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Influence of Social Media over the Stock Market

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ABSTRACT

This research analyzes investors' activity through social media and these media's influence over the Chicago Board Options Exchange Market Volatility Index (VIX) using a logit model and a fuzzy-set qualitative comparative analysis (fsQCA). The logit results show that social media sentiment influences stock markets. Meanwhile, the fsQCA results show that the investors' profile is important for explaining how social media influence the stock market. Particularly, holding period combined with experience in technical investors contributes to avoiding a raise in market risk, whereas for nontechnical investors message sentiment and experience form the combination that contributes to avoid a raise in market risk. © 2016 Wiley Periodicals, Inc.

From efficient market theory (Fama, 1970) to the recent emergence of behavioral finance, scholars have analyzed stock markets from different perspectives, proposing several theories to predict the stock markets' behavior. Over the years, researchers have considered many factors or variables to help in predicting markets, including information (Fama, 1970), certain patterns of behavior as herd behavior (Hirshleifer, Subrahmanyam, & Titman, 1994), or overconfidence (Odean, 1998), and some psychological theories like the prospect theory (Fiegenbaum, 1990).

More recently, new ways of sharing information and interacting with people have appeared due to the growth of digital technologies and rise in the use of the Internet. Internet users share information through social media, which comprises social networks such as Twitter, blogs, or forums such as Yahoo! Finance message boards, news Web sites such as The Wall Street Journal, and so forth. In this sense, investors, companies, institutions, and, at a more general level, society as a whole use social media to obtain and share information.

Nowadays, social media is a part of daily life, which requires the understanding of how social media influences society with a potential to change consumers' or investors' behavior, resulting in consequences that will undoubtedly reach markets at all levels. Some variables from social networks and their users can result helpful in predicting the market performance (Bissattini & Chistodoulou, 2013; Bollen, Mao, & Zeng, 2011). In this sense, one of the most used sources is StockTwits.com, which provides accurate data in order to predict market performance (Oh & Sheng, 2011). StockTwits.com is a social network similar to Twitter, where users share posts about stocks, indexes, and financial markets. The relationships among users take place through subscriptions to accounts as followers. One characteristic of StockTwits.com is that users share their opinions with their followers and with other users in real time, the sharing of information is quick, allowing faster reactions to stock market events. Another characteristic of StockTwits.com is the use of keywords that allow the classification of conversations by tickers (e.g., a tweet with a $SPX will be related to news about the S&P 500). Additionally, users' profile shows relevant information such as their experience as investors, their holding period, or the type of analysis they use to decide their investments. Considering all these features, and given that all messages users post are about financial issues, StockTwits.com is one of the most suitable social networks for analyzing the influence of social media activity over the stock market.

This research analyzes the influence of investors' activity through StockTwits.com over the Chicago Board Options Exchange Market Volatility Index (VIX). The purpose is to analyze the impact of StockTwits.com activity and StockTwits.com users on VIX, and analyze if investors' profile has any influence on VIX. With

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this aim, this research combines a logit model with a fuzzy-set qualitative comparative analysis (fsQCA). Logit models focus on the individual influence exerted over a categorical variable by certain predictors, whereas fsQCA analyzes the effect driven out from the combination of those predictors. These analyses take into account different variables related to social media activity such as users' experience, message sentiment, number of followers, and holding period. The study takes these variables from StockTwits.com users' profile and uses them with the aim of analyzing how investors' profile influences market risk. The sample contains daily data regarding messages posted by investors in StockTwits.com during the 2013–2015 period. This study contributes to discovering the effect that social networks have in stock markets through the analysis of the combination of social network users' characteristics, trying to understand which type of investor exerts a greater influence through their messages on social networks.

The structure of the article is as follows. In Section "Theoretical Background," a theoretical background is presented. Section "Method" describes the data and method. Section "Results and Discussion" presents and discusses the results from the analyses. Finally, Section "Conclusion" concludes and offers guidelines for future research.

