60	-2.30	1.99	3.57	6.96	5.69	0.95	0.94	0.92	0.93	0.89
2	-0.10	0.02	0.04	0.13	0.22	-1.44	0.31	0.58	2.33	3.31	0.97	0.96	0.94	0.95	0.96
3	0.01	0.02	0.00	-0.08	-0.05	0.13	0.24	0.06	-1.34	-0.71	0.96	0.95	0.93	0.94	0.96
4	0.06	0.06	0.05	-0.09	-0.05	0.75	1.03	0.86	-1.50	-0.67	0.95	0.96	0.94	0.94	0.95
Big	0.13	0.08	-0.02	-0.08	-0.23	1.53	1.34	-0.32	-1.64	-2.99	0.95	0.95	0.94	0.96	0.94
Five-Factor															
Small	-0.46	-0.06	0.15	0.50	0.88	-2.96	-0.78	2.26	6.90	6.47	0.84	0.92	0.92	0.91	0.83
2	-0.39	-0.20	-0.07	0.19	0.57	-2.35	-2.60	-1.10	2.95	4.84	0.83	0.93	0.94	0.94	0.88
3	-0.33	-0.28	-0.14	-0.06	0.36	-1.97	-3.08	-2.12	-0.85	2.73	0.83	0.91	0.94	0.93	0.85
4	-0.24	-0.20	-0.07	-0.08	0.37	-1.33	-2.27	-1.14	-1.13	2.56	0.80	0.91	0.94	0.93	0.81
Big	-0.22	-0.14	-0.08	0.01	0.25	-1.24	-1.58	-1.37	0.06	1.49	0.78	0.90	0.94	0.90	0.74
Six-Factor															
Small	-0.12	0.05	0.16	0.42	0.66	-1.31	0.70	2.39	6.28	6.02	0.95	0.94	0.92	0.93	0.89
2	0.02	-0.06	-0.05	0.10	0.31	0.24	-1.01	-0.80	1.79	4.66	0.97	0.96	0.94	0.95	0.96
3	0.07	-0.10	-0.10	-0.14	0.06	0.92	-1.64	-1.54	-2.43	0.82	0.97	0.96	0.94	0.95	0.96
4	0.19	-0.02	-0.03	-0.19	0.03	2.22	-0.40	-0.57	-3.14	0.45	0.96	0.96	0.95	0.95	0.95
Big	0.20	0.03	-0.08	-0.16	-0.15	2.23	0.56	-1.36	-3.17	-1.89	0.95	0.96	0.94	0.96	0.94

Table 8: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 North American *Size and Book-to-market* portfolios, January 1991-December 2015. The table reports Alphas (a), t-statistics t (a) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
CAPM															
Small	-0.45	-0.19	0.20	0.26	0.56	-1.41	-0.76	0.94	1.35	2.97	0.54	0.62	0.64	0.63	0.64
2	-0.61	-0.15	0.11	0.17	0.20	-2.40	-0.68	0.65	1.21	1.20	0.65	0.66	0.72	0.77	0.68
3	-0.07	-0.12	0.10	0.12	0.29	-0.31	-0.74	0.85	0.95	2.08	0.67	0.78	0.83	0.78	0.75
4	-0.05	-0.06	0.15	0.14	0.22	-0.26	-0.52	1.48	1.11	1.61	0.72	0.86	0.85	0.79	0.77
Big	-0.03	-0.01	0.00	0.06	-0.15	-0.26	-0.08	-0.01	0.51	-1.02	0.83	0.91	0.89	0.80	0.78
Three-Factor															
Small	-0.38	-0.18	0.11	0.11	0.30	-2.51	-1.60	1.20	1.42	4.05	0.90	0.92	0.93	0.94	0.94
2	-0.45	-0.14	0.00	-0.02	-0.10	-4.30	-1.54	-0.05	-0.37	-1.74	0.94	0.95	0.95	0.95	0.96
3	0.06	-0.14	-0.01	-0.08	0.04	0.61	-1.45	-0.12	-0.92	0.62	0.94	0.92	0.92	0.91	0.94
4	0.14	-0.07	0.04	-0.03	-0.02	1.27	-0.82	0.47	-0.37	-0.28	0.91	0.92	0.90	0.88	0.93
Big	0.16	0.03	-0.06	-0.07	-0.34	2.53	0.43	-0.88	-0.88	-3.54	0.94	0.92	0.92	0.91	0.91
Four-Factor															
Small	-0.36	-0.16	0.12	0.12	0.28	-2.31	-1.33	1.22	1.55	3.68	0.90	0.92	0.93	0.94	0.94
2	-0.33	-0.11	0.01	0.01	-0.09	-3.36	-1.19	0.12	0.13	-1.45	0.95	0.95	0.95	0.95	0.96
3	0.00	-0.11	0.03	-0.02	0.05	0.02	-1.09	0.35	-0.24	0.73	0.94	0.92	0.93	0.92	0.94
4	0.12	-0.03	0.05	0.00	0.02	1.04	-0.34	0.60	0.04	0.32	0.91	0.92	0.90	0.88	0.93
Big	0.18	0.02	-0.02	-0.03	-0.28	2.75	0.27	-0.32	-0.45	-2.95	0.94	0.92	0.92	0.91	0.91
Five-Factor															
Small	-0.08	-0.03	0.23	0.20	0.36	-0.60	-0.27	2.54	2.59	4.72	0.92	0.92	0.94	0.95	0.95
2	-0.27	-0.01	-0.02	-0.04	-0.16	-2.66	-0.12	-0.32	-0.61	-2.64	0.95	0.95	0.95	0.95	0.96
3	0.16	-0.10	-0.06	-0.17	-0.01	1.52	-1.02	-0.78	-2.04	-0.14	0.94	0.92	0.93	0.92	0.94
4	0.29	-0.01	-0.02	-0.15	-0.07	2.58	-0.12	-0.29	-1.61	-0.89	0.92	0.92	0.91	0.89	0.93
Big	0.06	-0.03	-0.04	-0.01	-0.17	0.99	-0.44	-0.53	-0.10	-1.85	0.95	0.93	0.92	0.91	0.92
Six-Factor															
Small	-0.08	-0.02	0.23	0.20	0.34	-0.59	-0.16	2.47	2.63	4.41	0.92	0.92	0.94	0.95	0.95
2.00	-0.19	0.01	-0.01	-0.01	-0.14	-1.97	0.06	-0.15	-0.22	-2.34	0.95	0.95	0.95	0.95	0.96
3.00	0.11	-0.08	-0.03	-0.12	0.00	1.01	-0.79	-0.37	-1.45	0.01	0.94	0.93	0.93	0.92	0.94
4.00	0.26	0.02	-0.01	-0.11	-0.03	2.31	0.19	-0.12	-1.21	-0.38	0.92	0.92	0.91	0.90	0.93
Big	0.08	-0.03	-0.01	0.01	-0.14	1.30	-0.49	-0.11	0.18	-1.49	0.95	0.92	0.92	0.91	0.92

Table 9: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 North American *Size and Momentum* portfolios, January 1991- December 2015. The table reports Alphas (*a*), t-statistics t (*a*) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
CAPM															
Small	-0.58	0.26	0.52	0.76	0.94	-2.20	1.61	3.27	4.00	3.56	0.64	0.69	0.66	0.61	0.56
2	-0.60	0.18	0.21	0.34	0.49	-2.48	1.17	1.43	2.16	1.78	0.70	0.73	0.73	0.69	0.56
3	-0.50	0.03	0.24	0.30	0.36	-2.23	0.23	1.93	2.14	1.44	0.71	0.78	0.79	0.74	0.58
4	-0.50	0.11	0.25	0.19	0.44	-2.21	0.89	2.61	1.84	1.87	0.70	0.80	0.85	0.84	0.58
Big	-0.50	-0.05	-0.01	0.18	0.26	-2.46	-0.42	-0.16	1.74	1.21	0.69	0.80	0.83	0.82	0.59
Three-Factor															
Small	-0.75	0.05	0.33	0.61	0.88	-3.72	0.61	4.12	5.87	5.23	0.79	0.91	0.92	0.88	0.82
2	-0.75	-0.02	0.02	0.19	0.47	-3.63	-0.24	0.27	2.05	2.75	0.79	0.90	0.91	0.90	0.83
3	-0.62	-0.14	0.07	0.16	0.37	-2.92	-1.27	0.81	1.69	2.15	0.75	0.87	0.90	0.88	0.80
4	-0.62	-0.04	0.13	0.12	0.47	-2.80	-0.38	1.69	1.26	2.46	0.72	0.87	0.90	0.87	0.73
Big	-0.52	-0.09	-0.04	0.18	0.38	-2.59	-0.88	-0.53	1.86	1.89	0.70	0.84	0.88	0.83	0.67
Four-Factor															
Small	-0.22	0.20	0.33	0.48	0.53	-1.88	2.52	4.03	4.92	4.08	0.93	0.93	0.92	0.90	0.90
2	-0.16	0.17	0.05	0.06	0.00	-1.71	2.25	0.60	0.77	0.04	0.96	0.94	0.91	0.92	0.95
3	-0.04	0.09	0.10	0.00	-0.08	-0.36	1.04	1.11	0.00	-0.72	0.93	0.92	0.90	0.91	0.93
4	-0.01	0.17	0.15	-0.03	-0.03	-0.11	2.22	1.84	-0.36	-0.31	0.93	0.92	0.90	0.90	0.91
Big	0.03	0.12	-0.05	-0.04	-0.18	0.26	1.49	-0.60	-0.53	-1.86	0.92	0.91	0.87	0.92	0.92
Five-Factor															
Small	-0.43	0.05	0.34	0.64	1.00	-2.17	0.56	4.05	6.01	5.75	0.81	0.91	0.92	0.89	0.83
2	-0.51	-0.08	-0.08	0.07	0.49	-2.47	-0.85	-0.97	0.72	2.72	0.80	0.90	0.92	0.90	0.83
3	-0.40	-0.21	-0.02	0.02	0.31	-1.86	-1.92	-0.27	0.23	1.74	0.76	0.87	0.91	0.89	0.80
4	-0.41	-0.11	0.03	0.01	0.43	-1.83	-1.10	0.34	0.12	2.15	0.72	0.87	0.91	0.88	0.73
Big	-0.30	-0.10	-0.09	0.02	0.40	-1.48	-0.98	-1.02	0.26	1.93	0.71	0.84	0.88	0.85	0.67
Six-Factor															
Small	-0.03	0.17	0.34	0.54	0.71	-0.24	2.09	3.99	5.43	5.51	0.94	0.93	0.92	0.90	0.91
2	-0.05	0.07	-0.05	-0.02	0.11	-0.60	1.01	-0.62	-0.29	1.18	0.96	0.94	0.92	0.92	0.96
3	0.05	-0.03	0.00	-0.10	-0.04	0.46	-0.32	0.04	-1.21	-0.41	0.93	0.93	0.91	0.92	0.93
4	0.06	0.06	0.04	-0.10	0.02	0.52	0.80	0.56	-1.21	0.21	0.93	0.93	0.91	0.91	0.91
Big	0.13	0.07	-0.09	-0.14	-0.05	1.15	0.85	-1.04	-2.05	-0.56	0.92	0.91	0.88	0.92	0.93

Table 10: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 European *Size and Book-to-market* portfolios, January 1991- December 2015. The table reports Alphas (*a*), t-statistics t (*a*) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High
CAPM															
Small	-0.52	-0.10	-0.01	0.13	0.32	-2.76	-0.63	-0.07	0.95	2.20	0.66	0.72	0.75	0.77	0.73
2	-0.24	-0.04	0.06	0.22	0.29	-1.39	-0.28	0.42	1.62	1.92	0.73	0.81	0.80	0.79	0.76
3	-0.18	0.02	0.05	0.08	0.23	-1.12	0.18	0.40	0.63	1.64	0.77	0.84	0.84	0.84	0.82
4	-0.03	0.02	0.09	0.08	0.13	-0.20	0.22	1.02	0.73	0.94	0.84	0.89	0.91	0.87	0.84
Big	-0.08	0.08	0.01	0.09	-0.08	-0.70	1.04	0.12	0.94	-0.56	0.83	0.92	0.95	0.92	0.86
Three-Factor															
Small	-0.46	-0.10	-0.06	0.01	0.12	-4.43	-1.27	-0.81	0.14	2.16	0.90	0.93	0.94	0.96	0.96
2	-0.17	-0.07	-0.05	0.05	0.04	-2.06	-1.01	-0.88	0.81	0.77	0.94	0.95	0.96	0.96	0.97
3	-0.06	-0.01	-0.07	-0.08	0.00	-0.62	-0.19	-0.86	-1.16	0.00	0.92	0.94	0.93	0.94	0.95
4	0.09	-0.02	0.00	-0.07	-0.10	1.03	-0.26	0.06	-0.87	-1.26	0.92	0.93	0.94	0.93	0.94
Big	0.12	0.14	0.02	0.02	-0.25	1.56	2.01	0.32	0.23	-2.57	0.93	0.93	0.96	0.94	0.93
Four-Factor															
Small	-0.42	-0.05	0.00	0.02	0.10	-3.86	-0.63	-0.02	0.26	1.66	0.90	0.93	0.94	0.96	0.96
2	-0.10	0.05	-0.04	0.04	0.02	-1.20	0.76	-0.74	0.60	0.28	0.94	0.96	0.96	0.96	0.97
3	0.02	-0.02	-0.07	-0.08	0.02	0.25	-0.26	-0.91	-1.11	0.20	0.92	0.94	0.93	0.94	0.95
4	0.16	0.02	0.01	-0.02	-0.07	1.69	0.18	0.13	-0.21	-0.84	0.92	0.93	0.94	0.93	0.94
Big	0.16	0.07	0.01	0.01	-0.11	2.03	0.99	0.18	0.18	-1.13	0.93	0.94	0.96	0.94	0.94
Five-Factor															
Small	-0.18	0.05	0.08	0.01	0.10	-1.70	0.64	1.11	0.08	1.74	0.91	0.94	0.95	0.96	0.96
2	0.00	0.03	-0.06	-0.01	0.04	0.00	0.43	-0.97	-0.20	0.60	0.95	0.96	0.96	0.96	0.97
3	0.16	-0.01	-0.16	-0.16	-0.03	1.67	-0.15	-1.95	-2.09	-0.38	0.94	0.94	0.94	0.94	0.95
4	0.26	-0.02	-0.09	-0.10	-0.11	2.79	-0.21	-1.15	-1.16	-1.26	0.93	0.93	0.94	0.93	0.94
Big	0.12	-0.05	0.03	0.04	0.02	1.51	-0.68	0.48	0.50	0.25	0.93	0.95	0.96	0.94	0.95
Six-Factor															
Small	-0.20	0.06	0.09	0.01	0.10	-1.86	0.71	1.28	0.19	1.57	0.91	0.94	0.95	0.96	0.96
2	0.01	0.09	-0.06	-0.01	0.02	0.15	1.30	-0.86	-0.16	0.38	0.95	0.96	0.96	0.96	0.97
3	0.17	-0.02	-0.15	-0.15	-0.01	1.82	-0.21	-1.80	-1.92	-0.18	0.94	0.94	0.94	0.94	0.95
4	0.27	0.01	-0.07	-0.06	-0.09	2.89	0.07	-0.90	-0.73	-1.00	0.93	0.93	0.94	0.93	0.94
Big	0.15	-0.06	0.03	0.04	0.07	1.80	-0.85	0.39	0.42	0.70	0.93	0.95	0.96	0.94	0.95

Table 11: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 European *Size and Momentum* portfolios, January 1991- December 2015. The table reports Alphas (a), t-statistics t (a) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High
CAPM															
Small	-0.93	-0.08	0.21	0.59	1.21	-4.70	-0.62	1.60	4.49	6.20	0.71	0.76	0.75	0.73	0.59
2	-0.81	-0.08	0.23	0.50	0.90	-4.01	-0.58	1.84	3.98	5.10	0.74	0.79	0.80	0.78	0.69
3	-0.58	-0.10	0.20	0.35	0.65	-3.04	-0.83	1.80	2.94	3.74	0.78	0.83	0.85	0.82	0.71
4	-0.53	0.02	0.15	0.29	0.61	-2.64	0.15	1.54	2.72	3.85	0.76	0.89	0.88	0.86	0.74
Big	-0.53	-0.10	0.12	0.18	0.23	-2.65	-0.94	1.61	1.81	1.34	0.78	0.88	0.93	0.86	0.70
Three-Factor															
Small	-1.06	-0.21	0.07	0.49	1.16	-7.21	-2.54	1.01	6.42	8.39	0.84	0.91	0.92	0.91	0.80
2	-0.97	-0.23	0.10	0.41	0.86	-5.96	-2.83	1.41	5.20	7.32	0.84	0.93	0.94	0.92	0.87
3	-0.74	-0.23	0.08	0.26	0.63	-4.40	-2.58	1.16	3.15	4.50	0.83	0.92	0.94	0.91	0.81
4	-0.66	-0.08	0.05	0.23	0.60	-3.41	-0.81	0.65	2.49	4.25	0.78	0.91	0.92	0.90	0.80
Big	-0.58	-0.15	0.10	0.22	0.35	-2.92	-1.37	1.47	2.24	2.10	0.79	0.89	0.94	0.87	0.73
Four-Factor															
Small	-0.42	-0.02	0.04	0.30	0.75	-4.56	-0.26	0.59	4.18	6.17	0.94	0.93	0.92	0.93	0.86
2	-0.19	0.00	0.09	0.19	0.42	-2.40	-0.07	1.23	2.73	4.71	0.96	0.95	0.94	0.94	0.93
3	0.03	0.03	0.11	0.01	0.08	0.31	0.41	1.40	0.15	0.80	0.95	0.94	0.94	0.94	0.91
4	0.21	0.24	0.05	-0.05	-0.01	1.80	3.05	0.64	-0.56	-0.08	0.93	0.94	0.92	0.93	0.92
Big	0.34	0.21	0.07	-0.18	-0.38	3.26	2.41	0.96	-2.68	-3.77	0.95	0.93	0.94	0.95	0.91
Five-Factor															
Small	-0.59	-0.17	0.02	0.39	1.11	-4.09	-1.84	0.20	4.87	7.33	0.87	0.91	0.93	0.92	0.80
2	-0.55	-0.19	-0.01	0.29	0.78	-3.32	-2.09	-0.12	3.52	6.11	0.86	0.93	0.94	0.92	0.87
3	-0.30	-0.20	0.01	0.07	0.45	-1.75	-2.03	0.15	0.84	2.98	0.85	0.92	0.94	0.92	0.82
4	-0.16	0.01	-0.05	0.04	0.45	-0.79	0.10	-0.52	0.36	2.93	0.81	0.91	0.92	0.90	0.80
Big	-0.12	-0.12	0.02	-0.04	0.12	-0.57	-1.00	0.25	-0.35	0.67	0.81	0.89	0.95	0.89	0.74
Six-Factor															
Small	-0.26	-0.05	0.01	0.29	0.86	-2.80	-0.62	0.11	3.91	6.74	0.95	0.93	0.93	0.93	0.86
2	-0.13	-0.05	0.00	0.17	0.52	-1.50	-0.66	0.02	2.37	5.59	0.96	0.95	0.94	0.94	0.93
3	0.12	-0.04	0.04	-0.06	0.13	1.20	-0.46	0.47	-0.76	1.22	0.95	0.94	0.94	0.94	0.91
4	0.31	0.20	-0.03	-0.11	0.09	2.64	2.40	-0.32	-1.30	0.92	0.93	0.95	0.92	0.93	0.93
Big	0.40	0.11	0.01	-0.25	-0.31	3.57	1.16	0.18	-3.56	-3.01	0.95	0.94	0.95	0.95	0.91

Table 12: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 Japanese *Size and Book-to-market* portfolios, January 1991- December 2015. The table reports Alphas (a), t-statistics t (a) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High
CAPM															
Small	0.21	0.16	0.22	0.26	0.41	0.65	0.62	0.93	1.25	1.83	0.61	0.64	0.67	0.71	0.68
2	0.14	-0.13	0.00	0.18	0.16	0.49	-0.61	0.02	1.01	0.83	0.64	0.74	0.71	0.76	0.74
3	-0.28	-0.09	-0.05	0.03	0.25	-1.20	-0.54	-0.30	0.18	1.39	0.72	0.81	0.80	0.79	0.77
4	-0.27	-0.03	-0.01	0.16	0.20	-1.59	-0.20	-0.09	1.18	1.22	0.82	0.87	0.85	0.83	0.80
Big	-0.17	-0.03	-0.01	0.21	0.41	-1.21	-0.27	-0.08	1.72	2.10	0.86	0.89	0.90	0.86	0.77
Three-Factor															
Small	0.17	0.06	0.12	0.12	0.15	0.96	0.49	0.98	1.41	1.91	0.88	0.92	0.91	0.96	0.96
2	0.22	-0.18	-0.14	0.02	-0.12	1.28	-1.79	-1.47	0.26	-2.19	0.88	0.94	0.94	0.96	0.98
3	-0.19	-0.07	-0.17	-0.17	-0.03	-1.33	-0.68	-1.88	-2.12	-0.47	0.89	0.92	0.94	0.95	0.96
4	-0.14	-0.03	-0.11	-0.03	-0.08	-1.05	-0.25	-1.04	-0.31	-0.93	0.90	0.91	0.90	0.92	0.94
Big	0.08	-0.01	-0.09	0.06	0.13	0.89	-0.13	-0.92	0.56	0.85	0.94	0.92	0.92	0.90	0.85
Four-Factor															
Small	0.19	0.09	0.12	0.12	0.15	1.07	0.74	0.99	1.44	1.85	0.88	0.92	0.91	0.95	0.96
2	0.19	-0.16	-0.12	0.03	-0.12	1.11	-1.55	-1.26	0.41	-2.16	0.88	0.94	0.94	0.96	0.98
3	-0.19	-0.05	-0.15	-0.15	-0.04	-1.28	-0.53	-1.68	-1.89	-0.61	0.89	0.92	0.94	0.95	0.96
4	-0.14	-0.01	-0.09	0.00	-0.07	-1.06	-0.09	-0.87	-0.04	-0.78	0.90	0.91	0.90	0.92	0.94
Big	0.08	0.00	-0.05	0.05	0.13	0.86	0.04	-0.55	0.44	0.79	0.94	0.92	0.93	0.90	0.85
Five-Factor															
Small	0.17	0.06	0.10	0.13	0.15	0.93	0.49	0.81	1.58	1.85	0.88	0.92	0.91	0.96	0.96
2	0.15	-0.16	-0.13	0.05	-0.09	0.88	-1.54	-1.37	0.67	-1.72	0.88	0.94	0.94	0.96	0.98
3	-0.20	-0.06	-0.17	-0.15	0.00	-1.37	-0.60	-1.85	-1.89	-0.07	0.89	0.92	0.94	0.95	0.96
4	-0.15	0.00	-0.09	-0.01	-0.07	-1.15	-0.02	-0.83	-0.12	-0.74	0.90	0.91	0.90	0.92	0.94
Big	0.10	0.01	-0.09	0.05	0.13	1.03	0.10	-0.89	0.52	0.81	0.94	0.92	0.92	0.90	0.85
Six-Factor															
Small	0.18	0.08	0.10	0.13	0.15	1.01	0.68	0.84	1.60	1.80	0.88	0.92	0.91	0.96	0.96
2	0.13	-0.14	-0.12	0.06	-0.09	0.78	-1.38	-1.23	0.75	-1.74	0.88	0.94	0.94	0.96	0.98
3	-0.20	-0.05	-0.16	-0.13	-0.02	-1.34	-0.49	-1.72	-1.74	-0.21	0.89	0.92	0.94	0.95	0.97
4	-0.15	0.01	-0.08	0.01	-0.06	-1.15	0.08	-0.73	0.06	-0.65	0.90	0.91	0.90	0.92	0.94
Big	0.09	0.02	-0.06	0.05	0.12	1.00	0.20	-0.62	0.43	0.77	0.94	0.92	0.93	0.90	0.85

Table 13: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 Japanese *Size and Momentum* portfolios, January 1991- December 2015. The table reports Alphas (*a*), t-statistics t (*a*) and adjusted R-squared of the tested models.

	α					$t(\alpha)$					R^2				
	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High
CAPM															
Small	0.29	0.41	0.36	0.47	0.23	1.00	1.89	1.77	2.26	0.83	0.62	0.67	0.67	0.65	0.60
2	0.03	0.09	0.17	0.20	0.19	0.12	0.44	0.95	1.04	0.84	0.69	0.73	0.73	0.72	0.70
3	0.01	-0.04	0.08	0.16	0.18	0.02	-0.24	0.52	1.00	0.89	0.73	0.78	0.75	0.78	0.71
4	0.01	0.03	0.03	-0.03	0.19	0.04	0.23	0.26	-0.23	0.99	0.75	0.82	0.84	0.83	0.74
Big	-0.09	-0.18	-0.16	0.04	0.09	-0.37	-1.29	-1.49	0.36	0.44	0.73	0.85	0.89	0.87	0.72
Three-Factor															
Small	0.05	0.20	0.17	0.29	0.12	0.31	1.78	1.86	2.62	0.63	0.87	0.91	0.94	0.90	0.82
2	-0.18	-0.13	-0.02	0.04	0.13	-1.02	-1.36	-0.16	0.36	0.83	0.86	0.94	0.93	0.92	0.85
3	-0.19	-0.24	-0.07	0.06	0.17	-1.09	-2.24	-0.72	0.52	1.04	0.84	0.91	0.90	0.90	0.81
4	-0.17	-0.13	-0.09	-0.10	0.20	-0.89	-1.11	-0.88	-0.85	1.17	0.80	0.89	0.89	0.87	0.78
Big	-0.22	-0.22	-0.20	0.03	0.22	-0.94	-1.66	-1.96	0.28	1.15	0.74	0.86	0.90	0.88	0.75
Four-Factor															
Small	0.21	0.25	0.16	0.23	0.01	1.69	2.41	1.80	2.25	0.03	0.93	0.92	0.93	0.92	0.86
2	0.01	-0.06	-0.02	-0.03	0.00	0.08	-0.78	-0.24	-0.31	-0.04	0.95	0.95	0.93	0.93	0.91
3	0.00	-0.16	-0.07	-0.02	0.01	0.04	-1.79	-0.71	-0.16	0.06	0.95	0.94	0.90	0.92	0.92
4	0.04	-0.04	-0.07	-0.16	0.03	0.34	-0.39	-0.63	-1.53	0.28	0.93	0.93	0.90	0.89	0.90
Big	0.04	-0.10	-0.18	-0.05	0.01	0.28	-1.02	-1.75	-0.60	0.05	0.92	0.92	0.90	0.92	0.93
Five-Factor															
Small	0.05	0.21	0.19	0.31	0.09	0.29	1.85	2.07	2.76	0.45	0.87	0.91	0.94	0.90	0.82
2	-0.18	-0.09	0.02	0.06	0.12	-1.02	-0.93	0.23	0.56	0.74	0.86	0.94	0.93	0.92	0.85
3	-0.16	-0.19	-0.04	0.07	0.12	-0.90	-1.84	-0.39	0.67	0.71	0.84	0.92	0.91	0.90	0.82
4	-0.13	-0.09	-0.07	-0.11	0.13	-0.65	-0.79	-0.65	-0.93	0.74	0.81	0.89	0.90	0.87	0.79
Big	-0.12	-0.17	-0.23	-0.01	0.15	-0.52	-1.28	-2.19	-0.09	0.79	0.75	0.86	0.90	0.89	0.75
Six-Factor															
Small	0.17	0.25	0.18	0.26	0.00	1.39	2.36	2.01	2.58	0.01	0.93	0.92	0.94	0.92	0.86
2	-0.04	-0.04	0.01	0.01	0.02	-0.36	-0.50	0.14	0.07	0.13	0.95	0.95	0.93	0.94	0.91
3	-0.01	-0.14	-0.04	0.02	0.00	-0.14	-1.55	-0.42	0.18	-0.03	0.95	0.94	0.91	0.93	0.92
4	0.03	-0.02	-0.05	-0.15	0.00	0.26	-0.26	-0.48	-1.48	0.03	0.93	0.93	0.90	0.90	0.90
Big	0.07	-0.08	-0.21	-0.07	-0.01	0.50	-0.83	-2.04	-0.80	-0.08	0.92	0.92	0.91	0.92	0.93

Table 14: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 Asia Pacific *Size and Book-to-market* portfolios, January 1991- December 2015. The table reports Alphas (*a*), t-statistics t (*a*) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
CAPM															
Small	-0.21	-0.40	-0.03	0.37	0.82	-0.63	-1.59	-0.12	1.60	3.11	0.56	0.69	0.71	0.69	0.61
2	-0.80	-0.52	-0.31	-0.13	0.10	-3.75	-2.63	-1.70	-0.67	0.41	0.74	0.79	0.78	0.78	0.71
3	-0.50	-0.35	0.04	0.06	0.00	-2.35	-1.91	0.21	0.34	-0.01	0.74	0.79	0.81	0.81	0.74
4	-0.10	0.18	-0.10	0.12	0.15	-0.61	1.15	-0.66	0.84	0.77	0.81	0.82	0.84	0.85	0.81
Big	-0.14	0.05	0.10	0.01	0.17	-0.99	0.49	0.92	0.06	0.73	0.85	0.92	0.91	0.86	0.75
Three-Factor															
Small	0.15	-0.14	0.13	0.44	0.71	0.66	-0.90	1.01	3.63	6.03	0.78	0.88	0.91	0.92	0.93
2	-0.55	-0.31	-0.17	-0.17	-0.21	-3.58	-2.42	-1.39	-1.40	-1.86	0.86	0.91	0.90	0.92	0.94
3	-0.18	-0.15	0.17	0.02	-0.33	-1.06	-1.01	1.16	0.16	-2.15	0.84	0.86	0.88	0.87	0.88
4	0.09	0.29	0.01	0.09	-0.24	0.63	1.92	0.10	0.61	-1.60	0.85	0.83	0.86	0.87	0.90
Big	0.11	0.14	0.08	-0.25	-0.39	0.94	1.45	0.70	-2.21	-2.38	0.90	0.94	0.91	0.91	0.88
Four-Factor															
Small	0.07	-0.15	0.07	0.38	0.59	0.30	-0.91	0.50	3.02	4.94	0.78	0.88	0.91	0.92	0.93
2	-0.53	-0.17	-0.11	-0.19	-0.23	-3.31	-1.27	-0.84	-1.55	-1.92	0.86	0.92	0.90	0.92	0.94
3	-0.09	-0.13	0.12	0.10	-0.25	-0.49	-0.81	0.82	0.65	-1.59	0.84	0.86	0.88	0.87	0.88
4	0.10	0.31	0.14	0.18	-0.15	0.67	1.95	0.95	1.25	-0.94	0.85	0.83	0.86	0.87	0.90
Big	0.06	0.12	0.14	-0.24	-0.27	0.47	1.26	1.24	-1.99	-1.59	0.91	0.93	0.91	0.91	0.89
Five-Factor															
Small	0.25	-0.06	0.09	0.47	0.73	1.06	-0.35	0.67	3.69	5.98	0.80	0.89	0.91	0.92	0.93
2	-0.36	-0.19	-0.18	-0.18	-0.11	-2.23	-1.40	-1.33	-1.48	-0.98	0.87	0.91	0.90	0.92	0.94
3	0.11	-0.21	-0.06	-0.04	-0.23	0.62	-1.33	-0.40	-0.26	-1.43	0.85	0.86	0.88	0.87	0.88
4	0.05	0.13	-0.19	-0.11	-0.14	0.30	0.84	-1.37	-0.76	-0.92	0.85	0.83	0.87	0.88	0.90
Big	0.17	0.02	0.00	-0.22	-0.05	1.37	0.26	-0.01	-1.88	-0.31	0.91	0.94	0.91	0.92	0.90
Six-Factor															
Small	0.22	-0.04	0.05	0.43	0.64	0.91	-0.23	0.36	3.26	5.12	0.80	0.89	0.91	0.92	0.93
2	-0.35	-0.06	-0.12	-0.22	-0.14	-2.10	-0.43	-0.86	-1.75	-1.17	0.87	0.92	0.90	0.92	0.94
3	0.17	-0.19	-0.09	0.03	-0.18	0.94	-1.16	-0.59	0.16	-1.08	0.85	0.86	0.88	0.87	0.88
4	0.05	0.17	-0.07	-0.02	-0.06	0.30	1.06	-0.48	-0.12	-0.39	0.85	0.83	0.87	0.88	0.90
Big	0.10	0.01	0.07	-0.18	0.05	0.83	0.06	0.60	-1.52	0.31	0.91	0.94	0.92	0.92	0.90

Table 15: Alphas from the CAPM, three-factor, four-factor, five-factor, and the six-factor regressions on the 25 Asia Pacific *Size and Momentum* portfolios, January 1991- December 2015. The table reports Alphas (*a*), t-statistics t (*a*) and adjusted R-squared of the tested models.

	α					t(α)					R^2				
	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High	Low	2.00	3.00	4.00	High
							CAPM								
Small	-0.54	0.25	0.61	1.13	0.93	-2.00	1.12	3.11	4.71	3.33	0.69	0.68	0.70	0.61	0.63
2	-1.38	-0.09	0.12	0.34	0.47	-5.43	-0.46	0.68	1.87	1.77	0.75	0.76	0.75	0.74	0.65
3	-1.15	-0.21	0.13	0.42	0.34	-4.82	-1.33	0.83	2.64	1.41	0.77	0.83	0.81	0.81	0.71
4	-0.70	-0.02	0.11	0.33	0.20	-3.02	-0.13	0.77	2.53	0.91	0.78	0.85	0.84	0.85	0.74
Big	-0.07	-0.18	0.19	0.18	0.34	-0.27	-1.02	1.61	1.33	1.45	0.70	0.82	0.90	0.86	0.68
							Three-Factor								
Small	-0.56	0.27	0.71	1.23	1.12	-3.46	1.97	5.77	7.80	6.03	0.89	0.88	0.89	0.84	0.84
2	-1.53	-0.17	0.09	0.41	0.59	-8.22	-1.29	0.72	3.32	3.01	0.87	0.90	0.87	0.89	0.82
3	-1.26	-0.25	0.14	0.50	0.48	-5.87	-1.83	1.01	3.66	2.53	0.82	0.88	0.86	0.87	0.82
4	-0.94	-0.08	0.19	0.37	0.41	-4.34	-0.50	1.42	2.80	2.00	0.81	0.86	0.85	0.85	0.80
Big	-0.34	-0.35	0.18	0.20	0.45	-1.34	-2.10	1.56	1.52	1.94	0.73	0.84	0.90	0.86	0.69
							Four-Factor								
Small	-0.07	0.45	0.60	1.01	0.57	-0.54	3.35	4.75	6.36	3.64	0.93	0.89	0.89	0.85	0.90
2	-0.79	0.07	0.02	0.18	-0.02	-6.60	0.53	0.12	1.52	-0.15	0.95	0.91	0.88	0.90	0.89
3	-0.48	0.01	0.20	0.32	-0.14	-3.08	0.04	1.44	2.31	-0.94	0.91	0.89	0.86	0.88	0.90
4	-0.17	0.24	0.23	0.12	-0.14	-1.04	1.65	1.62	0.98	-0.77	0.91	0.88	0.85	0.87	0.85
Big	0.67	0.22	0.25	-0.16	-0.39	3.97	1.70	2.06	-1.30	-2.30	0.89	0.91	0.90	0.90	0.85
							Five-Factor								
Small	-0.44	0.33	0.72	1.19	1.09	-2.58	2.33	5.69	7.19	5.99	0.89	0.88	0.89	0.84	0.86
2	-1.34	-0.14	0.04	0.39	0.76	-7.01	-1.05	0.26	2.95	3.81	0.88	0.90	0.88	0.89	0.83
3	-1.10	-0.28	0.09	0.48	0.59	-4.97	-1.97	0.63	3.32	2.96	0.83	0.88	0.86	0.87	0.82
4	-0.86	-0.15	-0.01	0.23	0.37	-3.77	-0.99	-0.05	1.71	1.72	0.81	0.86	0.86	0.86	0.80
Big	-0.20	-0.31	0.08	0.09	0.50	-0.76	-1.76	0.71	0.64	2.04	0.73	0.84	0.91	0.87	0.69
							Six-Factor								
Small	0.01	0.50	0.64	1.00	0.63	0.04	3.55	4.92	6.05	4.10	0.93	0.89	0.90	0.85	0.91
2	-0.68	0.06	-0.04	0.17	0.21	-5.56	0.44	-0.30	1.39	1.29	0.95	0.91	0.88	0.90	0.90
3	-0.41	-0.06	0.14	0.31	0.01	-2.54	-0.41	0.99	2.14	0.06	0.91	0.89	0.86	0.88	0.90
4	-0.15	0.13	0.04	0.02	-0.13	-0.91	0.86	0.26	0.15	-0.70	0.91	0.89	0.86	0.87	0.85
Big	0.72	0.22	0.13	-0.24	-0.28	4.14	1.64	1.07	-1.97	-1.57	0.89	0.91	0.91	0.91	0.85

Table 16: Statistical summary to explain regressions of monthly excess returns on 25 *Size and Book-to-market* portfolios with (5x5) and without (4x5) microcaps: January 1991 to December 2015. The regressions have used the CAPM, three-factor, four-factor, five-factor and six- factor models to explain returns on portfolios formed on *Size and Book-to-market* in Global, North American, Japanese and Asia Pacific markets using global and local factors. The GRS statistic tests whether all alphas of 25 (5x5) or 20 (4x5) portfolios are jointly zero.$|a|$ is the average absolute alpha for a set of regression of 25 or 20 portfolios; R^2 is the mean adjusted R^2; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the Sharpe ratio of intercepts. The critical values for GRS statistic are: 90%: 1.45; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25.

	Global Factors										Local Factors									
	5 x 5					4 x 5					5 x 5					4 x 5				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	
Global																				
CAPM	3.93	0.16	0.82	0.11	0.60	1.72	0.12	0.85	0.10	0.35										
Three-Factor	3.54	0.11	0.95	0.06	0.58	3.39	0.09	0.96	0.06	0.51										
Four-Factor	3.11	0.09	0.95	0.06	0.56	2.81	0.07	0.96	0.06	0.47										
Five-Factor	3.35	0.10	0.96	0.06	0.61	2.88	0.09	0.96	0.06	0.50										
Six-Factor	3.18	0.09	0.96	0.06	0.60	2.59	0.08	0.96	0.06	0.48										
North America																				
CAPM	3.38	0.30	0.66	0.19	0.56	1.96	0.28	0.68	0.17	0.38	3.18	0.18	0.74	0.16	0.55	1.61	0.14	0.77	0.15	0.34
Three-Factor	3.25	0.27	0.77	0.15	0.56	2.72	0.26	0.77	0.15	0.45	2.96	0.12	0.93	0.09	0.53	2.4	0.10	0.93	0.08	0.42
Four-Factor	2.61	0.29	0.77	0.16	0.52	2.25	0.29	0.77	0.15	0.42	2.57	0.10	0.93	0.09	0.51	1.94	0.08	0.93	0.08	0.39
Five-Factor	2.95	0.44	0.78	0.16	0.57	3.02	0.38	0.78	0.15	0.51	2.54	0.11	0.93	0.09	0.51	1.71	0.09	0.93	0.08	0.37
Six-Factor	2.62	0.44	0.78	0.16	0.54	2.67	0.40	0.78	0.16	0.49	2.32	0.09	0.93	0.09	0.50	1.43	0.07	0.93	0.08	0.35
Europe																				
CAPM	1.91	0.14	0.68	0.17	0.42	1.02	0.12	0.70	0.17	0.27	1.93	0.13	0.82	0.13	0.42	1.1	0.10	0.84	0.12	0.29
Three-Factor	1.75	0.15	0.77	0.15	0.41	0.97	0.14	0.78	0.15	0.27	2.16	0.09	0.94	0.07	0.45	1.6	0.07	0.94	0.08	0.34
Four-Factor	1.62	0.11	0.77	0.15	0.41	0.72	0.10	0.78	0.15	0.24	1.96	0.07	0.94	0.08	0.45	1.4	0.06	0.94	0.08	0.34
Five-Factor	1.78	0.22	0.78	0.16	0.44	1.34	0.22	0.79	0.15	0.34	1.50	0.08	0.94	0.08	0.41	1.4	0.08	0.95	0.08	0.35
Six-Factor	1.77	0.19	0.78	0.16	0.45	1.25	0.19	0.79	0.15	0.33	1.74	0.08	0.95	0.08	0.45	1.6	0.08	0.95	0.08	0.38
Japan																				
CAPM	1.42	0.25	0.27	0.33	0.36	1.50	0.29	0.29	0.32	0.33	1.27	0.16	0.77	0.18	0.34	1.19	0.14	0.80	0.17	0.29
Three-Factor	1.13	0.40	0.35	0.32	0.33	1.16	0.43	0.36	0.31	0.30	1.19	0.11	0.92	0.11	0.33	1.45	0.10	0.92	0.10	0.33
Four-Factor	1.07	0.36	0.35	0.33	0.33	1.10	0.41	0.35	0.31	0.30	1.12	0.10	0.92	0.11	0.32	1.36	0.09	0.92	0.10	0.32
Five-Factor	1.07	0.52	0.39	0.33	0.34	1.16	0.53	0.40	0.32	0.32	1.14	0.10	0.92	0.11	0.33	1.37	0.09	0.92	0.10	0.32
Six-Factor	0.97	0.47	0.39	0.33	0.33	1.05	0.50	0.40	0.32	0.31	1.10	0.09	0.92	0.11	0.33	1.32	0.09	0.92	0.10	0.32
Asia Pacific																				
CAPM	3.36	0.30	0.50	0.29	0.56	1.47	0.27	0.51	0.28	0.33	3.30	0.23	0.77	0.19	0.55	1.5	0.20	0.81	0.18	0.33
Three-Factor	3.03	0.22	0.56	0.28	0.54	1.26	0.19	0.57	0.27	0.31	2.84	0.22	0.89	0.14	0.52	2.4	0.20	0.89	0.14	0.42
Four-Factor	2.57	0.21	0.56	0.28	0.51	0.96	0.18	0.57	0.28	0.28	2.36	0.20	0.89	0.15	0.50	1.9	0.18	0.89	0.14	0.40
Five-Factor	3.08	0.29	0.58	0.29	0.58	1.54	0.26	0.59	0.28	0.36	2.07	0.17	0.89	0.14	0.47	1.28	0.14	0.89	0.14	0.33
Six-Factor	2.82	0.28	0.58	0.29	0.57	1.32	0.25	0.59	0.28	0.34	1.83	0.15	0.89	0.15	0.46	1.1	0.12	0.89	0.15	0.31

Table 17: Statistical summary to explain regressions of monthly excess returns on 25 *Size and Momentum* portfolios with (5x5) and without (4x5) microcaps: January 1991 to December 2015. The regressions have used the CAPM, three-factor, four-factor, five-factor and six- factor models to explain returns on portfolios formed on *Size and Momentum* portfolios in Global, North American, Japanese, and Asia Pacific markets using global and local factors. The GRS statistic tests whether all alphas of 25 (5x5) or 20 (4x5) portfolios are jointly zero. $|a|$ is the average absolute alpha for a set of regression of 25 or 20 portfolios; R^2 is the mean adjusted R^2; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the Sharpe ratio of intercepts. The critical values for GRS statistic are: 90%: 1.45; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25.

	Global Factors										Local Factors									
	5 x 5					4 x 5					5 x 5					4 x 5				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$
Global																				
CAPM	4.99	0.33	0.78	0.13	0.68	2.53	0.26	0.80	0.13	0.43										
Three-Factor	4.88	0.32	0.88	0.10	0.68	2.52	0.28	0.88	0.10	0.44										
Four-Factor	4.03	0.12	0.95	0.07	0.64	2.14	0.07	0.95	0.06	0.41										
Five-Factor	5.00	0.25	0.88	0.11	0.74	3.23	0.21	0.88	0.11	0.53										
Six-Factor	4.64	0.14	0.95	0.07	0.72	3.22	0.10	0.95	0.07	0.54										
North America																				
CAPM	4.05	0.46	0.63	0.20	0.61	1.83	0.40	0.64	0.19	0.36	3.74	0.35	0.71	0.18	0.59	1.61	0.29	0.73	0.17	0.34
Three-Factor	3.63	0.44	0.69	0.18	0.59	1.53	0.39	0.69	0.18	0.34	3.58	0.32	0.83	0.13	0.58	1.4	0.27	0.83	0.13	0.32
Four-Factor	3.05	0.36	0.77	0.16	0.56	1.53	0.32	0.77	0.16	0.35	3.13	0.13	0.92	0.09	0.56	1.32	0.08	0.92	0.09	0.32
Five-Factor	3.12	0.45	0.70	0.19	0.59	1.55	0.38	0.70	0.19	0.37	3.25	0.26	0.84	0.14	0.58	0.91	0.21	0.83	0.14	0.27
Six-Factor	2.90	0.46	0.78	0.16	0.57	1.70	0.40	0.78	0.16	0.39	2.96	0.12	0.92	0.09	0.56	1.16	0.07	0.92	0.09	0.31
Europe																				
CAPM	5.72	0.42	0.65	0.19	0.73	4.09	0.37	0.67	0.18	0.54	5.72	0.41	0.78	0.14	0.73	4.2	0.36	0.80	0.14	0.55
Three-Factor	5.26	0.42	0.72	0.17	0.71	4.05	0.38	0.73	0.17	0.55	5.76	0.42	0.87	0.11	0.74	4.2	0.38	0.87	0.12	0.56
Four-Factor	4.37	0.21	0.76	0.16	0.67	3.06	0.15	0.78	0.16	0.50	4.25	0.18	0.93	0.09	0.67	3.4	0.14	0.94	0.09	0.53
Five-Factor	4.47	0.38	0.73	0.18	0.70	3.60	0.34	0.74	0.18	0.56	4.56	0.25	0.88	0.12	0.72	3.6	0.19	0.88	0.12	0.56
Six-Factor	4.11	0.26	0.77	0.16	0.68	3.19	0.22	0.79	0.16	0.53	4.11	0.18	0.93	0.09	0.69	3.6	0.16	0.94	0.09	0.58
Japan																				
CAPM	1.06	0.23	0.26	0.33	0.31	0.76	0.26	0.28	0.32	0.24	0.87	0.15	0.74	0.19	0.28	0.54	0.10	0.77	0.18	0.20
Three-Factor	1.00	0.38	0.33	0.31	0.31	0.76	0.43	0.34	0.31	0.24	0.88	0.15	0.87	0.14	0.29	0.69	0.14	0.86	0.14	0.22
Four-Factor	1.21	0.32	0.35	0.32	0.35	0.96	0.38	0.36	0.31	0.28	0.81	0.08	0.92	0.11	0.28	0.60	0.06	0.92	0.10	0.21
Five-Factor	1.02	0.47	0.37	0.32	0.33	0.96	0.51	0.38	0.32	0.29	0.88	0.12	0.87	0.14	0.29	0.71	0.11	0.86	0.14	0.23
Six-Factor	1.21	0.41	0.39	0.32	0.37	1.13	0.46	0.4	0.32	0.32	0.85	0.08	0.92	0.11	0.29	0.67	0.05	0.92	0.10	0.23
Asia Pacific																				
CAPM	5.03	0.51	0.48	0.30	0.68	4.72	0.44	0.49	0.29	0.59	5.57	0.42	0.76	0.20	0.72	5.08	0.35	0.78	0.19	0.61
Three-Factor	4.88	0.45	0.54	0.28	0.68	4.66	0.39	0.55	0.28	0.59	5.73	0.51	0.85	0.16	0.75	5.34	0.45	0.84	0.17	0.64
Four-Factor	4.05	0.32	0.56	0.28	0.64	3.79	0.26	0.56	0.28	0.55	4.46	0.30	0.89	0.14	0.69	3.96	0.24	0.89	0.14	0.57
Five-Factor	3.83	0.36	0.56	0.29	0.65	3.68	0.3	0.56	0.29	0.56	4.71	0.47	0.85	0.17	0.71	4.01	0.40	0.84	0.17	0.58
Six-Factor	3.47	0.29	0.57	0.29	0.63	3.29	0.23	0.58	0.29	0.54	3.78	0.28	0.89	0.15	0.66	3.00	0.21	0.89	0.15	0.52

Table (16) and (17) report summary of GRS tests on 25 SBM and 25 SM portfolios respectively for global, North American, Japanese, and Asia Pacific regions. Similar to Fama and French (2012) and Gregory, Tharyan and Christidis (2013), the GRS test statistic, average absolute alphas, mean adjusted R-squared values, the average standard error of alphas, and Sharpe ratio of alphas are reported. As this research extends the study of Fama and French (2012, 2015), hence, results with (5 x 5), and without (4 x 5) microcaps are reported. Further, the performance is also assessed by using global and local factors.

Regarding the performance of asset pricing models in all regions, findings show that asset pricing models produce low average Sharpe ratio of alphas in Japanese region on both sets of test portfolios. Results also show that excluding microcaps, improves the performance of asset pricing models. Findings do not report a notable difference in the performance of asset pricing models by using global and local factors. However, the average Sharpe ratio of alphas is marginally reduced by using local factors, particularly, in the North American region. In Asia Pacific region, the performance improves with global factors on 25 SM portfolios as I find lower average Sharpe ratios of alphas by using global factor than local factors.

Regarding the comparison of the performance of asset pricing models on each region, I find that four-factor model outperforms all other models under investigation including six-factor model, as I find lower average Sharpe ratio of alphas with the four-factor model on all regions except Japan. In Japan, the momentum returns are relatively less strong than other regions. These findings are consistent with results of Chui, Titman, & Wei (2010) and Fama and French (2012). Chui, Titman, & Wei (2010) find that momentum returns are higher in cultures that value individual lifestyles. They argue that as Japan ranks low on individualism that is why momentum returns are not stronger in Japan. However, like Fama and French (2012), I believe that low momentum in Japan can be the result of a chance as low individualism might also produce momentum.

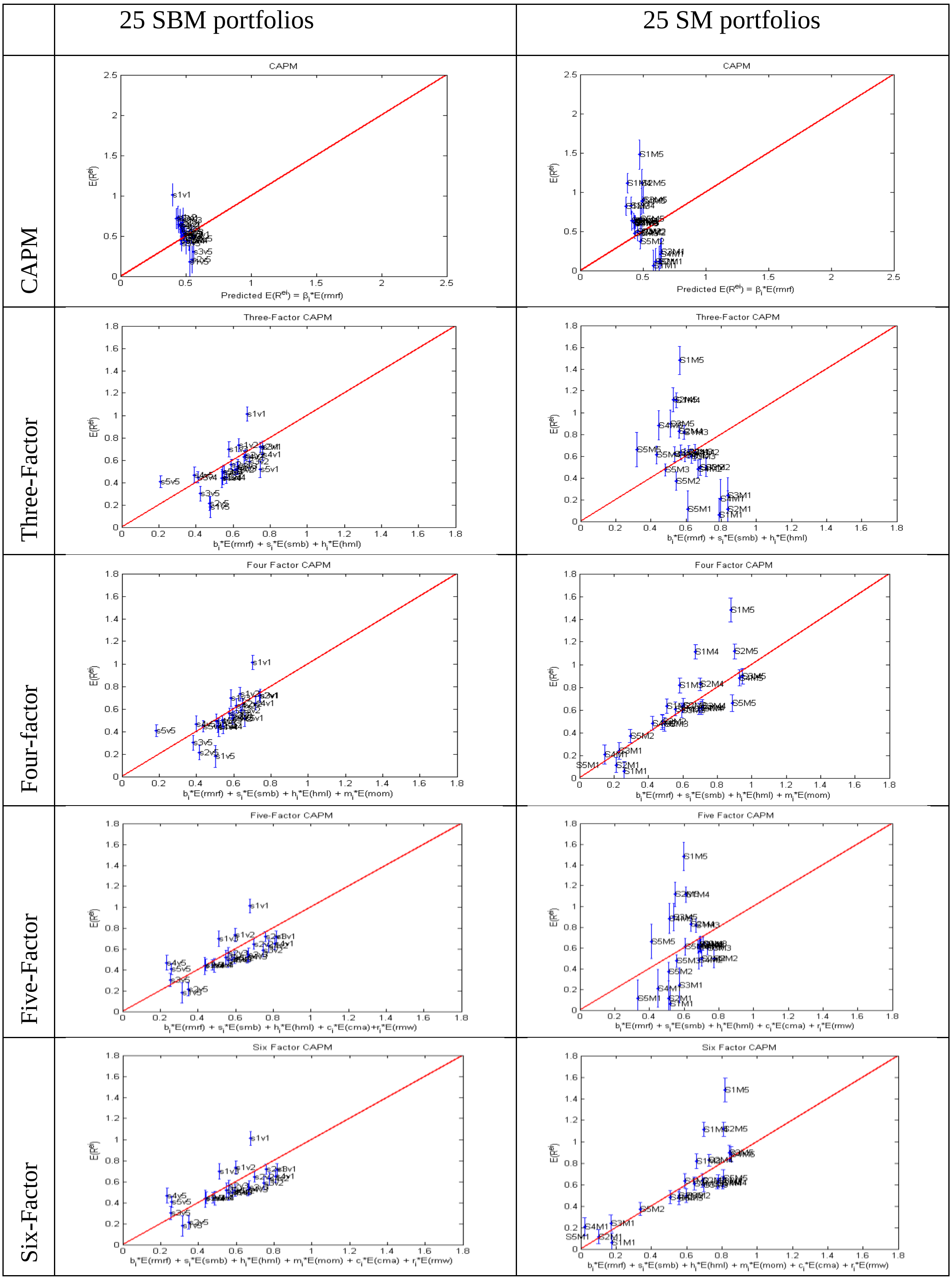


Figure 5: Actual and predicted returns with single-factor, three-factor, four-factor, five-factor, and six-factor models on 25 Size and Book-to-market (SBM) and 25 Size and Momentum (SM) portfolios in Global region.

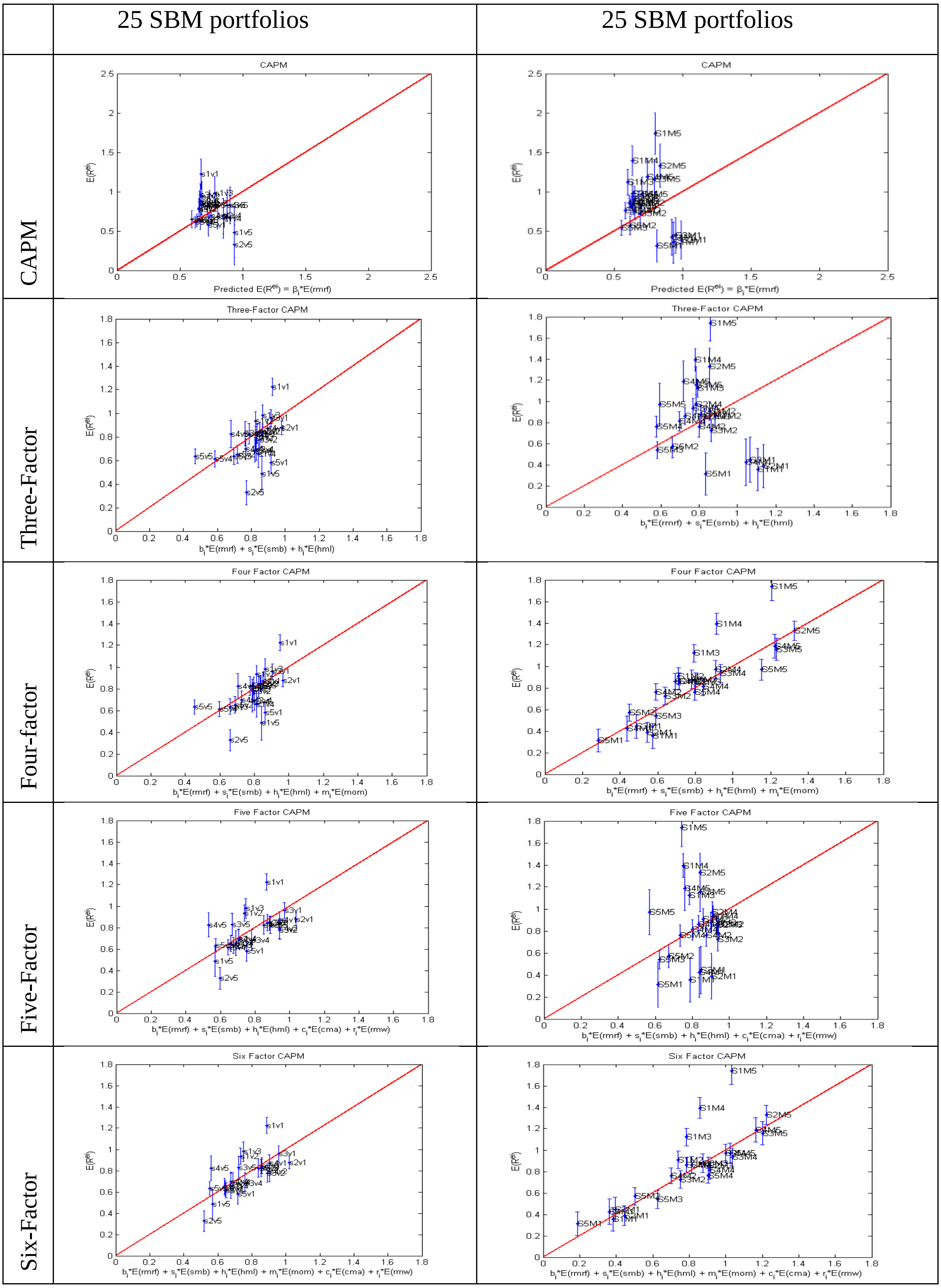


Figure 6: Actual and predicted returns with single-factor, three-factor, four-factor, five-factor, and six-factor models on *25 Size and Momentum* portfolios in North American region.

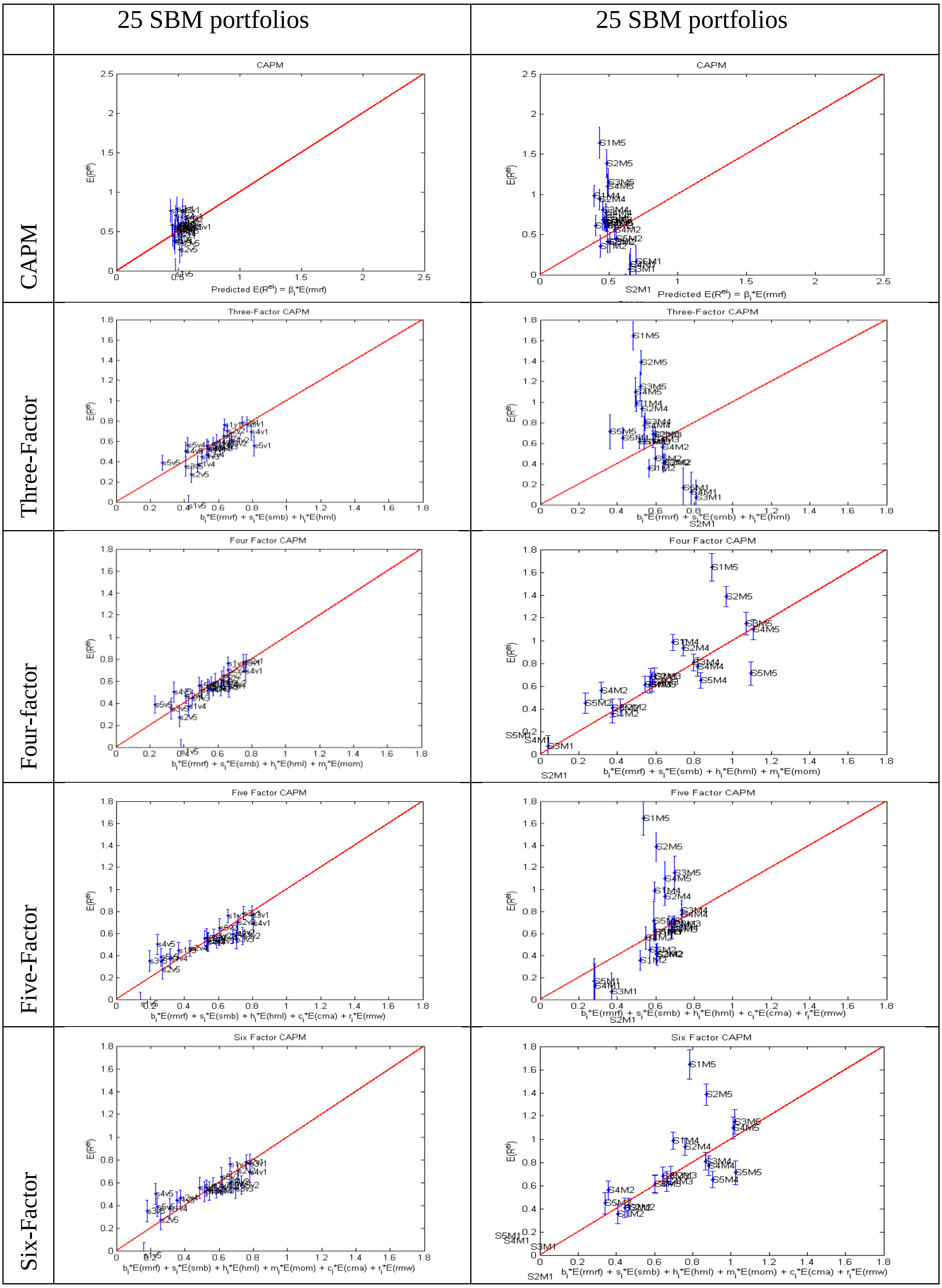


Figure 7: Actual and predicted returns with single-factor, three-factor, four-factor, five-factor, and six-factor models on *25 SBM and 25 SM* portfolios in European region.

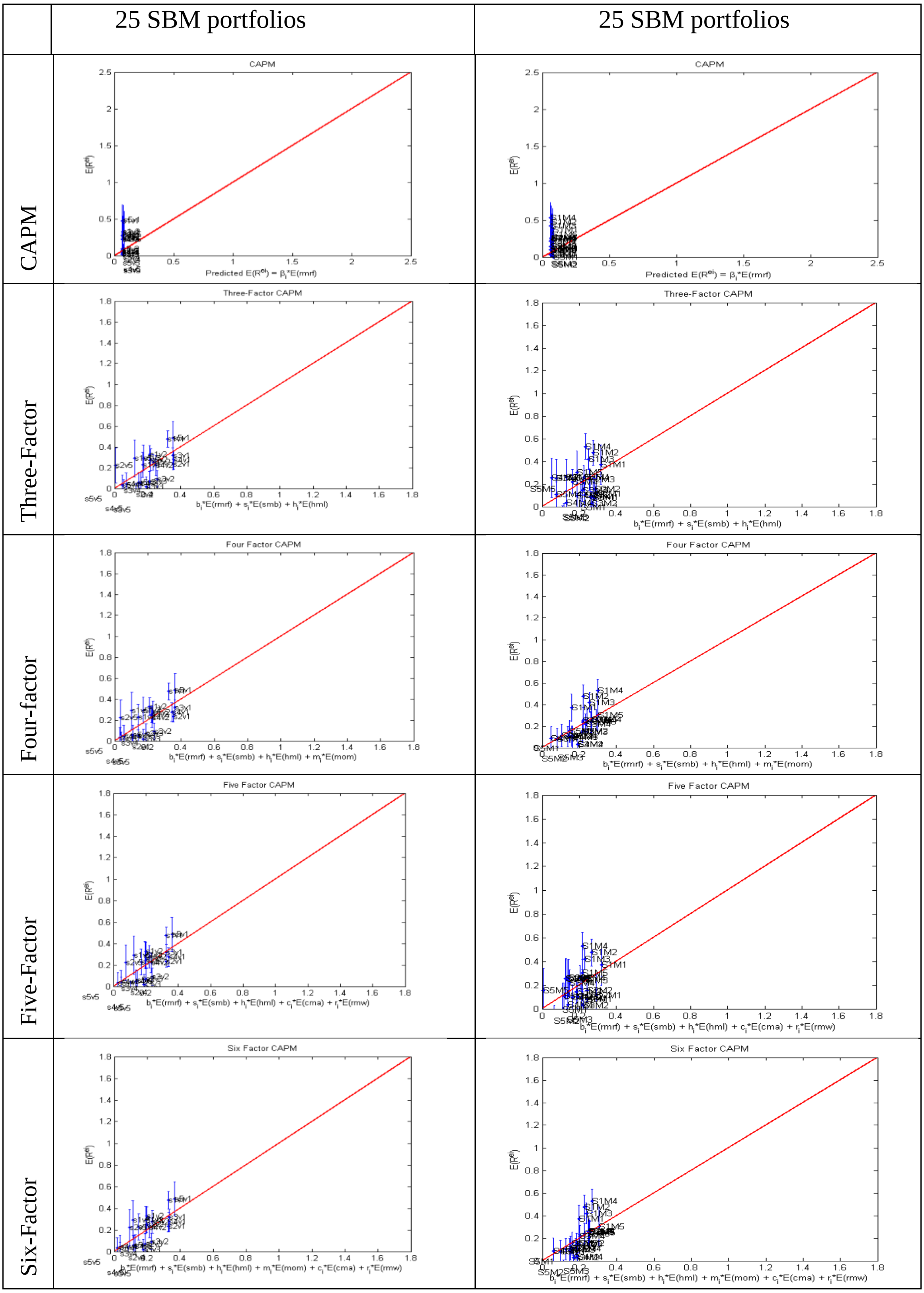


Figure 8: Actual and predicted returns with single-factor, three-factor, four-factor, five-factor, and six-factor models on *25 SBM and 25 SM* portfolios in Japanese region.

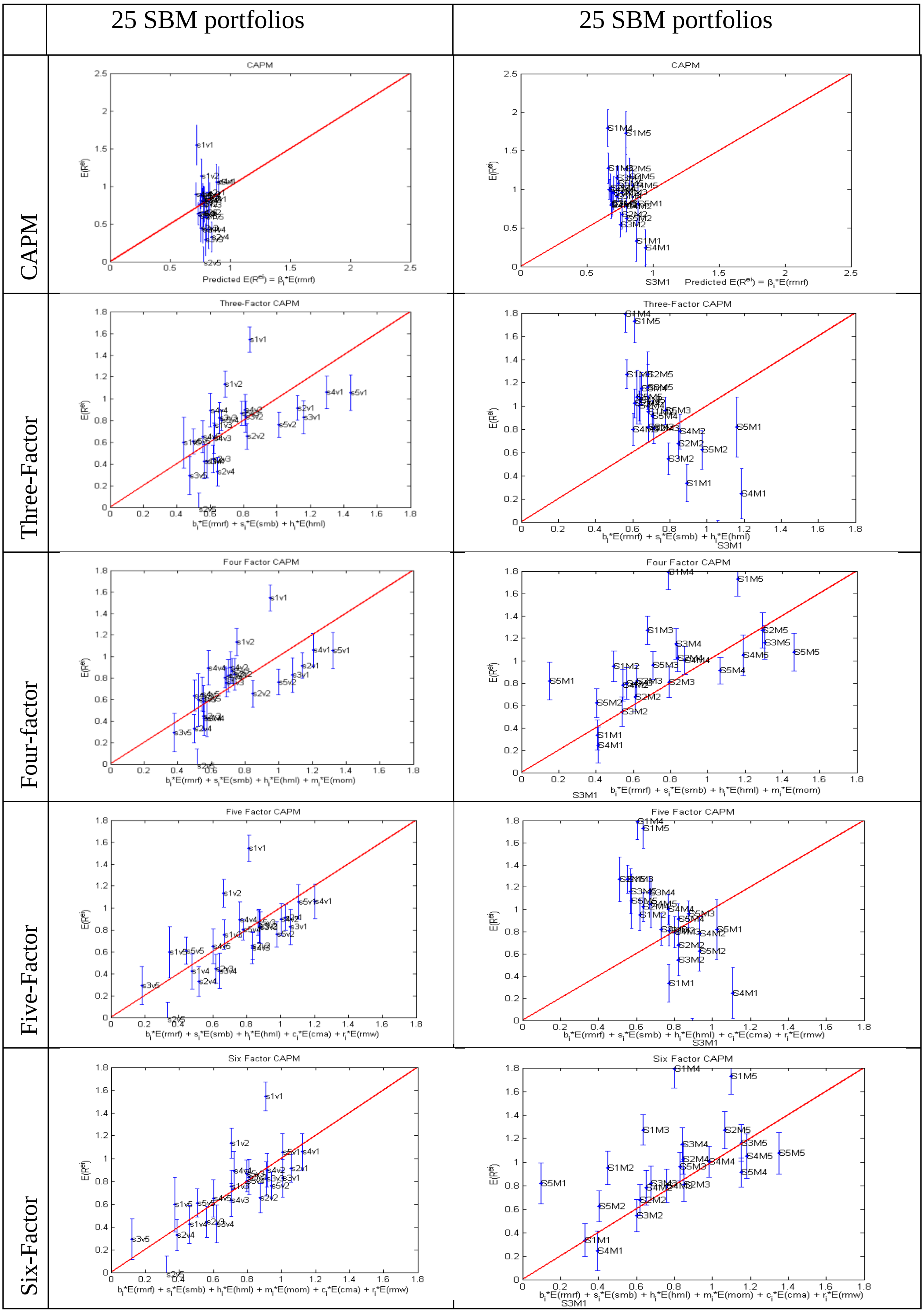


Figure 9: Actual and predicted returns with single-factor, three-factor, four-factor, five-factor, and six-factor models on *25 SBM and 25 SM* portfolios in Asia Pacific region.

I further compare actual and predicted returns with the graphical presentation as shown in Figures (5) – (9). I take guideline from Cochrane (2014) in comparing actual and predicted returns. Standard error bars show the deviations of portfolios from the security market line. The 25 SBM portfolios are denoted by *SV*. The smallest and lowest value portfolio is denoted by S_1V_1, whereas largest and highest value portfolio is denoted by S_5V_5. In a similar way, the 25 SM portfolios are denoted by *SM* . The smallest with lowest momentum portfolios is denoted by S_1M_1, whereas largest with highest momentum portfolio is denoted by S_5M_5. The plots provide the in-depth overview of the empirical performance of models and show whether the model under investigation, predicts the actual average returns. Figure (5) shows the performance of the empirical factor models in global region on the 25 SBM and the 25 SM portfolios. The three-factor and the five-factor models perform comparatively better on the 25 SBM portfolios than on the 25 SM portfolios. However, the four-factor and the six-factor models outperform CAPM, the three-factor and the five-factor model on the 25 SBM portfolios. Further, the four-factor and the six-factor models produce less pricing errors and provide better prediction than the other competing asset pricing models. Figures (6) – (9) show the performance of the empirical factor models in North American, European, Japanese, and Asia Pacific regions on the 25 SBM and the 25 SM portfolios. Figures (6) – (9) also suggest superior performance of the four-factor and six-factor models in the North American, the European, the Japanese, and the Asia Pacific regions. Figures show that the CAPM, the three-factor and the five-factor models perform reasonably well on the SBM portfolios, but they struggle to predict actual average returns on the 25 SM portfolios. On the other hand, the four-factor and the six-factor models are able to predict average returns with less pricing errors on both sets of test portfolios.

4.1.3 Cross-Sectional Results

In addition to time-series analysis, I also perform cross-sectional analysis to assess the performance of asset pricing models under investigation. I perform Fama and Macbeth (1973) methodology as this is traditional and robust in assessing the performance of asset pricing models and is widely used in asset pricing literature (Fama & French, 1993, 1996, 2006, 2008; Gregory, Tharyan, and Christidis, 2013; Kan, Robotti, & Shanken, 2013).

I perform cross-sectional tests in the full-period (1991 – 2015), and also in the sub-period (2003 - 2015) to examine any difference in empirical performance of asset pricing models. For robustness, I also perform the Fama-MacBeth test with Generalised Least Square (GLS) methodology and report result in Appendix (A). Kan, Robotti and Shanken (2013) employ both OLS and GLS methods in a comparative study of asset pricing models and find similar results.

4.1.3.1 Testable Implications in Cross-Section

I assess asset pricing models in cross-section with two testable implications. 1) Firstly, I consider the significance level of cross-sectional alpha. An asset pricing model can only be valid if alpha is insignificant. Significant alphas are referred as pricing errors (Gregory, Tharyan, and Christidis, 2013). 2) I consider a positive estimate of the market coefficient for the validity of asset pricing models. The traditional finance theory emphasises that the relation between market risk and stock returns should be positive (Sharpe, 1964). The positive estimate of the market coefficient is also considered an important testable implication in the recent study of asset pricing models. For instance (Maio & Santa-Clara, 2012) refer the positive estimate of market coefficient as a plausible estimate of the relative risk aversion (RRA), whereas negative estimate as implausible. In a similar vein, I consider the positive estimate of market coefficient as a second testable implication for the validity of asset pricing models under investigation. 3) I also consider cross-sectional R-squared value. The higher R-squared value is desirable for the validity of an asset pricing model.

4.1.3.2 Analysis and Discussion of cross-sectional tests

Firstly, I perform cross-sectional tests on 25 SBM and 25 SM portfolios in the global region. The results are reported in Table (18). I do not find convincing results in the full –period (1991 – 2015) on the global region on both sets of test portfolios. I find significant cross-sectional alphas with a negative estimate of the market coefficient for all models under investigation. However, the performance of the five-factor, and six-factor models improve in the sub-period (2003 – 2015), as I find a positive estimate of the market coefficient with insignificant alphas with these models on both sets of test portfolios. I find significant size, value, momentum, investment, and operating profitability premiums with three-, four-, and five-factor models. I find higher R-squared values with the six-factor model on both sets of test portfolios.

Table (19) shows results in the North-American region with full period and sub-period analysis on the 25 SBM portfolios. Further, I use global and local factors to examine whether using global factor can improve the performance of asset pricing models. The results are shown in two pairs of columns. The first pair of the column shows results for global factors in the full period (1991 – 2015) and sub-period (2003 – 2015), whereas, the second pair shows results for local factors in the full period and sub-period.

In the full period analysis, I do not find convincing results with global or local factor except six-factor which performs reasonably well as it produces insignificant alpha with an insignificantly positive estimate of the cross-sectional market coefficient. In the sub-period analysis, I find that the CAPM, four-, five-, and six-factor models satisfy cross-sectional testable implications as these models produce a positive estimate of the market coefficient with insignificant cross-sectional alpha. On 25 SBM portfolios, I find significant premiums for momentum and operating profitability. Table (20) shows performance on the 25 SM portfolios in the North American region. When I use global factors, four-factor model performs comparatively better than other models, but in the sub-period, five-factor model performs better. By using local factors, I find that six-factor model outperforms other models both in full-period as well as sub-period analysis. I find a significantly positive estimate of the market coefficient with insignificant cross-sectional alpha, implying the validity of six-factor model on 25 SM portfolios in North-American region. On 25 SM portfolios, I find significant size, value, momentum, investment, and operating profitability premiums.

Table (21) shows cross-sectional results on the 25 SBM portfolios in the European region with the global and local factors. In the full period analysis, I do not find convincing results with global factors. When I use local factors, CAPM, five-, and six-factor models produce a better result. In the sub-period analysis, I find reasonable results with global factors, as all asset pricing models produce a positive estimate of the market coefficient with insignificant cross-sectional alpha. When I use local factors, and perform sub-period analysis, I obtain reasonable estimates with CAPM, three-factor and four-factor models. On 25 SBM portfolios, I find significant size, value, investment, and operating profitability premiums.

Table (22) shows results in European region on 25 SM portfolios. Four-, five-, and six-factor models satisfy testable implication in the full period analysis with global factors. Whereas, five-, and six-factor models satisfy testable implication in the sub-period. When I use local factors, five-, and six-factor models produce a significantly positive estimate of the market coefficient in the full period analysis (2.0% per month and 1.99% per month respectively) with significant cross-sectional alpha. In the sub-period, only four-factor model satisfy testable implications. On 25 SM portfolios, I find significant size, value, momentum, investment, and operating profitability premiums.

