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Singh, VK, Nishant, R and Kitchen, PJ

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Self or Simulacra of Online Reviews: An Empirical Perspective

Vivek Kumar Singh*

ISDS, MUMA College of Business
University of South Florida, USA

Rohit Nishant

Supply Chain
ESC Rennes, Rennes, France

Philip J. Kitchen

Marketing,
University of Salford, UK & ESC Rennes, Rennes, France

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ABSTRACT

Online user-generated content (UGC) includes various forms of computer-mediated online reviews, ratings, and feedback. The impact of online consumer reviews has been widely studied particularly in e-commerce, online marketing, and consumer behavior domains using text-mining and sentiment analysis. Such studies often assume that consumer-submitted online reviews truly represent consumer experiences, but multiple studies on online social networks suggest otherwise. Drawing from the social network literature, this paper investigates the impact of peers on consumer willingness to write and submit online reviews. An empirical study using data from “Yelp,” a globally used online restaurant review website, shows that the number of friends and fans positively impacts the number of online consumer reviews written. Implications for research and practice are discussed.

Keywords: Online reviews, e-commerce, computer mediated communication, rating dimensions , eWom.

Introduction

Online reviews are a major form of computer-mediated communication (CMC) and play a key role in propagating online or electronic word-of-mouth (eWoM) (Kimmel, 2015; Parthasarathy & Forlani, 2010). The extant literature has extensively explored the impact of online reviews in e-commerce (Sparks & Browning, 2011), mobile apps (Takehara, Miki, Nitta, & Babaguchi, 2012), and health care (Eysenbach, Powell, Englesakis, Rizo, & Stern, 2004a, 2004b). These studies have used state of the art natural language processing (NLP) techniques to extract valence, variance (Park & Park, 2013), volume, and ratings dimensions that determine the impact

of online reviews. Valence indicates whether reviews are positive, negative, or neutral. Volume represents number of reviews, and is widely recognized as representing customer awareness (Duan, Gu, & Whinston, 2008; Ellison & Fudenberg, 1995; Yu, Liu, Huang, & An, 2012). Variance captures variations in rating levels (Clemons, Gao, & Hitt, 2006). Review length (Chevalier & Mayzlin, 2006) and ratings are essential in determining impact. Researchers have investigated effects of these review dimensions on the sales and performance of products and services. However, findings remain mixed (Chevalier & Mayzlin, 2006).

Undoubtedly, managers are deeply concerned about review valence and volume. Indeed, multiple studies have focused on managing negative reviews (Anderson & Simester, 2014; Chatterjee & Chatterjee, 2001; Ye, Zhang, & Law, 2009).

Researchers have used ratings to predict subsequent market performance (Chevalier & Mayzlin, 2006; Clemons et al., 2006; Koh, Hu, & Clemons, 2010a). They also consider trust and reliability because faked and manipulated reviews coexist alongside legitimate reviews (Hu, Bose, Koh, & Liu, 2012; Sparks & Browning, 2011). Ye et al. (2009) demonstrated that online reviews have declining, temporal impact. Yet, only a few studies have examined the factors that motivate customers to write product and service reviews (Dellarocas, Gao, & Narayan, 2010; Liu, Huang, An, & Yu, 2008; Takehara et al., 2012), including the impact of peers. This research gap must be addressed.

Methodologically, most studies regarding peer effects have used student samples resulting in mixed findings regarding peer impacts on school performance, for example (Eysenbach et al., 2004a; Ron & Toma, 2000). However, in online social network domains, peers positively impact individual behavior (Egebark & Ekström, 2011). The homophily effect (McPherson, Smith-Lovin, & Cook, 2001) explains that individuals tend to choose similar peers for their social

network. Motivated primarily by the dearth of literature on the role of peer effects relative to online reviews, this study investigates the following research question:

***RQ:** How do peers influence decisions to write online reviews?*

This paper study makes several contributions. The study finds that the peer effect positively motivates decisions to write reviews. This is specifically useful for managers who analyze reviews to infer consumer behavior. The study also suggests the need to recognize the peer effect and indicates that prevailing analytical techniques such as sentiment analysis alone may fail to provide a comprehensive rationale explaining positive or negative reviews. Although previous work may indicate that individual choice motivates review writers, this study brings the social network perspective to the subject of online reviews and thus extends the discourse.

