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Research article

Impact of political conflict on foreign direct investments in the mining sector: Evidence from the event study and spatial estimation

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A B S T R A C T

This study aims to investigate the impact of conflict on greenfield foreign direct investment (FDI) in the mining sector covering the period of the 1st quarter of 2003 until the 3rd quarter of 2017, across 151 countries. Unlike previous works, this paper focuses on testing two impacts. First, we test for a dynamic impact to uncover the effect of conflict on FDI over the contemporary and subsequent annual quarters. Second, we test for a spatial spillover impact. To achieve these goals, we apply both a panel spatial approach and an event study analysis, using a unique proprietary database *FDIMarkets*. The main findings are as follows. First, the presence of a dynamic impact depends on the intensity of the conflict for the particular country group, with higher levels of intensity being associated with a higher probability of the presence of a dynamic effect. Second, we find a significant negative spillover impact of *greenfield mining FDI* of neighbouring countries on the *greenfield mining FDI* of the FDI-receiving economy. We do not find, however, that *conflict* in neighbouring countries has a spatial spillover impact on *greenfield mining FDI* of the FDI-receiving economy.

Research ethics

We further confirm that any aspect of the work covered in this manuscript that has involved human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript.

1. Introduction

Conflict is one important cause of political instability and a consequence of poor institutional quality and governance. Wars destroy physical capital, human capital, and social capital. All three have a significant impact on economies in the long run. Physical infrastructure is crucial for economic development but, bridges and roads, and other physical infrastructure can be rebuilt quickly. It takes much longer to rebuild social and human capital. From an economic theory perspective, there is no consensus about the impact of conflict on economic performance. Neoclassical growth theory predicts that an economy recovers relatively quickly and converges to its steady state. Alternative models argue that catching up may take a long time, for instance, because human capital recovers only slowly (see Barro and Sala-i-Martin (2004)), or that countries can be trapped in a low-level equilibrium where conflict and poor performance coexist (Sachs, 2005).

This paper builds its framework on political risk theories, which focus on the impact of political instability and its associated risks on investment decisions. The seminal work of Kobrin (1979) reviews and formulates the potential channels of political risk impact on investments. It demonstrates that alterations in the political landscape have the potential to impact returns both directly, by causing harm to infrastructure and economic decline due to conflicts, and indirectly, by way of shifting of government policies, such as expropriation of property, local content regulations, and limitations on dividend repatriation.

Fatehi-Sedeh and Safizadeh (1989) also argue that political risk acts as a deterrent in the process of making foreign investment decisions, whereas the return on investment serves as the motivating factor. Therefore, when political risk rises, investors may not reduce or withdraw their funds due to the anticipated return on investment. Our paper contributes by evidencing the inconsistencies of the conflict impacts among different geographies and scales of conflict.

We have chosen the mining sector specifically as it often plays a pivotal role in a country's economy. It contributes significantly to GDP, exports, and government revenue in many resource-rich nations. The

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economic importance of mining makes it a critical sector for understanding the dynamics of FDI and conflict. (Measham et al., 2013). Moreover, mining sectors are often associated with valuable natural resources like minerals, metals, and fossil fuels. These resources are finite and can be a source of massive wealth. Consequently, they are prone to disputes over control, ownership, and distribution of benefits, which can be affected by conflicts (Blair et al., 2022).

Previous studies on the conflict-FDI relationship are relatively limited and the findings are inclusive. Some reports found that some firms make a profit from investments in conflict zones. For instance, the human rights organization Corporate Watch (2006) reports that notwithstanding the enormous risks of investing in a conflict area, some well-known UK firms have made significant profits from investing in Iraq (Chen, 2017) while Guidolin and La Ferrara (2007) showed that some firms in the diamond industry profited from armed conflicts in Angola. Furthermore, data from the Financial Times shows that the largest greenfield investment in the mining sector in Iraq during the period 2003–2016 was from Lebanon for the interest of Make oil company with an investment of 3 billion US dollars directed to the Petroleum refineries sub-sector in Dahuk. Moreover, around 45 percent of investments in greenfield FDI have taken place in the first 5 years of the war that surged in 2003.

However, there is another strand of literature, which claims that multinational firms decrease their investments in conflict areas. For example, Oh and Oetzel (2011) show that MNCs are likely to reduce the number of subsidiaries in response to terrorist attacks in the host country, increasing political and economic instability. Li and Resnick (2003) suggested that there be could ethical and institutional factors that deter the MNCs from investing in conflict areas. Some MNCs require to have approval from their home government.

The real world provides us with some examples of how conflict could impact greenfield FDI investments in the mining sector. For example, the copper mines in Afghanistan have attracted Chinese smelting companies., JCCL is a giant Chinese smelter company that prefers to own copper fields instead of buying them from other producers in order to diminish its exposure to upstream raw material risk. (Downs, 2012). The Chinese companies were not the only ones interested investors in copper mining in Afghanistan. Companies from the USA, Kazakhstan, Canada, and Cyprus were interested in investing in the Aynak Copper Minefield in Afghanistan. Jiangxi Copper Co Ltd and Metallurgical Corp of China (MCC) took on a 30-year lease for the Aynak Copper Mine in 2008, which has an approximate reserve of 11.08 million tonnes of copper. However, due to the unstable situation in Afghanistan, the Mes Aynak copper mine invested by the company has not yet undergone substantial construction (Min and Shivani, 2021).

The conflict in Iraq is another example of how conflict can attract FDI in the mining sector. The USA, United Kingdom, France, Iran, Lebanon, Turkey, United Arab Emirates, and other countries have started investing in exploiting Coal, Oil and Natural Gas in addition to Metals in Iraq during the conflict time. Data from the Financial Times shows that the largest greenfield investments in the mining sector in Iraq during the period 2003–2016 were from Lebanon for the interest of Make oil company with an investment of 3 billion US dollars and directed to the Petroleum refineries sub-sector in Dahuk. Moreover, around 45 percent of investments in greenfield FDI took place in the first 5 years of the war which surged in 2003.

The purpose of this study is to investigate the impact of conflict on greenfield FDI. We attempt to identify the existence of an impact, its direction, and its magnitude. Furthermore, to test whether the impact and direction differ among diverse areas around the world. Unlike other works, for example (Liu and Zou, 2008; Doytch et al., 2015) this paper focuses on testing two new impacts: a dynamic impact, which investigates the impact of conflict on FDI over the contemporary and following periods, and a spatial impact. The spatial impact develops in three directions: an expected spillover impact of the outcome (FDI) variable on its neighbouring countries' outcomes; a spillover impact of the conflict variable, and a spillover impact of any unobserved variables.