Table (23) shows results in the Japanese region on 25 SBM portfolios with global and local factors. I find that except single factor CAPM, all asset pricing models satisfy cross-sectional testable implications on 25 SBM portfolios in Japanese region. Tables (24) shows results on the 25 SM portfolios in the Japanese region. I find strong size, value and investment premiums but I do not find momentum and profitability premiums in Japanese region.

Table (25) shows cross-sectional results on the 25 SBM portfolios in the Asia Pacific region. I do not find convincing results with global factors. However, five-factor, and six-factor models produce plausible estimates of market risk premium in the sub-period (2003 – 2015) with local factors. I find significant evidence of value, momentum, and investment premiums whereas, I find weak evidence of the size and operating profitability premiums in the Asian region. Table (26) shows results on the 25 SM portfolios. All the models produce significant cross-sectional alphas with negative estimates of market risk premium, implying poor performance of asset pricing models on the size and momentum portfolios in the Asian region.

Table 18: Fama-MacBeth Tests on the global 25 *Size and Book-to-market*, and 25 *Size and Momentum* portfolios for the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Size and Book to Market								Global Size and Momentum							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.16	4.47	4.25	0.14	1.10	3.30	3.29	0.10	1.84	5.22	5.02	0.22	1.81	3.26	3.20	0.27
γ_{RM}	-1.62	-3.04	-2.86		-0.25	-0.50	-0.50		-1.24	-2.87	-2.79		-0.88	-1.35	-1.34	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.57	5.71	5.52	0.55	1.37	4.19	4.12	0.53	1.78	4.65	4.32	0.63	1.64	5.51	5.32	0.65
γ_{RM}	-1.08	-2.92	-2.86		-0.58	-1.21	-1.20		-1.23	-2.80	-2.66		-0.84	-1.82	-1.80	
γ_{SMB}	0.12	1.07	1.07		0.13	1.04	1.04		0.26	2.18	2.16		0.22	1.73	1.72	
γ_{HML}	0.27	1.98	1.98		0.07	0.52	0.52		-0.47	-1.83	-1.73		-0.19	-0.47	-0.46	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.41	4.77	4.58	0.58	1.02	2.67	2.60	0.57	0.88	2.41	2.35	0.71	1.08	3.74	3.10	0.72
γ_{RM}	-0.91	-2.35	-2.29		-0.24	-0.46	-0.45		-0.39	-0.90	-0.88		-0.30	-0.66	-0.60	
γ_{SMB}	0.12	1.01	1.01		0.13	1.04	1.03		0.27	2.29	2.28		0.24	1.83	1.79	
γ_{HML}	0.28	2.11	2.11		0.07	0.58	0.58		0.04	0.16	0.15		0.89	2.47	2.09	
γ_{Mom}	0.75	1.27	1.23		0.68	1.18	1.15		0.67	2.91	2.91		0.40	1.44	1.43	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.87	4.26	3.99	0.66	0.76	1.48	1.37	0.63	1.47	4.53	4.20	0.74	0.53	1.43	1.08	0.72
γ_{RM}	-1.37	-2.70	-2.57		0.02	0.03	0.03		-0.94	-2.35	-2.24		0.24	0.46	0.39	
γ_{SMB}	0.11	0.92	0.92		0.17	1.33	1.33		0.27	2.26	2.24		0.31	2.39	2.29	
γ_{HML}	0.30	2.22	2.22		0.04	0.30	0.30		-0.46	-1.85	-1.75		0.74	2.38	1.85	
γ_{CMA}	0.17	0.97	0.93		-0.05	-0.29	-0.27		0.09	0.41	0.39		0.72	3.52	2.80	
γ_{RMW}	0.12	0.75	0.72		0.34	1.91	1.80		0.04	0.23	0.22		0.11	0.50	0.39	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.64	3.47	3.27	0.69	0.68	1.39	1.29	0.65	0.97	2.74	2.03	0.77	0.55	1.48	1.12	0.78
γ_{RM}	-1.13	-2.10	-2.00		0.10	0.16	0.15		-0.50	-1.20	-0.97		0.22	0.44	0.37	
γ_{SMB}	0.10	0.90	0.90		0.16	1.28	1.28		0.24	2.05	1.99		0.30	2.38	2.32	
γ_{HML}	0.31	2.29	2.28		0.05	0.37	0.37		0.94	2.64	2.03		0.87	2.23	1.72	
γ_{Mom}	0.60	1.00	0.95		0.56	0.98	0.92		0.69	3.01	3.00		0.39	1.40	1.39	
γ_{CMA}	0.15	0.81	0.78		-0.07	-0.35	-0.33		0.25	1.20	0.95		0.73	3.55	2.84	
γ_{RMW}	0.17	0.98	0.94		0.31	1.73	1.64		-0.54	-2.81	-2.18		0.05	0.24	0.19	

Table 19: Fama-MacBeth Tests on the *25 Size and Book-to-market* portfolios in the North American region with global and local factors. The analysis covers the full period January 1981-December 2015, and sub-period: January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.18	1.82	1.81	0.28	0.60	1.08	1.08	0.24	1.26	1.99	1.98	0.27	0.56	1.08	1.08	0.24
γ_{RM}	-0.41	-0.55	-0.55		0.25	0.36	0.36		-0.45	-0.67	-0.67		0.26	0.36	0.36	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.49	4.29	4.18	0.54	1.07	2.18	2.16	0.50	1.60	4.84	4.71	0.54	1.33	2.58	2.54	0.50
γ_{RM}	-0.80	-1.71	-1.68		-0.25	-0.40	-0.40		-0.90	-2.18	-2.14		-0.52	-0.85	-0.84	
γ_{SMB}	0.27	1.77	1.75		0.13	0.73	0.73		0.16	0.97	0.97		0.11	0.60	0.60	
γ_{HML}	0.16	1.08	1.08		-0.02	-0.16	-0.16		0.21	1.09	1.09		-0.04	-0.21	-0.21	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.97	2.59	2.17	0.57	0.19	0.33	0.28	0.55	1.17	3.41	2.89	0.57	0.68	1.29	1.14	0.55
γ_{RM}	-0.14	-0.27	-0.24		0.70	1.00	0.88		-0.41	-0.96	-0.86		0.12	0.19	0.18	
γ_{SMB}	0.09	0.56	0.51		0.00	0.03	0.02		0.15	0.91	0.90		0.13	0.71	0.71	
γ_{HML}	0.20	1.40	1.35		0.02	0.15	0.14		0.26	1.36	1.35		-0.03	-0.18	-0.18	
γ_{Mom}	2.33	4.49	3.87		1.74	2.84	2.48		2.82	4.58	4.00		1.95	2.74	2.46	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.08	2.12	2.05	0.62	-0.33	-0.41	-0.35	0.61	1.21	2.81	2.72	0.62	0.66	0.89	0.82	0.62
γ_{RM}	-0.33	-0.50	-0.49		1.27	1.33	1.15		-0.52	-1.04	-1.02		0.11	0.14	0.13	
γ_{SMB}	0.28	1.87	1.85		0.04	0.22	0.20		0.19	1.14	1.14		0.21	1.21	1.20	
γ_{HML}	0.11	0.73	0.72		-0.16	-1.09	-1.02		0.18	0.93	0.92		-0.08	-0.45	-0.44	
γ_{CMA}	0.17	0.84	0.83		0.02	0.10	0.09		0.46	1.84	1.80		-0.15	-0.63	-0.59	
γ_{RMW}	0.21	1.47	1.44		0.28	1.72	1.53		0.20	0.90	0.88		0.50	2.23	2.13	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.62	1.18	0.93	0.65	-0.06	-0.08	-0.07	0.63	1.22	2.83	2.25	0.66	0.65	0.87	0.79	0.64
γ_{RM}	0.20	0.29	0.24		0.99	1.05	0.91		-0.47	-0.94	-0.78		0.13	0.16	0.14	
γ_{SMB}	0.14	0.91	0.80		0.05	0.27	0.24		0.20	1.22	1.21		0.19	1.08	1.08	
γ_{HML}	0.17	1.13	1.07		-0.04	-0.29	-0.27		0.24	1.28	1.27		-0.05	-0.32	-0.32	
γ_{Mom}	2.54	4.89	4.00		1.51	2.60	2.28		3.27	5.15	4.24		1.37	2.13	1.97	
γ_{CMA}	-0.08	-0.42	-0.35		-0.02	-0.14	-0.13		-0.04	-0.14	-0.12		-0.19	-0.82	-0.76	
γ_{RMW}	0.42	2.91	2.45		0.18	1.12	1.00		0.47	2.00	1.71		0.42	1.88	1.76	

Table 20: Fama-MacBeth Tests on *25 Size and Momentum* portfolios in the North American region with global and local factors. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.37	4.17	4.14	0.18	0.94	1.85	1.85	0.22	1.41	4.22	4.19	0.17	0.92	1.75	1.75	0.22
γ_{RM}	-0.52	-1.18	-1.18		-0.04	-0.07	-0.07		-0.53	-1.26	-1.25		-0.02	-0.03	-0.03	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.87	4.19	3.88	0.60	1.24	2.75	2.69	0.60	1.90	3.99	3.73	0.60	1.25	2.76	2.72	0.60
γ_{RM}	-1.23	-2.25	-2.11		-0.41	-0.71	-0.70		-1.17	-2.27	-2.16		-0.44	-0.78	-0.77	
γ_{SMB}	0.47	3.04	2.93		0.25	1.31	1.30		0.38	2.23	2.21		0.18	1.01	1.01	
γ_{HML}	-0.31	-1.15	-1.08		-0.07	-0.18	-0.18		-0.42	-1.19	-1.13		-0.05	-0.12	-0.12	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.69	1.40	1.35	0.66	1.42	3.10	2.95	0.63	0.97	1.71	1.68	0.66	1.21	2.58	2.54	0.64
γ_{RM}	0.07	0.12	0.12		-0.61	-1.05	-1.01		-0.30	-0.49	-0.48		-0.39	-0.69	-0.68	
γ_{SMB}	0.31	1.94	1.91		0.30	1.58	1.53		0.36	2.13	2.13		0.18	1.02	1.01	
γ_{HML}	0.27	0.94	0.92		-0.33	-1.04	-1.00		0.15	0.36	0.35		0.03	0.06	0.06	
γ_{Mom}	0.57	2.30	2.29		0.13	0.44	0.43		0.68	2.38	2.38		0.14	0.46	0.46	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.16	2.29	1.98	0.70	0.64	1.47	1.41	0.65	1.43	3.13	2.77	0.70	0.81	1.60	1.55	0.67
γ_{RM}	-0.28	-0.44	-0.38		0.20	0.34	0.33		-0.69	-1.34	-1.22		0.02	0.03	0.02	
γ_{SMB}	0.36	2.30	2.13		0.12	0.72	0.70		0.37	2.16	2.13		0.18	1.01	1.00	
γ_{HML}	-0.30	-1.16	-1.04		0.11	0.28	0.27		-0.34	-0.90	-0.83		-0.16	-0.33	-0.32	
γ_{CMA}	0.47	2.06	1.83		0.28	1.06	1.02		0.55	1.76	1.61		0.22	0.80	0.78	
γ_{RMW}	-0.13	-0.51	-0.45		-0.03	-0.12	-0.12		-0.39	-1.35	-1.23		-0.10	-0.31	-0.30	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.89	1.74	1.43	0.72	0.78	1.79	1.64	0.68	-0.63	-1.16	-0.78	0.73	0.72	1.50	1.45	0.71
γ_{RM}	-0.04	-0.06	-0.05		0.04	0.06	0.06		**1.26**	**2.15**	**1.52**		0.10	0.17	0.17	
γ_{SMB}	0.17	0.99	0.88		0.18	1.04	0.99		0.22	1.30	1.24		0.18	1.02	1.01	
γ_{HML}	0.48	1.45	1.23		-0.34	-1.01	-0.93		1.76	3.98	2.83		-0.02	-0.04	-0.04	
γ_{Mom}	0.52	2.13	2.06		0.18	0.61	0.60		0.72	2.54	2.52		0.16	0.50	0.50	
γ_{CMA}	0.71	3.04	2.60		0.15	0.63	0.58		1.42	4.41	3.18		0.27	1.04	1.01	
γ_{RMW}	-0.63	-2.29	-1.91		0.08	0.41	0.38		-1.11	-3.66	-2.63		-0.11	-0.33	-0.32	

Table 21: Fama-MacBeth Tests on the *25 Size and Book-to-market* portfolios in the European region with global and local factors. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.55	1.07	1.07	0.15	0.75	1.35	1.35	0.19	0.22	0.41	0.41	0.16	0.81	1.46	1.46	0.19
γ_{RM}	-0.01	-0.03	-0.03		0.13	0.22	0.22		0.32	0.54	0.54		0.10	0.14	0.14	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.92	2.49	2.44	0.50	-0.07	-0.13	-0.12	0.51	1.14	2.79	2.74	0.51	-0.33	-0.54	-0.52	0.51
γ_{RM}	-0.42	-0.97	-0.96		0.76	1.35	1.32		-0.60	-1.20	-1.19		1.14	1.50	1.46	
γ_{SMB}	-0.08	-0.53	-0.52		0.22	1.38	1.36		-0.03	-0.20	-0.20		0.17	1.10	1.10	
γ_{HML}	0.40	2.46	2.45		-0.13	-0.75	-0.74		0.30	2.07	2.07		-0.02	-0.11	-0.11	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.88	2.32	2.27	0.53	-0.37	-0.65	-0.59	0.56	0.88	1.94	1.89	0.54	-0.52	-0.81	-0.75	0.56
γ_{RM}	-0.38	-0.87	-0.85		1.05	1.76	1.65		-0.33	-0.60	-0.59		1.33	1.72	1.62	
γ_{SMB}	-0.07	-0.43	-0.43		0.30	1.85	1.77		-0.03	-0.19	-0.19		0.17	1.14	1.13	
γ_{HML}	0.40	2.45	2.44		-0.11	-0.68	-0.64		0.30	2.05	2.05		0.00	-0.01	-0.01	
γ_{Mom}	0.11	0.21	0.20		0.92	1.47	1.35		0.62	0.99	0.97		0.69	1.12	1.05	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.47	0.95	0.92	0.60	-0.41	-0.72	-0.59	0.60	0.38	0.68	0.66	0.60	1.07	1.24	0.88	0.60
γ_{RM}	-0.05	-0.10	-0.10		1.00	1.70	1.49		0.16	0.26	0.25		-0.23	-0.24	-0.18	
γ_{SMB}	-0.04	-0.26	-0.26		0.27	1.67	1.52		-0.01	-0.05	-0.05		0.22	1.43	1.42	
γ_{HML}	0.32	1.89	1.87		-0.05	-0.27	-0.24		0.26	1.84	1.84		-0.01	-0.05	-0.05	
γ_{CMA}	0.17	0.75	0.74		-0.34	-1.71	-1.47		0.24	1.25	1.23		-0.46	-2.03	-1.53	
γ_{RMW}	0.28	1.46	1.43		0.50	2.50	2.13		0.17	0.76	0.74		0.87	3.85	2.93	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.47	0.94	0.92	0.63	-0.35	-0.64	-0.52	0.63	0.40	0.71	0.69	0.63	0.97	1.11	0.76	0.63
γ_{RM}	-0.05	-0.09	-0.09		0.94	1.64	1.42		0.14	0.22	0.22		-0.14	-0.15	-0.11	
γ_{SMB}	-0.05	-0.31	-0.31		0.26	1.64	1.48		0.00	-0.04	-0.04		0.22	1.49	1.48	
γ_{HML}	0.32	1.86	1.84		-0.04	-0.25	-0.22		0.26	1.82	1.82		-0.03	-0.16	-0.16	
γ_{Mom}	-0.15	-0.25	-0.25		-0.15	-0.24	-0.21		-0.16	-0.26	-0.25		-0.40	-0.60	-0.44	
γ_{CMA}	0.19	0.83	0.81		-0.32	-1.66	-1.42		0.26	1.36	1.33		-0.40	-1.79	-1.30	
γ_{RMW}	0.27	1.45	1.42		0.54	2.53	2.12		0.17	0.74	0.72		0.94	3.96	2.90	

Table 22: Fama-MacBeth Tests on the 25 *Size and Momentum* portfolios in the European region with global and local factors. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.35	5.35	4.97	0.25	2.64	3.91	3.73	0.27	2.58	5.25	4.86	0.25	2.67	3.87	3.70	0.28
γ_{RM}	-1.69	-3.52	-3.33		-1.40	-2.11	-2.04		-2.02	-3.54	-3.34		-1.70	-2.11	-2.04	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.20	5.18	4.62	0.54	1.80	4.16	3.84	0.53	2.10	4.92	4.34	0.55	1.47	3.02	2.81	0.53
γ_{RM}	-1.27	-2.96	-2.73		-0.70	-1.40	-1.35		-1.43	-2.85	-2.61		-0.58	-0.89	-0.86	
γ_{SMB}	0.03	0.16	0.15		0.08	0.50	0.48		0.10	0.73	0.72		0.17	1.08	1.07	
γ_{HML}	-0.84	-3.02	-2.76		-0.60	-1.60	-1.49		-1.22	-3.48	-3.12		-0.79	-2.04	-1.92	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.41	1.04	0.98	0.63	0.85	2.01	1.80	0.62	-0.15	-0.35	-0.31	0.63	0.74	1.53	1.46	0.62
γ_{RM}	0.09	0.22	0.21		0.04	0.08	0.08		0.68	1.36	1.27		0.13	0.19	0.19	
γ_{SMB}	0.21	1.35	1.31		0.27	1.62	1.54		0.14	1.04	1.03		0.20	1.27	1.27	
γ_{HML}	0.24	0.85	0.81		0.51	1.73	1.58		0.64	1.77	1.63		0.25	0.83	0.81	
γ_{Mom}	1.13	4.18	4.11		0.79	2.59	2.54		0.98	4.13	4.12		0.76	2.37	2.37	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.66	1.63	0.88	0.65	0.57	1.22	0.67	0.66	-1.41	-2.77	-1.29	0.68	1.02	2.21	1.35	0.66
γ_{RM}	0.36	0.83	0.51		0.15	0.30	0.21		2.00	3.45	1.78		-0.18	-0.28	-0.20	
γ_{SMB}	0.03	0.16	0.11		0.53	3.16	2.19		0.20	1.52	1.35		0.33	2.16	2.04	
γ_{HML}	-0.60	-2.24	-1.34		1.07	3.48	2.03		-0.97	-3.08	-1.56		0.23	0.76	0.52	
γ_{CMA}	1.41	6.29	3.75		0.89	4.41	2.69		1.63	5.33	2.61		0.35	1.72	1.16	
γ_{RMW}	-0.31	-1.60	-0.93		0.60	2.75	1.62		0.48	2.16	1.07		0.95	3.52	2.29	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.65	1.57	0.89	0.69	0.71	1.52	0.84		-1.45	-2.83	-1.34	0.71	1.02	2.21	1.14	0.68
γ_{RM}	0.34	3.92	2.21		0.05	0.10	0.07		**1.99**	**3.44**	**1.81**		-0.17	-0.27	-0.17	
γ_{SMB}	0.04	1.56	0.88		0.53	3.16	2.20		0.09	0.68	0.61		0.34	2.20	2.01	
γ_{HML}	-0.32	-4.68	-2.63		0.93	3.04	1.78		0.48	1.32	0.66		-0.36	-1.16	-0.69	
γ_{Mom}	0.94	0.81	0.46		0.73	2.39	2.00		1.00	4.22	4.08		0.73	2.27	2.23	
γ_{CMA}	1.47	6.90	3.82		0.96	5.09	3.16		2.20	7.53	3.77		0.63	3.20	1.87	
γ_{RMW}	-0.41	0.11	0.06		0.59	2.75	1.63		-0.79	-2.97	-1.47		1.35	4.45	2.43	

Table 23: Fama-MacBeth Tests on the *25 Size and Book-to-market* portfolios in the Japanese region with global and local factors. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.87	1.37	1.34	0.13	1.36	2.54	2.48	0.13	0.40	0.52	0.52	0.15	0.40	0.66	0.65	0.12
γ_{RM}	-0.91	-1.40	-1.38		-0.94	-1.32	-1.30		-0.24	-0.28	-0.28		0.39	0.52	0.52	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	-0.43	-0.71	-0.68	0.49	-0.27	-0.49	-0.44	0.49	-0.60	-0.92	-0.90	0.50	-0.23	-0.38	-0.36	0.51
γ_{RM}	0.44	0.65	0.62		0.50	0.66	0.60		0.63	0.87	0.86		0.78	1.13	1.09	
γ_{SMB}	0.18	0.70	0.68		0.57	2.24	2.04		0.15	0.78	0.78		0.41	1.88	1.87	
γ_{HML}	0.57	2.57	2.50		0.58	2.25	2.05		0.38	2.20	2.19		0.31	1.70	1.70	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	-0.45	-0.75	-0.68	0.52	-0.34	-0.59	-0.52	0.53	-0.21	-0.32	-0.30	0.53	-0.26	-0.43	-0.40	0.56
γ_{RM}	0.39	0.57	0.52		0.58	0.75	0.68		0.28	0.38	0.36		0.81	1.17	1.11	
γ_{SMB}	0.31	1.24	1.15		0.54	2.20	2.00		0.15	0.78	0.78		0.40	1.86	1.85	
γ_{HML}	0.61	2.70	2.53		0.55	2.15	1.95		0.38	2.22	2.21		0.32	1.73	1.73	
γ_{Mom}	0.83	1.20	1.10		0.33	0.38	0.34		1.00	1.54	1.48		-0.56	-0.73	-0.69	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	-0.56	-0.80	-0.76	0.56	-0.26	-0.44	-0.38	0.57	-0.18	-0.32	-0.30	0.56	-0.06	-0.11	-0.10	0.59
γ_{RM}	0.55	0.73	0.70		0.51	0.60	0.53		0.24	0.36	0.34		0.64	0.94	0.88	
γ_{SMB}	0.12	0.55	0.53		0.60	2.47	2.22		0.15	0.76	0.76		0.38	1.77	1.77	
γ_{HML}	0.58	2.60	2.51		0.59	2.20	1.97		0.44	2.55	2.54		0.35	1.87	1.86	
γ_{CMA}	0.33	1.49	1.44		0.23	1.18	1.06		-0.25	-0.79	-0.74		0.16	0.49	0.46	
γ_{RMW}	0.00	0.02	0.02		-0.44	-1.57	-1.39		0.47	1.18	1.11		0.30	1.02	0.94	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	-0.62	-0.87	-0.76	0.59	-0.30	-0.50	-0.43	0.60	-0.07	-0.12	-0.12	0.60	-0.18	-0.31	-0.27	0.65
γ_{RM}	0.54	0.71	0.63		0.53	0.63	0.56		0.15	0.21	0.20		0.77	1.12	1.01	
γ_{SMB}	0.23	1.03	0.93		0.58	2.34	2.11		0.15	0.75	0.75		0.36	1.67	1.66	
γ_{HML}	0.62	2.75	2.51		0.54	1.96	1.76		0.42	2.42	2.40		0.34	1.83	1.81	
γ_{Mom}	1.03	1.27	1.13		0.25	0.26	0.23		0.78	1.11	1.05		-0.66	-0.81	-0.71	
γ_{CMA}	0.42	1.88	1.70		0.18	0.88	0.80		-0.10	-0.29	-0.27		0.31	0.96	0.86	
γ_{RMW}	0.17	0.61	0.54		-0.36	-1.24	-1.10		0.34	0.84	0.79		0.27	0.91	0.81	

Table 24: Fama-MacBeth Tests on the *25 Size and Momentum* portfolios in the Japanese region with global and local factors. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.75	1.43	1.41	0.17	1.45	2.50	2.43	0.18	0.55	0.81	0.81	0.15	1.26	1.96	1.95	0.10
γ_{RM}	-0.75	-1.21	-1.19		-1.01	-1.25	-1.23		-0.38	-0.49	-0.49		-0.44	-0.61	-0.61	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.33	0.72	0.71	0.56	0.46	0.78	0.73	0.50	0.47	0.76	0.76	0.56	0.31	0.37	0.36	0.42
γ_{RM}	-0.46	-0.82	-0.81		-0.49	-0.64	-0.61		-0.43	-0.64	-0.63		0.25	0.27	0.26	
γ_{SMB}	0.28	1.33	1.32		0.50	2.25	2.15		0.29	1.41	1.41		0.47	1.71	1.68	
γ_{HML}	-0.03	-0.09	-0.09		0.08	0.13	0.12		-0.17	-0.38	-0.38		0.31	0.41	0.39	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.16	0.32	0.31	0.60	0.46	0.92	0.86	0.60	0.20	0.31	0.31	0.59	0.68	1.11	1.09	0.61
γ_{RM}	-0.29	-0.53	-0.52		-0.49	-0.72	-0.69		-0.17	-0.25	-0.25		-0.15	-0.21	-0.21	
γ_{SMB}	0.30	1.39	1.38		0.50	2.19	2.10		0.29	1.38	1.38		0.57	2.52	2.51	
γ_{HML}	0.12	0.30	0.29		0.08	0.21	0.19		0.04	0.09	0.09		-0.08	-0.17	-0.16	
γ_{Mom}	0.25	0.68	0.68		0.14	0.31	0.30		0.12	0.44	0.44		0.08	0.29	0.29	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.81	1.40	1.32	0.65	0.77	1.67	1.49	0.62	0.57	0.93	0.89	0.64	0.53	0.82	0.80	0.63
γ_{RM}	-0.74	-1.23	-1.17		-0.83	-1.25	-1.16		-0.51	-0.85	-0.82		0.01	0.01	0.01	
γ_{SMB}	0.37	1.63	1.56		0.50	2.29	2.12		0.25	1.68	1.61		0.54	2.34	2.32	
γ_{HML}	-0.01	-0.03	-0.03		-0.22	-0.68	-0.61		-0.05	0.33	0.32		0.05	0.10	0.10	
γ_{CMA}	-0.24	-0.74	-0.70		-0.01	-0.05	-0.04		-0.43	-0.98	-0.94		-0.13	-0.36	-0.36	
γ_{RMW}	0.13	0.47	0.45		-0.19	-0.85	-0.77		0.13	-0.67	-0.64		-0.01	-0.02	-0.02	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.67	1.27	1.20	0.69	0.45	0.83	0.62	0.67	0.13	0.21	0.20	0.67	0.83	1.36	1.30	0.68
γ_{RM}	-0.60	-1.12	-1.07		-0.62	-0.90	-0.72		-0.09	-0.14	-0.13		-0.30	-0.42	-0.41	
γ_{SMB}	0.39	1.63	1.56		0.71	2.74	2.16		0.23	1.07	1.06		0.59	2.52	2.51	
γ_{HML}	0.12	0.32	0.30		0.01	0.03	0.02		0.27	0.60	0.57		-0.17	-0.39	-0.38	
γ_{Mom}	0.25	0.68	0.65		0.78	1.55	1.24		0.14	0.52	0.52		0.08	0.27	0.27	
γ_{CMA}	-0.18	-0.62	-0.59		-0.35	-1.29	-1.00		-0.31	-0.76	-0.73		0.17	0.47	0.45	
γ_{RMW}	0.10	0.36	0.34		-0.36	-1.45	-1.12		-0.04	-0.11	-0.10		0.06	0.17	0.17	

Table 25: Fama-MacBeth Tests on the *25 Size and Book-to-market* portfolios in the Asia Pacific region with global and local factors by using OLS method. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	4.49	4.66	3.70	0.08	2.56	2.31	2.24	0.15	0.92	1.16	1.16	0.06	2.18	1.98	1.95	0.16
γ_{RM}	-3.26	-3.57	-2.88		-1.17	-1.16	-1.13		-0.18	-0.22	-0.22		-1.05	-0.87	-0.86	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.84	5.35	4.27	0.31	2.66	2.65	2.44	0.34	3.13	5.08	4.62	0.37	1.93	2.51	2.45	0.38
γ_{RM}	-2.95	-4.05	-3.30		-1.28	-1.36	-1.27		-2.39	-3.40	-3.16		-0.90	-0.99	-0.97	
γ_{SMB}	0.33	1.25	1.03		0.13	0.43	0.40		0.06	0.36	0.35		0.08	0.33	0.32	
γ_{HML}	0.90	3.01	2.49		0.32	1.23	1.15		0.56	3.00	2.97		0.42	1.95	1.94	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.09	4.31	3.41	0.35	2.26	2.20	1.95	0.38	2.34	3.38	2.93	0.41	1.25	1.75	1.66	0.41
γ_{RM}	-2.20	-3.06	-2.47		-0.97	-1.02	-0.92		-1.53	-1.99	-1.77		-0.20	-0.23	-0.23	
γ_{SMB}	0.16	0.60	0.49		0.15	0.46	0.42		-0.04	-0.20	-0.20		0.03	0.11	0.11	
γ_{HML}	0.91	3.07	2.52		0.29	1.08	0.98		0.58	3.09	3.04		0.38	1.75	1.74	
γ_{Mom}	1.89	3.33	2.72		1.34	1.83	1.65		1.95	2.53	2.23		1.02	1.86	1.79	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.12	3.95	2.95	0.43	1.64	1.63	1.38	0.42	2.24	3.34	3.05	0.48	0.68	0.76	0.68	0.49
γ_{RM}	-1.72	-2.07	-1.57		-0.17	-0.16	-0.14		-1.52	-2.01	-1.87		0.35	0.34	0.31	
γ_{SMB}	0.28	1.06	0.82		0.33	1.16	1.01		0.05	0.26	0.26		0.13	0.58	0.57	
γ_{HML}	0.57	2.14	1.69		0.26	1.01	0.89		0.62	3.30	3.27		0.43	1.97	1.94	
γ_{CMA}	1.37	5.23	4.07		0.66	2.90	2.53		1.03	3.57	3.33		0.77	2.09	1.91	
γ_{RMW}	-0.26	-1.09	-0.83		-0.19	-0.60	-0.52		0.17	0.75	0.72		0.16	0.59	0.55	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.79	3.60	2.84	0.47	1.37	1.33	1.10	0.46	1.47	2.11	1.82	0.51	-0.03	-0.04	-0.03	0.52
γ_{RM}	-1.51	-1.84	-1.47		0.02	0.02	0.01		-0.68	-0.88	-0.78		1.07	1.11	0.97	
γ_{SMB}	0.14	0.52	0.42		0.26	0.95	0.81		-0.03	-0.15	-0.15		0.09	0.40	0.40	
γ_{HML}	0.63	2.31	1.91		0.25	0.97	0.84		0.63	3.36	3.31		0.39	1.79	1.75	
γ_{Mom}	1.40	2.46	2.00		1.41	2.17	1.85		1.79	2.52	2.22		1.13	2.06	1.81	
γ_{CMA}	1.13	4.38	3.58		0.62	2.65	2.27		0.89	3.16	2.83		0.66	1.83	1.60	
γ_{RMW}	-0.14	-0.58	-0.47		-0.19	-0.59	-0.50		0.11	0.49	0.46		0.12	0.44	0.40	

Table 26: Fama-MacBeth Tests on the *25 Size and Momentum* portfolios in the Asia Pacific region with global and local factors. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.46	6.49	5.71	0.12	4.21	6.88	6.05	0.12	3.60	6.47	5.89	0.13	3.73	6.47	5.99	0.12
γ_{RM}	-2.30	-4.02	-3.62		-2.41	-3.65	-3.32		-2.72	-4.18	-3.90		-2.42	-3.12	-2.97	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.52	6.57	5.18	0.41	4.48	7.65	5.20	0.43	2.49	6.67	6.04	0.43	4.11	8.03	5.49	0.44
γ_{RM}	-2.14	-3.82	-3.13		-3.24	-4.59	-3.35		-1.60	-3.12	-2.95		-3.03	-4.28	-3.35	
γ_{SMB}	0.11	0.44	0.36		0.53	1.77	1.26		0.07	0.39	0.38		0.32	1.30	1.17	
γ_{HML}	-1.17	-3.06	-2.47		-1.21	-2.65	-1.83		-1.27	-2.62	-2.40		-2.04	-2.76	-1.93	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.89	6.08	5.33	0.46	3.55	7.92	6.70	0.48	2.36	6.17	5.93	0.48	3.60	7.41	6.25	0.50
γ_{RM}	-1.67	-3.24	-2.92		-2.20	-3.92	-3.52		-1.50	-2.90	-2.83		-2.48	-3.64	-3.31	
γ_{SMB}	0.07	0.28	0.25		0.33	1.18	1.02		0.05	0.27	0.27		0.17	0.72	0.71	
γ_{HML}	-0.66	-1.62	-1.44		-0.37	-1.06	-0.91		-0.19	-0.48	-0.46		-0.89	-1.75	-1.51	
γ_{Mom}	1.32	3.08	2.80		1.49	3.94	3.62		0.92	3.45	3.44		0.95	3.16	3.13	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.00	6.43	3.92	0.53	3.89	7.48	5.25	0.53	2.50	6.08	4.74	0.52	3.64	7.80	5.98	0.53
γ_{RM}	-1.13	-2.17	-1.43		-2.35	-3.73	-2.86		-1.53	-2.87	-2.45		-2.47	-3.71	-3.20	
γ_{SMB}	0.39	1.45	0.94		0.62	2.01	1.47		-0.11	-0.60	-0.57		0.12	0.52	0.50	
γ_{HML}	-1.14	-3.25	-2.08		-0.90	-2.34	-1.68		-0.48	-0.95	-0.76		-1.17	-1.99	-1.57	
γ_{CMA}	0.81	3.00	1.94		0.39	1.77	1.31		1.62	4.62	3.73		0.79	2.31	1.89	
γ_{RMW}	-0.39	-1.30	-0.82		0.25	1.09	0.80		-0.03	-0.09	-0.07		0.58	1.19	0.94	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.79	5.90	3.71	0.56	3.59	7.67	6.33	0.56	2.44	5.90	4.63	0.56	3.51	7.61	6.17	0.58
γ_{RM}	-0.97	-1.90	-1.29		-1.92	-3.46	-3.06		-1.49	-2.77	-2.37		-2.34	-3.54	-3.16	
γ_{SMB}	0.37	1.39	0.93		0.29	1.12	0.95		-0.11	-0.57	-0.55		0.11	0.49	0.47	
γ_{HML}	-0.88	-2.44	-1.60		-0.33	-0.96	-0.80		-0.34	-0.82	-0.67		-0.93	-1.84	-1.53	
γ_{Mom}	1.42	3.41	2.37		1.55	4.11	3.73		0.95	3.55	3.51		0.96	3.17	3.14	
γ_{CMA}	0.91	3.51	2.34		0.42	1.90	1.63		1.65	4.94	4.03		0.75	2.12	1.80	
γ_{RMW}	-0.47	-1.61	-1.04		-0.07	-0.34	-0.29		-0.06	-0.18	-0.15		0.52	1.09	0.91	

4.2 Application of Gold as a zero-beta asset in the U.S. Market

I examine the applicability of gold as a zero-beta asset in a comparative vein of Black, Jensen and Scholes (1972) who estimate their two-factor model under the assumption of restricted borrowing. They argue that borrowing at the risk-free rate is not accessible to all investors and propose a zero-beta portfolio of risky assets that can replace a risk-free rate under this assumption. However, they emphasise that a zero-beta portfolio that replaces risk-free rate must be a minimum variance portfolio. A minimum variance portfolio is located on the efficient frontier (Markowitz, 1952). Only the efficient assets are located on the efficient frontier. Hence, it is important to examine the market efficiency of gold markets. If gold is an efficient asset, then it must be located on the efficient minimum-variance frontier. This study performs a battery of market efficiency tests to assess the efficiency of global gold markets. I examine the market efficiency of US, European, Japanese, UK, Canadian and Swiss gold markets.

4.2.1.1 Market efficiency tests

Firstly, I use LM (1988) parametric variance ratio tests and Wright (2000) non-parametric variance ratio tests to examine efficiency level of gold markets. Results are shown in Tables (27) and (28) where q shows a number of days, M1 and M2 show results of parametric LM (1988) test. M1 test the *RWS* hypothesis and M2 test the *MDS* hypothesis. R1, R2, and S1 are the ranks and signs of the non-parametric test of Wright (2000).R1 and R2 show ranks and test the random walks (RWS) and S1 is the sign that tests the martingale sequence difference hypothesis (MDS).

Table 27: Variance ratio test results of daily spot gold price return series in US, Europe and Japan: January 1981 to December 2015.

Period	M1	M2	R1	R2	S1
United States ($)					
q=15	-0.80	-0.54	-3.06***	-2.24	-2.27***
q=20	-1.06	-0.72	-2.96***	-2.30	-2.28***
q=25	-1.44	-0.98	-2.80***	-2.35*	-2.11***
q=30	-1.76*	-1.21	-2.71***	-2.43*	-1.90**
Europe (€)					
q=15	-1.63	-1.13	-3.48***	-2.72**	-3.41***
q=20	-1.65*	-1.15	-3.35***	-2.69**	-3.42***
q=25	-2.01**	-1.42	-3.32***	-2.81***	-3.44***
q=30	-2.35**	-1.68*	-3.39***	-3.00***	-3.44***
Japan (¥)					
q=15	-2.03**	-1.42	-2.90***	-2.84***	-3.14***
q=20	-2.12**	-1.50	-2.76***	-2.80***	-2.90***
q=25	-2.62***	-1.88*	-2.83***	-3.04***	-2.89***
q=30	-3.06***	-2.22**	-2.97***	-3.30***	-2.95***

Note: A test statistic with *, **, and *** indicates significance at 10%, 5%, and 1% levels respectively.

Table 28: Variance ratio test results of daily spot gold price return series in UK, Canada and Switzerland: January 1981 to December 2015.

Period	M1	M2	R1	R2	S1
UK (£)					
q=15	-0.89	-0.58	-1.43	-1.47	-0.55
q=20	-0.94	-0.63	-1.48	-1.52	-0.68
q=25	-1.40	-0.95	-1.69	-1.83	-0.69
q=30	-1.65	-1.12	-1.84	-2.02	-0.69
Canada (CAD)					
q=15	-2.93***	-1.90*	-4.79***	-3.98***	-4.72***
q=20	-2.78***	-1.83*	-4.66***	-3.86***	-4.85***
q=25	-3.00***	-2.01*	-4.49***	-3.83***	-4.80***
q=30	-3.14***	-2.13**	-4.36***	-3.82***	-4.76***
Switzerland (SFr)					
q=15	-3.03***	-2.14**	-3.85***	-3.62***	-2.92***
q=20	-2.85***	-2.05**	-3.52***	-3.33***	-2.95***
q=25	-3.12***	-2.28**	-3.46***	-3.40***	-3.04***
q=30	-3.40***	-2.52**	-3.44***	-3.51***	-3.02***

Note: A test statistic with *, **, and *** indicates significance at 10%, 5%, and 1% levels respectively.

LM (1988) test confirms that the U.S. gold market is weak form efficient. However, Wright (2002) non-parametric test produces less convincing evidence but insignificant second rank (R2) supports findings of LM (1988) test. Among gold markets, U.K. markets show greater efficiency as LM (1988) parametric and Wright (2000) non-parametric tests do not reject null hypotheses of random walks *(RWS)* and martingale difference sequence (*MDS)* that confirm stronger efficiency in the U.K. gold market. Figure (10) shows plots of variance ratios in above mentioned global gold markets. Plots show that the variance ratio in the U.S. and the U.K. is closer to 1 that confirms efficiency in those markets.

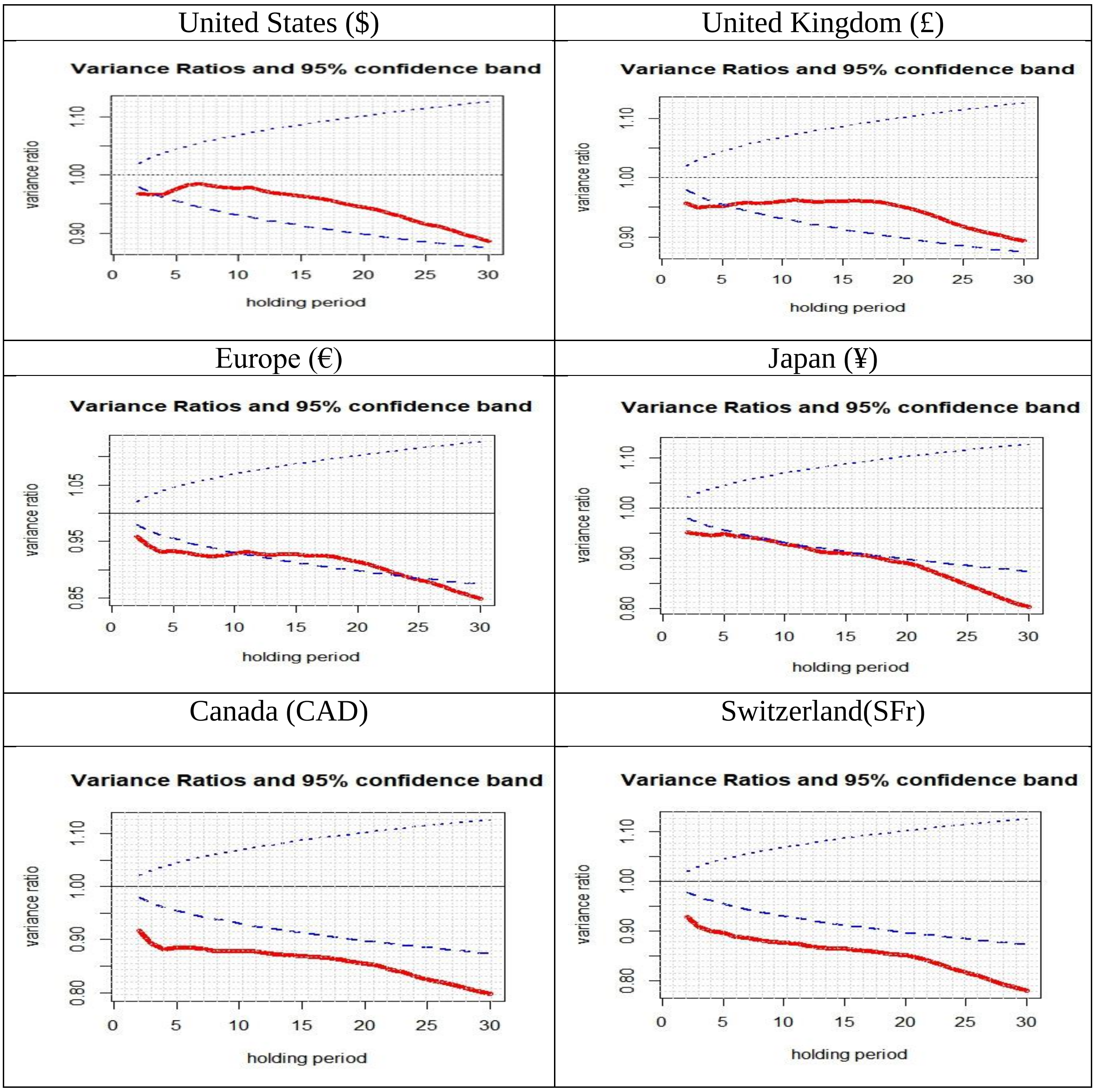


Figure 10: Plot of Variance Ratio Test in the US, UK, European, Japanese, Canadian and Swiss gold markets

Table 29: Portmanteau Test of market efficiency in the US, UK, European, Japanese, Canadian and Swiss gold markets, January 1981 to December 2015.

	Portmanteau test statistic	P-Value	Portmanteau test statistic	P-Value	Portmanteau test statistic	P-Value
	1981-2015		1991-2015		2000-2015	
United States ($)	4.28	0.04	0.14	0.71	0.17	0.68
United Kingdom(£)	1.39	0.24	0.08	0.78	0.73	0.40
Europe (€)	7.33	0.01	2.11	0.15	2.25	0.13
Japan (¥)	9.03	0.00	0.01	0.91	0.03	0.87
Canada (CAD)	23.78	0.00	4.62	0.03	4.3	0.04
Switzerland(SFr)	18.80	0.00	1.36	0.24	1.54	0.22

After performing variance ratio of LM (1988), ranks and signs of Write (2000) and Automatic Portmanteau test of Escanciano and Lobato (2009), I confirm that the U.K. gold market is more efficient than other markets. Sub-sample result of Portmanteau test from 1991 to 2015 signifies that global gold markets have achieved efficiency after 1991 onwards as null hypothesis of a random walk is not rejected in any market except Canadian market that is efficient. Contrary to Wright (2000) tests, the Automatic Portmanteau test does not reject MDS hypothesis in the U.S. market and provides stronger evidence of market efficiency in the U.S. and the U.K. gold markets. Results of the Automatic Portmanteau test are reported in Table (29).

I further perform multiple variance ratio tests of Whang (2003) on using three different time-periods (1981-2015, 1990-2015, and 2000-2015) by using 6 different sub-samples. The sampling periods are chosen by using the rule cited in Whang and Kim (2003)[31]. It enables to deeply investigate market efficiency as this procedure employs multiple sub-sampling to test weak form efficiency. Results are reported in Table (30) and show that the efficiency of gold market greatly increased from 2000 onwards. These results are consistent with results of Wang, Wei, & Wu (2011) who find that gold markets achieved greater efficiency after

[31] we employ six different subsamples (denoted $b1,\ldots, b6$) for each sample size N: particularly, we use equally spaced grid having subsample sizes with the range $2.5\times N^{0.3}<b<3.5\times N^{0.6}$

2000 in the U.S. gold market. I find less convincing evidence in the Swiss, Canadian and Japanese markets. Portmanteau and multiple variance ratio tests confirm that European gold markets have achieved efficiency from 1990 onwards. The U.S. gold market exhibits weak form efficiency for the whole sample period from 1981 to 2015 and efficiency improves with the increasing sample size. This efficiency improves from 1990 onwards and becomes even stronger from 2000 onwards.

Table 30: Multiple Variance ratio tests in the US, European, Japanese, UK, Canadian and Swiss markets. *b1,b2,.....b6* shows sub-samples of different lengths that increase from b1,b2,…b6. P-values are reported for the null hypothesis that the gold price series of the corresponding market follow a random walk.

b	*b1*	*b2*	*b3*	*b4*	*b5*	*b6*
Panel A N=4174 2000-2015						
United States ($)	0.21	0.25	0.25	0.25	0.22	0.24
Europe (€)	0.11	0.10	0.11	0.09	0.06	0.08
Japan (¥)	0.00	0.00	0.00	0.00	0.00	0.01
United Kingdom (£)	0.03	0.04	0.06	0.09	0.10	0.12
Canada (CAD)	0.01	0.02	0.02	0.01	0.02	0.03
Switzerland(SFr)	0.01	0.01	0.01	0.05	0.05	0.03
Panel B N=6524 1990-2015						
United States ($)	0.13	0.18	0.25	0.26	0.26	0.26
Europe (€)	0.17	0.21	0.19	0.15	0.13	0.14
Japan (¥)	0.09	0.15	0.20	0.23	0.24	0.21
United Kingdom (£)	0.37	0.34	0.31	0.28	0.33	0.36
Canada (CAD)	0.03	0.06	0.13	0.17	0.18	0.14
Switzerland(SFr)	0.04	0.05	0.05	0.05	0.06	0.05
Panel C N=9132 1981-2015						
United States ($)	0.03	0.07	0.11	0.15	0.14	0.12
Europe (€)	0.04	0.05	0.06	0.06	0.06	0.05
Japan (¥)	0.01	0.02	0.06	0.08	0.09	0.08
United Kingdom (£)	0.42	0.40	0.40	0.39	0.38	0.42
Canada (CAD)	0.01	0.01	0.01	0.01	0.01	0.01
Switzerland(SFr)	0.00	0.00	0.00	0.00	0.01	0.02

4.2.1.2 Gold position on minimum variance frontier

Gold must be located on minimum variance frontier to satisfy conditions of Black, Jensen and Scholes (1972). Contrary to Treasury bill yield, gold exhibits higher volatility and this study underlines this limitation and does not attempt to use gold as a risk-free asset[32]. Instead, it explores the applicability of gold as a zero-beta asset in a comparative vein of Black, Jensen and Scholes (1972). Hence, this study is unique and distinct from Black, Jensen and Scholes (1972). However, I still consider the restriction that gold must be located on the efficient frontier to be qualified as a potential zero-beta asset that may replace risk-free rate or zero-beta portfolio in empirical asset pricing models.

I use a range of test portfolios and plot the gold return to find whether it is located on the efficient frontier. This study uses the end of month London Bullion Gold Price as is confirmed from a battery of efficiency tests that the London Gold market exhibits stronger efficiency than other global markets.

[32] One of the feature of a risk-free asset is that it produces zero variance. However, gold is a volatile asset and is not expected to produce a zero variance. It is used as a zero-beta asset in a comparative vein of Black, Jensen, and Scholes (1972) when they use a portfolio of risky assets. When risky assets are combined in a single portfolio, the overall variance of a portfolio reduces to a minimum level due to cumulative effect of variance of individual risky assets (Blume & Friend, 1973).

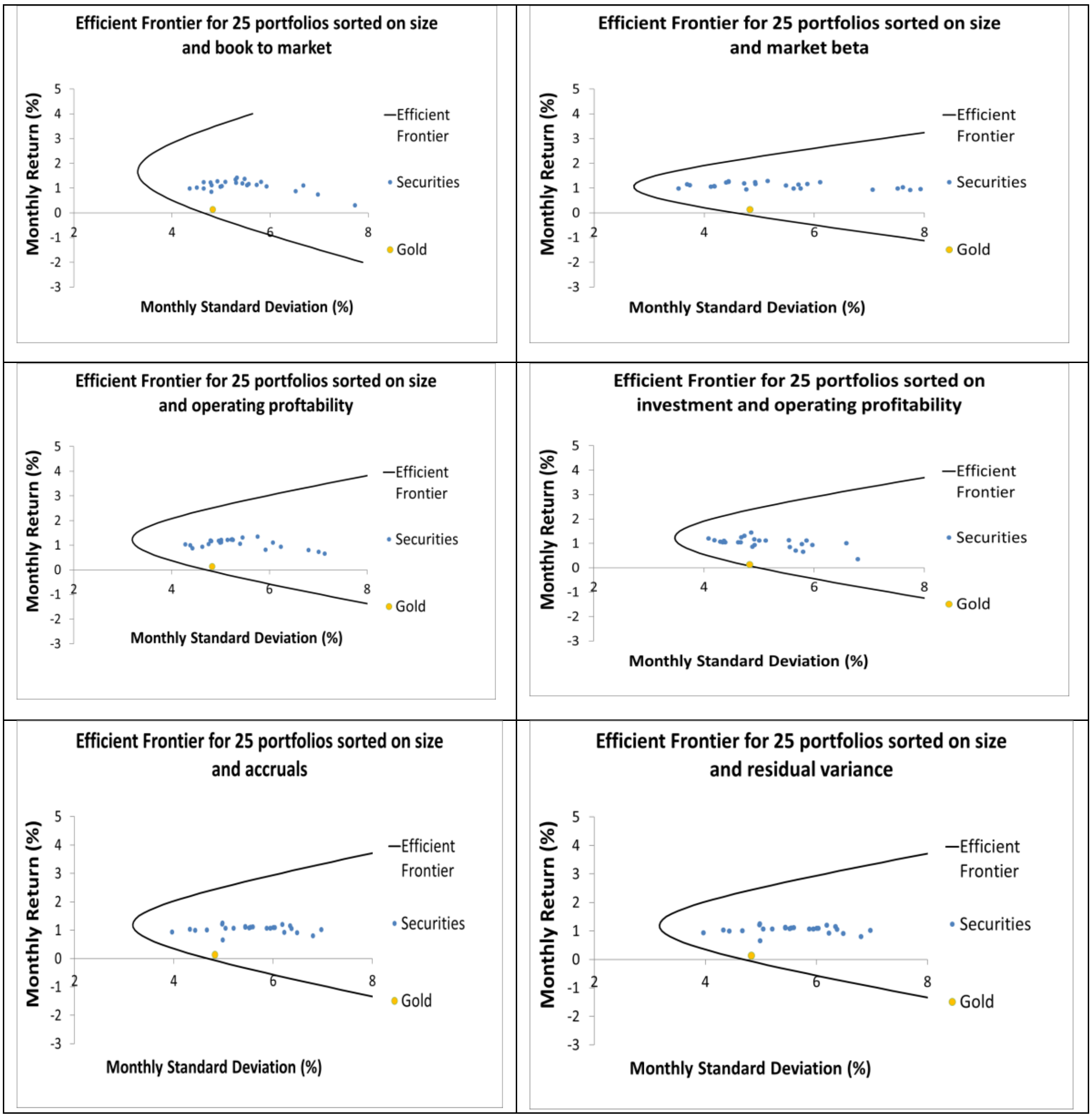


Figure 11:Position of gold on the minimum-variance Frontier in the U.S. equity market when it is plotted against the *25 Size and Book-to-market, 25 Size and Operating profitability, 25 Size and Accruals, 25 Size and Market Beta, 25 Investment and Operating profitability, and 25 Size and Residual Variance portfolios.*

This study follows Clarke, De Silva, and Thorley (2006) and Kan and Smith (2008) in estimating minimum-variance frontier. Figure (11) shows that gold is located near to the efficient frontier when it is plotted along the 25 portfolios sorted on size and book-to-market, the 25 portfolios sorted on size and market beta. It is located much closer to the efficient frontier when it is plotted along the 25 portfolios sorted on size and operating profitability, the 25 portfolios sorted on size and accruals, and the 25 portfolios sorted on the size and residual variance. It is located exactly on the efficient frontier when it is plotted along the 25 portfolios sorted on investment and profitability.

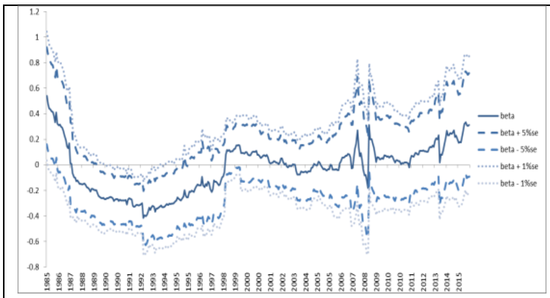
Hence, gold is the efficient asset as is supported from the findings of efficiency tests and it is located at the efficient frontier when it is plotted against test portfolios. On the other hand, I find that the Treasury bill rate is not that efficient and hence, gold has advantages over Treasury bill rate as it does not satisfy efficient restrictions of equilibrium models that are emphasised in Weil (1989) study.

4.2.1.3 Descriptive Analysis

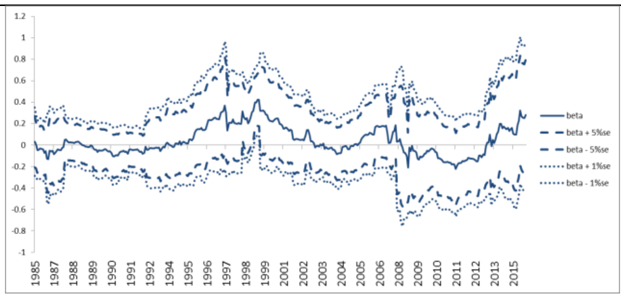
I begin the empirical analysis by assessing the summary statistics for the independent variables in the time-series regressions. In Table (31), I report the summary statistics and pairwise correlations for the return on gold, Treasury bills, the excess market return, the difference $R_g - R_F$ between the return on gold and the return on Treasury Bills, SMB, HML, RMW, CMA and MOM. In Table (31), the return on Treasury bills show a significantly positive mean return, whereas the average gold return is insignificantly positive and is lower than that of Treasury bills. However, the standard deviation and kurtosis of the gold return is much higher than that of Treasury bills due to its higher volatility. The higher kurtosis for gold shows the ability of gold to swiftly react in the wake of market uncertainty. On the other hand, the gold return has a much lower skewness than Treasury bills, which signifies gold returns are more normally distributed. In Panel B, the correlation matrix shows a nearly zero correlation between the excess gold return and the excess market return. Furthermore, the correlation of gold with the Fama-French and Carhart (momentum) factors is very close to zero.

Table 31: Summary statistics for the returns on gold, market, Treasury bills, Fama-French and Carhart (Momentum) factors, January 1981-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), Panel B reports correlations among the factor returns. Panel C reports the results of the regression $R_{G,t} - R_{F,t} = \alpha + \beta\left[R_{m,t} - R_{F,t}\right] + e_{i,t}$

Panel A: Summary Statistics									
	R_g	$R_g - R_F$	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
Mean	0.14	-0.22	0.60	0.36	0.11	0.34	0.58	0.34	0.33
Std	4.83	4.87	4.45	0.28	2.92	2.93	4.49	2.49	2.01
Kurtosis	1.89	1.81	2.42	0.51	5.36	2.30	12.14	12.99	2.03
Skewness	-0.14	-0.15	-0.72	0.70	0.46	0.12	-1.59	-0.47	0.42
t-mean	0.59	-0.92	2.78	25.98	0.76	2.37	2.67	2.82	3.41
Panel B: Correlations									
	R_g	$R_g - R_F$	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
R_g	1.00								
$R_g - R_F$	0.99	1.00							
$R_m - R_F$	0.02	0.02	1.00						
R_f	-0.11	-0.17	-0.06	1.00					
SMB	0.06	0.06	0.19	-0.07	1.00				
HML	-0.07	-0.08	-0.28	0.11	-0.17	1.00			
MOM	0.04	0.03	-0.17	0.05	0.03	-0.19	1.00		
RMW	-0.09	-0.09	-0.34	0.03	-0.44	0.29	0.10	1.00	
CMA	0.00	-0.01	-0.40	0.07	-0.07	0.68	0.03	0.15	1.00
Panel C: Gold beta									
	Coefficient	*t-stat*							
Intercept	-0.235	-0.979							
$R_m - R_F$	0.027	0.509							



Rolling gold betas against excess market return in the U.S.market. Gold betas are estimating with 60 month rolling window from January 1981 to December 2015



Rolling gold betas against excess market return in the U.K. market. Gold betas are estimating with 60 month rolling window from January 1981 to December 2015

Figure 12: Rolling Gold betas in U.S. and U.K. market

Black, Jensen, and Scholes (1972) find that the zero-beta factor is consistent with the traditional model as long as the mean excess return on zero-beta factor is close to zero. I have assessed the return of gold relative to the Treasury bill risk-free rate, and I find likewise that the average return is zero, both for the whole sample and in sub-period analysis. Results are not reported for space reasons but are available from the authors on request.

In Figure (13), I use 6-month moving averages of the 1-month returns on gold and Treasury bills to illustrate their trends in different time periods. The returns on gold and Treasury bills have always tended to move in opposite directions, widening during periods of financial crisis, e.g. the stock market crash of 1987, the Mexican peso crisis in 1994, the dot-com bubble in 1993, and the global financial crisis of 2008. This flight-to-safety feature of gold makes it a safe-haven asset during times of market turmoil and crisis, as argued by Baur and Lucey (2010), Baur and McDermott (2010), Kontonikas, MacDonald, and Saggu (2013), O'Connor, Lucey, Batten, and Baur (2015).

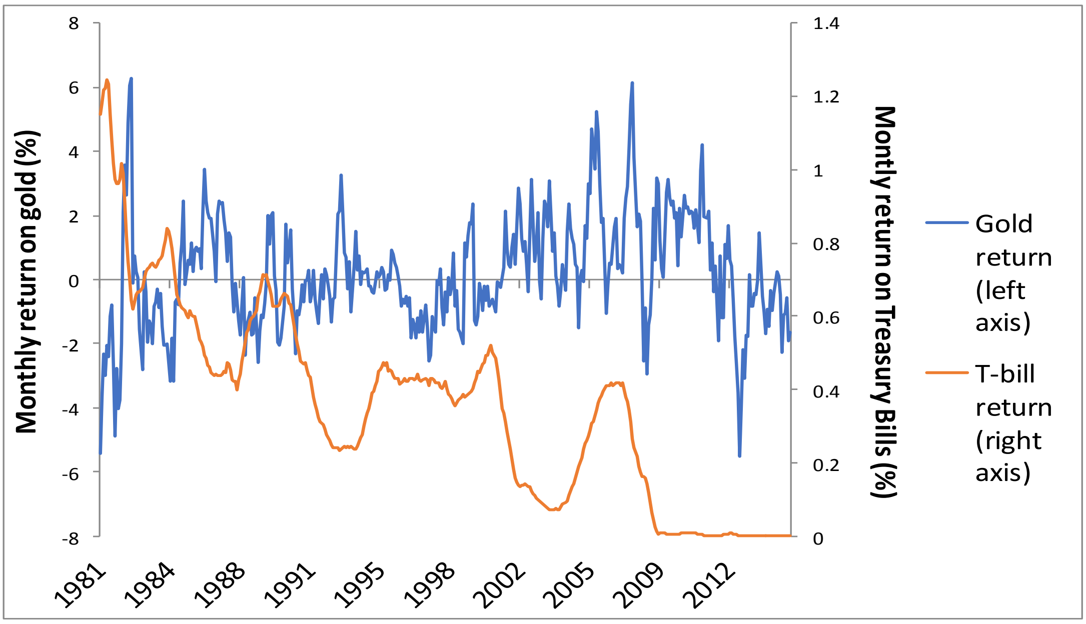


Figure 13: 6-Month Moving Averages of the 1-month return on Gold and Treasury bills from January 1981 to December 2015.

4.2.1.4 Tests of factor models in the U.S. equity market

I begin my analyses by using the returns on the 25 test portfolios sorted on *Size* and *Book-to-market* since these test portfolios have been extensively used in asset pricing literature (Fama and French, 2012, 2015; Gregory, Tharyan, and Christidis, 2013).

Table (32) shows the time series alphas, t-statistics, and R-squared values for the CAPM, three-factor, four-factor, five-factor and six-factor models, and their gold analogues. The comparison of the traditional and the gold zero-beta models show that pricing errors are reduced and R-squared values are improved when the gold return is used as a zero-beta asset. Like Black, Jensen, and Scholes (1972), I find that the gold zero-beta models produce significantly negative alphas for small, low book-to-market portfolios and positive alphas for high book-to-market portfolios.

Table (33) presents a summary of GRS test results for traditional CAPM and gold zero-beta models. I estimate models with (denoted 5x5) and without microcaps (denoted 4x5) to assess whether the zero-beta models enable to price smaller stocks which have been reported challenging and difficult to price by traditional models (Fama and French, 2012). I show results in four pairs of columns, contrasting results from traditional and gold zero-beta models, with and without microcaps. Compared to traditional CAPM models, I obtain higher R-squared and lower Sharpe ratio of alphas with zero-beta models. In particular, for the six-factor model, I find improved performance with the gold zero-beta model, obtaining only four significant pricing errors compared to eight with the traditional model. However, all the models fail to pass GRS test at the 5% level. The failure of the GRS test implies either limited improvement on the size and book to market portfolios with gold zero-beta models or alternative cross-sectional tests need to be used to obtain robust results.

Table 32: Alphas from the CAPM, three-factor, four-factor, five-factor and six-factor regressions on 25 *Size and Book-to-market* portfolios, January 1981-December 2015. The table reports Alphas *(a)*, t-statistics *t(a)* and adjusted R-squared of the tested models.

Return on T-Bills as R_f

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
CAPM															
Small	-0.87	0.06	0.15	0.43	0.44	-3.61	0.27	0.96	2.64	2.60	0.60	0.59	0.66	0.61	0.61
2	-0.42	0.10	0.31	0.37	0.28	-2.34	0.71	2.37	2.84	1.65	0.73	0.74	0.73	0.72	0.66
3	-0.24	0.20	0.19	0.32	0.49	-1.54	1.77	1.78	2.61	3.28	0.76	0.82	0.79	0.73	0.68
4	-0.02	0.09	0.11	0.33	0.21	-0.19	0.98	0.94	3.03	1.41	0.83	0.86	0.79	0.77	0.70
Big	0.03	0.09	0.10	-0.03	0.22	0.39	1.12	0.97	-0.25	1.34	0.89	0.87	0.77	0.69	0.62
Three-Factor															
Small	-0.70	0.08	0.06	0.27	0.17	-5.60	0.86	0.87	3.87	2.33	0.89	0.92	0.94	0.93	0.93
2	-0.24	0.06	0.14	0.13	-0.08	-3.22	0.91	1.98	2.08	-1.19	0.96	0.95	0.93	0.94	0.95
3	-0.02	0.12	0.01	0.05	0.14	-0.32	1.47	0.07	0.65	1.51	0.95	0.90	0.89	0.88	0.87
4	0.17	0.00	-0.10	0.10	-0.13	2.17	-0.05	-1.05	1.17	-1.28	0.93	0.88	0.86	0.87	0.85
Big	0.19	0.04	-0.06	-0.34	-0.14	3.67	0.52	-0.73	-4.15	-1.15	0.95	0.89	0.85	0.88	0.81
Four-Factor															
Small	-0.61	0.07	0.09	0.22	0.20	-4.82	0.79	1.31	3.21	2.69	0.90	0.92	0.94	0.93	0.93
2	-0.16	0.08	0.15	0.11	-0.07	-2.25	1.25	2.14	1.69	-1.12	0.96	0.95	0.93	0.94	0.95
3	0.02	0.13	0.03	0.07	0.18	0.26	1.51	0.36	0.84	1.85	0.95	0.90	0.89	0.88	0.87
4	0.17	0.02	-0.06	0.11	-0.07	2.12	0.27	-0.65	1.30	-0.64	0.93	0.88	0.86	0.87	0.85
Big	0.18	0.03	-0.05	-0.28	-0.04	3.40	0.44	-0.64	-3.39	-0.35	0.95	0.89	0.85	0.89	0.82
Five-Factor															
Small	-0.43	0.24	0.05	0.25	0.16	-3.84	2.82	0.77	3.51	2.18	0.92	0.94	0.94	0.93	0.93
2	-0.11	0.00	0.02	0.04	-0.08	-1.51	0.06	0.33	0.67	-1.28	0.96	0.95	0.94	0.94	0.95
3	0.12	0.03	-0.11	-0.09	0.05	1.61	0.36	-1.45	-1.16	0.49	0.95	0.91	0.90	0.90	0.88
4	0.25	-0.18	-0.29	0.02	-0.17	3.20	-2.24	-3.29	0.21	-1.55	0.94	0.90	0.88	0.87	0.85
Big	0.12	-0.11	-0.17	-0.37	0.07	2.32	-1.59	-2.04	-4.39	0.58	0.96	0.91	0.86	0.88	0.83
Six-Factor															
Small	-0.39	0.22	0.08	0.22	0.18	-3.45	2.58	1.11	3.10	2.47	0.92	0.94	0.94	0.93	0.93
2	-0.07	0.03	0.04	0.03	-0.08	-0.98	0.40	0.67	0.56	-1.22	0.96	0.95	0.94	0.94	0.95
3	0.13	0.04	-0.08	-0.06	0.08	1.81	0.52	-1.07	-0.80	0.86	0.95	0.91	0.90	0.90	0.88
4	0.24	-0.14	-0.24	0.04	-0.12	3.05	-1.77	-2.78	0.43	-1.07	0.94	0.90	0.89	0.87	0.86
Big	0.11	-0.10	-0.15	-0.32	0.12	2.29	-1.40	-1.83	-3.87	0.98	0.96	0.91	0.86	0.89	0.83

Gold as a zero beta asset

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
G-CAPM															
Small	-0.74	0.11	0.16	0.42	0.43	-2.95	0.52	1.01	2.55	2.51	0.66	0.71	0.80	0.78	0.78
2	-0.32	0.14	0.31	0.35	0.28	-1.70	0.99	2.40	2.73	1.69	0.78	0.84	0.85	0.85	0.80
3	-0.14	0.23	0.19	0.31	0.48	-0.87	2.01	1.80	2.52	3.26	0.82	0.89	0.89	0.86	0.82
4	0.05	0.12	0.12	0.32	0.21	0.42	1.30	1.05	2.88	1.42	0.88	0.92	0.89	0.89	0.83
Big	0.02	0.07	0.06	-0.08	0.20	0.26	0.88	0.52	-0.57	1.20	0.95	0.94	0.89	0.84	0.79
G-Three-Factor															
Small	-0.65	0.07	0.02	0.21	0.13	-5.12	0.71	0.31	2.89	1.84	0.92	0.95	0.96	0.96	0.96
2	-0.20	0.07	0.12	0.11	-0.06	-2.65	0.99	1.78	1.72	-0.92	0.97	0.97	0.96	0.97	0.97
3	0.02	0.14	0.01	0.06	0.17	0.20	1.68	0.16	0.72	1.77	0.96	0.95	0.94	0.94	0.93
4	0.20	0.04	-0.06	0.11	-0.08	2.64	0.41	-0.66	1.29	-0.77	0.96	0.93	0.92	0.94	0.91
Big	0.16	0.04	-0.08	-0.33	-0.09	3.18	0.50	-0.93	-4.00	-0.75	0.98	0.95	0.94	0.94	0.89
G-Four-Factor															
Small	-0.55	0.06	0.04	0.16	0.15	-4.35	0.61	0.55	2.14	2.03	0.92	0.95	0.96	0.96	0.96
2	-0.12	0.09	0.13	0.08	-0.05	-1.67	1.31	1.87	1.28	-0.78	0.97	0.97	0.96	0.97	0.97
3	0.06	0.15	0.04	0.07	0.21	0.85	1.77	0.43	0.90	2.15	0.96	0.95	0.94	0.94	0.93
4	0.22	0.07	-0.02	0.12	-0.01	2.73	0.80	-0.21	1.42	-0.08	0.96	0.93	0.93	0.94	0.92
Big	0.15	0.03	-0.08	-0.27	0.01	2.84	0.41	-0.91	-3.29	0.07	0.98	0.95	0.94	0.94	0.90
G-Five-Factor															
Small	-0.40	0.18	-0.01	0.16	0.11	-3.63	2.14	-0.11	2.16	1.46	0.94	0.96	0.97	0.96	0.96
2	-0.07	0.02	0.02	0.02	-0.05	-0.99	0.36	0.34	0.39	-0.79	0.97	0.97	0.97	0.97	0.97
3	0.15	0.08	-0.08	-0.06	0.11	2.12	0.95	-1.03	-0.73	1.13	0.97	0.95	0.95	0.95	0.93
4	0.29	-0.08	-0.19	0.05	-0.07	3.81	-1.01	-2.15	0.54	-0.68	0.96	0.94	0.93	0.94	0.91
Big	0.09	-0.08	-0.18	-0.34	0.11	1.90	-1.20	-2.13	-4.09	0.91	0.98	0.96	0.94	0.94	0.90
G-Six-Factor															
Small	-0.36	0.16	0.01	0.13	0.12	-3.28	1.89	0.13	1.74	1.67	0.94	0.96	0.97	0.96	0.96
2	-0.03	0.04	0.04	0.02	-0.05	-0.49	0.68	0.64	0.27	-0.71	0.97	0.97	0.97	0.97	0.97
3	0.17	0.09	-0.05	-0.03	0.14	2.32	1.12	-0.66	-0.38	1.50	0.97	0.95	0.95	0.95	0.93
4	0.29	-0.04	-0.15	0.06	-0.02	3.72	-0.53	-1.64	0.75	-0.21	0.96	0.94	0.94	0.94	0.91
Big	0.09	-0.07	-0.16	-0.30	0.15	1.85	-1.01	-1.95	-3.62	1.28	0.98	0.96	0.94	0.95	0.91

Table 33: Statistical summary of GRS tests to explain regressions of monthly excess returns over Treasury bills and gold return on *25 Size and Book-to-market Portfolios*: January 1981 to December 2015. The regressions use the CAPM, three-factor, four-factor, five-factor and six-factor models to explain excess returns on 25 Size and Book-to-market portfolios. The GRS statistic tests the null hypothesis that the alphas of all 25 portfolios are jointly equal to zero. $|a|$ is the average absolute alpha for a set of regression on the *25 Size and Book-to-market portfolios* with (5 x 5) and without microcaps (4 x 5); R^2 is the mean adjusted R-Squared; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the average Sharpe ratio of alphas. The critical values for the GRS statistic are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25.

	Return on T-Bills as R_f						Gold as a zero-beta asset						Return on T-Bills as R_f					Gold as a zero-beta asset				
	5 x 5						5 x 5						4 x 5					4 x 5				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	N p<=0.05	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	N p<=0.05	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$
CAPM	6.15	0.24	0.73	0.14	0.63	9	4.51	0.23	0.84	0.14	0.54	9	3.48	0.21	0.76	0.13	0.42	2.86	0.20	0.86	0.13	0.38
Three-Factor	6.00	0.14	0.90	0.08	0.63	8	4.34	0.13	0.95	0.08	0.54	6	3.71	0.11	0.90	0.08	0.44	3.07	0.11	0.95	0.08	0.40
Four-Factor	5.26	0.13	0.91	0.08	0.60	8	3.78	0.12	0.95	0.08	0.51	7	2.98	0.10	0.90	0.08	0.40	2.51	0.10	0.95	0.08	0.37
Five-Factor	5.34	0.14	0.91	0.08	0.62	10	3.77	0.12	0.95	0.08	0.51	8	3.29	0.12	0.91	0.08	0.43	2.74	0.11	0.95	0.08	0.39
Six-Factor	4.97	0.13	0.91	0.08	0.60	8	3.50	0.11	0.95	0.08	0.50	4	2.89	0.11	0.91	0.08	0.41	2.45	0.10	0.95	0.08	0.37

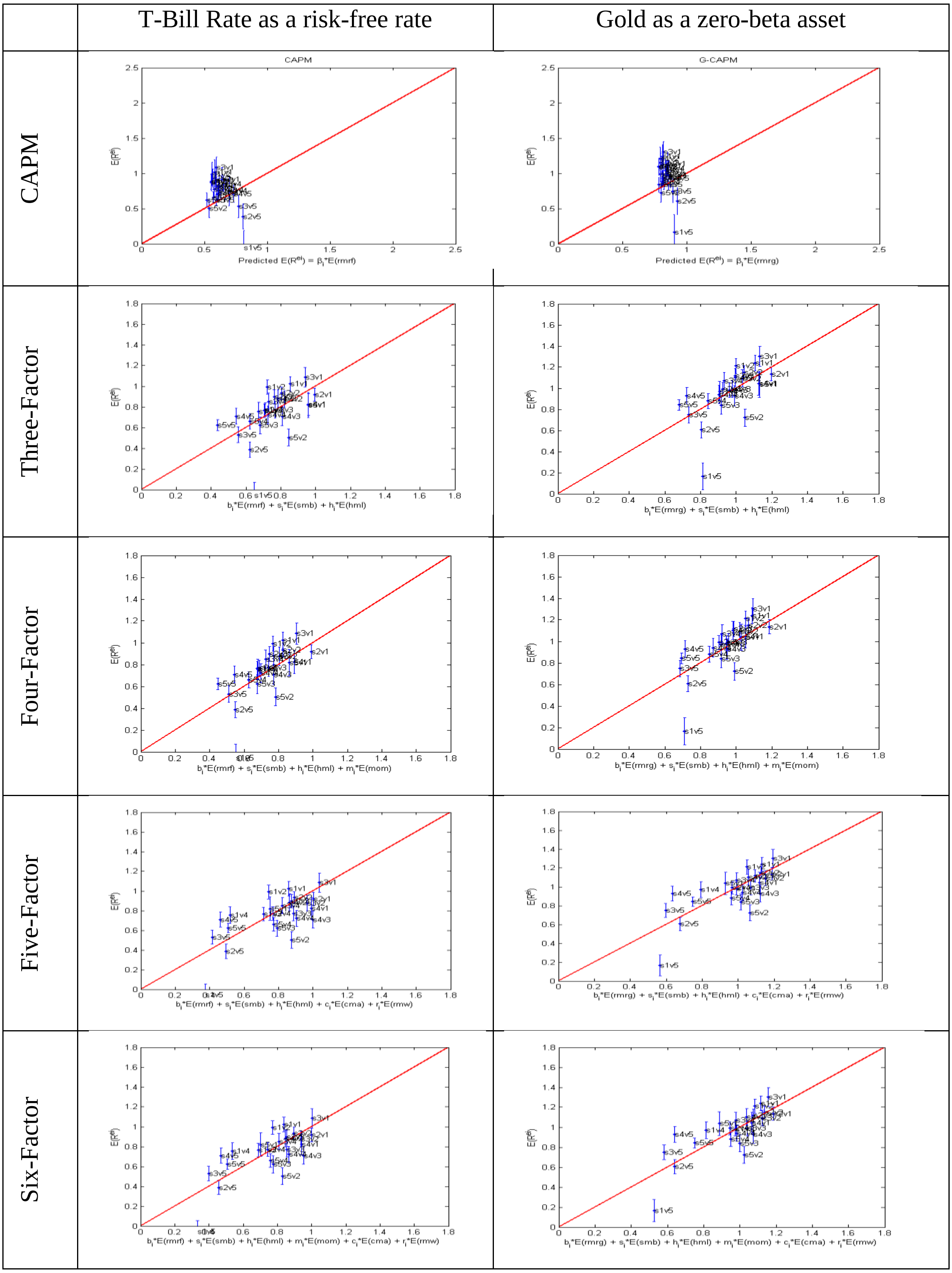


Figure 14: Actual and predicted returns with CAPM, three-factor, four-factor, five-factor, six-factor and their analogues, G-CAPM, G-three-factor, G-four-factor, G-five-factor, and G-six factor models on the *25 Size and Book-to-market* Portfolios.