THEORETICAL BACKGROUND

The study of the influence of blogs and microblogs over stock markets is relatively recent. Some authors have analyzed the relationship between microblogging messages and stock markets. Wysocki (1998), for example, analyzes the messages of Yahoo! message boards, finding that message volume predicts changes in next-day stock returns. However, Tumarkin and Whitelaw (2001) showed that the number of messages of RagingBull.com does not predict next-day stock returns. In this sense, Sprenger, Tumasjan, Sandner, and Welpe (2014) report no relationship between Twitter messages volume and stock returns, but they find relationship between messages volume and trading volume. Meanwhile, Bordino et al. (2012) show that querying activity of Yahoo! search can anticipate movements in trading activity of the same stocks; and Oliveira, Cortez, and Areal (2013) state that StockTwits.com posting volume can improve the forecast of trading volume. In this sense, they argue that social media can have influence over the stock market.

H1: A relationship exists between social media indicators and stock markets.

Recently, some researchers have studied the relationship between the sentiment or mood extracted from microblogging messages and stock markets. Thus, Antweiler and Frank (2004) establish that bullishness indices constructed using methods from computational linguistics have a relationship with trading volume, so that they show some predictive capability. They also find that the observed relationship is stronger from trading volume to bullishness than from bullishness to trading volume. In this sense, Sprenger et al. (2014) discovers a significant relationship between bullishness and returns. Furthermore, Tetlcok (2007) shows that media pessimism can predict down movements in stock prices. Meanwhile, Zhang, Fuehres, and Gloor (2011) state that collective hope and fear present a negative correlation with Dow Jones, NASDAQ, and S&P 500, and a positive correlation with VIX. Regarding the association between mood and stock market indicators, Bollen et al. (2011) show that public mood can improve the accuracy of the predictions about Dow Jones. Another variable extracted from microblogging messages is collective economic opinion calculated as the count of retweets containing a certain type of words such as dollar, job, or economy (Zhang, Fuehres, & Gloor, 2012). Zhang et al. (2012) show that this variable presents a correlation with financial market movements. In this sense, Giannini and Irvine (2012) measure the divergence of investors' opinions from Twitter and establish that divergence of opinions in the preannouncement period turns into more negative postearnings announcement returns. However, the most used variable in last years is the sentiment extracted from microblogging messaging. Thus, Oh and Sheng (2011) show that stock microblog sentiments have predictive power for market returns; Ranco, Aleksovski, Caldarelli, Grčar, and Mozetič (2015) show that sentiment from Twitter relates to the direction of cumulative abnormal returns; and Rao and Srivastava (2012) elaborate a simple hedging strategy based on trade signals from Twitter (including sentiment) with a high predicting accuracy (91%). However, Oliveira et al. (2013) do not find evidence of returns predictability using sentiment indicators, and Logunov and Panchenko (2011) do not find any relationship between Dow Jones index returns and sentiment indices, justifying these results by arguing that the construction of the index is too simple. However, experts can use information from microblogs to make accurate predictions about returns and about stock market movements, and consequently implement good trading strategies, especially based on sentiment analysis (Bissattini & Christodoulou, 2013; Ruiz, Hristidis, Castillo, Gionis, & Jaimes, 2012).

H2: Social media sentiment influences stock markets.

A vast majority of researchers have analyzed the relationship between stock market variables and one microblogging variable such as posting volume (Tumarkin & Whitelaw, 2001; Wysocki, 1998) or message sentiment (Bissattini & Christodoulou, 2013). However, some authors have analyzed two or more microblogging variables together and their influence in stock market.

In this regard, Antweiler and Frank (2004) analyze the relationship between stock market and the messages volume, the bullishness, and the agreement extracted from Yahoo! Finance and RagingBull.com message boards. Meanwhile, Ruiz et al. (2012) simulated investments taking into account different microblogging variables, such as number of tweets and number of different users that posted a tweet. Sprenger et al. (2014) show that some microblogging variables have a relationship with the quality of the investment advice, such as messages volume, followership, and the number of retweets, concluding that users who provide high-quality investment advice receive more attention in microblogging forums measured by means of higher levels of retweets and larger followership.

H3: Interaction among microblogging variables influences stock markets.