The study uses secondary data provided by Yelp,¹ a CMC platform for customers to report their restaurant experiences. The Yelp dataset challenge² provided the data. We We thus use a rigorous econometrics-based panel model for the analysis.

The rest of the article is organized as follows. First ,the literature regarding online reviews and peer effects that provided the basis for this study is reviewed. In the following sections we provide hypotheses, results, conclusions, and offer some future research directions.

LITERATURE REVIEW

Online reviews and peer effects form the basis for the hypotheses, although information systems and computer science reviewers have focused more extensively on online reviews than on peer effects.

¹ <http://www.yelp.com/>

² http://www.yelp.com/dataset_challenge

Online reviews

Multiple disciplines such as computer science, information systems, and marketing have widely studied online reviews in contexts ranging from movie reviews to books (Table 1). They have extracted online review information using the same techniques and quantification used for text analysis, which is a part of NLP.

Chevalier (2006) conducted seminal study of the impact of reviews on online book stores. Duan et al. (2008) demonstrated the impact of online reviews on movie sales. Managers are more concerned about negative reviews, particularly negative polarity according to a real number scale $[-1, +1]$ with -1 representing extreme negative polarity and $+1$ representing extreme positive polarity. Chatterjee (2001) examined consumers who had already made brand decisions for the effect of negative reviews on evaluations of retailers and patronage intentions. The study provided strategies for countering negative reviews.

Unfortunately, fake reviewers who have no purchase record contribute about 5% of reviews, and most fake reviews are generally negative (Anderson & Simester, 2014). Ye et al. (2009) researched travel website reviews and provided a comprehensive comparison of sentiment classification techniques.

←-----Table 1 here----->

Besides polarity, rating is another quantitative dimension predicting online review impacts. Chevalier and Mayzlin (2006) examined effects of ratings on two major book stores and found that lower ratings had more impact than higher ratings on book sales. User demographics and cultural differences also affect consumer rating behavior (Koh et al., 2010b). Drawing from

hyper-differentiation and resonance marketing theory, Clemons et al. (2006) demonstrated that product review ratings and variance positively impact the speed of product growth in the market. Multiple studies show that volume of consumer reviews positively impacts product performance, that word-of-mouth (WOM) (Wien & Olsen, 2014) reduces motivation to conduct cost and benefit analyses before making decisions, and that a large volume of WOM greatly impacts consumer behavior (Duan et al., 2008; Ellison & Fudenberg, 1995). Duan et al. (2008) studied the persuasive and awareness impact of online reviews on daily box office movie sales. Unlike earlier studies, the authors considered online movie reviews as an endogenous factor. They argued that review volume impacts movie sales and vice versa. Moreover, they empirically demonstrated that online reviews fail to significantly affect movie sales but that volume does affect movie sales and increases awareness.

Also, Yu et al. (2012) analyzed review valence and volume for predicting movie sales and proposed a novel algorithm for sentiment estimation. Dellarocas et al. (2010) studied willingness to write reviews for different categories of movies and consequent sales. They found that consumers review movies that are relatively ignored and less successful. However, consumers are also likely to review movies that have had a large number of reviews in the past. Liu et al. (2008) analyzed the impact of online reviews on consumer purchase decisions and suggested that a large volume of reviews limited consumers' ability to find useful reviews. The authors presented an algorithm to calculate whether consumers could find useful reviews. Takehara et al. (2012) analyzed microblog websites to extract consumer restaurant preferences and recommendations. Harrison et al. (2014) further examined restaurant reviews to track the spread of disease.