Figure (14) shows the actual and predicted returns from the traditional and gold zero-beta models on the 25 size and book to market portfolios. Standard error bars show that the gold zero-beta models predict actual average returns comparatively better than traditional empirical factor models. Portfolio returns predicted from the traditional models show more deviation from the security market line than gold zero-beta models.

Table 34: Fama-MacBeth Tests with *25 Size and Book-to-market* portfolios, with (5 x 5) and without microcaps (4 x 5), January 1981-December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. The first and the third columns report results with return on Treasury bills as risk-free rate whereas the second and fourth columns report results with gold as a zero-beta asset. γ is the average coefficient, t-fm is the t-statistic from the Fama-MacBeth procedure, t-sh is the Shanken (1992) error-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
	5 x 5				5 x 5				4 x 5				4 x 5			
CAPM	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	1.84	3.68	3.58	0.22	3.86	2.77	2.54	0.18	1.31	2.54	2.52	0.23	2.55	1.92	1.87	0.19
γ_{RM}	-1.06	-1.94	-1.90		-2.87	-2.00	-1.84		-0.54	-0.99	-0.98		-1.56	-1.15	-1.12	
Three-Factor	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	1.67	5.50	5.32	0.52	2.79	3.34	3.18	0.51	1.26	3.17	3.12	0.54	2.32	2.40	2.33	0.54
γ_{RM}	-1.02	-2.76	-2.70		-1.94	-2.18	-2.09		-0.62	-1.40	-1.38		-1.46	-1.45	-1.41	
γ_{SMB}	0.06	0.40	0.40		0.07	0.46	0.46		0.16	1.12	1.12		0.16	1.11	1.11	
γ_{HML}	0.36	2.42	2.42		0.37	2.52	2.51		0.27	1.86	1.86		0.27	1.86	1.86	
Four-Factor	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.15	0.38	0.30	0.56	-1.28	-1.40	-1.11	0.55	0.14	0.29	0.25	0.57	0.60	0.52	0.49	0.57
γ_{RM}	0.55	1.16	0.94		**2.21**	**2.29**	**1.84**		0.54	1.05	0.93		0.29	0.25	0.23	
γ_{SMB}	0.10	0.68	0.67		0.09	0.59	0.57		0.14	0.95	0.95		0.16	1.06	1.06	
γ_{HML}	0.40	2.70	2.64		0.38	2.57	2.53		0.31	2.12	2.10		0.30	2.01	2.00	
γ_{Mom}	3.57	4.87	3.84		3.09	5.79	4.72		2.50	3.17	2.77		1.51	2.35	2.22	
Five-Factor	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	1.77	5.00	4.63	0.63	2.45	2.33	2.20	0.62	1.14	2.95	2.90	0.62	2.65	2.48	2.37	0.61
γ_{RM}	-1.17	-2.82	-2.67		-1.66	-1.51	-1.43		-0.50	-1.15	-1.13		-1.80	-1.62	-1.55	
γ_{SMB}	0.16	1.09	1.09		0.17	1.16	1.16		0.16	1.12	1.12		0.16	1.09	1.08	
γ_{HML}	0.32	2.22	2.21		0.33	2.25	2.24		0.27	1.82	1.82		0.28	1.92	1.92	
γ_{CMA}	-0.27	-1.23	-1.16		-0.07	-0.32	-0.30		0.18	0.64	0.63		0.12	0.43	0.42	
γ_{RMW}	0.64	3.20	3.04		0.53	2.52	2.42		0.11	0.48	0.48		0.10	0.43	0.42	
Six-Factor	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.62	1.47	1.42	0.66	0.03	0.02	0.02	0.66	0.15	0.30	0.30	0.65	1.30	1.14	1.12	0.65
γ_{RM}	0.06	0.12	0.10		0.87	0.79	0.65		0.53	1.01	0.88		-0.41	-0.34	-0.32	
γ_{SMB}	0.15	1.03	1.02		0.15	1.04	1.03		0.13	0.90	0.89		0.14	0.97	0.97	
γ_{HML}	0.39	2.70	2.67		0.38	2.59	2.56		0.33	2.22	2.20		0.32	2.20	2.19	
γ_{Mom}	3.21	5.38	4.38		2.95	5.59	4.66		2.70	3.52	3.00		1.77	2.66	2.46	
γ_{CMA}	-0.20	-0.94	-0.78		-0.21	-0.93	-0.78		-0.04	-0.14	-0.12		-0.09	-0.32	-0.30	
γ_{RMW}	0.54	2.74	2.34		0.57	2.72	2.34		0.31	1.30	1.14		0.31	1.27	1.19	

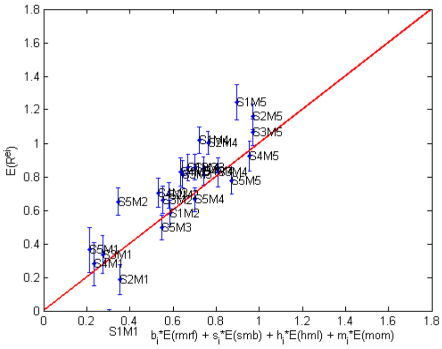
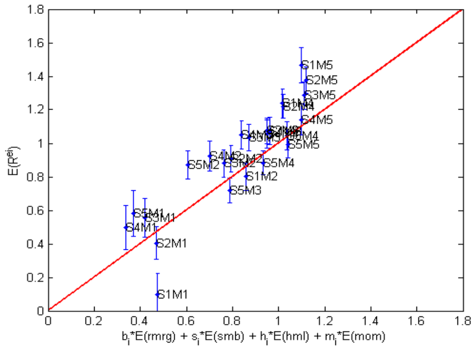
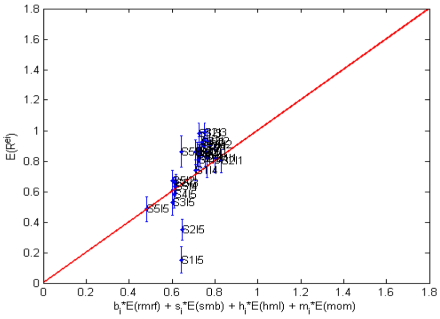
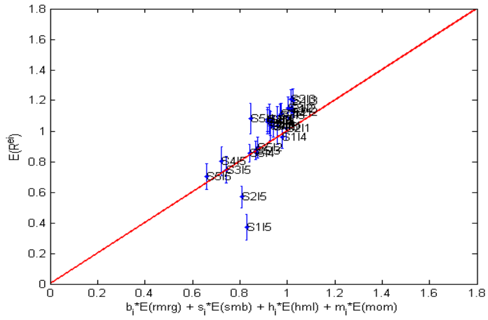
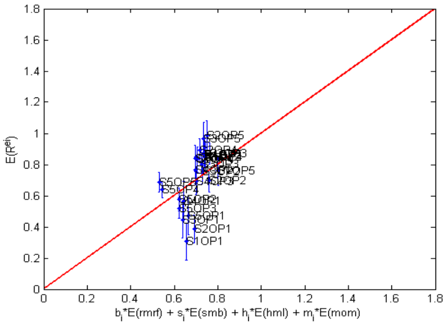
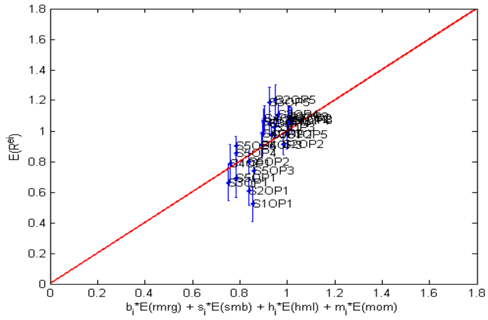
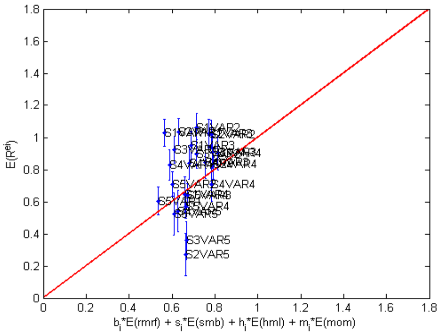
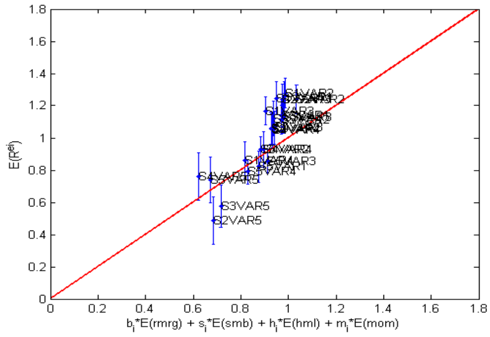
Table (34) reports the second stage-cross sectional results for traditional and gold zero-beta models for portfolios sorted on size and book-to-market. In the cross-sectional analysis, a zero-beta six-factor model outperforms as it produces much lower cross-sectional alphas (γ_0 =0.03, t-stat=0.02) and produces an postive estimate of the price of market risk (γ_{RM}= 0.87). For robustness checks, I also perform sub-period tests on the 25 portfolios sorted on size and book-to-market and the 25 portfolios sorted on size and momentum. The results are reported in Appendix (B). However,I do not find difference in the cross-sectional R-squared values as I find in time series results.

Fama and French (2012, 2015) find that the four-factor model does a better job in explaining average returns than other models. I, therefore compare the performance of traditional and zero-beta G-four-factor models on a wide range of test portfolios.

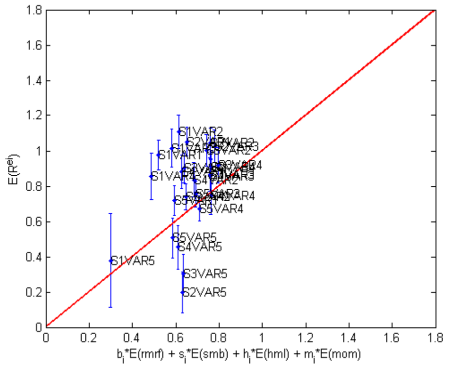
Table 35: Statistical summary of the GRS test to explain four-factor and G-four-factor regressions, January 1981 to December 2015. The GRS statistic tests the null hypothesis that the alphas of all portfolios are jointly equal to zero. $|a|$ is the average absolute alpha; R^2 is the mean adjusted R-Squared; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the average Sharpe ratio of alphas. The critical values for GRS statistic are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25. Panel A shows results on *25 Size and Momentum*, *25 Size and Investment*, 25 *Size and Operating profitability*, Panel B shows results on *25 Size and Accruals*, *25* Size and Variance, *25 Size and Residual Variance*, *25 Size and Market Beta* portfolios with (5 x 5) and without microcaps (4 x 5), Panel C shows results on *32 Size, Book-to-market and Operating Profitability*, *32 Size, Book-to-market and investment*, *32 Size, Operating profitability and Investment* with (5 x 5) and without microcaps (4 x 5), and Panel D shows results on *35 Size and Net share Issues portfolios* with (5 x 5) and without microcaps (4 x 5).

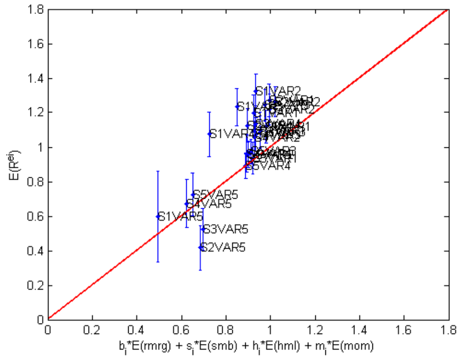
	Return on T-Bills as R_f						Gold as a zero-beta asset						Return on T-Bills as R_f					Gold as zero-beta asset				
	5 x 5						5 x 5						4 x 5					4 x 5				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$
Panel A																						
25 Size and Momentum	3.38	0.15	0.90	0.09	0.48	10	3.23	0.15	0.94	0.09	0.47	10	2.57	0.12	0.90	0.09	0.37	2.59	0.14	0.94	0.09	0.37
25 Size and Investment	3.77	0.13	0.91	0.08	0.51	7	3.22	0.12	0.95	0.08	0.47	6	2.22	0.11	0.91	0.08	0.35	1.91	0.11	0.95	0.08	0.32
25 Size and Operating Profitability	2.56	0.13	0.90	0.09	0.42	6	2.12	0.11	0.94	0.09	0.38	5	2.10	0.13	0.90	0.09	0.34	1.86	0.11	0.94	0.09	0.32
Panel B																						
25 Size and Accruals	2.66	0.12	0.90	0.09	0.43	7	2.10	0.11	0.94	0.09	0.38	2	2.22	0.12	0.90	0.08	0.35	1.87	0.12	0.94	0.09	0.32
25 Size and Variance	4.38	0.22	0.85	0.10	0.55	12	3.90	0.18	0.91	0.11	0.52	7	2.22	0.17	0.85	0.10	0.35	1.76	0.13	0.92	0.10	0.31
25 Size and Residual Variance	2.50	0.22	0.85	0.10	0.42	12	2.13	0.18	0.91	0.11	0.38	10	2.13	0.18	0.87	0.09	0.34	1.92	0.14	0.92	0.10	0.32
25 Size and Market Beta	1.23	0.10	0.88	0.09	0.29	5	1.10	0.08	0.93	0.10	0.27	2	1.35	0.11	0.87	0.09	0.27	1.20	0.08	0.93	0.10	0.25
	2 x 4 x 4						2 x 4 x 4						4 x 4					4 x 4				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$		GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$		GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$
Panel C																						
32 Size, BM and OP	2.83	0.17	0.84	0.11	0.51	9	2.60	0.15	0.90	0.11	0.48	7	2.92	0.13	0.79	0.12	0.36	2.87	0.12	0.88	0.12	0.35
32 Size, BM and Inv	2.69	0.14	0.86	0.09	0.49	11	2.19	0.12	0.93	0.09	0.44	9	2.54	0.14	0.82	0.10	0.33	2.09	0.12	0.91	0.10	0.30
32 Size, OP and Inv	3.94	0.18	0.86	0.10	0.60	14	3.48	0.16	0.92	0.10	0.56	10	2.71	0.14	0.81	0.11	0.34	2.74	0.13	0.90	0.11	0.34
	5 x 7						5 x 7						4 x 7					4 x 7				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$		GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$		GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$
Panel D: 35 Size and Net Share Issue	3.50	0.16	0.85	0.10	0.59	8	3.00	0.14	0.91	0.10	0.54	7	2.56	0.14	0.84	0.10	0.45	2.26	0.13	0.91	0.10	0.42

In Table (35), Panel A presents a summary of GRS test results for the traditional and gold zero-beta four-factor models, for test assets of 25 portfolios, sorted respectively on size and momentum, size and investment, and size and operating profitability, Panel B presents results on sets of 25 portfolios, sorted respectively on size and accruals, size and variance, size and residual variance, and size and market beta. Panel C presents results on three sets of 32 portfolios sorted simultaneously on size, book-to-market and operating profitability, on size, book-to-market and investment, and on size, operating profitability and investment, respectively, while Panel D presents results for test assets of 35 portfolios sorted on size and net share issues. I do not report the alpha coefficients, t-statistics and R-squared values for space reasons, but only report the summary of GRS tests, in which I report the GRS test score, mean adjusted R-squared, Sharpe ratio of alphas and number of significant alpha coefficients across all test portfolios. The performance of zero-beta G-four-factor models remains superior across all test portfolios since I obtain higher mean adjusted R-squared values and lower Sharpe ratio of alphas with gold zero-beta models. Furthermore, the zero-beta G-four-factor models produce fewer significant pricing errors on all test portfolios. However, the traditional and gold zero-beta four-factor model succeeds in passing the GRS test only on size and market portfolios, where the zero-beta four-factor model produces just two pricing errors compared to five with the traditional four-factor model. As expected, performance is considerably improved without microcaps are omitted for both traditional and zero-beta models.

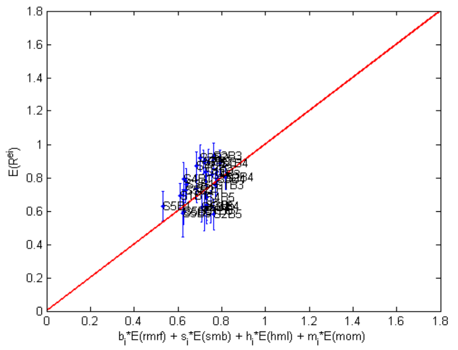
25 Size and Momentum		
25 Size and Investment		
25 Size and Operating profitability		
25 Size and Variance		

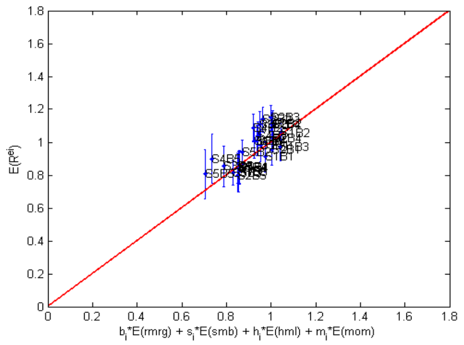
25 Size and Residual Variance



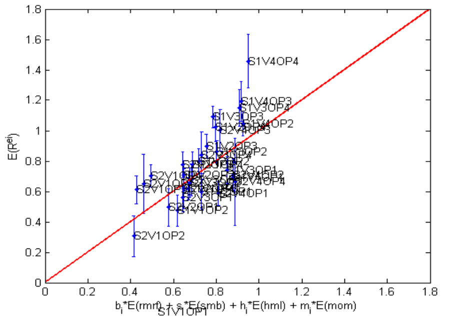


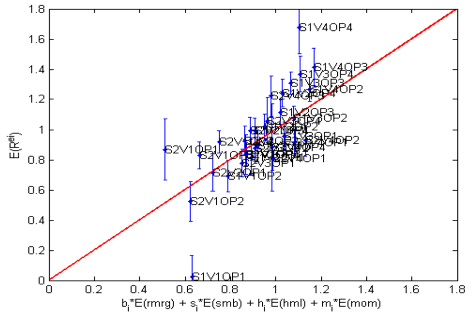
25 Size and Market Beta



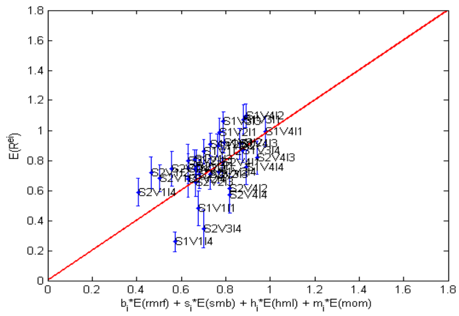


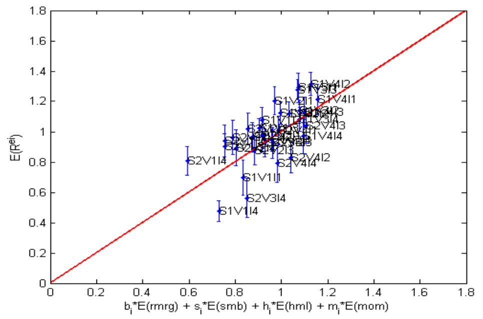
32 Size, Book-to-market and Operating Profitability





32 Size, Book-to-market and investment





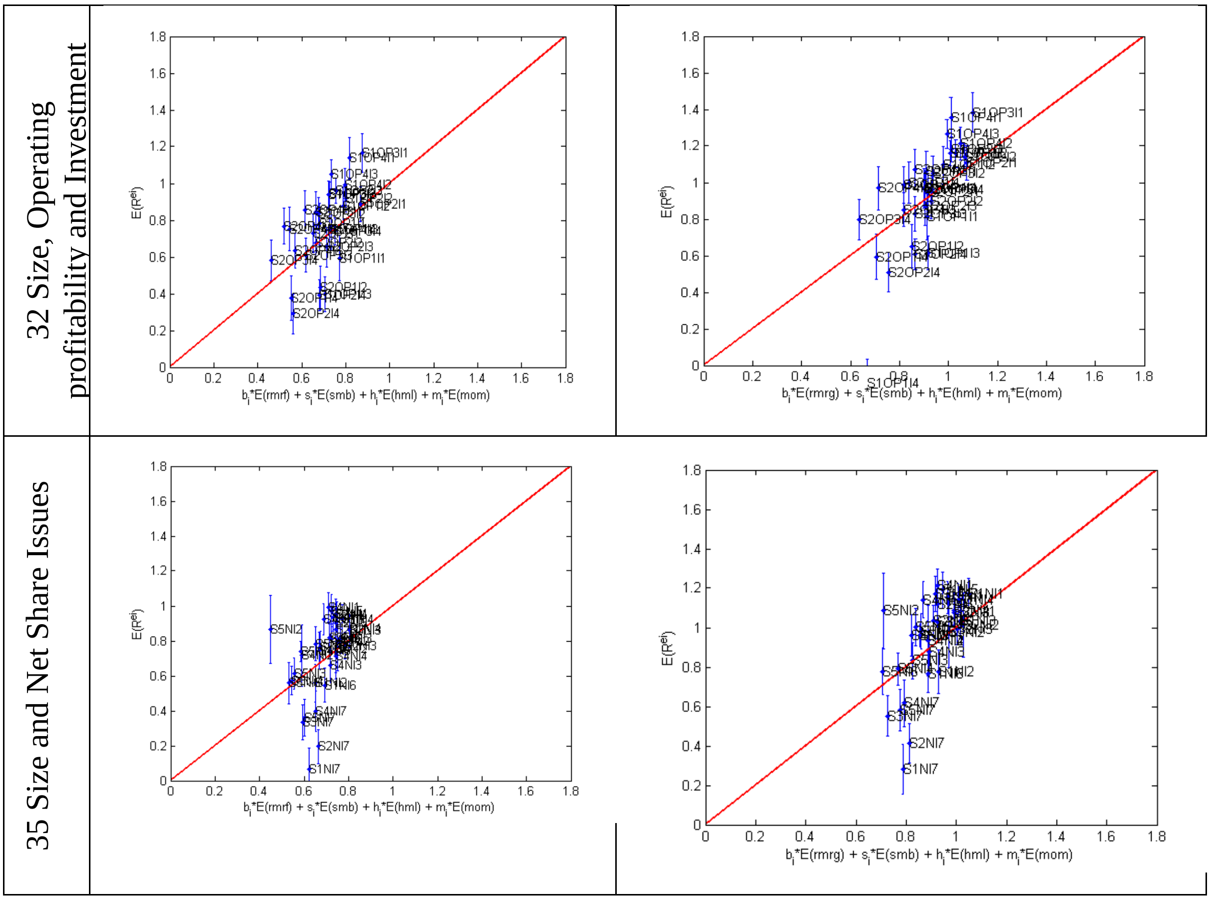


Figure 15: Actual and predicted returns with the four-factor and its analogue G-four-factor on ***25 Size and Momentum, 25 Size and Investment, 25 Size and Operating profitability portfolios, 25 Size and Variance, 25 Size and Residual Variance, 25 Size and Market Beta, 32 Size, Book-to-market and Operating Profitability, 32 Size, Book-to-market and investment, 32 Size, Operating profitability and Investment portfolios, and 35 Size and Net Share Issues portfolios.***

Figure (15) shows the actual and predicted returns from the traditional four-factor and the G-four-factor model on above-mentioned different sets of test portfolios. Standard error bars show that the G-four-factor model predicts actual average returns comparatively better than traditional four-factor model. Portfolio returns predicted from the traditional four-factor model shows more deviation from the security market line than the G-four-factor model, particularly, the performance of G-four-factor model is noteworthy on the 25 size and variance, the 25 size and residual variance and the 25 size and market beta portfolios.

Table 36: Fama-MacBeth Tests for four-factor and G-four-factor, January 1981 to December 2015. Results represent monthly percent returns. Panel A shows results on 25 Size and Momentum, 25 Size and Investment, and 25 Size and Operating profitability portfolios, Panel B shows results on *25 Size and Variance, 25 Size and Residual Variance, and 25 Size and Market Beta portfolios.* Panel C shows results on *32 Size, Book-to-market and Operating Profitability, 32 Size, Book-to-market and investment, and 32 Size, Operating profitability and Investment portfolios,* and Panel D shows results on *35 Size and Net Share Issues* portfolios. Results for all test portfolios are shown with (5 x 5) and without microcaps (4 x 5), γ is the average coefficient, t-fm is the t-statistics from Fama-MacBeth procedure, t-sh is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
Panel A	5 x 5				5 x 5				4 x 5				4 x 5			
25 Size and Momentum																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	-0.05	-0.09	-0.09	0.65	-3.99	-2.36	-1.79	0.64	0.71	1.44	1.42	0.65	-0.42	-0.26	-0.25	0.64
γ_{RM}	0.69	1.25	1.20		**4.85**	**2.82**	**2.17**		-0.03	-0.06	-0.06		1.31	0.82	0.78	
γ_{SMB}	0.11	0.72	0.71		0.08	0.51	0.48		0.17	1.15	1.14		0.15	0.96	0.95	
γ_{HML}	0.76	1.97	1.88		1.11	3.06	2.41		0.33	0.98	0.97		0.50	1.52	1.47	
γ_{Mom}	0.68	3.04	3.03		0.71	3.18	3.15		0.52	2.34	2.34		0.55	2.44	2.43	
25 Size and Investment																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.10	0.24	0.22	0.55	-1.12	-0.99	-0.91	0.53	0.62	1.49	1.45	0.56	2.33	1.81	1.75	0.56
γ_{RM}	0.55	1.20	1.12		**2.01**	**1.70**	**1.56**		0.04	0.09	0.08		-1.46	-1.10	-1.06	
γ_{SMB}	0.07	0.47	0.47		0.05	0.36	0.36		0.09	0.59	0.59		0.11	0.72	0.72	
γ_{HML}	0.68	3.46	3.30		0.68	3.48	3.33		0.54	2.79	2.77		0.43	2.18	2.15	
γ_{Mom}	1.63	2.38	2.19		1.03	1.72	1.58		0.48	0.70	0.68		-0.20	-0.32	-0.31	
25 Size and Operating Profitability																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.06	0.15	0.13	0.51	-0.87	-0.88	-0.80	0.49	0.46	1.03	0.94	0.53	0.46	0.40	0.37	0.52
γ_{RM}	0.57	1.20	1.09		**1.75**	**1.69**	**1.53**		0.18	0.36	0.34		0.41	0.34	0.33	
γ_{SMB}	0.06	0.39	0.39		0.05	0.37	0.37		0.12	0.81	0.81		0.13	0.90	0.89	
γ_{HML}	0.71	2.87	2.62		0.60	2.60	2.43		0.55	2.27	2.14		0.48	2.04	1.97	
γ_{Mom}	2.07	2.65	2.35		1.58	2.19	1.99		1.75	2.46	2.27		1.32	1.78	1.69	

	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
Panel B																
25 Size and Accruals																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.45	1.18	1.04	0.48	0.30	0.30	0.28	0.46	0.57	1.49	1.31	0.47	0.87	0.86	0.79	0.46
γ_{RM}	0.27	0.57	0.51		0.63	0.58	0.54		0.13	0.27	0.24		0.03	0.03	0.03	
γ_{SMB}	0.10	0.62	0.61		0.09	0.57	0.56		0.15	0.99	0.97		0.17	1.13	1.12	
γ_{HML}	0.24	0.75	0.67		0.18	0.56	0.53		0.12	0.42	0.38		0.01	0.03	0.03	
γ_{Mom}	2.45	3.35	2.96		1.71	2.43	2.27		2.42	2.78	2.46		1.86	2.19	2.04	
25 Size and Variance																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.06	0.26	0.21	0.70	-1.75	-2.29	-1.80	0.68	0.57	1.08	1.07	0.45	0.47	0.45	0.44	0.43
γ_{RM}	0.57	1.79	1.58		**2.63**	**3.13**	**2.52**		0.08	0.15	0.15		0.40	0.36	0.36	
γ_{SMB}	0.54	3.17	2.96		0.53	3.15	2.91		0.23	1.53	1.53		0.23	1.51	1.51	
γ_{HML}	0.55	2.14	1.84		0.49	2.00	1.68		0.26	1.58	1.57		0.27	1.65	1.64	
γ_{Mom}	2.94	4.70	3.90		2.84	4.78	3.86		0.15	0.23	0.23		0.09	0.15	0.15	
25 Size and Residual Variance																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.58	2.57	2.47	0.72	0.40	0.52	0.50	0.71	-0.06	-0.19	-0.15	0.70	-1.01	-1.12	-0.93	0.68
γ_{RM}	-0.01	-0.03	-0.03		0.42	0.49	0.48		0.72	1.84	1.50		1.93	1.97	1.67	
γ_{SMB}	0.23	1.37	1.35		0.23	1.36	1.34		0.53	3.01	2.68		0.42	2.42	2.26	
γ_{HML}	0.76	2.75	2.67		0.69	2.64	2.58		0.48	1.72	1.38		0.39	1.46	1.27	
γ_{Mom}	0.38	0.57	0.55		0.39	0.59	0.57		3.61	4.00	3.08		2.52	3.27	2.76	
25 Size and Market Beta																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.06	0.20	0.19	0.61	-0.62	-0.81	-0.77	0.60	0.11	0.29	0.26	0.63	-0.14	-0.16	-0.15	0.63
γ_{RM}	0.59	1.60	1.52		**1.51**	**1.84**	**1.75**		0.56	1.31	1.20		1.05	1.10	1.04	
γ_{SMB}	0.11	0.74	0.73		0.09	0.58	0.57		0.17	1.10	1.09		0.16	1.05	1.05	
γ_{HML}	0.35	1.06	0.99		0.36	1.10	1.05		0.16	0.50	0.46		0.15	0.46	0.44	
γ_{Mom}	1.60	2.73	2.56		1.01	1.45	1.38		2.09	2.95	2.68		1.33	1.94	1.84	

Panel C

	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
	2 x 4 x 4				2 x 4 x 4				4 x 4				4 x 4			
	γ		t-sh	R^2	γ		t-sh	R^2	γ		t-sh	R^2	γ		t-sh	R^2
32 Size, Book to Market and Operating Profitability																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.36	0.71	0.69	0.46	-1.78	-1.86	-1.66	0.44	0.29	0.28	0.26	0.49	1.66	0.91	0.87	0.46
γ_{RM}	0.27	0.49	0.48		2.64	2.63	2.37		0.38	0.37	0.36		-0.74	-0.40	-0.39	
γ_{SMB}	0.06	0.44	0.44		0.06	0.38	0.38		0.13	0.24	0.23		0.46	1.02	0.98	
γ_{HML}	0.46	2.90	2.88		0.48	3.11	3.05		0.17	0.96	0.94		0.13	0.73	0.72	
γ_{Mom}	0.95	1.63	1.58		1.11	1.90	1.72		1.36	1.74	1.66		0.96	1.25	1.20	
32 Size, Book to Market and Investment																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	1.40	3.51	3.38	0.46	0.73	0.63	0.59	0.45	1.45	2.41	2.32	0.41	2.13	1.29	1.23	0.41
γ_{RM}	-0.76	-1.68	-1.63		0.14	0.12	0.11		-0.72	-1.17	-1.13		-1.20	-0.72	-0.69	
γ_{SMB}	0.15	1.02	1.02		0.14	0.97	0.97		0.46	1.11	1.07		0.37	0.93	0.89	
γ_{HML}	0.27	1.86	1.85		0.30	2.06	2.06		0.05	0.32	0.32		0.06	0.36	0.36	
γ_{Mom}	0.92	1.53	1.48		1.61	2.89	2.73		0.77	1.09	1.05		0.98	1.49	1.43	
32 Size, Investment and Operating Profitability																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.35	1.09	0.96	0.44	-0.68	-0.79	-0.70	0.44	0.36	0.84	0.80	0.40	0.58	0.53	0.51	0.40
γ_{RM}	0.29	0.75	0.68		**1.54**	**1.68**	**1.50**		0.24	0.52	0.50		0.25	0.22	0.21	
γ_{SMB}	0.02	0.15	0.15		0.04	0.25	0.25		-0.51	-1.50	-1.44		-0.36	-1.06	-1.04	
γ_{HML}	0.66	3.69	3.52		0.62	3.46	3.29		0.26	1.30	1.27		0.19	0.93	0.91	
γ_{Mom}	2.15	4.89	4.44		1.93	4.52	4.11		1.10	2.09	2.01		0.89	1.77	1.73	

Panel D: 35 Size and Net Share

	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
	5 x 7				5 x 7				4 x 7				4 x 7			
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.27	0.74	0.62	0.44	-0.13	-0.17	-0.15	0.44	0.63	1.49	1.29	0.43	1.00	1.15	1.04	0.44
γ_{RM}	0.41	0.95	0.82		1.05	1.26	1.12		0.05	0.11	0.10		-0.10	-0.11	-0.10	
γ_{SMB}	0.04	0.29	0.28		0.03	0.23	0.22		0.07	0.50	0.49		0.11	0.72	0.71	
γ_{HML}	0.58	2.66	2.38		0.48	2.27	2.11		0.43	1.94	1.78		0.33	1.49	1.41	

Table (36) assesses the ability of traditional and zero-beta four-factor models to explain the cross-section of returns on the portfolios explored above. The traditional four-factor model does a reasonable job as I cannot reject the null hypothesis that second-stage pricing errors are significantly different from zero. In general, for the traditional four-factor model, I obtain an insignificantly positive estimate of the market risk premium and an insignificant cross-sectional alpha. The exceptions are for the 25 size and residual variance portfolios, and the 32 size, book-to-market and investment portfolios, where I find alphas for the traditional model are significant and the market risk premia are negative, contrary to theory. However, in these instances, I find that the corresponding gold zero-beta model succeeds, having insignificant alphas and a positive estimate of the market risk premium, in line with theory.

Satisfyingly, I obtain a positive estimate of the market risk premium with the gold zero-beta four-factor model on all test portfolios in Table (36). The estimate of the market risk premium is significant on the 25 size and momentum, and 32 size, book-to-market and investment portfolios, however, when I exclude microcap portfolios, I obtain insignificantly positive cross-sectional market coefficients, and results are similar and comparable to the traditional four-factor model. I infer from this that employing gold as a zero-beta asset help to price smaller stocks.

Kothari, Shanken and Sloan (1995) find that the conclusions made on CAPM tests are sensitive to the time period employed. I, therefore, perform sub-period analysis and find that zero-beta models perform better during periods of market uncertainty. The results are not reported but they are available from the authors on request.

Table 37: Fama - MacBeth Test on the *25 Size and Momentum* portfolios with the five-factor model, January 1981 to December 2015. Results represent monthly percent returns. The first four factors are the cross-sectional pricing of the four factors of Carhart's (1997) four-factor model and γ_{RES} is the pricing of $R_t^{G\perp}$, the orthogonalised portion of the gold return against the Carhart four factors. t-fm is the Fama-MacBeth t-statistic, whereas, t-sh is the t-statistic obtained from the Shanken (1992) procedure. I adopt the Ferguson and Shockley (2003) methodology to derive this factor, adding the alpha and the residual from the time-series regression: $R_t^{Gold} = a_0 + a_1 R_t^{Mkt-R_F} + a_2 R_t^{SMB} + a_3 R_t^{HML} + a_4 R_t^{MOM}$.

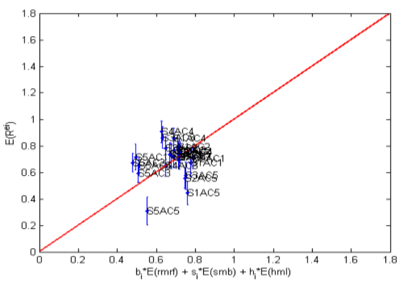
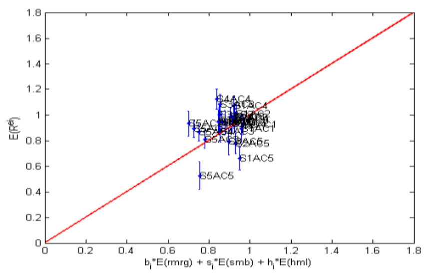
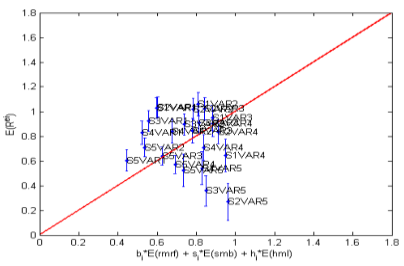
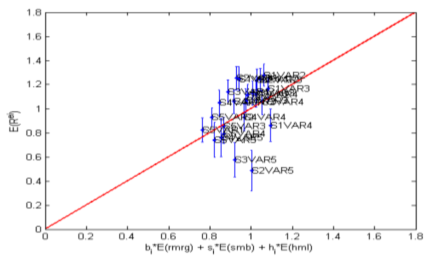
	γ_0	γ_{RM}	γ_{SMB}	γ_{HML}	γ_{MOM}	γ_{RES}	R^2
γ	-0.92	**1.60**	0.06	0.99	0.71	**-4.39**	0.67
t-fm	-1.50	**2.53**	0.39	2.53	3.17	**-3.35**	
t-sh	-1.04	**1.80**	0.36	1.81	3.11	**-2.33**	

As a robustness test, I derive the orthogonalised gold residual factor, $R_t^{G\perp}$, as above, and include it as fifth factor in the traditional four-factor model, for portfolios sorted on size and momentum, in order to test whether the return on gold contains additional explanatory power beyond the four-factor model. Table (37) demonstrates that this residual factor $R_t^{G\perp}$ is significant in the cross section, and therefore adds significant information beyond the four-factor model in explaining portfolio returns.

Table 38: Statistical summary of GRS tests to explain the three-factor and G-three-factor regressions, January 1981 to December 2015. The GRS statistic tests the null hypothesis that the alphas of all portfolios are jointly equal to zero. $|a|$ is the average absolute alpha; R^2 is the mean adjusted R-squared; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the average Sharpe ratio of alphas. The critical values for the GRS statistic are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25. Panel A shows results on *25 Size and Variance, 25 Size and Residual Variance, 25 Size and Market Beta portfolios, and Panel B shows results on 35 Size and Net Share Issues portfolios* with (5 x 5) and without microcaps (4 x 5).

	Return on t-Bills as R_f						Gold as a zero-beta asset						Return on T-Bills as R_f					Gold as a zero-beta asset				
	5 x 5						5 x 5						4 x 5					4 x 5				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)	*GRS*	$\|a\|$	R^2	$s(a)$	$SR(a)$	*GRS*	$\|a\|$	R^2	$s(a)$	$SR(a)$
Panel A																						
25 Size and Accruals	3.12	0.12	0.90	0.08	0.46	9	2.37	0.12	0.94	0.09	0.40	7	2.50	0.11	0.90	0.08	0.36	2.02	0.11	0.94	0.08	0.32
25 Size and Variance	5.05	0.28	0.84	0.10	0.58	12	4.24	0.21	0.90	0.11	0.53	9	2.68	0.22	0.85	0.10	0.38	1.63	0.16	0.91	0.11	0.29
25 Size and Residual Variance	2.78	0.23	0.84	0.11	0.43	13	2.05	0.18	0.90	0.11	0.37	9	2.76	0.21	0.86	0.09	0.38	2.14	0.17	0.92	0.10	0.33
25 Size and Market Beta	1.63	0.15	0.87	0.09	0.33	13	**1.32**	**0.10**	**0.92**	**0.10**	**0.30**	10	1.94	0.16	0.87	0.09	0.32	**1.54**	**0.11**	**0.92**	**0.10**	**0.28**
	5 x 7						5 x 7						4 x 7					4 x 7				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$		*GRS*	$\|a\|$	R^2	$s(a)$	$SR(a)$		*GRS*	$\|a\|$	R^2	$s(a)$	$SR(a)$	*GRS*	$\|a\|$	R^2	$s(a)$	$SR(a)$
Panel B																						
35 Size and Net Share Issues	3.50	0.16	0.85	0.10	0.59	15	3.00	0.14	0.91	0.10	0.54	6	2.56	0.14	0.84	0.10	0.45	2.26	0.13	0.91	0.10	0.42

After assessing the performance of the gold zero-beta four-factor model, I assess the performance of the three-factor gold zero-beta model against the traditional three-factor model on test assets of the 25 portfolios sorted respectively on size and accruals, on size and variance, on size and residual variance, and on size and market beta, and 35 portfolios sorted on size and net share issues. The results of the GRS test in Table (38) show that the gold zero-beta three-factor model produces lower Sharpe ratio of alphas *SR(a)* and higher adjusted R-squared values on all test portfolios compared to the traditional three-factor model. The zero-beta three-factor model passes the GRS test at the 5% level on the size and market beta portfolios *(GRS=1.32),* whereas the traditional three-factor model fails the GRS test on these test portfolios *(GRS=1.63)*, with and without microcaps. Furthermore, the zero-beta three-factor model produces fewer significant pricing errors on all test portfolios, particularly on portfolios sorted on size and net share issues, where it only produces six significant time-series alphas, compared to fifteen with the traditional three-factor model.

Size and Accruals		
Size and Variance		

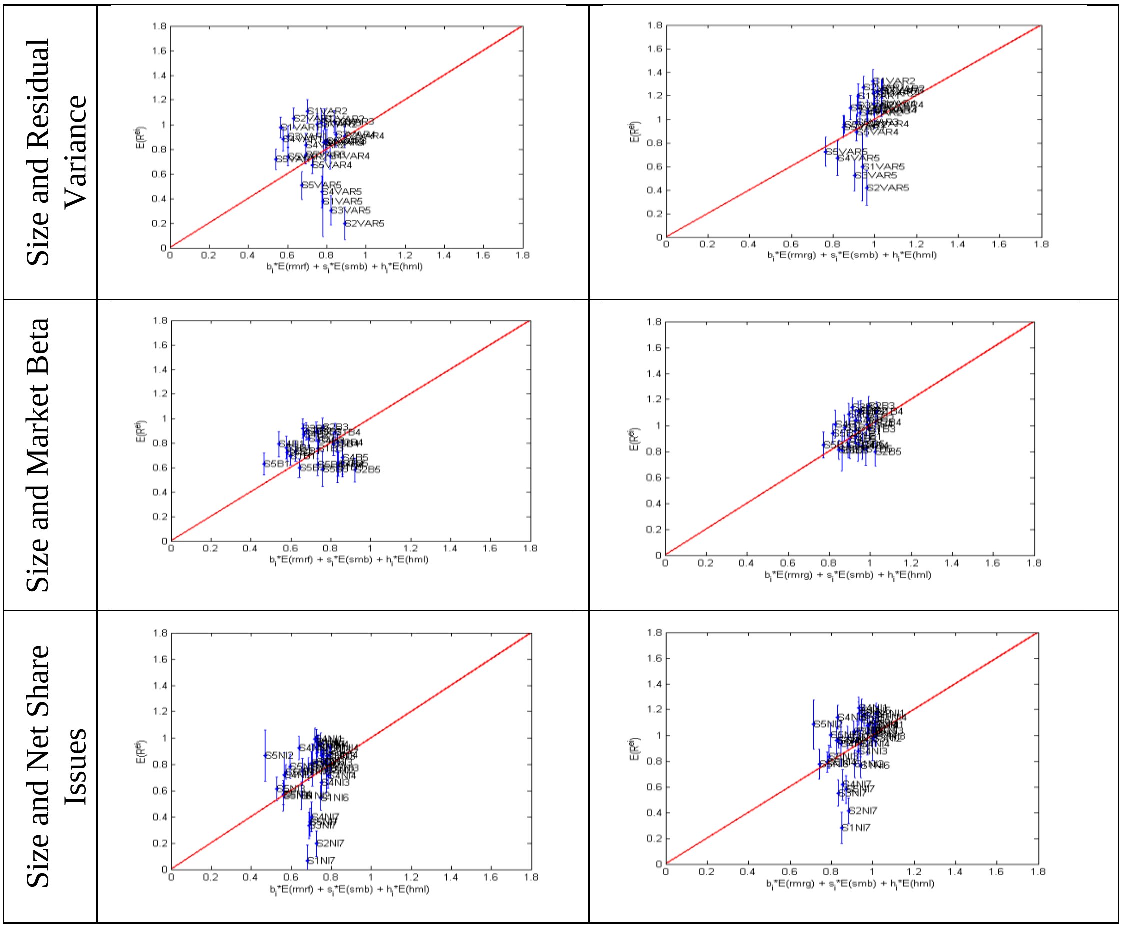


Figure 16: Actual and Predicted Returns with Three-factor and G-Three-factor Models on the *25 Size and Accruals, 25 Size and Variance, 25 Size and Residual Variance, 25 Size and Market Beta, and 35 Size and Net Share Issues* portfolios.

Figure (16) shows the actual and predicted returns from the traditional three-factor and the G-three-factor model on the above-mentioned test portfolios. Standard error bars show that the G-three-factor model predicts actual average returns better than traditional three-factor model. The performance of G-three-factor model is noteworthy on the 25 size and variance and the 25 size and market beta portfolios.

Table 39: Fama-MacBeth Tests for three-factor and G-three-factor model, January 1981 to December 2015. Results represent monthly percent returns. Panel A shows results on the *25 Size and Accruals, 25 Size and Variance, 25 Size and Residual Variance, 25 Size and Market Beta portfolios*. Panel B shows results on the *35 Size and Net Share Issues* portfolios with (5 x 5) and without microcaps (4 x 5), γ is the average coefficient, t-fm is the t-statistics from the Fama-MacBeth procedure, t-sh is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

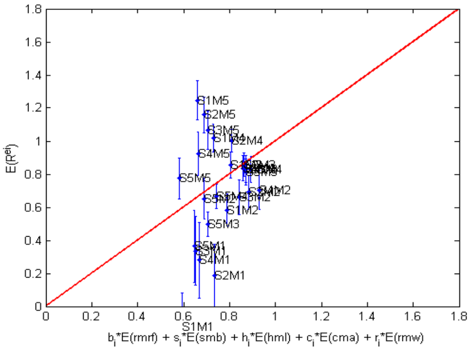
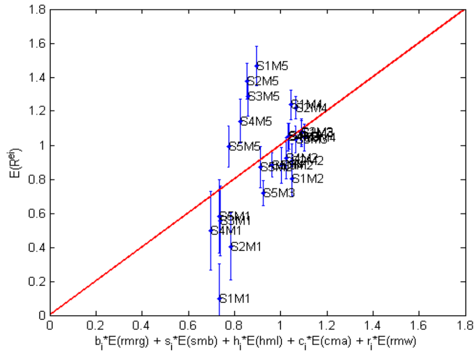
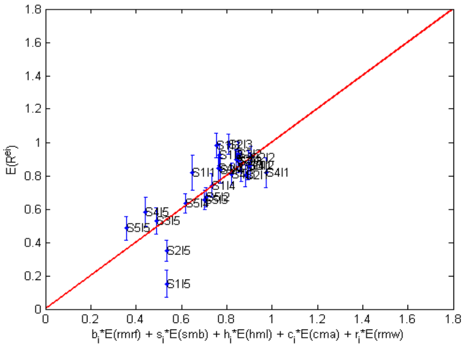
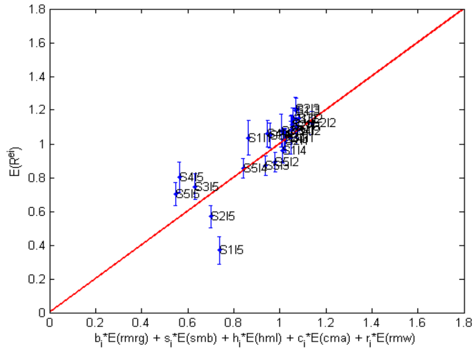
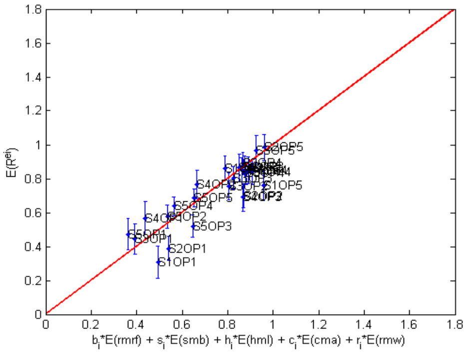
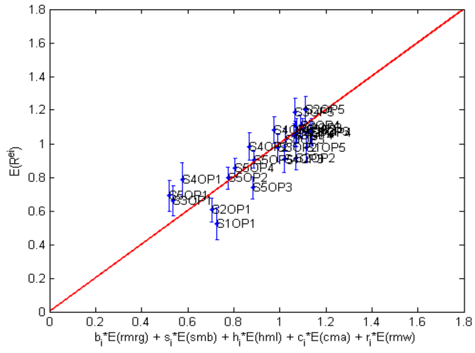
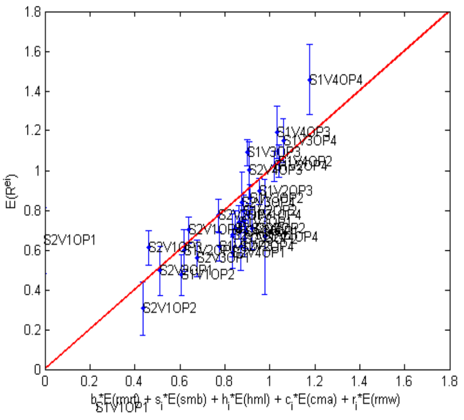
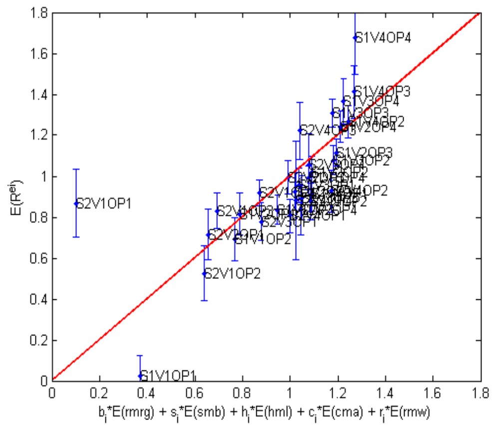
	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
	5 x 5				5 x 5				4 x 5				4 x 5			
Panel A:	γ		t-sh	R^2	γ		t-sh	R^2	γ		t-sh	R^2	γ		t-sh	R^2
25 Size and Accruals																
	1.01	3.12	3.10	0.45	1.85	1.84	1.82	0.43	1.08	3.17	3.15	0.43	2.27	2.51	2.45	0.41
	-0.33	-0.80	-0.80		-0.97	-0.89	-0.88		-0.43	-1.02	-1.02		-1.42	-1.45	-1.42	
	0.05	0.35	0.35		0.06	0.41	0.41		0.13	0.85	0.85		0.15	0.96	0.96	
	0.20	0.62	0.61		0.15	0.46	0.46		0.04	0.16	0.16		-0.03	-0.10	-0.10	
25 Size and Variance																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.57	3.08	2.94	0.62	-0.09	-0.14	-0.13	0.61	0.66	1.54	1.53	0.42	0.75	0.68	0.67	0.40
γ_{RM}	0.03	0.12	0.11		0.91	1.28	1.22		-0.01	-0.02	-0.02		0.12	0.10	0.10	
γ_{SMB}	-0.17	-1.00	-0.99		-0.18	-1.07	-1.06		0.23	1.53	1.53		0.23	1.52	1.52	
γ_{HML}	0.89	3.26	3.15		0.90	3.45	3.32		0.26	1.56	1.56		0.26	1.60	1.59	
25 Size and Residual Variance																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.53	2.15	2.06	0.62	0.35	0.44	0.42	0.62	0.61	2.49	2.40	0.66	0.83	1.12	1.09	0.65
γ_{RM}	0.03	0.08	0.08		0.45	0.52	0.51		-0.04	-0.13	-0.13		-0.02	-0.03	-0.03	
γ_{SMB}	0.07	0.40	0.39		0.07	0.41	0.40		0.09	0.59	0.59		0.12	0.75	0.75	
γ_{HML}	0.88	2.97	2.88		0.81	2.99	2.90		0.78	2.81	2.74		0.70	2.68	2.63	
25 Size and Market Beta																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.46	1.68	1.65	0.59	0.21	0.28	0.27	0.58	0.72	2.45	2.43	0.61	0.85	1.05	1.05	0.60
γ_{RM}	0.16	0.48	0.48		0.65	0.80	0.78		-0.07	-0.19	-0.19		0.03	0.03	0.03	
γ_{SMB}	0.04	0.26	0.26		0.04	0.27	0.27		0.09	0.61	0.61		0.09	0.62	0.62	
γ_{HML}	0.59	1.74	1.71		0.55	1.77	1.74		0.36	1.07	1.06		0.36	1.07	1.06	
Panel B: 35 Size and Net Share Issues																
	5 x 7				5 x 7				4 x 7				4 x 7			
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.77	2.44	2.38	0.40	0.64	0.89	0.87	0.41	1.22	3.40	3.34	0.39	1.81	2.24	2.19	0.40
γ_{RM}	-0.12	-0.32	-0.32		0.23	0.30	0.29		-0.56	-1.36	-1.34		-0.95	-1.09	-1.07	
γ_{SMB}	0.02	0.14	0.14		0.02	0.12	0.12		0.11	0.75	0.74		0.11	0.75	0.75	
γ_{HML}	0.61	2.77	2.74		0.63	2.92	2.88		0.38	1.74	1.72		0.40	1.81	1.79	

Table (39) shows that the gold zero-beta three-factor models perform better in explaining cross-sectional returns than the traditional three-factor model on test portfolios which are not sorted on the Fama-French factors. For the traditional model, I obtain significant cross-sectional alphas for portfolios sorted on size and variance, on size and residual variance, and on size and net share issues at the 5% level. By contrast, the gold zero-beta three-factor model on these test assets yields insignificant cross-sectional alphas. Furthermore, the traditional three-factor model produces an implausibly negative estimate of the market risk premium, whereas the gold zero-beta three-factor model produces an insignificant but economically plausible and positive estimate for all test portfolios, except for those sorted on size and accruals. When I exclude microcaps, I obtain similar and comparable estimates for the traditional and gold zero-beta three-factor models, showing that gold as zero-beta factor improves the pricing of microcaps in particular. The actual and predicted returns estimated from traditional and zero-beta three-factor models are shown in Figure (16).

I also examine the applicability of gold as a zero-beta asset on the Fama-French (2015) five-factor model. The results are shown in Table (40) in four pairs of columns for comparison, as before. Panel A shows results for test assets of 25 portfolios, sorted on size and momentum, on size and investment, and on size and operating profitability. I find relative lower Sharpe ratios of alphas *SR (a)* with the gold zero-beta five-factor models, and higher mean adjusted R-squared, compared to the traditional five-factor models, showing that the gold zero-beta models perform notably better. For instance, for the G-five factor model, I obtain an R-squared of 0.90 on the 25 size and momentum portfolios, as compared to 0.84 for the traditional five-factor model; for the G-five-factor model, I obtain an R-squared of 0.96 on portfolios sorted on size and investment, and size and operating profitability, as compared 0.92 for the traditional five-factor model. In Panel B, the traditional five-factor model produces ten significant alphas for the 32 portfolios sorted on size, book-to-market and operating profitability, whereas the G-five-factor model produces only seven significant alphas. It also yields lower Sharpe ratio *SR (a)* of alphas than the traditional five-factor model. The G-five-factor similarly outperforms on the 35 portfolios sorted on size and net share issues.

Table 40: Statistical summary of the GRS test to explain five-factor and G-five-factor regressions, January 1981 to December 2015. The GRS statistic tests the null hypothesis that the alphas of all portfolios are jointly equal to zero. $|a|$ is the average absolute alpha; R^2 is the mean adjusted R-squared; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the average Sharpe ratio of alphas. The critical values for GRS statistic are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25. Panel A shows results on the *25 Size and Momentum, Size and Investment, 25 Size and Operating Profitability* with (5 x 5) and without microcaps (4 x 5), Panel B shows results on the *32 size, book-to-market and operating profitability*, *32 size, book-to-market and investment* with (5 x 5) and without microcaps (4 x 5), and Panel C shows results on 35 Size and Net Share Issues portfolios with (5x5) and without microcaps (4 x 5).

	Return on t-Bills as R_f						Gold as a zero-beta asset						Return on T-Bills as R_f					Gold as a zero-beta asset				
Panel A	5 x 5						5 x 5						4 x 5					4 x 5				
	GRS	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)	GRS	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)	*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$	*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$
25 Size and Momentum	3.47	0.24	0.84	0.12	0.50	10	3.49	0.20	0.90	0.12	0.49	9	2.75	0.21	0.84	0.12	0.39	2.91	0.17	0.90	0.12	0.40
25 Size and Investment	3.13	0.09	0.93	0.07	0.47	5	2.82	0.09	0.96	0.07	0.44	5	1.75	0.07	0.92	0.07	0.32	1.66	0.07	0.96	0.07	0.30
25 Size and Operating Profitability	2.41	0.08	0.92	0.08	0.42	4	2.11	0.08	0.96	0.08	0.38	4	1.69	0.07	0.92	0.07	0.31	1.65	0.08	0.96	0.07	0.30
Panel B	2 x 4 x 4						2 x 4 x 4						4 x 4					4 x 4				
	GRS	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$		*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$		*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$	*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$
32 Size, BM and OP	2.88	0.15	0.85	0.11	0.52	10	2.77	0.15	0.91	0.11	0.50	7	3.11	0.18	0.81	0.12	0.37	3.29	0.17	0.89	0.12	0.38
32 Size, BM and Inv	2.41	0.12	0.88	0.09	0.48	5	2.11	0.10	0.94	0.09	0.44	5	2.34	0.14	0.83	0.10	0.32	2.14	0.12	0.92	0.10	0.31
Panel C	5 x 7						5 x 7						4 x 7					4 x 7				
	GRS	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$		*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$		*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$	*GRS*	$\lvert a\rvert$	R²	$s(a)$	$SR(a)$
Panel C																						
35 Size and Net Share Issues	3.18	0.13	0.86	0.10	0.57	9	2.84	0.14	0.92	0.10	0.53	9	2.24	0.13	0.85	0.10	0.43	2.11	0.13	0.92	0.10	0.41

25 Size and Momentum		
25 Size and Investment		
25 Size and Operating profitability		
32 Size, Book-to-market and Operating Profitability		

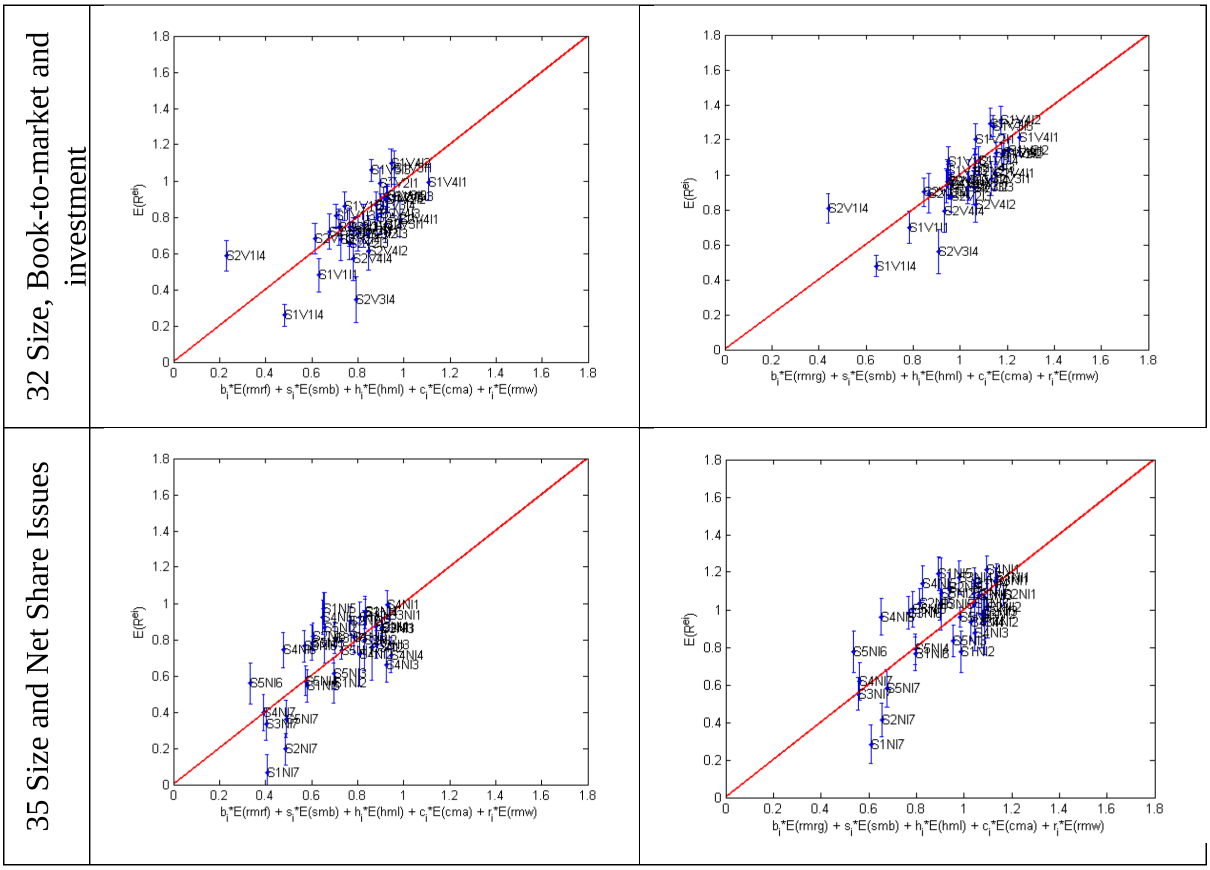


Figure 17: Actual and predicted returns with five-factor and its analogues G-five-factor on the *25 Size and Momentum, 25 Size and Investment, 25 Size and Operating profitability portfolios, 25 Size and Variance, 25 Size and Residual Variance, 25 Size and Market Beta, 32 Size, Book-to-market and Operating Profitability, 32 Size, Book-to-market and investment, 32 Size, Operating profitability and Investment portfolios, and 35 Size and Net Share Issues portfolios*.

Figure (17) shows the actual and predicted returns from the traditional five-factor and the G-five-factor model on the above-mentioned test portfolios. Standard error bars show that the G-five-factor model predicts actual average returns better than traditional five-factor model. G-five-factor models explain linear relationship of risk and return comparatively better than their traditional versions.

Table 41: Fama-MacBeth Tests for the five-factor and G-five-factor model, January 1981 to December 2015. Results represent monthly percent returns. γ is the average coefficient, t-fm is the t-statistics from Fama-MacBeth procedure, t-sh is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models. Panel A shows results on the *25 Size and Momentum, Size and Investment and 25 Size and Operating Profitability portfolios*, Panel B shows results on the *32 Size, Book-to-market and Operating profitability, 32 size, Book-to-market and Investment portfolios, and 32 Size, Operating Profitability and Investment* portfolios. Panel C shows results on the *35 Size and Net Share Issues* portfolios. All results are shown with (5 x 5) and without microcaps (4 x 5).

	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
	γ		t-sh	R^2	γ		t-sh	R^2	γ		t-sh	R^2	γ		t-sh	R^2
Panel A	5 x 5				5 x 5				4 x 5				4 x 5			
25 Size and Momentum																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.70	1.71	1.65	0.68	-3.33	-2.51	-1.98	0.67	0.82	2.01	1.93	0.68	-0.45	-0.34	-0.32	0.67
γ_{RM}	0.00	-0.01	-0.01		**4.26**	**3.13**	**2.49**		-0.14	-0.32	-0.31		1.35	0.98	0.92	
γ_{SMB}	0.23	1.54	1.53		0.24	1.59	1.54		0.22	1.44	1.43		0.21	1.39	1.38	
γ_{HML}	-0.54	-1.73	-1.67		-0.45	-1.50	-1.24		-0.52	-1.46	-1.41		-0.55	-1.54	-1.46	
γ_{CMA}	0.08	0.27	0.26		0.67	2.60	2.11		-0.14	-0.37	-0.36		-0.02	-0.06	-0.06	
γ_{RMW}	0.52	2.13	2.06		0.46	1.91	1.58		0.52	1.67	1.61		0.59	1.83	1.73	
25 Size and Investment																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.71	2.10	2.04	0.62	0.25	0.22	0.22	0.60	0.71	2.02	1.98	0.62	2.12	1.74	1.67	0.61
γ_{RM}	-0.07	-0.19	-0.18		0.61	0.51	0.50		-0.07	-0.16	-0.16		-1.24	-0.99	-0.95	
γ_{SMB}	0.10	0.67	0.66		0.09	0.62	0.62		0.13	0.84	0.84		0.09	0.62	0.62	
γ_{HML}	0.32	1.07	1.05		0.34	1.15	1.12		0.28	0.90	0.88		0.53	1.68	1.62	
γ_{CMA}	0.33	3.18	3.17		0.32	3.07	3.06		0.26	2.45	2.45		0.25	2.33	2.32	
γ_{RMW}	0.32	1.27	1.24		0.31	1.30	1.27		0.34	1.32	1.30		0.05	0.19	0.18	
25 Size and Operating Profitability																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.50	1.19	1.18	0.59	1.69	1.85	1.81	0.56	0.38	0.86	0.85	0.62	1.92	1.85	1.81	0.56
γ_{RM}	0.15	0.31	0.31		-0.80	-0.83	-0.81		0.26	0.54	0.53		-1.04	-0.83	-0.81	
γ_{SMB}	0.03	0.19	0.19		0.02	0.16	0.16		0.06	0.44	0.44		0.08	0.16	0.16	
γ_{HML}	0.26	1.29	1.28		0.19	0.99	0.98		0.19	0.90	0.89		0.13	0.99	0.98	
γ_{CMA}	-0.01	-0.06	-0.06		-0.18	-0.97	-0.96		0.01	0.03	0.03		-0.15	-0.97	-0.96	
γ_{RMW}	0.32	2.58	2.57		0.32	2.54	2.54		0.31	2.42	2.41		0.29	2.54	2.54	

	Return on T-Bills as R_f				Gold as a zero beta asset				Return on T-Bills as R_f				Gold as a zero beta asset			
Panel B	2 x 4 x 4				2 x 4 x 4				4 x 4				4 x 4			
32 Size, Book to Market and Operating Profitability																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.13	0.24	0.23	0.51	-1.79	-1.68	-1.54	0.51	1.31	1.42	1.37	0.57	3.79	1.98	1.77	0.56
γ_{RM}	0.45	0.79	0.77		**2.58**	**2.33**	**2.15**		-0.61	-0.68	-0.66		-2.87	-1.50	-1.34	
γ_{SMB}	0.11	0.79	0.79		0.11	0.74	0.73		0.66	1.25	1.21		0.72	1.28	1.15	
γ_{HML}	0.32	2.13	2.12		0.33	2.15	2.13		0.08	0.47	0.47		0.02	0.12	0.12	
γ_{CMA}	-0.02	-0.11	-0.11		-0.03	-0.20	-0.19		-0.05	-0.23	-0.23		0.00	0.00	0.00	
γ_{RMW}	0.31	2.31	2.31		0.32	2.40	2.37		0.08	0.45	0.44		0.08	0.49	0.46	
32 Size, Book to Market and Investment																
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	1.15	2.94	2.86	0.50	-0.24	-0.21	-0.20	0.50	1.06	1.69	1.64	0.48	0.26	0.13	0.13	0.48
γ_{RM}	-0.55	-1.27	-1.24		1.02	0.87	0.84		-0.34	-0.52	-0.51		0.67	0.34	0.33	
γ_{SMB}	0.18	1.26	1.26		0.20	1.38	1.38		0.60	1.03	1.00		0.51	0.89	0.86	
γ_{HML}	0.21	1.46	1.46		0.19	1.28	1.27		-0.02	-0.12	-0.11		-0.03	-0.17	-0.17	
γ_{CMA}	0.27	2.70	2.69		0.28	2.70	2.70		0.22	1.91	1.89		0.23	2.00	1.99	
γ_{RMW}	0.31	1.66	1.63		0.44	2.49	2.44		-0.09	-0.31	-0.30		-0.09	-0.29	-0.28	
25 Size and Net Share Issues																
Panel C	5 x 7				5 x 7				4 x 7				4 x 7			
	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.38	1.15	1.12	0.48	-0.46	-0.57	-0.54	0.48	0.57	1.42	1.40	0.48	0.65	0.68	0.66	0.49
γ_{RM}	0.27	0.67	0.66		**1.36**	**1.56**	**1.50**		0.10	0.21	0.21		0.24	0.23	0.23	
γ_{SMB}	0.10	0.67	0.67		0.08	0.53	0.52		0.13	0.87	0.86		0.14	0.91	0.91	
γ_{HML}	0.03	0.14	0.14		0.03	0.12	0.11		-0.12	-0.45	-0.45		-0.11	-0.39	-0.38	
γ_{CMA}	0.25	1.35	1.33		0.30	1.56	1.51		0.28	1.28	1.26		0.26	1.13	1.11	

Table (41) reports the second stage results for the above regressions and assesses the ability of the traditional and G-five-factor models to explain returns in cross-section. For the traditional five-factor model, I can reject the null hypothesis that pricing errors are significantly different from zero for the 25 size and investment portfolios at the 5% significance level. In panel B, I likewise reject the null hypothesis for the 32 size, book-to-market and investment portfolios. I also obtain an implausibly negative estimate of the market risk premium for the traditional five-factor model on the 25 size and momentum, the 25 size and investment and the 32 size, book-to-market and investment portfolios. The G-five-factor model performs much better: the only portfolio where I can reject the null hypothesis of zero pricing errors at the 5% level is for the 25 size and momentum portfolios. Additionally, I obtain an insignificantly positive estimate of the market risk premium on the 25 size and investment and significantly positive estimate for the 25 size and momentum portfolios and for the 32 size, book-to-market and investment portfolios. In summary, I find that the G-five-factor model does a better job in those portfolios where the traditional five-factor model struggles to explain the cross-section of returns.

4.2.1.5 Gold as a zero-beta asset: Evidence from U.S. Industries

Having compared the performance on portfolios sorted on security-specific factors, I now move to compare the performance of 49 test portfolios sorted on *industries*. Industry portfolio exposures to a gold return factor have already been found in the ICAPM framework (Chan & Faff, 1998; Davidson, Faff, and Hillier, 2003). Tables (42) and (43) report the time series regression alphas, t-statistics, and R-squared values for the CAPM, three-factor, four-factor, and five-factor models, together with their gold analogues, while Table (44) reports GRS test statistics, the mean adjusted R-squared, and mean absolute alpha. These results show that first-stage pricing errors are reduced and R-squared values are substantially improved when gold is used as a zero-beta asset, compared to the conventional models.

Table 42: Alphas from the CAPM, G-CAPM, three-factor, G-three-factor regressions on the *49 industry portfolios*, January 1981- December 2015. The table reports alphas (a), t-statistics t(a) and adjusted R-squared of the tested models.

	Return on T-Bills as R_f			Gold as a zero beta asset			Return on T-Bills as R_f			Gold as a zero beta asset		
	CAPM			G-CAPM			Three-Factor			G-Three-Factor		
	α	t(α)	R^2	α	t(α)	R^2	α	t(α)	R^2	α	t(α)	R^2
Agriculture	0.20	0.79	0.30	0.16	0.62	0.55	0.15	0.60	0.32	0.08	0.31	0.56
Food Products	0.58	3.37	0.37	0.46	2.47	0.68	0.51	3.04	0.41	0.38	2.16	0.72
Candy & Soda	0.51	1.79	0.26	0.42	1.46	0.53	0.33	1.17	0.29	0.25	0.89	0.55
Beer & Liquor	0.65	3.22	0.32	0.54	2.51	0.63	0.66	3.26	0.34	0.52	2.50	0.65
Tobacco Products	0.81	2.75	0.19	0.71	2.37	0.46	0.70	2.39	0.22	0.60	2.06	0.49
Recreation	-0.12	-0.51	0.49	-0.11	-0.46	0.66	-0.23	-0.99	0.52	-0.22	-0.93	0.68
Entertainment	0.15	0.64	0.60	0.22	0.92	0.70	0.01	0.03	0.62	0.11	0.45	0.72
Printing and Publishing	-0.02	-0.11	0.66	-0.04	-0.25	0.81	-0.17	-1.04	0.68	-0.17	-1.08	0.82
Consumer Goods	0.23	1.49	0.53	0.14	0.90	0.77	0.19	1.25	0.54	0.10	0.62	0.78
Apparel	0.21	1.00	0.55	0.19	0.90	0.73	0.06	0.30	0.57	0.06	0.27	0.74
Healthcare	0.04	0.14	0.35	0.04	0.14	0.56	-0.12	-0.45	0.39	-0.12	-0.46	0.58
Medical Equipment	0.22	1.33	0.58	0.20	1.22	0.76	0.26	1.56	0.58	0.22	1.30	0.77
Pharmaceutical Products	0.43	2.57	0.49	0.37	2.11	0.73	0.54	3.35	0.54	0.45	2.73	0.76
Chemicals	0.05	0.32	0.67	0.09	0.57	0.79	-0.12	-0.77	0.70	-0.04	-0.26	0.81
Rubber and Plastic Products	0.15	0.85	0.61	0.15	0.83	0.77	-0.01	-0.04	0.69	-0.01	-0.08	0.82
Textiles	0.16	0.56	0.44	0.14	0.49	0.63	-0.25	-1.01	0.59	-0.23	-0.96	0.72
Construction Materials	0.02	0.11	0.66	0.05	0.30	0.78	-0.21	-1.26	0.72	-0.13	-0.79	0.81
Construction	-0.32	-1.47	0.61	-0.21	-0.93	0.69	-0.53	-2.56	0.66	-0.38	-1.77	0.73
Steel Works Etc	-0.55	-2.29	0.62	-0.36	-1.43	0.64	-0.67	-2.91	0.66	-0.45	-1.84	0.68
Fabricated Products	-0.51	-1.88	0.41	-0.49	-1.82	0.59	-0.67	-2.70	0.52	-0.67	-2.71	0.66
Machinery	-0.22	-1.32	0.73	-0.11	-0.61	0.78	-0.32	-2.00	0.76	-0.18	-1.10	0.81
Electrical Equipment	0.13	0.83	0.74	0.20	1.22	0.81	0.11	0.70	0.74	0.21	1.25	0.81
Automobiles and Trucks	-0.13	-0.51	0.54	-0.09	-0.35	0.68	-0.46	-2.03	0.62	-0.36	-1.54	0.72
Aircraft	0.15	0.74	0.57	0.14	0.70	0.74	-0.01	-0.07	0.59	0.01	0.06	0.75
Shipbuilding, Railroad Equipment	0.00	-0.01	0.40	0.05	0.17	0.55	-0.26	-0.93	0.45	-0.17	-0.59	0.58
Defense	0.42	1.54	0.23	0.39	1.39	0.47	0.22	0.81	0.26	0.19	0.71	0.50
Precious Metals	-0.20	-0.37	0.04	0.39	0.91	0.00	-0.26	-0.47	0.05	0.36	0.83	0.02
Non-Metallic and Industrial Metal Mining	-0.19	-0.63	0.39	0.08	0.27	0.40	-0.40	-1.32	0.43	-0.07	-0.25	0.43
Coal	-0.39	-0.80	0.20	-0.19	-0.38	0.23	-0.55	-1.13	0.21	-0.32	-0.65	0.24
Petroleum and Natural Gas	0.09	0.41	0.36	0.11	0.50	0.59	-0.07	-0.31	0.40	-0.03	-0.13	0.62
Utilities	0.33	2.00	0.24	0.21	1.12	0.61	0.18	1.12	0.35	0.04	0.26	0.69
Communication	0.15	0.96	0.62	0.09	0.61	0.81	0.14	0.91	0.63	0.09	0.56	0.81
Personal Services	-0.12	-0.58	0.52	-0.14	-0.67	0.71	-0.23	-1.10	0.54	-0.25	-1.21	0.72
Business Services	-0.06	-0.53	0.83	-0.03	-0.26	0.90	-0.02	-0.23	0.86	-0.01	-0.08	0.92
Computers	-0.18	-0.75	0.59	-0.11	-0.45	0.69	0.10	0.43	0.65	0.14	0.60	0.74
Computer Software	0.06	0.24	0.63	0.19	0.72	0.68	0.49	2.38	0.75	0.57	2.74	0.80
Electronic Equipment	-0.15	-0.69	0.67	-0.06	-0.28	0.74	0.10	0.49	0.74	0.16	0.77	0.81
Measuring and Control Equipment	-0.16	-0.81	0.68	-0.05	-0.24	0.74	0.01	0.05	0.76	0.09	0.51	0.81
Business Supplies	0.11	0.68	0.60	0.11	0.62	0.77	-0.07	-0.42	0.64	-0.05	-0.31	0.80
Shipping Containers	0.22	1.11	0.53	0.21	1.05	0.72	0.11	0.54	0.54	0.11	0.57	0.72
Transportation	0.08	0.51	0.63	0.04	0.28	0.80	-0.07	-0.43	0.66	-0.09	-0.59	0.82
Wholesale	0.04	0.28	0.72	0.04	0.33	0.85	-0.04	-0.30	0.75	-0.04	-0.31	0.87
Retail	0.33	2.08	0.65	0.26	1.69	0.83	0.31	1.97	0.65	0.24	1.52	0.83
Restaurants, Hotels, Motels	0.29	1.73	0.56	0.22	1.33	0.77	0.20	1.22	0.57	0.14	0.82	0.78
Banking	0.08	0.46	0.62	0.05	0.27	0.79	-0.26	-1.77	0.76	-0.23	-1.54	0.86
Insurance	0.20	1.19	0.60	0.15	0.88	0.79	-0.04	-0.30	0.70	-0.05	-0.35	0.84
Real Estate	-0.44	-1.74	0.46	-0.41	-1.62	0.62	-0.78	-3.65	0.62	-0.73	-3.41	0.73
Trading	0.06	0.42	0.78	0.12	0.77	0.84	-0.05	-0.34	0.79	0.04	0.29	0.85
Other	-0.38	-1.82	0.58	-0.38	-1.84	0.74	-0.44	-2.13	0.59	-0.43	-2.08	0.74

Table 43: Alphas from four-factor, G-four-factor, five-factor and G-five-factor regressions on the *49 industry portfolios*, January 1981- December 2015. The table reports Alphas (a), t-statistics t(a) and the adjusted R-squared of the tested models.