Studies have already stressed the importance of the investors' profile. Thus, information about the experience of the investors, their preferences about investing in the long or the short term, the analysis that they do to decide when and where to invest, or the number of followers may be relevant. In fact, Giannini and Irvine (2012) measure social network impact as a function of the number of followers of a certain user, whereas Sprenger et al. (2014) use the number of followers to measure the user's influence. Li and Hendler (2013) use the trading experience and the investing approach of the investors to classify the sample of their study with the aim of characterizing the investors' attention dynamics related to trading.

H4: The investors' profile is important for understanding how social media activity influences stock markets.

METHOD

Data

This study uses the microblogging platform StockTwits.com as data source for stock microblogging activity, instead of other potential microblogging contexts (e.g., Twitter, Facebook), because the only users of this platform are the financial community and all messages are available through the Web site's application programming interface (API). The analyzed period comprises from January 1, 2013 to August 31, 2015. During this period, 90.786 stock-related microblogging messages holding the dollar-tagged ticker symbol of S&P 500 index were collected. The data are focused on the S&P 500 in order to adequately reflect the entire range of U.S. equities, and because it is the basis used to calculate the VIX index.

In order to obtain the message sentiment of the stock-related microblogging messages, the study uses the sentiment analysis software Stanford CoreNLP Natural Language Processing Toolkit (Manning et al., 2014). The results show a sentiment value for each message classified into a Likert scale from -2 (very negative sentiment) to 2 (very positive sentiment), being 0 the neutral sentiment.

With the aim of obtaining a balanced database for the fsQCA analysis, the study deletes days without VIX activity (weekends and holidays). To create two representative samples of the type of investors, the authors considered the analysis that the investor used. The final two samples contain 674 days: the first sample comprises users who use technical analysis, and the second one includes users who use another type of analysis such as fundamental analysis, global macroanalysis, or momentum analysis.

Variables/Conditions

The dependent variable is *vrisk* (variation of risk), which collects the daily variation of the VIX index. In the logit model, this is a binary variable in terms of 1 and 0, so that if the variation is positive the variable takes the value 1 and the value 0 otherwise (see Section "Logit Model"). Meanwhile, in the fsQCA model, this variable collects the calibrated variations (see Section "fuzzy-set Qualitative Comparative Analysis").

The set of independent variables in the system includes daily sentiment, daily experience, daily holding period, and number of followers. The calculation of daily sentiment, daily experience, and daily holding period is as follows: the sentiment of each message was multiplied by the number of messages posted by the user who wrote that message on a certain day t, and then the calculation of daily average of all users is as a weighted average, resulting in a sentiment that is always negative (see Table 1); the study multiplies the experience of each user by the number of messages that user posted on a certain day t, and then the study calculates the daily average of all users as a weighted average; the study multiplies the holding period of each user by the number of messages that user posted on day t, then calculating the daily average of all users as a weighted average. Acting this way, the experience, the sentiment, and the holding period for a certain day with high message activity exert a heavier effect than the experience, the sentiment, and the holding period of another day with low message activity. Finally, the study calculates followers as the average of the followers for each user that post one or more messages in a given day t.

Logit Model

The logit model is a binary choice regression model that uses the logistic function as the cumulative distribution function. This is a suitable approach for analyzing the individual influence certain variables exert over the dichotomous variation of market risk defined in Section "Variables/Conditions." With this aim, the model

Table 1. Summary Statistics.

Variable	Observed	Mean	SD	Minimum	Maximum
		Technical Analysis			
vrisk	674	0.4584	0.4986	0.0000	1.0000
exp	674	5.6482	0.8011	3.7500	9.3132
sent	674	−1.6422	0.2522	−2.6600	−0.8750
holdp	674	3.9346	0.5249	2.5926	5.7396
follow	674	18,512.7400	4483.3290	7254.0870	37,600.0000
		Nontechnical Analysis			
vrisk	674	0.4570	0.4985	0.0000	1.0000
exp	674	5.1471	1.4032	2.8333	15.4000
sent	674	−1.8276	0.4002	−4.2500	−0.9623
holdp	674	5.4224	1.6668	2.6000	23.0435
follow	674	35,710.3700	19,120.7100	7840.5450	201,977.8000

vrisk = variation of VIX; exp = experience; sent = sentiment; holdp = holding period; follow = followers.
N = 674 days (January 2013–August 2015).