As online reviews continue to have increased impact, some organizations provide fake reviews, raising reliability concerns. Sparks and Browning (2011) explored online review characteristics for impacts on consumer trust and choice when using travel websites. Hu et al. (2012) proposed that manipulated reviews can be identified by writing style, ratings, sentiments, and readability. Hu et al. (2008) demonstrated the importance of contextual information, especially reviewer details, along with reviewer exposure and reputation. Moreover, they showed that reviews have decreasing impact over time.

Researchers have quantified online reviews using polarity, rating, and volume for measuring impacts on business output variables. However, the literature to date is limited in that little attempt has been made to satisfy the desires of researchers and practitioners to understand motivations for writing reviews (Rensink, 2013) because reviews are used so extensively in various contexts and are considered to report legitimate experiences in using goods and services. Apart from consumer experiences, Rensink (2013) posited seven key motivational factors that encourage review writing: venting negative feelings, helping other consumers, warning other consumers, enhancing the self, gaining social benefits, helping companies, and seeking advice. The study was limited, however, in that the authors used survey data to measure user perceptions.

Moreover, the research has failed to consider social factors. Consequently, this study addresses peer impact as a motivating factor. First, however, , the literature regarding peer effects largely from social psychology and information systems literatures is reviewed.

Peer Effect

Researchers have found that the peer effect has significant positive impacts in various contexts and group settings, such as student achievement, especially for low-ability students in various disciplines (Zimmer & Toma, (2000; Ost, 2010); student reading progress (Schneeweis & Winter-Ebmer, 2007; performance of mathematics and science students (Vandenbergh, 2002); and across student groups enrolled in various disciplines (Brunello, De Paola, & Scoppa, 2010). Positive impacts have also been found on individual entrepreneurial skills (Falck, Heblich, & Luedemann, 2012); drug use (Marimoutou et al., 2010), housing satisfaction (Vera-Toscano & Ateca-Amestoy, 2008); financial decisions, especially in stock market strategies (Kaustia & Knuepfer, 2012), employee attendance (Hesselius, Johansson, & Nilsson, 2009); and individual characteristics (Miller, 2010). Peer effects have been shown to have greater impact in science disciplines than in the humanities. Zabel (2008) provided a measure of peer effect that Powell, Tauras, and Ross (2005) used to show that an increase in the number of peers who smoke increases the probability that a student will smoke. Schreck, Fisher, and Miller (2004) examined peer networks to evaluate individual vulnerabilities. Payne and Cornwell (2007) argued that the peer effect causes behavior and attribution to be transmitted among individuals. Gaechter, Nosenzo, and Sefton (2013) demonstrated that the social preference model can predict peer effect changes.

Most studies confirm that peer effect has varying impacts in different group contexts. However, Eysenbach et al. (2004a) examined the peer effect on electronic communities and health-related support groups and found no significant peer-to-peer effect in communities, although the authors suggested further evaluation was needed. Foster (2006) found no significant peer effect on performance of students living in a hostel.

The literature is scant regarding the peer effect in online social networks. The few studies conducted have attempted to understand social network evolution. Smith, Windmeijer, and Wright (2014) posited a positive peer effect in online donations. Lewis, Gonzalez, and Kaufman (2012) studied peer influence in an online social network. McPherson et al. (2001) studied homophilia in social networks.

In summary, mixed results for peer effect is observed in different contexts. Most studies posit significant positive impacts, but the literature investigating peer effects in online review contexts and impacts on consumer choice is limited. Therefore, the current study is justified.