The data on conflict employed was obtained from the One-sided Violence dataset of Uppsala Conflict Data Program (Eck and Hultman, 2007; Pettersson et al., 2019). The unique greenfield FDI data, *FDI-Markets*, was obtained from *the Financial Times* and tracks FDI inflow in the mining sector from 2003 to 2017. Both conflict and greenfield FDI data were aggregated on a quarterly basis. To fulfill the study's goals and avoid the problem of endogeneity, we use a three-fold methodology. The first part is designed to obtain a valid instrument for the conflict variable; the second part uses this instrument to test for a dynamic impact of conflict on FDI in the mining sector; and the last part addresses the spatial models that test the spillover impact.

The key contributions of this paper are multi-fold. First, to the best of our knowledge, this study is amongst the pioneering empirical works that test the conflict-FDI nexus. Most of the previous studies focused on terrorism and foreign firms. Second, the majority of empirical studies on conflict and FDI have tested the impact using aggregated data. We, on the other hand, employ a unique proprietary disaggregated data set from *FDIMarkets*. The data is aggregated from individual FDI investment deals in the mining sector exclusively and is aggregated on a quarterly basis. Third, we make a methodological contribution as well in terms of the event study approach used to determine the dynamic impact of conflict on greenfield FDI and uses a spatial econometric approach to infer the spillover impact.

Regarding the dynamic effect, we find that the presence of a dynamic impact depends on the intensity of the conflict for the particular country group, with higher levels of intensity being associated with a higher probability of a presence of a dynamic effect. Second, we find a significant negative spillover impact of *greenfield mining FDI* of neighbouring countries on the *greenfield mining FDI* of the FDI-receiving economy. We do not find, however, that *conflict* in neighbouring countries has a spatial spillover impact on *greenfield mining FDI* of the FDI-receiving economy.

The rest of the paper is structured as follows. Section 2 reviews the literature that discusses possible links between conflict and FDI; Section 3 discusses the methodology, data collection, and models. Section 4 presents the key results followed by conclusions and suggested policy implications.

2. Literature review

The capital stock is an accumulation of investments, and therefore, when a state comes to be involved in an armed conflict, the capital stock tends to decrease (Zafeer, 2015). In other words, a conflict discourages investments, both foreign a domestic. This discouragement could have two mechanisms. First, the destructive nature of conflict diminishes the capital stock since armed forces and rebels target infrastructure that is either damaged or demolished. Second, an armed conflict increases the depreciation rate of physical capital, encourages capital flight, deters new investment opportunities, and accelerates loss for businesses.

The difference between conflict in general and terrorism, in particular, is narrow. The critical difference between the two is in their legal interpretations. Overall, an armed conflict is a situation in which specific acts of violence are considered legal and others are illegal, while any act of violence termed as "terrorist" is always unlawful. The fundamental target of an armed conflict is to prevail over the enemy's armed forces.[1]

[1] For example, when the US declared war against the Taliban in Afghanistan, the US forces aimed to damage the power of the Taliban. At the same time, Euskadi Ta Askatasuna (ETA) was an armed Basque nationalist and separatist terrorist organization engaged in a violent campaign of bombing, assassinations, and kidnappings in the Southern Basque Country and throughout the Spanish territory. Its goal was gaining independence for the Basque Country. Between 1968 and 2010, it killed 829 people (including 340 civilians) and injured thousands more, the actions of ETA were considered terrorist events. (CICR, 2015).

Terrorist acts do not necessarily have such a goal.

Different studies have attempted to investigate the impact of terrorism on FDI, yet this relationship is ambiguous. Various strands of research find a negative impact of terrorism on FDI (Enders and Sandler, 1996; Abadie and Gardeazabal, 2003; Tarzi, 2005; Büsse Hefeker, 2007; Abadie and Gardeazabal, 2008; Jensen, 2008; Busse and Hefeker, 2007; Desbordes, 2010; Agrawal, 2011). Others find an insignificant relationship (Enders, et al., 2006; Li, 2006; Powers and Choi, 2012; Ouyang & Rajan, 2017). Very few studies find a positive impact of terrorism on FDI (Lutz and Lutz, 2017).

For example, Enders and Sandler (1996) investigate the impact of terrorism on FDI in specific countries in the period from 1975 to 1991. The results show that, on average, terrorism reduces the net inflow of FDI to Spain by 13.5% and to Greece-by 11.9%. Conversely, Abadie and Gardeazabal (2008) find only an indirect impact. The authors argue that terrorism has caused a detrimental investment reputation for Spain. Abadie and Gardeazabal (2008) inferred the impact of terrorism on investment using the synthetic control method, which measures the opportunity cost of a counterfactual scenario which could be the non-occurrence of the terrorist attacks.

Further, Agrawal's (2011) results support a negative relationship. The author measures the economic significance of an armed conflict and points out that one standard deviation change in terrorist risk changes net FDI by 5% in the opposite direction. Bezić et al. (2016) also report that in developed countries transnational terrorism affects the total inflow of FDI negatively, and Abadie & Gardeazabal (2003) and Alomar and El-Sakka (2011) find the same result for developing countries. This negative impact is supported also by Schöllhammer and Nigh (1984). Schöllhammer and Nigh (1984) find that the German FDI outflows to less developed countries are affected negatively by internal conflict in the host states. In addition, Nigh (1985) argues that both inter and intrastate conflicts affect the outflows of U.S. manufacturing FDI to developing countries. In contrast, only inter-state conflicts matter for U. S. manufacturing FDI outflows to developed countries. Further, Biglaiser and Staats (2010) include conflict as one of the determinants of FDI in developing countries during the period 1976–2004, and the authors find a negative impact of the lagged level of conflict on FDI. Similarly, Enders et al. (2006) also point out the negative impact of terrorist attacks against the US interests on US FDI outflows to OECD countries, where this impact becomes insignificant for non-OECD countries.

However, some studies reveal mixed or ambiguous results. For example, Powers and Choi (2012) find that terrorism, which targets multinational corporations, harms FDI, while the impact becomes insignificant if terrorists attack non-business targets. Ouyang and Ramkishen (2017) claim that terrorist events do not alter domestic mergers and acquisitions (M&A) investments. However, the frequency and intensity of terrorist events significantly affect foreign M&As. Finally, Efobi et al., 2018 identify an insignificant impact of terrorism on FDI except in highly developed countries. And Khayat (2016), who tests several components of conflict risk, finds that the impact of internal and external conflict on FDI is insignificant.

Mihalache (2011) reveals that FDI can act as a moderator of conflict risk if certain conditions are met. Specifically, the author finds that FDI in sectors with low capital intensity, such as agriculture, footloose manufacturing industries, and finance sectors is not affected by conflict, while FDI in sectors that rely heavily on physical assets, such as mining and manufacturing, and some tertiary industries, declines considerably during the conflict. Depetris and Rohner (2009) also support the above by finding pointing out that the impact of conflict on FDI diminishes with the share of the manufacturing sector in GDP it increases with the share of the primary sector in GDP.