	Return on T-Bills as R_f			Gold as a zero beta asset			Return on T-Bills as R_f			Gold as a zero beta asset		
	Four Factor			G-Four-Factor			Five-factor			G-Five-Factor		
	α	t(α)	R^2	α	t(α)	R^2	α	t(α)	R^2	α	t(α)	R^2
Agriculture	0.10	0.39	0.32	0.01	0.04	0.56	0.00	0.01	0.32	-0.09	-0.35	0.56
Food Products	0.44	2.57	0.42	0.28	1.57	0.72	0.13	0.83	0.52	0.00	-0.03	0.78
Candy & Soda	0.36	1.27	0.29	0.26	0.91	0.55	-0.01	-0.04	0.32	-0.07	-0.24	0.58
Beer & Liquor	0.55	2.69	0.35	0.39	1.86	0.66	0.24	1.26	0.44	0.11	0.55	0.72
Tobacco Products	0.67	2.26	0.22	0.55	1.86	0.49	0.17	0.58	0.30	0.12	0.41	0.55
Recreation	-0.08	-0.33	0.53	-0.08	-0.33	0.69	-0.52	-2.23	0.56	-0.44	-1.89	0.70
Entertainment	0.20	0.88	0.64	0.31	1.34	0.73	0.00	0.00	0.62	0.17	0.71	0.72
Printing and Publishing	-0.16	-0.95	0.68	-0.16	-1.00	0.82	-0.36	-2.24	0.70	-0.32	-2.02	0.83
Consumer Goods	0.14	0.89	0.54	0.02	0.15	0.78	-0.12	-0.82	0.60	-0.21	-1.44	0.82
Apparel	0.20	0.97	0.58	0.18	0.88	0.75	-0.19	-0.97	0.64	-0.14	-0.70	0.78
Healthcare	-0.23	-0.85	0.39	-0.22	-0.83	0.58	-0.59	-2.35	0.48	-0.50	-2.02	0.64
Medical Equipment	0.20	1.21	0.58	0.15	0.92	0.77	0.11	0.62	0.59	0.06	0.38	0.77
Pharmaceutical Products	0.45	2.78	0.55	0.35	2.11	0.77	0.31	1.90	0.57	0.21	1.28	0.79
Chemicals	-0.03	-0.21	0.71	0.06	0.38	0.81	-0.32	-2.00	0.72	-0.15	-0.92	0.81
Rubber and Plastic Products	0.04	0.24	0.69	0.03	0.17	0.82	-0.22	-1.34	0.71	-0.18	-1.12	0.83
Textiles	0.03	0.14	0.62	0.03	0.12	0.75	-0.51	-2.06	0.62	-0.41	-1.68	0.74
Construction Materials	-0.17	-1.03	0.72	-0.08	-0.47	0.81	-0.51	-3.17	0.75	-0.32	-1.92	0.83
Construction	-0.53	-2.52	0.66	-0.34	-1.57	0.73	-0.71	-3.41	0.67	-0.43	-2.00	0.73
Steel Works Etc	-0.53	-2.27	0.66	-0.26	-1.08	0.69	-0.47	-2.01	0.67	-0.16	-0.66	0.70
Fabricated Products	-0.47	-1.90	0.54	-0.49	-2.00	0.68	-0.74	-2.96	0.55	-0.72	-2.92	0.68
Machinery	-0.15	-0.97	0.77	0.00	0.02	0.83	-0.35	-2.09	0.76	-0.12	-0.72	0.81
Electrical Equipment	0.12	0.73	0.74	0.25	1.43	0.81	0.02	0.15	0.74	0.20	1.17	0.81
Automobiles and Trucks	-0.21	-0.93	0.65	-0.10	-0.44	0.75	-0.46	-1.96	0.62	-0.28	-1.19	0.72
Aircraft	0.09	0.44	0.60	0.11	0.55	0.75	-0.27	-1.37	0.62	-0.17	-0.87	0.76
Shipbuilding, Railroad Equipment	-0.21	-0.74	0.45	-0.10	-0.35	0.58	-0.72	-2.59	0.50	-0.48	-1.70	0.61
Defense	0.21	0.74	0.26	0.17	0.60	0.50	-0.12	-0.44	0.33	-0.11	-0.40	0.55
Precious Metals	-0.29	-0.53	0.05	0.45	1.03	0.02	-0.30	-0.52	0.05	0.56	1.27	0.02
Non-Metallic and Industrial Metal Mining	-0.28	-0.91	0.43	0.11	0.37	0.45	-0.53	-1.70	0.43	-0.02	-0.07	0.43
Coal	-0.65	-1.30	0.21	-0.35	-0.70	0.24	-0.69	-1.36	0.21	-0.31	-0.63	0.24
Petroleum and Natural Gas	-0.07	-0.33	0.40	-0.03	-0.13	0.62	-0.23	-1.04	0.41	-0.15	-0.73	0.62
Utilities	0.08	0.50	0.36	-0.08	-0.49	0.70	0.03	0.19	0.36	-0.17	-1.01	0.71
Communication	0.17	1.10	0.63	0.10	0.65	0.81	0.18	1.12	0.64	0.09	0.55	0.82
Personal Services	-0.34	-1.62	0.55	-0.35	-1.71	0.73	-0.52	-2.59	0.59	-0.49	-2.47	0.75
Business Services	0.00	-0.04	0.86	0.01	0.13	0.92	-0.08	-0.82	0.86	-0.05	-0.44	0.92
Computers	0.31	1.38	0.67	0.34	1.51	0.76	0.47	2.10	0.68	0.46	2.10	0.77
Computer Software	0.61	2.91	0.75	0.70	3.34	0.80	0.69	3.31	0.76	0.79	3.82	0.81
Electronic Equipment	0.26	1.31	0.75	0.32	1.62	0.82	0.41	2.09	0.77	0.45	2.35	0.83
Measuring and Control Equipment	0.07	0.39	0.76	0.17	0.93	0.82	0.07	0.41	0.77	0.19	1.07	0.83
Business Supplies	0.01	0.06	0.65	0.02	0.15	0.80	-0.37	-2.33	0.68	-0.28	-1.77	0.82
Shipping Containers	0.18	0.89	0.54	0.18	0.89	0.72	0.02	0.08	0.56	0.05	0.23	0.73
Transportation	-0.01	-0.04	0.66	-0.04	-0.28	0.82	-0.23	-1.50	0.69	-0.23	-1.52	0.84
Wholesale	-0.06	-0.48	0.75	-0.06	-0.48	0.87	-0.24	-1.99	0.78	-0.20	-1.70	0.88
Retail	0.32	1.94	0.65	0.22	1.40	0.83	0.11	0.73	0.69	0.05	0.32	0.85
Restaurants, Hotels, Motels	0.22	1.31	0.57	0.14	0.80	0.78	-0.13	-0.85	0.65	-0.17	-1.10	0.83
Banking	-0.20	-1.29	0.76	-0.15	-1.03	0.86	-0.25	-1.66	0.77	-0.18	-1.21	0.87
Insurance	-0.06	-0.40	0.70	-0.06	-0.44	0.84	-0.15	-1.01	0.71	-0.13	-0.90	0.85
Real Estate	-0.61	-2.86	0.64	-0.57	-2.66	0.74	-0.89	-4.09	0.63	-0.79	-3.62	0.74
Trading	0.00	-0.02	0.79	0.12	0.74	0.85	0.20	1.40	0.81	0.32	2.14	0.87
Other	-0.39	-1.86	0.59	-0.38	-1.81	0.74	-0.55	-2.57	0.59	-0.50	-2.36	0.74

Table 44: Statistical summary of the GRS test in explaining monthly excess returns over Treasury bills and gold return for the 49 *Industry Portfolios*: January 1981 to December 2015. Results represent monthly percent returns. The regressions use the CAPM, three-factor, four-factor, five-factor and six-factor models to explain excess returns on Industry portfolios. The GRS statistic tests the null hypothesis that the alphas of all 49 portfolios are jointly equal to zero. $|a|$ is the average absolute alpha for a set of time-series regressions of the 49 portfolios; R^2 is the mean adjusted R-Squared; $s(a)$ is the mean standard error of the alphas; and $SR(a)$ is the average Sharpe ratio of the alphas. The critical values for the GRS statistic are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25.

Return on T-Bills as R_f						
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)
CAPM	1.24	0.23	0.52	0.22	0.41	7
Three-Factor	1.82	0.26	0.56	0.21	0.50	12
Four-Factor	1.73	0.24	0.57	0.21	0.50	8
Five-Factor	1.81	0.32	0.59	0.21	0.52	18
Gold as a zero beta asset						
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	No. of P-Values (p<=0.05)
G-CAPM	1.18	0.20	0.68	0.22	0.40	4
G-Three-Factor	1.65	0.22	0.71	0.21	0.48	8
G-Four-Factor	1.64	0.20	0.71	0.21	0.48	4
G-Five-Factor	1.74	0.26	0.73	0.21	0.50	11

I find that gold zero-beta models outperform traditional models, having lower GRS test scores and higher mean adjusted R-squared values. Though the single-factor CAPM and G-CAPM both pass the GRS test at the 5% level, I observe that the gold zero-beta models have a lower number of significant pricing errors compared to the traditional models. For instance, while the single-factor G-CAPM produces four significant pricing errors, the traditional CAPM produces seven. For each model in turn, I obtain fewer significant pricing errors and higher times-series R-squared values by using gold return as a proxy of the zero-beta rate.

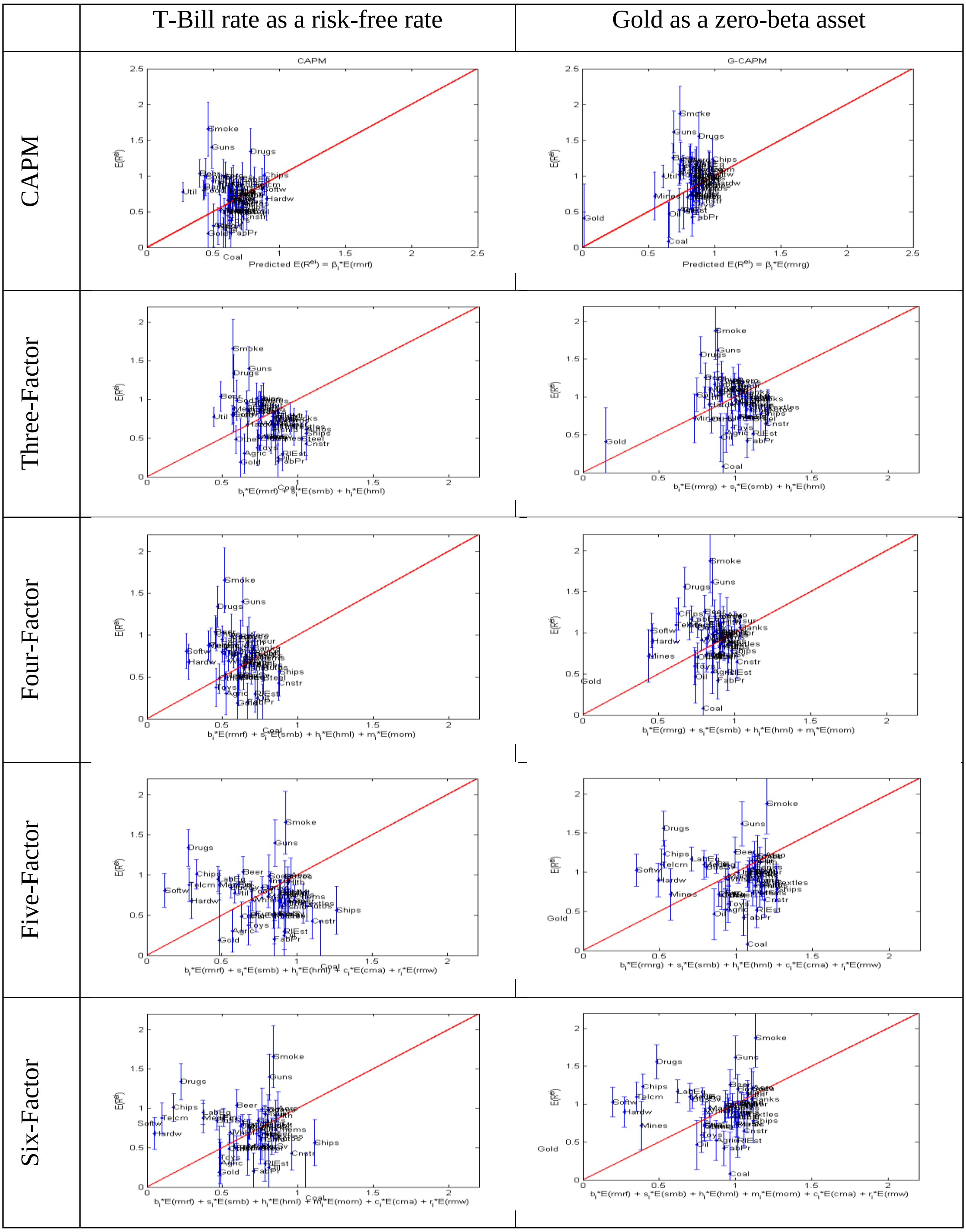


Figure 18: Actual and predicted returns with the CAPM, three-factor, four-factor, five-factor, six-factor and their analogues, G-CAPM, G-three-factor, G-four-factor, G-five-factor, and G-six factor models on 49 U.S. Industries.

Figure (18) shows the actual and predicted returns from the traditional empirical factor models and their gold zero-beta analogues on the 49 industry portfolios. Standard error bars show that the gold zero-beta models predict actual average returns better than their traditional versions.

Table 45: Fama-MacBeth Tests on the *49 Industry* Portfolios, January 1981-December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. The first column reports result with the Treasury bill rate as risk-free assets whereas the second column reports gold as a zero-beta asset. γ is the average coefficient, t-sh is the t-statistic after correcting for errors-in-variables (Shanken, 1992), and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as R_f				Gold as a zero beta asset			
CAPM	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.82	3.11	3.11	0.09	0.54	1.69	1.69	0.11
γ_{RM}	-0.15	-0.45	-0.45		0.35	0.79	0.79	
Three-Factor	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.54	1.94	1.90	0.20	0.53	1.64	1.62	0.26
γ_{RM}	0.23	0.65	0.65		0.46	1.02	1.01	
γ_{SMB}	-0.56	-2.50	-2.47		-0.47	-2.10	-2.08	
γ_{HML}	-0.05	-0.28	-0.28		-0.05	-0.24	-0.24	
Four-Factor	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.64	2.23	2.18	0.23	0.54	1.60	1.58	0.30
γ_{RM}	0.12	0.34	0.34		0.45	0.95	0.94	
γ_{SMB}	-0.59	-2.56	-2.52		-0.50	-2.37	-2.35	
γ_{HML}	-0.06	-0.30	-0.30		-0.05	-0.24	-0.24	
γ_{Mom}	-0.38	-0.75	-0.73		-0.14	-0.28	-0.28	
Five-Factor	γ	t-fm	t-sh	R^2	γ	t-fm	t-sh	R^2
Intercept	0.28	0.88	0.85	0.28	0.49	1.47	1.44	0.33
γ_{RM}	0.43	1.15	1.12		0.47	1.03	1.01	
γ_{SMB}	-0.56	-2.42	-2.36		-0.42	-2.02	-2.00	
γ_{HML}	-0.22	-1.15	-1.13		-0.16	-0.83	-0.83	
γ_{CMA}	-0.18	-0.82	-0.79		-0.12	-0.63	-0.62	
γ_{RMW}	0.38	1.76	1.71		0.27	1.40	1.38	

Table (45) shows the second stage Fama - MacBeth (1973) regression results for the 49 industry portfolios. I obtain positive a market risk premium for the G-CAPM with an insignificant cross-sectional alpha, whereas the traditional CAPM produces an implausible negative market risk premium with a significant cross-sectional alpha, showing that the single-factor CAPM improves with gold as a zero-beta asset. While I obtain insignificantly positive market risk premia for both the traditional four-factor model and its gold analogue, I find that the gold model outperforms, since it has an insignificant second-stage alpha, whereas that for the conventional model is significant. While the traditional five-factor model performs better than the traditional four-factor model, since it has an insignificant alpha with a positive market risk premium, its gold analogue is still superior since it has a higher R-squared. I note that the average cross-sectional R-squared is higher for the single, three, four and five-factor models when I use gold as a zero-beta asset with industry portfolios.

I also perform robustness checks, I estimate models with Generalised Method of Moments (GMM) by adopting the Cochrane (2009) methodology and report the results in Table (86)-(88).

4.2.2 Application of Gold as a Zero-Beta asset in the U.K. Market

After assessing the applicability of gold as a zero-beta asset in the U.S. equity market, I examine its application in the U.K. equity market. I have already assessed efficiency of the U.K. gold market and have confirmed that the null hypotheses of random walks (RWS) and MDS are not rejected with LM (1988) parametric variance ratio tests, Wright (2000) non-parametric variance ratio tests, Portmanteau test and Whang and Kim (2003) multiple variance ratio tests.

4.2.2.1 Gold Position on Minimum Variance Frontier

After assessing market efficiency, I now determine the position of gold on the minimum variance efficient frontier. I use the portfolio dataset from the Exeter Business School website that is freely available[33]. Gregory, Tharyan, and Christidis (2013) have examined the performance of the three-factor and four-factor model in the U.K. equity market and provide a reliable portfolio dataset on the U.K. equity market that is constructed from the London Business School Share Price Database. Their portfolio dataset can be utilised to examine the applicability of gold as a zero-beta asset in the U.K. equity market.

I use the 25 portfolios sorted on size and book-to-market (*25 SBM*), the 25 portfolios sorted on size and momentum (*25 SM*), the 25 portfolios sorted on standard deviation (*25 SD*). I find that gold is located near the minimum variance frontier when it plotted along the *25 SBM* portfolios. I further find that the gold is located on the minimum variance frontier when it is plotted along the *25 SM*, and *25 SD* portfolios as shown in Fig. (19). If gold is an efficient asset also located on the minimum variance frontier, then its applicability as a zero-beta asset can be assessed in empirical asset pricing.

[33] Exeter Business School website: http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/files/

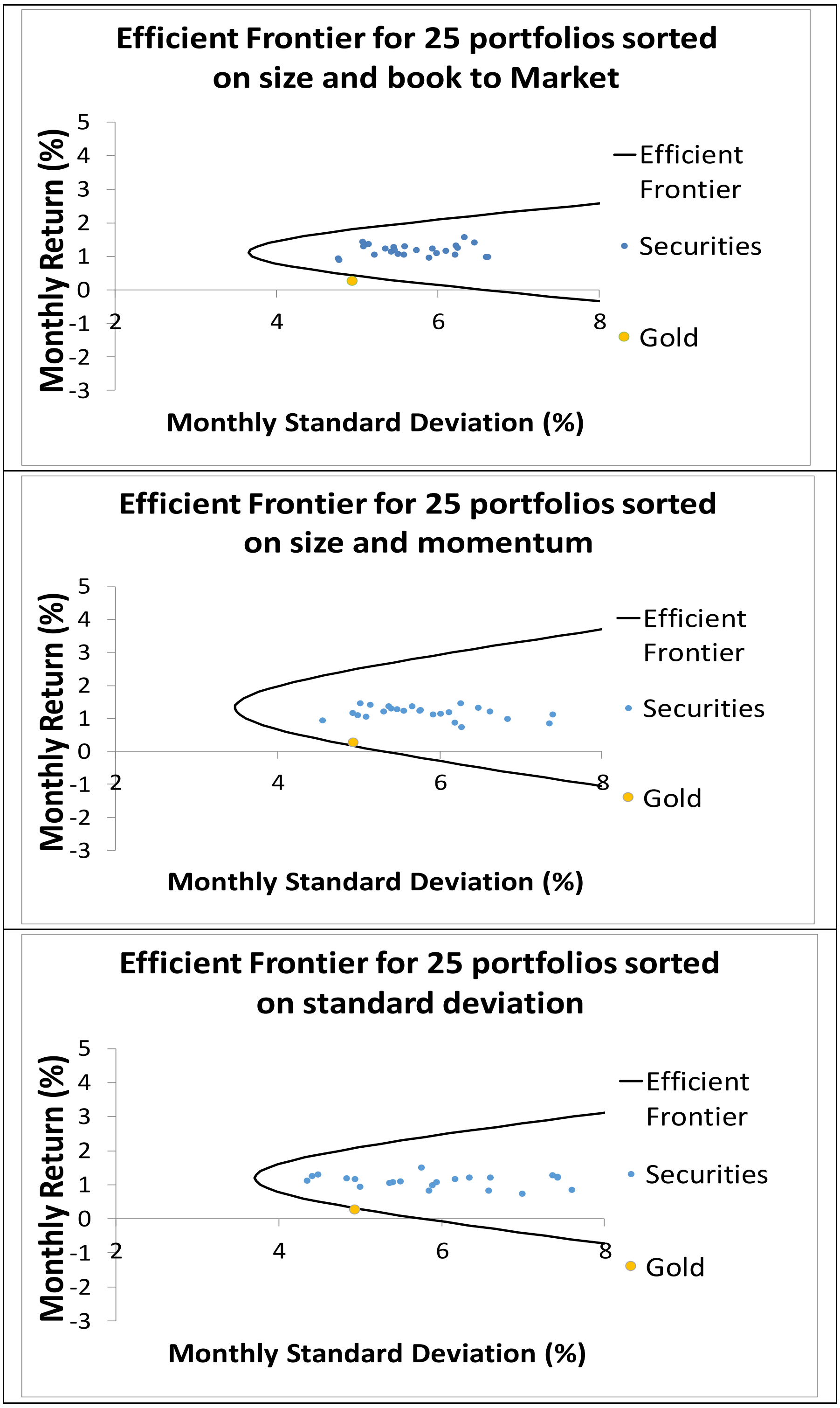


Figure 19: Position of gold on Minimum Variance Frontier in the U.K. equity Market portfolios when it is plotted along the 25 Size and Book-to-market, 25 Size and Momentum and 25 Size and Standard Deviation

4.2.2.2 Test of Factor Models

4.2.2.3 Descriptive Analysis

After examining the position of gold on minimum variance frontier, I employ gold as a zero-beta asset and compare the performance with standard empirical factor models that utilise 1-month Treasury bill rate. Firstly, I perform descriptive and correlation analysis of U.K. gold return with value-weighted market return, Fama and French (1993), size (SMB), value (HML), and Carhart (1997) Momentum *(MOM)* factors. Results are reported in Table (46) that shows that mean the return of gold is half (0.25) that of Treasury bill rate (0.50) with a higher standard deviation of (4.94) as compared to Treasury bill rate (0.50). This needs to be highlighted that I do not intend to employ gold as a risk-free rate instead it uses as a zero-beta asset that is located on the minimum variance of the efficient frontier. *Panel B* of Table (46) shows that gold is not correlated with the market return and empirical factors. Panel C confirm that gold beta is zero in the U.K. equity market.

Table 46: Summary statistics for the returns on gold, market, Treasury bills, Fama - French and Carhart (Momentum) factors, January 1981-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), Panel B reports correlations among the factor returns. Panel C reports the results of the regression
$R_{G,t} - R_{F,t} = \alpha + \beta[R_{m,t} - R_{F,t}] + e_{i,t}$

Panel A: Summary statistics							
	R_g	$R_g - R_F$	$R_m - R_F$	*RF*	*SMB*	*HML*	*MOM*
Mean	0.25	-0.24	0.52	0.50	0.15	0.30	1.00
STD	4.94	4.98	4.49	0.32	3.06	3.18	4.29
Kurtosis	1.50	1.46	3.73	-0.84	2.17	6.59	5.69
Skewness	0.15	0.14	-0.99	0.18	0.10	-0.52	-0.96
t-mean	1.05	-1.00	2.37	31.62	1.03	1.92	4.76
Panel B: Correlations							
	R_g	$R_g - R_F$	$R_m - R_F$	*RF*	*SMB*	*HML*	*MOM*
R_g	1.00						
$R_g - R_F$	1.00	1.00					
$R_m - R_F$	0.01	0.01	1.00				
R_f	-0.08	-0.14	-0.01	1.00			
SMB	-0.03	-0.02	-0.01	-0.10	1.00		
HML	-0.06	-0.06	0.06	0.05	-0.06	1.00	
MOM	0.04	0.04	-0.15	0.02	-0.07	-0.52	1.00
Panel C:Gold Beta							
	Coefficient	*t-stat*					
Intercept	-0.25	-1.01					
$R_m - R_F$	0.01	0.14					

4.2.2.4 Time Series Tests

After assessing the efficiency and zero-beta nature of gold in the U.K. market, I perform asset pricing tests and compare the performance of the zero-beta versions of asset pricing models with the traditional Fama and French (1993, 2015) and Carhart (1997) asset pricing models.

I follow the methodology of Fama and French (1993, 1996, and 2015) and Gregory, Tharyan, and Christidis (2013) in performing time series tests. I report alphas, t-statistics, and R-squared from time series regressions for the CAPM, three-factor, four-factor and their analogues where I use gold as a zero-beta asset. Significant alphas denote the pricing errors and higher R-squared value shows the model performance. Table (47) shows time-series results for the 25 size and book-to-market (*SBM*) portfolios. Results with 1-month Treasury bill yield and gold as a zero beta asset are reported in two separate columns. Findings show that when I use gold as a zero-beta asset, the R-squared of the model improves that signifies better performance of the model. Further, the number of significant alphas (pricing errors) are also reduced. For instance, I find the four significant alphas with the CAPM, three significant alphas in the three-factor as compared to the three significant alphas with G-CAPM and one significant alpha with the G-three-factor model. Table (48) shows results on the 25 size and momentum (*SM*) portfolios and again I notice that the R-squared values are improved with the used of gold as a zero-beta asset with the CAPM, three-factor and four-factor models. Further lower number of pricing errors are reported in the gold analogues of the CAPM and three-factor models. Table (49) reports time series results for the 25 standard deviation (*SD*) portfolios. The zero-beta gold analogues outperform traditional three-factor and four-factor models on 25 *SD* portfolios as I find 5 pricing errors with three-factor models and three pricing errors with the four-factor model as compared to the three pricing errors with the G-three-factor model and zero pricing error with the G-four-factor model. Further, G-CAPM, G-three-factor and G-four-factor models bring noticeable improvement in the R-squared values.

Table (50) shows the summary of Gibbon, Ross and Shanken (1989, *GRS*) test over the above mentioned three sets of test portfolios. I perform tests with (5x5) and without (4x5) microcaps (small stocks) to examine whether the applicability of gold as a zero-beta asset helps to improve pricing of small stocks in the U.K. equity market. Findings show that G-CAPM, G-three-factor and G-four-factor models produce lower values of *GRS* test statistic, lower Sharpe ratio of alphas, *SR (a)*, and higher R-squared values than traditional models. Further, I also obtain evidence from the lower values of *GRS and SR(a)* that pricing of small stocks is improved with the G-factor models.

Table 47: Alphas from the CAPM, three-factor and four-factor regressions on the *25 Size and Book-to-market* portfolios, January 1981- December 2015. The table reports Alphas (*a*), t-statistics t(*a*) and adjusted R-squared of the tested models.

	T-Bills as Risk Free Rate															Gold as zero beta asset														
	α					t(α)					R^2					α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
	CAPM															**G-CAPM**														
Small	0.06	0.23	0.38	0.43	0.50	0.25	1.15	2.12	2.43	2.95	0.45	0.42	0.49	0.52	0.54	0.03	0.21	0.32	0.38	0.46	0.12	1.01	1.74	2.15	2.66	0.67	0.67	0.74	0.75	0.76
2	-0.04	0.15	0.28	0.32	0.27	-0.17	0.73	1.55	1.71	1.31	0.47	0.54	0.53	0.55	0.54	-0.04	0.12	0.24	0.30	0.26	-0.16	0.57	1.34	1.60	1.25	0.66	0.74	0.75	0.75	0.73
3	-0.08	-0.10	0.15	0.17	0.51	-0.34	-0.60	0.88	0.97	2.49	0.52	0.65	0.66	0.63	0.57	-0.05	-0.09	0.16	0.15	0.51	-0.24	-0.52	0.98	0.85	2.51	0.68	0.79	0.8	0.8	0.74
4	0.04	0.00	0.23	0.15	0.30	0.25	-0.01	1.60	0.85	1.64	0.63	0.71	0.72	0.69	0.66	0.07	0.03	0.24	0.16	0.32	0.42	0.17	1.67	0.90	1.71	0.77	0.83	0.84	0.81	0.79
Big	-0.02	-0.09	0.00	0.03	0.20	-0.17	-0.74	0.03	0.24	1.18	0.68	0.75	0.78	0.73	0.59	-0.04	-0.09	0.03	0.05	0.17	-0.31	-0.81	0.24	0.38	0.99	0.84	0.88	0.88	0.85	0.78
	Three-Factor															**G-Three-Factor**														
Small	0.01	0.15	0.22	0.21	0.24	0.06	1.12	1.98	2.06	2.80	0.76	0.75	0.81	0.84	0.88	-0.02	0.12	0.17	0.18	0.21	-0.10	0.92	1.41	1.64	2.31	0.86	0.86	0.89	0.91	0.93
2	0.00	0.01	0.11	0.12	-0.04	0.01	0.06	0.79	0.88	-0.27	0.77	0.74	0.71	0.76	0.81	0.00	-0.01	0.09	0.11	-0.04	0.02	-0.10	0.59	0.78	-0.28	0.85	0.85	0.84	0.87	0.89
3	-0.01	-0.15	-0.01	-0.05	0.21	-0.07	-1.24	-0.07	-0.36	1.51	0.80	0.82	0.79	0.79	0.80	0.01	-0.14	0.01	-0.06	0.23	0.07	-1.10	0.09	-0.46	1.62	0.87	0.89	0.88	0.88	0.88
4	0.13	-0.08	0.10	-0.04	0.04	0.95	-0.58	0.82	-0.31	0.32	0.78	0.76	0.78	0.79	0.81	0.16	-0.05	0.12	-0.03	0.07	1.13	-0.37	0.93	-0.18	0.48	0.86	0.86	0.88	0.87	0.88
Big	0.17	-0.01	0.02	-0.03	0.12	1.83	-0.09	0.18	-0.24	0.84	0.84	0.78	0.78	0.77	0.72	0.15	-0.02	0.05	-0.01	0.09	1.52	-0.19	0.37	-0.08	0.64	0.92	0.89	0.88	0.87	0.85
	Four-Factor CAPM															**G-Four-Factor**														
Small	-0.12	0.07	0.18	0.18	0.25	-0.74	0.53	1.58	1.68	2.68	0.77	0.76	0.81	0.84	0.88	-0.15	0.03	0.10	0.13	0.20	-0.94	0.22	0.83	1.12	2.01	0.86	0.86	0.89	0.91	0.93
2	-0.06	0.19	0.14	0.06	0.00	-0.35	1.19	0.91	0.42	-0.02	0.77	0.75	0.71	0.76	0.81	-0.05	0.16	0.09	0.04	0.00	-0.31	0.97	0.61	0.28	-0.03	0.85	0.86	0.84	0.87	0.89
3	0.06	-0.01	-0.01	0.05	0.24	0.38	-0.05	-0.04	0.34	1.63	0.80	0.83	0.79	0.79	0.80	0.09	0.02	0.02	0.03	0.26	0.59	0.12	0.18	0.23	1.78	0.87	0.90	0.88	0.88	0.88
4	0.09	-0.01	0.06	0.04	0.19	0.58	-0.07	0.44	0.29	1.30	0.78	0.76	0.78	0.79	0.81	0.13	0.03	0.08	0.07	0.23	0.85	0.20	0.60	0.49	1.54	0.86	0.86	0.87	0.87	0.88
Big	0.27	0.01	-0.08	-0.07	0.19	2.70	0.11	-0.66	-0.52	1.23	0.84	0.78	0.78	0.77	0.72	0.23	-0.01	-0.05	-0.04	0.14	2.23	-0.05	-0.39	-0.30	0.93	0.92	0.89	0.88	0.87	0.85

Table 48: Alphas from the CAPM, three-factor and four-factor regressions on 25 *Size and Momentum* portfolios, January 1981- December 2015. The table reports Alphas (a), t-statistics t(a) and adjusted R-squared of the tested models.

	T-Bills as Risk Free Rate														
	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
	CAPM														
Small	0.33	0.25	0.50	0.55	0.43	1.37	1.46	2.68	3.08	2.28	0.42	0.51	0.47	0.49	0.48
2	-0.22	0.24	0.26	0.24	0.15	-0.80	1.21	1.40	1.44	0.77	0.42	0.53	0.54	0.59	0.58
3	-0.02	0.35	0.26	-0.22	0.13	-0.06	1.97	1.68	-1.24	0.60	0.54	0.60	0.68	0.67	0.56
4	-0.16	0.07	0.18	0.26	0.35	-0.81	0.40	1.23	1.96	2.00	0.64	0.65	0.75	0.76	0.68
Big	-0.34	0.04	-0.02	0.10	0.07	-1.76	0.35	-0.15	0.79	0.40	0.62	0.76	0.74	0.73	0.61
	Three-Factor CAPM														
Small	0.03	0.05	0.30	0.39	0.33	0.16	0.44	2.38	3.18	2.66	0.76	0.80	0.76	0.76	0.78
2	-0.57	0.08	0.08	0.09	0.07	-3.00	0.54	0.60	0.65	0.46	0.73	0.73	0.77	0.74	0.74
3	-0.31	0.14	0.10	-0.38	0.13	-1.68	1.08	0.83	-2.95	0.77	0.75	0.79	0.80	0.82	0.75
4	-0.39	-0.13	0.05	0.20	0.35	-2.27	-0.89	0.36	1.65	2.35	0.75	0.77	0.81	0.80	0.77
Big	-0.43	-0.01	0.03	0.17	0.21	-2.33	-0.10	0.31	1.45	1.23	0.64	0.78	0.76	0.76	0.67
	Four-Factor CAPM														
Small	0.33	0.07	0.31	0.36	0.25	2.03	0.61	2.31	2.76	1.92	0.77	0.80	0.76	0.76	0.79
2	-0.15	0.07	0.02	0.12	0.18	-0.80	0.43	0.15	0.85	1.14	0.75	0.72	0.78	0.74	0.75
3	0.10	0.28	0.17	-0.17	0.08	0.57	2.07	1.30	-1.29	0.46	0.77	0.80	0.80	0.83	0.75
4	-0.07	0.17	0.17	0.23	0.29	-0.39	1.20	1.26	1.84	1.81	0.76	0.79	0.81	0.80	0.77
Big	-0.03	0.02	0.09	0.04	0.37	-0.15	0.16	0.76	0.35	2.06	0.68	0.78	0.76	0.76	0.67

	Gold as zero beta asset														
	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
	G-CAPM														
Small	0.30	0.20	0.43	0.49	0.41	1.24	1.17	2.24	2.69	2.13	0.65	0.75	0.73	0.74	0.71
2	-0.21	0.20	0.23	0.21	0.14	-0.78	1.04	1.26	1.26	0.69	0.61	0.74	0.75	0.79	0.75
3	0.02	0.34	0.25	-0.21	0.17	0.08	1.95	1.64	-1.22	0.77	0.68	0.77	0.83	0.80	0.70
4	-0.12	0.07	0.20	0.25	0.41	-0.58	0.37	1.36	1.93	2.28	0.75	0.80	0.85	0.87	0.78
Big	-0.32	0.04	-0.04	0.09	0.10	-1.64	0.30	-0.30	0.75	0.53	0.76	0.88	0.87	0.86	0.76
	G-Three-Factor														
Small	0.01	0.01	0.24	0.34	0.31	0.05	0.09	1.78	2.63	2.44	0.85	0.89	0.87	0.87	0.88
2	-0.55	0.06	0.06	0.06	0.06	-2.90	0.38	0.44	0.47	0.39	0.81	0.85	0.88	0.86	0.85
3	-0.26	0.14	0.10	-0.37	0.16	-1.40	1.10	0.84	-2.84	0.99	0.82	0.88	0.89	0.89	0.83
4	-0.33	-0.12	0.07	0.19	0.40	-1.91	-0.87	0.56	1.64	2.64	0.82	0.87	0.89	0.90	0.84
Big	-0.41	-0.02	0.01	0.17	0.23	-2.19	-0.13	0.11	1.37	1.34	0.78	0.89	0.89	0.88	0.80
	G-Four-Factor														
Small	0.29	0.01	0.21	0.28	0.21	1.80	0.06	1.52	2.06	1.62	0.86	0.89	0.87	0.87	0.88
2	-0.14	0.03	-0.01	0.08	0.17	-0.71	0.21	-0.06	0.59	1.06	0.83	0.85	0.88	0.86	0.85
3	0.17	0.28	0.17	-0.15	0.14	0.89	2.07	1.30	-1.15	0.79	0.84	0.89	0.89	0.90	0.83
4	0.01	0.18	0.20	0.23	0.37	0.04	1.21	1.52	1.85	2.26	0.83	0.88	0.89	0.90	0.84
Big	0.00	0.01	0.05	0.03	0.39	0.00	0.11	0.44	0.26	2.20	0.80	0.89	0.89	0.88	0.80

Table 49: Alphas from the CAPM, three-factor and four-factor regressions on 25 *Standard Deviation* portfolios, January 1981- December 2015. The table reports Alphas (a), t-statistics t(a) and adjusted R-squared of the tested models.

	Retunr on Treasury Bills as a Risk free Rate										Return of gold as a zero-beta asset									
		CAPM			Three Factor			Four Factor				CAPM			Three Factor			Four Factor		
	$\bar{R}$	α	t(α)	R^2	α	t(α)	R^2	α	t(α)	R^2	$\bar{R}$	α	t(α)	R^2	α	t(α)	R^2	α	t(α)	R^2
SD1	0.62	0.27	1.76	0.47	0.26	1.66	0.47	0.21	1.29	0.47	0.86	0.21	1.25	0.74	0.19	1.16	0.74	0.11	0.61	0.75
SD2	0.74	0.35	2.51	0.59	0.37	2.63	0.59	0.35	2.37	0.59	0.98	0.31	2.18	0.80	0.33	2.28	0.80	0.29	1.88	0.80
SD3	0.80	0.39	2.96	0.63	0.42	3.19	0.65	0.33	2.39	0.65	1.05	0.35	2.53	0.83	0.37	2.72	0.83	0.26	1.81	0.83
SD4	0.43	-0.05	-0.35	0.68	-0.03	-0.24	0.69	-0.09	-0.64	0.69	0.67	-0.07	-0.48	0.84	-0.05	-0.37	0.84	-0.12	-0.83	0.84
SD5	0.68	0.23	1.65	0.65	0.24	1.74	0.66	0.21	1.45	0.66	0.92	0.19	1.31	0.83	0.20	1.40	0.83	0.15	1.00	0.83
SD6	0.54	0.05	0.29	0.64	0.01	0.06	0.65	0.14	0.83	0.65	0.78	0.03	0.20	0.81	0.00	-0.03	0.81	0.11	0.68	0.81
SD7	0.66	0.19	1.37	0.67	0.17	1.19	0.67	0.14	0.96	0.67	0.90	0.19	1.36	0.83	0.16	1.17	0.83	0.13	0.90	0.83
SD8	0.31	-0.24	-1.45	0.66	-0.23	-1.38	0.67	0.02	0.14	0.69	0.55	-0.23	-1.37	0.80	-0.22	-1.30	0.81	0.04	0.22	0.82
SD9	0.58	0.07	0.46	0.64	0.06	0.35	0.65	0.05	0.27	0.65	0.83	0.06	0.37	0.81	0.04	0.27	0.81	0.03	0.18	0.81
SD10	1.01	0.48	2.78	0.62	0.42	2.46	0.64	0.19	1.07	0.65	1.25	0.49	2.82	0.78	0.43	2.52	0.79	0.21	1.17	0.80
SD11	0.57	0.06	0.37	0.68	0.01	0.09	0.69	-0.07	-0.45	0.69	0.81	0.08	0.54	0.82	0.04	0.26	0.82	-0.04	-0.24	0.82
SD12	0.47	-0.07	-0.43	0.63	-0.16	-0.94	0.67	-0.13	-0.71	0.67	0.71	-0.07	-0.37	0.78	-0.15	-0.86	0.80	-0.11	-0.61	0.80
SD13	0.57	0.03	0.19	0.61	0.02	0.11	0.65	0.06	0.32	0.65	0.81	0.06	0.31	0.76	0.04	0.23	0.78	0.09	0.48	0.78
SD14	0.70	0.13	0.66	0.61	0.12	0.62	0.63	-0.04	-0.20	0.64	0.95	0.18	0.90	0.74	0.16	0.85	0.75	0.03	0.15	0.76
SD15	0.67	0.09	0.50	0.66	-0.02	-0.14	0.70	0.04	0.25	0.70	0.91	0.10	0.56	0.79	-0.01	-0.04	0.82	0.07	0.39	0.82
SD16	0.32	-0.28	-1.36	0.60	-0.44	-2.37	0.68	-0.41	-2.12	0.68	0.56	-0.21	-1.01	0.72	-0.36	-1.96	0.77	-0.31	-1.58	0.77
SD17	0.23	-0.37	-1.63	0.55	-0.46	-2.07	0.59	-0.37	-1.59	0.59	0.47	-0.33	-1.41	0.69	-0.41	-1.83	0.71	-0.30	-1.28	0.71
SD18	0.71	0.12	0.60	0.59	0.06	0.32	0.64	0.05	0.22	0.64	0.96	0.18	0.85	0.72	0.12	0.59	0.75	0.13	0.60	0.75
SD19	0.70	0.07	0.29	0.55	-0.03	-0.12	0.63	0.33	1.41	0.65	0.95	0.10	0.42	0.68	0.01	0.05	0.74	0.38	1.64	0.75
SD20	0.73	0.09	0.38	0.55	0.01	0.04	0.63	0.02	0.07	0.63	0.97	0.13	0.54	0.68	0.05	0.23	0.74	0.09	0.37	0.74
SD21	0.76	0.15	0.60	0.52	0.10	0.43	0.58	0.15	0.59	0.58	1.01	0.21	0.81	0.65	0.16	0.66	0.69	0.23	0.92	0.69
SD22	0.35	-0.27	-1.02	0.50	-0.37	-1.48	0.56	-0.19	-0.72	0.56	0.59	-0.18	-0.67	0.60	-0.28	-1.10	0.65	-0.06	-0.24	0.66
SD23	0.30	-0.36	-0.99	0.37	-0.45	-1.42	0.52	-0.13	-0.39	0.52	0.54	-0.26	-0.70	0.47	-0.35	-1.08	0.59	0.01	0.03	0.59
SD24	0.52	-0.06	-0.20	0.39	-0.12	-0.44	0.55	-0.19	-0.68	0.55	0.76	-0.03	-0.10	0.54	-0.08	-0.30	0.67	-0.14	-0.48	0.67
SD25	0.20	-0.42	-0.88	0.24	-0.45	-1.12	0.46	-0.37	-0.87	0.45	0.45	-0.31	-0.66	0.32	-0.35	-0.85	0.51	-0.22	-0.51	0.51

Table 50: Statistical summary of GRS tests to explain regressions of monthly excess returns over Treasury bills and gold return on *25 Size and Book-to-market*, *25 Size and Momentum and 25 Standard* Deviation portfolios: January 1981 to December 2015. The regressions use the CAPM, three-factor, and four-factor models to explain excess returns. The GRS statistic tests the null hypothesis that the alphas of all 25 portfolios are jointly equal to zero. $|a|$ is the average absolute alpha for a set of regression on the 25 portfolios with (5 x 5) and without microcaps (4 x 5); R^2 is the mean adjusted R-Squared; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the average Sharpe ratio of alphas. The critical values for the GRS statistic are: 90%: 1.41; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25.

	Return on T-Bills as Risk free Rate										Return on Gold Return as a return on zero beta asset									
	5 x 5					4 x 5					5 x 5					4 x 5				
	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$	GRS	$\|a\|$	R^2	$s(a)$	$SR(a)$
25 Size and Book to Market																				
CAPM	0.92	0.19	0.60	0.18	0.24	0.83	0.16	0.63	0.17	0.20	0.79	0.18	0.77	0.18	0.23	0.79	0.16	0.78	0.17	0.20
Three-Factor	0.83	0.09	0.78	0.13	0.23	0.70	0.07	0.78	0.13	0.19	0.70	0.09	0.88	0.13	0.21	0.65	0.07	0.87	0.13	0.18
Four-Factor	0.83	0.11	0.79	0.14	0.25	0.67	0.09	0.78	0.14	0.20	0.64	0.10	0.88	0.14	0.22	0.56	0.09	0.87	0.14	0.18
25 Size and Momentum																				
CAPM	2.35	0.23	0.60	0.18	0.39	1.80	0.18	0.63	0.18	0.30	1.98	0.22	0.77	0.18	0.36	1.74	0.18	0.78	0.18	0.30
Three-Factor	2.46	0.20	0.76	0.14	0.40	2.19	0.20	0.76	0.14	0.34	2.13	0.19	0.86	0.14	0.37	2.08	0.19	0.86	0.15	0.33
Four-Factor	1.69	0.17	0.77	0.15	0.35	1.25	0.14	0.76	0.15	0.27	1.50	0.15	0.86	0.15	0.33	1.26	0.14	0.86	0.15	0.27
25 Standard Deviation																				
CAPM	1.68	0.20	0.57	0.21	0.33	1.25	0.18	0.56	0.22	0.25	1.39	0.18	0.72	0.21	0.30	1.17	0.17	0.70	0.23	0.24
Three-Factor	1.71	0.20	0.62	0.19	0.33	1.32	0.18	0.62	0.21	0.26	1.38	0.18	0.76	0.20	0.30	1.19	0.17	0.74	0.21	0.25
Four-Factor	1.24	0.17	0.62	0.21	0.30	0.87	0.15	0.63	0.22	0.22	0.96	0.15	0.76	0.21	0.27	0.77	0.14	0.74	0.22	0.21

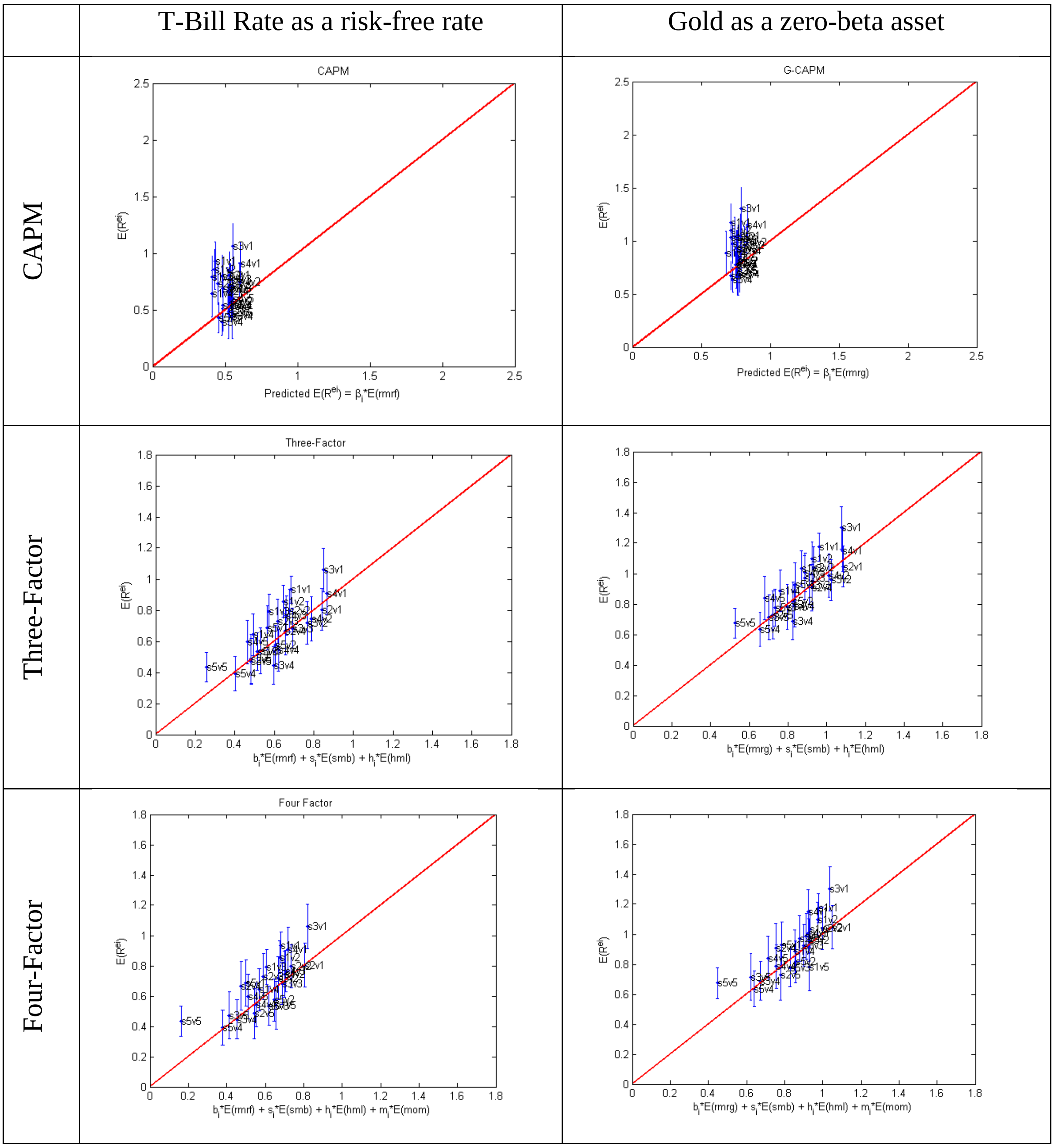


Figure 20: Actual and predicted returns with CAPM, three-factor, four-factor and their analogues, G-CAPM, G-three-factor and G-four-factor models on the *25 Size and Book-to-market* Portfolios

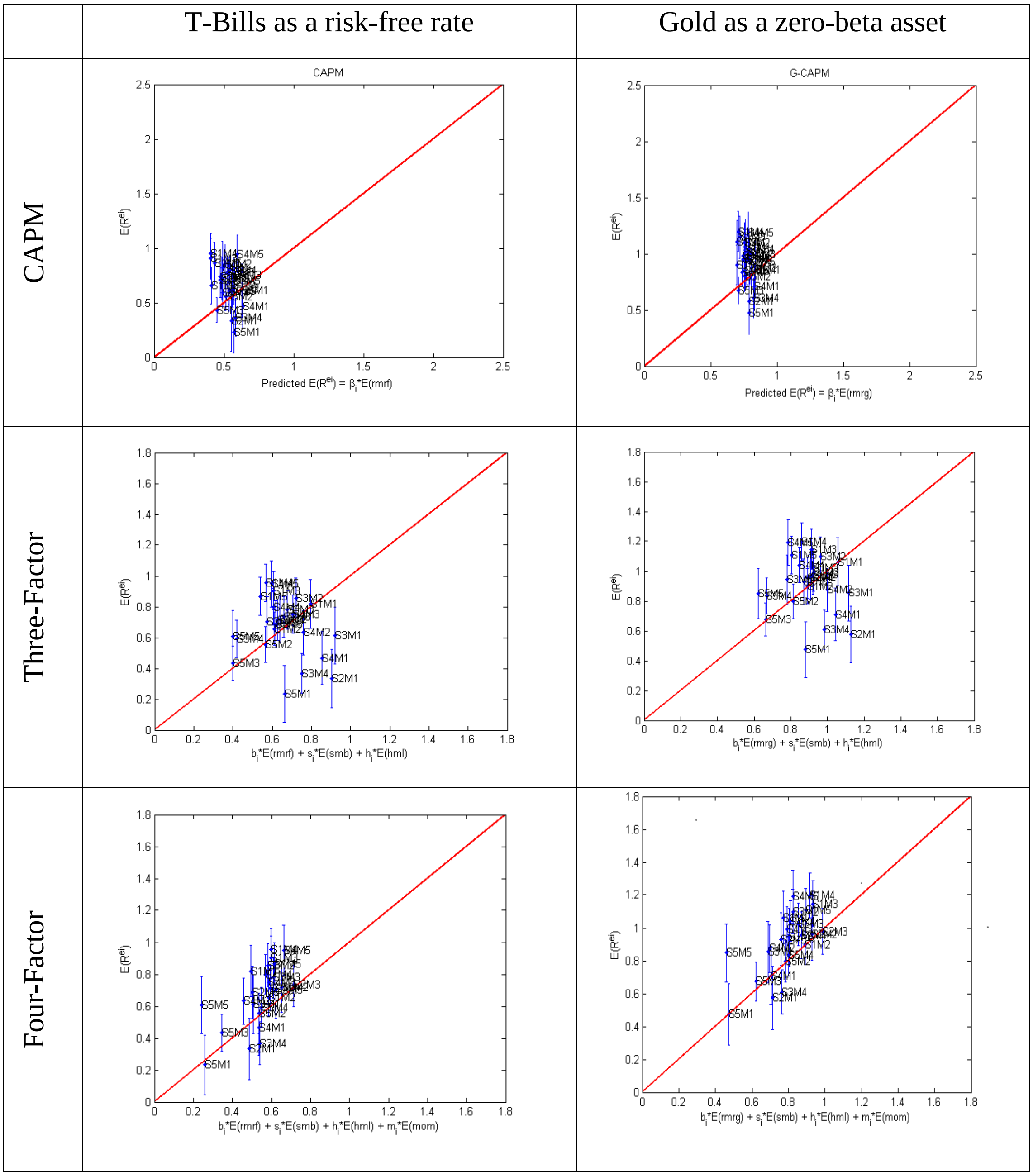


Figure 21: Actual and predicted returns with CAPM, three-factor, four-factor and their analogues, G-CAPM, G-three-factor, G-four-factor models on the 25 *Size and Momentum* Portfolios

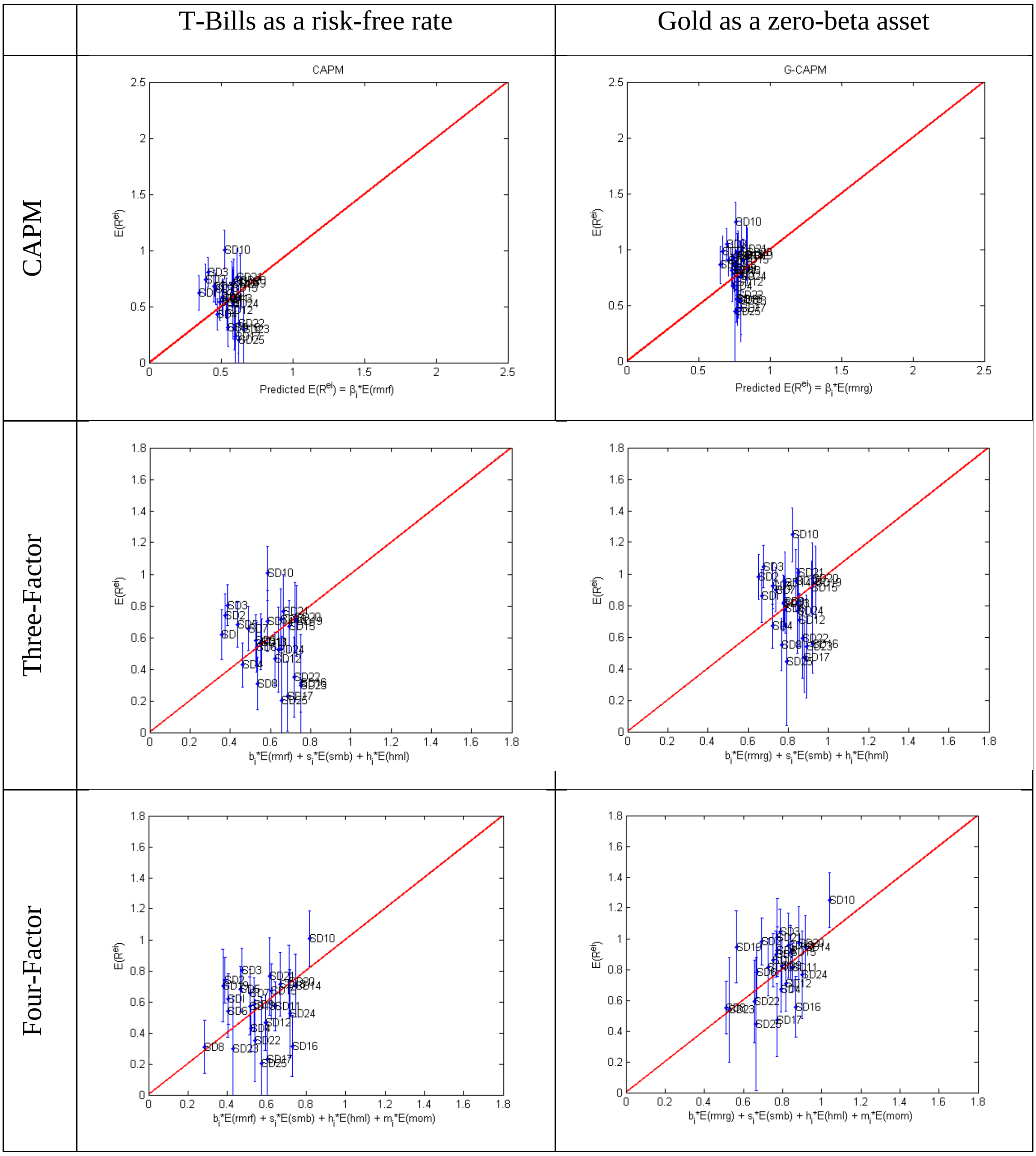


Figure 22: Actual and predicted returns with CAPM, three-factor, four-factor and their analogues, G-CAPM, G-three-factor, G-four-factor models on the *25 Standard Deviation* portfolios

Figure (21) and (22) show the performance of the empirical factor models in the U.K. market on the 25 size and book to market portfolios and the 25 size and momentum portfolios. Standard error bars show that the gold zero-beta models predict actual average returns better than their traditional versions.

Table 51: Fama-MacBeth Tests with *25 Standard Deviation* portfolios in the U.K. equity market in the full-period, January 19811-December 2015, and sub-period, January 2007-December 2011, and January 2011-December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, three-factor, and four-factor models. γ is the average coefficient, t-stat is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as a R_F			Gold as a zero beta asset			Return on T-Bills as a R_F			Gold as a zero beta asset			Return on T-Bills as a R_F			Gold as a zero beta asset		
	1981-2015			1981-2015			2007-2011			2007-2011			2011-2015			2011-2015		
	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2
CAPM																		
Intercept	1.03	1.48	0.13	1.37	1.30	0.11	0.16	0.17	0.14	-1.50	-1.05	0.14	2.08	1.06	0.13	2.64	1.14	0.09
γ_{RM}	-0.45	-0.94		-0.54	-0.60		0.12	0.11		-0.02	-0.01		-1.51	-1.84		-1.79	-1.39	
Three Factor																		
Intercept	0.74	1.25	0.26	0.64	0.76	0.26	-0.32	-1.05	0.31	-2.69	-1.50	0.29	2.01	1.04	0.28	1.20	0.72	0.30
γ_{RM}	-0.11	-0.23		0.27	0.30		0.65	0.44		1.28	0.49		-1.55	-2.09		-0.34	-0.40	
γ_{SMB}	-0.15	-0.81		-0.26	-3.21		-0.48	-0.75		-0.56	-0.82		0.70	0.57		0.51	0.47	
γ_{HML}	0.03	0.09		-0.06	-0.16		0.08	0.12		0.21	0.25		-0.83	-1.73		-1.07	-2.36	
Four Factor																		
Intercept	0.52	0.94	0.31	0.13	0.17	0.31	-0.33	-1.26	0.35	-2.68	-1.50	0.33	2.04	1.05	0.35	1.21	0.73	0.36
γ_{RM}	0.12	0.22		0.78	0.80		0.68	0.45		1.28	0.49		-1.51	-2.05		-0.33	-0.39	
γ_{SMB}	-0.14	-0.67		-0.19	-1.28		-0.48	-0.75		-0.55	-0.81		0.63	0.54		0.45	0.44	
γ_{HML}	0.05	0.14		-0.02	-0.06		0.15	0.19		0.27	0.29		-0.67	-1.42		-0.98	-2.23	
γ_{Mom}	0.80	1.18		0.94	1.32		0.01	0.01		-0.06	-0.05		1.07	0.68		1.33	0.78	

4.2.2.5 Cross-Sectional Tests

In addition to the time-series test, I also perform a cross-sectional test to obtain further evidence. I perform cross-sectional Fama-MacBeth (1973) test on the 25 SD portfolios. Gregory, Tharyan, and Christidis (2013) report poor performance of Fama and French (1993) three-factor model in the U.K. equity market, particularly on portfolios that are sorted on standard deviation.

Hence, I report results on standard deviation portfolios to provide further robust evidence for the applicability of gold as a zero-beta asset in the U.K. equity market.

The cross-sectional test is performed from 1981 to 2015 over 420 months. Gregory, Tharyan, and Christidis (2013) methodology is adopted in performing Fama-MacBeth test. Additionally, I perform tests in the sub-periods to obtain further evidence. This study chooses the sub-periods of 5-years (60 months) from 2007 to 2011 and then from 2011 to 2015 to assess the performance of the G-factor models during (2007-2011) and after the financial crisis (2011-2015).

Results are reported in Table (51) for the CAPM, three-factor, four-factor and their zero-beta gold analogues over the full period and sub-periods. Findings show that zero-beta gold analogue of three-factor model performs comparatively better than the traditional model as it produces economically meaningful and plausible (positive) estimate of market risk premium when traditional three-factor model produces implausible (negative) estimate over the full period. Similarly, G-four-factor model performs comparatively better than traditional four-factor when the test is performed over the full period.

When the test is performed in the sub-period of the financial crisis (2007-2011), G-three-factor and G-four-factor models produce higher positive values of the market risk premia than traditional three-factor and four-factor models. Higher risk premia reflect reasonable estimates of the market risk during that time period as equity markets were in the stage of financial recovery and it was reasonable to expect a higher premium for bearing higher risk.

When the cross-sectional test is performed from 2011 to 2015, this study does not find convincing results with any model under investigation. It is surprising that findings also do not report cross-sectional pricing error over the full period or in the sub-period with traditional and zero-beta G-factor models.

4.2.3 Assessing gold return as a zero-beta rate in international markets

After examining the applicability of gold as a zero-beta asset in the U.S. and U.K. equity markets, this study further assesses its applicability in global regions to obtain robust evidence. This study examines its applicability in the Global, North American, European, Japanese and Asia Pacific regions. There are a number of equity markets in those regions and this examination would enable to obtain robust evidence in global regions to find whether gold can be utilised as a zero-beta asset.

4.2.3.1 Gold Betas in Global Markets

I estimate gold betas in global markets to find whether gold beta is equivalent to zero. A zero gold beta would imply that the gold returns are not related to market returns. In other words, zero correlation of gold returns with market returns would protect investors in the case of market volatility or unprecedented market shocks. End of month's London Bullion gold price is used and is expressed in U.S. Dollars. London gold price is used as I have already confirmed from a range of market efficiency tests that the U.K. gold market exhibits weak form efficiency. I use Global, North American, European, Japanese and Asia Pacific market returns to estimate gold betas. I estimate gold betas from 1991-2015 as multiple variance ratio tests for the market efficiency show that global gold markets exhibit greater efficiency from 1990 onwards. Results are shown in Table (52) that confirm that the gold beta is zero in the North American market. Hence, firstly, I examine the applicability of gold as a zero-beta asset in the North American market.

Table 52: Estimation of gold beta in the global, North America, European, Japanese, and Asian Pacific Markets with the regression reports the results of the regression $R_{G,t} - R_{F,t} = \alpha + \beta\left[R_{m,t} - R_{F,t}\right] + e_{i,t}$. Sample period of January 1991 to December 2015 is used.

	Gold Beta	t-stat
Global	0.13	2.11
North America	0.05	0.76
Europe	0.11	2.15
Japan	0.12	2.54
Asia Pacific	0.19	4.57

4.2.3.2 Descriptive Analysis

After finding that gold has a zero beta only in the North American region, I assess the application of gold return as a proxy of the zero-beta rate in North America. Firstly, I perform descriptive analysis of gold price factor with the market and empirical factors. I use market (*MKT*) size (*SMB)*, value (*HML)*, momentum (*MOM)*, investment (*CMA)* and profitability (*RMW)* that are obtained from the Ken French website. I use these factors as I examine the empirical performance of five empirical asset pricing models such as CAPM, three-factor, four-factor, five-factor, six-factor and their analogues where I use gold as a zero-beta asset. Summary statistics in Table (53) show that gold mean is closer to the mean of 1-month Treasury bill yield but shows higher standard deviation as it exhibits higher volatility. I estimate models in absence of risk-free rate in spirit of Black, Jensen, and Scholes (1972) as they estimate their two-factor model without risk-free rate and assume that risk-free rate does not exist. Correlation matrix in *Panel B* of Table (53) shows that gold shows nearly zero correlation with the market (0.04) and very weak correlation with empirical factors, for instance it shows 0.16 with size *(SMB),* -0.06 with value (*HML*), 0.08 with momentum (*MOM*), -0.10 with operating profitability (*RMW*) and -0.07 with investment prices factor (*CMA*).

Table 53: Summary statistics for the returns on gold, Treasury bills, Fama-French, and Carhart (Momentum) factors in the North American market, January 1991-December 2015. Panel A reports average monthly returns, standard deviation, kurtosis, skewness, t-mean (ratio of the mean to its standard error), Panel B reports correlations among the factor returns.

North America									
Panel A	R_g	$R_g - R_F$	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
Mean	0.34	0.11	0.67	0.23	0.21	0.23	0.65	0.33	0.28
Std	4.53	4.55	4.27	0.18	2.81	3.28	4.91	2.47	2.69
Kurtosis	1.64	1.53	1.66	-1.54	4.83	4.86	8.43	9.39	4.96
Skewness	-0.11	-0.06	-0.72	0.00	0.33	0.57	-0.19	0.14	0.99
t-mean	1.29	0.42	2.72	21.77	1.26	1.21	2.29	2.34	1.80
Obs.	300	300	300	300	300	300	300	300	300
Correlations									
Panel B	R_g	$R_g - R_F$	$R_m - R_F$	R_f	*SMB*	*HML*	*MOM*	*RMW*	*CMA*
R_g	1.00								
$R_g - R_F$	1.00	1.00							
$R_m - R_F$	0.04	0.04	1.00						
R_f	-0.05	-0.09	0.00	1.00					
SMB	0.16	0.16	0.18	-0.04	1.00				
HML	-0.06	-0.06	-0.24	0.06	-0.13	1.00			
MOM	0.08	0.08	-0.14	0.06	0.18	-0.25	1.00		
RMW	-0.10	-0.10	-0.39	0.06	-0.41	0.43	-0.05	1.00	
CMA	-0.07	-0.07	-0.43	0.04	-0.16	0.79	-0.09	0.38	1.00

4.2.3.3 Time Series Tests

After descriptive analysis, I perform time-series tests. I use the 25 portfolios sorted on size and book-to-market ratios and the 25 portfolios sorted on size and momentum as test portfolios in the North American region. Test portfolios are also obtained from Ken French website. I follow the methodology detailed in Fama and French (1993, 2012 and 2015) and report alphas, t-statistics, and R-squared from time series regressions for the CAPM, three-factor, four-factor, and five-factor and six-factor model and their analogues where I use gold as a zero-beta asset. Significant alpha is the pricing error and R-squared is the coefficient of determination that explains the goodness of model fit. Tables (54) shows time-series results for the 25 size and book-to-market portfolios. Results with 1-month Treasury bill yield and gold as a zero-beta asset are reported in two separate columns. Findings show that when I use gold as a zero-beta asset, the R-squared of the model improves that signifies better performance of the model. Further, the number of significant alphas (pricing errors) are also reduced. For instance, I find four significant alphas in the G-four factor, six significant alphas in the G-five-factor and three significant alphas in the G-six-factor model as compared to the five significant alphas in the four-factor model, seven significant alphas in the five-factor model and five significant alphas in the six-factor model.

Table (55) shows time series results on the 25 size and momentum portfolios. Table (55) shows similar results in favour of gold as a zero-beta asset as I find high R-squared and less pricing errors when I use the 25 SM portfolios. For instance, I find four significant alphas with the G-four-factor as compared to the five significant alphas with the traditional four-factor, six-significant alphas with G-five-factor as compared to the seven significant alphas with the traditional five-factor and three significant alphas with G-six-factor model as compared to the five pricing errors with the five-factor model. Improvement in the R-squared can be noticed in each model as well.

Tables (56) and (57) report summary of Gibbon, Ross and Shaken (1989, GRS) tests on the *25 SBM* and *25 SM* portfolios. GRS test statistics, average standard errors of alphas *s(a)*, absolute alphas $|a|$, R-squared, and Sharpe ratios of alphas *SR(a)*. Lower GRS test statistic, lower *SR(a)*, lower absolute alphas $|a|$ and higher R-squared signify better performance of the models. I employ global and local factors to deeply assess model performance with 1-month Treasury bill yield and gold as a zero-beta asset. Further, I perform GRS tests with (5x5) and with (4x5) microcaps to examine whether usability of gold as a zero-beta asset helps to improve pricing of small stocks as Fama and French (2012, 2015) admit the difficulty in pricing small stocks with traditional empirical factor models.

Results in Table (56) shows that when I use gold as a zero-beta asset on the 25 SBM portfolios, I obtain lower values of GRS, $|a|$, and *SR(a)* as compared to the models in which I use 1-month Treasury bill yield. Further improvement in the R-squared models is also noticed. Superior performance of gold as a zero-beta asset is reported on both global and local factors on 25 SBM portfolios in North American region. Similar findings are obtained in Table (57) on 25 SM portfolio as model performance of G-CAPM, G-three-factor and G-four-factor is considerably better than traditional CAPM, three-factor, and four-factor models as zero-beta gold analogues produces lower GRS, lower *SR(a),* and higher R-squared values. However, traditional five-factor and six-factor models perform better than their gold analogues on 25 SM portfolios in North American region.

Table 54: Alphas from the CAPM, G-CAPM, three-factor, G-three-factor, four-factor, G-four-factor, five-factor, G-five-factor, six-factor and G-six-factor regressions on the *25 Size and Book-to-market* portfolios in the North American market, January 1991- December 2015. The table reports Alphas (α), t-statistics t(α) and adjusted R-squared of the tested models.