RESEARCH HYPOTHESES

Although most review research analyzes review impacts, recent studies use linguistic techniques to check review validity and to understand motivations to write reviews, especially deceptive and fake reviews (Luca & Zervas, 2013; Mayzlin, Dover, & Chevalier, 2014). Moreover, some economic incentive-based models are also proposed to examine fake reviews. However, Anderson and Simester (2014) argued that social status may motivate legitimate customers to write fake reviews, such as reviewing products they have not purchased. On social network-based review websites such as Yelp, reviewers form a network of online friends and followers who then receive one another's reviews. This study uses the peer effect literature to argue that the peer effect will positively motivate individuals to write website reviews. The effect will increase as the number of social network friends increase. Therefore, the following hypothesis is posited:

HYPOTHESIS 1 (H1): *The number of reviews individuals post is positively associated with their number of friends.*

Besides following friends' reviews on the social network, individuals can also follow other favored reviewers, similar to having followers on other popular social network websites such as Twitter, Facebook, and LinkedIn. Fans and followers act as silent observers or active supporters who determine reviewers' popularity on the social network platforms and motivate them to write reviews. The well-documented impact of silent observers is called the Hawthorne effect or observer effect (McCarney et al., 2007). Moreover, the leadership literature has established that followers impact their leaders' behaviors (Kellerman, 2008). Consequently, the following hypothesis is proposed:

HYPOTHESIS 2 (H2): The number of reviews individuals post is positively associated with their number of fans.

DATA COLLECTION

The Yelp challenge provided the secondary data for this research. Yelp is a restaurant review website. Users can create their profiles on the website and write reviews about their past dining experiences. The platform is similar to online social networks in that it allows friendship linkages. It also provides generic features such as votes and review stars, and unique features such as fans. The unit of analysis is an individual. The dataset provides JavaScript Object Notation³ (JSON) files which was converted to comma-separated values (CSV) format using Python⁴ scripting. Furthermore, separate datasets were merged to generate the complete data set. **RESEARCH**

METHOD

³ It is a syntax

⁴ A programming language

As mentioned earlier, this study used secondary data to test the hypotheses because of difficulties in conducting experiments on online social network platforms and review websites. In such contexts, review platforms provide datasets that can be used as a major source of research data. An econometrics-based model was used to investigate and test the hypotheses. Table 2 shows the key variables.

<-----Table 2 here----->

The study recognizes that a comprehensive research model is as good as a well-developed theory in the rapidly developing information systems discipline (Alter, 2015) Therefore, the empirical specification includes the main variables of interest as well as several control variables. Besides motivations coming from friends and fans, individuals might be motivated to write website reviews to garner appreciation in the form of votes, compliments, and ratings. The regression model is presented in equation (1) below:

$$\begin{aligned}
 reviewCount_i = & \beta_0 + \beta_1 * fans_i + \beta_2 * averageStars_i + \beta_3 * averageVotes_i \\
 & + \beta_4 * numberOfFriends_i + \beta_5 * averageComplements_i + \beta_6 * numberOfDays_i \\
 & + \epsilon_i \dots \dots \dots (1)
 \end{aligned}$$

RESULTS AND DISCUSSION

<-----Table 3 here----->

The descriptive statistics of key variables is shown in Table 3. 10,000 users were randomly sampled from a dataset of more than 200,000. Three outlier samples were removed, resulting in a final sample size of 9,997.

The users included in this analysis have an average of about 2 years experience on the website and a minimum of about 6 months (Table 2). The correlation analysis of the variables was conducted and the correlation matrix of key variables presented in Table 4.

<-----Table 4 here----->

As the correlation matrix clearly shows, most correlation among the variables was less than 0.07. The highest correlation was between the variables *averageCompliments* and *averageVotes*: 0.85. Table 5 shows regression results.

<-----Table 5 here----->

As Table 5 shows, both *numberOfFriends* and *numberOfFans* were highly significant ($p < 0.05$), confirming H1 and H2. However, contrary to knowledge gleaned from the literature, ratings showed no significant impact on number of reviews. One plausible explanation is that reviewers perceive ratings and votes to be analogous feedback. Prior studies considered only ratings, without including votes or compliments because most online social platforms do not capture that data. Surprisingly, average number of compliments is negatively related to number of reviews. Perhaps reviewers become more conscientious as the average compliments increased and focused on quality rather than quantity for their reviews. The estimate for *numberOfDays* (Individual experience on the platform) was positive and significant. It is plausible that as reviewers gain experience, they enjoy the experience and are therefore motivated to write reviews.