3. Empirical model and data

In this study, we apply a Spatial Durbin Model (SDM) to test the existence of the spatial effect of conflict on FDI:

$$Y_{it} = \rho W Y_{it} + \propto \iota_N + X_{it}\beta + W X_{it}\theta + W Z_{it}\tau + \mathcal{E}_{it} \tag{1}$$

where.

- Y_{it} is $(N \times \mathbf{1})$ vector containing *greenfield FDI deals in the mining sector*, aggregated quarterly. Since N = 196 countries, ι_N is an $N\times1$ vector of those associated with the constant term parameter $\propto$. The *greenfield FDI deals* entail the establishment of new production facilities, such as offices, buildings, plants, and factories, as well as intangible capital (Liu and Zou, 2008). The greenfield FDI data encompasses the 1st quarter of 2003 until the 3rd quarter of 2017, across 151 host economies. The data is sourced from *FDIMarkets* (Financial Times) and is transformed into (1 + ln (FDI)) form, following Feenstra and Sasahara (2018) to cope with the zero values of the panel data structure.
- X_{it} is $(N \times K)$ matrix (K = 4) of other determinants of mining FDI, including natural resource rents share of % of GDP (Doytch and Eren, 2012); inflation rate (Alam, Shah, 2013), official exchange rate (Doytch et al., 2015), and control of corruption (Brada et al., 2019; Doytch and Ashraf, 2023). *Natural resources rents (% of GDP)* include the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents. Estimates of natural resources rents are calculated as the difference between the price of a commodity and the average cost of producing it. Data on natural resources rents are retrieved from the World Bank data. *Control of corruption* is an index of corruption ranging from −2.5 (weak) to 2.5 (strong) control of corruption (Kraay, et al., 2010). It is sourced from Worldwide Government indicators. The *rate of inflation* is the annual growth rate of the GDP implicit deflator, defined as the ratio of GDP in current local currency to GDP in constant local currency (Banerji and Sugata, 1992; Sayek, 2009). The data is sourced from the World Bank. The official *exchange rate* refers to the exchange rate determined by national authorities or to the rate determined in the legally sanctioned exchange markets. It is calculated as an annual average based on monthly averages (local currency units relative to the U.S. dollar) (Froot and Stein, 1991; Grubert and Mutti, 1991; Swenson, 1994)., The explanatory variables are associated with a set of parameters β which are represented in a $K\times1$ vector.
- Z_{it} is a binary variable corresponding to the number of conflict fatalities occurring at time t in country i, aggregated quarterly. WZ_{it} is the spatial matrix, associated with the *conflict* variable, Z_{it}. *Conflict* is a binary variable, with $Z_{it} = 1$ if the number of fatalities satisfies two conditions, $Z_{it} = 0$ otherwise. The *first condition* concerns the number of fatalities per year (m). According to our methodology, m has three different specifications: $m \geq 25$ in model 1; $m \geq 100$ in model 2; and $m \geq 200$ in model 3. The second condition concerns the quarter *q*. The examined quarter *q* has witnessed at least one fatality. The data is obtained from the *One-sided violence*[2] dataset of the *Uppsala Conflict Data Program (UCDP)* (Eck and Hultman, 2007; Pettersson et al., 2019). The *Uppsala Conflict Dataset* has three different estimations for one-sided violence, and this study uses the "best estimate".[3]
- W is an $(N \times N)$ Spatial Weighting Matrix which refers to the spatial composition of the spatial units included in the sample. It contains data on geographic nighbouhood of world countries, which was extracted from the GADM database (www.gadm.org), and processed with GeoDa software to generate the Spacital Weighting Matrix.

[2] One-sided violence is the use of armed force by the government of a state or by a formally organized group against civilians which results in at least 25 deaths. Extrajudicial killings in custody are excluded (Pettersson, 2019).

[3] Best estimate: The UCDP Best estimate consists of the aggregated most reliable numbers for all incidents of one-sided violence during a year. If different reports provide different estimates, an examination is made as to what source is most reliable. If no such distinction can be made, UCDP as a rule includes the lower figure given (Pettersson, 2019).

- Ɛ is a vector of disturbances for country i and time t and Ɛ is independently and identically distributed.

Table 7 and Table 8 present the descriptive statistics and the matrix of correlation of the above-mentioned variables.

To cope with the potential endogeneity of the conflict variable, we select an instrument, satisfying the conditions that it is not correlated with the error term, but is closely associated with the instrumented regressor (Greene, 2003; Cameron and Trivedi, 2005). We believe that the causality between conflict and FDI in mining sector could be bi-directional; therefore, this could bias our estimations due to endogeneity. We choose conflict in neighbouring countries z_{it} as an instrument for conflict in the FDI-receiving economy. This instrument satisfies the above mentioned two assumptions as it is assumed not to have a spillover impact on FDI in neighbouring countries; in other words, conflict in country x will not impact the FDI in mining sector of a neighbouring country. Moreover, conflict in country can be a causation for conflict in the FDI-receiving economy.

Therefore, the instrument z_{it} follow a Spatial Autoregressive (SAR) process to capture the effect of conflict in one country on the conflict in its neighbours.

$$z_{it} = \rho W z_{it} + \propto \iota_N + X_{it}\beta + u_{it} \tag{2}$$

In the preceding, we expect that ρ is significant. When this is satisfied, the model is ready to predict the fitted values of z_{it} that serves as an instrument for conflict.

When the (SAR) process is incorporated in eq. (1), we derive the complete empirical model:

$$Y_{it} = \rho W Y_{it} + \propto \iota_N + X_{it}\beta + W X_{it}\theta + W z_{it}\tau + \varepsilon_{it} \tag{3}$$

Table 1
Summary of the dynamic impact of *conflict* on *Greenfield mining FDI*.

	Conflict >25 (Model 1)	Conflict >100 (Model 2)	Conflict >200 (Model 3)
World countries [full sample]			
D_{tq+1}	0.0414	0.158	0.457
D_{tq}	−0.248*	−0.419**	−0.674
D_{tq-1}	0.147	0.163	−0.209
D_{tq-2}	−0.216**	−0.168	0.498
D_{tq-3}	−0.350***	−0.449**	−1.013*
Sub-Sahara countries			
D_{tq+1}	−0.0659	0.466	0.845
D_{tq}	−0.211	−0.342**	−0.204
D_{tq-1}	0.0366	−0.386**	−0.787
D_{tq-2}	−0.169	0.141	0.790
pD_{tq-3}	−0.218	−0.392	−0.740
South Asia countries			
D_{tq+1}	0.180	0.788	1.781*
D_{tq}	−0.795***	−0.523	0.0196
D_{tq-1}	0.538	−1.003***	−1.042
D_{tq-2}	0.160	0.700***	0.359
D_{tq-3}	0.295	0.162	0.233
MENA countries			
D_{tq+1}	0.353	0.122	−0.672
D_{tq}	−0.142	−0.130	−0.255
D_{tq-1}	0.207	0.425	0.891
D_{tq-2}	−0.379*	−0.286	0.0895
D_{tq-3}	−0.460	−0.776**	−1.835
Oil Countries			
D_{tq+1}	0.324	0.0534	0.225
D_{tq}	−0.126	−0.260	−0.177***
D_{tq-1}	0.280	0.0782	−0.0293
D_{tq-2}	−0.210	−0.220	0.102***
D_{tq-3}	−0.436	−0.0288	0.336*

Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

Table 2
The summary of one-year aggregate impact of *conflict* on *Greenfield mining FDI*.