	Return on T-Bills as R_f														
	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
	CAPM														
Small	-0.45	-0.19	0.20	0.26	0.56	-1.41	-0.76	0.94	1.35	2.97	0.54	0.62	0.64	0.63	0.64
2.00	-0.61	-0.15	0.11	0.17	0.20	-2.40	-0.68	0.65	1.21	1.20	0.65	0.66	0.72	0.77	0.68
3.00	-0.07	-0.12	0.10	0.12	0.29	-0.31	-0.74	0.85	0.95	2.08	0.67	0.78	0.83	0.78	0.75
4.00	-0.05	-0.06	0.15	0.14	0.22	-0.26	-0.52	1.48	1.11	1.61	0.72	0.86	0.85	0.79	0.77
Big	-0.03	-0.01	0.00	0.06	-0.15	-0.26	-0.08	-0.01	0.51	-1.02	0.83	0.91	0.89	0.80	0.78
	Three-Factor CAPM														
Small	-0.38	-0.18	0.11	0.11	0.30	-2.51	-1.60	1.20	1.42	4.05	0.90	0.92	0.93	0.94	0.94
2.00	-0.45	-0.14	0.00	-0.02	-0.10	-4.30	-1.54	-0.05	-0.37	-1.74	0.94	0.95	0.95	0.95	0.96
3.00	0.06	-0.14	-0.01	-0.08	0.04	0.61	-1.45	-0.12	-0.92	0.62	0.94	0.92	0.92	0.91	0.94
4.00	0.14	-0.07	0.04	-0.03	-0.02	1.27	-0.82	0.47	-0.37	-0.28	0.91	0.92	0.90	0.88	0.93
Big	0.16	0.03	-0.06	-0.07	-0.34	2.53	0.43	-0.88	-0.88	-3.54	0.94	0.92	0.92	0.91	0.91
	Four-Factor CAPM														
Small	-0.36	-0.16	0.12	0.12	0.28	-2.31	-1.33	1.22	1.55	3.68	0.90	0.92	0.93	0.94	0.94
2.00	-0.33	-0.11	0.01	0.01	-0.09	-3.36	-1.19	0.12	0.13	-1.45	0.95	0.95	0.95	0.95	0.96
3.00	0.00	-0.11	0.03	-0.02	0.05	0.02	-1.09	0.35	-0.24	0.73	0.94	0.92	0.93	0.92	0.94
4.00	0.12	-0.03	0.05	0.00	0.02	1.04	-0.34	0.60	0.04	0.32	0.91	0.92	0.90	0.88	0.93
Big	0.18	0.02	-0.02	-0.03	-0.28	2.75	0.27	-0.32	-0.45	-2.95	0.94	0.92	0.92	0.91	0.91
	Five-Factor CAPM														
Small	-0.08	-0.03	0.23	0.20	0.36	-0.60	-0.27	2.54	2.59	4.72	0.92	0.92	0.94	0.95	0.95
2.00	-0.27	-0.01	-0.02	-0.04	-0.16	-2.66	-0.12	-0.32	-0.61	-2.64	0.95	0.95	0.95	0.95	0.96
3.00	0.16	-0.10	-0.06	-0.17	-0.01	1.52	-1.02	-0.78	-2.04	-0.14	0.94	0.92	0.93	0.92	0.94
4.00	0.29	-0.01	-0.02	-0.15	-0.07	2.58	-0.12	-0.29	-1.61	-0.89	0.92	0.92	0.91	0.89	0.93
Big	0.06	-0.03	-0.04	-0.01	-0.17	0.99	-0.44	-0.53	-0.10	-1.85	0.95	0.93	0.92	0.91	0.92
	Six-Factor CAPM														
Small	-0.08	-0.02	0.23	0.20	0.34	-0.59	-0.16	2.47	2.63	4.41	0.92	0.92	0.94	0.95	0.95
2.00	-0.19	0.01	-0.01	-0.01	-0.14	-1.97	0.06	-0.15	-0.22	-2.34	0.95	0.95	0.95	0.95	0.96
3.00	0.11	-0.08	-0.03	-0.12	0.00	1.01	-0.79	-0.37	-1.45	0.01	0.94	0.93	0.93	0.92	0.94
4.00	0.26	0.02	-0.01	-0.11	-0.03	2.31	0.19	-0.12	-1.21	-0.38	0.92	0.92	0.91	0.90	0.93
Big	0.08	-0.03	-0.01	0.01	-0.14	1.30	-0.49	-0.11	0.18	-1.49	0.95	0.92	0.92	0.91	0.92

	Gold as a zero beta asset														
	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
	G-CAPM														
Small	-0.23	-0.03	0.31	0.30	0.58	-0.69	-0.12	1.41	1.56	3.12	0.57	0.67	0.73	0.76	0.77
2.00	-0.41	0.00	0.17	0.19	0.23	-1.55	-0.02	1.00	1.38	1.35	0.69	0.72	0.81	0.86	0.80
3.00	0.11	0.00	0.16	0.13	0.30	0.45	-0.02	1.28	1.06	2.15	0.71	0.83	0.89	0.87	0.86
4.00	0.09	0.01	0.17	0.15	0.21	0.44	0.06	1.71	1.25	1.58	0.78	0.91	0.92	0.88	0.87
Big	-0.05	-0.04	-0.01	0.00	-0.13	-0.44	-0.53	-0.18	0.00	-0.91	0.91	0.95	0.94	0.90	0.87
	G-Three-Factor														
Small	-0.33	-0.16	0.11	0.07	0.27	-2.19	-1.37	1.18	0.83	3.69	0.91	0.93	0.95	0.96	0.96
2.00	-0.40	-0.11	-0.02	-0.03	-0.09	-3.81	-1.29	-0.27	-0.55	-1.53	0.95	0.96	0.97	0.97	0.98
3.00	0.11	-0.10	0.01	-0.06	0.06	1.08	-1.00	0.14	-0.80	0.80	0.95	0.94	0.95	0.95	0.96
4.00	0.19	-0.05	0.06	0.00	0.00	1.64	-0.54	0.68	0.04	0.05	0.94	0.95	0.95	0.93	0.96
Big	0.13	0.01	-0.05	-0.08	-0.26	2.05	0.12	-0.69	-1.02	-2.64	0.97	0.96	0.96	0.96	0.94
	G-Four-Factor														
Small	-0.30	-0.13	0.11	0.07	0.25	-1.96	-1.09	1.20	0.86	3.32	0.91	0.93	0.95	0.96	0.96
2.00	-0.29	-0.08	-0.01	-0.01	-0.07	-2.95	-0.94	-0.17	-0.14	-1.23	0.96	0.96	0.97	0.97	0.98
3.00	0.07	-0.06	0.05	-0.01	0.07	0.66	-0.60	0.62	-0.14	0.94	0.95	0.94	0.95	0.95	0.96
4.00	0.17	-0.01	0.07	0.05	0.05	1.50	-0.07	0.87	0.52	0.64	0.94	0.95	0.95	0.93	0.96
Big	0.14	0.00	-0.01	-0.05	-0.20	2.13	-0.07	-0.13	-0.67	-2.04	0.97	0.96	0.96	0.96	0.94
	G-Five-Factor														
Small	-0.08	-0.03	0.20	0.11	0.30	-0.58	-0.26	2.22	1.38	4.00	0.93	0.94	0.96	0.96	0.96
2.00	-0.25	-0.01	-0.04	-0.05	-0.12	-2.52	-0.07	-0.54	-0.86	-2.01	0.96	0.96	0.97	0.97	0.98
3.00	0.21	-0.05	-0.02	-0.13	0.03	2.07	-0.55	-0.26	-1.57	0.38	0.95	0.95	0.96	0.95	0.96
4.00	0.32	0.00	0.02	-0.06	-0.02	2.89	0.05	0.25	-0.65	-0.21	0.94	0.95	0.95	0.94	0.96
Big	0.04	-0.04	-0.02	-0.04	-0.10	0.63	-0.64	-0.32	-0.55	-1.12	0.98	0.96	0.96	0.96	0.95
	G-Six-Factor														
Small	-0.08	-0.02	0.20	0.11	0.28	-0.56	-0.14	2.14	1.37	3.70	0.93	0.94	0.96	0.96	0.96
2.00	-0.18	0.01	-0.03	-0.03	-0.10	-1.91	0.10	-0.41	-0.52	-1.73	0.96	0.96	0.97	0.97	0.98
3.00	0.17	-0.03	0.01	-0.08	0.04	1.66	-0.31	0.14	-1.01	0.53	0.95	0.95	0.96	0.96	0.96
4.00	0.30	0.03	0.04	-0.02	0.02	2.66	0.33	0.43	-0.22	0.27	0.94	0.95	0.95	0.94	0.96
Big	0.05	-0.05	0.01	-0.03	-0.07	0.87	-0.69	0.08	-0.33	-0.79	0.98	0.96	0.96	0.96	0.95

Table 55: Alphas from the CAPM, G-CAPM, three-factor, G-three-factor, four-factor, G-four-factor, five-factor, G-five-factor, six-factor and G-six-factor regressions on the *25 Size and Momentum* portfolios in the North American market, January 1991- December 2015. The table reports Alphas (α), t-statistics t(α) and adjusted R-squared of the tested models.

Return on T-Bills as R_f

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
CAPM															
Small	-0.58	0.26	0.52	0.76	0.94	-2.20	1.61	3.27	4.00	3.56	0.64	0.69	0.66	0.61	0.56
2.00	-0.60	0.18	0.21	0.34	0.49	-2.48	1.17	1.43	2.16	1.78	0.70	0.73	0.73	0.69	0.56
3.00	-0.50	0.03	0.24	0.30	0.36	-2.23	0.23	1.93	2.14	1.44	0.71	0.78	0.79	0.74	0.58
4.00	-0.50	0.11	0.25	0.19	0.44	-2.21	0.89	2.61	1.84	1.87	0.70	0.80	0.85	0.84	0.58
Big	-0.50	-0.05	-0.01	0.18	0.26	-2.46	-0.42	-0.16	1.74	1.21	0.69	0.80	0.83	0.82	0.59
Three-Factor CAPM															
Small	-0.75	0.05	0.33	0.61	0.88	-3.72	0.61	4.12	5.87	5.23	0.79	0.91	0.92	0.88	0.82
2.00	-0.75	-0.02	0.02	0.19	0.47	-3.63	-0.24	0.27	2.05	2.75	0.79	0.90	0.91	0.90	0.83
3.00	-0.62	-0.14	0.07	0.16	0.37	-2.92	-1.27	0.81	1.69	2.15	0.75	0.87	0.90	0.88	0.80
4.00	-0.62	-0.04	0.13	0.12	0.47	-2.80	-0.38	1.69	1.26	2.46	0.72	0.87	0.90	0.87	0.73
Big	-0.52	-0.09	-0.04	0.18	0.38	-2.59	-0.88	-0.53	1.86	1.89	0.70	0.84	0.88	0.83	0.67
Four-Factor CAPM															
Small	-0.22	0.20	0.33	0.48	0.53	-1.88	2.52	4.03	4.92	4.08	0.93	0.93	0.92	0.90	0.90
2.00	-0.16	0.17	0.05	0.06	0.00	-1.71	2.25	0.60	0.77	0.04	0.96	0.94	0.91	0.92	0.95
3.00	-0.04	0.09	0.10	0.00	-0.08	-0.36	1.04	1.11	0.00	-0.72	0.93	0.92	0.90	0.91	0.93
4.00	-0.01	0.17	0.15	-0.03	-0.03	-0.11	2.22	1.84	-0.36	-0.31	0.93	0.92	0.90	0.90	0.91
Big	0.03	0.12	-0.05	-0.04	-0.18	0.26	1.49	-0.60	-0.53	-1.86	0.92	0.91	0.87	0.92	0.92
Five-Factor CAPM															
Small	-0.43	0.05	0.34	0.64	1.00	-2.17	0.56	4.05	6.01	5.75	0.81	0.91	0.92	0.89	0.83
2.00	-0.51	-0.08	-0.08	0.07	0.49	-2.47	-0.85	-0.97	0.72	2.72	0.80	0.90	0.92	0.90	0.83
3.00	-0.40	-0.21	-0.02	0.02	0.31	-1.86	-1.92	-0.27	0.23	1.74	0.76	0.87	0.91	0.89	0.80
4.00	-0.41	-0.11	0.03	0.01	0.43	-1.83	-1.10	0.34	0.12	2.15	0.72	0.87	0.91	0.88	0.73
Big	-0.30	-0.10	-0.09	0.02	0.40	-1.48	-0.98	-1.02	0.26	1.93	0.71	0.84	0.88	0.85	0.67
Six-Factor CAPM															
Small	-0.03	0.17	0.34	0.54	0.71	-0.24	2.09	3.99	5.43	5.51	0.94	0.93	0.92	0.90	0.91
2.00	-0.05	0.07	-0.05	-0.02	0.11	-0.60	1.01	-0.62	-0.29	1.18	0.96	0.94	0.92	0.92	0.96
3.00	0.05	-0.03	0.00	-0.10	-0.04	0.46	-0.32	0.04	-1.21	-0.41	0.93	0.93	0.91	0.92	0.93
4.00	0.06	0.06	0.04	-0.10	0.02	0.52	0.80	0.56	-1.21	0.21	0.93	0.93	0.91	0.91	0.91
Big	0.13	0.07	-0.09	-0.14	-0.05	1.15	0.85	-1.04	-2.05	-0.56	0.92	0.91	0.88	0.92	0.93

Gold as a zero beta asset

	α					t(α)					R^2				
	Low	2	3	4	High	Low	2	3	4	High	Low	2	3	4	High
G-CAPM															
Small	-0.38	0.27	0.50	0.76	1.07	-1.40	1.68	3.17	4.08	4.02	0.68	0.82	0.81	0.75	0.63
2.00	-0.40	0.20	0.20	0.34	0.64	-1.53	1.31	1.42	2.17	2.30	0.73	0.84	0.85	0.82	0.63
3.00	-0.32	0.05	0.24	0.30	0.49	-1.36	0.40	1.99	2.16	1.95	0.75	0.87	0.88	0.85	0.65
4.00	-0.34	0.10	0.22	0.18	0.53	-1.44	0.81	2.38	1.80	2.25	0.75	0.90	0.93	0.91	0.68
Big	-0.43	-0.09	-0.09	0.12	0.31	-2.13	-0.80	-0.89	1.20	1.43	0.80	0.90	0.92	0.91	0.72
G-Three-Factor															
Small	-0.63	0.03	0.26	0.55	0.90	-3.03	0.30	3.13	5.05	5.39	0.82	0.94	0.95	0.92	0.86
2.00	-0.60	-0.03	-0.01	0.14	0.50	-2.79	-0.29	-0.15	1.46	2.92	0.82	0.94	0.95	0.94	0.86
3.00	-0.47	-0.12	0.07	0.13	0.40	-2.11	-1.08	0.79	1.33	2.31	0.79	0.92	0.94	0.93	0.84
4.00	-0.45	-0.03	0.12	0.10	0.47	-1.96	-0.31	1.53	1.07	2.49	0.77	0.93	0.95	0.93	0.80
Big	-0.43	-0.10	-0.08	0.15	0.37	-2.10	-0.99	-1.03	1.51	1.86	0.80	0.92	0.94	0.92	0.77
G-Four-Factor															
Small	-0.14	0.15	0.25	0.42	0.60	-1.19	1.85	2.94	4.19	4.57	0.94	0.96	0.95	0.93	0.91
2.00	-0.06	0.14	0.00	0.02	0.10	-0.56	1.84	0.05	0.23	0.99	0.96	0.96	0.95	0.95	0.96
3.00	0.07	0.08	0.09	-0.02	0.01	0.57	1.01	1.08	-0.24	0.12	0.94	0.95	0.94	0.95	0.94
4.00	0.11	0.15	0.13	-0.03	0.03	0.89	1.99	1.65	-0.39	0.30	0.94	0.96	0.95	0.95	0.93
Big	0.07	0.08	-0.10	-0.05	-0.12	0.63	1.00	-1.16	-0.71	-1.22	0.95	0.95	0.94	0.96	0.94
G-Five-Factor															
Small	-0.34	0.01	0.23	0.53	1.00	-1.71	0.13	2.70	4.92	5.91	0.84	0.94	0.95	0.92	0.86
2.00	-0.35	-0.08	-0.11	0.02	0.53	-1.70	-0.82	-1.38	0.23	3.03	0.84	0.94	0.95	0.94	0.86
3.00	-0.23	-0.16	-0.01	0.01	0.37	-1.07	-1.49	-0.07	0.09	2.13	0.81	0.92	0.95	0.93	0.84
4.00	-0.21	-0.08	0.03	0.01	0.45	-0.94	-0.81	0.42	0.10	2.29	0.79	0.93	0.95	0.94	0.80
Big	-0.22	-0.11	-0.14	0.02	0.37	-1.11	-1.07	-1.69	0.18	1.85	0.81	0.92	0.95	0.93	0.77
G-Six-Factor															
Small	0.02	0.11	0.22	0.43	0.75	0.18	1.39	2.60	4.38	5.97	0.95	0.96	0.95	0.94	0.93
2.00	0.05	0.06	-0.09	-0.06	0.21	0.54	0.81	-1.11	-0.71	2.24	0.97	0.97	0.95	0.95	0.96
3.00	0.17	0.00	0.02	-0.10	0.07	1.47	0.00	0.24	-1.20	0.66	0.95	0.96	0.95	0.95	0.94
4.00	0.21	0.07	0.05	-0.08	0.10	1.72	0.95	0.64	-1.07	0.88	0.94	0.96	0.95	0.95	0.93
Big	0.15	0.04	-0.14	-0.13	-0.02	1.41	0.46	-1.72	-1.87	-0.20	0.95	0.96	0.94	0.96	0.95

Table 56: Statistical summary to explain regressions of monthly excess returns. The regressions have used the CAPM, G-CAPM, three-factor, G-three-factor, four-factor, G-four-factor, five-factor, G-five-factor, six- factor, and G-six-factor models to explain returns on the *25 Size and Book-to-market* portfolios in North American market using global and local factors with (5x5) and without (4x5) microcaps: January 1991 to December 2015. The GRS statistic tests whether all alphas of 25 (5x5) or 20 (4x5) portfolios are jointly zero.$|a|$ is the average absolute alpha for a set of regression of 25 or 20 portfolios; R^2 is the mean adjusted R^2; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the Sharpe ratio of intercepts. The critical values for GRS statistic are: 90%: 1.45; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25.

	Global Factors										Local Factors									
	5 x 5					4 x 5					5 x 5					4 x 5				
	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$
Return on T-Bills as R_f																				
CAPM	3.38	0.66	0.19	0.30	0.56	1.96	0.68	0.17	0.28	0.38	3.18	0.74	0.16	0.18	0.55	1.61	0.77	0.15	0.141	0.34
Three Factor	3.25	0.77	0.15	0.27	0.56	2.72	0.77	0.15	0.26	0.45	2.96	0.93	0.09	0.12	0.53	2.40	0.93	0.08	0.101	0.42
Four Factor	2.61	0.77	0.16	0.29	0.52	2.25	0.77	0.15	0.29	0.42	2.57	0.93	0.09	0.10	0.51	1.94	0.93	0.08	0.076	0.39
Five Factor	2.95	0.78	0.16	0.44	0.57	3.02	0.78	0.15	0.38	0.51	2.54	0.93	0.09	0.11	0.51	1.71	0.93	0.08	0.093	0.37
Six Factor	2.62	0.78	0.16	0.44	0.54	2.67	0.78	0.16	0.40	0.49	2.32	0.93	0.09	0.09	0.50	1.43	0.93	0.08	0.07	0.35
Gold as a zero beta asset																				
G-CAPM	2.59	0.77	0.19	0.29	0.49	1.49	0.80	0.18	0.27	0.33	2.49	0.82	0.17	0.16	0.48	1.21	0.85	0.15	0.129	0.30
G-Three-Factor	2.51	0.85	0.15	0.26	0.49	1.98	0.86	0.15	0.25	0.38	2.32	0.95	0.09	0.11	0.47	1.70	0.95	0.08	0.091	0.35
G-Four-Factor	1.95	0.85	0.16	0.27	0.44	1.54	0.86	0.15	0.26	0.35	2.00	0.95	0.09	0.09	0.44	1.34	0.96	0.08	0.074	0.32
G-Five-Factor	2.27	0.86	0.16	0.35	0.48	2.18	0.87	0.15	0.29	0.42	2.01	0.96	0.09	0.09	0.45	1.24	0.96	0.08	0.079	0.31
G-Six-Factor	1.98	0.86	0.16	0.34	0.46	1.86	0.87	0.15	0.30	0.39	1.82	0.96	0.09	0.08	0.43	1.02	0.96	0.08	0.065	0.28

Table 57 Statistical summary to explain regressions of monthly excess returns. The regressions have used the CAPM, G-CAPM, three-factor, G-three-factor, four-factor, G-four-factor, five-factor, G-five-factor, six- factor, and G-six-factor models to explain returns on the *25 Size and Momentum* portfolios in North American market using global and local factors with (5x5) and without (4x5) microcaps: January 1991 to December 2015. The GRS statistic tests whether all alphas of 25 (5x5) or 20 (4x5) portfolios are jointly zero.$|a|$ is the average absolute alpha for a set of regression of 25 or 20 portfolios; R^2 is the mean adjusted R^2; $s(a)$ is the mean standard error of alphas; and $SR(a)$ is the Sharpe ratio of intercepts. The critical values for GRS statistic are: 90%: 1.45; 95%: 1.56; 97.5%: 1.69; 99%: 1.86 and 99.9%: 2.25.

	Global Factors										Local Factors									
	5 x 5					4 x 5					5 x 5					4 x 5				
	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$	GRS	R^2	$s(a)$	$\|a\|$	$SR(a)$
Return on T-Bills as R_f																				
CAPM	4.05	0.63	0.20	0.46	0.61	1.83	0.64	0.19	0.40	0.36	3.74	0.71	0.18	0.35	0.59	1.61	0.73	0.17	0.287	0.34
Three Factor	3.63	0.69	0.18	0.44	0.59	1.53	0.69	0.18	0.39	0.34	3.58	0.83	0.13	0.32	0.58	1.38	0.83	0.13	0.271	0.32
Four Factor	3.05	0.77	0.16	0.36	0.56	1.53	0.77	0.16	0.32	0.35	3.13	0.92	0.09	0.13	0.56	1.32	0.92	0.09	0.078	0.32
Five Factor	3.12	0.70	0.19	0.45	0.59	1.55	0.70	0.19	0.38	0.37	3.25	0.84	0.14	0.26	0.58	0.91	0.83	0.14	0.206	0.27
Six Factor	2.90	0.78	0.16	0.46	0.57	1.70	0.78	0.16	0.40	0.39	2.96	0.92	0.09	0.12	0.56	1.16	0.92	0.09	0.065	0.31
Gold as a zero beta asset																				
G-CAPM	3.61	0.75	0.20	0.43	0.58	1.52	0.76	0.19	0.36	0.33	3.34	0.80	0.18	0.34	0.55	1.31	0.81	0.17	0.281	0.31
G-Three-Factor	3.34	0.80	0.18	0.40	0.56	1.33	0.80	0.18	0.35	0.31	3.24	0.89	0.13	0.28	0.55	1.13	0.88	0.14	0.237	0.29
G-Four-Factor	2.88	0.85	0.16	0.34	0.54	1.40	0.86	0.16	0.30	0.33	2.89	0.95	0.09	0.12	0.53	1.15	0.95	0.09	0.073	0.30
G-Five-Factor	3.42	0.81	0.18	0.37	0.59	1.88	0.81	0.18	0.31	0.39	3.26	0.89	0.13	0.23	0.57	1.02	0.89	0.13	0.176	0.28
G-Six-Factor	3.21	0.86	0.16	0.37	0.58	2.02	0.86	0.16	0.32	0.41	3.03	0.95	0.09	0.13	0.55	1.29	0.95	0.09	0.09	0.32

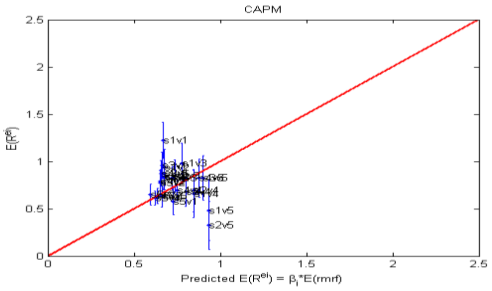
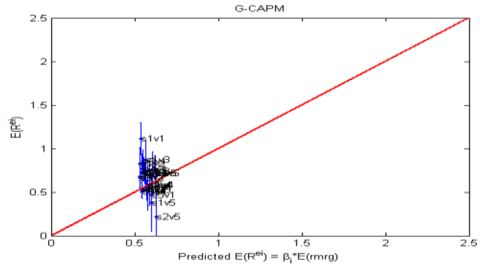
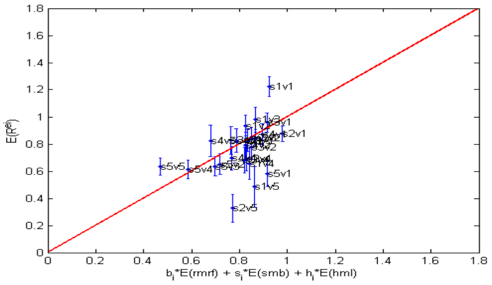
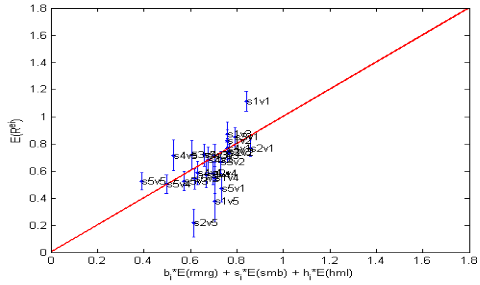
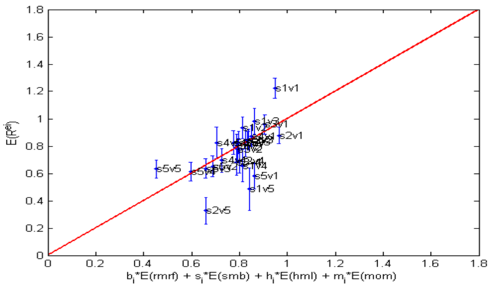
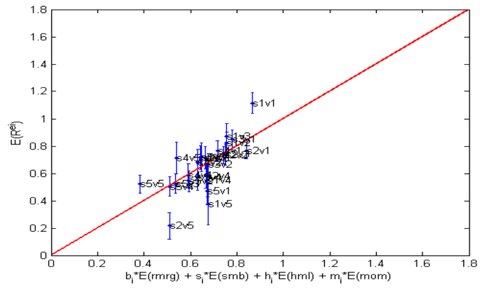
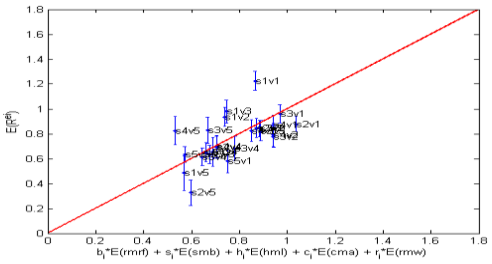
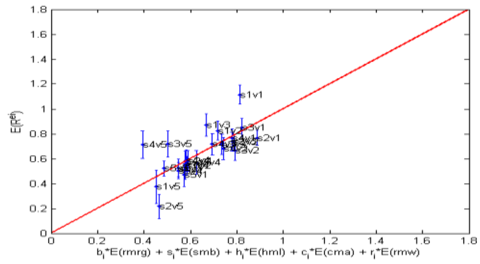
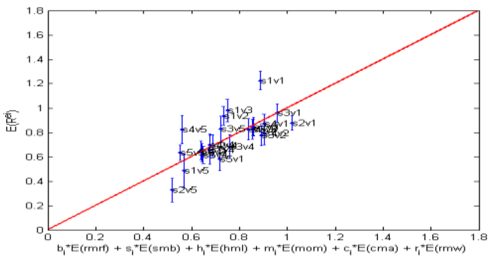
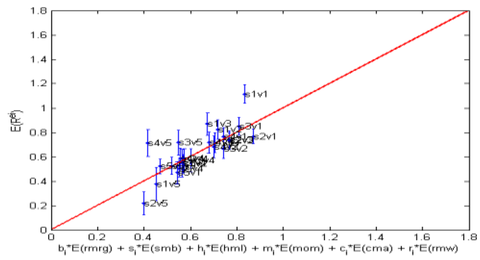
	T-Bill Rate as a risk-free rate	Gold as a zero-beta asset
CAPM		
Three-Factor		
Four-Factor		
Five-Factor		
Six-Factor		

Figure 23: Actual and predicted returns with the CAPM, three-factor, four-factor, five-factor, six-factor and their analogues, G-CAPM, G-three-factor, G-four-factor, G-five-factor, and G-six factor models on the *25 Size and Book-to-market* Portfolios

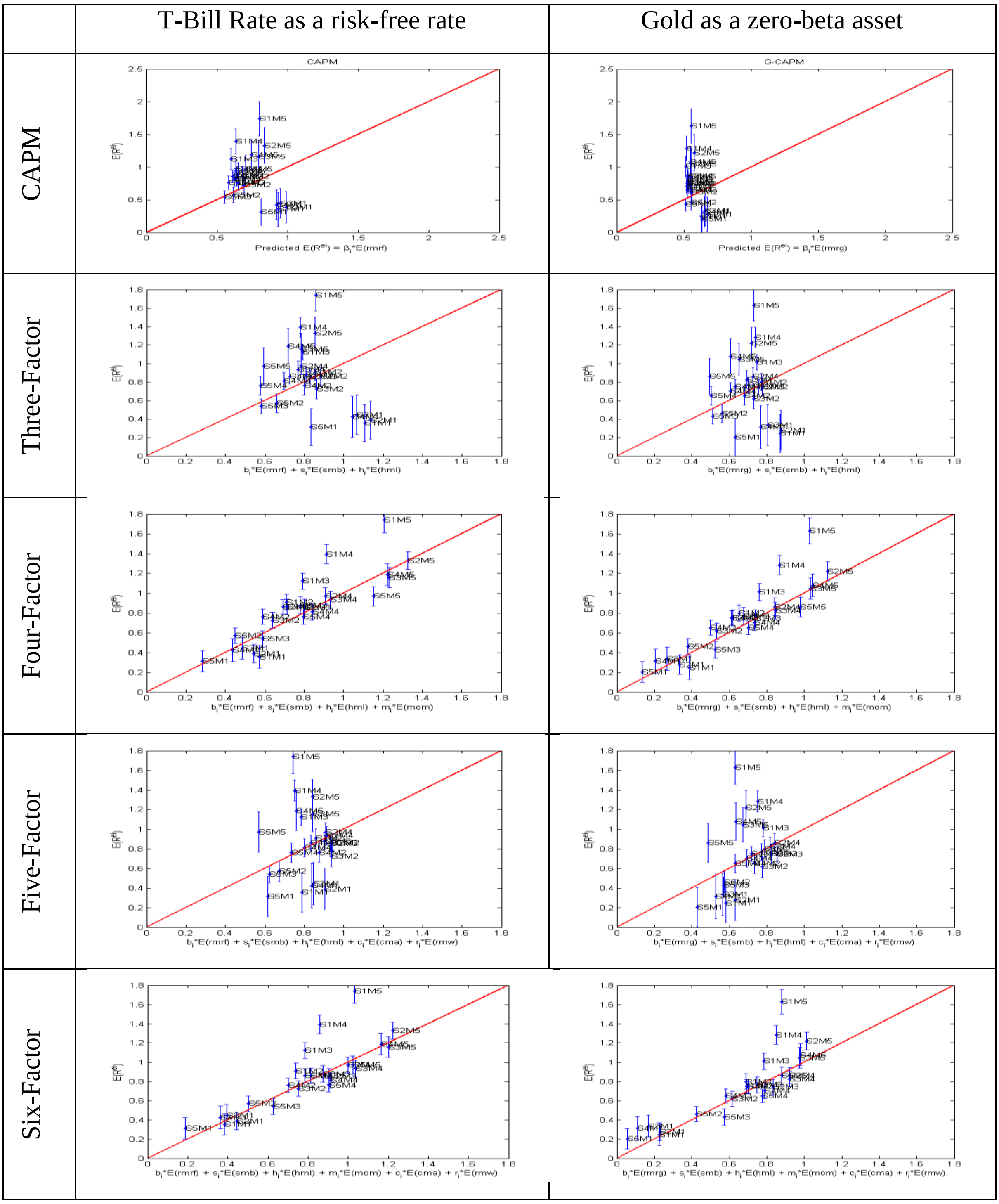


Figure 24: Actual and predicted returns with the CAPM, three-factor, four-factor, five-factor, six-factor and their analogues, G-CAPM, G-three-factor, G-four-factor, G-five-factor, and G-six factor models on the 25 *Size and Momentum* portfolios in the North American region

Figure (23) and (24) show the performance of the empirical factor models in the North American region on the 25 size and book to market portfolios and the 25 size and momentum portfolios. Standard error bars show that the gold zero-beta models predict actual average returns better than their traditional versions.

4.2.3.4 Cross-Sectional Tests

After performing time-series tests, I perform Fama-MacBeth (1973) cross-sectional tests over the above mentioned five asset pricing models on 25 SBM and 25 SM portfolios. Results are reported in Tables (58) – (61). I report the average cross-sectional coefficient (γ), t-statistic (*t-stat*), and adjusted cross-sectional R-squared from the Fama-MacBeth procedure. I perform cross-sectional tests on both global and local factors. I also perform sub-period cross-sectional test from 2003 to 2015 in addition to the full period test (1991 to 2015).

Table (58) reports results on the 25 SBM portfolios when global factors are used in the North American region. Similar to time series results, I find similar evidence in cross-section as gold zero-beta models perform outperform traditional models. For instance, traditional four-factor and five-factor models produce significant cross-sectional pricing errors that disappear with the G-four-factor and G-five-factor models when Fama-MacBeth tests are performed over the full period. Further, G-four-factor produces positive estimates of market coefficients as compared to the traditional four-factor model that produces a negative implausible estimate of market risk premium. In the sub-period, traditional models and their gold zero beta analogues produce comparative and similar results.

Table (59) shows results on 25 SBM portfolios in the North American region when local factors are used. Again gold zero-beta models produce better results. When Fama-MacBeth test is performed over the full-period (1991-2015), the traditional four-factor and six-factor models produce significant cross-sectional alphas (pricing errors) whereas these pricing errors are not produced with the G-four-factor and G-six-factor models. Traditional and their zero-beta gold analogues both perform comparatively better when cross-sectional tests are performed in the sub-period as traditional four-,five-,six-factor models and their zero-beta gold analogues, G-four-, G-five-, and G-six factor models produce an economically meaningful estimate of market risk premia.

Table (60) shows results on 25 SM portfolios with global factors in the North American region. Findings show that gold zero-beta models also perform better on 25 SM portfolios. For instance, the traditional five-factor model produces significant cross-sectional alpha when the cross-sectional test is performed over the full period from 1991 to 2015. Whereas, its zero-beta gold analogue G-four-factor model produces insignificant cross-sectional alpha. When this test is performed in the sub-period, traditional three-factor and four-factor models produce significant cross-sectional alphas at 5% significance level whereas six-factor model produces significant cross-sectional alpha at the 10% significance level. On the other hand, their zero-beta gold analogues produce insignificant cross-sectional alphas implying that pricing errors disappear with their corresponding zero-beta gold analogues.

Table (61) shows results on the 25 SM portfolios with local factors in cross-sectional tests. Six-factor model outperforms gold zero-beta model in the full-period and sub-period tests implying superior performance of the six-factor model in cross-section. These results are consistent with time-series tests as is shown in Table (57). However, G-three-factor, G-four-factor, and G-five-factor models outperform traditional three-factor, four-factor, and five-factor models in cross-section. For instance, G-three-factor and G-four-factor models produce insignificant cross-sectional alphas as compared to traditional three-factor and four-factor models that produce significant cross-sectional alphas (pricing errors) when Fama MacBeth (1973) test is performed from 2003- 2015. In the full-period, similar results are produced with these models. When this test is performed in the full-period (1991 to 2015), the traditional five-factor model produces significant cross-sectional alpha at the 5% significance level, and at the 10% level in the sub-period (2003-2015). However, its zero-beta gold analogue produces insignificant cross-sectional alpha implying better performance of G-five-factor model than the traditional five-factor model in cross-section.

Table 58: Fama-MacBeth Tests with the *25 Size and Book-to-market* portfolios in the North American market by using global factors in the full-period, January 1991-December 2015, and sub-period, January 2003-December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. γ is the average coefficient, t-stat is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as R_f			Gold as a zero beta asset			Return on T-Bills as R_f			Gold as a zero beta asset		
	1991-2015			1991-2015			2003-2015			2003-2015		
	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2
CAPM												
Intercept	1.18	1.81	0.28	1.76	1.25	0.24	0.60	1.07	0.24	-0.14	-0.12	0.20
γ_{RM}	-0.41	-0.55		-1.08	-0.74		0.25	0.36		0.34	0.26	
Three Factor												
Intercept	1.49	4.19	0.54	2.14	3.37	0.54	1.07	2.14	0.50	0.71	0.80	0.50
γ_{RM}	-0.80	-1.72		-1.53	-2.09		-0.25	-0.40		-0.51	-0.51	
γ_{SMB}	0.27	1.74		0.30	1.92		0.13	0.72		0.13	0.75	
γ_{HML}	0.16	1.07		0.16	1.11		-0.02	-0.16		-0.02	-0.14	
Four Factor												
Intercept	0.97	2.56	0.57	0.26	0.32	0.57	0.19	0.33	0.55	-1.31	-1.17	0.55
γ_{RM}	-0.14	-0.27		0.43	0.48		0.70	0.99		1.47	1.18	
γ_{SMB}	0.09	0.56		0.05	0.29		0.00	0.03		0.04	0.21	
γ_{HML}	0.20	1.37		0.20	1.32		0.02	0.15		0.01	0.06	
γ_{Mom}	2.33	4.42		2.52	4.43		1.74	2.79		1.80	2.70	
Five Factor												
Intercept	1.08	2.10	0.62	1.69	1.85	0.61	-0.33	-0.41	0.61	-0.61	-0.52	0.60
γ_{RM}	-0.33	-0.50		-1.11	-1.09		1.27	1.32		0.81	0.63	
γ_{SMB}	0.28	1.83		0.32	2.03		0.04	0.22		0.18	1.06	
γ_{HML}	0.11	0.72		0.13	0.85		-0.16	-1.11		-0.11	-0.78	
γ_{CMA}	0.17	0.84		0.12	0.59		0.02	0.10		-0.03	-0.18	
γ_{RMW}	0.21	1.45		0.21	1.44		0.28	1.66		0.24	1.48	
Six Factor												
Intercept	0.62	1.17	0.65	-0.32	-0.30	0.64	-0.06	-0.08	0.63	-1.13	-0.93	0.63
γ_{RM}	0.20	0.29		0.94	0.81		0.99	1.04		1.34	1.01	
γ_{SMB}	0.14	0.90		0.09	0.56		0.05	0.27		0.10	0.62	
γ_{HML}	0.17	1.12		0.16	1.06		-0.04	-0.29		0.00	0.02	
γ_{Mom}	2.54	4.81		2.78	4.82		1.51	2.55		1.87	2.86	
γ_{CMA}	-0.08	-0.42		-0.10	-0.51		-0.02	-0.14		-0.05	-0.28	
γ_{RMW}	0.42	2.81		0.44	2.92		0.18	1.10		0.14	0.93	

Table 59: Fama-MacBeth Tests with *25 Size and Book-to-market* portfolios in the North American market by using local factors in the full-period, January 1991-December 2015, and sub-period, January 2003-December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. γ is the average coefficient, t-stat is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as R_f			Gold as a zero beta asset			Return on T-Bills as R_f			Gold as a zero beta asset		
	1991-2015			1991-2015			2003-2015			2003-2015		
	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2
CAPM												
Intercept	1.26	1.97	0.27	1.89	1.43	0.23	0.56	1.00	0.24	-0.23	-0.18	0.20
γ_{RM}	-0.45	-0.67		-1.20	-0.88		0.26	0.40		0.42	0.31	
Three Factor												
Intercept	1.60	4.71	0.54	2.23	3.75	0.53	1.33	2.53	0.50	1.17	1.21	0.50
γ_{RM}	-0.90	-2.19		-1.65	-2.44		-0.52	-0.85		-1.00	-0.93	
γ_{SMB}	0.16	0.96		0.15	0.92		0.11	0.59		0.10	0.53	
γ_{HML}	0.21	1.08		0.22	1.12		-0.04	-0.21		-0.03	-0.18	
Four Factor												
Intercept	1.17	3.35	0.57	0.82	1.23	0.57	0.68	1.28	0.55	-0.42	-0.39	0.56
γ_{RM}	-0.41	-0.96		-0.18	-0.24		0.12	0.19		0.58	0.48	
γ_{SMB}	0.15	0.90		0.15	0.91		0.13	0.70		0.13	0.75	
γ_{HML}	0.26	1.34		0.26	1.34		-0.03	-0.18		-0.03	-0.21	
γ_{Mom}	2.82	4.51		2.92	4.47		1.95	2.70		1.96	2.56	
Five Factor												
Intercept	1.21	2.77	0.62	1.74	2.34	0.62	0.66	0.88	0.62	0.53	0.48	0.62
γ_{RM}	-0.52	-1.05		-1.17	-1.44		0.11	0.14		-0.40	-0.33	
γ_{SMB}	0.19	1.13		0.18	1.11		0.21	1.18		0.20	1.14	
γ_{HML}	0.18	0.92		0.18	0.95		-0.08	-0.45		-0.07	-0.41	
γ_{CMA}	0.46	1.81		0.34	1.30		-0.15	-0.63		-0.22	-1.01	
γ_{RMW}	0.20	0.89		0.23	1.00		0.50	2.16		0.51	2.19	
Six Factor												
Intercept	1.22	2.80	0.66	1.04	1.32	0.65	0.65	0.87	0.64	0.04	0.03	0.64
γ_{RM}	-0.47	-0.94		-0.41	-0.48		0.13	0.16		0.10	0.08	
γ_{SMB}	0.20	1.20		0.20	1.21		0.19	1.05		0.19	1.04	
γ_{HML}	0.24	1.26		0.24	1.26		-0.05	-0.33		-0.05	-0.30	
γ_{Mom}	3.27	5.07		3.28	4.85		1.37	2.10		1.42	2.08	
γ_{CMA}	-0.04	-0.14		-0.02	-0.07		-0.19	-0.82		-0.24	-1.11	
γ_{RMW}	0.47	1.97		0.47	1.92		0.42	1.83		0.42	1.86	

Table 60: Fama-MacBeth Tests with *25 Size and Momentum* portfolios in the North American market by using global factors in the full-period, January 1991-December 2015, and sub-period, January 2003-December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. γ is the average coefficient, t-stat is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as R_f			Gold as a zero beta asset			Return on T-Bills as R_f			Gold as a zero beta asset		
	1991-2015			1991-2015			2003-2015			2003-2015		
	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2
CAPM												
Intercept	1.37	4.08	0.18	2.10	2.83	0.19	0.94	1.82	0.22	0.33	0.26	0.21
γ_{RM}	-0.52	-1.18		-1.33	-1.65		-0.04	-0.07		-0.08	-0.06	
Three Factor												
Intercept	1.87	4.12	0.60	2.79	3.14	0.60	1.24	2.69	0.60	1.06	0.97	0.59
γ_{RM}	-1.23	-2.26		-2.20	-2.33		-0.41	-0.71		-0.85	-0.73	
γ_{SMB}	0.47	2.94		0.51	3.07		0.25	1.28		0.24	1.27	
γ_{HML}	-0.31	-1.16		-0.26	-1.03		-0.07	-0.18		-0.10	-0.29	
Four Factor												
Intercept	0.69	1.39	0.66	0.61	0.66	0.66	1.42	3.03	0.63	1.35	1.27	0.62
γ_{RM}	0.07	0.12		0.00	0.00		-0.61	-1.05		-1.15	-1.00	
γ_{SMB}	0.31	1.90		0.32	1.89		0.30	1.54		0.28	1.54	
γ_{HML}	0.27	0.94		0.21	0.79		-0.33	-1.05		-0.32	-1.02	
γ_{Mom}	0.57	2.26		0.57	2.27		0.13	0.43		0.14	0.46	
Five Factor												
Intercept	1.16	2.27	0.70	1.03	0.97	0.69	0.64	1.45	0.65	-0.16	-0.16	0.65
γ_{RM}	-0.28	-0.44		-0.31	-0.28		0.20	0.34		0.31	0.27	
γ_{SMB}	0.36	2.24		0.35	2.10		0.12	0.71		0.14	0.82	
γ_{HML}	-0.30	-1.17		-0.33	-1.25		0.11	0.28		0.04	0.11	
γ_{CMA}	0.47	2.03		0.47	2.01		0.28	1.04		0.22	0.84	
γ_{RMW}	-0.13	-0.51		-0.17	-0.71		-0.03	-0.12		-0.07	-0.36	
Six Factor												
Intercept	0.89	1.72	0.72	1.08	1.02	0.72	0.78	1.77	0.68	0.16	0.16	0.69
γ_{RM}	-0.04	-0.06		-0.33	-0.29		0.04	0.06		-0.04	-0.04	
γ_{SMB}	0.17	0.98		0.18	1.02		0.18	1.01		0.20	1.15	
γ_{HML}	0.48	1.44		0.48	1.41		-0.34	-1.02		-0.38	-1.20	
γ_{Mom}	0.52	2.09		0.53	2.10		0.18	0.61		0.15	0.51	
γ_{CMA}	0.71	2.97		0.70	2.95		0.15	0.62		0.10	0.41	
γ_{RMW}	-0.63	-2.32		-0.61	-2.47		0.08	0.41		0.00	-0.02	

Table 61: Fama-MacBeth Tests with the *25 Size and Momentum* portfolios in the North American market by using local factors in the full-period, January 1991-December 2015, and sub-period, January 2003-December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. γ is the average coefficient, t-stat is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional R-Squared of the tested models.

	Return on T-Bills as R_f			Gold as a zero beta asset			Return on T-Bills as R_f			Gold as a zero beta asset		
	1991-2015			1991-2015			2003-2015			2003-2015		
	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2
CAPM												
Intercept	1.41	4.13	0.17	2.19	2.89	0.18	0.92	1.72	0.22	0.28	0.20	0.21
γ_{RM}	-0.53	-1.26		-1.41	-1.71		-0.02	-0.03		-0.02	-0.02	
Three Factor												
Intercept	1.90	3.93	0.60	2.96	3.10	0.60	1.25	2.70	0.60	1.54	1.20	0.59
γ_{RM}	-1.17	-2.29		-2.37	-2.40		-0.44	-0.78		-1.37	-1.00	
γ_{SMB}	0.38	2.18		0.39	2.21		0.18	0.99		0.16	0.90	
γ_{HML}	-0.42	-1.19		-0.36	-1.06		-0.05	-0.12		-0.11	-0.24	
Four Factor												
Intercept	0.97	1.70	0.66	1.31	1.28	0.66	1.21	2.53	0.64	1.35	1.14	0.62
γ_{RM}	-0.30	-0.49		-0.75	-0.70		-0.39	-0.69		-1.18	-0.92	
γ_{SMB}	0.36	2.08		0.37	2.10		0.18	0.99		0.17	0.91	
γ_{HML}	0.15	0.36		0.10	0.26		0.03	0.06		0.04	0.09	
γ_{Mom}	0.68	2.34		0.67	2.32		0.14	0.45		0.14	0.45	
Five Factor												
Intercept	1.43	3.09	0.70	1.58	1.67	0.70	0.81	1.58	0.67	0.45	0.40	0.67
γ_{RM}	-0.69	-1.35		-0.97	-0.96		0.02	0.03		-0.27	-0.22	
γ_{SMB}	0.37	2.11		0.37	2.12		0.18	0.99		0.18	0.99	
γ_{HML}	-0.34	-0.91		-0.33	-0.89		-0.16	-0.33		-0.13	-0.28	
γ_{CMA}	0.55	1.74		0.56	1.72		0.22	0.79		0.17	0.64	
γ_{RMW}	-0.39	-1.36		-0.38	-1.31		-0.10	-0.31		-0.08	-0.26	
Six Factor												
Intercept	-0.63	-1.16	0.73	-2.33	-2.25	0.73	0.72	1.48	0.71	0.38	0.36	0.70
γ_{RM}	1.26	2.13		**2.86**	**2.60**		0.10	0.17		-0.20	-0.18	
γ_{SMB}	0.22	1.28		0.19	1.09		0.18	0.99		0.18	1.00	
γ_{HML}	1.76	3.92		1.87	4.24		-0.02	-0.04		-0.07	-0.18	
γ_{Mom}	0.72	2.50		0.73	2.53		0.16	0.49		0.15	0.47	
γ_{CMA}	1.42	4.31		1.55	4.57		0.27	1.02		0.19	0.72	
γ_{RMW}	-1.11	-3.73		-1.27	-4.12		-0.11	-0.33		-0.09	-0.27	

4.3 Application of gold as a hedging factor in the two factor Model

Table 62: Gold factor exposure with a two-factor augmented model for the 40 MSCI world industry portfolios: 1995:01 – 2015:12. α_i is the estimated alpha, β_i is the estimated beta for the market portfolio, γ_i is the estimated gold factor, ϕ_i is the Cochrane and Orcutt (1949) first order autoregressive coefficient, R^2 is the R-squared and DW is the Durbin Watson statistic.

Industry	α_i	t-stat	β_i	t-stat	γ_i	t-stat	ϕ_i	t-stat	R^2	DW
Airlines	-0.20	-0.72	1.09	20.55	-0.01	-0.18	0.00	-0.03	0.63	2.00
Auto and Components	-0.05	-0.26	1.03	26.16	0.02	0.50	-0.04	-0.65	0.73	2.04
Automobiles	-0.06	-0.27	1.02	23.53	0.01	0.27	-0.07	-1.04	0.69	2.09
Banks	-0.42	-2.40	1.25	38.57	-0.05	-1.32	0.00	0.01	0.86	2.00
Capital Goods	-0.10	-0.79	1.11	49.07	0.03	1.19	0.00	-0.03	0.91	1.99
Chemicals	0.09	0.51	0.97	29.18	0.03	0.86	-0.05	-0.74	0.78	2.08
Commercial Banks	-0.38	-2.14	1.25	38.56	-0.05	-1.28	0.01	0.13	0.86	1.98
Communications Equipment	-0.26	-0.53	1.34	15.84	-0.11	-1.22	0.08	1.30	0.50	1.84
Construction and Engineering	-0.35	-1.22	1.04	21.42	0.09	1.72	0.10	1.57	0.65	1.81
Distributors	-0.75	-1.61	0.99	10.69	-0.09	-0.88	-0.07	-1.04	0.32	2.13
Diversified Financials	-0.28	-1.43	1.46	40.15	-0.07	-1.73	-0.01	-0.08	0.87	2.01
Diversified Financials Services	-0.35	-1.27	1.53	31.83	-0.11	-2.05	0.07	1.13	0.80	1.86
Electronic Equipment Manufacturers	-0.17	-0.74	1.19	30.64	0.08	1.81	0.10	1.58	0.80	1.81
Electric Utilities	-0.02	-0.11	0.50	14.50	0.07	1.84	0.00	-0.01	0.47	2.00
Energy	0.09	0.40	0.82	18.45	0.07	1.31	-0.08	-1.20	0.58	2.17
Food Products	0.37	2.12	0.52	15.33	-0.02	-0.46	-0.05	-0.73	0.49	2.09
Financials	-0.31	-2.36	1.27	51.52	-0.04	-1.43	0.01	0.16	0.92	1.98
Gas Utilities	0.19	1.12	0.54	15.07	0.14	3.37	-0.12	-1.96	0.50	2.24
Health Care Equipment and Supplies	0.52	2.64	0.60	14.73	-0.08	-1.74	-0.12	-1.84	0.46	2.23
Health Care	0.52	2.88	0.57	15.96	-0.05	-1.18	-0.07	-1.12	0.51	2.13
Household Products	0.49	1.75	0.46	9.27	-0.03	-0.53	0.05	0.79	0.25	1.89
Industrial Conglomerates	-0.06	-0.27	1.16	27.94	-0.02	-0.44	-0.06	-0.99	0.76	2.12
Insurance	-0.16	-1.03	1.21	39.62	-0.02	-0.67	-0.04	-0.62	0.86	2.06
Information Technology	0.21	0.61	1.09	19.01	-0.03	-0.46	0.11	1.76	0.59	1.78
Machinery	-0.13	-0.70	1.14	34.52	0.07	1.81	0.08	1.23	0.83	1.83
Marine	-0.36	-1.00	1.05	17.93	0.11	1.74	0.13	2.00	0.57	1.74
Materials	-0.25	-1.24	1.09	28.25	0.09	2.15	-0.01	-0.21	0.77	2.01
Metals and Mining	-0.62	-1.73	1.17	18.45	0.17	2.44	0.04	0.64	0.59	1.91
Pharmaceuticals	0.42	2.05	0.55	13.85	-0.06	-1.23	-0.03	-0.54	0.44	2.06
Real Estate	-0.18	-0.82	1.03	24.32	0.02	0.39	-0.05	-0.82	0.71	2.10
Retailing	0.40	1.86	0.90	20.89	0.00	-0.05	-0.06	-0.96	0.64	2.11
Road and Rail	0.16	0.82	0.67	17.95	0.00	-0.10	-0.01	-0.10	0.57	2.01
Technology Hardware and Equipment	0.10	0.26	1.15	19.06	-0.04	-0.52	0.12	1.89	0.59	1.76
Tobacco	0.67	1.70	0.53	8.14	0.02	0.28	0.11	1.75	0.20	1.78
Trading Companies and Distributors	-0.29	-0.95	1.02	16.44	0.13	1.89	-0.08	-1.27	0.53	2.14
Transportation	0.03	0.22	0.81	32.42	0.01	0.30	-0.04	-0.65	0.81	2.08
Textiles and Apparel	0.20	1.09	1.09	29.50	0.04	1.07	-0.06	-0.94	0.78	2.11
Utilities	-0.05	-0.29	0.57	17.64	0.08	2.09	0.01	0.22	0.57	1.97
Wireless Telecommunication Services	0.31	0.77	0.73	9.91	0.02	0.24	0.02	0.32	0.29	1.96
Water Utilities	0.68	2.62	0.41	7.47	-0.07	-1.06	-0.12	-1.98	0.19	2.24

Table 63: Gold factor exposure with a two-factor augmented model for the 48 U.S. industry portfolios: 1995:01 – 2015:12. α_i is the estimated alpha, β_i is the estimated beta for the market portfolio, γ_i is the estimate gamma of the gold factor, ϕ_i is the Cochrane and Orcutt (1949) first order autoregressive coefficient, R^2 is the R-squared, and DW is the Durbin Watson statistic.

Industry	α_i	t-stat	β_i	t-stat	γ_i	t-stat	ϕ_i	t-stat	R^2	DW
Agriculture	0.50	1.42	0.67	8.15	0.10	1.32	-0.06	-0.89	0.21	2.12
Aircraft	0.38	1.29	0.99	15.57	-0.07	-1.10	0.03	0.47	0.50	1.94
Apparel	0.34	1.05	0.97	14.94	-0.04	-0.70	0.08	1.24	0.47	1.83
Automobiles and Trucks	-0.38	-1.19	1.33	17.60	-0.05	-0.63	-0.09	-1.40	0.54	2.20
Banking	0.07	0.28	1.04	18.26	-0.14	-2.64	-0.09	-1.48	0.57	2.17
Beer & Liquor	0.58	2.12	0.49	7.94	-0.02	-0.35	-0.02	-0.36	0.20	2.04
Business Services	-0.04	-0.20	1.30	27.03	-0.02	-0.39	-0.07	-1.07	0.74	2.13
Business Supplies	0.12	0.51	0.85	16.59	0.02	0.44	-0.02	-0.24	0.52	2.03
Candy & Soda	0.74	1.75	0.73	7.91	-0.06	-0.69	0.00	-0.07	0.20	2.00
Chemicals	0.05	0.20	1.02	19.11	0.08	1.65	0.04	0.60	0.60	1.92
Coal	-0.12	-0.15	1.20	7.14	0.49	3.11	0.06	1.01	0.21	1.88
Communication	-0.10	-0.51	0.99	22.35	-0.06	-1.34	0.02	0.24	0.67	1.97
Computers	-0.08	-0.26	1.51	20.83	-0.08	-1.10	-0.04	-0.57	0.63	2.06
Construction	0.07	0.22	1.16	17.00	0.07	1.15	0.06	0.95	0.54	1.88
Construction Materials	-0.04	-0.15	1.11	18.74	0.01	0.11	-0.11	-1.71	0.57	2.21
Consumer Goods	0.36	1.65	0.58	12.24	-0.01	-0.29	0.01	0.18	0.38	1.97
Defense	0.87	2.01	0.44	5.06	0.05	0.60	0.09	1.47	0.10	1.82
Electrical Equipment	0.07	0.39	1.24	26.40	0.06	1.29	-0.15	-2.46	0.72	2.30
Electronic Equipment	-0.27	-0.88	1.58	22.18	-0.11	-1.62	-0.04	-0.71	0.66	2.09
Entertainment	-0.12	-0.34	1.35	19.33	0.09	1.47	0.08	1.20	0.61	1.84
Fabricated Products	-0.60	-1.58	1.11	12.82	0.01	0.11	-0.04	-0.70	0.39	2.07
Food Products	0.58	2.58	0.44	9.21	0.00	-0.09	0.02	0.39	0.26	1.95
Healthcare	0.17	0.45	0.66	8.31	0.04	0.56	0.06	0.99	0.23	0.77
Insurance	0.19	0.88	0.92	18.07	-0.06	-1.31	-0.12	-1.87	0.55	2.23
Machinery	-0.17	-0.70	1.32	25.24	0.12	2.49	0.02	0.27	0.72	1.96
Measuring and Control Equipment	-0.10	-0.42	1.30	23.08	0.08	1.59	-0.03	-0.52	0.68	2.06
Medical Equipment	0.40	2.11	0.76	17.02	0.03	0.61	-0.09	-1.43	0.53	2.17
Non-Metallic and Industrial Metal	-0.24	-0.67	1.18	14.19	0.58	7.37	-0.06	-0.97	0.51	2.11
Personal Services	-0.08	-0.25	0.86	12.67	-0.02	-0.29	0.00	0.05	0.39	1.99
Petroleum and Natural Gas	0.25	0.90	0.74	11.60	0.20	3.34	-0.06	-0.96	0.37	2.11
Pharmaceutical Products	0.60	2.93	0.61	12.55	-0.02	-0.51	-0.11	-1.70	0.38	2.21
Precious Metals	-0.51	-1.03	0.37	3.09	1.60	14.03	-0.12	-1.93	0.46	2.23
Printing and Publishing	-0.12	-0.53	1.00	19.37	-0.07	-1.44	-0.04	-0.66	0.60	2.08
Real Estate	-0.32	-0.74	1.16	12.71	0.02	0.25	0.04	0.69	0.40	1.92
Recreation	-0.27	-0.87	0.90	13.00	0.02	0.30	-0.04	-0.64	0.40	2.08
Restaraunts,Hotels,Motels	0.43	1.79	0.70	14.16	-0.04	-0.79	0.07	1.19	0.45	1.84
Retail	0.36	1.76	0.85	19.05	-0.11	-2.56	0.00	-0.02	0.60	2.00
Rubber and Plastic Products	0.13	0.48	0.97	16.16	0.04	0.65	-0.01	-0.23	0.51	2.02
Ship building, Railroad Equipment	0.64	1.60	1.04	12.19	0.10	1.20	0.04	0.67	0.38	1.91
Shipping Containers	0.04	0.11	1.04	16.77	0.00	-0.07	0.07	1.19	0.51	1.85
Steel Works Etc	-0.86	-2.74	1.59	22.72	0.22	3.40	-0.01	-0.23	0.68	2.01
Textiles	-0.03	-0.07	1.20	12.90	-0.16	-1.80	0.02	0.38	0.41	1.95
Tobacco Products	1.00	2.23	0.47	5.00	0.04	0.51	0.05	0.82	0.09	1.90
Trading	-0.08	-0.32	1.45	30.16	-0.01	-0.31	0.10	1.52	0.79	1.81
Transportation	0.20	0.87	0.88	18.47	-0.09	-2.02	0.08	1.24	0.58	1.84
Utilities	0.48	1.99	0.39	7.21	0.03	0.57	-0.02	-0.29	0.17	2.03
Wholesale	0.08	0.40	0.83	20.15	0.05	1.38	0.06	1.03	0.63	1.87
Other industries	-0.45	-1.53	1.04	16.02	-0.05	-0.89	-0.01	-0.12	0.51	2.01

After assessing applicability of gold return as a zero-beta rate, I examine the extra-market sensitivity of the gold price factor on the global and U.S. industries. Tables (62) and (63) report results of estimating a regression with the two-factor augmented model on the 40 world industries and 48 U.S. industries respectively, over the full sample period from January 1995 to December 2015.

Regression results on world industries show that thirteen industries (33%) show exposure to the gold price factor at some level of significance. Out of thirteen industries, five industries have a significant exposure to the gold factor at the 5% level, whereas eight industries have a significant exposure at the 10% level. From this group of industries, Diversified Financial have a significant negative exposure whereas Gas Utilities, Materials and Mining, Utilities, Electronic Equipment Manufacturers, Electric Utilities, machinery, Marine, Trading Companies and Distributors have a significant positive exposure. Regarding results on U.S. industries, thirteen industries (27%) show significance to the gold price factor at some level of significance. Out of thirteen industries, nine industries (19%) have a significant exposure at the 5% level, whereas four industries have a significant exposure at the 10% level. Four industries, namely, Banking, Retail, Textiles, and Transportation have a significant negative exposure, whereas seven industries having a significantly positive exposure are Chemicals, Coal, Machinery, Measuring and Control Equipment, Non-Metallic and Industrial Metal, Petroleum and Natural Gas, Precious Metals, and Steel industries.

Among all the industry portfolios, I find a comparative stronger gold factor exposure in the U.S. industries where nine industries (19%) show significance at the 5% level, whereas only five world industries (13%) exhibit exposure at this level of significance. Further, four U.S. industries show a significantly negative exposure as compared to the only one (Diversified Financial) among global industries.

4.3.1 Stability tests of gold factor exposures

It is important to identify the determinants of the gold price to understand the positive or negative exposures of a gold price factor in the sub-period analyses. Firstly, gold is valued as a dollar per ounce. The appreciation of dollar reduces the price of gold whereas depreciation of the dollar value increases the price of gold. In case of the depreciation of a U.S. dollar, the returns of industry portfolios may go down. In such case, extra market sensitivity on a gold price factor could be positive. Secondly, the unprecedented downfall of financial markets also affects gold price. During financial instability, investors tend to keep gold as it retains its intrinsic value. In such conditions, the industry returns also go down and price of gold increases. The second sub-period (2002 – 2008) covers the period of the financial crisis so that one would expect a positive gold factor exposure in that sub-period.

Table (64) shows results for the world industries with a two-factor augmented model in three sub-periods. In the first sub-period from 1995 to 2001, I find that six world industry portfolios exhibit exposure at the 10% level. Chemicals and Water Utilities show a negative exposure whereas Construction & Engineering, Health Care, Pharmaceuticals, and Wireless Telecommunication Services exhibit positive exposure at the 10% significance level.

Table 64: Gold factor exposure with a two-factor augmented model for the 40 world industry portfolios over three sub-periods. β_i is the estimated beta for the market portfolio, $R_{w,t}$ (value-weighted world index), γ_i is the estimated gamma of the gold factor, $R_{gold,t}$. All returns are expressed in the U.S. Dollars. For each industry portfolio, the model is estimated with seemingly unrelated regression and Wald test is performed for each hypothesis.

Industry	β_i						γ_i						Wald tests					
	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	$H_{01}:\gamma_{i1}=\gamma_{i2}=\gamma_{i3}$ x^2	*P-Val.*	$H_{02}:\gamma_{i1}=\gamma_{i2}$ x^2	*P-Value*	$H_{03}:\gamma_{i2}=\gamma_{i3}$ x^2	*P-Value*
Airlines	1.38	10.20	1.13	16.51	0.96	11.64	-0.04	-0.25	-0.02	-0.30	-0.02	-0.22	0.01	1.00	0.01	0.92	0.00	0.99
Auto and Components	1.07	11.14	0.98	16.88	1.01	18.24	-0.08	-0.74	0.17	2.65	-0.01	-0.12	5.84	0.05	4.01	0.05	3.75	0.05
Automobiles	1.10	10.38	0.96	15.02	1.01	16.43	-0.10	-0.79	0.18	2.62	-0.01	-0.20	6.04	0.05	4.14	0.04	3.89	0.05
Banks	1.41	16.69	1.06	23.41	1.34	33.66	0.02	0.19	-0.13	-2.65	0.03	0.74	6.33	0.04	1.92	0.17	5.95	0.01
Capital Goods	1.17	18.74	1.13	28.27	1.08	47.94	0.05	0.68	0.03	0.65	0.01	0.40	0.33	0.85	0.06	0.81	0.12	0.72
Chemicals	1.00	10.68	0.99	18.32	0.92	27.84	-0.17	-1.62	0.17	2.83	-0.02	-0.61	10.98	0.00	7.92	0.00	7.31	0.01
Commercial Banks	1.41	16.68	1.06	23.83	1.34	33.35	0.02	0.20	-0.13	-2.72	0.03	0.70	6.38	0.04	1.99	0.16	5.94	0.01
Communications Equipment	2.11	7.93	1.45	14.21	0.93	15.31	-0.17	-0.56	-0.22	-2.02	-0.10	-1.40	0.92	0.63	0.03	0.86	0.92	0.34
Construction and Engineering	0.91	6.75	1.13	13.40	1.07	24.45	0.24	1.55	0.01	0.15	0.01	0.28	1.98	0.37	1.61	0.21	0.00	1.00
Distributors	2.15	7.21	0.98	12.29	0.63	8.46	-0.48	-1.41	0.11	1.24	-0.19	-2.23	7.64	0.02	2.80	0.09	6.01	0.01
Diversified Financials	1.54	18.66	1.30	22.99	1.53	27.48	0.06	0.64	-0.06	-0.92	-0.08	-1.25	1.58	0.45	1.06	0.30	0.08	0.78
Diversified Financials Services	1.53	18.63	1.22	17.10	1.75	21.21	0.06	0.64	-0.15	-1.94	-0.08	-0.82	2.96	0.23	2.95	0.09	0.34	0.56
Electronic Equipment Manufac	1.30	12.61	1.40	19.88	1.07	31.06	0.12	1.06	0.01	0.18	0.03	0.84	0.67	0.72	0.64	0.42	0.06	0.81
Electric Utilities	0.25	2.94	0.58	10.76	0.55	11.76	0.12	1.27	0.10	1.62	-0.01	-0.18	2.38	0.30	0.06	0.80	1.73	0.19
Energy	0.61	6.55	0.77	9.13	0.91	15.64	-0.09	-0.84	0.14	1.54	0.05	0.79	2.66	0.27	2.64	0.10	0.59	0.44
Food Products	0.65	7.01	0.52	9.27	0.48	13.03	-0.06	-0.57	-0.05	-0.86	0.01	0.23	0.91	0.63	0.00	0.95	0.70	0.40
Financials	1.37	20.95	1.14	30.93	1.33	44.62	0.04	0.54	-0.08	-1.92	-0.01	-0.27	2.61	0.27	1.93	0.16	1.59	0.21
Gas Utilities	0.31	3.36	0.63	11.29	0.58	11.96	0.03	0.26	0.24	3.98	0.05	0.90	6.37	0.04	3.15	0.08	5.36	0.02
Health Care Equipment and Su	0.56	5.06	0.50	7.91	0.63	13.28	-0.06	-0.51	-0.01	-0.13	-0.12	-2.14	1.54	0.46	0.15	0.70	1.53	0.22
Health Care	0.80	7.79	0.47	9.08	0.55	13.31	0.18	1.57	-0.02	-0.30	-0.10	-2.05	5.33	0.07	2.41	0.12	1.26	0.26

Table 64: (Continued)

Industry	β_i						γ_i						Wald tests					
													$H_{01}:\gamma_{i1}=\gamma_{i2}=\gamma_{i3}$		$H_{02}:\gamma_{i1}=\gamma_{i2}$		$H_{03}:\gamma_{i2}=\gamma_{i3}$	
	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	x^2	*P-Val.*	x^2	*P-Value*	x^2	*P-Value*
Household Products	0.85	5.39	0.34	5.79	0.40	8.29	0.19	1.05	-0.08	-1.28	-0.06	-1.12	2.01	0.37	1.98	0.16	0.05	0.82
Industrial Conglomerates	1.29	12.40	1.04	14.21	1.21	23.69	0.07	0.57	-0.04	-0.54	0.02	0.33	0.71	0.70	0.61	0.44	0.40	0.53
Insurance	1.16	12.60	1.13	25.73	1.30	40.58	0.06	0.60	-0.01	-0.25	-0.03	-0.71	0.65	0.72	0.42	0.52	0.06	0.81
Information Technology	1.62	8.80	1.22	17.05	0.77	19.51	0.03	0.15	-0.08	-1.05	-0.04	-0.94	0.35	0.84	0.27	0.61	0.18	0.67
Machinery	1.03	13.80	1.27	21.91	1.12	26.15	0.00	0.02	0.07	1.11	0.04	0.85	0.40	0.82	0.40	0.53	0.11	0.73
Marine	1.00	8.25	1.21	10.41	1.00	12.72	0.09	0.65	0.66	1.02	0.07	0.81	0.01	1.00	0.00	0.94	0.00	0.99
Materials	1.06	10.95	1.15	17.96	1.06	22.03	-0.12	-1.08	0.19	2.71	0.05	0.82	5.87	0.05	5.43	0.02	2.52	0.11
Metals and Mining	1.05	7.24	1.30	12.20	1.15	12.69	0.03	0.21	0.22	1.88	0.17	1.61	0.82	0.67	0.81	0.37	0.09	0.76
Pharmaceuticals	0.80	7.08	0.47	7.55	0.52	12.31	0.20	1.54	-0.03	-0.48	-0.12	-2.35	5.43	0.07	2.57	0.11	1.01	0.32
Real Estate	1.12	8.45	1.01	17.07	1.02	22.35	0.07	0.44	0.01	0.08	0.01	0.11	0.15	0.93	0.14	0.71	0.00	1.00
Retailing	1.09	9.67	0.99	13.77	0.78	15.75	0.11	0.84	0.01	0.10	-0.04	-0.78	1.26	0.53	0.44	0.51	0.29	0.59
Road and Rail	0.54	6.10	0.64	10.42	0.72	15.98	-0.06	-0.55	-0.03	-0.46	0.01	0.27	0.53	0.77	0.04	0.84	0.27	0.60
Technology Hardware and Equipment	1.64	8.65	1.31	18.01	0.81	17.21	-0.06	-0.30	-0.09	-1.09	-0.05	-0.83	0.18	0.92	0.01	0.92	0.18	0.67
Tobacco	0.33	1.59	0.67	6.32	0.48	9.51	0.09	0.36	0.08	0.67	-0.11	-1.90	2.59	0.27	0.00	0.97	2.13	0.14
Trading Companies and Distributors	1.03	5.79	1.11	10.31	0.94	17.27	0.03	0.17	0.23	1.99	0.04	0.57	2.22	0.33	0.71	0.40	2.18	0.14
Transportation	0.85	14.89	0.77	17.26	0.84	28.30	0.02	0.24	-0.01	-0.28	0.00	0.10	0.14	0.93	0.12	0.72	0.08	0.77
Textiles and Apparel	1.33	13.21	1.14	28.14	0.98	18.39	0.11	0.98	-0.03	-0.75	0.03	0.50	1.81	0.40	1.42	0.23	0.71	0.40
Utilities	0.30	3.94	0.67	12.24	0.60	14.35	0.08	0.96	0.11	1.82	0.01	0.21	1.72	0.42	0.05	0.82	1.60	0.21
Wireless Telecommunication Services	1.04	4.27	0.86	8.91	0.54	10.23	0.45	1.64	-0.08	-0.77	-0.08	-1.24	3.57	0.17	3.26	0.07	0.00	0.98
Water Utilities	0.18	1.07	0.49	6.39	0.43	6.77	-0.33	-1.74	-0.01	-0.17	-0.02	-0.34	2.48	0.29	2.34	0.13	0.01	0.92

Table 65: Gold factor exposure with a two-factor augmented model for the 48 U.S. industry portfolios over three sub-periods. β_i is the estimated beta for the market portfolio, $R_{US,t}$ (value-weighted U.S. index), γ_i is the estimated gamma of the gold factor, $R_{gold,t}$. All returns are expressed in the U.S. Dollars. For each industry portfolio, the model is estimated with seemingly unrelated regression and Wald test, is performed for each hypothesis.