CONCLUSION AND FUTURE RESEARCH

This article investigated individual motivations to write online reviews on review platforms and social network websites. Using data from Yelp, a widely used restaurant review website, the study shows that the number of fans and friends are key motivators encouraging individuals to write reviews. Thus, quantity of friends and fans matter in the context of online reviews and thereby pave the way for exploring more qualitative factors such as characteristics of friends and fans. The study also validate the role of ratings, votes, and compliments.

This study has several implications for research. First, our study suggests that while the role of qualitative factors need exploration, quantitative factors do matter as far as motivation to write reviews is concerned. Second, contrary to our expectation, encouragements such as compliments could demotivate reviewers. Thus, future research should to reinvestigate the motivating role of encouragements and compliments in online contexts. Finally, while the present research establishes the direct effects of aspects such as number of fans and friends, there is ample scope to investigate interaction effects.

This study also offers key managerial implications. First, the extant big data analytics and e-commerce literature considers online reviews to be independent assessments of individual product or service experiences. This study demonstrates that peers and fans impact online reviews. Second, only a couple of websites, including Yelp, have built-in social network designs that allow researchers to estimate peer effects. Managers should design their product and service websites to allow estimations and incorporations of peer impacts. Finally, this research will assist managers in designing social media-based advertising. Restaurant managers and owners can target customers who have higher network centrality (number of peers) and offer them incentives to visit the restaurant and write reviews that positively motivate restaurant visits.

Thus, whether from a methodological or managerial perspective, it is evident that the the field of online reviews is ripe for further and more varied investigations. In particular, attention is directed to the influence of others in writing subsequent positive (or negative) reviews, which as indicated, so far has received almost no attention.

This study has a few limitations. Cross-sectional data is used to model and test the hypotheses, although it is difficult to control for individual heterogeneity using such data. Future studies can use panel data for exploration and also access and explore other datasets to ascertain the generalizability of findings reported here.

REFERENCES

- Alter, S. (2015). Nothing Is More Practical than a Good Theory ... except possibly a Good Paradigm or Framework or Model or Metaphor. In *Thirty Sixth Internation Conference on Information Systems, Fort Worth 2015* (pp. 1–10).
- Anderson, E. T., & Simester, D. I. (2014). Reviews Without a Purchase: Low Ratings, Loyal Customers, and Deception. *Journal of Marketing Research (JMR)*, *51*(3), 249–269. <http://doi.org/http://dx.doi.org/10.1509/jmr.13.0209>
- BRUNELLO, G., DE PAOLA, M., & SCOPPA, V. (2010). Peer Effects in Higher Education: Does the Field of Study Matter? *Economic Inquiry*. <http://doi.org/10.1111/j.1465-7295.2009.00235.x>
- Chatterjee, P., & Chatterjee, P. (2001). Online Reviews: Do Consumers Use Them? *Advances in Consumer Research*, *28*, 129–134. <http://doi.org/10.2139/ssrn.900158>
- Chevalier, J. a, & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, *43*(3), 345–354. <http://doi.org/10.1509/jmkr.43.3.345>
- Clemons, E. K., Gao, G. G., & Hitt, L. M. (2006). When Online Reviews Meet A Study of the Hyperdifferentiation : Craft Beer Industry. *Journal of Management Information Systems*, *23*(2), 149–171. <http://doi.org/10.2753/MIS0742-1222230207>
- Dellarocas, C., Gao, G., & Narayan, R. (2010). Are Consumers More Likely to Contribute Online Reviews for Hit or Niche Products? *Journal of Management Information Systems*, *27*(2), 127–158. <http://doi.org/10.2753/MIS0742-1222270204>
- Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? - An empirical investigation of panel data. *Decision Support Systems*, *45*(4), 1007–1016. <http://doi.org/10.1016/j.dss.2008.04.001>
- Egebark, J., & Ekström, M. (2011). Like What You Like or Like What Others Like ? - Conformity and Peer Effects on Facebook. *October*, (886), 1–26. <http://doi.org/10.2139/ssrn.1948802>