	Conflict >25 (Model 1)	Conflict >100 (Model 2)	Conflict >200 (Model 3)
World			
one year Interval	−0.438*** (0.107)	−0.527*** (0.194)	−0.443 (0.309)
Sub-Saharan			
one year Interval	−0.505*** (0.162)	−0.598** (0.299)	0.0564 (0.0531)
South Asia			
one year Interval	0.416*** (0.0792)	0.288*** (0.100)	1.399 (1.623)
MENA			
one year Interval	−0.163 (0.327)	−0.500 (0.321)	−0.615** (0.247)
Oil Countries			
one year Interval	0.0118 (0.304)	−0.454* (0.276)	−0.210*** (0.0464)

Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

Table 3
Summary of the impact of the interaction between natural resources and one-year aggregate *conflict* on *Greenfield mining FDI*.

	Conflict >25 (Model 1)	Conflict >100 (Model 2)	Conflict >200 (Model 3)
World			
One -year Interval	−0.659***	−0.671**	−0.163
One -year Interval X Natural Resources Rent	0.0186**	0.0102	−0.0121
Sub-Saharan			
one year Interval	−0.736***	−1.216**	−0.735***
One -year Interval X Natural Resources Rent	0.0159	0.0423**	0.0671***
South Asia			
one year Interval	0.202	0.0251	0.613
One -year Interval X Natural Resources Rent	0.204	0.222	0.261
MENA			
one year Interval	−0.696***	−0.493	0.538
One -year Interval X Natural Resources Rent	0.0268**	−0.000417	−0.0313
Oil Countries			
one year Interval	−0.792***	−0.543*	−0.212***
One -year Interval X Natural Resources Rent	0.0456***	0.00559	1.372**

Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

4. Empirical methodology

4.1. Spatial interactions

Spatial associations are often observed for socio-demographic and economic determinants (Moscone and Knapp, 2005; Kostov, 2009; Elhorst and Fréret, 2009; Moscone et al., 2012), and empirically, spatial panel-data models have become a well-known tool for determining the existence of spatial spillovers. However, changes in observations tend to be affected by changes in closer observations rather than observations of more distant units. In other words, it has become generally acknowledged that observations from geographically close entities are not independent but spatially correlated (Tobler, 1970).

Manski (1993) reports three types of interaction effects that may help in explaining why changes in observations tend to be affected by changes in neighbourhood units: first, when the behaviour of the dependent variable relies on the decision taken by other spatial

Table 4
The estimation results of Fixed effects Spatial Durbin Model (SDM).

VARIABLES	Conflict >25 (Model 1)	Conflict >100 (Model 2)	Conflict >200 (Model 3)
	SDM FE	SDM FE	SDM FE
Conflict	5.135	56.95***	4.865
	(14.44)	(19.08)	(14.83)
Inflation	−1.424	−0.497	−1.383*
	(0.956)	(0.750)	(0.824)
Exchange rate	1.04e-08*	−7.70e-10	5.67e-09
	(5.44e-09)	(6.91e-09)	(6.77e-09)
Control of Corruption	9.490	24.78	9.631
	(19.55)	(20.64)	(20.07)
Natural Resources Rent	−1.110	0.158	−1.175
	(1.609)	(0.741)	(1.543)
Rho	−0.00752***	−0.0129***	−0.0175***
	(0.00264)	(0.00382)	(0.00261)
sigma2_e	220,594**	228,112**	219,511**
	(95,285)	(97,638)	(94,538)
W (Conflict)	36.69	−16.54	34.90
	(47.78)	(37.37)	(46.75)
W (Inflation)	6.675	4.521	6.971
	(6.233)	(4.805)	(6.678)
W (Exchange rate)	−7.81e-09	−3.10e-08	−2.47e-08
	(3.22e-08)	(2.79e-08)	(3.49e-08)
W (Control of Corruption)	−1.400	−6.692	−1.729
	(55.99)	(19.82)	(56.16)
W (Natural Resources Rent)	0.624	2.415***	0.0196
	(1.344)	(0.832)	(1.518)
Observations	11,564	11,564	11,564
R-squared	0.005	0.009	0.004
Number of Countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes
Country fixed effect	Yes	NO	Yes

Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq$ 25, besides, the quarter q had witnessed at least one fallen fatality.

dependent variables, in so-called endogenous interaction effects; second, if there are exogenous interaction effects, and these may happen when the behaviour of the dependent variable depends on the decision of independent explanatory variables taken by other spatial units, and third, if there are the correlated effects, where similar unobserved environmental characteristics result in similar behaviour. Therefore, Manski (1993) suggests the following spatial interactions model:

$$Y_{it} = \rho W Y_{it} + \propto \iota_N + X_{it}\beta + W X_{it}\theta + u_{it} \quad u_{it} = \lambda W u_{it} + \varepsilon_{it} \tag{4}$$

where W is an $(N \times N)$ matrix which refers to the spatial composition of the spatial units included in the sample. Each element of the matrix is binary and equal to one when two units are neighbours, and no unit can be a neighbour on its own. Therefore, the diagonal elements of the matrix are set to zero. Lee (2004) shows that W should be a non-negative matrix of known constants. Non-negative matrix factorization (NMF) delivers profound explanations of complicated latent relationships (Gao, et al., 2019).

Further, WY represents the endogenous interaction effects for the dependent variable, WX is the exogenous interaction effects among the independent variables, Wu is the interaction effects among the disturbance terms of the different spatial units. ρ is the spatial autoregressive coefficient, λ the spatial autocorrelation coefficient, and θ denotes a $K \times 1$ vector of fixed but unknown parameters.

Manski's model, also known as the general nesting spatial (GNS), suffers from an identification problem, as it commonly leads to an overparameterized model that will ultimately lower the level of significance for parameters (Elhorst, 2014) and it will not give accurate clarifications of the reasons for using the spatial models discussed in this section previously see (Manski, 1993). Therefore, Elhorst (2010) taxonomy implies that by imposing some restrictions, the models can explain how to gain more explanations of how spatially interacting observations can affect each other. Fig. 1 introduces Elhorst's taxonomy of spatial dependence models.