Industry	β_i						γ_i						Wald tests					
	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	$H_{01}:\gamma_{i1}=\gamma_{i2}=\gamma_{i3}$ χ^2	*P-Val.*	$H_{02}:\gamma_{i1}=\gamma_{i2}$ χ^2	*P-Value*	$H_{03}:\gamma_{i2}=\gamma_{i3}$ χ^2	*P-Value*
Agriculture	0.39	2.84	0.69	5.60	0.97	6.36	-0.13	-0.70	0.19	1.82	0.08	0.69	2.20	0.33	2.15	0.14	0.43	0.51
Aircraft	0.84	6.35	1.02	10.46	1.06	16.69	-0.26	-1.40	-0.02	-0.27	-0.04	-0.86	1.43	0.49	1.41	0.24	0.05	0.82
Apparel	0.80	6.15	1.03	12.78	1.12	10.97	0.03	0.14	-0.04	-0.53	-0.06	-0.79	0.22	0.90	0.10	0.76	0.07	0.79
Automobiles and Trucks	0.91	7.70	1.53	12.12	1.63	12.26	-0.37	-2.23	0.13	1.25	-0.10	-0.91	6.85	0.03	6.48	0.01	2.33	0.13
Banking	0.84	7.89	0.91	9.25	1.40	17.77	-0.17	-1.11	-0.04	-0.53	-0.17	-2.79	1.66	0.44	0.51	0.48	1.61	0.21
Beer & Liquor	0.55	4.05	0.44	4.98	0.51	7.70	-0.28	-1.48	0.13	1.73	-0.03	-0.56	5.45	0.07	4.04	0.04	3.00	0.08
Business Services	1.59	15.69	1.31	19.83	0.93	19.30	0.09	0.61	-0.08	-1.42	-0.01	-0.36	1.61	0.45	1.16	0.28	0.93	0.34
Business Supplies	0.61	5.81	0.82	10.76	1.17	20.84	0.09	0.63	0.05	0.83	-0.05	-1.07	2.14	0.34	0.06	0.80	1.67	0.20
Candy & Soda	0.55	2.83	0.94	6.34	0.72	6.84	-0.35	-1.27	0.18	1.43	-0.16	-1.90	6.13	0.05	3.04	0.08	5.06	0.02
Chemicals	0.65	6.63	1.13	13.73	1.36	20.52	-0.06	-0.44	0.03	0.44	0.17	3.29	4.36	0.11	0.35	0.55	2.75	0.10
Coal	0.69	2.40	1.70	6.27	1.51	5.61	-0.10	-0.25	0.62	2.76	0.70	3.29	3.18	0.20	2.44	0.12	0.07	0.79
Communication	0.88	9.84	1.20	16.21	0.92	18.58	0.08	0.61	-0.09	-1.40	-0.09	-2.29	1.60	0.45	1.35	0.25	0.00	0.97
Computers	1.84	11.93	1.54	15.70	1.10	13.15	-0.18	-0.83	-0.19	-2.27	0.06	0.86	5.66	0.06	0.00	0.98	5.28	0.02
Construction	0.93	7.96	1.25	9.86	1.40	14.68	-0.21	-1.26	0.29	2.80	-0.05	-0.72	9.65	0.01	6.61	0.01	7.27	0.01
Construction Materials	0.77	7.92	1.06	13.02	1.61	16.62	-0.32	-2.38	0.19	2.79	-0.06	-0.80	13.48	0.00	11.24	0.00	5.99	0.01
Consumer Goods	0.58	5.83	0.49	7.09	0.71	11.57	-0.15	-1.06	0.03	0.47	0.01	0.14	1.36	0.51	0.25	0.25	0.07	0.79
Defense	0.19	1.10	0.44	2.91	0.81	8.08	0.06	0.25	0.17	1.39	-0.09	-1.10	3.19	0.20	0.18	0.67	3.10	0.08
Electrical Equipment	1.17	12.94	1.22	16.12	1.37	18.74	-0.04	-0.31	0.13	2.12	0.03	0.45	2.30	0.32	1.49	0.22	1.57	0.21
Electronic Equipment	1.87	12.54	1.68	14.16	1.12	17.84	-0.23	-1.10	-0.16	-1.62	-0.01	-0.29	2.49	0.29	0.09	0.76	1.73	0.19
Entertainment	1.02	9.46	1.58	15.10	1.63	12.46	-0.04	-0.26	0.00	0.02	0.22	2.13	3.26	0.20	0.05	0.82	2.62	0.11
Fabricated Products	0.85	6.43	1.16	7.87	1.39	8.49	-0.18	-0.95	0.01	0.10	0.03	0.25	0.63	0.63	0.40	0.40	0.91	0.91
Food Products	0.30	2.92	0.55	8.43	0.53	8.75	-0.05	-0.35	-0.02	-0.31	0.03	0.73	0.68	0.71	0.05	0.83	0.51	0.48
Healthcare	0.54	3.22	0.56	4.38	0.94	9.86	0.00	0.00	0.11	1.06	0.01	0.14	0.65	0.72	0.19	0.66	0.62	0.43
Insurance	0.63	5.86	1.05	13.84	1.15	21.05	-0.24	-1.56	0.09	1.43	-0.11	-2.58	8.35	0.02	3.94	0.05	6.94	0.01

Table 65 (continued)

Industry	β_i						γ_i						Wald tests					
	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	1995/2001	t-stat	2002/2008	t-stat	2009/2015	t-stat	$H_{01}:\gamma_{i1}=\gamma_{i2}=\gamma_{i3}$ x^2	$P\text{-}Val.$	$H_{02}:\gamma_{i1}=\gamma_{i2}$ x^2	$P\text{-}Value$	$H_{03}:\gamma_{i2}=\gamma_{i3}$ x^2	$P\text{-}Value$
Machinery	1.14	11.57	1.42	16.98	1.48	19.74	-0.07	-0.51	0.16	2.33	0.16	2.65	2.51	0.28	2.27	0.13	0.00	0.96
Measuring and Control Equipment	1.34	11.74	1.46	16.73	1.04	14.95	0.20	1.22	0.02	0.30	0.07	1.29	1.02	0.60	0.97	0.32	0.29	0.59
Medical Equipment	0.65	8.03	0.81	10.37	0.86	12.29	0.06	0.51	0.00	0.06	0.04	0.79	0.28	0.87	0.17	0.68	0.22	0.64
Non-Metallic and Industrial Metal	0.72	6.34	1.42	9.42	1.52	10.38	0.24	1.51	0.66	5.24	0.55	4.77	4.36	0.11	4.24	0.04	0.38	0.54
Personal Services	0.84	7.44	0.64	6.00	1.15	9.34	0.00	0.00	-0.07	-0.82	0.02	0.16	0.49	0.78	0.16	0.69	0.45	0.50
Petroleum and Natural Gas	0.49	4.65	0.73	6.08	1.02	12.27	-0.08	-0.54	0.32	3.20	0.18	2.78	5.03	0.08	5.02	0.03	1.29	0.26
Pharmaceutical Products	0.55	5.34	0.64	8.96	0.67	9.91	0.13	0.87	-0.11	-1.87	0.04	0.80	4.79	0.09	2.33	0.13	3.73	0.05
Precious Metals	0.46	2.20	0.46	2.49	0.25	1.28	2.83	9.56	1.48	9.69	1.29	8.43	22.03	0.00	16.48	0.00	0.79	0.37
Printing and Publishing	0.76	10.23	0.95	12.35	1.31	13.21	-0.01	-0.09	0.04	0.61	-0.17	-2.14	4.26	0.12	0.16	0.69	4.17	0.04
Real Estate	0.53	4.50	1.35	9.99	1.93	11.82	0.12	0.74	0.12	1.04	-0.18	-1.36	3.40	0.18	0.00	0.97	2.92	0.09
Recreation	0.57	4.31	1.06	9.89	1.12	11.68	-0.19	-1.01	0.03	0.30	0.08	1.08	1.86	0.40	1.07	0.30	0.23	0.63
Restaraunts,Hotels,Motels	0.52	5.16	0.89	11.18	0.75	13.69	-0.12	-0.87	-0.10	-1.52	0.04	0.81	3.58	0.17	0.02	0.88	2.94	0.09
Retail	0.86	9.58	0.89	13.05	0.80	13.60	-0.23	-1.82	-0.15	-2.58	-0.03	-0.56	4.06	0.13	0.38	0.54	2.66	0.10
Rubber and Plastic Products	0.68	6.18	0.95	10.54	1.34	14.30	0.10	0.66	0.03	0.45	0.01	0.08	0.33	0.85	0.16	0.69	0.07	0.80
Ship building, Railroad Equipment	0.44	3.33	1.03	7.89	1.74	12.49	-0.01	-0.06	0.08	0.77	0.08	0.73	0.21	0.90	0.19	0.66	0.00	0.98
Shipping Containers	0.98	7.59	1.04	10.60	1.08	16.25	-0.29	-1.60	0.06	0.79	0.06	1.18	3.60	0.17	3.22	0.07	0.00	0.98
Steel Works Etc	1.44	12.11	1.83	14.18	1.66	16.39	0.26	1.55	0.32	2.98	0.04	0.48	4.89	0.09	0.10	0.76	4.43	0.04
Textiles	0.58	5.03	1.25	8.91	1.99	11.24	-0.47	-2.88	-0.01	-0.11	-0.23	-1.66	5.32	0.07	5.17	0.02	1.46	0.23
Tobacco Products	0.12	0.66	0.65	3.60	0.68	7.16	0.00	0.01	0.08	0.57	0.02	0.28	0.16	0.92	0.08	0.78	0.14	0.70
Trading	1.51	16.08	1.50	20.15	1.34	19.28	-0.07	-0.53	0.05	0.78	-0.03	-0.47	1.11	0.58	0.65	0.42	0.81	0.37
Transportation	0.74	8.44	0.81	9.97	1.12	18.09	-0.21	-1.70	-0.05	-0.75	-0.08	-1.59	1.30	0.52	1.28	0.26	0.10	0.75
Utilities	0.08	0.80	0.70	8.16	0.49	6.72	-0.18	-1.33	0.13	1.79	0.00	-0.06	4.60	0.10	4.00	0.05	2.03	0.15
Wholesale	0.66	7.78	0.98	15.68	0.92	21.53	0.01	0.04	0.09	1.75	0.03	0.91	1.06	0.59	0.43	0.51	0.94	0.33
Other industries	0.97	7.34	0.88	8.43	1.29	15.85	0.16	0.84	-0.09	-1.04	-0.09	-1.44	1.66	0.44	1.45	0.23	0.00	0.98

It is surprising that the exposure has considerably increased in the second sub-period (2002 to 2008), in which as I find that twelve industries exhibit significance to gold factor exposure at some level. Out of twelve industries, eight world industries (20%), namely, Auto and Components, Automobiles, Banks, Commercial Banks, Chemicals, Communications Equipment, Gas Utilities, Materials, and Trading Companies & Distributors have a significant exposure at the 5% level. The four industries namely, Financials, Diversified Financial Services, Metals & Mining, and Utilities exhibit a significant exposure at the 10% level. The three industry portfolios namely, Banks, Commercial Banks and Communications Equipment show a significantly negative coefficient. However, five industry portfolios namely, Auto and Components, Automobiles, Chemicals, Gas Utilities, Materials, Trading Companies show a significant positive exposure.

In the third sub-period of 2009 to 2015, five industries exhibit significant exposure at some level. The four industry portfolios namely, Distributors, Health Care, Health Care Equipment and Supplies, and Pharmaceuticals show a significant negative exposure at the 5% level. The Tobacco industry shows a negative exposure at the 10% level. It is interesting that I do not find significant positive exposure in the last sub-period unlike the full period sample and the second sub-period where I find a considerable number of industries showing a significant positive exposure.

Table (65) shows results for the 48 U.S. industries in three-sub-periods. In the first sub-period from 1995-2001, I find that seven U.S. industries exhibit exposure at some significance level. Four industries namely, Automobiles, Construction Materials, Precious Metals and Textiles show significant exposure to the gold price factor at the 5% level. Three other industries, namely, Retails, Shipping Containers, Insurance & Transportation exhibit significant exposure at the 10% level. I note that the U.S. industries exhibit relative stronger exposure if

I compare the gold factor exposure with the world industries in the first sub-period. I also find that except Precious Metals, all other industries exhibit a negative exposure in the first-sub-period.

In the second sub-period from 2002-2008, seventeen industries show exposure at some significance level, and that is almost double as compared to the first sub-period (1995 – 2001). Out of seventeen industries, eleven industries namely, Coal, Computers, Construction, Construction Materials, Electrical Equipment, Machinery, Non-Metallic & Industrial Metal, Petroleum & Natural Gas, Precious Metals, Retail, and Steel Works show a significant exposure at the 5% level. Six other industries namely, Agriculture, Beer & Liquor, Electronic Equipment, Pharmaceutical Products, Utilities, and Wholesale have a significant exposure at the 10% level. Thirteen industries namely, Agriculture, Beer & Liquor, Coal, Construction, Construction Materials, Electrical Equipment, Machinery, Non-Metallic & Industrial Metal, Petroleum & Natural Gas, Precious Metals, Steel Works, Utilities, and Wholesale show a positive coefficient whereas, four industries namely, Computers, Electronic Equipment, Pharmaceutical Products, and Retail show a negative coefficient.

In the final sub-period, thirteen U.S. industries have a significant gold factor exposure at some significance level. It is comparatively less than the second sub-period (2002-2008), but it is higher than the first sub-period. Out of thirteen industries, eleven industries namely, Banking, Chemicals, Coal, Communication, Entertainment, Insurance, Machinery, Non-Metallic & Industrial Metals, Petroleum & Natural Gas, Precious Metals, Printing & Publishing, exhibit a significant exposure at the 5% level. Textiles, and Candy & Soda industries show a significantly negative exposure at the 10% level. Seven industries namely, Chemicals, Coal, Entertainment, Machinery, Non-Metallic & Industrial Metals, Petroleum & Natural Gas, Precious Metals, have a significant positive coefficient whereas six industries namely, Banking, Communication, Insurance, Printing and Publishing, and Textiles have a significantly negative coefficient.

For each industry portfolio, I test the equality of the gold factor with the following hypothesis:

$H_{3.1}: \gamma_{i1} = \gamma_{i2} = \gamma_{i3}$

$H_{3.2}: \gamma_{i1} = \gamma_{i2}$

$H_{3.3}: \gamma_{i2} = \gamma_{i3}$ … (3.37a)

To test equality of the gold factor exposure in different sub-periods, I perform a Wald test for each hypothesis in Eq. (3.37a). Results are reported in Tables (64) and (65) for the world and U.S. industries respectively The results are shown by chi-squared values with associated p-values.

Regarding results on global industries, for the first hypothesis $H_{3.1}: \gamma_{i1} = \gamma_{i2} = \gamma_{i3}$, the null hypothesis is rejected for eight industries namely, Auto & Components, Automobiles, Banks, Commercial banks, Chemicals, Distributors, Gas utilities, and Materials at the 5% significance level. It implies that the gold factor exposure has not remained stable for these industries in three sub-periods. In case of the second hypothesis, $H_{3.2}: \gamma_{i1} = \gamma_{i2}$, the null hypothesis is rejected for four industry portfolios namely, Auto & Components, Automobiles, Chemicals, and Materials. In those industries, the gold factor exposure has changed, as it has remained insignificantly negative in the first sub-period, 1995 – 2001, and has changed to significantly positive in the second sub – period, 2002 – 2008. For the final hypothesis, $H_{3.3}: \gamma_{i2} = \gamma_{i3}$, the gold factor exposure showed variation in seven industry portfolios, namely, Auto & Components, Automobiles, Banks, Commercial Banks, Chemicals, Distributors and Gas Utilities. In those two sub-periods, the gold factor exposure changes from positive to negative in Automobiles including Auto & Components, Chemicals and Distributors. It implies that industries exhibiting a positive exposure from 2002 – 2008, show a negative exposure to the gold price factor after the financial crisis. The above results also signify that the gold factor exposure is weaker in the first sub-period and it has started to become significant in the second and third sub-periods. The findings from this study support views of Baur (2014) as the gold factor exposure increases with positive changes in gold prices and decreases with negative price changes.

Regarding results on the U.S. industries, for the first hypothesis. For the first hypothesis, $H_{3.1}: \gamma_{i1} = \gamma_{i2} = \gamma_{i3}$, the null hypothesis is rejected on six industries at 5% level, namely Automobiles & Trucks, Candy & Soda, Construction including Construction Materials, Insurance and Precious Metals. It implies that the gold factor exposure has significantly altered in three sub-periods in those industries. For the second hypothesis, $H_{3.2}: \gamma_{i1} = \gamma_{i2}$, the null hypothesis is rejected for ten industries implying that gold factor exposure significantly changed from first sub-period to the second sub-period. These industries include, Automobiles & Trucks, Beer & Liquor, Construction, Construction Materials, Insurance, Non-Metallic & Industrial Metals, Petroleum & Natural Gas, Precious Metals, Textiles and Utilities. In those two sub-periods, the gold price exposure changes from negative to positive in industries namely, Automobiles & Trucks, Beer & Liquor, Construction including Construction Materials, Insurance, Petroleum & Natural Gas, and Utilities. Furthermore, the significantly positive exposure becomes insignificant in Precious Metals whereas, significantly negative exposure becomes insignificant in Textile industry. With regard to the third hypothesis, $H_{3.3}: \gamma_{i2} = \gamma_{i3}$, the null hypothesis is rejected over eight industries at the 5% level. These industries include Candy & Soda, Computers, Construction, Construction

Materials, Insurance, Pharmaceutical Products, Printing & Publishing, and Steel Works. I note that the gold price changes from positive to significantly negative in industries including Candy & Soda, Insurance, and Printing & Publishing. Whereas, Construction industry including Construction Materials, changes their sign of gold price factor from significantly positive to insignificantly negative. These findings are similar to world industries as the industries which exhibit positive exposure from 2002 – 2008, exhibits negative exposure from 2009 – 2015. These findings support views of Todorova (2017) as I find positive as well as negative gold premia for the same industries in different sub-periods. Furthermore, the exposure of gold price factor is higher in the second and third sub-periods as compared to the first sub-period both in the U.S. and global industries.

4.3.2 Test of Merton negative correlation prediction

Merton (1973) predicts a negative correlation between the market beta and the gold price factors in the Intertemporal CAPM. I present the cross-correlations of the market betas and the gold price factors in Table (66) to examine whether the gold price factor meets requirements of Merton theory. Firstly, over a full sample period (reported in Table 62 and 63), I find a negative cross-correlation between the beta and gamma with both world (-0.10) and U.S. industry portfolios (-0.16), which is consistent with the Merton theory. For world industries, I find a negative cross-correlation (-0.17) in the first sub-period (1995 – 2001) and a weak negative correlation (-0.04) in the second sub-period (2002 – 2008). However, I find a significantly positive correlation (0.33) in the final sub-period (2009 – 2015). The evidence in the final sub-period is not convincing as it contradicts ICAPM assumption. On the other hand, for the U.S. industries, I find a negative correlation in the sub-periods including pooled sub-periods: (a) -0.06 (1995/2001); (b) -0.06 (2002/2008); (c) -0.20 (2009/2015); and (d) -

0.12 (1995/2015- pooled sub-periods). However, I find weak negative cross-correlations in sub-periods, but it is still comparatively better evidence as compared to global industries because I find a negative cross-correlation both in the full sample and sub-periods in the U.S. industries. Consequently, the gold price factor to be used in the Merton (1973) ICAPM, is a better candidate in the U.S. market, than in the world markets due to its relatively consistent hedging features in the U.S. equity market.

Table 66: Cross-Correlations between the market beta and the gold price factor. The market beta and gamma estimates are obtained from a regression with following the two-factor model

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_i R_{gold,t} + e_{i,t}$$

where, $R_{i,t}$ is the return on the industry portfolio *i* in month *t*, $R_{m,t}$ is the return on the market portfolio in month *t*, $R_{gold,t}$ is the return on holding gold in month *t*.

	Subperiods				
	1995/2015	1995/2001	2002/2008	2009/2015	Pooled Sub-Periods
World Industry Portfolios	-0.10	-0.17	-0.04	0.33***	-0.05
US Industry Portfolios	-0.16	-0.06	-0.06	-0.20	-0.12

*** Significantly different from zero at the 5% level

Table 67: Forecasting ability of gold to predict aggregate market returns and market volatility. This table shows the results for the long horizon regressions over value-weighted market return and market variance *(SVAR)* at horizons of 1, 12, and 36 months ahead, where gold is used as a forecasting variable. The sample includes observations from 1995:01-2015:12. The coefficient of predictive regressions, t-statistic, p-value, and percentage of R-squared values are reported.

	1995 - 2015	
	Market	*SVAR*
		q = 1
Coefficient	0.05	-0.68
T-Stat	0.62	-1.10
R-Squared	0.00	0.01
		q = 12
Coefficient	0.05	-0.75
T-Stat	1.09	-2.10
R-Squared	0.00	0.01
		q = 36
Coefficient	0.05	-0.86
T-Stat	1.34	-2.02
R-Squared	0.00	0.01

Table (67) shows that gold, however, gold does not show correlation with the market and its beta is insignificantly different from zero. On the other hand, it predicts stock market variance *(SVAR)* in the second and third moment and hence, satisfies one of the criteria of the ICAPM which states that the candidate state variable must forecast aggregate market returns or volatility in the first or second moment (Maio and Santa-Clara, 2012).

4.3.3 Asset pricing tests

4.3.3.1 Multivariate Tests

Multivariate tests provide further empirical evidence whether gold price factor is a potential hedging factor for the ICAPM model. As before, I estimate the model in the full sample period and sub-periods as well. Wald test statistics for the null hypothesis of joint significance are reported in Tables (68) and (69) for the world and U.S. industries respectively. Tables report Wald test statistics with their respective p-values for the above-defined hypotheses. In the multivariate tests, however, I find a weak evidence among global and U.S. industries as null hypothesis of joint significance is rejected, but overall, I find a convincing evidence in favour of the two-factor model in the global and U.S. industries.

Table 68: Multivariate Tests for equality and significance of the market and gold price factors for the world industries. χ^2 is the test statistics from the Wald tests following χ^2 distributions with degrees of freedom highlighting in the final row. Each test statistic χ^2 is shown with its associated p-value.

	$H_o: b_1 = b_2 \dots = b_{40}$		$H_o: \delta_1 = \delta_2 \dots = \delta_{40}$		$H_o: \delta_1 = \delta_2 \dots = \delta_{40} = 0$	
Panel A: group I global industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	58.22	0.00	0.77	0.64	0.70	0.72
1995 - 2001	10.08	0.00	0.46	0.90	0.42	0.94
2002 - 2008	36.68	0.00	2.28	0.02	2.06	0.04
2009 - 2015	29.01	0.00	1.05	0.41	0.94	0.50
Degrees of Freedom	9		9		10	
Panel B: group II global industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	33.41	0.00	1.32	0.23	1.84	0.05
1995 - 2001	12.28	0.00	1.18	0.32	1.61	0.12
2002 - 2008	7.87	0.00	0.82	0.60	1.10	0.37
2009 - 2015	25.98	0.00	0.80	0.62	0.72	0.70
Degrees of Freedom	9		9		10	

Table 68: Continued

	$H_o: b_1 = b_2 \dots = b_{40}$		$H_o: \delta_1 = \delta_2 \dots = \delta_{40}$		$H_o: \delta_1 = \delta_2 \dots = \delta_{40} = 0$	
Panel C: group III global industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	38.82	0.00	2.21	0.02	2.15	0.02
1995 - 2001	10.96	0.00	1.09	0.38	0.99	0.46
2002 - 2008	16.04	0.00	2.40	0.02	2.50	0.01
2009 - 2015	23.02	0.00	1.56	0.14	1.47	0.16
Degrees of Freedom	9		9		10	
Panel D: group IV global industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	31.76	0.00	1.40	0.19	1.28	0.24
1995 - 2001	8.70	0.00	2.39	0.02	2.42	0.01
2002 - 2008	19.78	0.00	0.97	0.47	0.89	0.55
2009 - 2015	29.31	0.00	1.89	0.07	1.71	0.09
Degrees of Freedom	9		9		10	

Table 69: Multivariate Tests for equality and significance of market and gold factor for the U.S. industries. χ^2 is the test statistics from Wald tests following χ^2 distributions with degrees of freedom highlighting in the final row. Each test statistic χ^2 is shown with its associated p-value.

	$H_o: b_1 = b_2 ... = b_{48}$		$H_o: \delta_1 = \delta_2 ... = \delta_{48}$		$H_o: \delta_1 = \delta_2 ... = \delta_{48} = 0$	
Panel A: group I US industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	13.05	0.00	0.89	0.55	0.82	0.63
1995 - 2001	3.11	0.00	0.44	0.93	0.42	0.95
2002 - 2008	10.12	0.00	0.81	0.63	0.80	0.65
2009 - 2015	7.85	0.00	2.23	0.02	2.05	0.03
Degrees of Freedom	11		11		12	
Panel B: group II US industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	12.83	0.00	2.35	0.01	2.60	0.00
1995 - 2001	6.55	0.00	2.02	0.04	1.86	0.05
2002 - 2008	6.89	0.00	1.98	0.04	1.93	0.04
2009 - 2015	6.44	0.00	2.37	0.01	2.82	0.00
Degrees of Freedom	11		11		12	

Table 69: (Continued)

	$H_o: b_1 = b_2 \ldots = b_{48}$		$H_o: \delta_1 = \delta_2 \ldots = \delta_{48}$		$H_o: \delta_1 = \delta_2 \ldots = \delta_{48} = 0$	
Panel C: group III US industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	20.17	0.00	21.93	0.00	20.11	0.00
1995 - 2001	8.88	0.00	10.90	0.00	10.66	0.00
2002 - 2008	10.03	0.00	9.82	0.00	9.01	0.00
2009 - 2015	9.89	0.00	9.61	0.00	8.84	0.00
Degrees of Freedom	11		11		12	
Panel D: group IV US industries						
	χ^2	*P-Value*	χ^2	*P-Value*	χ^2	*P-Value*
1995 - 2015	15.77	0.00	1.72	0.07	1.66	0.08
1995 - 2001	8.69	0.00	1.61	0.11	1.53	0.13
2002 - 2008	8.88	0.00	2.01	0.04	1.93	0.04
2009 - 2015	12.02	0.00	1.44	0.17	1.39	0.19
Degrees of Freedom	11		11		12	

4.3.3.2 GMM Test

In the GMM test, the null hypothesis of the joint significance of the market and gold price factors is tested over the full sample period as well as over each sub-period for each industry group, using GMM system of equations. The results are reported in Table (70) and (71) for the world and U.S. industry groups respectively. The GMM tests verify findings of earlier results that gold is not a useless factor both in the world and U.S. industries. Results reveal that gold remains a significant factor in the full period as well as sub-periods. However, I find a weak evidence in the final sub-period in global industries as the null hypothesis of joint significance is rejected in three industry groups. However, I find a convincing evidence in first (1995 – 2001) and second (2002 – 2008). Asian financial crisis (1997) and global financial crisis (2008) remain at their peak in the first and second sub-periods. Hence, the empirical evidence supports this argument that gold serves as a strong hedging factor during times of financial stress. In the U.S. industries, I find a strong evidence of joint significance both in the full sample period and in the sub-periods. In all industry groups, I find evidence at the 5% significant level, implying that gold is not a useless factor for any industry group.

4.3.3.3 Cross-sectional test: First stage GMM and Fama-MacBeth test

I also estimate gold price factor using first stage GMM procedure adopted by Maio and Santa-Clara (2012), and Lutzenberger (2015). Results with the first-stage GMM are reported in Tables (70) and (71). Further, I also conduct Fama-MacBeth (1973) regressions following the methodology detailed in Cochrane (2009, Chapter 13) and employed by Gregory, Tharyan, and Christidis (2013), and Blackburn & Cakici (2017). Results for the global and the U.S. industries with the Fama-MacBeth procedure is reported in Tables (72) and (73).

Table 70: GMM tests of the two-factor model with a world market factor and a gold price factor for world industries. Results represent monthly percent returns. ϕ_g is the estimate of the gold price factor from first-stage GMM, gmm-t is the asymptotic GMM robust t-statistics. GMM is the test statistic for the null hypothesis that the two-factor ICAPM model is distributed as a χ^2 with (*N-1*) degrees of freedom.

	Group I				Group II				Group III				Group IV			
	ϕ_g	gmm-t	GMM	*P-Val*	ϕ_g	gmm-t	GMM	*P-Val*	ϕ_g	gmm-t	GMM	*P-Val*	ϕ_g	gmm-t	GMM	*P-Val*
1995 - 2015	-1.41	-0.68	11.14	0.19	-1.69	-0.97	15.21	0.12	-1.57	-1.15	13.75	0.09	2.95	1.51	9.37	0.31
1995 - 2001	3.85	1.45	31.84	0.00	-0.93	-0.66	14.63	0.15	0.02	0.01	12.71	0.12	2.52	1.92	17.58	0.06
2002 - 2008	2.70	1.17	15.54	0.11	3.45	1.11	7.42	0.69	1.78	0.84	16.01	0.10	0.90	0.42	11.66	0.31
2009 - 2015	-4.92	-1.56	17.75	0.02	-6.31	-1.23	56.96	0.00	-3.54	-1.68	20.26	0.01	1.56	0.73	11.66	0.31

Table 71: GMM tests of the two-factor model with a market factor and a gold price factor for U.S. industries. Results represent monthly percent returns. ϕ_g is the estimate of the gold price factor from first-stage GMM, gmm-t is the asymptotic GMM robust t-statistics. GMM is the test statistic for the null hypothesis that the two-factor ICAPM model is distributed as a χ^2 with (*N-1*) degrees of freedom.

	Group I				Group II				Group III				Group IV			
	ϕ_g	gmm-t	GMM	*P-Val*	ϕ_g	gmm-t	GMM	*P-Val*	ϕ_g	gmm-t	GMM	*P-Val*	ϕ_g	gmm-t	GMM	*P-Val*
1995 - 2015	0.72	0.39	17.03	0.15	-0.02	-0.02	8.68	0.56	-0.24	-0.53	13.70	0.32	-0.24	-0.18	8.39	0.75
1995 - 2001	0.26	0.13	16.58	0.17	0.78	0.90	12.97	0.23	-0.48	-0.92	8.35	0.76	-1.09	-0.96	12.45	0.41
2002 - 2008	2.44	1.08	28.53	0.00	2.08	1.11	7.45	0.83	1.25	1.60	12.57	0.40	-0.18	-0.11	6.87	0.87
2009 - 2015	-0.85	-0.63	9.90	0.45	-2.85	-1.69	26.56	0.00	-1.74	-1.91	20.34	0.06	1.41	0.64	5.17	0.88

Table 72: Fama-MacBeth Test of the two-factor model for the global industries. The full sample represents the 40 global industries. The 40 industries are divided into four groups. Results represent monthly percent returns. Results are shown for the full period (1995 - 2015), and sub-periods (1995 - 2001, 2001 - 2008, and 2009 - 2015). The table reports average coefficients for the two-factor model. γ is the average coefficient, t-fm is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional adjusted R-Squared.

	1995-2015			1995-2001			2002-2008			2009-2015		
Full Sample	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	0.86	3.59	0.21	0.46	0.98	0.17	0.64	1.87	0.24	0.74	1.89	0.23
γ_{RM}	-0.49	-1.16		-0.08	-0.13		-0.64	-0.92		-0.11	-0.14	
γ_{GOLD}	-0.85	-0.71		**1.98**	**2.10**		**2.60**	**1.71**		**-2.57**	**-1.51**	
Group I	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	1.12	4.18	0.22	0.47	0.76	0.22	0.56	1.72	0.20	1.36	2.58	0.29
γ_{RM}	-0.69	-1.62		0.13	0.19		-0.72	-1.05		-0.66	-0.78	
γ_{GOLD}	-1.41	-0.68		**3.85**	**2.16**		**2.70**	**1.61**		**-4.92**	**-1.91**	
Group II	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	0.38	1.02	0.18	-0.04	-0.09	0.01	0.01	0.01	0.23	-0.02	-0.05	0.21
γ_{RM}	-0.01	-0.02		0.05	0.09		-0.02	-0.02		0.70	0.86	
γ_{GOLD}	-1.69	-0.96		-0.93	-0.68		3.13	1.40		**-6.31**	**-1.92**	
Group III	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	0.96	2.87	0.19	0.41	0.88	0.14	0.83	1.52	0.13	0.75	1.73	0.20
γ_{RM}	-0.58	-1.17		0.02	0.02		-0.71	-0.83		-0.23	-0.28	
γ_{GOLD}	-1.57	-1.14		0.02	0.01		1.78	1.06		**-3.54**	**-1.81**	
Group IV	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	1.02	3.00	0.16	1.12	1.68	0.23	0.73	1.66	0.22	0.93	1.98	0.22
γ_{RM}	-0.54	-1.05		-0.46	-0.62		-0.83	-1.08		-0.07	-0.08	
γ_{GOLD}	**2.95**	**1.64**		**2.52**	**2.08**		0.90	0.42		1.56	0.77	

Table 73: Fama-MacBeth Test of the two-factor model for the U.S. industries. The full sample represents the 48 U.S. industries. The 48 industries are divided into four groups. Results represent monthly percent returns. Results are shown for the full period (1995 - 2015), and sub-periods (1995 - 2001, 2001 - 2008, and 2009 - 2015). The table reports average coefficients for the two-factor model. γ is the average coefficient, t-fm is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional adjusted R-Squared.

	1995-2015			1995-2001			2002-2008			2009-2015		
Full Sample	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	1.02	3.54	0.20	0.92	1.71	0.21	0.36	0.98	0.23	1.24	3.20	0.29
γ_{RM}	-0.06	-0.14		0.36	0.50		-0.17	-0.31		0.14	0.22	
γ_{GOLD}	-0.23	-0.51		-0.33	-0.66		**1.36**	**1.73**		**-1.75**	**-2.01**	
Group I	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	1.15	3.25	0.13	1.35	1.93	0.14	0.55	1.39	0.09	0.90	1.72	0.16
γ_{RM}	-0.21	-0.41		-0.14	-0.13		-0.54	-0.85		0.67	0.88	
γ_{GOLD}	0.81	0.44		0.26	0.13		2.44	1.16		-0.85	-0.62	
Group II	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	1.47	3.44	0.12	1.31	2.36	0.05	0.47	0.67	0.17	1.52	2.51	0.13
γ_{RM}	-0.48	-0.89		-0.15	-0.19		-0.34	-0.38		-0.03	-0.04	
γ_{GOLD}	-0.02	-0.02		0.78	0.90		1.88	1.06		**-3.38**	**-2.06**	
Group III	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	2.30	2.29	0.26	1.19	2.01	0.35	0.33	0.59	0.32	1.21	2.13	0.40
γ_{RM}	0.34	0.34		0.34	0.44		0.04	0.06		0.07	0.09	
γ_{GOLD}	-0.54	-0.54		-0.48	-0.97		1.25	1.59		-1.74	-1.93	
Group IV	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2	γ	t-fm	R^2
Intercept	0.76	1.92	0.10	0.21	0.35	0.17	0.33	0.52	0.07	1.00	1.52	0.18
γ_{RM}	0.13	0.29		1.02	1.34		-0.24	-0.33		0.47	0.57	
γ_{GOLD}	-0.24	-0.18		-1.09	-0.93		-0.18	-0.11		1.41	0.67	

Results for the estimation of a real risk premium show variations in the gold price factor in the sub-period analyses. I find positive real gold premia in the second sub-period (2002 – 2008) whereas negative premia in the third sub-period (2009-2015) in the global and U.S. industries. Evidence from the sub-period analyses shows that the market price has experienced considerable gains in the third sub-period which covers the period of post-financial crisis, whereas, the gold price has experienced real losses. The exposure of the gold price factor also varies across industry groups which signifies that the gold factor exposure is industry-specific. Results from the Fama and MacBeth (1973) cross-sectional tests provide further convincing evidence in favour of the two-factor model. I find an evidence of the significant gold price with the Fama-MacBeth tests at the 5% level. The gold price factor is significantly positive in the first sub-period (1995 – 2001) at the 5% level in global industries. The first sub-period covers the period of the Asian financial crisis (1997). In the second sub-period, it is positively significant and it changes to negatively significant at the 10% level in the third sub-period. Among U.S. industries, I find a weak gold factor exposure in the first sub-period which becomes positively strong in the second sub-period. These findings imply that the benefits of gold investment are realised during times of financial distress. Gold investments produce reasonable profits when market price goes down in the wake of economic uncertainty and these profits significantly rise during abrupt market crashes. In the third sub-period (2009 – 2015), the gold price factor is negatively significant at the 5% level which covers the period of the post-financial crisis. This shows that gold has become a strong hedging factor in the global and U.S. asset pricing. Despite falling gold price, portfolio managers can use gold as a strategic hedging investment. Rational investors invest in gold during favourable market conditions when gold price experiences declining trend. Gold investments protect investors from extreme financial losses in unprecedented extreme market shocks.

4.3.3.4 Role of Gold in multifactor Models

I also explore the role of gold in multifactor models where I utilise gold as an additional variable with oil prices, term-structure, default spread, inflation, money supply and exchange rate in the extended time period from 1981 to 2015 in the U.S. equity market. The 25 size and book-to-market portfolios are used as test portfolios. In cross-section, I examine this model in the different time periods from 1981 to 1994, 1995 to 2002, 2002 to 2008 and then from 2009 to 2015. I find significant gold price factor from 1981 to 2015 and in sub-period of 1995 to 1994. Results are shown in Appendix (D).

4.4 Application of Multifactor Models

4.4.1 Descriptive Analysis

I use the empirical, macroeconomic, and state variables in the multifactor models. The sample period includes 420 months from January 1981 to December 2015 in the U.S. equity market. The details of the data sources are explained in the data section.

Table (74) shows descriptive analysis of macroeconomic variables (exchange rate, money supply and inflation), commodity prices (oil, gold), state variables (1-month Treasury bill yield, default rate, term-structure, dividend yield, price-earnings ratios, value spread), empirical factors (size, value, investment, profitability, liquidity, and momentum), market return of S&P 500, and stock variance *(SVAR)*. *SVAR* is computed by using the sum of squared daily returns on S&P 500 index (Welch & Goyal, 2008). Mean average return of most variables under investigation is positive except term (-0.17), dividend yield (-0.08), liquidity (-0.01) and momentum (-0.16) that show negative mean returns. In terms of standard deviation, momentum (6.17), liquidity (4.91), gold (4.83), and oil prices (3.93) show greater standard deviation than other variables. It implies these variables show greater volatility than other variables. In terms of kurtosis and skewness, majority of the variables under investigation have outliers as the data is heavy-tailed, particularly I find high positive kurtosis in *SVAR* (93.25), oil prices 21.24), operating profitability (12.41), exchange rate (10.05), money supply (9.56), and inflation (9.05). The descriptive results are consistent with the results of Fama and French (2012 & 2015).

Skewness shows that the empirical factors including gold (-0.14) are normally distributed where state variables are moderately skewed, whereas macroeconomic variables are highly skewed for sample period (1981-2015).

Table 74: Descriptive analysis of excess return on S&P 500 (*RMRF*), stock variance (*SVAR*), Default Spread, *TERM*, Dividend Yield (*DY*), Price Earning Ratio (*PE*), Value Spread (*VS*), 1-Month T-bill, Liquidity factor (*LIQ*), *Exchange Rate*, *Money Supply*, Inflation (*CPI*), Gold, Industrial production (*IND*), Size (*SMB*), Value (HML), Operating Profitability (*OP*), Investment (*CMA*), Momentum (*MOM).*

		Mean	Standard Deviation	Kurtosis	Skewness
RMRF (S&P 500)	*RMRF*	0.28	1.58	5.45	-1.19
SVAR	*SVAR*	0.26	0.54	93.25	8.65
Default Spread	*DEF*	0.03	3.22	4.31	0.52
TERM	*TERM*	-0.17	2.41	5.67	-0.66
Dividend Yield	*DY*	-0.08	1.61	4.61	0.86
Price Earning Ratio	*PE*	0.11	1.58	4.43	-1.00
Value Spread	*VS*	0.26	1.05	2.85	0.19
1-Month Tbill	*RF*	0.36	0.29	0.61	0.73
Liquidity factor	*LIQ*	-0.01	4.91	0.02	-0.04
Exchange Rate	*Exchange*	0.14	2.05	10.05	1.46
Money Supply	*Money Su*	0.21	0.36	9.56	1.54
Inflation (CPI)	*Inflation*	0.10	0.12	9.05	-0.91
Gold	*Gold*	0.14	4.83	1.89	-0.14
Industrial production	*IND*	0.10	0.12	0.01	9.04
Size	*SMB*	0.11	2.91	4.92	0.44
Value	*HML*	0.34	2.92	2.20	0.14
Operating Profitability	*RMW*	0.35	2.48	12.41	-0.42
Investment	*CMA*	0.33	2.01	2.05	0.43
Momentum	*MOM*	-0.16	6.17	3.74	0.03

Table 75: Correlation matrix of excess return on S&P 500 (*RMRF)*, stock variance (*SVAR)*, Default Spread, *TERM*, Dividend Yield (*DY*), Price Earning Ratio (*PE*), Value Spread (*VS*), *1-Month T-bill*, Liquidity factor (*LIQ)*, *Exchange Rate*, *Money Supply*, Inflation (*CPI)*, Gold, Industrial production (*IND*), Size (*SMB*), Value (*HML*), Operating Profitability *(OP*), Investment *(CMA)*, and Momentum *(MOM)*.

	RMRF	*SVAR*	*DEF*	*TERM*	*DY*	*PE*	*VS*	*RF*	*LIQ*	*Ex. Rate*	*MS*	*Inflation*	*Gold*	*IND*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
RMRF	1																		
SVAR	-0.38	1.00																	
DEF	-0.05	0.29	1.00																
TERM	0.01	-0.15	-0.53	1.00															
DY	-0.67	0.45	0.24	-0.07	1.00														
PE	0.67	-0.45	-0.22	0.05	-0.99	1.00													
VS	-0.12	0.00	0.03	-0.05	0.13	-0.14	1.00												
RF	-0.06	-0.11	0.06	-0.01	0.01	-0.01	0.16	1.00											
LIQ	-0.04	0.00	-0.03	0.03	-0.05	0.01	0.10	0.33	1.00										
Exchange Rate	0.06	0.01	0.17	-0.19	-0.02	0.03	0.02	0.08	0.06	1.00									
Money Supply	-0.05	0.21	0.02	-0.20	0.07	-0.05	-0.03	-0.13	-0.16	0.02	1.00								
Inflation	-0.06	-0.27	-0.15	0.24	0.01	-0.07	0.06	0.38	0.22	0.07	-0.12	1.00							
Gold	0.02	0.00	-0.04	-0.09	-0.02	0.02	-0.05	-0.13	0.08	0.16	0.15	0.03	1.00						
IND	-0.06	-0.27	-0.15	0.24	0.01	-0.07	0.05	0.38	0.23	0.07	-0.12	1.00	0.03	1.00					
SMB	0.14	-0.14	-0.18	0.07	-0.24	0.20	-0.08	0.10	0.30	-0.02	-0.01	0.10	0.08	0.10	1.00				
HML	-0.22	-0.04	-0.05	0.06	0.05	-0.08	0.07	0.23	0.17	0.00	-0.04	0.13	-0.05	0.13	0.10	1.00			
RMW	-0.21	0.07	0.13	-0.13	0.18	-0.15	0.11	-0.26	-0.43	-0.04	0.16	-0.17	-0.10	-0.17	-0.57	-0.16	1.00		
CMA	-0.24	-0.03	-0.06	0.10	0.13	-0.12	0.02	-0.11	-0.43	-0.04	0.06	-0.08	-0.05	-0.08	-0.12	0.53	0.20	1.00	
MOM	-0.10	-0.09	0.07	-0.05	0.19	-0.15	-0.02	-0.22	-0.55	-0.02	0.03	-0.12	-0.01	-0.12	-0.30	-0.35	0.39	0.19	1.00

Table (75) shows correlation matrix of all variables under investigation. Price-earnings ratio *(PE)* shows strong positive correlation (0.99), whereas dividend yield shows strong negative correlation (-0.98). Other state variables such as default yield (-0.23), value spread (-0.13), *HML* (-0.11), *CMA* (-0.22), *RMW* (-0.23) and *MOM* (-0.11) show a weak negative correlation. Term structure and liquidity also show nearly zero correlation with the market returns and stock market variance (*SVAR*).

Recent asset pricing studies (Cochrane 2005, Maio and Santa-Clara, 2012, Lutzenberger, 2015) emphasise on assessing criteria of multifactor ICAPM models by using predictive regressions and GMM tests. Hence, initially, I discuss the ICAPM criteria and perform the predictive regressions and GMM tests to assess the performance of the multifactor models. However, I also perform time series analysis with VECM model for robustness and report the results in Appendix (D). The VECM model is implemented to provide further detail of the short term and long-term association of market returns with the macro and state variables.

4.4.2 Assessing criteria of the ICAPM

Firstly, I assess the main criterion of the ICAPM that it produces a plausible estimate of the market risk premium in cross-section. The negative estimate of the market risk premium is economically not meaningful, as it does not provide useful information about the level of the market risk. Then, I perform long-horizon predictive regressions to assess the second criterion of the ICAPM; whether state variables *(S)* are able to forecast future investment opportunities. In order to assess the criterion 3(a), I perform a single variable predictive regression and examine the sign of the correlation between a state variable and aggregate expected returns and then compare this sign with the estimate of the risk price. Likewise, I perform a single predictive regression over the market volatility to assess the criterion 3(b). In addition to single variable predictive regressions, I also perform multiple variable predictive regression for each multifactor model over the expected market return and expected market volatility in the right-hand side whereas the existing values of state variables *(S)* in the left-hand side of the predictive regression. Multiple variable predictive regressions enable to assess the forecasting power of the state variables *(S)* of each multifactor model. This approach provides an overview of the marginal predictive power of each state variable on changes in future market returns and future market volatility in a nested model. Predictive regression methodology is very popular in financial economics and extensively used and discussed by various researchers (for instance, see Keim & Stambaugh, 1986; Campbell, 1987; Campbell & Shiller, 1988; Rapach & Wohar, 2006; Maio, 2017 and many others).

When I perform predictive regressions on the state variables to evaluate the ICAPM criteria, I also employ associated state variables[34] that I construct from the empirical factors. For a proxy of investment opportunities, I use the value-weighted aggregate equity monthly market return that is obtained from the Ken French database, and stock variance *(SVAR)* of S&P 500 to investigate whether the chosen state variables forecast future market returns or market volatility. In performing single predictive regressions, I follow the methodology of Maio and Santa-Clara (2012) and Lutzenberger (2015).

4.4.3 Predictive regressions

4.4.3.1 Single predictive regressions

Results of single predictive regressions for the potential state variables are shown in Tables (76) – (79). Single predictive regressions for each state variable is performed at horizons of 1, 12, and 36 months ahead over weighted market return and stock market variance *(SVAR)* to

[34] Associated state variables are the alternative proxies of the state variables as are defined in 3.5.4.3

assess the forecasting ability of each state variable. I show the predictive ability of state variables including Treasury bill yield *(RF)*, term structure *(Term)*, default risk *(DEF)*, dividend yield *(DY)*, price earnings ratio *(PE)*, value spread *(VS)*, inflation, *(CPI)*, industrial production *(In)* and *(GOLD)* to forecast market return and volatility. Among state variables, I find strong evidence in favour of dividend yield, price earnings ratio, value spread, inflation and industrial production as they forecast aggregate market returns or volatility. These findings are consistent with results of Maio and Santa-Clara (2012) in the U.S. market. Whereas, I do not find evidence in favour of liquidity and gold that I introduce as alternative state variables in this study.

Single predictive regressions for the associated state variables that are constructed from the empirical factors, such as size *SMB**, value *HML**, momentum *Mom**, investment, CMA*, operating profitability *RMW** and liquidity *LIQ** are also performed over the market returns and stock market variance.

Table 76: Single predictive regressions for ICAPM state variables. This table shows the results for the single long-horizon regressions over the value-weighted market returns at horizons of 1, 12, and 36 months ahead. The forecasting variables include Treasury bill yield *(RF)*, term structure *(Term)*, dividend yield *(DY)*, price earnings ratio *(PE)*, and value spread *(VS)*, inflation, *(CPI)*, industrial production and gold. The sample includes observations from 1981:01–2015:12. The coefficient of predictive regressions, t-statistic, p-value, and percentage of R-squared values are reported.

	TERM	*DEF*	*DY*	*RF*	*PE*	*VS*	*CPI*	*In*	*GOLD*
					q = 1				
Coefficient	0.01	-0.04	-0.24	0.00	0.24	-0.03	0.00	0.00	0.02
T-Stat	0.17	-0.72	-13.23	-0.88	13.71	-2.56	-0.70	-0.71	0.37
R-Squared	0.00	0.00	0.44	0.00	0.45	0.01	0.00	0.00	0.00
					q = 12				
Coefficient	0.00	-0.04	-0.24	0.00	0.24	-0.03	0.00	0.00	0.03
T-Stat	0.02	-0.53	-11.87	-1.21	12.11	-1.98	-1.17	-1.18	0.37
R-Squared	0.00	0.00	0.44	0.00	0.45	0.01	0.01	0.01	0.00
					q = 36				
Coefficient	0.00	-0.04	-0.24	0.00	0.24	-0.03	0.00	0.00	0.03
T-Stat	-0.01	-0.53	-11.60	-2.30	15.65	-2.96	-0.93	-0.95	0.26
R-Squared	0.00	0.00	0.45	0.00	0.45	0.02	0.00	0.00	0.00

Table 77: Single predictive regressions for ICAPM state variables. This table shows the results for the single long-horizon regressions over the stock market variance *(SVAR)* at horizons of 1, 12, and 36 months ahead. The forecasting variables include Treasury bill yield (RF), term structure *(Term)*, dividend yield *(DY)*, price earnings ratio *(PE)*, and value spread *(VS)*, inflation, *(CPI)*, industrial production and gold. The sample includes observations from 1981:01–2015:12. The coefficient of predictive regression, t-statistic, p-value, and percentage of R-squared values are reported.

	TERM	*DEF*	*DY*	*RF*	*PE*	*VS*	*CPI*	*In*	*GOLD*
					q = 1				
Coefficient	-0.60	1.72	1.34	-0.05	-1.34	0.01	-0.06	-0.06	-0.03
T-Stat	-1.80	3.68	6.65	-1.26	-6.56	0.11	-1.53	-1.53	-0.06
R-Squared	0.02	0.08	0.20	0.01	0.21	0.00	0.07	0.07	0.00
					q = 12				
Coefficient	-0.60	1.73	1.33	-0.06	-1.34	0.00	-0.06	-0.06	-0.06
T-Stat	-1.82	3.74	7.12	-1.39	-6.67	0.08	-1.62	-1.62	-0.14
R-Squared	0.02	0.08	0.20	0.01	0.21	0.00	0.07	0.07	0.00
					q = 36				
Coefficient	-0.61	1.72	1.33	-0.06	-1.33	0.00	-0.06	-0.06	-0.08
T-Stat	-2.36	3.06	6.78	-1.67	-7.28	-0.02	-1.67	-1.67	-0.16
R-Squared	0.02	0.08	0.20	0.02	0.21	0.00	0.08	0.08	0.00

Table 78: Single predictive regressions for ICAPM state variables constructed from empirical factors. This table shows the results for the single long-horizon regressions over the value-weighted market return at horizons of 1, 12, and 36 months ahead. The forecasting variables are the associated state variables for the size (*SMB**), value (*HML**), momentum (*MOM**), investment (*CMA**), operating profitability (*RMW**), and liquidity (*LIQ**). These state variables are constructed by using the cumulative sum of the last 60 months following Maio and Santa-Clara (2012) methodology to produce innovation in the state variables constructed from empirical factors. The sample includes observations from 1981:01–2015:12. The coefficient of predictive regression, t-statistic, p-value, and percentage of R-squared values are reported.

	*SMB**	*HML**	*MOM**	*CMA**	*RMW**	*LIQ**
			q = 1			
Coefficient	0.10	-0.18	-0.14	-0.15	-0.16	-0.06
T-Stat	3.20	-2.67	-1.31	-3.47	-3.29	-0.96
R-Squared	0.02	0.05	0.01	0.06	0.04	0.00
			q = 12			
Coefficient	0.10	-0.19	-0.13	-0.15	-0.16	-0.06
T-Stat	3.52	-1.79	-0.81	-1.80	-1.69	-0.14
R-Squared	0.02	0.06	0.01	0.06	0.05	0.00
			q = 36			
Coefficient	0.11	-0.20	-0.17	-0.18	-0.18	0.00
T-Stat	4.55	-2.06	-1.44	-2.69	-0.71	0.01
R-Squared	0.03	0.07	0.03	0.14	0.06	0.00

Table 79: Single predictive regressions for ICAPM state variables constructed from empirical factors. This table shows the results for the single long-horizon regressions over the stock market variance (*SVAR*) at horizons of 1, 12, and 36 months ahead. The forecasting variables are the associated state variables for the size (*SMB**), value (*HML**), momentum (*MOM**), investment (*CMA**), operating profitability (*RMW**), and liquidity (LIQ*). These state variables are constructed by using the cumulative sum of the last 60 months following Maio and Santa-Clara (2012) methodology to produce innovation in the state variables constructed from empirical factors. The sample includes observations from 1981:01–2015:12. The coefficient of predictive regression, t-statistic, p-value, and percentage of R-squared are reported.

	*SMB**	*HML**	*MOM**	*CMA**	*RMW**	*LIQ**
			q = 1			
Coefficient	-0.90	-0.29	-1.10	-0.13	0.45	0.01
T-Stat	-3.30	-0.61	-1.24	-0.50	1.51	0.01
R-Squared	0.02	0.00	0.01	0.00	0.00	0.00
			q = 12			
Coefficient	-0.93	-0.33	-1.00	-0.13	0.48	-0.12
T-Stat	-3.19	-0.81	-0.94	-0.31	2.25	-0.04
R-Squared	0.03	0.00	0.01	0.00	0.01	0.00
			q = 36			
Coefficient	-1.01	-0.28	-0.66	0.11	0.60	-0.82
T-Stat	-3.71	-0.56	-1.12	0.55	2.33	-0.51
R-Squared	0.03	0.00	0.01	0.00	0.01	0.01

4.4.3.2 Multiple Predictive Regressions

Table (80) - (85) show results of multiple predictive regressions for the above-mentioned ICAPM models. Hahn and Lee (2006) state variables (term structure and default spread) predict stock variance but do not show convincing results in predicting market returns. The Petkova (2006) factors significantly predict market returns and stock variance at the 5% significance level. The Petkova alternative version where I include inflation and industrial production as additional factors show a strong evidence in predicting market returns and stock variance. In Campbell and Vuolteenaho (2004) model, only price earnings ratio shows a strong evidence to predict market returns whereas all its factors, term, price-earnings ratios and value spread significantly predict stock variance.

Table (82) and (83) show the predictive performance of the Pástor & Stambaugh (2003) model, Fama and French (1993) ICAPM that includes term structure and default spread, and the newly proposed augmented ICAPM model that includes inflation and industrial production with the Fama and French (1993) factors. I do not find convincing evidence for the Pástor & Stambaugh (2003) four-factor model with the multiple predictive regressions. Likewise, I find a weak evidence in favour of the Fama and French (1993) augmented ICAPM models. These findings confirm the prediction of Fama and French (1996) that there is a scope of including state variables with the Fama and French (1993) model.

Tables (84) and (85) show results of the multiple predictive regressions for the Fama and French (1993) three-factor, Carhart (1996) four-factor, Fama and French (2015) five-factor and the six-factor model which is the five-factor augmented model with the momentum price factor. Tables show a strong ability of these models in predicting aggregate market returns and stock variance. I find a significant evidence for the empirical factor in predicting aggregate market returns. However, size is only priced with the Fama and French (1993) three-factor model. The size factor becomes redundant with the addition of momentum, investment, or operating profitability factors. Further, I also find a strong evidence in favour of the six-factor model as the momentum does not become redundant with the addition of investment and profitability factors. This evidence is contradictory to the Fama and French (2015) study who claim that the momentum becomes redundant with the investment and profitability factors.

Table 80: Multiple Predictive regressions with the ICAPM state variables over value-weighted market return at horizons of 1, 12, and 36 months ahead. Forecasting variables include the term-structure (*TERM*), default risk (*DEF*), dividend yield (*DY*), 1-month Treasury bill rate (*RF)*, price–earnings ratio (*PE*), and the value spread (*VS*). HL, P, P*, and CV refer to Hahn and Lee (2006) model, Petkova (2006), Petkova augmented model and Campbell and Vuolteenaho (2004) models respectively. The sample includes observations from 1981:01–2015:12 and q observations are removed with each respective q-horizon regression, for q = 1, 12, 36. Each multiple regression is reported with q lags in line 1, slope estimates in line 2 and Newey-West t-statistic in line 3.

	TERM	*DEF*	*DY*	*RF*	*PE*	*VS*	*CPI*	*IN*	R^2
	q = 1								
HL	-0.05	-0.09							0.00
	-0.21	-0.58							
	q = 12								
	-0.07	-0.10							0.00
	-0.29	-0.60							
	q = 36								
	-0.09	-0.11							0.00
	-0.92	-0.75							
	q = 1								
P	0.06	0.19	-1.92	-1.03					0.46
	0.95	3.75	-20.15	-2.88					
	q = 12								
	0.06	0.18	-1.90	-1.04					0.46
	0.64	4.15	-24.17	-2.43					
	q = 36								
	0.08	0.19	-1.92	-0.90					0.46
	1.47	6.34	-18.37	-3.37					
	q = 1								
	0.08	0.18	-0.85	-1.91			-1.08	-1.22	0.46
	1.05	3.70	-2.26	-19.29			-0.90	-1.66	
	q = 12								
P*	0.07	0.18	-0.83	-1.90			-1.27	-1.09	0.46
	0.76	4.20	-1.85	-23.00			-1.71	-2.67	
	q = 36								
	0.09	0.19	-0.72	-1.91			-1.11	-1.09	0.46
	1.56	7.19	-2.71	-18.20			-2.71	-2.67	
	q = 1								
CV	-0.04				1.87	-0.13			0.45
	-0.66				20.99	-0.97			
	q = 12								
	-0.05				1.86	-0.12			0.45
	-0.64				23.04	-0.74			
	q = 36								
	-0.05				1.86	-0.16			0.46
	-1.33				20.04	-1.83			

Table 81: Multiple Predictive regressions with the ICAPM state variables over stock market variance (*SVAR*) at horizons of 1, 12, and 36 months ahead. Forecasting variables include the term-structure (*TERM*), default risk (*DEF*), dividend yield (*DY*), 1-month Treasury bill rate (*RF*), price–earnings ratio (*PE*), and the value spread (VS). HL, P, P*, and CV refer to Hahn and Lee (2006) model, Petkova (2006), Petkova augmented model and Campbell and Vuolteenaho (2004) models respectively. The sample includes observations from 1981:01–2015:12 and q observations are removed with each respective q-horizon regression, for q = 1, 12, 36. Each multiple regression is reported with q lags in line 1, slope estimates in line 2 and Newey-West t-statistic in line 3.

	TERM	*DEF*	*DY*	*RF*	*PE*	*VS*	*CPI*	*IN*	R^2
	q = 1								
HL	0.00	0.05							0.08
	0.14	1.86							
	q = 12								
	0.00	0.05							0.08
	0.24	1.87							
	q = 36								
	0.01	0.05							0.08
	0.61	2.64							
	q = 1								
P	0.00	0.03	0.13	-0.24					0.25
	-0.34	1.60	2.40	-1.39					
	q = 12								
	0.00	0.03	0.13	-0.26					0.25
	-0.31	2.46	3.58	-1.35					
	q = 36								
	0.00	0.03	0.14	-0.32					0.26
	-0.33	3.54	3.25	-2.06					
	q = 1								
	0.01	0.03	-0.06	0.14			-1.11	-1.11	0.30
	0.46	1.99	-0.54	2.69			-1.44	-1.44	
	q = 12								
P*	0.01	0.03	-0.08	0.14			-1.15	-1.15	0.30
	0.51	2.95	-0.67	3.97			-1.88	-1.89	
	q = 36								
	0.01	0.03	-0.12	0.14			-1.23	-1.22	0.32
	1.32	6.42	-1.67	2.95			-2.53	-2.54	
	q = 1								
CV	-0.03				-0.15	-0.03			0.23
	-2.91				-2.53	-1.50			
	q = 12								
	-0.03				-0.16	-0.04			0.23
	-4.60				-2.81	-1.53			
	q = 36								
	-0.03				-0.16	-0.04			0.23
	-6.06				-3.56	-1.86			

Table 82: Multiple Predictive regressions with the ICAPM state variables over value-weighted market return at horizons of 1, 12, and 36 months ahead. Forecasting variables include the associated state variables for size (*SMB**), value (*HML**), momentum (*CMOM**), investment (*CMA**), operating profitability (*RM*W*), liquidity (*CLIQ*), term structure (*TERM*), and Default risk (*DEF*). PS and FFICAPM, FF ICAPM, FF ICAPM* show the Pástor & Stambaugh (2003) model, Fama and French (1993) ICAPM and newly proposed augmented ICAPM model respectively. The sample includes observations from 1981:01–2015:12 and q observations are removed with each respective q-horizon regression, for q = 1, 12, 36. Each multiple regression is reported with q lags in line 1, slope estimates in line 2 and Newey-West t-statistic in line 3.

	*SMB**	*HML**	*MOM**	*CMA**	*RMW**	*LIQ**	*CPI*	*IND*	*TERM*	*DEF*	R^2
	q = 1										
PS	0.23	-0.29				-0.03					0.08
	2.41	-2.92				-1.00					
	q = 12										
	0.22	-0.31				-0.05					0.09
	1.69	-2.18				-1.12					
	q = 36										
	0.23	-0.35				0.05					0.10
	1.23	-1.32				0.56					
	q = 1										
FF ICAPM	0.20	-0.30							-0.01	-0.06	0.08
	2.36	-3.11							-0.09	-0.43	
	q = 12										
	0.19	-0.32							-0.02	-0.06	0.08
	1.61	-2.23							-0.08	-0.35	
	q = 36										
	0.23	-0.34							-0.05	-0.06	0.10
	1.43	-1.27							-0.43	-0.33	
	q = 1										
FF ICAPM*	0.21	-0.29					-1.94	-1.90			0.08
	2.50	-3.00					-0.52	-0.51			
	q = 12										
	0.21	-0.31					-2.41	-2.38			0.09
	1.68	-1.98					-0.94	-0.93			
	q = 36										
	0.24	-0.33					-1.62	-1.58			0.10
	1.05	-1.05					-0.47	-0.46			

Table 83: Multiple Predictive regressions with the ICAPM state variables over stock market variance (*SVAR*) return at horizons of 1, 12, and 36 months ahead. Forecasting variables include the associated state variables for size (*SMB**), value (*HML**), momentum (*CMOM**), investment (*CMA**), operating profitability (*RMW**), liquidity (*CLIQ*), term structure (*TERM*), and Default risk (*DEF*). PS and FFICAPM, FF ICAPM, FF ICAPM* show the Pástor & Stambaugh (2003) model, Fama and French (1993) ICAPM and newly proposed augmented ICAPM model respectively. The sample includes observations from 1981:01–2015:12 and q observations are removed with each respective q-horizon regression, for q = 1, 12, 36. Each multiple regression is reported with q lags in line 1, slope estimates in line 2 and Newey-West t-statistic in line 3.

	*SMB**	*HML**	*MOM**	*CMA**	*RMW**	*LIQ**			*TERM*	*DEF*	R^2
	q = 1										
PS	-0.03	-0.01				0.00					0.02
	-1.81	-0.65				0.81					
	q = 12										
	-0.03	-0.01				0.00					0.03
	-1.90	-1.03				0.20					
	q = 36										
	-0.03	0.00				-0.01					0.04
	-1.68	-0.46				-0.78					
	q = 1										
FF ICAPM	-0.02	0.00							0.00	0.05	0.09
	-1.33	-0.37							0.10	1.41	
	q = 12										
	-0.02	-0.01							0.00	0.05	0.10
	-1.57	-0.85							0.27	1.89	
	q = 36										
	-0.02	-0.01							0.01	0.05	0.10
	-0.69	-0.24							0.45	1.44	
	q = 1										
FF ICAPM*	-0.02	0.00					-1.16	-1.16			0.09
	-1.49	-0.01					-1.10	-1.10			
	q = 12										
	-0.02	0.00					-1.19	-1.19			0.10
	-1.72	-0.53					-1.40	-1.40			
	q = 36										
	-0.03	0.00					-1.34	-1.34			0.12
	-1.95	-0.16					-1.64	-1.64			

Table 84: Multiple Predictive regressions with the ICAPM state variables over value-weighted market return at horizons of 1, 12, and 36 months ahead. Forecasting variables are the associated state variables for size (SMB*), value (HML*), momentum (CMOM), investment (CMA*), operating profitability (RMW*). FF3, C, FF5 and six-factor show the Fama and French (1993), Carhart (1997), Fama and French (2015) five-factor, and five-factor augmented model with momentum price factor respectively. The sample includes observations from 1981:01–2015:12 and q observations are removed with each respective q-horizon regression, for q = 1, 12, 36. Each multiple regression is reported with q lags in line 1, slope estimates in line 2 and Newey-West t-statistic in line 3.

	*SMB**	*HML**	*MOM**	*CMA**	*RMW**	R^2
	q = 1					
FF3	0.21	-0.30				0.08
	2.42	-3.04				
	q = 12					
	0.20	-0.32				0.08
	1.67	-2.11				
	q = 36					
	0.24	-0.34				0.09
	0.99	-1.03				
	q = 1					
C	0.15	-0.36	-0.11			0.10
	1.79	-3.72	-2.27			
	q = 12					
	0.17	-0.35	-0.12			0.10
	1.72	-2.60	-1.21			
	q = 36					
	0.22	-0.42	-0.22			0.15
	1.46	-2.30	-6.27			
	q = 1					
FF5	0.02	-0.28		-0.12	-0.28	0.12
	0.22	-1.97		-0.66	-2.51	
	q = 12					
	0.02	-0.29		-0.12	-0.28	0.12
	0.14	-1.53		-0.35	-2.31	
	q = 36					
	0.03	-0.14		-0.61	-0.31	0.20
	0.15	-1.08		-3.06	-3.19	
	q = 1					
Six-factor	0.01	-0.34	-0.07	-0.05	-0.26	0.12
	0.13	-2.52	-1.40	-0.27	-2.64	
	q = 12					
	0.03	-0.34	-0.06	-0.06	-0.26	0.13
	0.19	-2.25	-0.91	-0.19	-2.61	
	q = 36					
	0.04	-0.22	-0.13	-0.52	-0.27	0.21
	0.22	-1.66	-3.05	-2.69	-2.34	

Table 85: Multiple Predictive regressions with the ICAPM state variables over stock market variance (*SVAR*) at horizons of 1, 12, and 36 months ahead. Forecasting variables are the associated state variables for size (*SMB**), value (*HML**), momentum (*CMOM**), investment (*CMA**), operating profitability (*RMW**). FF3, C, FF5 and six-factor show the Fama and French (1993), Carhart (1997), Fama and French (2015) five-factor, and five-factor augmented model with momentum price factor respectively. The sample includes observations from 1981:01–2015:12 and q observations are removed with each respective q-horizon regression, for q = 1, 12, 36. Each multiple regression is reported with q lags in line 1, slope estimates in line 2 and Newey-West t-statistic in line 3.

	*SMB**	*HML**	*MOM**	*CMA**	*RMW**	R^2
	q = 1					
FF3	-0.02	0.00				0.02
	-1.67	-0.44				
	q = 12					
	-0.03	-0.01				0.03
	-1.98	-0.92				
	q = 36					
	-0.03	-0.01				0.03
	-2.07	-0.69				
	q = 1					
C	-0.03	-0.01	-0.01			0.05
	-1.95	-1.50	-2.28			
	q = 12					
	-0.03	-0.01	-0.01			0.05
	-1.99	-1.48	-2.01			
	q = 36					
	-0.03	-0.01	-0.01			0.05
	-2.10	-1.35	-1.43			
	q = 1					
FF5	-0.03	0.00		-0.01	0.00	0.02
	-1.52	-0.14		-0.56	-0.21	
	q = 12					
	-0.03	-0.01		-0.01	0.00	0.03
	-1.75	-0.47		-0.33	-0.23	
	q = 36					
	-0.03	-0.01		0.02	0.00	0.04
	-2.10	-1.31		1.45	-0.24	
	q = 1					
Six-factor	-0.03	-0.02	-0.02	0.01	0.00	0.05
	-1.65	-1.35	-2.42	0.71	0.29	
	q = 12					
	-0.03	-0.02	-0.02	0.01	0.00	0.05
	-1.71	-1.26	-2.16	0.71	0.43	
	q = 36					
	-0.03	-0.02	-0.02	0.03	0.00	0.05
	-2.15	-3.08	-1.77	3.32	0.79	

4.4.4 Cross-sectional GMM tests

After predictive regressions, I examine the fundamental criterion of ICAPM which states that the model should produce an economically plausible estimate of the market price factor. In other words, the cross-sectional regression should produce the positive estimate of the market coefficient. Following Maio and Santa-Clara (2012), Lutzenberger (2015), Cooper and Maio (2016), I use the first stage GMM methodology. First stage GMM is similar to OLS cross-sectional methodology but is considered more robust than traditional cross-sectional methodology. I report the cross-sectional pricing error *(Constant),* factor risk premia and cross-sectional R-squared. Results are reported in Tables (86) – (91). I compare twelve ICAPM models in this study. First is the two-factor ICAPM where I employ gold as a hedging factor. Second is the Hahn and Lee (2006) model that uses market (*MKT*), the term (*Term*) and default risk (*DEF*) as factor loadings. The third is the Petkova (2006) ICAPM that employs the market (*MKT*), term-structure (*Term*), default spread (*DEF*), dividend yield *(DY),* and Treasury bill yield *(RF).* Fourth is the alternative Petkova model (P*) augmented model with inflation and industrial production. The fifth model is the Campbell and Vuolteenaho (2004) that uses market (*MKT*), term (*Term*), price earnings ratio *(PE)* ratio and value spread *(VS)*. Brennan, Wang, & Xia (2004) emphasize that Fama and French (1993) factors are consistent with Merton's ICAPM and hence, sixth is the Fama and French (1993) three-factor model. Seventh is the Fama and French (1993) ICAPM model that uses market, size, and value with the term-structure and default risk. Eighth is the alternative Fama and French (1993) ICAPM (FF ICAPM*) that uses inflation (*CPI)* and industrial production (*IND)* with Fama and French (1993) factors. Ninth is the Carhart (1997) four-factor model that uses momentum with Fama and French (1993) factors, the tenth is the Pástor and Stambaugh (2003) four-factor model that uses liquidity price factor (*LIQ*) in addition to Fama and French (1993) factors. Eleventh is the

Fama and French (2015) five-factor model, and twelfth is the Fama and French (2015) augmented model with the momentum price factor. I test these models on the 25 size and book-to-market portfolios and 30 industry portfolios. I follow Brennan, Wang, & Xia (2004) in choosing 30 U.S. industries as asset portfolios to assess the performance of the ICAPM models as they stress that 30 industry portfolios are suitable test portfolios to examine empirical performance of the ICAPM models.

Tables (86) – (88) reports results on the 25 size and book-to-market portfolios. In order to gain further evidence for gold as a zero-beta asset, I perform first-stage GMM tests in two different methods. In the first case, I use the 1-month Treasury bill yield as a risk-free rate and in the second case, I employ gold as a zero-beta asset. Twelve models are estimated by using Treasury bill rate as a proxy of the zero-beta rate whereas eleven models are estimated by using gold return as a proxy of the zero-beta rate. The two-factor model where gold is utilized as another factor is estimated with Treasury bill rate as a risk-free rate.

I do not find convincing results for the two-factor model on both sets of test portfolios. When I use the Treasury bill rate as a risk-free rate, I find that the ICAPM models produce the negative (implausible) estimates of the market risk premia with the significant cross-sectional alphas (pricing errors) on the 25 size and book-to-market portfolios. However, when gold return is used as a zero-beta rate, I do not find any pricing error with the Petkova (2006) model as is shown in Table (86).

Results in Table (87) show that only the Carhart (1997) four-factor model meets the main condition of the ICAPM and produces a positive insignificant estimate of the market risk premium on the 25 size and book-to-market portfolios. When I use gold return as a zero-beta rate with the four-factor model, I obtain the plausible and significant estimate of the market price factor. Further, when I use gold as a zero-beta asset in the six-factor model, the six-factor model also produces an economically meaningful estimate of the market coefficient. However, when 1-month Treasury bill yield is used as a risk-free rate, an implausible estimate of the market coefficient is produced.

Tables (89) - (91) report results on the 30 industry portfolios and show a comparison of the twenty-three asset pricing models. Findings reveal that the ICAPM multifactor models perform reasonably well on industry portfolios whereas empirical factor models particularly, Pástor & Stambaugh (2003) and Carhart (1997) models produce the significant pricing errors on industry portfolios. When gold return is used as a proxy of the zero-beta rate, pricing errors of Pástor & Stambaugh (2003) and Carhart (1997) models become insignificant and R-squared values of these models are significantly improved. One could argue that R-squared values increase with the addition of factors and improvement in the R-squared value does not necessarily mean improvement of model performance (Chan, Jegadeesh, and Lakonishok, 1996). In this study, the proposed gold zero-beta models improve R-squared without including additional factors.

The third important criterion of the ICAPM states that the state variables should produce the same sign in cross-section as they produce in predictive regression. I find that most of the state variables under investigation produce the same sign in time series regression as in cross-section and meet this condition. However, the associated state variables from empirical factors (*HML**, *MOM**) produce different signs in predictive regressions than in cross-section. Hence, these empirical factor models struggle to meet the final criterion of the ICAPM.

Table 86: Factor risk premia for ICAPM state variables. This table shows the factor risk premia produced from the cross-sectional GMM (first-stage) test. The *25 size and book-to-market* portfolios portfolios from the U.S. equity market are used as test portfolios. γ_M shows market risk price, γ_G, γ_{TERM}, γ_{DEF}, γ_{DY}, γ_{RF}, γ_{PE}, γ_{CPI}, γ_{IND}, show price of the gold, term-structure (*TERM*), default risk (*DEF*), dividend yield (*DY*), Treasury bill yield, (*RF)* price-earnings ratio (*PE*), value spread (*VS*), inflation (*CPI*) and industrial production (*IND*) respectively. HL, P and CV refer to Hahn and Lee (2006) model, Petkova (2006), and Campbell and Vuolteenaho (2004) models respectively. The first row related to each model shows prices of risk factors for the factor loadings of ICAPM models and the second line shows GMM robust asymptotic t-statistics. The column R^2 shows OLS cross-sectional R-squared. In Panel A, models are estimated by using 1-month Treasury bill yield as a risk free rate, whereas in Panel B, models are estimated by using gold as a zero-beta asset.

	Treasury Bill rate as a risk-free rate											
	Constant	λ_M	λ_G	λ_{term}	λ_{def}	λ_{dy}	λ_{rf}	λ_{pe}	λ_{vs}	λ_{CPI}	λ_{In}	R^2
2F ICAPM	1.74	-0.95	-0.53									0.37
	4.05	-2.02	-0.38									
HL	1.97	-1.23		0.08	-0.52							0.42
	4.10	-2.41		0.17	-0.75							
P	1.95	-1.17		0.27	-1.30	0.50	0.11					0.49
	5.74	-2.79		0.41	-1.06	1.32	1.10					
P*	2.15	-1.46		1.65	-1.78	0.32	0.23			-0.12	-0.11	
	3.31	-2.12		1.34	-0.72	0.49	1.15			-1.71	-1.57	
CV	2.37	-1.61		0.36				-0.35	-0.40			0.43
	6.77	-3.83		0.60				-1.35	-0.85			
	Gold return as a zero-beta rate											
	Constant	λ_M		λ_{term}	λ_{def}	λ_{dy}	λ_{rf}	λ_{pe}	λ_{vs}	λ_{CPI}	λ_{In}	R^2
HL	4.28	-3.32		0.03	-0.41							0.36
	3.12	-2.39		0.06	-0.56							
P	1.90	-0.91		0.24	-1.19	0.44	0.11					0.49
	1.45	-0.68		0.38	-1.16	1.63	1.00					
P*	0.30	0.70		0.76	-1.48	0.56	-2.17			-0.05	-0.05	
	0.18	0.41		0.89	-0.89	1.60	-1.43			-1.25	-1.25	
CV	3.92	-2.92		0.66				-0.55	-0.17			0.37
	2.90	-2.10		1.10				-2.62	-0.38			

Table 87: Factor risk premia for ICAPM state variables with 1-month Treasury Bill rate as a risk-free rate. This table shows the factor risk premia produced from the cross-sectional GMM (first-stage) test. The *25 size and book-to-market* portfolios portfolios from the U.S. equity market are used as test portfolios. γ_M shows market risk price, $\gamma_{smb}, \gamma_{hml}, \gamma_{Mom}, \gamma_{CMA}, \gamma_{RMW}, \gamma_{TERM}, \gamma_{DEF}, \gamma_{LIQ}, , \gamma_{CPI}, , \gamma_{IND}$, show market price for size (*SMB*), value (*HML*), momentum (*Mom*), investment (C*MA*), operating profitability (*RMW*), term-structure (T*ERM*), default risk (*DEF*), liquidity (*LIQ*), inflation (*CPI)* and industrial production (*IND*) respectively. FF3, FF ICAPM, FF ICAPM*, C, PS and Six-factor model refer to Fama and French (1993) model, their augmented model with term-structure and default risk, newly proposed FF ICAPM* augmented with CPI and industrial production, Carhart (1997), Pástor & Stambaugh (2003) four-factor liquidity, and Fama and French (2015) model augmented with momentum price factor , respectively. The first row related to each model shows prices of risk factors for the factor loadings of ICAPM models and the second line shows GMM robust asymptotic t-statistics. The column R^2 shows OLS cross-sectional R-squared.

Treasury Bill rate as a risk-free rate													
	Constant	λ_M	λ_{smb}	λ_{hml}	λ_{Mom}	λ_{cma}	λ_{rmw}	λ_{term}	λ_{def}	λ_{Liq}	λ_{CPI}	λ_{In}	R^2
FF3		1.67	-1.02	0.06	0.36								0.53
		5.76	-2.76	0.40	2.40								
FF ICAPM	1.57	-0.95	0.09	0.35				-0.31	1.24				0.59
	5.06	-2.50	0.60	2.33				-0.62	1.97				
FF ICAPM*	1.55	-0.93	0.10	0.32							-0.05	-0.05	0.54
	4.84	-2.38	0.67	2.13							-1.67	-1.67	
C	0.15	0.55	0.10	0.40	3.57								0.72
	0.23	0.80	0.67	2.67	3.00								
PS	1.65	-1.00	0.06	0.36						0.20			0.54
	5.50	-2.70	0.40	2.40						0.26			
FF 5-Factor	1.77	-1.17	0.16	0.32		-0.27	0.64						
	4.21	-2.49	1.07	2.13		-1.13	2.67						
Six-Factor	0.62	0.06	0.15	0.39	3.21	-0.20	0.54						0.78
	0.95	0.09	1.00	2.60	3.87	-0.65	1.86						

Table 88: Factor risk premia for ICAPM state variables with the 1-month gold return as a zero-beta rate. This table shows the factor risk premia produced from the cross-sectional GMM (first-stage) test. The 25 *size and book-to-market* portfolios from the U.S. equity market are used as test portfolios. γ_M shows market risk price, γ_{smb}, γ_{hml}, γ_{Mom}, γ_{CMA}, γ_{RMW}, γ_{TERM}, γ_{DEF}, γ_{LIQ}, γ_{CPI} , γ_{IND} show market price for size (*SMB*), value (*HML*), momentum (*Mom*), investment (C*MA*), operating profitability (*RMW*), term-structure (T*ERM*), default risk (*DEF*), liquidity (*LIQ*), inflation (*CPI)* and industrial production (*IND*) respectively. FF3, FF ICAPM, FF ICAPM*, C, PS and Six-factor model refer to Fama and French (1993) model, their augmented model with term-structure and default risk, newly proposed FF ICAPM* augmented with CPI and industrial production, Carhart (1997), Pástor & Stambaugh (2003) four-factor liquidity, and Fama and French (2015) model augmented with momentum price factor , respectively. The first row related to each model shows prices of risk factors for the factor loadings of ICAPM models and the second line shows GMM robust asymptotic t-statistics. The column R^2 shows OLS cross-sectional R-squared.