- Ellison, G., & Fudenberg, D. (1995). Word-of-mouth communication and social learning. *Quarterly Journal of Economics*, 110(1), 93–125. <http://doi.org/10.2307/2118512>
- Eysenbach, G., Powell, J., Englesakis, M., Rizo, C., & Stern, A. (2004a). Health related virtual communities and electronic support groups: systematic review of the effects of online peer to peer interactions. *BMJ (Clinical Research Ed.)*, 328(7449), 1166. <http://doi.org/10.1136/bmj.328.7449.1166>
- Eysenbach, G., Powell, J., Englesakis, M., Rizo, C., & Stern, A. (2004b). Primary care Health related virtual communities and electronic support groups. *BMJ (Clinical Research Ed.)*, 328(May), 1–6.
- Falck, O., Heblich, S., & Luedemann, E. (2012). Identity and entrepreneurship: do school peers shape entrepreneurial intentions? *Small Business Economics*, 39(1), 39–59. <http://doi.org/10.1007/s11187-010-9292-5>
- Foster, G. (2006). It's not your peers, and it's not your friends: Some progress toward understanding the educational peer effect mechanism. *Journal of Public Economics*, 90(8-9), 1455–1475. <http://doi.org/10.1016/j.jpubeco.2005.12.001>
- Gächter, S., Nosenzo, D., & Sefton, M. (2013). Peer effects in pro-social behavior: Social norms or social preferences? *Journal of the European Economic Association*, 11(3), 548–573. <http://doi.org/10.1111/jeea.12015>
- Harrison, C., Jorder, M., Stern, H., Stavinsky, F., Reddy, V., Hanson, H., ... Balter, S. (2014). Using Online Reviews by Restaurant Patrons to Identify Unreported Cases of Foodborne Illness — New York City, 2012–2013. *Mmwr*, 63(20), 441–445. Retrieved from <http://www.cdc.gov/mmwr/preview/mmwrhtml/mm6320a1.htm>
- Hesseliuss, P. (2009). Sick of your colleagues' absence? *Journal of the European Economic Association*, 7(2-3), 583–594. <http://doi.org/10.1162/JEEA.2009.7.2-3.583>
- Hu, L. H. L., Taylor, G., Wan, H.-B. W. H.-B., & Irving, M. (2009). A review of short-term electricity price forecasting techniques in deregulated electricity markets. *Universities Power Engineering Conference (UPEC), 2009 Proceedings of the 44th International*.
- Hu, N., Bose, I., Koh, N. S., & Liu, L. (2012). Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems*, 52(3), 674–684. <http://doi.org/10.1016/j.dss.2011.11.002>
- Kaustia, M., & Knüpfer, S. (2012). Peer performance and stock market entry. *Journal of Financial Economics*, 104(2), 321–338. <http://doi.org/10.1016/j.jfineco.2011.01.010>
- Kellerman, B. (2008). *Followership: How followers are creating change and changing leaders*. Harvard Business School Press.
- Kimmel, A. J. and K. P. . (2015). *Word of Mouth and Social Media*, Routledge.
- Koh, N. S., Hu, N., & Clemons, E. K. (2010a). Do online reviews reflect a product's true perceived quality? An investigation of online movie reviews across cultures. *Electronic Commerce Research and Applications*, 9(5), 374–385. <http://doi.org/10.1016/j.elerap.2010.04.001>
- Koh, N. S., Hu, N., & Clemons, E. K. (2010b). Do online reviews reflect a product's true perceived quality? An investigation of online movie reviews across cultures. *Electronic Commerce Research and Applications*, 9(5), 374–385. <http://doi.org/10.1016/j.elerap.2010.04.001>
- Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences*, 109(1), 68–72. <http://doi.org/10.1073/pnas.1109739109>
- Liu, Y., Huang, X., An, A., & Yu, X. (2008). Modeling and predicting the helpfulness of online