proposed is as follows:

$$vrisk_t = \beta_0 + \beta_1 exp_t + \beta_2 sent_t + \beta_3 holdp_t + \beta_4 follow_t + \delta mn_t + e_t, \quad (1)$$

where:

- $vrisk_t$: variation between risk of day t and day $t-1$;
- exp_t: weighted average of experience for users that posted at least one message in day t;
- $sent_t$: weighted average of sentiment for messages posted in day t;
- $holdp_t$: weighted average for the holding period of users that posted at least one message in day t;
- $follow_t$: average of followers for users that posted at least one message in day t; and
- mn_t: monthly dummy variables.

fsQCA

Qualitative comparative analysis (QCA) is an analytic technique that combines quantitative and qualitative methodologies (Ragin, 1987, 2006, 2008). Although this technique originally focused on small samples, further developments have adapted QCA for application in bigger samples.

This research uses fsQCA, one of the QCA variants, and applies a method of direct calibration (Ragin, 2008). This calibration method uses three thresholds to determine the membership or nonmembership to the set. Precisely, fsQCA assigns membership values to conditions on a scale from 0.0 (total exclusion) to 1.0 (total membership), with 0.5 as the maximum ambiguity point. This assignation is the set calibration.

To transform ordinary data in fuzzy sets, the study uses the following thresholds: 90th percentile (total membership), 50th percentile (maximum ambiguity), and 10th percentile (total exclusion). In particular, for the *vrisk* condition (variation of risk), the value 0 represents the medium point.

QCA establishes relationships among conditions in terms of necessity and sufficiency in order to produce the outcome (Ragin, 2008). Thus, this research deploys a necessity analysis, distinguishing between technical investors and nontechnical investors, with the aim of finding the necessary conditions to avoid a positive variation in market risk. The study defines the following sufficiency model, where the conditions are the ones described in Section "Variables/Conditions":

$$vrisk = f\ (\exp, sent, holdp, follow) \quad (2)$$

RESULTS AND DISCUSSION

Table 1 shows the summary descriptive statistics of message features for the two previously defined samples (technical investors and nontechnical investors).

These data show that experience of users who use technical analysis has a mean of 5.65, whereas the mean experience of users who do not use technical analysis is 5.15, which implies that users who use technical analysis tend to have a little more experience than the users that do not use technical analysis. The sentiment has a negative mean in both samples, but the mean is more negative in the sample of users who do not use technical analysis, which means that the use of other type of analysis different from the technical approach leads to a more pessimistic opinion. The mean of the holding period is higher when considering users who do not use technical analysis. Finally, the average number of followers for users who do not use technical analysis is higher than the number of followers for users who do, but the standard deviation is higher too, which means that some users do not use technical analysis and have a higher number of followers, and other users do not use technical analysis and have a lower number of followers, whereas users who use technical analysis have a more homogeneous number of followers.

Table 2. Summary Statistics after Calibration.

Variable	Observed	Mean	SD	Minimum	Maximum
		Technical Analysis			
vrisk	674	0. 4834	0. 3207	0	1
exp	674	0. 4974	0. 3378	0	1
sent	674	0. 5003	0. 3363	0	1
holdp	674	0. 4920	0. 3420	0	1
follow	674	0. 4914	0. 3353	0	1
		Nontechnical Analysis			
vrisk	674	0. 4800	0. 3226	0	1
exp	674	0. 4783	0. 3350	0	1
sent	674	0. 5091	0. 3296	0	1
holdp	674	0. 4882	0. 3393	0	1
follow	674	0. 4818	0. 3404	0	1

vrisk = variation of VIX; exp = experience; sent = sentiment; holdp = holding period; follow = followers.

N = 674 days (January 2013–August 2015).

Table 3. Logit Regression.

	Technical	Nontechnical
Dependent Variable	vrisk	vrisk
exp	0.1323 ($p = 0.589$)	−0.0427 ($p = 0.683$)
sent	−0.0935 ($p = 0.885$)	***0.5569*** ($p = 0.080$)
holdp	−0.4491 ($p = 0.122$)	−0.0081 ($p = 0.913$)
follow	-3.92×10^{-6} ($p = 0.852$)	$6.61 \times {}^{-6}$ ($p = 0.199$)
Goodness-of-fit test	0.7287	0.5673

Method = logit regression; vrisk = variation of VIX; exp = experience; sent = sentiment; holdp = holding period; follow = followers.