Table 5
The estimation results of Fixed effects Spatial Autoregressive Model (SAR).

VARIABLES	(Model 1)	(Model 2)	(Model 3)
	SAR FE	SAR FE	SAR FE
Conflict	2.649	61.36***	2.292
	(13.76)	(18.03)	(14.15)
Inflation	−0.314	0.187	−0.682*
	(0.361)	(0.284)	(0.352)
Exchange rate	9.94e-09**	−4.18e-09	2.20e-09
	(4.76e-09)	(6.10e-09)	(6.10e-09)
Control of Corruption	9.299	15.41	9.101
	(19.91)	(10.25)	(20.47)
Natural Resources Rent	0.451	1.645**	−0.260
	(0.757)	(0.694)	(0.731)
rho	−0.00926***	−0.00962***	−0.0183***
	(0.00330)	(0.00358)	(0.00290)
sigma2_e	221,657**	228,921**	220,300**
	(97,052)	(98,940)	(96,085)
Observations	11,564	11,564	11,564
R-squared	0.001	0.003	0.000
Number of Countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes
Country fixed effect	Yes	No	Yes

Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq$ 25, besides, the quarter q had witnessed at least one fallen fatality.

Table 6
The estimation results of Fixed effects Spatial Error Model (SEM).

VARIABLES	(Model 1)	(Model 2)	(Model 3)
	SEM FE	SEM FE	SEM FE
Conflict	2.772	60.97***	2.469
	(13.77)	(18.01)	(14.15)
Inflation	−0.293	0.211	−0.635*
	(0.373)	(0.290)	(0.352)
Exchange rate	9.93e-09**	−4.27e-09	2.09e-09
	(4.76e-09)	(6.17e-09)	(6.22e-09)
Control of Corruption	9.272	15.32	9.045
	(19.95)	(10.14)	(20.56)
Natural Resources Rent	0.457	1.651**	−0.252
	(0.756)	(0.693)	(0.725)
lambda	−0.00898***	−0.0167***	−0.0198***
	(0.00346)	(0.00519)	(0.00448)
sigma2_e	221,658**	229,063**	220,301**
	(97,053)	(99,062)	(96,084)
Observations	11,564	11,564	11,564
R-squared	0.001	0.003	0.000
Number of Countries	196	196	196
Robust	Yes	Yes	Yes
Country clustering	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes
Country fixed effect	Yes	No	Yes

Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1, the dependent variable is Greenfield FDI in all models, the independent variable Conflict is a binary variable that equals 1 if the number of fatalities in a year $t \geq$ 25, besides, the quarter q had witnessed at least one fallen fatality.

Table 7
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
(1) Number of fatalities quarterly	11,564	46.477	295.34	0	7407
(2) FDI inflow quarter	11,564	136.059	727.581	0	36,800
(3) Inflation	11,564	6.042	9.374	−27.632	174.858
(4) Exchange Rate	11,564	1,446,449.5	1.336e+08	−3.995e+08	6.723e+09
(5) Control of Corruption	11,564	−.022	.996	−2.222	2.586
(6) Natural Resources Rent	11,564	7.34	11.544	−17.032	81.95

Table 8
Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Number of fatalities quarterly	1.000					
(2) FDI inflow quarter	0.011	1.000				
(3) Inflation	0.023	0.037	1.000			
(4) Exchange Rate	0.001	0.001	−0.007	1.000		
(5) Control of Corruption	−0.171	−0.010	−0.273	−0.028	1.000	
(6) Natural Resources Rent	0.068	0.068	0.249	0.020	−0.376	1.000

Different approaches have been suggested as to which model to start with. Kelejian and Prucha (1999) suggest starting with spatial autocorrelation models (SAC): however, as mentioned earlier, Anselin (2013) suggests starting from the specific and moving to the general approach, which implies commencing analysis with a non-spatial linear regression such as OLS, and then to conduct tests to identify the need to add spatial terms. Nevertheless, this study follows LeSage and Pace (2009) stating that by starting with the Spatial Durbin Model (SDM) and imposing restrictions, it will be easy to obtain the Spatial Autoregressive model (SAR) and the Spatial Error Model (SEM) models. This paper uses the maximum likelihood approach to infer the spatial impacts.

4.2. Dynamic impact

To examine the dynamic impact of exogenous conflict variation on greenfield FDI, the study follows Karafiath's (1998) model representing the event study by using dummies:

$$\mathrm{Y}_{\mathrm{iqt}} = \alpha + \varphi \mathbf{X}_{\mathrm{iqt}} + \sum_{j=1}^{-3} \beta \mathrm{D}_{\mathrm{t}(q+j)} + \delta_i + \varepsilon_{\mathrm{it}} \tag{5}$$

Where, Y_{it} is greenfield FDI in the mining sector, i, and t represent country and time respectively, $q \in (1,4)$ represents a quarter, γ_t is the year-fixed effect which controls for any fixed unobserved heterogeneity for year-specific, or for any other shocks that affect greenfield FDI, and δ_i is the country-fixed effect and captures any fixed country-specific unobserved heterogeneity.

$\mathrm{D}_{\mathrm{q(t+j)}}$ denotes the treatment effect if the instrumented conflict breaks out at year t and quarter $q+j$, $j \in (1,-3)$, where D is a binary measure that represents the instrumented conflict in which the total number of fatalities is equal to or above 25 persons in a certain year and country. Later, for a robustness check, this identification will be replaced, to define the binary variable as the aggregate number of fatalities equal to or greater than 100, and then 200 persons. The dummies reflect the dynamic effect of conflict events on FDI during five periods (q+1; q+0; q-1; q-2; q-3). The first period is a placebo since it is a leading dummy to test if the treatment has any impact on the outcome before its outbreak. In other words, the purpose of this step is to test if the current conflict event has any effect on the greenfield FDI of the last quarter: therefore, it can be expected that the coefficient of this dummy should be insignificant. The second dummy D_0 represents the contemporaneous quarter to the conflict event, and the other dummies represent the three quarters following the contemporary quarter. This enables the model to test the dynamic impact of conflict on FDI. The statistical precision of the binary measure coefficients $\beta' s$ are the main coefficients of interest that capture the dynamic impact of conflict on greenfield FDI. X_i is a set of covariates of different controls, as per eq. (1), φ is a vector of coefficients and $\varepsilon_{\mathrm{it}}$ is the error term.