- reviews. *Proceedings - IEEE International Conference on Data Mining, ICDM*, 443–452. <http://doi.org/10.1109/ICDM.2008.94>
- Luca, M., & Zervas, G. (2013). Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud. *Harvard Business School NOM ...*, 1–25. <http://doi.org/10.2139/ssrn.2293164>
- Marimoutou, C., Queyriaux, B., Michel, R., Verret, C., Haus-Cheymol, R., Mayet, A., ... Boutin, J.-P. (2010). Survey of alcohol, tobacco, and cannabis use in the French army. *Journal of Addictive Diseases*, 29(1), 98–106. <http://doi.org/10.1080/10550880903436028>
- Mayzlin, D., Dover, Y., & Chevalier, J. (2014). Promotional Reviews : An Empirical Investigation of Online Review Manipulation. *American Economic Review*, 104(8), 2421–2455. <http://doi.org/10.1257/aer.104.8.2421>
- McCarney, R., Warner, J., Iliffe, S., van Haselen, R., Griffin, M., & Fisher, P. (2007). The Hawthorne Effect: a randomised, controlled trial. *BMC Medical Research Methodology*, 7(1), 30. <http://doi.org/10.1186/1471-2288-7-30>
- Mcpherson, M., Smith-lovin, L., & Cook, J. M. (2001). BIRDS OF A FEATHER: Homophily in Social Networks. *Annual Review of Sociology*, 27, 415–444. <http://doi.org/10.1146/annurev.soc.27.1.415>
- Miller, H. V. (2010). If your friends jumped dff of a bridge, would you do it too? Delinquent peers and susceptibility to peer influence. *Justice Quarterly*, 27(4), 473–491. <http://doi.org/10.1080/07418820903218974>
- Ost, B. (2010). The role of peers and grades in determining major persistence in the sciences. *Economics of Education Review*, 29(6), 923–934. <http://doi.org/10.1016/j.econedurev.2010.06.011>
- Park, S. B., & Park, D. H. (2013). The Effect of Low- versus High-Variance in Product Reviews on Product Evaluation. *Psychology and Marketing*, 30(7), 543–554.
- Parthasarathy, M., & Forlani, D. (2010). Do satisfied customers bad-mouth innovative products? *Psychology and Marketing*, 27(12), 1134–1153.
- Payne, D. C., & Cornwell, B. (2007). Reconsidering peer influences on delinquency: Do less proximate contacts matter? *Journal of Quantitative Criminology*, 23(2), 127–149. <http://doi.org/10.1007/s10940-006-9022-y>
- Rensink, J. . (Maarten). (2013). What motivates people to write online reviews and which role does personality play ?, (July).
- Ron, W. Z., & Toma, E. F. (2000). Peer effects in private and public schools across countries, 19(1), 75–92.
- Schneeweis, N., & Winter-Ebmer, R. (2007). Peer effects in Austrian schools. *Empirical Economics*, 32(2-3), 387–409. <http://doi.org/10.1007/s00181-006-0091-4>
- Schreck, C. J., Fisher, B. S., & Miller, J. M. (2004). The social context of violent victimization: A study of the delinquent peer effect. *Justice Quarterly*, 21(1), 23–47. <http://doi.org/10.1080/07418820400095731>
- Smith, S., Windmeijer, F., & Wright, E. (2014). Peer effects in charitable giving: Evidence from the (running) field. *Economic Journal*, 125, 1053–1071. <http://doi.org/10.1111/econj.12114>
- Sparks, B. a., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, 32(6), 1310–1323. <http://doi.org/10.1016/j.tourman.2010.12.011>
- Takehara, T., Miki, S., Nitta, N., & Babaguchi, N. (2012). Extracting Context Information from Microblog Based on Analysis of Online Reviews. *2012 IEEE International Conference on*