Monthly dummy variables were included in the regression, but they are not reported. p Values are shown next to their coefficients. Coefficients that are significant at a 95% confidence level are reported in bold. Coefficients that are significant at a 90% confidence level are reported in bold and italics.

N = 674 days (January 2013–August 2015).

Table 2 shows descriptive statistics after the calibration. Table 3 shows the estimation using the logit method for each sample. Regarding technical investors, only monthly dummies are significant for the explanation of the qualitative variation of VIX, whereas users' experience, message sentiment, holding period, and number of followers are not significant. These results may be indicating that technical users take into account other factors apart from the ones proposed to decide their investment strategy, such as charts analysis or temporal context. Considering nontechnical users, no significant relation exists between the variables, except for message sentiment, which shows a positive influence, indicating that the sentiment disclosed by this type of investors exerts some influence over market risk. These results confirm hypothesis 4.

In addition to the logit estimation results, and following Woodside (2013), this study performs an fsQCA to obtain a deeper insight of the interaction between social network variables and stock market. The necessity analysis yield no necessary conditions to avoid a positive variation in market risk, in so far as consistency is below 0.9 (Schneider, Schulze-Bentrop, & Paunescu, 2010). Table 4 shows the results of this necessity analysis.

Table 4. Analysis of Necessary Conditions.

	Technical Analysis		Nontechnical Analysis	
Conditions Tested: vrisk	Consistency	Coverage	Consistency	Coverage
Exp	0.6232	0.6472	0.6089	0.6619
∼exp	0.6085	0.6254	0.6206	0.6186
Sent	0.6127	0.6326	0.6282	0.6655
∼sent	0.6216	0.6426	0.6282	0.6655
Holdp	0.6168	0.6476	0.6202	0.6606
∼holdp	0.6107	0.6210	0.6079	0.6177
Follow	0.6176	0.6492	0.5917	0.6386
∼follow	0.6259	0.6357	0.6326	0.6348

∼ Represents the NOT operator.

Vrisk = variation of VIX; exp = experience; sent = sentiment; holdp = holding period; follow = followers.

N = 674 days (January 2013–August 2015).

For the sufficiency analysis, the study uses the intermediate solution because this solution incorporates the hypotheses that are consistent with the referred literature (Schneider & Wagemann, 2012; Table 5).

The results from the sufficiency analysis show that eight combinations of the different features considered in this research contribute to explain a nonpositive variation in the VIX index. That is, these combinations represent the eight paths where the volatility does not get higher and, as a consequence, they contribute to avoid a raise in the risk perceived in the market.

The first three combinations (paths 1–3) refer to technical investors, whereas the other five combinations (paths 4–8) relate to nontechnical investors. These combinations fit into two different categories. A first set includes combinations where experience and sentiment appear simultaneously. This first set includes paths 3, 4, 5, 7, and 8. Except for path 3, the combinations in this first set refer to nontechnical investors.

A second set includes combinations where experience and holding period appear jointly. This second set includes paths 1, 2, and 6. Except for path 6, the combinations in this second set refer to technical investors.

Focusing on the first set, path 3 informs that in a context of weak negative sentiment (*sent*), experienced technical investors (*exp*) with large audiences (*follow*) contribute to avoiding a raise in market risk. For nontechnical investors, in a context of strong negative sentiment (∼*sent*), the risk does not increase, even if they are not experienced investors (∼*exp*), when their audience is small (∼*follow*), as shown in path 4, or when they focus on the long term (*holdp*), as in path 5. Finally, nontechnical investors in a context with weak negative sentiment (*sent*) contribute to avoiding a raise in market risk when they have experience as investors

Table 5. Analysis of Sufficiency Conditions.