Gold as a zero-beta asset													
	Constant	λ_M	λ_{smb}	λ_{hml}	λ_{Mom}	λ_{cma}	λ_{rmw}	λ_{term}	λ_{def}	λ_{Liq}			R^2
FF 3-Factor	2.79	-1.94	0.07	0.37									0.51
	3.36	-2.20	0.47	2.47									
FF ICAPM	2.31	-1.49	0.10	0.36				-0.36	1.24				0.57
	2.72	-1.64	0.67	2.57				-0.72	2.00				
FF ICAPM*	2.40	-1.57	0.10	0.34							-0.05	-0.05	0.54
	2.76	-1.74	0.67	2.27							-1.67	-1.67	
C	-1.28	**2.21**	0.09	0.38	3.09								0.72
	-0.96	**1.61**	0.56	2.71	4.35								
PS	2.87	-2.01	0.07	0.37						-0.13			0.51
	3.19	-2.12	0.47	2.47						-0.15			
FF 5-Factor	1.81	-1.17	0.16	0.32		-0.27	0.64						
	3.55	-2.49	1.07	2.13		-1.13	2.67						0.64
Six-Factor	0.03	0.87	0.15	0.38	2.95	-0.21	0.57						0.78
	0.02	0.52	1.00	2.53	3.83	-0.62	1.84						

Table 89: Factor risk premia for ICAPM state variables. This table shows the factor risk premia produced from the cross-sectional GMM (first-stage) test. The 30 U.S. industry portfolios are used as test portfolios. γ_M shows market risk price, γ_G, γ_{TERM}, γ_{DEF}, γ_{DY}, γ_{RF}, γ_{PE}, γ_{VS}, γ_{CPI}, γ_{IND} show price of gold, the term-structure (*TERM*), default risk (*DEF*), dividend yield (*DY*), Treasury bill yield (*RF)* price-earnings ratio (*PE*), value spread (*VS*), inflation (*CPI*) and industrial production (*IND*) factors respectively. HL, P, P* and CV refer to Hahn and Lee (2006) model, Petkova (2006), Petkova augmented model with inflation and industrial production factors, and Campbell and Vuolteenaho (2004) model respectively. The first row related to each model shows prices of risk factors for the factor loadings of ICAPM models and the second line shows GMM robust asymptotic t-statistics. The column R^2 shows OLS cross-sectional R-squared. In Panel A, models are estimated by using 1-month Treasury bill yield as a risk free rate, whereas in Panel B, models are estimated by using gold as a zero-beta asset.

Treasury Bills as risk-free rate												
	Constant	λ_M	λ_G	λ_{term}	λ_{def}	λ_{dy}	λ_{rf}	λ_{pe}	λ_{vs}	λ_{CPI}	λ_{In}	R^2
2F ICAPM	0.96	-0.25	-0.71									0.49
	3.56	-0.74	-1.69									
HL	0.52	0.20		-0.62	1.07							0.40
	1.30	0.43		-1.15	1.39							
P	0.34	0.36		-0.73	1.20	-0.16	0.10					0.48
	0.77	0.73		-1.22	1.25	-0.55	1.25					
P*	0.46	0.24		-0.65	0.94	-0.10	0.09			0.00	0.00	0.50
	1.35	0.60		-1.20	1.24	-0.37	1.00			0.00	0.00	
CV	0.39	0.26		-0.71				-0.23	0.97			0.55
	0.78	0.48		-0.75				-0.74	1.73			
Gold as a zero-beta asset												
	Constant	λ_M		λ_{term}	λ_{def}	λ_{dy}	λ_{rf}	λ_{pe}	λ_{vs}	λ_{CPI}	λ_{In}	R^2
HL	0.37	0.56		-0.72	0.81							0.53
	0.79	0.98		-1.44	1.40							
P	0.40	0.53		-0.53	0.30	0.06	-0.53					0.58
	0.83	0.91		-1.04	0.45	0.26	-1.33					
P*	0.36	0.58		-0.64	0.47	-0.01	-0.46			0.00	0.01	0.59
	0.88	1.12		-1.31	0.69	-0.04	-1.12			0.00	0.33	
CV	0.23	0.66		-0.51				-0.06	0.54			0.66
	0.49	1.16		-0.77				-0.30	1.29			

Table 90: Factor risk premia for ICAPM state variables with 1-month Treasury Bill rate as a risk-free rate. This table shows the factor risk premia produced from the cross-sectional GMM (first-stage) test. The 30 U.S. industry portfolios are used as test portfolios. γ_M shows market risk price, γ_{SMB}, γ_{hml}, γ_{Mom}, γ_{CMA}, γ_{RMW}, γ_{TERM}, γ_{DEF}, γ_{LIQ}, γ_{CPI}, γ_{IND}, show market price for size (*SMB*), value (*HML*), momentum (*Mom*), investment (C*MA*), operating profitability (*RMW*), term-structure (T*ERM*), default risk (*DEF*), liquidity (*LIQ*), inflation (*CPI)* and industrial production (*IND*) respectively. FF3, FF ICAPM, FF ICAPM*, C, PS and Six-factor model refer to Fama and French (1993) model, their augmented model with term-structure and default risk, newly proposed FF ICAPM* augmented with CPI and industrial production, Carhart (1997), Pástor & Stambaugh (2003) four-factor liquidity, and Fama and French (2015) model augmented with momentum price factor , respectively. The first row related to each model shows prices of risk factors for the factor loadings of ICAPM models and the second line shows GMM robust asymptotic t-statistics. The column R^2 shows OLS cross-sectional R-squared.

Treasury Bills as risk-free rate													
	Constant	λ_M	λ_{SMB}	λ_{hml}	λ_{Mom}	λ_{CMA}	λ_{RMW}	λ_{TERM}	λ_{DEF}	λ_{LIQ}	λ_{CPI}	λ_{IND}	R^2
FF3	0.60	0.14	-0.49	-0.03									0.25
	1.76	0.35	-1.53	-0.15									
FF ICAPM	0.35	0.38	-0.35	-0.05				0.86	-0.70				0.41
	0.83	0.81	-1.21	-0.25				0.92	-1.27				
FF ICAPM*	0.70	0.05	-0.38	-0.10							-0.02	-0.02	0.38
	2.33	0.14	-1.31	-0.45							-0.67	-0.67	
C	0.84	-0.12	-0.55	-0.06	-0.76								0.32
	2.90	-0.32	-1.53	-0.29	-0.89								
PS	0.72	0.00	-0.27	-0.01						-0.56			0.43
	2.40	0.00	-1.13	-0.05						-1.08			
Five-Factor	0.27	0.38	-0.44	-0.26		-0.28	0.55						0.60
	0.87	1.03	-1.33	-1.30		-0.88	1.90						
Six-Factor	0.43	0.19	-0.50	-0.33	-0.67	-0.22	0.52						0.68
	1.39	0.50	-1.35	-1.50	-0.81	-0.73	1.86						

Table 91: Factor risk premia for ICAPM state variables with the 1-month gold return as a zero-beta rate. This table shows the factor risk premia produced from the cross-sectional GMM (first-stage) test. The 30 U.S. industry portfolios are used as test portfolios. γ_M shows market risk price, γ_{SMB}, γ_{hml}, γ_{Mom}, γ_{CMA}, γ_{RMW}, γ_{TERM}, γ_{DEF}, γ_{LIQ}, γ_{CPI}, γ_{IND}, show market price for size (*SMB*), value (*HML*), momentum (*Mom*), investment (C*MA*), operating profitability (*RMW*), term-structure (T*ERM*), default risk (*DEF*), liquidity (*LIQ*), inflation (*CPI)* and industrial production (*IND*) respectively. FF3, FF ICAPM, FF ICAPM*, C, PS and Six-factor model refer to Fama and French (1993) model, their augmented model with term-structure and default risk, newly proposed FF ICAPM* augmented with CPI and industrial production, Carhart (1997), Pástor & Stambaugh (2003) four-factor liquidity, and Fama and French (2015) model augmented with momentum price factor , respectively. The first row related to each model shows prices of risk factors for the factor loadings of ICAPM models and the second line shows GMM robust asymptotic t-statistics. The column R^2 shows OLS cross-sectional R-squared.

Gold as a zero-beta asset													
	$Constant$	λ_M	λ_{SMB}	λ_{hml}	λ_{Mom}	λ_{CMA}	λ_{RMW}	λ_{TERM}	λ_{DEF}	λ_{LIQ}	λ_{CPI}	λ_{IND}	R^2
FF 3-Factor	0.27	0.69	-0.46	0.01									0.45
	0.57	1.23	-1.53	0.05									
FF ICAPM	0.14	0.82	-0.51	-0.03				-0.78	-0.13				0.61
	0.26	1.32	-1.46	-0.14				-1.47	-0.16				
FF ICAPM*	0.47	0.49	-0.41	-0.03							-0.01	-0.01	0.48
	1.24	1.00	-1.46	-0.14							-0.33	-0.33	
C	0.27	0.69	-0.46	0.01	-0.09								0.45
	0.60	1.28	-1.31	0.05	-0.13								
PS	0.49	0.47	-0.35	0.01						-0.34			0.50
	1.29	0.96	-1.35	0.05						-0.67			
Five-Factor	0.26	0.63	-0.21	-0.20		-0.11	0.37						0.67
	0.55	1.15	-0.72	-1.05		-0.41	1.48						
Six-Factor	0.37	0.47	-0.34	-0.28	-0.49	-0.09	0.40						0.72
	0.84	0.90	-0.94	-1.33	-0.67	-0.35	1.54						

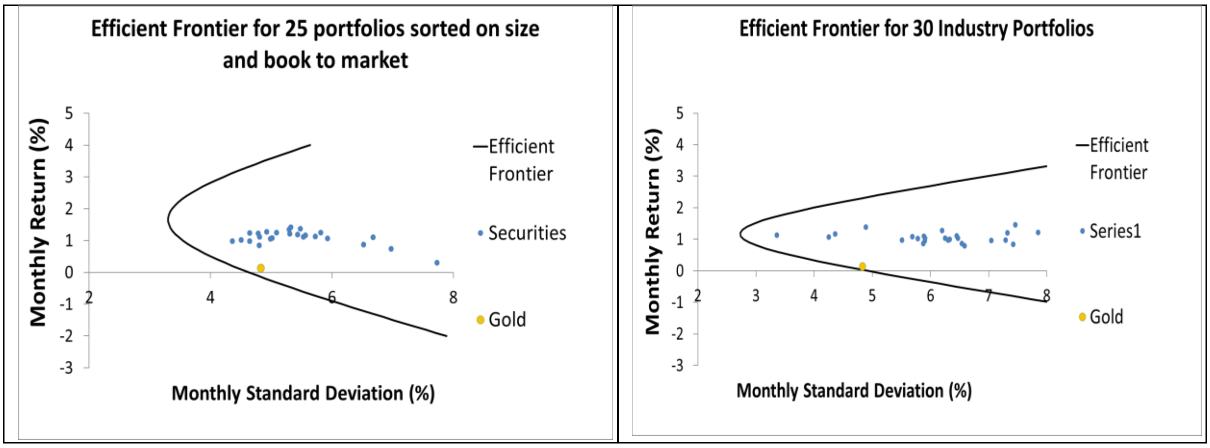


Figure 25: Position of gold on *25 Size Book-to-market* and *30 Industry* Portfolios

4.4.5 Gold augmented models

I also examine cross-sectional performance by augmenting gold factor with the above-mentioned ICAPM models. I include gold as an associated state variable to examine whether it improves the model performance. I find that the addition of gold returns does not influence the model performance as cross-sectional pricing errors remain nearly the same, and the insignificant cross-sectional gold factor is produced.

4.5 Summary of Results

Results can be summarised as follows: firstly, I obtain significant evidence in favour of the six-factor model as momentum plays a crucial role in explaining the cross-section of average returns on both sets of test portfolio, the 25 size and value and the 25 size and momentum in global regions. In cross-section, the six-factor model outperforms in all regions except Japanese region where I do not find momentum patterns. Fama and French (2015) only show time series results and I show that the cross-sectional tests are crucial to assess the performance of asset pricing models. In time series tests, five-factor and six- models produce similar results on the 25 size and book-to-market portfolios but in cross-section, Fama and French (2015) struggle to explain the variation of average returns without momentum factor in the North America, Europe and Asia Pacific. I also verify the prediction of Fama and French (2015) that it would be crucial to include momentum factor when their five-factor is tested on momentum portfolios as is evident with the higher R-squared produced with the six-factor model.

Secondly, when the gold return is utilised as a proxy of a zero-beta rate, the performance of empirical factor models is improved both in time-series and cross-sectional results. I find that the pricing of smaller stocks is improved when the gold return is used as a zero-beta rate, particularly with the four-factor model. Moreover, applicability of gold return as a zero-beta rate helps to improve the performance of the empirical factor models during the financial crisis. Further, I also find a significant improvement in the cross-sectional performance of three-factor, four-factor and five-factor models on test portfolios sorted on accruals, variance, market beta, and net share issues.

Thirdly, I also examine the extra market sensitivity of the gold price factor and find that many U.S. and global industries show a significant exposure to this commodity. I identify industries that show significant exposure during, before, and after the financial crisis and find many useful applications for investors and portfolio managers. I further examine the role of gold with the other macro (money supply, inflation, exchange rate, oil prices) and state variables (term structure and default spread). I find significant gold price factor showing the prominent role of gold in asset pricing.

Fourthly, I employ macro and state variables to improve asset pricing. I examine the innovative role of macro factors in asset pricing and develop two new multifactor models by using inflation and industrial production with the Fama and French (1993) and Petkova (2006) models. Including these models, I compare the performance of the twelve multifactor models. First is the two-factor ICAPM where I employ gold as a hedging factor. Second is the Hahn and Lee (2006) model, third is the Petkova (2006) ICAPM, fourth is the alternative Petkova model augmented model with inflation and industrial production. Fifth is the Campbell and Vuolteenaho (2004) ICAPM, sixth is the Fama and French (1993) three-factor model, seventh is the Fama and French (1993) augmented ICAPM that uses term-structure and default risk with their three factors. Eighth is the alternative Fama and French (1993) ICAPM that uses inflation and industrial production with Fama and French (1993) factors. Ninth is the Carhart (1997) four-factor model, the tenth is the Pástor and Stambaugh (2003) four-factor model, the eleventh is the Fama and French (2015) five-factor model, and twelfth is the Fama and French (2015) augmented model with the momentum price factor. Moreover, I also examine their zero-beta analogues that employs gold return as a proxy of the zero-beta rate. Finally, I assess twenty-three multifactor models with the strict testable criteria of Merton (1973) ICAPM theory on the 25 size and book-to-market and the 25 size and momentum portfolios. I find that the zero-beta versions outperform other multifactor models on both sets of test portfolios.

Chapter Five

Conclusion

The emergence of the Asian crisis and Dot-com bubble in the late 1990s challenged the empirical application of Sharpe (1964) single-factor Capital asset pricing model (CAPM) as it failed to predict the crisis. After a decline in the popularity of the CAPM due to its empirical weakness and reliance on a single market factor, Fama and French (1993) three-factor and Carhart (1997) four-factor models have become the most popular models that have received global recognition. However, the emergence of the global financial crisis of 2008 has also challenged their empirical application. These asset pricing models also have some theoretical and empirical limitations and have received criticism in various international markets. Campbell and Vuolteenaho (2004), Hahn and Lee (2006), and Petkova (2006) have proposed alternative multifactor Intertemporal CAPM models that utilise a different set of state variables in addition to the market factor. They claim the superior performance of their respective models as compared to the three-factor model in explaining cross-sectional average returns. Maio and Santa-Clara (2012) compare eight empirical and multifactor models and find that the three-factor and four-factor models perform comparatively better than other competing models in the U.S. equity market. Lutzenberger (2015) replicates this study in the European region and reports superior performance of the four-factor model.

Recently, Fama and French (2015) have come forward with the five-factor model and reports its superior performance with the time series tests in the U.S. equity market. However, the debate of improving asset pricing continues in the modern dynamic financial markets as each asset pricing model has its own theoretical and empirical limitations. This study attempts to improve asset pricing in four different ways by using empirical, zero-beta, macro and state variables. Firstly, this study attempts to improve asset pricing in international equity markets and attempts to fill the research gaps in the Fama and French (2015) study. It assesses the performance of the six-factor model in different global regions with the time series and cross-sectional tests. Further, this study assesses its performance on the test portfolios sorted on momentum as is recommended in Fama and French (2015) study.

Secondly, it explores the applicability of gold as a zero-beta asset in international equity markets. After the global financial crisis, gold has been widely recognised as a safe-haven asset and I examine its unexplored role of a zero-beta asset for the first time in asset pricing literature in global markets. Fama and French (2015) show that the five-factor model improves their three-factor model but they also highlight its empirical limitation. For instance, it struggles to explain average returns of small stocks. Pricing of small stocks have remained a challenging problem in asset pricing and the other competing asset pricing models, for example, the three-factor and the four-factor also produce pricing errors when it comes to pricing small stocks as is documented in Fama and French (2012, 2015). I test the zero-beta gold models with and without small stocks and find that the application of gold as a zero-beta asset helps to improve pricing of small stocks. Further, I also find it helps to improve estimation performance of empirical factor models in the U.S., U.K. regions in particular and North America in general. The main application of gold zero-beta models is to improve empirical performance of traditional asset pricing models. The proposed zero-beta models models are robust than traditional models as they provide 1) better estimates of expected returns for securities or portfolios; 2) improve pricing of small stocks; and 3) provide better estimates of expected returns in crisis period.

Thirdly, it examines the applicability of gold as a hedging factor in international and U.S. equity markets. It also examines gold with other prominent macro and state variables in the multifactor APT model to examine its ability in explaining cross-sectional variation of equity returns. Fourthly, this study examines a range of empirical and multifactor ICAPM models with multiple predictive regressions and GMM cross-sectional tests. It examines the performance of twelve competing asset pricing models that are tested with Treasury bill rate as a proxy of risk-free and gold returns as a proxy of a zero-beta rate. I employ a range of macroeconomic and state variables and propose alternative augmented versions of Petokova and Fama-French ICAPM models that outperform their original versions.

Hence, this study contributes to improve asset pricing by using empirical, zero-beta, macro and state variables. This study extracts key findings from each attempt that are discussed below in detail.

5.1 Assessment of empirical factor models

Firstly, I evaluate the performance of empirical factor models. I assess the performance of single-factor, three-factor, four-factor, five-factor and five-factor augmented model with momentum factor on two sets of left-hand side (LHS) test portfolios that are sorted on size and book-to-market, and size and momentum in global, North America, Europe, Japanese and Asia Pacific region. I use a time period of January 1995 to December 2015 and also examine performance in the sub-period from January 2003 to December 2015.

I perform Gibbons, Ross and Shanken (1989) tests for time-series analysis, whereas, I utilise Fama and MacBeth (1973) procedure for cross-sectional tests over an extended dataset of 25 years. Further, I perform sub-period cross-sectional analysis for robustness. Findings from the asset pricing tests reveal that the Fama and French (2015) five-factor model reasonably performs better than the three-factor model in North-American, European, and Asian Pacific regions on size and value portfolios.

Time-series results from the four regions suggest that the addition of momentum factor with the Fama and French (2015) five factors help in improving explanatory power particularly on the size and momentum portfolios. The evidence from cross-sectional results confirms time-series results as the six-factor model outperforms other models in the North American region on size and momentum portfolios as I obtain a significant positive estimate of market risk premium when other models produce implausible estimates.

In North American and European regions, I find significant size, value, momentum, investment and profitability premia. Further, four-factor, five-factor, and six-factor models produce economically plausible estimates of the market risk premia on the size and value portfolios. In the European region, four-factor, five-factor, and six-factor models produce positive estimates of market coefficients in the full period on the size and momentum portfolios.

In Asia Pacific region, I find size, value, momentum and investment patterns. In time-series results, I find the lowest Sharpe ratio of alphas with the four-factor model. In cross-section, I do not find convincing results in the full period. However, in sub-period, five-, and six-factor models produce an economically meaningful estimate of market risk when other models produce economically implausible negative estimates on the size and value portfolios. I do not find convincing results on the size and momentum portfolios in Japanese and Asian Pacific region.

However, I do not find significant momentum, investment, and profitability premia, in the Japanese region, instead I only find the significant size and value premia. I find the superior performance of the three-factor model in time-series tests as the three-factor model produces lower Sharpe ratio of alphas. Results of this study are contradictory to Daniel, Titman, & Wei (2001) findings who reject three-factor model in Japanese region.

5.2 Gold as a zero-beta asset

After assessing the performance of the six-factor model, I attempt to improve pricing of small stocks by employing gold as a zero beta asset. I find gold beta insignificantly different from zero in the U.S. and U.K. equity markets. Further, I also confirm weak form efficiency in those markets with a battery of market efficiency tests. When gold is plotted against Fama-French test portfolios, it is located on the minimum variance frontier of risky assets that satisfy one of the crucial condition of Black, Jensen and Scholes (1972) zero-beta factor.

Findings from this study show that the use of an appropriate riskless asset can play an important role in improving the empirical performance of the asset pricing models. In the present study, I have used gold as a zero-beta asset in an attempt to improve the estimation of expected returns for a wide variety of portfolios of U.S. stocks over a time sample of 35 years. Our principal results relate to the three-factor, four-factor and the five-factor models. For all these, I find that when I use gold as a zero-beta factor in place of the T-Bill yield as a risk-free rate, I obtain higher mean adjusted R-squared values and lower Sharpe ratios of alphas in time-series, showing that gold as a zero-beta asset helps to improve the time-series performance of traditional empirical factor models. The GRS test verifies that the portfolios formed with excess returns on Treasury bills, exhibit more deviation from the ex-post efficiency than the portfolios formed with excess gold returns.

For the second-stage, cross-sectional results, I find that the use of gold as a zero-beta factor brings improvements in two aspects. Firstly, findings of this study suggest that the application of gold return as a zero-beta rate enable to improve the pricing of smaller stocks in empirical asset pricing. The gold zero-beta models generate economically plausible prices of market risk on test assets which include microcaps, when the traditional models with T-bill rates as risk-free assets tend to fail on these, producing negative estimates of the price of market risk.

Secondly, I find that using gold as a zero-beta asset diminishes the magnitude of pricing errors for those cases where the traditional models leave significant cross-sectional pricing of the intercept. It implies that the proposed models provide better estimation of expected returns than traditional models. Findings show that the size, book-to-market and momentum factors are reported as significantly priced factors in the cross-sectional regression for the U.S. market. The findings for multifactor models from this study share view with (Chan, Jegadeesh, & Lakonishok, 1996) that additional risk factor adds extra returns and gives optimistic view of the market which can be misleading for portfolio selection.

I also identify the specific test assets on which the gold zero-beta models clearly outperform the traditional models. Firstly, the G-four- and five-factor models perform better for portfolios sorted on size and momentum and on portfolios simultaneously sorted on size, book-to-market and investment. Secondly, the G-three-factor model performs better for portfolios sorted on size and variance, on size and residual variance, and on size and market beta.

I also perform robustness checks to assess the applicability of gold return instead of risk-free rate in sub-periods. For this purpose, I test traditional and gold zero-beta models in three sub-periods before (2007), during (2007-2011), and after the financial crisis (2011- 2015) that enable me to assess its empirical application in sub-periods and make conclusive statements. Findings confirm that the application of gold return as a zero-beta rate enables to improve the performance of the traditional empirical factor models particularly during and after the financial crisis. Findings also show that the traditional empirical factor models provide reasonable estimates of the market risk price after the financial crisis as market recovery enables to achieve the efficiency which is the main underlying requirement for CAPM's theory. However, the empirical performance of gold zero-beta models has remained better than traditional models in the final sub-period. Findings conclude that the use of gold as the risk-free rate has profound empirical applications in improving pricing of small risky stocks and performance of factor models.

5.2.1 International Markets

I obtain further robust findings when I examine the application of gold as a zero-beta asset in the U.K. equity market. Pricing errors with the single-factor, three-factor and four-factor models are reduced and R-squared values are improved when I employ the gold return as a zero-beta rate. Further, the position of the gold is found on the minimum variance frontier on the LHS test portfolios sorted on size and book-to-market, size and momentum and standard deviation in the U.K. market. Further, gold zero-beta models produce better estimates than tradition factor models in the cross-sectional sub-period analyses.

Among global regions, I find gold beta equivalent to zero only in the North American region. Hence, I assess its applicability in North America. In North American regions, the performance of empirical factor models and their zero-beta gold analogues are comparable with the U.S. equity market where gold zero-beta versions outperform traditional versions.

5.2.2 Recommendation for Portfolio Managers and Policy Makers

Gold return as a zero-beta rate can be useful in security analysis since it provides an alternative estimate for assessing whether the securities are undervalued or overvalued. Asset pricing models that utilise gold as a zero-beta asset may help investors to make better investment decisions. Findings reveal that the time series regression of the security risk premiums over gold returns includes macroeconomic effect as time series predictive regressions confirm that gold forecasts macroeconomic and state variables such as term structure, default spread, money supply and exchange rate.

Gold as an alternative of Treasury bill rate may help to overcome the empirical weaknesses of the factor models during time periods of market volatility and uncertainty as I obtain better estimates of the actual market returns both in small and large datasets. The precise estimation of returns will enable investors to assess whether the securities are well priced while making investment decisions. Gold zero-beta models may work as a whistle-blower for regulatory authorities as it can help them to determine the fair return on Treasury bills.

5.3 Gold as a hedging factor

After exploring the role of gold as a zero-beta asset in international equity markets, I examine the role of gold as a hedging factor in the U.S. asset pricing. Earlier, Davidson, Hillier and Faff (2003) explore extra market sensitivity of a gold price factor on global industries from 1975 to 1994 and I extend this study from 1995 to 2015. Further, I advance on them to examine the role of gold in the U.S. industries. Hence, this study provides an updated and robust evidence on the role of gold as a hedging factor in the U.S. and global asset pricing.

I find a striking evidence regarding gold as a hedging factor in asset pricing. The main findings of my research can be summarised as follows. Firstly, I find a significant evidence of the gold factor exposure in the U.S. and world industries in the full-period and sub-period analysis. Among world industries, I find a strong exposure with positive premia in the first (1995 – 2001) and second sub-period (2002 – 2008) which covers the periods of the Asian (1997) and global financial crisis (2008). This exposure has declined on world industries in the third sub-period which covers the period of financial recovery. Among U.S. industries, this exposure remains stronger in all three-sub-periods. Further, the gold factor exposure remains stronger even in the third sub-period. Despite after the financial crisis and declining gold prices, the U.S. industries continue to show a significant gold factor exposure.

Secondly, I find that the Merton theory of negative correlation is comparatively better satisfied with the U.S. industries as the gold factor shows a negative cross-correlation with the market betas in the full sample period and sub-sample periods.

Thirdly and most importantly, I also re-examine the two-factor model from the perspective of the above-mentioned criteria. I find that, however, gold is a zero-beta asset, it predicts stock market variance in the second moment and satisfies the second and third criteria of the ICAPM. Fourthly, I find the evidence from sub-period analysis that the gold factor exposure varies over time. Industries that have produced the positive risk premia in the second sub-period (2002 – 2008), produce the negative risk premia in the first (1995 – 2001) and third sub-period (2009 – 2015). Fifthly, when I categorise industries into groups and perform multivariate and GMM tests, I find the evidence in favour of a two-factor model. However, I do not find the convincing evidence on each industry group in each sub-period which implies that the gold factor exposure is industry specific. Sixthly, the cross-sectional evidence from the Fama-MacBeth tests shows that the gold price factor is significantly positive in the first sub-period (1995 – 2001) in global industries, whereas it is negatively significant from 2009 – 2015 in U.S. industries. Further, the real gold premium is positive in the second sub-period (2002-2008) in both global and U.S. industries, which covers the period of the financial crisis (2008). It implies that the benefits of hedging are more realised during uncertain market conditions as gold offers the positive real returns in such conditions.

5.3.1 Recommendation for Portfolio Managers and Policy Makers

When I use gold as a hedging factor in the two-factor ICAPM, various U.S. and global industries show a significant gold factor exposure. Some industries have shown a positive exposure, whereas other industries have shown a negative exposure to this commodity.

Among world industries, notable examples with significant positive exposure are the Automobiles, Chemicals, Electric Utilities, Gas Utilities, Machinery, Materials, Mining, Electronic Equipment Manufacturers, Marine, and Trading Companies. Important examples of negative exposure are the Banks including Commercial Banks, Diversified Financial, Communications Equipment, and Health Care. Among U.S. industries, notable examples with significant positive exposure are the Agriculture, Beer & Liquor, Coal, Chemicals, Construction, Entertainment, Machinery, Petroleum & Natural Gas, Precious Metals, Steel industry, and Wholesale. Notable examples with significant negative exposure are the Automobiles, Banking, Electronic Equipment, Retail, Textiles, and Transportation.

These findings can be useful for portfolio investment managers. During the financial crisis, gold prices increased and industries have shown a significantly positive exposure and investors benefitted with gold investment. Despite falling gold prices after the financial crisis, gold still plays a role as a hedging factor as industries show a significant negative gold factor exposure. Results reveal that the portfolio managers view gold investment as a strategic hedging investment that protects them from potential losses in the wake of market shocks or unforeseen economic events. Besides investors, these findings also have useful implications for regulatory bodies and policy makers in Central Banks.

5.3.2 Role of gold in APT Models

After assessing the empirical application of gold as a hedging factor in the two-factor model, I use gold with the oil price, term structure, default spread, inflation, exchange rate and money supply as additional variables in the multifactor APT model in the U.S. equity market. I have used APT in the spirit of Ross (1977) who marks that stock returns can be determined by macro and state variables. I employ Johansen (1988) co-integrating tests, the VECM, and first-stage GMM procedure to assess the performance of the multifactor model. Findings of the VECM suggest that there is a short-run causality that runs from gold prices, oil prices, default spread, inflation and money supply to stock returns. I do not find evidence of the long run causality in this model. This model confirms the role of gold in influencing stock returns.

The cross-sectional evidence supports time series results as I find a significant gold price factor with the first-stage GMM procedure. These results verify findings of the two-factor model that gold is a potential factor to be included in asset pricing models. Oil prices, exchange rate, money supply, inflation, term structure and default spread are widely used variables in the multifactor APT and ICAPM models but when these factors are augmented with a gold price factor, then a significant gold price factor is produced in time series and cross-sectional asset pricing tests. These findings provide empirical evidence of the significance of a gold price factor among other macro and state factors. However, gold is a zero-beta asset and is not correlated with the market return, but its importance as a traditional hedging factor dominates in global markets.

5.4 Macro and state variables in asset pricing

Finally, I compare the empirical performance of a range of multifactor models with the strict testable implications of Merton (1973) theory. I find that a multifactor model must satisfy three main criteria of an ICAPM model. Firstly, the potential state variables must forecast first or second moment of market returns. Secondly, the ICAPM candidate forecasts the variations in investment opportunities with the same sign that is produced in cross-section. Thirdly, a suitable ICAPM must produce a positive and economically plausible estimate of the market risk premium in cross-section.

I examine the twelve multifactor models and compare their performance with the above-mentioned criteria. Among twelve multifactor models, six multifactor models include the ICAPM models and the other six are the empirical factor models. Among ICAPM models, I propose new asset pricing models by augmenting inflation and industrial production with Fama and French (1993) and Petkova (2006) models.

To assess second criteria, I employ single predictive regressions for each potential state variable to assess whether the candidate state variable is able to forecast first or second moment of aggregate market returns and market volatility. Further, I perform multiple predictive regressions for each multifactor model to assess the predictive ability of the candidate state variables. To assess first and third criteria, I perform first-stage GMM analyses to obtain cross-sectional risk premia for the candidate state variables. I employ 1-month Treasury bill rate and monthly gold return as a proxy of a zero-beta rate to obtain robust and conclusive findings.

Results suggest that the inflation and industrial production are the potential macro variables that can be used with the Fama-French or ICAPM models as these factors meet the essential criteria for the multifactor models. Both factors forecast aggregate stock returns and stock market variance and produce significant risk premia in cross-section when they are augmented with the Fama and French (1993) and Petkova (2006) models on the size and book to market portfolios. However, cross-sectional pricing errors and implausible estimates of market risk premia are produced with these new models on the size and book-to-market portfolios. Though, when gold return is used as a zero-beta rate, these new versions reasonably satisfy the Merton (1973) criteria on the size and book to market portfolios. These macro factors are not priced on industry portfolios as the original Fama and French (1993) and Petkova (2006) models perform well on industry portfolios.

Findings show that most of the traditional multifactor ICAPM models meet the ICAPM criteria on industry portfolios and my views agree with the Brennan, Wang, & Xia (2004) that industry portfolios are the suitable test portfolios to examine the performance of ICAPM models. Further, I also find supportive evidence for gold as a zero-beta rate over all the ICAPM models under investigation. Like empirical factor models, ICAPM models also produce higher R-squared values and economically meaningful estimates of the relative risk aversion (RRA), when the gold return is employed as a proxy of a zero-beta rate in those models. Particularly, the performance of Pástor and Stambaugh (2003) four-factor model and Petkova (2006) five-factor model significantly improve with this application on both test portfolios as they produce insignificant cross-sectional alphas as compared to their traditional versions where they produce significant pricing errors.

5.5 Applications of research

I extract many useful applications for the financial services industry from this comprehensive study of asset pricing. Despite the development of the various multifactor models, a puzzle of exploring appropriate risk factors continues in the context of the U.S. and global asset pricing.

5.5.1 Five-Factor augmented Model

I find that the Fama and French (2015) five-factor model is a very useful contribution and it helps in improving their three-factor model. Performance of the five-factor model is further improved when it is augmented with the momentum factor. Findings from the multiple predictive regressions show that all the factors significantly predict aggregate market returns and market volatility. Results confirm that the six-factor model meets the underlying criteria of the multifactor models. Further, it outperforms the four-factor model in global regions of North America, Asia Pacific and Europe. The three-factor model has faced criticism due to its limited ability to perform on the size and value portfolios. This traditional problem remains unsolved even with the extended version of the five-factor model as it fails to perform on the portfolios sorted on size and momentum.

5.5.2 Performance on Momentum and other Portfolios

Inability to perform on other portfolios is the main weakness of the Fama-French models. They have also admitted this weakness in Fama and French (1996) when they suggest that there is a scope of inclusion of state variables in the three-factor model, as their model does not perform on momentum portfolios. Their five-factor model also struggles to explain cross-sectional variations of average returns on momentum portfolios and produces significant pricing error. However, its zero-beta gold analogue performs comparatively better and produces economically plausible estimates with insignificant pricing error in the U.S. equity market and also in the North American region when it is tested over different time periods.

Further, I also improve three-factor model on a range of test portfolios (variance, market beta and net share issues), as its zero-beta gold analogue produces positive estimates of the market risk premia with insignificant pricing errors. Hence, a zero-beta gold factor can be the potential state variable that is recommended in their study (Fama and French, 1996). I find three main applications from this research:

5.5.3 Pricing of Small Stocks

Application of the gold return as a zero-beta rate helps in improving pricing of smaller and risky stocks. Pricing small stock has remained a challenging puzzle in asset pricing. Gregory, Tharyan, Christidis (2013) find difficulty in pricing smaller stock in the U.K. equity market. Fama and French (2012, 2015) also admit difficulty in pricing smaller stocks in the U.S. and global equity markets as they are more volatile and risky than large stocks. I test the traditional and their gold zero-beta analogues with and without smaller stocks. The traditional four-factor model produces an insignificant cross-sectional estimate of the market price when portfolios of small stocks are included in LHS test portfolios. On the other hand, I obtain significant cross-sectional estimates when I utilise gold return as a zero-beta rate with this model on a range of test portfolios, i.e., the 25 portfolios sorted on size and book-to-market, the 25 portfolios sorted on size and momentum, the 25 portfolios sorted on size and investment, the 25 portfolios sorted on size and operating profitability, the 25 portfolios sorted on size and variance, the 25 portfolios sorted on size and market beta and also on the 32 portfolios sorted on the size, value and operating profitability. This is the main application of gold return as a zero-beta rate in empirical asset pricing.

5.5.4 Performance on Industry Portfolios

Gold plays a crucial role when it comes to price global or U.S. industries. I have assessed its application in two different ways and find robust results. Firstly, I examine its applications as a zero-beta rate with the CAPM, three-factor, four-factor and five-factor models in the U.S. 48 industries and find that the tested models produce less pricing errors than the traditional models. Further, explanatory power (R-squared) of the models are remarkably improved in time series and cross-section tests. For robustness, I compare empirical performance of twelve empirical and ICAPM models on 30 U.S. industries with the GMM cross-sectional tests. Findings confirm that the application of gold as a zero-beta rate reduce pricing errors and improve explanatory power for all tested models. Particularly, Pástor and Stambaugh (2003), and Carhart (1997) four-factor model produce significant cross-sectional alphas that become insignificant with the applicability of gold return as a zero-beta rate.

Secondly, when I assess the extra market sensitivity of a gold price factor, I find a prominent influence of gold on industries as a number of global and U.S. industries show significant exposure to this commodity. Despite a zero-beta asset, gold forecasts stock market variance and satisfies the crucial implication of a state variable in asset pricing.

5.5.5 Pricing in Uncertainty

Gold has been traditionally explored from the perspective of hedging investment asset as it is globally recognised as a safe-haven and hedging asset that provides protection in the wake of extreme market shocks. I explore its safe haven feature from the perspective of a zero-beta asset. However, gold is not correlated with the market but in extreme market conditions, gold return moves in the opposite direction of the market returns and works as a hedging asset. This makes gold a suitable asset to be used for the proxy of a zero-beta rate than the Treasury bill rate as changes in the Treasury bill rate are comparatively very slow and provide little help in improving estimation of expected returns during periods of market uncertainty.

The cross-sectional findings in the sub-period of the financial crisis reveal that the four-factor and the six-factor models produce better estimates of the market risk price when the gold return is used as a proxy of the zero-beta rate than their traditional versions. During volatile market conditions, gold price reacts swiftly than Treasury bill rate and in such conditions, if the gold return is used as a zero-beta rate, then comparatively reasonable estimates of expected returns are obtained in cross-section. If Treasury bill is used under volatile market conditions, then negative estimates of the market risk price are obtained with the traditional asset pricing models that are least useful for portfolio managers or investors in understanding the level of the market risk in the prospective periods.

5.5.6 Scope for future research

Findings from the application of gold as a zero-beta asset suggest four possible extensions: firstly, I conjecture that gold zero-beta models are particularly useful during financial crises when the risk-free rate as measured by Treasury bills tends to be artificially depressed below the natural risk-free rate as a policy measure. This is because the Treasury bill rate moves in response to the federal fund rate (FFR) that is usually reduced by the Federal Reserve in response to the extreme market shock. As recent research suggests that forecasting models can predict future gold prices (Wang, Wei, & Wu, 2011; Mihaylov, Cheong, & Zurbruegg, 2015), the findings of these findings open prospects for future research in predicting market booms and crashes.

Secondly, it can be further explored in the individual equity markets of those economies where gold markets are efficient. However, Ntim, English, Nwachukwu, & Wang (2015) have examined efficiency of 28 gold markets and report strong weak form efficiency only in the U.S. and U.K. markets. Other gold markets in emerging markets can be examined to assess its application. Further, a portfolio of zero-beta precious metals can be constructed to achieve further robust findings.

Thirdly, this research has identified a scope of research to address the empirical weakness of the factor models when they are tested on industries and momentum portfolios. Robust factor models can be developed to overcome this empirical weakness. Macro and state variables may also be used to develop robust asset pricing models to obtain reliable estimates of expected returns in the wake of the political or economic crisis.

Fourthly and most importantly, further research can be undertaken to obtain a robust proxy of a zero-beta rate. A combination of zero-beta assets could be used to develop a more robust proxy of the zero-beta rate.

5.6 Limitations

This study has some limitations that need to be highlighted as well. Firstly, when I employ gold return as a proxy of a zero-beta rate, then this study estimates expected returns in absence of risk-free rate. Gold return is not ex-ante unlike return on Treasury bill rate as investors already have the information of the return on Treasury bills in advance that is hardly possible for gold when I use spot prices. Hence, this study does not intend to replace risk-free rate instead it proposes an alternative method to estimate expected returns. Further, I have not assessed applicability of other precious metals such as silver in this thesis.

Secondly, when I employ gold return as a substitute zero-beta rate, then this approach is similar to the approach of using alternative numeraire, a term that is more common in financial derivatives that allows the expression of the price of one asset in terms of units of another asset. When I utilise a 1-month Treasury-bill as a risk-free rate and subtract from stock or portfolio returns to obtain the excess returns, this is conceptually equivalent if I convert all raw asset prices into numbers of units of a zero-coupon bond maturing in 1 months' time, and then performing all return calculations in terms of prices expressed in this numeraire. The choice of 1 month- Treasury bill rate is a standard but not obligatory. Hence, one could alternatively choose another asset that will have a nonzero value in one month's time in a similar way as one chooses the binomial option in terms of units of the underlying stock. In this way, I can also choose another asset to be a numeraire. For instance, in this study, I have used the price of a fixed weight of gold instead of a 1-month T-Bill. When I employ gold return as a substitute of a zero-beta rate, I transform all asset prices into units of a fixed weight of gold at each time point and then work in terms of these gold-transformed prices. I quote stock prices in terms of ounces of gold instead of quoting in units of Treasury bills. This helps in developing an alternative and parallel technique for estimating stock returns with asset pricing models.

Thirdly, application of gold return as a zero-beta rate is limited to the efficiency level of the gold market of the economy where such model is investigated. Among developed markets, I only find evidence of the efficiency of gold markets in the U.S. and U.K. markets whereas gold markets in other economies are less efficient and hence, its application does not produce economically meaningful results.

Fourthly, this study is limited to using gold return as a proxy of zero-beta rate rather than considering a portfolio of risky securities that Black, Jensen and Scholes (1972) originally suggests while explaining their zero-beta model. This study assumes that using a zero-beta rate on gold has some advantages over a portfolio of risky assets due to its traditional and historical safe-haven abilities. A portfolio of risky assets still faces risk of losing its value in different time periods but gold has maintained the reputation of retaining its value over centuries. Other researchers have employed various other proxies of a zero-beta rate. For instance, Davidson, Hillier and Faff (2003) estimate their model in absence of risk-free rate whereas Kan, Robotti, and Shanken (2013) employ Treasury bill rate as a proxy of a zero-beta rate.

Fifthly, when I explore gold as a hedging factor, then this research is limited to the global and U.S. industries. The role of gold in the European, Australian and Japanese industries is not investigated as it was beyond the scope of this study.

Sixthly, I only examine the multifactor ICAPM models in the U.S. equity market to maintain consistency in the research. The role of gold is more deeply examined in the U.S. equity market than other developed markets due to the sheer size of its equity market and dominant gold holding position in developed economies.

Seventhly, this study had limitations in data collection of stock prices due to the unavailability of CRSP database (The Centre for Research in Security Prices), Wharton Research Data Services (WRDS) or Compustat database. Due to this reason, Datastream and web databases are utilised in this study.

Bibliography

[1]. Abbas, Q., Ayub, U., Sargana, S. M., & Saeed, S. K. (2011). From regular-beta CAPM to downside-beta CAPM. *European Journal of Social Sciences*, *21*(2), 189–203.

[2]. Agarwal, V., & Naik, N. Y. (2004). Risks and portfolio decisions involving hedge funds. *Review of Financial Studies*, *17*(1), 63–98.

[3]. Aizenman, J., & Inoue, K. (2013). Central banks and gold puzzles. *Journal of the Japanese and International Economies*, *28*(Supplement C), 69–90. https://doi.org/10.1016/j.jjie.2013.02.001

[4]. Albuquerque, R., Eichenbaum, M., Luo, V. X., & Rebelo, S. (2016). Valuation Risk and Asset Pricing. *The Journal of Finance*, *71*(6), 2861–2904. https://doi.org/10.1111/jofi.12437

[5]. Altay, E. (2003). *The effect of macroeconomic factors on asset returns: A comparative analysis of the German and the Turkish stock markets in an APT framework*. Univ., Wirtschaftswiss. Fak.

[6]. Ang, A. (2009). Evaluation of active management of the Norwegian government pension fund–global.

[7]. Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, *61*(1), 259–299.

[8]. Ang, A., & Kjaer, K. N. (2012). Investing for the long run.

[9]. Antoniou, A., Garrett, I., & Priestley, R. (1998). Macroeconomic variables as common pervasive risk factors and the empirical content of the arbitrage pricing theory. *Journal of Empirical Finance*, *5*(3), 221–240. https://doi.org/10.1016/S0927-5398(97)00019-4

[10]. Appelbaum, B., & Dash, E. (2011). S. &P. Downgrades Debt Rating of US for the First Time. *New York Times*, *5*.

[11]. Arestis, P., Demetriades, P. O., & Luintel, K. B. (2001). Financial development and economic growth: the role of stock markets. *Journal of Money, Credit and Banking*, 16–41.

[12]. Arrow, K. J., & Debreu, G. (1954). Existence of an Equilibrium for a Competitive Economy.

Econometrica, *22*(3), 265–290. https://doi.org/10.2307/1907353.

[13]. Asness, C. S., Frazzini, A., & Pedersen, L. H. (2012). Leverage aversion and risk parity. *Financial Analysts Journal*, *68*(1), 47–59.

[14]. Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. *The Journal of Finance*, *68*(3), 929–985. https://doi.org/10.1111/jofi.12021

[15]. Asprem, M. (1989). Stock prices, asset portfolios and macroeconomic variables in ten European countries. *Journal of Banking & Finance, 13*(4), 589–612. https://doi.org/10.1016/0378-4266(89)90032-0

[16]. Avramov, D., & Chordia, T. (2006). Asset pricing models and financial market anomalies. *Review of Financial Studies*, *19*(3), 1001–1040.

[17]. Back, K., Li, T., & Ljungqvist, A. (2013). *Liquidity and governance*. National Bureau of Economic Research.

[18]. Bakshi, G., & Kapadia, N. (2003). Delta-hedged gains and the negative market volatility risk premium. *Review of Financial Studies*, *16*(2), 527–566.

[19]. Bampinas, G., & Panagiotidis, T. (2015). Are gold and silver a hedge against inflation? A two century perspective. *International Review of Financial Analysis*, *41*, 267–276. https://doi.org/10.1016/j.irfa.2015.02.007

[20]. Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18.

[21]. Barberis, N., Greenwood, R., Jin, L., & Shleifer, A. (2015). X-CAPM: An extrapolative capital asset pricing model. *Journal of Financial Economics*, *115*(1), 1–24. https://doi.org/10.1016/j.jfineco.2014.08.007

[22]. Barro, R. J., & Misra, S. (2016). Gold Returns. *The Economic Journal*, *126*(594), 1293–1317. https://doi.org/10.1111/ecoj.12274

[23]. Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics*, *54*(Supplement C), 235–247. https://doi.org/10.1016/j.eneco.2015.11.022

[24]. Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics*, *12*(1), 129–156.

[25]. Baur, D. G. (2014). Gold mining companies and the price of gold. *Review of Financial Economics*, *23*(4), 174–181. https://doi.org/10.1016/j.rfe.2014.07.001

[26]. Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, *45*(2), 217–229.

[27]. Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, *34*(8), 1886–1898.

[28]. Belousova, J., & Dorfleitner, G. (2012). On the diversification benefits of commodities from the perspective of euro investors. *Journal of Banking & Finance*, *36*(9), 2455–2472. https://doi.org/10.1016/j.jbankfin.2012.05.003

[29]. Bera, A. K., & Bilias, Y. (2001). Rao's score, Neyman's C(α) and Silvey's LM tests: an essay on historical developments and some new results. *Journal of Statistical Planning and Inference, 97*(1), 9–44. https://doi.org/10.1016/S0378-3758(00)00343-8

[30]. Białkowski, J., Bohl, M. T., Stephan, P. M., & Wisniewski, T. P. (2015). The gold price in times of crisis. *International Review of Financial Analysis*, *41*, 329–339. https://doi.org/10.1016/j.irfa.2014.07.001

[31]. Bjørnland, H. C., & Leitemo, K. (2009). Identifying the interdependence between US monetary policy and the stock market. *Journal of Monetary Economics*, *56*(2), 275–282.

[32]. Black, F. (1972). Capital Market Equilibrium with Restricted Borrowing. *The Journal of Business*, *45*(3), 444–455.

[33]. Black, F. (1995). Estimating Expected Return. *Financial Analysts Journal*, *51*(1), 168–171. https://doi.org/10.2469/faj.v51.n1.1873

[34]. Black, F., Jensen, M., & Scholes, M. (1972). The capital asset pricing model: Some empirical evidence. In *Studies in the theory of capital market, Michael C. Jensen, ed.* New York: Praeger Publishers.

[35]. Blackburn, D. W., & Cakici, N. (2017). Overreaction and the cross-section of returns:

International evidence. *Journal of Empirical Finance*, *42*, 1–14. https://doi.org/10.1016/j.jempfin.2017.02.001

[36]. Blitz, D., & Van Vliet, P. (2007). The volatility effect: Lower risk without lower return. *Journal of Portfolio Management*, 102–113.

[37]. Blose, L. E., & Shieh, J. C. P. (1995). The impact of gold price on the value of gold mining stock. *Review of Financial Economics*, *4*(2), 125–139. https://doi.org/10.1016/1058-3300(95)90002-0

[38]. Blume, M. E. (1970). Portfolio theory: a step toward its practical application. *The Journal of Business*, *43*(2), 152–173.

[39]. Blume, M. E., & Friend, I. (1973). A NEW LOOK AT THE CAPITAL ASSET PRICING MODEL. *The Journal of Finance*, *28*(1), 19–34. https://doi.org/10.1111/j.15406261.1973.tb01342.x

[40]. Bodurtha, J. N., & Mark, N. C. (1991). Testing the CAPM with Time-Varying Risks and Returns. *The Journal of Finance*, *46*(4), 1485–1505. https://doi.org/10.1111/j.1540-6261.1991.tb04627.x

[41]. Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected stock returns and variance risk premia. *Review of Financial Studies*, *22*(11), 4463–4492.

[42]. Bordo, M. D. (1981). The classical gold standard: some lessons for today. *Federal Reserve Bank of St. Louis Review*, (May), 2–17.

[43]. Bornholt, G. (2013). The Failure of the Capital Asset Pricing Model (CAPM): An Update and Discussion. *Abacus*, *49*, 36–43. https://doi.org/10.1111/j.1467-6281.2012.00382.x

[44]. Bredin, D., Conlon, T., & Potì, V. (2015). Does gold glitter in the long-run? Gold as a hedge and safe haven across time and investment horizon. *International Review of Financial Analysis*, *41*, 320–328. https://doi.org/10.1016/j.irfa.2015.01.010

[45]. Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, *7*(3), 265–296.

[46]. Breeden, D. T., Gibbons, M. R., & Litzenberger, R. H. (1989). Empirical tests of the consumption-oriented CAPM. *The Journal of Finance*, *44*(2), 231–262.

[47]. Brennan, M. J. (1971). Capital market equilibrium with divergent borrowing and lending rates.

Journal of Financial and Quantitative Analysis, *6*(05), 1197–1205.

[48]. Brennan, M. J. (1971). Capital Market Equilibrium with Divergent Borrowing and Lending Rates. *Journal of Financial and Quantitative Analysis*, *6*(5), 1197–1205. https://doi.org/10.2307/2329856

[49]. Brennan, M. J., Wang, A. W., & Xia, Y. (2004). Estimation and test of a simple model of intertemporal capital asset pricing. *The Journal of Finance*, *59*(4), 1743–1776.

[50]. Brooks, C. (2014). *Introductory econometrics for finance*. Cambridge university press.

[51]. Burmeister, E., & McElroy, M. B. (1988). Joint estimation of factor sensitivities and risk premia for the arbitrage pricing theory. *The Journal of Finance*, *43*(3), 721–733.

[52]. Burmeister, E., & Wall, K. D. (1986). The arbitrage pricing theory and macroeconomic factor measures. *Financial Review*, *21*(1), 1–20.

[53]. Burrell, G., & Morgan, G. (1979). *Sociological paradigms and organisational analysis* (Vol. 248). london: Heinemann.

[54]. Burton, J. (1998). Revisiting the capital asset pricing model. *Dow Jones Asset Manager*, 20–28.

[55]. Callahan, M. (2002). To Hedge or Not to Hedge…That Is the Question Empirical Evidence from the North American Gold Mining Industry 1996–2000. *Financial Markets, Institutions & Instruments*, *11*(4), 271–288. https://doi.org/10.1111/1468-0416.11401

[56]. Campbell, J. Y. (1987). Stock returns and the term structure. *Journal of Financial Economics*, *18*(2), 373–399.

[57]. Campbell, J. Y. (1991). A Variance Decomposition for Stock Returns. *The Economic Journal*, *101*(405), 157–179. https://doi.org/10.2307/2233809

[58]. Campbell, J. Y., & Cochrane, J. H. (2000). Explaining the poor performance of consumption-based asset pricing models. *The Journal of Finance*, *55*(6), 2863–2878.

[59]. Campbell, J. Y., Lo, A. W. C., & MacKinlay, A. C. (1997). *The econometrics of financial markets* (Vol. 2). princeton University press Princeton, NJ.

[60]. Campbell, J. Y., & Shiller, R. J. (1988). The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *The Review of Financial Studies*, *1*(3), 195–228.

https://doi.org/10.1093/rfs/1.3.195

[61]. Campbell, J. Y., & Vuolteenaho, T. (2004). Bad Beta, Good Beta. *American Economic Review*, *94*, 1249–1275.

[62]. Capie, F., Mills, T. C., & Wood, G. (2005). Gold as a hedge against the dollar. *Journal of International Financial Markets, Institutions and Money*, *15*(4), 343–352.

[63]. Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82.

[64]. Cecchetti, S. G. (2009). Crisis and Responses: The Federal Reserve in the Early Stages of the Financial Crisis (Digest Summary). *Journal of Economic Perspectives*, *23*(1), 51–75.

[65]. Cenesizoglu, T., & Reeves, J. J. (2012). CAPM, Components of Beta and the Cross Section of Expected Returns. Presented at the 25th Australasian Finance and Banking Conference.

[66]. Chan, H., & Faff, R. (1998). The sensitivity of Australian industry equity returns to a gold price factor. *Accounting & Finance*, *38*(2), 223–244. https://doi.org/10.1111/1467-629X.00011

[67]. Chan, L. K., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and stock returns in Japan. *The Journal of Finance*, *46*(5), 1739–1764.

[68]. Chan, L. K., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *The Journal of Finance*, *51*(5), 1681–1713.

[69]. Charles, A., Darné, O., & Kim, J. H. (2011). Small sample properties of alternative tests for martingale difference hypothesis. *Economics Letters*, *110*(2), 151–154. https://doi.org/10.1016/j.econlet.2010.11.018

[70]. Chaudhuri, K., & Smiles, S. (2004). Stock market and aggregate economic activity: evidence from Australia. *Applied Financial Economics*, *14*(2), 121–129.

[71]. Chaussé, P. (2010). Computing generalized method of moments and generalized empirical likelihood with R. *Journal of Statistical Software*, *34*(11), 1–35.

[72]. Chen, N..F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, 383–403.

[73]. Cheung, Y.-L., & Mak, S.-C. (1992). The international transmission of stock market fluctuation between the developed markets and the Asian-Pacific markets. *Applied Financial Economics*, *2*(1), 43–47.

[74]. Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: do stocks overreact? *Journal of Financial Economics*, *31*(2), 235–268.

[75]. Chua, J. H., Sick, G., & Woodward, R. S. (1990). Diversifying with Gold Stocks. *Financial Analysts Journal*, *46*(4), 76–79.

[76]. Chui, A. C. w., Titman, S., & Wei, K. c. J. (2010). Individualism and Momentum around the World. *The Journal of Finance*, *65*(1), 361–392. https://doi.org/10.1111/j.1540-6261.2009.01532.x

[77]. Ciner, C., Gurdgiev, C., & Lucey, B. M. (2013). Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis*, *29*, 202–211. https://doi.org/10.1016/j.irfa.2012.12.001

[78]. Clare, A. D., & Thomas, S. H. (1994). Macroeconomic Factors, the Apt and the UK Stock market. *Journal of Business Finance & Accounting*, *21*(3), 309–330. https://doi.org/10.1111/j.1468-5957.1994.tb00322.x

[79]. Clare, A., Priestley, R., & Thomas, S. (1997). Is beta dead? The role of alternative estimation methods. *Applied Economics Letters*, *4*(9), 559–562.

[80]. Clarke, R. G., De Silva, H., & Thorley, S. (2006). Minimum-variance portfolios in the US equity market. *The Journal of Portfolio Management*, *33*(1), 10–24.

[81]. Coakley, J., Dotsis, G., Liu, X., & Zhai, J. (2014). Investor sentiment and value and growth stock index options. *The European Journal of Finance*, *20*(12), 1211-1229.

[82]. Cochrane, J. (2014). Advanced Investments Business 35150. Retrieved November 14, 2017, from https://faculty.chicagobooth.edu/john.cochrane/teaching/35150_advanced_investments/

[83]. Cochrane, J. H. (1996). A Cross-Sectional Test of an Investment-Based Asset Pricing Model. *Journal of Political Economy*, *104*(3), 572–621. https://doi.org/10.1086/262034

[84]. Cochrane, J. H. (1999). *New facts in finance*. National Bureau of Economic Research. Retrieved

from http://www.nber.org/papers/w7169

[85]. Cochrane, J. H. (2005). Asset pricing, Vol. 1.

[86]. Cochrane, J. H. (2009). *Asset Pricing: (Revised Edition)*. Princeton University Press.

[87]. Colander, D., Föllmer, H., Haas, A., Goldberg, M. D., Juselius, K., Kirman, A., … Sloth, B. (2009). The financial crisis and the systemic failure of academic economics. *Univ. of Copenhagen Dept. of Economics Discussion Paper*, (9–3).

[88]. Connor, G., & Korajczyk, R. A. (1986). Performance measurement with the arbitrage pricing theory: A new framework for analysis. *Journal of Financial Economics*, *15*(3), 373–394.

[89]. Connor, G., & Korajczyk, R. A. (1988). Risk and return in an equilibrium APT. *Journal of Financial Economics*, *21*(2), 255–289. https://doi.org/10.1016/0304-405X(88)90062-1

[90]. Constantinides, G. M., & Duffie, D. (1996). Asset Pricing with Heterogeneous Consumers. *Journal of Political Economy*, *104*(2), 219–240. https://doi.org/10.1086/262023

[91]. Cooper, I., & Maio, P. (2016). Equity risk factors and the Intertemporal CAPM. *Crosssection of Stock Returns*.

[92]. Cornett, M. M., McNutt, J. J., Strahan, P. E., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, *101*(2), 297–312. https://doi.org/10.1016/j.jfineco.2011.03.001

[93]. Coval, J. D., & Shumway, T. (2001). Expected option returns. *The Journal of Finance*, *56*(3), 983–1009.

[94]. Daniel, K., Titman, S., & Wei, K. C. J. (2001). Explaining the Cross-Section of Stock Returns in Japan: Factors or Characteristics? *The Journal of Finance*, *56*(2), 743–766. https://doi.org/10.1111/0022-1082.00344

[95]. Davidson, S., Faff, R., & Hillier, D. (2003). Gold factor exposures in international asset pricing. *Journal of International Financial Markets, Institutions & Money*, *13*, 271. https://doi.org/10.1016/S1042-4431(02)00048-3

[96]. Dee, J., Li, L., & Zheng, Z. (2013). Is gold a hedge or a safe haven? Evidence from inflation and stock market. *International Journal of Development and Sustainability*, *2*(1), 1–16.

[97]. DeFusco, R. A., McLeavey, D. W., Pinto, J. E., & Runkle, D. E. (2007). Quantitative Investment Analysis. *CFA Institute Investment Books*, *2007*(2), 1–600.

[98]. DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, *22*(5), 1915–1953.

[99]. Dempsey, M. (2013). The Capital Asset Pricing Model (CAPM): The History of a Failed Revolutionary Idea in Finance? *Abacus*, *49*, 7–23. https://doi.org/10.1111/j.1467-6281.2012.00379.x

[100]. Diamonte, R. L., Liew, J. M., & Stevens, R. L. (1996). Political risk in emerging and developed markets. *Financial Analysts Journal*, *52*(3), 71–76.

[101]. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427–431.

[102]. Dickey, D. A., & Pantula, S. G. (1987). Determining the order of differencing in autoregressive processes. *Journal of Business & Economic Statistics*, *5*(4), 455–461.

[103]. Dionne, G., & Garand, M. (2003). Risk management determinants affecting firms' values in the gold mining industry: new empirical results. *Economics Letters*, *79*(1), 43–52. https://doi.org/10.1016/S0165-1765(02)00286-0

[104]. El-Sharif, I., Brown, D., Burton, B., Nixon, B., & Russell, A. (2005). Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. *Energy Economics*, *27*(6), 819–830. https://doi.org/10.1016/j.eneco.2005.09.002

[105]. Elton, E. J., Gruber, M. J., Brown, S. J., & Goetzmann, W. N. (2009). *Modern portfolio theory and investment analysis*. John Wiley & Sons.

[106]. Engle, R. F. (1984). Chapter 13 Wald, likelihood ratio, and Lagrange multiplier tests in econometrics. In *Handbook of Econometrics* (Vol. 2, pp. 775–826). Elsevier. https://doi.org/10.1016/S1573-4412(84)02005-5

[107]. Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: Journal of the Econometric Society*, 251–276.

[108]. Escanciano, J. C., & Lobato, I. N. (2009). An automatic Portmanteau test for serial correlation.

Journal of Econometrics, *151*(2), 140–149. https://doi.org/10.1016/j.jeconom.2009.03.001

[109]. Evans, G. W. (1991). Pitfalls in testing for explosive bubbles in asset prices. *The American Economic Review*, *81*(4), 922–930.

[110]. Faff, R., & Chan, H. (1998). A multifactor model of gold industry stock returns: evidence from the Australian equity market. *Applied Financial Economics*, *8*(1), 21–28. https://doi.org/10.1080/096031098333212

[111]. Faff, R., & Hillier, D. (2004). An International Investigation of the Factors that Determine Conditional Gold Betas. *Financial Review*, *39*(3), 473–488. https://doi.org/10.1111/j.0732-8516.2004.00085.x

[112]. Fama, E. F. (1970). Multiperiod Consumption-Investment Decisions. *The American Economic Review*, *60*(1), 163–174.

[113]. Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *The American Economic Review*, *71*(4), 545–565.

[114]. Fama, E. F. (1990). Stock returns, expected returns, and real activity. *The Journal of Finance*, *45*(4), 1089–1108.

[115]. Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, *46*(5), 1575–1617.

[116]. Fama, E. F. (1996). Multifactor portfolio efficiency and multifactor asset pricing. *Journal of Financial and Quantitative Analysis*, *31*(04), 441–465.

[117]. Fama, E. F. (1998). Determining the number of priced state variables in the ICAPM. *Journal of Financial and Quantitative Analysis*, *33*(02), 217–231.

[118]. Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*(1), 3–25. https://doi.org/10.1016/0304-405X(88)90020-7

[119]. Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, *25*(1), 23–49. https://doi.org/10.1016/0304-405X(89)90095-0

[120]. Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of*

Finance, *47*(2), 427–465.

[121]. Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

[122]. Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, *51*(1), 55–84.

[123]. Fama, E. F., & French, K. R. (1998). Value versus growth: The international evidence. *The Journal of Finance*, *53*(6), 1975–1999.

[124]. Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives*, *18*, 25–46.

[125]. Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. *Journal of Financial Economics*, *82*(3), 491–518.

[126]. Fama, E. F., & French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics*, *83*(3), 667–689. https://doi.org/10.1016/j.jfineco.2006.01.003

[127]. Fama, E. F., & French, K. R. (2008). Dissecting Anomalies. *The Journal of Finance*, *63*(4), 1653–1678. https://doi.org/10.1111/j.1540-6261.2008.01371.x

[128]. Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance*, *65*(5), 1915–1947.

[129]. Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), 457–472. https://doi.org/10.1016/j.jfineco.2012.05.011

[130]. Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

[131]. Fama, E. F., & French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of financial Economics*, *123*(3), 441-463

[132]. Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 607–636.

[133]. Fama, E. F., & Schwert, G. W. (1977). Asset returns and inflation. *Journal of Financial Economics*, *5*(2), 115–146.

[134]. Ferguson, M. F., & Shockley, R. L. (2003). Equilibrium “Anomalies.” *The Journal of Finance, 58*(6), 2549–2580. https://doi.org/10.1046/j.1540-6261.2003.00615.x

[135]. Ferson, W. E., Sarkissian, S., & Simin, T. T. (2003). Spurious regressions in financial economics? *The Journal of Finance*, *58*(4), 1393–1414.

[136]. Ferson, W., Nallareddy, S., & Xie, B. (2013). The “out-of-sample” performance of long run risk models. *Journal of Financial Economics*, *107*(3), 537-556.

[137]. Flannery, M. J., & Protopapadakis, A. A. (2002). Macroeconomic factors do influence aggregate stock returns. *Review of Financial Studies*, *15*(3), 751–782.

[138]. Fletcher, J., & Forbes, D. (2002). UK Unit Trust Performance: Does it Matter Which Benchmark or Measure is Used? *Journal of Financial Services Research*, *21*(3), 195–218.

[139]. Forbes. (2018). New York Stock Exchange - The World’s Biggest Stock Exchanges. Retrieved February 4, 2018, from https://www.forbes.com/pictures/eddk45iglh/new-york-stock-exchange/

[140]. Francis, B. B., Hasan, I., & Hunter, D. M. (2008). Can hedging tell the full story? Reconciling differences in United States aggregate- and industry-level exchange rate risk premium. *Journal of Financial Economics*, *90*(2), 169–196. https://doi.org/10.1016/j.jfineco.2007.10.007

[141]. French, J. (2017). Macroeconomic Forces and Arbitrage Pricing Theory. *Journal of Comparative Asian Development,16*(1), 1-20.

[142]. Friend, I., & Blume, M. (1970). Measurement of portfolio performance under uncertainty. *The American Economic Review*, *60*(4), 561–575.

[143]. Friend, I., Landskroner, Y., & Losq, E. (1976). The demand for risky assets under uncertain inflation. *The Journal of Finance*, *31*(5), 1287–1297.

[144]. Galagedera, D. U. A., & Galagedera, D. U. A. (2007). A review of capital asset pricing models. *Managerial Finance*, *33*(10), 821–832.

[145]. Geda, A. (2015). *Applied time series econometrics: a practical guide for macroeconomic researchers with a focus on Africa*. University of Nairobi Press.

[146]. Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica*, *57*(5), 1121–1152. https://doi.org/10.2307/1913625

[147]. Giovannini, A., & Jorion, P. (1989). The time variation of risk and return in the foreign exchange and stock markets. *The Journal of Finance*, *44*(2), 307–325.

[148]. Granger, C. W. (1986). Developments in the study of cointegrated economic variables. *Oxford Bulletin of Economics and Statistics*, *48*(3), 213–228.

[149]. Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111–120.

[150]. Gregory, A., Tharyan, R., & Christidis, A. (2013). Constructing and testing alternative versions of the Fama–French and Carhart models in the UK. *Journal of Business Finance & Accounting, 40*(1–2), 172–214.

[151]. Griffin, J. M. (2002). Are the Fama and French factors global or country specific? *Review of Financial Studies*, *15*(3), 783–803.

[152]. Guardian. (2011). Global financial crisis: five key stages 2007-2011. Retrieved from https://www.theguardian.com/business/2011/aug/07/global-financial-crisis-key-stages.

[153]. Guermat, C. (2014). Yes, the CAPM is testable. *Journal of Banking & Finance, 46*, 31–42.

[154]. Gultekin, N. B. (1983). Stock market returns and inflation: evidence from other countries. *The Journal of Finance*, *38*(1), 49–65.

[155]. Guo, H. (2006). On the Out-of-Sample Predictability of Stock Market Returns. *The Journal of Business*, *79*(2), 645–670. https://doi.org/10.1086/499134

[156]. Hahn, J., & Lee, H. (2006). Yield Spreads as Alternative Risk Factors for Size and Book-to-Market. *Journal of Financial and Quantitative Analysis*, *41*(2), 245–269. https://doi.org/10.1017/S0022109000002052

[157]. Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, 1029–1054.

[158]. Harris, R. D. F., & Shen, J. (2017). The Intrinsic Value of Gold: An Exchange Rate-Free Price Index. *Journal of International Money and Finance*. https://doi.org/10.1016/j.jimonfin.2017.09.007

[159]. Haugen, R. A., & Baker, N. L. (1996). Commonality in the determinants of expected stock

returns. *Journal of Financial Economics*, *41*(3), 401–439.

[160]. Herbst, A. F. (1983). Gold versus U.S. Common Stocks: Some Evidence on Inflation Hedge Performance and Cyclical Behavior. *Financial Analysts Journal*, *39*(1), 66–74. https://doi.org/10.2469/faj.v39.n1.66

[161]. Hillier, D., Draper, P., & Faff, R. (2006). Do precious metals shine? An investment perspective. *Financial Analysts Journal*, *62*(2), 98–106.

[162]. Ho, T. S. Y., & Lee, S. (1986). Term structure movements and pricing interest rate contingent claims. *The Journal of Finance, 41*(5), 1011–1029.

[163]. Ho, Y.-K. (1985). A test of the incrementally efficient market hypothesis for the London gold market. *Economics Letters*, *19*(1), 67–70. https://doi.org/10.1016/0165-1765(85)90105-3

[164]. Hoang, T. H. V., Lean, H. H., & Wong, W.-K. (2015). Is gold good for portfolio diversification? A stochastic dominance analysis of the Paris stock exchange. *International Review of Financial Analysis*, *42*, 98–108. https://doi.org/10.1016/j.irfa.2014.11.020

[165]. Hodrick, R. J. (1992). Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement. *The Review of Financial Studies*, *5*(3), 357–386. https://doi.org/10.1093/rfs/5.3.351

[166]. Hood, M., & Malik, F. (2013). Is gold the best hedge and a safe haven under changing stock market volatility? *Review of Financial Economics*, *22*(2), 47–52. https://doi.org/10.1016/j.rfe.2013.03.001

[167]. Hou, K., & Robinson, D. T. (2006). Industry concentration and average stock returns. *The Journal of Finance*, *61*(4), 1927–1956.

[168]. Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*,*28*(3), 650-705.

[169]. Humpe, A., & Macmillan, P. (2009). Can macroeconomic variables explain long-term stock market movements? A comparison of the US and Japan. *Applied Financial Economics, 19*(2), 111–119.

[170]. Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels.

Journal of Econometrics, *115*(1), 53–74.

[171]. Iqbal, A., Akbar, S., & Shiwakoti, R. K. (2013). The long run performance of UK firms making multiple rights issues. *International Review of Financial Analysis*, *28*, 156-165.

[172]. Jaffe, J. F. (1989). Gold and Gold Stocks as Investments for Institutional Portfolios. *Financial Analysts Journal*, *45*(2), 53–59. https://doi.org/10.2469/faj.v45.n2.53

[173]. Jaffe, J., & Westerfield, R. (1985). The Week-End Effect in Common Stock Returns: The International Evidence. *The Journal of Finance*, *40*(2), 433–454.

[174]. Jagannathan, R., Skoulakis, G., & Wang, Z. (2002). Generalized methods of moments: Applications in finance. *Journal of Business & Economic Statistics*, *20*(4), 470–481.

[175]. Jagannathan, R., & Wang, Z. (1998). An Asymptotic Theory for Estimating Beta-Pricing Models Using Cross-Sectional Regression. *The Journal of Finance*, *53*(4), 1285–1309. https://doi.org/10.1111/0022-1082.00053

[176]. Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65–91.

[177]. Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of Finance*, *23*(2), 389–416.

[178]. Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2), 231–254.

[179]. Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica: Journal of the Econometric Society*, 1551–1580.

[180]. Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*(2), 169–210.

[181]. Johnson, R. A., & Wichern, D. W. (1992). *Applied multivariate statistical analysis* (Vol. 4). Prentice hall Englewood Cliffs, NJ.

[182]. Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. *The Journal of Finance*, *51*(2), 463–491.

[183]. Jorion, P. (1991). The pricing of exchange rate risk in the stock market. *Journal of Financial and Quantitative Analysis*, *26*(03), 363–376.

[184]. Joy, M. (2011). Gold and the US dollar: Hedge or haven? *Finance Research Letters*, *8*(3), 120–131. https://doi.org/10.1016/j.frl.2011.01.001

[185]. Joyce, M., Miles, D., Scott, A., & Vayanos, D. (2012). Quantitative Easing and Unconventional Monetary Policy–an Introduction*. *The Economic Journal*, *122*(564), F271–F288.

[186]. Joyce, M., Tong, M., & Woods, R. (2011). The United Kingdom's quantitative easing policy: design, operation and impact. *Bank of England Quarterly Bulletin*.

[187]. Kan, R., Robotti, C., & Shanken, J. (2013). Pricing Model Performance and the Two-Pass Cross-Sectional Regression Methodology. *The Journal of Finance*, *68*(6), 2617–2649. https://doi.org/10.1111/jofi.12035

[188]. Kan, R., & Smith, D. R. (2008). The Distribution of the Sample Minimum-Variance Frontier. *Management Science*, *54*(7), 1364–1380. https://doi.org/10.1287/mnsc.1070.0852

[189]. Kan, R., & Zhang, C. (1999). Two-Pass Tests of Asset Pricing Models with Useless Factors. *The Journal of Finance*, *54*(1), 203–235. https://doi.org/10.1111/0022-1082.00102

[190]. Kandir, S. Y. (2008). Macroeconomic variables, firm characteristics and stock returns: Evidence from Turkey. *International Research Journal of Finance and Economics*, *16*(1), 35–45.

[191]. Kat, H. M., & Oomen, R. C. A. (2006). *What Every Investor Should Know About Commodities, Part Ii: Multivariate Return Analysis* (SSRN Scholarly Paper No. ID 908609). Rochester, NY: Social Science Research Network. Retrieved from https://papers.ssrn.com/abstract=908609

[192]. Keim, D. B., & Stambaugh, R. F. (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics*, *17*(2), 357–390. https://doi.org/10.1016/0304-405X(86)90070-X

[193]. Kolev, G. I. (2013). Two gold return puzzles.

[194]. Kontonikas, A., MacDonald, R., & Saggu, A. (2013). Stock market reaction to fed funds rate surprises: State dependence and the financial crisis. *Journal of Banking & Finance*, *37*(11),

4025–4037. https://doi.org/10.1016/j.jbankfin.2013.06.010

[195]. Kothari, S. P., & Shanken, J. (1992). Stock return variation and expected dividends: A time-series and cross-sectional analysis. *Journal of Financial Economics*, *31*(2), 177–210.

[196]. Kothari, S. P., Shanken, J., & Sloan, R. G. (1995). Another Look at the Cross-section of Expected Stock Returns. *The Journal of Finance*, *50*(1), 185–224. https://doi.org/10.1111/j.1540-6261.1995.tb05171.x

[197]. Kozicki, S. (1999). How useful are Taylor rules for monetary policy? *Economic Review-Federal Reserve Bank of Kansas City*, *84*(2), 5.

[198]. Kreps, D. M., & Porteus, E. L. (1978). Temporal Resolution of Uncertainty and Dynamic Choice Theory. *Econometrica*, *46*(1), 185–200. https://doi.org/10.2307/1913656

[199]. Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1), 159–178.

[200]. Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, *32*(1), 23–43.

[201]. Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, *49*(5), 1541–1578.

[202]. Le Bris, D., & Rezaee, A. (2017). Stocks and bonds during the gold standard. *Economics Letters*, *159*(Supplement C), 119–122. https://doi.org/10.1016/j.econlet.2017.07.021

[203]. Lee, B. (1992). Causal relations among stock returns, interest rates, real activity, and inflation. *The Journal of Finance*, *47*(4), 1591–1603.

[204]. Lettau, M., & Ludvigson, S. (2001). Consumption, aggregate wealth, and expected stock returns. *The Journal of Finance*, *56*(3), 815–849.

[205]. Lettau, M., & Ludvigson, S. (2003). *Understanding trend and cycle in asset values: Reevaluating the wealth effect on consumption*. National Bureau of Economic Research.