- Multimedia and Expo Workshops*, 248–253. <http://doi.org/10.1109/ICMEW.2012.49>
- Vandenberghe, V. (2002). Evaluating the magnitude and the stakes of peer effects analysing science and math achievement across OECD. *Applied Economics*, *34*(10), 1283–1290. <http://doi.org/10.1080/00036840110094446>
- Vera-Toscano, E., & Ateca-Amestoy, V. (2008). The relevance of social interactions on housing satisfaction. *Social Indicators Research*, *86*(2), 257–274. <http://doi.org/10.1007/s11205-007-9107-5>
- Wien, A. H., & Olsen, S. O. (2014). Understanding the relationship between individualism and word of mouth: A self-enhancement explanation. *Psychology and Marketing*, *31*(6), 416–425.
- Ye, Q., Zhang, Z., & Law, R. (2009). Sentiment classification of online reviews to travel destinations by supervised machine learning approaches. *Expert Systems with Applications*, *36*(3 PART 2), 6527–6535. <http://doi.org/10.1016/j.eswa.2008.07.035>
- Yu, X., Liu, Y., Huang, X., & An, A. (2012). Mining online reviews for predicting sales performance: A case study in the movie domain. *IEEE Transactions on Knowledge and Data Engineering*, *24*(4), 720–734. <http://doi.org/10.1109/TKDE.2010.269>
- Zabel, J. E. (2008). The Impact of Peer Effects on Student Outcomes in New York City Public Schools. *Education* *3.2*, 197–249.

Context	Key research papers	Number of papers
Movies	(Clemons, 2010b; Duan et al., 2008; Koh, Hu, & Liu et al., 2008; Yu et al., 2012)	14
Food/Restaurants	(Harrison et al., 2014; Takehara et al., 2012)	2
Online retail	(Chatterjee & Chatterjee, 2001; Dellarocas et al., 2010; Hu, Taylor, Wan, & Irving, 2009)	3
Tourism	(Chatterjee & Chatterjee, 2001; Sparks & Browning, 2011; Ye et al., 2009)	6
Books	(Hu, Bose, Koh, & Liu, 2012)	3

Variable	Description
<i>ReviewCount</i>	Number of reviews on the website
<i>Fans</i>	Number of fans
<i>averageStars</i>	Average number of ratings received for all reviews
<i>averageVotes</i>	Average number of votes received on Yelp
<i>numberOfFriends</i>	Number of friends
<i>averageCompliments</i>	Average number of compliments received
<i>numberOfDays</i>	Individual experience on the platform

Variable	Mean	Standard Deviation	Minimum	Maximum
<i>numberOfFans</i>	35.39	98.63	1	3330
<i>averageStars</i>	3.71	1.00	0	5
<i>averageVotes</i>	50.78	515.66	0	28768
<i>numberOfFriends</i>	7.87	50.77	0	1958
<i>averageCompliments</i>	3.51	69.22	0	4393.91
<i>numberOfDays</i>	1330.47	684.25	184	3652
<i>reviewCount</i>	35.39	98.63	1	3330

#observations= 9997

	Variable	1	2	3	4	5	6	7
1	<i>reviewCount</i>	1.00						
2	<i>numberOfFans</i>	0.56	1.00					
3	<i>averageStars</i>	0.01	0.01	1.00				
4	<i>numberOfFriends</i>	0.45	0.76	0.02	1.00			
5	<i>averageVotes</i>	0.52	0.72	0.01	0.58	1.00		
6	<i>averageCompliments</i>	0.39	0.58	0.01	0.47	0.85	1.00	
7	<i>numberOfDays</i>	0.32	0.14	0.02	0.13	0.11	0.06	1.00

Independent Variables	Dependent variable: <i>reviewCount</i>		
	Coefficient	Standard Error	p > t
<i>numberOfFans</i>	2.38**	0.10	0.000
<i>averageStars</i>	-0.33	0.75	0.656
<i>numberOfFriends</i>	0.05**	0.02	0.015
<i>averageVotes</i>	0.06***	0.00	0.000
<i>averageCompliments</i>	-0.20***	0.02	0.000
<i>numberOfDays</i>	0.34***	0.00	0.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$