4.3. The Spatial Durbin Model (SDM)

Imposing a restriction on Manski's Model by letting $\lambda = 0$ leads to the Spatial Durbin Model.

$$Y_{it} = \rho W Y_{it} + \propto \iota_N + \mathrm{X}_{it}\beta + W\mathrm{X}_{it}\theta + \mathcal{E}_{it} \tag{6}$$

The Spatial Durbin Model enables the researcher to infer the impact of greenfield FDI in the mining sector in neighbouring countries on a specific country's greenfield FDI. At the same time, it assesses the impact of the exogenous explanatory variables of both the country and its neighbours on the dependent variable. Table 4 presents the results of the

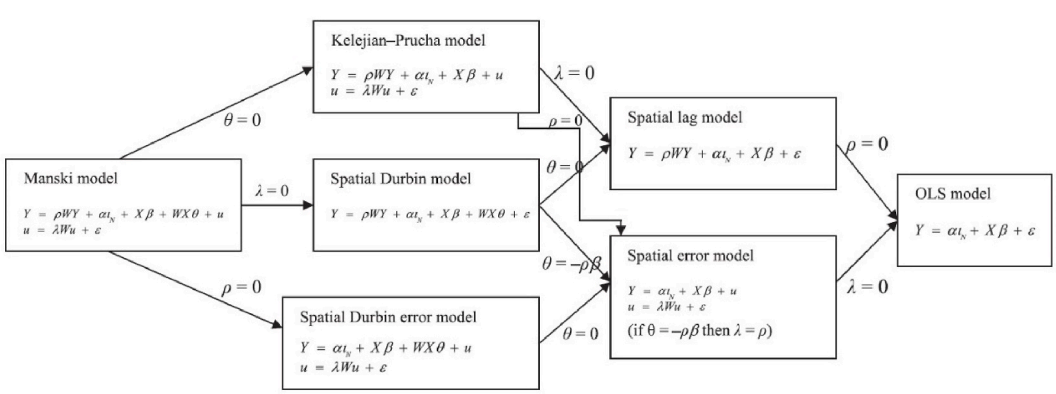

Fig. 1. The relationships between different spatial dependence models for cross-section data.
Source: (Elhorst, 2010)

SDM models. Model 1 includes the country-fixed effects, model 2 includes the time-fixed effect, and model 3 includes both.

However, to only capture the effect of greenfield FDI in the mining sector in one country on its neighbourhood countries, the Spatial Lag Model also called the Spatial Autoregressive model (SAR) can be used for this purpose. The SAR model is a special case of the SDM model in the case of the restriction θ = 0. In that case, the model becomes:

$$Y_{it} = \rho W Y_{it} + \propto \iota_N + X_{it}\beta + \varepsilon_{it} \tag{7}$$

Table 5 presents the results of the SAR models. SAR Model 1 includes the country-fixed effects, SAR Model 2 includes the time-fixed effect, and SAR Model 3 includes both.

Further, by imposing both restrictions, θ = 0 and $\rho = 0$ restrictions on Manski's model, the SAR Model becomes the Spatial Error Model (SEM) described below:

$$Y_{it} = \propto \iota_N + X_{it}\beta + u_{it} \quad u_{it} = \lambda W u_t + \varepsilon_{it} \tag{8}$$

Table 6 presents the results of the SEM models. SEM Model 1 includes a country-fixed effect only, SEM Model 2 includes a time-fixed effect, and SEM Model 3 includes both.

4.4. Direct and indirect effects

The interpretation of the parameters grows deeper and more sophisticated in models with spatial lags for the explanatory or dependent variables. Several econometricians have pointed out that models with spatial lags in the dependent variable necessitate unique explanations of the parameters (Le Gallo, et al., 2003; Kim et al., 2003; Kelejian et al., 2006; Anselin and Le Gallo, 2006). Moreover, spatial regression models take advantage of the complex interdependence structure between units, and thus a change in an explanatory variable for one unit will have an indirect influence on all other units. This means that there are both direct and indirect marginal effects, as well as total marginal effects (Belotti, et al., 2017).

The average direct effect is similar to that of the β coefficients of a non-spatial linear model calculated using the OLS method. In other words, the impact is simply represented by the effect of explanatory factors on the dependent variable for a specific country. However, the indirect effect is represented the impact of explanatory variables on the dependent variables of other countries. Moreover, by using dynamic models such as SDM and SAR, it is possible to obtain a direct effect, an indirect effect, and a total effect in both the short-term and the long-term.

The idea of short-term effects and long-term effects was developed when the spatial Durbin model with dynamic effects was considered in several pieces of research. The focus of these pieces of research is on growth and convergence among countries or regions (Ertur and Koch, 2007; Elhorst, 2010). Typically, these analyses regress the dependent variable of a specific country on either the dependent variable in neighbouring territories, or the initial values (lagged values) of the dependent variable in the country and neighbouring economies, or on a set of explanatory variables in the country and neighbouring countries.

5. Results and discussion

We begin the analysis with an assessment of the dynamic impact of *conflict* on *greenfield FDI in the mining sector* for the full sample (Table 1). Further, we examine the spatial impact of *conflict* on *greenfield FDI in the mining sector*. Table 4 shows the estimation results of the Spatial Durbin Model (SDM). As discussed earlier, this estimation allows us to examine the impact of *greenfield mining FDI* in neighbouring countries on a specific country's *greenfield mining FDI*, while at the same time, it assesses the impact of the exogenous explanatory variables of a specific country on its neighbour's outcome variable.

The results show that a spatial impact on *greenfield mining FDI* exists and it runs in a negative direction, i.e. the inflow of *greenfield mining FDI* in country i decreases the same investments in the neighbourhood countries. The same results have been obtained from the Spatial Autoregressive Model (SAR) in Table 5. However, the spillover impact of *conflict* in country i on *greenfield mining FDI* in neighbourhood countries is insignificant.

Table 6 shows the estimation results of the Spatial Error Model (SEM). The model investigates the impact of unobserved variables, represented by the error term on the error term of neighbouring countries. The results show that the unobserved variables in country i can affect the *greenfield mining FDI* in a neighbouring country.

5.1. The dynamic impact and one-year aggregate models

Table 1 shows that the placebo dummy successfully satisfies the preceding assumption, i.e. the upcoming conflict event should not have any impact on the current value of FDI. This assumption has been fulfilled for the suggested three models.

To calculate the impact of dummy conflict on logarithmic greenfield FDI, the study uses the following equation suggested by (Halvorsen and Palmquist, 1980)[4]

$$\%\Delta Y = 100 \times \left(e^{\beta - 1}\right)$$

in Model 1 (Table 1 – the full sample), when conflict fatalities ≥25, the dynamic impact is significant and negative over the three periods. Generally, the event of a conflict outbreak decreases contemporaneous *greenfield mining FDI* by 24.8%. However, the results in model 1 show that the conflict does not have any impact on the next quarter's *greenfield mining FDI*, yet the impact exists for the following two quarters when it decreases FDI by 21.6% and 35% respectively. In Model 2, defined as when conflict fatalities ≥100, the dynamic impact of *conflict* on *greenfield mining FDI* exists for the contemporaneous and the fourth quarters only. The dynamic impact appears to fade away when the model retains highly intense conflict events, i.e. when conflict fatalities ≥200 as in Model 3. In this case, *greenfield mining FDI* is reduced only in the fourth quarter. Thus, when a highly intense conflict event occurs, *greenfield mining FDI* declines by 63.7%.