[206]. Lewellen, J., Nagel, S., & Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics*, *96*(2), 175–194. https://doi.org/10.1016/j.jfineco.2009.09.001

[207]. Lintner, J. (1965a). SECURITY PRICES, RISK, AND MAXIMAL GAINS FROM DIVERSIFICATION - Lintner - 1965 - The Journal of Finance - Wiley Online Library. Retrieved October 29, 2017, from http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.1965.tb02930.x/full

[208]. Lintner, J. (1965b). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 13–37.

[209]. Liu, L. X., & Zhang, L. (2008). Momentum profits, factor pricing, and macroeconomic risk. *The Review of Financial Studies*, *21*(6), 2417–2448.

[210]. Liu, P., Shao, Y., & Yeager, T. J. (2009). Did the repeated debt ceiling controversies embed default risk in US Treasury securities? *Journal of Banking & Finance*, *33*(8), 1464–1471.

[211]. Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of financial Economics*, *82*(3), 631-671.

[212]. Lo, A. W., & MacKinlay, A. C. (1988). Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test. *The Review of Financial Studies*, *1*(1), 41–66. https://doi.org/10.1093/rfs/1.1.41

[213]. Lo, A. W., & MacKinlay, A. C. (1990). Data-snooping biases in tests of financial asset pricing models. *Review of Financial Studies*, *3*(3), 431–467.

[214]. Low, R. K. Y., Yao, Y., & Faff, R. (2016). Diamonds vs. precious metals: What shines brightest in your investment portfolio? *International Review of Financial Analysis*, *43*, 1–14. https://doi.org/10.1016/j.irfa.2015.11.002

[215]. Lucas Jr, R. E. (1978). Asset prices in an exchange economy. *Econometrica: Journal of the Econometric Society*, 1429–1445.

[216]. Luger, R. (2003). Exact non-parametric tests for a random walk with unknown drift under conditional heteroscedasticity. *Journal of Econometrics*, *115*(2), 259–276. https://doi.org/10.1016/S0304-4076(03)00097-6

[217]. Lütkepohl, H. (2004). Vector autoregressive and vector error correction models. *Applied Time*

Series Econometrics.

[218]. Lutzenberger, F. T. (2015). Multifactor models and their consistency with the ICAPM: Evidence from the European stock market. *European Financial Management, 21*(5), 1014–1052.

[219]. Mackinlay, A. C., & Richardson, M. P. (1991). Using Generalized Method of Moments to Test Mean-Variance Efficiency. *The Journal of Finance, 46*(2), 511–527. https://doi.org/10.1111/j.1540-6261.1991.tb02672.x

[220]. Maio, P. (2013). Intertemporal CAPM with conditioning variables. *Management Science*, *59*(1), 122–141.

[221]. Maio, P. F. (2017). *Do Traded Risk Factors Outperform Non-Traded Factors?* (SSRN Scholarly Paper No. ID 2535572). Rochester, NY: Social Science Research Network. Retrieved from https://papers.ssrn.com/abstract=2535572

[222]. Maio, P., & Philip, D. (2013). Macro factors and the cross-section of stock returns. *Hanken School of Economics Working Paper*.

[223]. Maio, P., & Santa-Clara, P. (2012). Multifactor models and their consistency with the ICAPM. *Journal of Financial Economics*, *106*(3), 586–613. https://doi.org/10.1016/j.jfineco.2012.07.001

[224]. Malkiel, B. G., & Xu, Y. (2002). Idiosyncratic risk and security returns. *University of Texas at Dallas (November 2002)*.

[225]. Mankiw, N. G., & Shapiro, M. D. (1984). Risk and return: Consumption versus market beta.

[226]. Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77–91.

[227]. Markowitz, H. (1959). *Portfolio Selection, Efficent Diversification of Investments*. J. Wiley.

[228]. McCown, J. R., & Zimmerman, J. R. (2006). Is gold a zero-beta asset? Analysis of the investment potential of precious metals. *Analysis of the Investment Potential of Precious Metals (July 24, 2006)*.

[229]. Mehra, R., & Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of Monetary Economics*, *15*(2), 145–161. https://doi.org/10.1016/0304-3932(85)90061-3

[230]. Mensi, W., Hammoudeh, S., Al-Jarrah, I. M. W., Sensoy, A., & Kang, S. H. (2017). Dynamic risk spillovers between gold, oil prices and conventional, sustainability and Islamic equity

aggregates and sectors with portfolio implications. *Energy Economics*. https://doi.org/10.1016/j.eneco.2017.08.031

[231]. Merton, R. C. (1973). An Intertemporal Capital Asset Pricing Model. *Econometrica, 41*(5), 867–887. https://doi.org/10.2307/1913811

[232]. Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics*, *8*(4), 323–361.

[233]. Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), 483–510.

[234]. Mihaylov, G., Cheong, C. S., & Zurbruegg, R. (2015). Can security analyst forecasts predict gold returns? *International Review of Financial Analysis*, *41*(Supplement C), 237–246. https://doi.org/10.1016/j.irfa.2015.03.012

[235]. Mill, J. S. (1843). A System of Logic, 2 vols. *London: Parker*.

[236]. Mishkin, F. S. (2009). *Is monetary policy effective during financial crises?* National Bureau of Economic Research.

[237]. Moosa, I. A. (2011). The failure of neoclassical financial economics: CAPM and its pillars as an illustration. *Technical Finance*, 69.

[238]. Moosa, I. A. (2013). The capital asset pricing model (CAPM): the history of a failed revolutionary idea in finance? Comments and extensions. *Abacus, 49*(S1), 62–68.

[239]. Moskowitz, T. J., & Grinblatt, M. (1999). Do Industries Explain Momentum? *The Journal of Finance, 54*(4), 1249–1290. https://doi.org/10.1111/0022-1082.00146

[240]. Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the Econometric Society*, 768–783.

[241]. Neuman, W. L. (2005). *Social research methods: Quantitative and qualitative approaches* (Vol. 13). Allyn and bacon Boston, MA.

[242]. Nippani, S., & Smith, S. D. (2010). The increasing default risk of US Treasury securities due to the financial crisis. *Journal of Banking & Finance, 34*(10), 2472–2480.

https://doi.org/10.1016/j.jbankfin.2010.04.005

[243]. Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, *108*(1), 1–28.

[244]. Ntim, C. G., English, J., Nwachukwu, J., & Wang, Y. (2015). On the efficiency of the global gold markets. *International Review of Financial Analysis*, *41*, 218–236. https://doi.org/10.1016/j.irfa.2015.03.013

[245]. O'Connor, F. A., Lucey, B. M., Batten, J. A., & Baur, D. G. (2015). The financial economics of gold — A survey. *International Review of Financial Analysis*, *41*, 186–205. https://doi.org/10.1016/j.irfa.2015.07.005

[246]. Officer, R. R. (1973). The variability of the market factor of the New York Stock Exchange. *The Journal of Business*, *46*(3), 434–453.

[247]. Oglend, A., & Selland Kleppe, T. (2016). How regular are directional movements in commodity and asset prices? A Wald test. *Journal of Empirical Finance*, *38*(Part A), 290–306. https://doi.org/10.1016/j.jempfin.2016.07.001

[248]. Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. *Energy Economics*, *30*(5), 2587–2608. https://doi.org/10.1016/j.eneco.2008.04.003

[249]. Pastor, L., & Stambaugh, R. F. (2001). *Liquidity risk and expected stock returns*. National Bureau of Economic Research.

[250]. Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, *111*(3), 642–685. https://doi.org/10.1086/374184

[251]. Pearce, D. K., & Roley, V. V. (1983). The reaction of stock prices to unanticipated changes in money: A note. *The Journal of Finance*, *38*(4), 1323–1333.

[252]. Petkova, R. (2006). Do the Fama–French factors proxy for innovations in predictive variables? *The Journal of Finance*, *61*(2), 581–612.

[253]. Pierdzioch, C., Risse, M., & Rohloff, S. (2014). On the efficiency of the gold market: Results of a real-time forecasting approach. *International Review of Financial Analysis*, *32*(Supplement C), 95–108. https://doi.org/10.1016/j.irfa.2014.01.012

[254]. Pukthuanthong, K., & Roll, R. (2011). Gold and the Dollar (and the Euro, Pound, and Yen). *Journal of Banking & Finance*, *35*(8), 2070–2083.

[255]. Rad, A. A. (2011). Macroeconomic variables and stock market: evidence from iran. *International Journal of Economics and Finance Studies*, *3*(1), 1–10.

[256]. Rapach, D. E., & Wohar, M. E. (2006). Structural Breaks and Predictive Regression Models of Aggregate U.S. Stock Returns. *Journal of Financial Econometrics*, *4*(2), 238–274. https://doi.org/10.1093/jjfinec/nbj008

[257]. Reboredo, J. C. (2013). Is gold a safe haven or a hedge for the US dollar? Implications for risk management. *Journal of Banking & Finance*, *37*(8), 2665–2676. https://doi.org/10.1016/j.jbankfin.2013.03.020

[258]. Reboredo, J. C., & Rivera-Castro, M. A. (2014). Can gold hedge and preserve value when the US dollar depreciates? *Economic Modelling*, *39*, 168–173. https://doi.org/10.1016/j.econmod.2014.02.038

[259]. Reinganum, M. H. (1981). The Arbitrage Pricing Theory: Some Empirical Results. *Journal of Finance*, *36*, 313–321.

[260]. Reinganum, M. R. (1981). A new empirical perspective on the CAPM. *Journal of Financial and Quantitative Analysis*, *16*(04), 439–462.

[261]. Richards, N. D., Simpson, J., & Evans, J. (2009). The interaction between exchange rates and stock prices: An Australian context. *International Journal of Economics and Finance*, *1*(1), p3.

[262]. Roll, R. (1977). A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of Financial Economics*, *4*(2), 129–176.

[263]. Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*(3), 341–360.

[264]. Ross, S. A. (1977). The capital asset pricing model (capm), short-sale restrictions and related issues. *The Journal of Finance*, *32*(1), 177–183.

[265]. Rubinstein, M. (1975). Securities Market Efficiency in an Arrow-Debreu Economy. *The American Economic Review*, *65*(5), 812–824. https://doi.org/10.2307/1806622

[266]. Rubinstein, M. (1976). The valuation of uncertain income streams and the pricing of options. *The Bell Journal of Economics*, 407–425.

[267]. Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics*, *21*(5), 449–469. https://doi.org/10.1016/S0140-9883(99)00020-1

[268]. Salant, S. W., & Henderson, D. W. (1978). Market Anticipations of Government Policies and the Price of Gold. *Journal of Political Economy*, *86*(4), 627–648. https://doi.org/10.1086/260702

[269]. Sarno, L., & Thornton, D. L. (2003). The dynamic relationship between the federal funds rate and the Treasury bill rate: An empirical investigation. *Journal of Banking & Finance, 27*(6), 1079–1110.

[270]. Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance*, *44*(5), 1115–1153.

[271]. Shanken, J. (1985). Multivariate tests of the zero-beta CAPM. *Journal of Financial Economics*, *14*(3), 327–348. https://doi.org/10.1016/0304-405X(85)90002-9

[272]. Shanken, J. (1992). On the estimation of beta-pricing models. *Review of Financial Studies*, *5*(1), 1–55. https://doi.org/10.1093/rfs/5.1.1

[273]. Shapiro, M. D., & Mankiw, N. G. (1985). *Risk and Return: Consumption Beta Versus Market Beta*. Cowles Foundation for Research in Economics, Yale University.

[274]. Sharpe, W. F. (1963). A Simplified Model for Portfolio Analysis. *Management Science*, *9*(2), 277–293. https://doi.org/10.1287/mnsc.9.2.277

[275]. Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk*. *The Journal of Finance*, *19*(3), 425–442.

[276]. Sharpe, W. F. (1965). Risk-Aversion In The Stock Market: Some Empirical Evidence. *The Journal of Finance*, *20*(3), 416–422.

[277]. Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business, 39*(1), 119–138.

[278]. Sharpe, W. F., & Cooper, G. M. (1972). Risk-Return Classes of New York Stock Exchange Common Stocks, 1931-1967. *Financial Analysts Journal*, *28*(2), 46–81.

[279]. Sjaastad, L. A., & Scacciavillani, F. (1996). The price of gold and the exchange rate. *Journal of*

International Money and Finance, *15*(6), 879–897. https://doi.org/10.1016/S0261-5606(96)00045-9

[280]. Smith, G. (2002). London gold prices and stock price indices in Europe and Japan. *World Gold Council*, 1–30.

[281]. Strong, N., & Xu, X. G. (1997). Explaining the cross-section of UK expected stock returns. *The British Accounting Review*, *29*(1), 1–23.

[282]. Subrahmanyam, A. (2010). The Cross-Section of Expected Stock Returns: What Have We Learnt from the Past Twenty-Five Years of Research? *European Financial Management*, *16*(1), 27–42.

[283]. Taylor, J. B. (1993). Discretion versus policy rules in practice (Vol. 39, pp. 195–214). Elsevier.

[284]. Taylor, J. B. (2009). *The financial crisis and the policy responses: An empirical analysis of what went wrong*. National Bureau of Economic Research.

[285]. Taylor, N. J. (1998). Precious metals and inflation. *Applied Financial Economics*, *8*(2), 201–210. https://doi.org/10.1080/096031098333186

[286]. Titman, S., Wei, K. J., & Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, *39*(04), 677–700.

[287]. Tobin, J. (1958). Liquidity preference as behavior towards risk. *The Review of Economic Studies*, *25*(2), 65–86.

[288]. Todorova, N. (2017). The asymmetric volatility in the gold market revisited. *Economics Letters*, *150*(Supplement C), 138–141. https://doi.org/10.1016/j.econlet.2016.11.027

[289]. Tufano, P. (1996). Who manages risk? An empirical examination of risk management practices in the gold mining industry. *The Journal of Finance*, *51*(4), 1097–1137.

[290]. Tufano, P. (1998). The Determinants of Stock Price Exposure: Financial Engineering and the Gold Mining Industry. *The Journal of Finance*, *53*(3), 1015–1052. https://doi.org/10.1111/0022-1082.00042

[291]. Urich, T., & Wachtel, P. (1981). Market response to the weekly money supply announcements in the 1970s. *The Journal of Finance*, *36*(5), 1063–1072.

[292]. Van Hoang, T. H., Lahiani, A., & Heller, D. (2016). Is gold a hedge against inflation? New

evidence from a nonlinear ARDL approach. *Economic Modelling*, *54*, 54-66.

[293]. Wang, Y., Wei, Y., & Wu, C. (2011). Analysis of the efficiency and multifractality of gold markets based on multifractal detrended fluctuation analysis. *Physica A: Statistical Mechanics and Its Applications*, *390*(5), 817–827. https://doi.org/10.1016/j.physa.2010.11.002

[294]. Wei, C. (2003). Energy, the stock market, and the putty-clay investment model. *American Economic Review*, 311–323.

[295]. Weil, P. (1989). The equity premium puzzle and the risk-free rate puzzle. *Journal of Monetary Economics*, *24*(3), 401–421. https://doi.org/10.1016/0304-3932(89)90028-7

[296]. Weil, P. (1990). Nonexpected Utility in Macroeconomics. *The Quarterly Journal of Economics*, *105*(1), 29–42. https://doi.org/10.2307/2937817

[297]. Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, *21*(4), 1455–1508.

[298]. Whang, Y.-J., & Kim, J. (2003). A multiple variance ratio test using subsampling. *Economics Letters*, *79*(2), 225–230. https://doi.org/10.1016/S0165-1765(02)00330-0

[299]. Wiersema, U. F. (2008). *Brownian motion calculus*. John Wiley & Sons.

[300]. Worthington, A. C., & Pahlavani, M. (2007). Gold investment as an inflationary hedge: cointegration evidence with allowance for endogenous structural breaks. *Applied Financial Economics Letters*, *3*(4), 259–262. https://doi.org/10.1080/17446540601118301

[301]. Wright, J. H. (2000). Alternative Variance-Ratio Tests Using Ranks and Signs. *Journal of Business & Economic Statistics*, *18*(1), 1–9. https://doi.org/10.1080/07350015.2000.10524842

[302]. Wu, C.-C., & Chiu, J. (2017). Economic evaluation of asymmetric and price range information in gold and general financial markets. *Journal of International Money and Finance*, *74*(Supplement C), 53–68. https://doi.org/10.1016/j.jimonfin.2017.03.001

[303]. Yule, G. U. (1926). Why do we sometimes get nonsense-correlations between Time-Series?--a study in sampling and the nature of time-series. *Journal of the Royal Statistical Society*, 1–63.

[304]. Zhou, G. (2010). How much stock return predictability can we expect from an asset pricing

model? *Economics Letters*, *108*(2), 184–186. https://doi.org/10.1016/j.econlet.2010.05.008

[305]. World Gold Council (2017). Retrieved December 12, 2017, from https://www.gold.org/what-we-do/gold-market-structure/global-gold-market.

Appendixes

Appendix A: Empirical Factor Models in Global Markets

A.1 Generalised Least Square methodology

For robustness, I also employ Fama-MacBeth tests with Generalised Least Square (GLS) methodology. In the traditional Fama-MacBeth approach, first stage estimates are obtained with the Ordinary Least Square (OLS) estimation method. Shanken (1992) correction overcomes the issue of errors-in-variables bias in the second stage regression but autocorrelated and heteroscedastic errors may still remain with the first-stage estimates. When residuals are autocorrelated with each other, then Cochrane (2009) recommends GLS regression instead of the OLS regression.

I follow Kan, Robotti, & Shanken (2013) who perform Fama-MacBeth tests with both OLS and GLS estimation methods to compare the performance of asset pricing models.

In the GLS regression, $E(\alpha\alpha') = \frac{1}{T}(\Sigma + \beta \Sigma_F \beta')$ is employed as the error covariance matrix. Hence, the second stage estimates for the factor risk premia and cross-sectional alphas are obtained as:

$$\hat{\lambda} = (\beta'\Sigma^{-1}\beta)^{-1}\beta'\Sigma^{-1}E_T(R_e) \tag{1}$$

$$\hat{\alpha} = E_T(R_e) - \hat{\lambda}\,\beta \tag{2}$$

Cochrane (2009, Chapter 12) shows that the estimates from GLS cross-sectional regression are similar to the time series regression when excess factor returns are included in test portfolios.

He further points out that in some cases, OLS regression can be more robust to the GLS regression and finally recommends first-stage GMM that is analogue to the OLS cross-sectional regression.

The GLS cross-sectional method is equivalent to the GMM second stage procedure and it is used to improve the efficiency of cross-sectional regression i.e. it helps to produce more precise estimates in the second stage regression. Maio and Santa-Clata (2012) and Lutzenberger (2015) also have performed robustness tests with GLS but also cite Cochrane (1996; 2005) who documents limitation of second stage GMM and cross-sectional GLS methods. According to his argument, the GLS may produce extreme linear combinations due to the repackaging of portfolios. Hence, it may be less useful to average investors. However, Lewellen, Nagel, and Shanken (2010) recommend the GLS estimation methods and states that it is difficult to obtain higher R-squared with the GLS system rather than OLS estimation method. The GLS R-squared shows the closeness of test portfolio to the mean-variance frontier.

Table A 1: Fama-MacBeth Tests on the global 25 Size and Book-to-market, and 25 Size and Momentum portfolios for the full period January 1981-December 2015, and sub-period January 2003 to December 2015 by using GLS method. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Size and Book to Market								Global Size and Momentum							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.58	6.20	6.01	0.12	1.28	4.73	4.70	0.04	0.82	4.07	4.05	0.01	1.37	6.13	6.07	0.02
γ_{RM}	-1.08	-3.06	-3.01		-0.54	-1.21	-1.20		-0.32	-1.02	-1.02		-0.60	-1.42	-1.42	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.49	5.80	5.61	0.17	1.37	4.95	4.83	0.14	0.74	3.07	3.05	0.04	1.35	5.87	5.65	0.11
γ_{RM}	-1.00	-2.81	-2.76		-0.63	-1.40	-1.39		-0.25	-0.73	-0.73		-0.59	-1.39	-1.37	
γ_{SMB}	0.13	1.13	1.13		0.19	1.53	1.53		0.23	1.98	1.98		0.28	2.22	2.21	
γ_{HML}	0.33	2.46	2.46		0.08	0.68	0.68		0.14	0.68	0.68		0.18	0.81	0.79	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.32	4.74	4.53	0.21	1.21	3.73	3.62	0.16	0.23	0.84	0.79	0.14	1.23	4.89	4.63	0.13
γ_{RM}	-0.82	-2.19	-2.13		-0.47	-0.98	-0.97		0.23	0.64	0.62		-0.46	-1.06	-1.04	
γ_{SMB}	0.13	1.14	1.14		0.19	1.51	1.51		0.24	2.03	2.03		0.28	2.22	2.22	
γ_{HML}	0.33	2.48	2.47		0.09	0.70	0.70		0.47	2.11	2.03		0.33	1.30	1.25	
γ_{Mom}	0.86	1.86	1.79		0.56	1.15	1.13		0.67	2.94	2.94		0.37	1.34	1.34	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.82	4.91	4.49	0.29	1.40	3.86	3.71	0.18	0.68	2.63	2.54	0.07	1.06	3.32	3.08	0.14
γ_{RM}	-1.33	-2.97	-2.79		-0.66	-1.30	-1.27		-0.18	-0.52	-0.51		-0.29	-0.61	-0.59	
γ_{SMB}	0.13	1.12	1.12		0.20	1.59	1.59		0.22	1.90	1.90		0.29	2.30	2.29	
γ_{HML}	0.33	2.49	2.49		0.08	0.63	0.63		0.01	0.06	0.06		0.24	1.04	0.98	
γ_{CMA}	0.01	0.04	0.04		-0.05	-0.34	-0.33		0.31	1.72	1.68		0.29	1.75	1.67	
γ_{RMW}	0.20	1.42	1.34		0.15	0.99	0.96		0.01	0.05	0.05		0.09	0.54	0.51	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.46	3.58	3.20	0.35	1.32	3.62	3.39	0.22	0.26	0.90	0.79	0.16	1.04	3.24	3.01	0.15
γ_{RM}	-0.95	-1.98	-1.82		-0.58	-1.14	-1.10		0.20	0.56	0.52		-0.27	-0.57	-0.55	
γ_{SMB}	0.14	1.19	1.18		0.19	1.52	1.52		0.22	1.88	1.87		0.29	2.29	2.28	
γ_{HML}	0.33	2.49	2.49		0.09	0.70	0.69		0.73	2.42	2.19		0.29	1.11	1.05	
γ_{Mom}	1.07	2.18	2.00		0.70	1.37	1.31		0.67	2.93	2.93		0.37	1.33	1.33	
γ_{CMA}	-0.06	-0.41	-0.39		-0.09	-0.58	-0.56		0.39	2.15	1.99		0.29	1.71	1.63	
γ_{RMW}	0.31	2.05	1.89		0.11	0.77	0.73		-0.25	-1.53	-1.40		0.08	0.43	0.40	

Table A 2: Fama-MacBeth Tests on the 25 Size and Book-to-market portfolios in the North American region with global and local factors by using GLS method. The analysis covers the full period January 1981-December 2015, and sub-period: January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.51	5.39	5.29	0.07	0.76	2.18	2.18	0.00	1.54	5.54	5.44	0.09	0.72	2.03	2.03	0.00
γ_{RM}	-0.83	-2.09	-2.06		-0.04	-0.09	-0.09		-0.85	-2.28	-2.25		0.04	0.08	0.08	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.63	5.46	5.25	0.19	0.97	2.25	2.24	0.02	1.61	5.46	5.31	0.15	1.01	2.34	2.32	0.06
γ_{RM}	-0.95	-2.27	-2.21		-0.25	-0.43	-0.43		-0.91	-2.37	-2.33		-0.25	-0.46	-0.46	
γ_{SMB}	0.37	2.60	2.56		0.13	0.79	0.79		0.19	1.19	1.19		0.18	1.05	1.05	
γ_{HML}	0.21	1.44	1.43		0.03	0.21	0.21		0.25	1.33	1.33		-0.01	-0.04	-0.04	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.22	3.85	3.38	0.46	0.59	1.31	1.22	0.24	1.28	4.22	3.65	0.51	0.77	1.75	1.64	0.28
γ_{RM}	-0.47	-1.10	-1.00		0.17	0.29	0.28		-0.54	-1.39	-1.26		0.00	-0.01	-0.01	
γ_{SMB}	0.24	1.66	1.57		0.09	0.53	0.51		0.20	1.20	1.20		0.18	1.01	1.00	
γ_{HML}	0.21	1.46	1.43		0.04	0.27	0.27		0.25	1.33	1.33		-0.01	-0.08	-0.08	
γ_{Mom}	1.96	4.33	3.92		1.19	2.55	2.43		2.65	4.84	4.33		1.37	2.65	2.53	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.50	4.25	4.00	0.26	0.71	1.28	1.26	0.05	1.62	4.66	4.48	0.18	1.00	1.91	1.83	0.17
γ_{RM}	-0.85	-1.76	-1.68		0.05	0.08	0.08		-0.92	-2.17	-2.11		-0.25	-0.40	-0.38	
γ_{SMB}	0.38	2.69	2.63		0.12	0.70	0.70		0.20	1.24	1.24		0.21	1.18	1.18	
γ_{HML}	0.18	1.27	1.26		0.00	0.03	0.03		0.25	1.33	1.33		-0.02	-0.09	-0.09	
γ_{CMA}	0.01	0.04	0.03		0.02	0.15	0.15		0.13	0.54	0.53		-0.21	-1.00	-0.96	
γ_{RMW}	0.33	2.47	2.38		0.10	0.74	0.73		0.34	1.76	1.73		0.35	1.73	1.69	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.18	3.26	2.72	0.56	0.88	1.57	1.42	0.28	1.40	4.02	3.28	0.60	0.96	1.84	1.68	0.34
γ_{RM}	-0.52	-1.06	-0.92		-0.13	-0.19	-0.18		-0.67	-1.56	-1.35		-0.20	-0.32	-0.30	
γ_{SMB}	0.26	1.78	1.64		0.12	0.72	0.69		0.21	1.27	1.26		0.19	1.08	1.07	
γ_{HML}	0.19	1.34	1.30		0.06	0.42	0.41		0.26	1.36	1.36		-0.01	-0.08	-0.08	
γ_{Mom}	2.13	4.63	4.02		1.34	2.72	2.53		2.89	5.18	4.42		1.34	2.52	2.37	
γ_{CMA}	-0.10	-0.53	-0.47		-0.05	-0.33	-0.31		-0.07	-0.30	-0.27		-0.24	-1.12	-1.05	
γ_{RMW}	0.41	3.08	2.74		0.06	0.45	0.42		0.48	2.49	2.24		0.27	1.35	1.28	

Table A 3: Fama - MacBeth Tests on the 25 Size and Momentum portfolios in the North American region with global and local factors by using GLS method. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.92	3.84	3.83	0.00	0.81	2.86	2.86	0.00	1.00	4.07	4.06	0.01	0.74	2.55	2.55	0.00
γ_{RM}	-0.18	-0.50	-0.50		-0.13	-0.28	-0.28		-0.32	-0.92	-0.92		0.05	0.12	0.12	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.85	2.89	2.85	0.06	0.97	3.01	2.88	0.09	0.89	2.75	2.71	0.07	0.94	2.75	2.73	0.02
γ_{RM}	-0.08	-0.19	-0.19		-0.30	-0.60	-0.59		-0.23	-0.56	-0.56		-0.14	-0.29	-0.29	
γ_{SMB}	0.29	2.02	2.01		0.15	0.93	0.92		0.29	1.72	1.72		0.16	0.88	0.88	
γ_{HML}	0.24	1.18	1.17		-0.44	-1.94	-1.87		0.34	1.20	1.19		-0.13	-0.43	-0.43	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.23	0.65	0.60	0.17	1.05	3.00	2.83	0.09	0.13	0.32	0.30	0.18	0.93	2.48	0.46	0.02
γ_{RM}	0.62	1.33	1.26		-0.38	-0.74	-0.71		0.51	1.10	1.04		-0.13	-0.26	-0.26	
γ_{SMB}	0.19	1.32	1.28		0.16	1.01	0.99		0.26	1.58	1.57		0.16	0.88	0.88	
γ_{HML}	0.54	2.38	2.26		-0.49	-2.00	-1.91		0.84	2.58	2.45		-0.12	-0.35	-0.35	
γ_{Mom}	0.51	2.10	2.09		0.19	0.65	0.65		0.67	2.38	2.37		0.14	0.43	0.43	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.38	1.07	0.94	0.19	0.74	2.07	1.88	0.17	0.64	1.84	1.70	0.14	0.59	1.56	1.46	0.12
γ_{RM}	0.59	1.24	1.13		-0.06	-0.12	-0.11		0.03	0.07	0.07		0.22	0.44	0.43	
γ_{SMB}	0.28	1.90	1.80		0.08	0.53	0.51		0.27	1.64	1.63		0.14	0.80	0.79	
γ_{HML}	0.03	0.16	0.15		-0.43	-1.79	-1.66		0.50	1.61	1.52		-0.13	-0.44	-0.42	
γ_{CMA}	0.42	2.12	1.94		0.18	0.96	0.89		0.73	2.87	2.72		0.36	1.69	1.61	
γ_{RMW}	0.09	0.48	0.43		-0.07	-0.42	-0.39		-0.44	-1.74	-1.64		-0.19	-0.77	-0.73	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.19	0.51	0.45	0.23	0.85	2.30	2.02	0.20	-0.46	-1.08	-0.78	0.35	0.54	1.32	1.23	0.12
γ_{RM}	0.78	1.61	1.48		-0.17	-0.32	-0.29		1.08	2.24	1.74		0.27	0.50	0.48	
γ_{SMB}	0.18	1.15	1.09		0.11	0.70	0.66		0.21	1.28	1.24		0.14	0.79	0.79	
γ_{HML}	0.37	1.32	1.21		-0.54	-2.11	-1.90		1.62	4.01	3.08		-0.09	-0.27	-0.26	
γ_{Mom}	0.50	2.06	2.03		0.24	0.84	0.83		0.70	2.46	2.45		0.15	0.47	0.47	
γ_{CMA}	0.53	2.57	2.37		0.17	0.90	0.82		1.15	4.23	3.34		0.38	1.67	1.58	
γ_{RMW}	-0.12	-0.52	-0.47		-0.05	-0.26	-0.23		-0.90	-3.26	-2.54		-0.22	-0.81	-0.77	

Table A 4: Fama-MacBeth Tests on the 25 Size and Book to Market portfolios in the European region with global and local factors by using GLS method. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns .γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.55	1.07	1.07	0.15	0.75	1.35	1.35	0.19	0.22	0.41	0.41	0.16	0.81	1.46	1.46	0.19
γ_{RM}	-0.01	-0.03	-0.03		0.13	0.22	0.22		0.32	0.54	0.54		0.10	0.14	0.14	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.92	2.49	2.44	0.50	-0.07	-0.13	-0.12	0.51	1.14	2.79	2.74	0.51	-0.33	-0.54	-0.52	0.51
γ_{RM}	-0.42	-0.97	-0.96		0.76	1.35	1.32		-0.60	-1.20	-1.19		1.14	1.50	1.46	
γ_{SMB}	-0.08	-0.53	-0.52		0.22	1.38	1.36		-0.03	-0.20	-0.20		0.17	1.10	1.10	
γ_{HML}	0.40	2.46	2.45		-0.13	-0.75	-0.74		0.30	2.07	2.07		-0.02	-0.11	-0.11	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.88	2.32	2.27	0.53	-0.37	-0.65	-0.59	0.56	0.88	1.94	1.89	0.54	-0.52	-0.81	-0.75	0.56
γ_{RM}	-0.38	-0.87	-0.85		1.05	1.76	1.65		-0.33	-0.60	-0.59		1.33	1.72	1.62	
γ_{SMB}	-0.07	-0.43	-0.43		0.30	1.85	1.77		-0.03	-0.19	-0.19		0.17	1.14	1.13	
γ_{HML}	0.40	2.45	2.44		-0.11	-0.68	-0.64		0.30	2.05	2.05		0.00	-0.01	-0.01	
γ_{Mom}	0.11	0.21	0.20		0.92	1.47	1.35		0.62	0.99	0.97		0.69	1.12	1.05	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.47	0.95	0.92	0.60	-0.41	-0.72	-0.59	0.60	0.38	0.68	0.66	0.60	1.07	1.24	0.88	0.60
γ_{RM}	-0.05	-0.10	-0.10		1.00	1.70	1.49		0.16	0.26	0.25		-0.23	-0.24	-0.18	
γ_{SMB}	-0.04	-0.26	-0.26		0.27	1.67	1.52		-0.01	-0.05	-0.05		0.22	1.43	1.42	
γ_{HML}	0.32	1.89	1.87		-0.05	-0.27	-0.24		0.26	1.84	1.84		-0.01	-0.05	-0.05	
γ_{CMA}	0.17	0.75	0.74		-0.34	-1.71	-1.47		0.24	1.25	1.23		-0.46	-2.03	-1.53	
γ_{RMW}	0.28	1.46	1.43		0.50	2.50	2.13		0.17	0.76	0.74		0.87	3.85	2.93	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.47	0.94	0.92	0.63	-0.35	-0.64	-0.52	0.63	0.40	0.71	0.69	0.63	0.97	1.11	0.76	0.63
γ_{RM}	-0.05	-0.09	-0.09		0.94	1.64	1.42		0.14	0.22	0.22		-0.14	-0.15	-0.11	
γ_{SMB}	-0.05	-0.31	-0.31		0.26	1.64	1.48		0.00	-0.04	-0.04		0.22	1.49	1.48	
γ_{HML}	0.32	1.86	1.84		-0.04	-0.25	-0.22		0.26	1.82	1.82		-0.03	-0.16	-0.16	
γ_{Mom}	-0.15	-0.25	-0.25		-0.15	-0.24	-0.21		-0.16	-0.26	-0.25		-0.40	-0.60	-0.44	
γ_{CMA}	0.19	0.83	0.81		-0.32	-1.66	-1.42		0.26	1.36	1.33		-0.40	-1.79	-1.30	
γ_{RMW}	0.27	1.45	1.42		0.54	2.53	2.12		0.17	0.74	0.72		0.94	3.96	2.90	

Table A 5: Fama-MacBeth Tests on the 25 Size and Momentum portfolios in the European region with global and local factors by using GLS method. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns .γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.18	4.32	4.28	0.02	0.94	2.75	2.74	0.00	1.24	4.13	4.09	0.02	0.85	2.43	2.43	0.00
γ_{RM}	-0.59	-1.68	-1.67		-0.21	-0.46	-0.46		-0.68	-1.65	-1.64		-0.02	-0.04	-0.04	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	1.01	3.41	3.36	0.04	1.08	3.12	2.92	0.07	1.11	3.55	3.48	0.04	1.00	2.57	2.52	0.04
γ_{RM}	-0.48	-1.34	-1.33		-0.31	-0.68	-0.66		-0.56	-1.34	-1.33		-0.18	-0.30	-0.30	
γ_{SMB}	0.14	0.89	0.89		0.17	1.09	1.06		0.11	0.85	0.85		0.27	1.75	1.75	
γ_{HML}	0.33	1.59	1.58		0.50	2.26	2.16		0.34	1.35	1.33		0.20	0.83	0.83	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.18	0.52	0.46	0.19	0.69	1.89	1.62	0.19	0.06	0.17	0.15	0.25	0.70	1.73	1.62	0.15
γ_{RM}	0.19	0.48	0.45		0.04	0.09	0.09		0.45	0.97	0.88		0.13	0.22	0.21	
γ_{SMB}	0.14	0.91	0.85		0.22	1.37	1.29		0.10	0.77	0.76		0.26	1.69	1.69	
γ_{HML}	0.79	3.43	3.15		0.71	3.09	2.76		1.07	3.77	3.35		0.41	1.63	1.57	
γ_{Mom}	1.00	3.83	3.71		0.73	2.46	2.40		0.96	4.09	4.09		0.75	2.36	2.36	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.66	1.88	1.45	0.27	0.45	1.16	0.80	0.44	-0.80	-1.74	-1.13	0.29	0.77	1.93	1.30	0.38
γ_{RM}	0.06	0.15	0.13		0.21	0.44	0.36		1.31	2.46	1.74		0.05	0.09	0.07	
γ_{SMB}	0.08	0.51	0.45		0.31	1.96	1.62		0.17	1.24	1.19		0.35	2.27	2.20	
γ_{HML}	0.18	0.85	0.72		0.63	2.60	1.92		0.15	0.60	0.43		0.14	0.57	0.44	
γ_{CMA}	1.06	5.43	4.49		0.68	4.22	3.29		1.37	5.68	3.91		0.51	3.09	2.37	
γ_{RMW}	-0.14	-0.92	-0.76		0.41	2.24	1.65		0.26	1.46	1.01		0.72	3.31	2.42	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.29	0.78	0.59	0.37	0.43	1.04	0.71	0.45	-0.94	-2.05	-1.35	0.41	0.78	1.94	1.29	0.38
γ_{RM}	0.33	0.83	0.68		0.23	0.48	0.39		1.44	2.69	1.94		0.04	0.06	0.05	
γ_{SMB}	0.07	0.47	0.41		0.31	1.97	1.63		0.11	0.81	0.78		0.35	2.28	2.20	
γ_{HML}	0.72	2.81	2.24		0.65	2.48	1.82		0.88	2.87	2.02		0.12	0.41	0.31	
γ_{Mom}	1.00	3.80	3.49		0.70	2.33	2.16		1.00	4.26	4.23		0.76	2.38	2.37	
γ_{CMA}	1.22	6.08	4.91		0.67	4.05	3.13		1.51	6.19	4.34		0.52	3.03	2.27	
γ_{RMW}	-0.33	-2.08	-1.67		0.41	2.21	1.62		-0.42	-1.76	-1.21		0.74	3.09	2.20	

Table A 6: Fama-MacBeth Tests on the 25 Size and Book-to-market portfolios in the Japanese region with global and local factors by using GLS method. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.45	1.15	1.14	0.03	0.21	0.63	0.63	0.00	0.28	0.65	0.65	0.00	-0.06	-0.15	-0.15	0.04
γ_{RM}	-0.48	-0.98	-0.98		0.20	0.35	0.35		-0.01	-0.35	-0.35		0.64	1.22	1.22	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.09	0.20	0.20	0.18	-0.19	-0.53	-0.49	0.34	0.07	0.15	0.15	0.12	-0.25	-0.64	-0.62	0.31
γ_{RM}	-0.08	-0.16	-0.15		0.58	1.02	0.97		0.02	0.04	0.04		0.83	1.58	1.54	
γ_{SMB}	0.22	1.14	1.12		0.49	2.54	2.41		0.10	0.51	0.51		0.37	1.75	1.75	
γ_{HML}	0.43	2.11	2.09		0.48	2.25	2.12		0.33	1.93	1.93		0.29	1.62	1.61	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.04	0.09	0.08	0.24	-0.21	-0.59	-0.54	0.34	0.22	0.48	0.45	0.36	-0.23	-0.59	-0.56	0.32
γ_{RM}	-0.08	-0.16	-0.15		0.60	1.06	1.00		-0.11	-0.19	-0.18		0.81	1.53	1.49	
γ_{SMB}	0.25	1.28	1.24		0.48	2.49	2.36		0.09	0.46	0.46		0.37	1.76	1.76	
γ_{HML}	0.49	2.34	2.27		0.47	2.19	2.06		0.32	1.91	1.91		0.29	1.61	1.60	
γ_{Mom}	0.71	1.13	1.08		-0.07	-0.10	-0.10		1.31	2.41	2.30		-0.07	-0.11	-0.11	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	-0.12	-0.22	-0.21	0.20	-0.26	-0.65	-0.59	0.36	0.04	0.09	0.08	0.17	-0.32	-0.79	-0.73	0.35
γ_{RM}	0.06	0.09	0.09		0.68	1.09	1.01		0.07	0.12	0.11		0.90	1.67	1.60	
γ_{SMB}	0.20	1.00	0.98		0.54	2.67	2.48		0.10	0.53	0.53		0.37	1.74	1.74	
γ_{HML}	0.44	2.18	2.14		0.50	2.28	2.11		0.35	2.04	2.04		0.32	1.72	1.71	
γ_{CMA}	0.38	1.83	1.79		0.20	1.15	1.07		-0.12	-0.42	-0.42		0.21	0.74	0.70	
γ_{RMW}	-0.07	-0.32	-0.31		-0.34	-1.44	-1.32		0.25	0.73	0.71		0.16	0.64	0.60	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	-0.27	-0.47	-0.43	0.26	-0.26	-0.66	-0.59	0.36	0.19	0.40	0.37	0.37	-0.34	-0.84	-0.77	0.36
γ_{RM}	0.17	0.27	0.25		0.69	1.09	1.01		-0.07	-0.12	-0.12		0.93	1.70	1.62	
γ_{SMB}	0.23	1.14	1.08		0.55	2.59	2.40		0.08	0.43	0.43		0.37	1.75	1.75	
γ_{HML}	0.51	2.42	2.31		0.50	2.22	2.05		0.33	1.92	1.91		0.31	1.68	1.68	
γ_{Mom}	0.75	1.10	1.03		-0.38	-0.47	-0.43		1.39	2.39	2.26		-0.09	-0.13	-0.12	
γ_{CMA}	0.44	2.08	1.97		0.21	1.13	1.05		0.18	0.56	0.53		0.25	0.87	0.82	
γ_{RMW}	0.06	0.26	0.24		-0.35	-1.42	-1.29		0.07	0.21	0.19		0.14	0.56	0.53	

Table A 7: Fama-MacBeth Tests on the 25 Size and Momentum portfolios in the Japanese region with global and local factors by using GLS method. The analysis covers full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.51	1.49	1.48	0.06	1.18	3.80	3.72	0.12	0.58	1.38	1.38	0.04	1.31	3.23	3.18	0.07
γ_{RM}	-0.51	-1.14	-1.14		-0.95	-1.85	-1.83		-0.52	-0.99	-0.98		-0.75	-1.38	-1.37	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.47	1.33	1.32	0.08	1.08	2.99	2.88	0.20	0.55	1.25	1.24	0.09	1.29	2.78	2.70	0.24
γ_{RM}	-0.47	-1.03	-1.02		-0.94	-1.76	-1.73		-0.50	-0.92	-0.92		-0.74	-1.25	-1.23	
γ_{SMB}	0.15	0.79	0.78		0.22	1.15	1.13		0.17	0.85	0.85		0.52	2.35	2.34	
γ_{HML}	0.11	0.39	0.39		-0.18	-0.72	-0.70		0.13	0.41	0.41		-0.09	-0.24	-0.23	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.51	1.26	1.25	0.08	1.17	3.01	2.87	0.21	0.40	0.79	0.79	0.11	1.30	2.80	2.72	0.26
γ_{RM}	-0.50	-1.04	-1.03		-1.03	-1.87	-1.82		-0.35	-0.60	-0.60		-0.75	-1.27	-1.25	
γ_{SMB}	0.14	0.75	0.74		0.19	0.97	0.95		0.17	0.84	0.84		0.52	2.36	2.36	
γ_{HML}	0.08	0.25	0.25		-0.23	-0.87	-0.84		0.25	0.68	0.68		-0.09	-0.25	-0.25	
γ_{Mom}	0.04	0.12	0.12		0.14	0.35	0.34		0.14	0.54	0.54		0.08	0.28	0.28	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.59	1.32	1.30	0.09	1.18	3.08	2.76	0.34	0.68	1.52	1.44	0.19	1.23	2.61	2.52	0.27
γ_{RM}	-0.52	-1.10	-1.09		-1.12	-2.03	-1.89		-0.63	-1.15	-1.11		-0.67	-1.13	-1.10	
γ_{SMB}	0.17	0.88	0.88		0.27	1.41	1.32		0.13	0.64	0.63		0.51	2.26	2.25	
γ_{HML}	0.13	0.45	0.44		-0.32	-1.20	-1.10		0.36	0.99	0.95		-0.11	-0.29	-0.28	
γ_{CMA}	0.03	0.10	0.10		-0.24	-1.26	-1.17		-0.36	-1.09	-1.05		-0.17	-0.56	-0.54	
γ_{RMW}	0.10	0.46	0.45		-0.03	-0.14	-0.13		0.19	0.75	0.73		-0.02	-0.07	-0.07	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	0.62	1.31	1.29	0.09	0.88	1.98	1.66	0.40	0.56	1.10	1.05	0.21	1.23	2.58	2.48	0.27
γ_{RM}	-0.55	-1.10	-1.09		-0.89	-1.54	-1.37		-0.51	-0.86	-0.83		-0.67	-1.11	-1.09	
γ_{SMB}	0.17	0.84	0.83		0.40	1.86	1.64		0.13	0.63	0.62		0.51	2.25	2.24	
γ_{HML}	0.11	0.33	0.32		-0.24	-0.86	-0.74		0.44	1.11	1.06		-0.11	-0.29	-0.28	
γ_{Mom}	0.04	0.12	0.12		0.58	1.32	1.17		0.15	0.56	0.56		0.08	0.26	0.26	
γ_{CMA}	0.02	0.07	0.07		-0.40	-1.77	-1.53		-0.31	-0.90	-0.87		-0.17	-0.52	-0.51	
γ_{RMW}	0.11	0.48	0.47		-0.08	-0.44	-0.38		0.14	0.50	0.48		-0.02	-0.07	-0.07	

Table A 8: Fama-MacBeth Tests on the 25 Size and Book-to-market portfolios in the Asia Pacific region with global and local factors by using GLS method. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns. γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.29	5.22	4.57	0.17	1.37	2.18	2.17	0.01	2.36	4.28	4.14	0.07	1.05	1.82	1.82	0.00
γ_{RM}	-2.34	-3.70	-3.30		-0.41	-0.62	-0.62		-1.57	-2.42	-2.36		-0.01	-0.01	-0.01	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	3.08	4.77	4.20	0.21	1.26	1.85	1.84	0.01	2.68	4.80	4.47	0.26	0.74	1.17	1.15	0.05
γ_{RM}	-2.17	-3.30	-2.95		-0.30	-0.41	-0.41		-1.89	-2.89	-2.74		0.31	0.39	0.38	
γ_{SMB}	0.17	0.78	0.71		-0.03	-0.14	-0.14		-0.04	-0.26	-0.25		0.04	0.16	0.16	
γ_{HML}	0.56	2.56	2.36		0.11	0.48	0.47		0.59	3.21	3.20		0.38	1.80	1.80	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.87	4.42	3.76	0.32	1.11	1.63	1.49	0.11	2.27	3.81	3.48	0.31	0.66	1.04	0.99	0.10
γ_{RM}	-2.00	-3.03	-2.62		-0.23	-0.32	-0.30		-1.46	-2.13	-1.98		0.39	0.49	0.48	
γ_{SMB}	0.16	0.70	0.62		0.08	0.34	0.32		-0.07	-0.39	-0.38		0.03	0.12	0.12	
γ_{HML}	0.58	2.66	2.39		0.12	0.49	0.45		0.60	3.29	3.27		0.38	1.81	1.80	
γ_{Mom}	1.59	3.25	2.85		1.36	2.37	2.21		1.26	2.03	1.88		0.84	1.72	1.66	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.32	3.31	2.48	0.44	0.98	1.24	1.13	0.06	1.91	2.99	2.76	0.34	-0.52	-0.67	-0.56	0.16
γ_{RM}	-0.99	-1.34	-1.03		-0.09	-0.10	-0.09		-1.12	-1.56	-1.46		1.56	1.72	1.49	
γ_{SMB}	0.18	0.82	0.65		0.16	0.61	0.56		-0.02	-0.14	-0.14		0.10	0.45	0.45	
γ_{HML}	0.47	2.10	1.72		0.09	0.39	0.37		0.59	3.22	3.20		0.38	1.78	1.76	
γ_{CMA}	1.34	5.55	4.37		0.32	1.63	1.53		0.92	3.49	3.29		0.67	2.08	1.81	
γ_{RMW}	-0.25	-1.29	-1.01		0.17	0.77	0.71		0.27	1.25	1.21		0.24	0.91	0.83	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.34	3.34	2.53	0.51	1.13	1.42	1.25	0.13	1.56	2.34	2.09	0.38	-0.62	-0.80	-0.63	0.22
γ_{RM}	-1.05	-1.43	-1.11		-0.31	-0.36	-0.32		-0.76	-1.01	-0.93		1.67	1.84	1.54	
γ_{SMB}	0.15	0.69	0.55		0.19	0.72	0.65		-0.05	-0.27	-0.26		0.09	0.42	0.42	
γ_{HML}	0.53	2.35	1.93		0.11	0.45	0.41		0.61	3.30	3.27		0.38	1.79	1.76	
γ_{Mom}	1.29	2.58	2.05		1.49	2.52	2.27		1.22	1.97	1.79		0.98	1.95	1.65	
γ_{CMA}	1.27	5.20	4.13		0.26	1.34	1.22		0.91	3.47	3.21		0.73	2.26	1.91	
γ_{RMW}	-0.21	-1.08	-0.85		0.21	0.92	0.82		0.20	0.92	0.87		0.19	0.75	0.67	

Table A 9: Fama-MacBeth Tests on the 25 Size and Momentum portfolios in the Asia Pacific region with global and local factors by using GLS method. The analysis covers the full period January 1981-December 2015, and sub-period January 2003 to December 2015. The table reports average coefficients for the CAPM, three-factor, four-factor, five-factor, and six-factor models. Results represent monthly percent returns.γ is the average coefficient, fm-t is the t-statistics from the Fama-MacBeth procedure, sh-t is the Shanken (1992) errors-in-variables corrected t-statistic, and R^2 is the average cross-sectional R-Squared of the tested models.

	Global Factors								Local Factors							
	1991-2015				2003-2015				1991-2015				2003-2015			
CAPM	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.14	6.58	6.45	0.05	2.89	8.24	7.78	0.13	2.40	7.13	6.92	0.10	2.83	8.10	7.78	0.11
γ_{RM}	-0.87	-2.12	-2.09		-1.54	-3.19	-3.11		-1.49	-3.08	-3.04		-1.72	-2.93	-2.89	
Three Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.51	6.96	6.46	0.12	3.03	8.35	7.25	0.21	2.34	6.92	6.61	0.14	3.05	8.34	7.58	0.17
γ_{RM}	-1.00	-2.32	-2.20		-1.80	-3.60	-3.34		-1.40	-2.90	-2.83		-1.95	-3.26	-3.14	
γ_{SMB}	-0.16	-0.78	-0.74		0.30	1.35	1.22		-0.06	-0.35	-0.35		0.08	0.34	0.34	
γ_{HML}	-0.62	-2.23	-2.11		-0.59	-2.14	-1.90		-0.69	-2.09	-2.02		-0.61	-1.50	-1.39	
Four Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.10	5.26	4.94	0.19	2.90	7.87	6.88	0.25	2.23	6.47	6.25	0.16	2.90	7.77	7.18	0.23
γ_{RM}	-0.77	-1.76	-1.68		-1.68	-3.33	-3.10		-1.31	-2.68	-2.63		-1.79	-2.98	-2.89	
γ_{SMB}	-0.11	-0.55	-0.52		0.31	1.39	1.26		-0.07	-0.36	-0.36		0.05	0.23	0.23	
γ_{HML}	-0.22	-0.68	-0.65		-0.48	-1.68	-1.50		-0.41	-1.09	-1.06		-0.36	-0.86	-0.81	
γ_{Mom}	1.31	3.46	3.32		1.33	3.67	3.46		0.85	3.19	3.19		0.92	3.09	3.08	
Five Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.26	5.77	4.36	0.36	3.07	7.72	6.65	0.21	2.20	5.94	5.22	0.30	3.06	8.14	7.41	0.18
γ_{RM}	-0.54	-1.22	-0.99		-1.76	-3.39	-3.11		-1.26	-2.50	-2.33		-1.96	-3.24	-3.12	
γ_{SMB}	-0.08	-0.37	-0.30		0.29	1.30	1.17		-0.10	-0.56	-0.55		0.06	0.26	0.26	
γ_{HML}	-0.75	-2.62	-2.08		-0.63	-2.22	-1.96		-0.37	-1.02	-0.92		-0.55	-1.31	-1.22	
γ_{CMA}	0.54	2.34	1.86		0.03	0.14	0.13		1.22	3.89	3.50		0.34	1.09	1.02	
γ_{RMW}	0.06	0.25	0.19		0.15	0.81	0.72		0.31	1.03	0.94		0.33	0.81	0.75	
Six Factor	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2	γ	fm-t	sh-t	R^2
Intercept	2.09	5.07	3.95	0.38	3.13	7.87	6.67	0.29	2.12	5.56	4.91	0.31	2.88	7.46	6.87	0.23
γ_{RM}	-0.45	-1.01	-0.84		-1.80	-3.48	-3.16		-1.19	-2.34	-2.18		-1.79	-2.93	-2.83	
γ_{SMB}	-0.04	-0.20	-0.16		0.23	1.00	0.89		-0.10	-0.53	-0.52		0.06	0.25	0.25	
γ_{HML}	-0.52	-1.57	-1.27		-0.40	-1.31	-1.14		-0.20	-0.50	-0.45		-0.38	-0.88	-0.82	
γ_{Mom}	1.33	3.49	2.94		1.35	3.73	3.46		0.88	3.32	3.30		0.92	3.09	3.08	
γ_{CMA}	0.62	2.62	2.14		0.00	-0.02	-0.02		1.24	3.93	3.56		0.22	0.70	0.66	
γ_{RMW}	0.00	0.01	0.01		0.01	0.05	0.04		0.27	0.88	0.81		0.34	0.82	0.77	

Appendix B

B.1 Gold as a zero-beta asset: U.S. evidence in sub-periods

For robustness, I compare the cross-sectional performance of the CAPM, three-factor, four-factor, five-factor and the six-factor models with their zero-beta gold analogues in sub-periods. I perform the Fama-MacBeth tests in three sub-periods in the U.S. equity market, before the financial crisis (2003 to 2007), during the financial crisis (2007 to 2011), and after the financial crisis (2011 to 2015). These robustness tests are performed to gain further evidence of the role of gold in pricing small stocks. Fama-Macbeth tests are performed on the 25 portfolios sorted on size and book-to-market and the 25 portfolios sorted on size and momentum.

I find that the G-four-factor and G-six-factor models outperform their traditional versions on the size and book-to-market portfolios during financial crisis (2007-2011). They produce insignificant but positive estimates of the market risk premia during the period of the market uncertainty. The G-five-factor model produces the significant estimate of the market risk premium at the 10% significance level in the third sub-period (2011 - 2015).

On the other hand, the G-five-factor and G-six-factor models outperform traditional versions in the first (2003 – 2007) and the second sub-period (2007 – 2011) on the size and momentum portfolios. The second sub-period covers the period of market uncertainty. However, I do not find convincing results in the third sub-period on the size and momentum portfolios with tradition and their zero-beta gold analogue models as all models under investigation produce significant pricing errors. Sub-period tests provide additional supportive evidence that gold zero-beta models outperform traditional models during uncertain market conditions

Table B 1: Fama-MacBeth Tests with the *25 Size and Book-to-market* portfolios in three sub-periods, January 2003 to December 2007, January 2007 to December 2011, and January 2011 to December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, G-CAPM, three-factor, G-three-factor, four-factor, G-four-factor, five-factor, G-five-factor, six-factor, and G-six-factor models. γ is the average coefficient, t-stat is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional adjusted R-Squared of tested models.

	Retun on T-Bills R_f			Gold as zero beta asse			Retun on T-Bills R_f			Gold as a zero beta asse			Retun on T-Bills R_f			Gold as a zero beta asset		
	2003-20007			2003-2007			2007-2011			2007-2011			2011-2015			2011-2015		
	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2
CAPM																		
Intercept	0.57	1.12	0.25	-1.16	-0.51	0.23	1.31	1.52	0.20	0.50	0.32	0.21	1.26	1.94	0.21	1.91	1.25	0.24
γ_{RM}	0.44	0.75		1.06	0.44		-0.99	-0.89		-1.57	-0.84		-0.31	-0.38		-0.52	-0.29	
Three Factor																		
Intercept	0.69	1.77	0.48	-0.07	-0.06	0.48	1.50	2.31	0.49	1.62	0.96	0.48	0.67	1.34	0.52	-0.19	-0.13	0.52
γ_{RM}	0.26	0.51		-0.19	-0.14		-1.31	-1.38		-2.82	-1.41		0.38	0.57		1.73	1.04	
γ_{SMB}	0.25	0.83		0.25	0.86		0.08	0.24		0.10	0.29		-0.22	-0.77		-0.22	-0.77	
γ_{HML}	0.23	1.06		0.24	1.11		-0.54	-1.30		-0.48	-1.12		-0.20	-0.89		-0.22	-0.93	
Four Factor																		
Intercept	0.49	1.29	0.53	0.12	0.09	0.53	0.25	0.28	0.57	-2.60	-1.44	0.55	0.49	0.98	0.57	-0.78	-0.57	0.56
γ_{RM}	0.46	0.90		-0.37	-0.27		-0.05	-0.04		1.45	0.68		0.54	0.80		2.31	1.47	
γ_{SMB}	0.30	1.00		0.28	0.98		0.09	0.26		0.08	0.23		-0.18	-0.64		-0.19	-0.66	
γ_{HML}	0.24	1.09		0.23	1.10		-0.49	-1.18		-0.53	-1.25		-0.17	-0.74		-0.20	-0.86	
γ_{Mom}	1.10	1.40		0.95	1.20		3.22	2.16		3.36	2.46		1.31	1.92		1.17	1.82	
Five Factor																		
Intercept	0.20	0.48	0.58	-0.59	-0.52	0.57	1.15	1.70	0.60	-0.93	-0.93	0.59	0.55	1.01	0.62	-0.87	-0.68	0.61
γ_{RM}	0.74	1.34		0.34	0.26		-0.98	-1.00		-0.26	-0.26		0.50	0.69		2.42	1.62	
γ_{SMB}	0.35	1.18		0.30	1.05		0.15	0.46		0.15	0.15		-0.20	-0.73		-0.20	-0.71	
γ_{HML}	0.24	1.10		0.23	1.09		-0.52	-1.26		-0.53	-0.53		-0.22	-0.99		-0.27	-1.17	
γ_{CMA}	-0.05	-0.17		-0.08	-0.28		-0.13	-0.35		-0.11	-0.11		-0.11	-0.47		-0.20	-0.85	
γ_{RMW}	0.50	1.16		0.30	0.79		0.75	2.01		0.75	0.75		0.15	0.58		0.21	0.89	
Six Factor																		
Intercept	0.20	0.44	0.61	0.00	0.00	0.61	0.58	0.70	0.62	-2.15	-1.40	0.62	0.84	1.63	0.65	-0.39	-0.31	0.61
γ_{RM}	0.74	1.29		-0.26	-0.18		-0.39	-0.36		0.99	0.53		0.19	0.27		1.92	1.30	
γ_{SMB}	0.35	1.18		0.29	1.00		0.12	0.35		0.11	0.33		-0.16	-0.59		-0.17	-0.61	
γ_{HML}	0.24	1.10		0.23	1.11		-0.50	-1.20		-0.53	-1.25		-0.20	-0.90		-0.23	-1.01	
γ_{Mom}	0.22	0.21		1.03	1.02		2.29	1.49		2.51	1.59		1.54	2.42		1.54	2.51	
γ_{CMA}	-0.05	-0.17		-0.07	-0.26		-0.04	-0.12		-0.02	-0.07		-0.27	-1.19		-0.36	-1.55	
γ_{RMW}	0.50	1.05		0.05	0.12		0.41	0.99		0.38	0.89		0.10	0.40		0.12	0.52	

Table B 2: Fama-MacBeth Tests with the *25 Size and Momentum* portfolios in three sub-periods, January 2003 to December 2007, January 2007 to December 2011, and January 2011 to December 2015. Results represent monthly percent returns. The table reports average coefficients for the CAPM, G-CAPM, three-factor, G-three-factor, four-factor, G-four-factor, five-factor, G-five-factor, six-factor, and G-six-factor models. γ is the average coefficient, t-stat is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional adjusted R-Squared of tested models.

	Retun on T-Bills R_f			Gold as zero beta asset			Retun on T-Bills R_f			Gold as zero beta asset			Retun on T-Bills R_f			Gold as a zero beta asset		
	2003-20007			2003-2007			2007-2011			2007-2011			2011-2015			2011-2015		
	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2	γ	t-stat	R^2
CAPM																		
Intercept	0.73	2.08	0.21	0.05	0.03	0.21	0.23	0.19	0.29	-1.48	-0.63	0.27	2.95	3.75	0.20	3.54	1.43	0.18
γ_{RM}	0.31	0.65		-0.13	-0.07		0.09	0.07		0.39	0.16		-1.72	-2.06		-2.14	-0.79	
Three Factor																		
Intercept	0.93	1.98	0.55	0.18	0.10	0.41	1.06	1.41	0.62	1.75	0.83	0.61	2.43	3.79	0.58	1.62	1.23	0.56
γ_{RM}	0.02	0.03		-0.46	-0.24		-0.85	-0.83		-2.91	-1.24		-1.29	-1.71		-0.07	-0.04	
γ_{SMB}	0.36	1.15		0.33	1.13		0.30	0.86		0.25	0.74		-0.14	-0.50		-0.11	-0.38	
γ_{HML}	-0.32	-0.40		-0.11	-0.20		0.52	0.63		0.56	0.69		-0.63	-1.57		-0.88	-1.94	
Four Factor																		
Intercept	0.93	3.24	0.60	-0.52	-0.36	0.59	2.26	3.16	0.67	3.64	1.94	0.65	1.84	2.62	0.62	2.88	2.74	0.60
γ_{RM}	0.02	0.05		0.25	0.16		-2.04	-2.09		-4.81	-2.24		-0.68	-0.84		-1.28	-0.99	
γ_{SMB}	0.35	1.16		0.33	1.12		0.22	0.64		0.18	0.52		-0.21	-0.76		-0.21	-0.74	
γ_{HML}	-0.31	-0.67		-0.11	-0.19		-1.18	-1.65		-0.69	-0.90		-0.15	-0.45		0.00	0.01	
γ_{Mom}	0.19	0.47		0.20	0.50		-0.39	-0.48		-0.39	-0.47		0.73	1.76		0.72	1.79	
Five Factor																		
Intercept	0.81	2.40	0.63	-1.03	-0.77	0.61	0.08	0.09	0.69	-3.62	-1.84	0.68	1.93	3.11	0.64	3.48	3.21	0.63
γ_{RM}	0.15	0.30		0.77	0.52		0.08	0.07		2.41	1.09		-0.80	-1.08		-1.89	-1.43	
γ_{SMB}	0.37	1.19		0.38	1.29		0.40	1.14		0.44	1.26		-0.08	-0.27		-0.06	-0.22	
γ_{HML}	-0.36	-0.59		-0.47	-0.83		0.90	1.03		0.80	0.96		-0.69	-1.87		-0.70	-1.80	
γ_{CMA}	0.01	0.03		-0.04	-0.12		0.48	1.14		0.44	1.12		-0.09	-0.39		-0.03	-0.11	
γ_{RMW}	-0.05	-0.12		-0.02	-0.06		0.70	2.07		0.71	2.13		0.77	2.14		0.81	2.31	
Six Factor																		
Intercept	0.87	2.89	0.67	-0.92	-0.63	0.66	1.06	1.49	0.73	-2.02	-1.43	0.73	1.17	1.68	0.67	3.01	2.85	0.66
γ_{RM}	0.09	0.21		0.66	0.42		-0.87	-0.88		0.83	0.47		-0.05	-0.06		-1.42	-1.09	
γ_{SMB}	0.39	1.27		0.39	1.33		0.32	0.91		0.35	1.03		-0.15	-0.55		-0.13	-0.47	
γ_{HML}	-0.47	-1.02		-0.50	-1.01		-0.36	-0.56		-0.31	-0.40		-0.05	-0.16		-0.27	-0.76	
γ_{Mom}	0.18	0.44		0.18	0.45		-0.22	-0.27		-0.18	-0.21		0.68	1.64		0.65	1.64	
γ_{CMA}	-0.07	-0.21		-0.07	-0.21		0.23	0.64		0.31	0.81		-0.05	-0.22		-0.12	-0.45	
γ_{RMW}	0.01	0.03		0.00	0.00		0.71	2.09		0.75	2.28		0.73	2.04		0.63	1.92	

Appendix C

C.1 Excluding period of financial crisis

Table C 1: Fama-MacBeth Tests of the two-factor model for the global U.S. industries. The full sample represents the 40 world industries and the 48 U.S. industries. These industries are divided into four groups. Results represent monthly percent returns. Results are shown for the sub-period (2002 - 2006). The table reports average coefficients for the two-factor model. γ is the average coefficient, t-fm is the t-statistic from the Fama-MacBeth procedure, and R^2 is the average cross-sectional adjusted R-Squared.

Global Market				**US Market**			
	2002-2006				2002-2006		
Full Sample	γ	t-fm	R^2	Full Sample	γ	t-fm	R^2
Intercept	0.64	1.86	0.46	Intercept	0.71	2.02	0.56
γ_{RM}	-0.64	-0.91		γ_{RM}	0.15	0.26	
γ_{GOLD}	**2.60**	**1.70**		γ_{GOLD}	**1.39**	**1.79**	
Group I	γ	t-fm	R^2	Group I	γ	t-fm	R^2
Intercept	0.56	1.71	0.68	Intercept	-0.07	-0.16	0.65
γ_{RM}	-0.72	-1.04		γ_{RM}	1.23	1.72	
γ_{GOLD}	**2.70**	**1.60**		γ_{GOLD}	2.28	0.97	
Group II	γ	t-fm	R^2	Group II	γ	t-fm	R^2
Intercept	0.01	0.01	0.47	Intercept	0.75	1.23	0.80
γ_{RM}	-0.02	-0.02		γ_{RM}	-0.11	-0.14	
γ_{GOLD}	3.13	1.39		γ_{GOLD}	**2.97**	**1.87**	
Group III	γ	t-fm	R^2	Group III	γ	t-fm	R^2
Intercept	0.83	1.51	0.44	Intercept	0.89	1.71	0.71
γ_{RM}	-0.71	-0.82		γ_{RM}	-0.07	-0.11	
γ_{GOLD}	1.78	1.06		γ_{GOLD}	**1.30**	**1.61**	
Group IV	γ	t-fm	R^2	Group IV	γ	t-fm	R^2
Intercept	0.73	1.65	0.34	Intercept	1.11	2.24	0.31
γ_{RM}	-0.83	-1.07		γ_{RM}	-0.16	-0.25	
γ_{GOLD}	0.91	0.42		γ_{GOLD}	1.60	1.41	

Results in Tables (70) – (73) show that the gold produces positive returns during the second sub-period (2002-2008). However, one can argue that this sub-period covers the years of financial crisis (2008-09) and these positive returns could be influenced from the period of the financial crisis. In order to address this concern, I separate-out the period of the financial crisis and re-run the Fama-MacBeth tests from 2002- 2006. Results are reported in Table (C 1).

Findings from the sub-period (2002-2006) shows that gold still produces positive returns during this sub-period even and these positive returns increase during the period of the financial crisis (2007-08).

Appendix D

D.1 Role of Gold in the multifactor APT model

For robustness, I also assess the role of gold in the extended version of Ross (1976) and Roll (1077) APT model. I take guidance from Chen, Roll and Ross (1986), Burmeister and McElroy (1988) and Cochrane (2005, Chapter 12) in using APT model. I use gold, oil prices, money supply, exchange rate, term structure, default risk and inflation indices in the APT model. Burmeister and McElroy (1988) utilise term structure, default risk and inflation indices in their model, whereas other four variables include gold (Faff and Chan, 1998), oil prices (Park and Ratti, 2008), exchange rate (Richards, Simpson, and Evans, 2009) and money supply (Urich and Wachtel, 1981; Humpe and Macmillan, 2009; Bjørnland and Leitemo, 2009) in the APT models that have been used in the past studies. The testable APT equation with a seven-factor model is given as:

$$\overline{R_\iota} = I_0 + I_1 b_{i1} + I_2 b_{i2} + I_3 b_{i3} + I_4 b_{i4} + I_5 b_{i5} + I_6 b_{i6} + I_7 b_{i7} + e_i \qquad (1)$$

I_1= Term Structure

I_2= Default Risk

I_3= Unexpected change in Inflation

I_4= Unexpected change in gold price

I_5= Unexpected change in oil price

I_6= Unexpected change in money supply

I_7= Unexpected change in exchange rate

Firstly, I discuss the correlations of macroeconomic variables (exchange rate, money supply and inflation), commodities (gold and oil prices) and state variables (term structure and default risk). Correlation matrix in Table (D 1) shows a weak correlation of these variables with the market returns of S&P 500. Oil prices show stronger correlation (0.44) with inflation (CPI) whereas gold prices do not exhibit correlation with inflation, instead show a weak correlation with the exchange rate (0.16) and money supply (0.15). Descriptive analysis are show in Table (D 2).

Table D 1: Correlation matrix of macroeconomic factors, gold, oil and value-weighted market return of S&P 500, January 1981 to December 2015

	S&P500	*Exchange Rate*	*Money Supply*	*CPI*	*Gold*	*Oil*	*Default Spread*	*Term*
S&P 500	1							
Exchange Rate	0.03	1.00						
Money Supply	-0.07	0.02	1.00					
CPI	0.00	0.07	-0.12	1.00				
Gold	0.02	0.16	0.15	0.03	1.00			
Oil Price	-0.05	0.00	-0.17	0.44	0.04	1.00		
Default spread	-0.23	0.17	0.02	-0.15	-0.04	-0.05	1.00	
TERM	0.07	-0.19	-0.20	0.24	-0.09	0.15	-0.53	1.00

Table D 2: Descriptive analysis of macroeconomic factors and commodity prices (exchange rate, money supply, inflation (CPI), gold, oil price) ,value-weighted market return (S&P 500), and state variables (term structure and default spread), January 1981 to December 2015

	Mean	Std	Kurtosis	Skewness	T-Mean
S&P 500	0.28	1.58	5.45	-1.19	3.67
Exchange Rate	0.14	2.05	10.05	1.46	1.40
Money Supply	0.21	0.36	9.56	1.54	11.94
CPI	0.10	0.12	9.05	-0.91	18.00
Gold	0.14	4.83	1.89	-0.14	0.59
Oil Price	0.00	3.93	21.24	1.80	0.02
Default spread	0.03	3.22	4.31	0.52	0.22
TERM	-0.17	2.41	5.67	-0.66	-1.44

D.2 Time series results

In time series analysis, I use the macroeconomic factor loadings and prominent state variables such as term structure and default yield and examine the applicability of the APT model. I follow Lütkepohl (2004) in model selection and testing. Firstly, I examine the long-term association between market returns and factor loadings to assess whether I can implement the Vector Error Correction model (VECM) or unrestricted Vector Autoregressive (VAR) Model with Johnson test of co-integration. In this test, I find the long-term association of macroeconomic factors with market returns and hence, I implement the VECM model and use four lags in the model specification to assess the short run causality between macroeconomic fundamentals and market prices. Four lags are used according to the lag selection criteria in pre-estimation that enable me to deeply examine the influence of factor loadings on market returns.

In the VECM model, I employ gold, oil prices, money supply, exchange rate, term, default rate and inflation as independent variables and S&P 500 return as the dependent variable. Results in Table (D 3) show that I do not find the long run causality between macroeconomic variables and market returns but I do find short run causality that runs from macroeconomic variables to market returns. Particularly, strong short run causality is found between gold, oil and market prices at the 5% significance level. Results show that gold prices exhibit short run causality at the first lag whereas oil prices exhibit this short run causality at the third lag. It shows that oil prices also influence stock returns but the influence of gold prices on stock returns is relatively stronger than oil prices and other macroeconomic fundamentals. The evidence of short-run causality is also seen in Inflation (CPI), Money supply, and default rates at the 10% significance level.

Table D 3: Vector Error Correction Model that includes gold, oil price, default yield, term structure, inflation, exchange rate, money supply and S&P 500 return in the model. The model does not show long term association between factor loadings and market returns. The evidence of short run causality is found between gold, oil prices, default yield and market returns.

Coefficient of Co-integrating Equataion			0.00257
t-stat			-0.45
Constant			6.621
t-stat			-1.84
d(Lag1)S&P 500	0.21***	d(Lag1)Term	-5.19
	-3.69		(-0.66)
d(Lag2)S&P 500	-0.05	d(Lag2)Term	-2.17
	(-0.90)		(-0.27)
d(Lag 3)S&P 500	0.04	d(Lag 3)Term	-9.25
	-0.73		(-1.21)
d(Lag1)Gold	-0.0953*	d(Lag1)CPI	-6.78
	(-2.08)		(-1.87)
d(Lag2)Gold	-0.002	d(Lag2)CPI	-2.04
	(-0.03)		(-0.46)
d(Lag 3)Gold	-0.011	d(Lag 3)CPI	1.235
	(-0.23)		-0.28
d(Lag1)Oil Price	1.17	d(Lag1)Exchange Rate	0.002
	-1.85		-1.49
d(Lag2)Oil Price	0.44	d(Lag2)Exchange Rate	-0.00158
	-0.71		(-1.14)
d(Lag 3)Oil Price	-1.944***	d(Lag 3)Exchange Rate	0.001
	(-3.61)		-0.62
d(Lag1)Default Rate	2.30	d(Lag1)Money Supply	-0.07
	-0.16		(-0.48)
d(Lag2)Default Rate	-5.57	d(Lag2)Money Supply	0.272
	(-0.37)		-1.96
d(Lag 3)Default Rate	-23.05	d(Lag 3)Money Supply	-0.218
	(-1.68)		(-1.56)

Note: t statistics in parentheses,* $p<0.05$,** $p<0.01$, *** $p<0.001$

I also perform a diagnostic test to verify that there is no serial autocorrelation in the model. I perform the Lagrange-multiplier test (Engle, 1984; Bera & Bilias, 2001). The null hypothesis of the non-existence of autocorrelation is not rejected at the 5% level but is rejected at the 10% that shows a weak evidence in favour of the model.

Table D 4: Lagrange-multiplier Diagnostic Test of VECM model shown in Table (87)

Lag	χ^2	P-Value
1	79.53	0.09

D.3 Cross-section test

I further test this model by using first stage GMM test and find significant pricing errors in the model. However, I find a significant gold price factor in cross-section that confirms the extra market sensitivity of gold on market returns. In addition to gold, the term-structure is significant at the 10% significance level.

Table D 5: Cross-sectional estimates from the APT Model by using first-stage GMM regressions

	$Constant$	λ_M	λ_{Gold}	λ_{Oil}	λ_{def}	λ_{term}	λ_{cpi}	λ_{MS}	λ_{FX}	R^2
1981-2015	1.82	-1.15	-3.54	0.08	-1.03	1.49	-0.06	-0.13	0.89	0.54
	2.89	-1.85	-1.97	0.07	-1.05	1.54	-1.20	-0.68	1.07	
1981- 1995	0.70	0.09	-6.38	0.79	1.13	-0.83	0.09	-0.07	-0.14	0.69
	0.71	0.09	-2.71	0.51	0.67	-1.00	1.50	-0.47	-0.11	
1995-2015	1.36	-0.63	-3.40	0.13	-0.35	2.32	-0.08	-0.21	0.10	0.83
	2.00	-0.84	-1.32	0.12	-0.49	1.33	-1.60	-0.66	0.13	
1995-2002	1.83	-1.37	-1.15	0.61	-0.64	0.78	-0.02	0.01	-0.27	0.83
	2.51	-1.56	-1.07	0.72	-1.03	1.05	-1.00	0.14	-0.34	
2003-2008	1.30	-1.13	0.60	-1.06	-0.52	-0.55	-0.02	0.31	-0.07	0.64
	2.20	-1.71	0.40	-0.71	-0.83	-0.60	-0.40	2.82	-0.25	
2009 - 2015	2.15	-0.84	-1.58	-0.58	-0.43	-0.03	0.01	0.11	-0.71	0.60
	2.76	-0.99	-0.84	-0.46	-0.80	-0.04	0.25	0.61	-2.22	