Path Number		Raw Coverage	Unique Coverage	Consistency
			Technical Analysis	
1	~holdp*exp	0.3216	0.0603	0.7928
2	~follow*holdp*~exp	0.2511	0.0530	0.8121
3	follow*sent*exp	0.2798	0.0423	0.8051
	Solution coverage: 0.4303			
	Solution consistency: 0.7775			
			Nontechnical Analysis	
4	~follow*~sent*~exp	0.2661	0.0380	0.7992
5	holdp*~sent*~exp	0.2541	0.0136	0.8098
6	follow*~holdp*exp	0.2622	0.0373	0.8207
7	~holdp*sent*exp	0.2632	0.0275	0.8118
8	follow*sent*exp	0.2485	0.0325	0.7939
	Solution coverage: 0.4623			
	Solution consistency: 0.7678			

Note: Intermediate solution.
Frequency cutoff: 10; consistency cutoff: 0.80.
* Is the AND operator.
~ Represents the NOT operator.
vrisk = variation of VIX; exp = experience; sent = sentiment; holdp = holding period; follow = followers.
N = 674 days (January 2013–August 2015).

(*exp*), even if they focus on the short term (~*holdp*), as shown in path 7, and when they have a large audience (*follow*), as seen in path 8.

Turning the sights toward the second set, path 1 informs that experienced technical investors (*exp*) contribute to avoiding a raise in market risk, even if they focus on the short term (~*holdp*). However, when analyzing nonexperienced technical investors (~*exp*), they must focus on the long term (*holdp*) and have a small audience (~*follow*) in order to not increase market risk, as shown in path 2. Finally, nontechnical investors contribute to avoiding a raise in market risk if they have experience as investors (*exp*) and a large audience (*follow*), even if they focus on the short term (~*holdp*), as in path 6.

To sum up, social media activity that investors deploy proves to be significant for the variation of risk in financial markets, which is consistent with previous research (Sprenger et al., 2014), and confirms Hypothesis 1. For the explanation of this influence, the study identifies the combination of several social media variables along eight different paths, confirming Hypothesis 3. Sentiment is one of the most prominent variables in these combinations, appearing in five of eight selected paths, which confirms Hypothesis 2 and agrees with previous studies (Oh & Sheng, 2011; Rao & Srivastava, 2012). In addition, the relevant features change according to the investors' profile, confirming Hypothesis 4. In particular, for technical investors, the two most prominent features are experience and holding period; investors must have a wide experience and focus on the long term in order to contribute to avoiding a raise in market risk. However, when analyzing nontechnical investors, the two most relevant features are experience and sentiment, and these investors can contribute to avoiding a raise in market risk even in a context of strong negative sentiment.

CONCLUSION

This research uses a logit model and a fsQCA approach to analyze the influence of investors' activity through social media over the VIX index. The logit results show that none of the variables, except for temporal dummies, are significant for technical investors. Nevertheless, regarding nontechnical investors, message sentiment are significant according to the logit estimation. Meanwhile, the fsQCA analysis shows that a number of combinations of social media variables influence the stock market, but these combinations tend to vary depending on the type of investor. Thus, concentrating on technical investors, experience and holding period are the two main characteristics that combine in order to avoid a raise in market risk. Focusing on nontechnical investors, experience and sentiment appear as the two main explanatory features, and evidence shows that this type of investors can contribute to avoiding a raise in market risk even if the environment is strongly pessimistic.

Ultimately, these results prove that social networks influence investors' decisions, and that this influence leads to a variation of the market risk. Furthermore, this study shows how message sentiment has an important effect in the relationship between social networks and stock markets. Another contribution refers to how certain combinations among different social network variables are responsible for this observed effect over the stock market. Finally, investors' profile is important for explaining how social network activity influences stock markets. These conclusions are consistent with previous studies that find a correlation between social media activity and stock markets activity and they show the relevance of investors' social media activity. Investors should take this activity into account to elaborate more accurate investment strategies (Burisch & Wohlgemuth, 2016).

Regarding limitations and guidelines for further research, this study only uses daily data, whereas microblogs offer the possibility of intraday analysis, providing an interesting approach for future investigation. Additionally, this study focuses exclusively on the United States, so further research should consider enlarging the scope to investigate if these results are consistent in different contexts (Lynch & Jin, 2016). Although StockTwits.com is one of the most used microblogging platforms, future studies should explore other similar sources. Another possibility for research involves considering other financial indicators along the S&P 500 index, including stock indexes, individual stocks, or currency exchange ratios, in order to analyze the generalizability of the results in this study.

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