Table 2 shows the one-year aggregate impact of conflict on *greenfield mining FDI* across the global sample of countries. A one-year aggregate impact exists only for the low and medium scales of conflict. However, there is no impact of highly intense conflict events on *greenfield mining FDI*. When the magnitude of the conflict is defined as greater than 25 fatalities, the impact on *greenfield mining FDI* decreases by 35.5%. This number increases to 41% in Model 2, where the one-year aggregate conflict dummy is re-defined and restricted to cases above 100 fatalities. And in Model 3, where the one-year aggregate conflict dummy is re-defined as instances above 200 fatalities, Table 3 shows the summary of the interaction between the *natural resources rents* and the one-year aggregate conflict events and how this impacts the *greenfield mining FDI*.

The absence of a significant impact in Model 3 in both Tables 2 and 3 for the full sample, could be due to the heterogeneity of countries in the world sample in terms of the intensity of conflict events they experience. Therefore, we extend our analysis by stratifying the full sample according to geographical regions: Sub-Saharan Africa, South Asia, Middle East and North Africa (MENA), and Oil producing countries, to provide more in-depth analysis and to test if the preceded results hold.

[4] A common mistake is made when interpreting the coefficients of dummy variables in semilogarithmic regression models. Usually, analysts multiply the coefficient by 100. Consequently, they assume this is equal to the percentage effect of that dummy variable on the outcome variable. However, it is easily shown that this interpretation, while correct for continuous variables, is not correct for dummy variables and can result in substantial errors in the reporting of results.

5.1.1. The Sub-Saharan region

The results regarding the dynamic impact of *conflict* on *greenfield mining FDI* across Sub-Saharan countries, based on Model 2 (Cable 10) show significant impacts for the first two quarters, evaluated at −29% and −32% respectively, and only when conflict is defined as the total number of fatalities exceeds 100 causalities. However, the one-year aggregate impact shown in Table 2 reveals that the aggregate impact for the first four quarters is significant and negative for low and medium intensities of conflict. The impact is estimated to be −39.6% and −45% respectively.

Table 3 shows the impact of the interaction between natural resources and one-year aggregate conflict on greenfield FDI in the mining sector across Sub-Saharan countries. The impact of the *conflict* on *greenfield mining FDI* is negative in all models. However, its interaction with natural resources rents moderates this negative effect in countries with high–intensity conflict events (see Models 2 and 3 in Table 3). In Model 2, the one-year aggregate impact of *conflict* on *greenfield mining FDI* becomes positive when the natural resources rent equals 28.75, i.e. when the difference between the price of the natural resources and the average cost of producing it is 28.75 USD. Nonetheless, when conflict becomes more intense in Sub-Saharan countries, the negative impact disappears when the natural resources rent is above 10.95 USD. In summary, in Sub-Saharan countries*, greenfield mining FDI* declines less when profit opportunities become more likely.

5.1.2. South Asia

In contrast, the dynamic impact of *conflict* on *greenfield mining FDI* across South Asian countries is inconsistent. In Table 1, Model 1, reveals a negative impact, meaning that when a conflict event arises, *greenfield mining FDI* declines by 0.795%. However, in Model 2, when the model excludes low-scale conflict occurrences, the outbreak of a conflict decreases *greenfield mining FDI* by 1 percentage point. However, during the following quarter, the impact reverses. The results in Table 2 present The summary of one-year aggregate impact of conflict on *Greenfield mining* FDI. Results show a positive impact of conflict in terms of one-year aggregate impact on *greenfield mining FDI* when the conflict event is of low or medium intensity. The results in Table 3 displaying the summary of the impact of interaction between natural resources and one-year aggregate conflict on *greenfield mining FDI*, results are also conflicting as the impact no longer exists in any of the models.

5.1.3. The MENA region

In MENA countries, a dynamic impact does not exist. In Table 1, Model 1 shows that the impact is limited within the third quarter, and in Model 2, it is limited within the fourth quarter. However, we observe a one-year aggregate significant negative impact when the conflict intensity increases. Additionally, the possibility to obtain profit from natural resources rents in conflict areas may exist, but not in medium and high-intensity conflict situations as shown in Table 3.

5.1.4. The oil-producing countries

Table 1 shows the dynamic impact of *conflict* on *greenfield mining FDI* across oil-producing countries. This dynamic impact only exists in high-intensity conflict cases. However, it is inconsistent. In the first quarter, the impact of *conflict* on *greenfield mining FDI* is negative, and in the third and fourth quarters, it becomes positive. Moreover, the aggregate impact is negative.

5.2. The spatial models

We conduct further investigations to examine the spatial impact of conflict on greenfield FDI in the mining sector. Table 4 shows the estimation results of the Fixed Effects Spatial Durbin Model. As previously discussed, this estimation enables inference of the impact of *greenfield mining FDI* in neighbouring countries on the examined country's *greenfield mining FDI*. At the same time, it assesses the impact of the exogenous explanatory variables of the examined country on its neighbour's outcome variables. The results show that a spatial impact on *greenfield mining FDI* exists and it is negative. In other words, the inflow of *greenfield mining FDI* in country i decreases the same investments in neighbouring countries (j). The same result has been obtained from the SAR model in Table 5. However, the SAR models also show that the spillover impact of a conflict in country i on *greenfield mining FDI* in neighbouring countries is insignificant. Table 6 shows the estimation results of the Fixed Effects SEM. The model investigates the impact of unobserved variables, represented by the error term on the error term of neighbouring countries. The results show that unobserved variables in country i can affect greenfield FDI in neighbouring countries negatively.

Most of the results obtained from the previous models which revealed a negative impact of *conflict* on *greenfield mining FDI* matched previous literature findings (Enders and Sandler, 1996; Abadie & Gardeazabal, 2003, 2008; Agrawal, 2011). However, Robinson (1969) and Vernon and Wells (1981) suggest that the inconsistency in results exists as political instability could not be an effective determinant for FDI, as CEOs do not take political instability into account when making investment decisions.

A possible venue for future studies could be research that focuses on single cases of countries with the use of quasi-experimental designs, or the difference in difference and regression discontinuity designs. Single-case countries would allow for testing for the impact of conflict that arises in a specific country but not in surrounding areas. In summary, the outbreak of conflict events is a vital determinant of FDI flows as it has a negative impact. This negative impact can be extended to include subsequent periods as well.

The varying impacts of conflict on FDI across different country groups highlight the importance of conflict resolution and stability for attracting foreign investment. Countries experiencing high-intensity conflicts may struggle to attract FDI, while those with stable environments and fewer conflicts may have more success in this regard.

The negative spillover impact of conflict on greenfield FDI in the mining sector has implications for resource-rich countries. It suggests that conflict can deter foreign investment in this sector, potentially hindering economic development and resource extraction. Moreover, our findings emphasize that the presence and intensity of conflicts in different regions can affect the flow of global FDI. Investors may be more cautious and selective when considering investments in conflict-prone areas, which can impact the distribution of global capital flows This particular investing behaviour is evidence of risk-averseness of investors. Nevertheless, investors may have an interest in investing when conflict arises in one country and the investment decisions are driven by other factors One such important factor is the potential gains, which attract risk-prone investments.

6. Conclusion

The aim of this study was to investigate the impact of armed conflict on greenfield FDI in the mining sector. Unlike other works, this paper focuses on testing two impacts. First, we test for a dynamic impact, which investigates the impact of conflict on FDI in the contemporaneous and subsequent quarters, and second, we investigate the spatial spillover impact in three directions: the expected spillover impact of the outcome variable in one country on its neighbours' outcome; the spillover impact of conflict in neighbouring countries on greenfield mining FDI of an FDI-receiving country; and the spillover impact of any unobserved variables on greenfield mining FDI. We use a unique data set merged from two sources: the One-sided Violence data of the Uppsala Conflict Data Program (Eck and Hultman, 2007; Pettersson et al., 2019) and greenfield FDI data in the sector mining FDI obtained from the proprietary data set *FDIMarkets* by Financial Times. Both the conflict and the greenfield FDI data are aggregated on a quarterly basis. We obtain a valid instrument for the armed conflict variable and we use it to test for a dynamic impact of conflict on greenfield mining FDI and for a spatial spillover effect of conflict on FDI.

The dynamic impact results show an overall negative effect that lingers for up to four quarters. There are, however, some inconsistencies across different country groups. For example, this impact exists for the full sample, in particular when the conflict is defined to be an event with a total number of fatalities greater than 25 cases per year. This is not the case in Sub-Saharan Africa and South Asian countries where a dynamic impact exists only for two periods when the regression models exclude low-intensity conflict cases. However, in MENA countries, the dynamic impact does not exist at all. When the one-year aggregate impact of conflict on greenfield mining FDI is considered, the results show a negative and significant impact exists across the global sample, Sub-Saharan Africa, MENA, and Oil-producing countries.

Regarding the spatial spillovers of *conflict* on *greenfield mining FDI*, we conduct tests with three different methodologies: a Spatial Durbin Model (SDM), enabling evaluation of the impact of greenfield mining FDI in neighbouring countries on the *greenfield mining FDI* of the FDI-receiving country; a Spatial Autoregressive model (SAR), which captures the effect of *greenfield mining FDI* in one country on *greenfield mining FDI* of its neighbourhood countries only; and a Spatial Error Model (SEM), which investigates the impact of unobserved variables represented by the error term of our model on the error term of neighbouring countries.

The study concludes that there is a significant negative spillover impact of *conflict* on *greenfield mining FDI*. However, this impact does not exist when the model includes the lag-dependent variable as an additional explanatory variable. Moreover, *conflict* has no spillover impact on *greenfield mining FDI* in neighbouring countries. Some future venues of research could test for inter-regional spillovers within the same country.

The above-mentioned results emphasize several policy implications. Governments should prioritize efforts to mitigate conflicts, particularly in regions with high FDI potential. Implementing effective conflict resolution measures and ensuring stability and security can attract more foreign investments in the mining sector. By reducing conflict intensity, countries can improve their investment climate and increase the probability of positive dynamic impacts on mining FDI.

Moreover, given the negative spillover impact of *greenfield mining FDI* of neighbouring countries on the *greenfield mining FDI* of the receiving country, policymakers should design sector-specific investment policies. This could involve incentivizing more diversified investments or focusing on other sectors that are less prone to the above negative spillover effects. Governments may also encourage investments that promote technology transfer, local job creation, and environmental sustainability in the mining sector to counterbalance any negative spillover effects. On the regional level, neighbourhood countries should create a stable and FDI- friendly investment climate to attract FDI, namely for resource-rich neighbours.

Our study is subjected to several limitations that also suggest a variety of directions for future research. Our research focuses on a specific subset of FDI (greenfield FDI in the mining sector) and a specific type of conflict (armed conflict). This narrow focus may introduce selection bias, as it does not account for other types of FDI or conflicts that could also influence investment patterns. Second, this study finds no spillover impact of conflict on greenfield mining FDI in neighbouring countries, but it is possible that the chosen methodologies may not capture all possible spillover mechanisms accurately. Different spillover channels could exist and require further investigation. Lastly, the research focuses on the impact of conflict on FDI within a limited time frame (up to four quarters). Longer-term effects may not be fully captured, and the dynamics of FDI responses to conflict may evolve over time. All of the above are potential venues for future research.

Our findings provide important implications for managers and policymakers. The study highlights the negative impact of armed conflict on greenfield foreign direct investment (FDI) in the mining sector. Therefore, governments should prioritize efforts to mitigate and resolve conflicts, especially in regions with high FDI potential. This could involve diplomatic efforts, peace negotiations, and conflict prevention strategies. By reducing conflict intensity, countries can create a more stable and secure environment that is attractive to foreign investors. Given the negative spillover impact of greenfield mining FDI from neighbouring countries, policymakers should consider designing sector-specific investment policies. These policies could incentivize investments in other sectors that are less prone to such negative spillover effects. Diversifying the economy and encouraging investments in sectors with lower conflict-related risks can help reduce vulnerability.

Furthermore, to attract more foreign investments in the mining sector, governments should focus on improving the overall investment climate. This may include measures to enhance political stability, strengthen the rule of law, and ensure the security of investments. Investors are more likely to commit capital to countries where they feel their investments are secure. To counterbalance the negative spillover effects of neighbouring countries' FDI in the mining sector, governments can encourage investments that promote technology transfer, local job creation, and skills development. This can help maximize the positive economic impact of mining activities while minimizing potential negative consequences.

Credit authorship statement

Abdelrahman J K Alfar: I conceptualized the research, designed the econometric models, collected and processed the data, conducted the econometric analysis, and drafted the manuscript. Mohamed Elheddad: I contributed to the literature review, research design, and provided valuable insights for the econometric analysis. Nadia Doytch: I assisted in data collection and preparation, and provided critical feedback on the methodology and results. All authors: Contributed to the interpretation of the econometric results and offered suggestions for improving the manuscript. All authors have read and approved the final manuscript for submission. We acknowledge our respective contributions to this research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

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