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The impact technical and non-technical investors have on the stock market: Evidence from the sentiment extracted from social networks

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ABSTRACT

This research analyzes the differences between the activity shown by technical and non-technical investors by means of social media and its influence on measurement of market risk with the VIX index using a logit model. The results show that the activity of technical investors by means of social media has no effect on the risk perceived in the market. However, the sentiment of non-technical investors influences market risk, their experience, their holding period and their number of followers, reveal that investor profile is important when understanding how social networks influence stock market activity. Thus, we show that investor profile helps in understanding the influence of social networks over the stock market, and most importantly, this influence varies depending on the type of investor, either technical or non-technical.

1. Introduction

For decades, financial researchers have been trying to understand how stock markets work and how we can forecast how they will perform. Traditionally the view in the financial world has been that investors are completely rational, and that markets are efficient when prices fully reflect available information (Fama, 1970). However, sometimes a few anomalies occur because investors act irrationally so some researchers began to analyze certain biases or psychological theories about investors, such as, for example: overconfidence (Daniel and Titman, 1999), herd behavior (Avery and Zemsky, 1998) or underreaction and overreaction (Shiller, 1979, 1981). That is how behavioral finance appeared which has become a new school in finance.

Within behavioral finance, it is important to analyze investor sentiment because this improves the forecast of market returns (Bissattini and Christodoulou, 2013). There are different ways of calculating it. Firstly, this can be done using market indicators (Qiu and Welch, 2004; Bandopadhyaya and Jones, 2006; Baker and Wurgler, 2006); and secondly, with the emergence of social networks and with the breakthroughs in linguistic analysis software, a new type of sentiment has appeared, microblogging sentiment. This one is extracted from microblogging messages such as for example posts on Twitter (Bollen et al., 2011; Sprenger et al., 2014), messages on Yahoo! Finance (Antweiler and Frank, 2004), or posts on StockTwits.com, a social network specialized in financial markets (Oh and Sheng, 2011; Rao and Srivastava, 2012). Moreover, there are different types of investors and their relationship with stock markets can also be different. For example, the sentiments of individual or institutional investors may not be the same, and reveal more or less rationality (Verma and Verma, 2008). Additionally, the characteristics of investors in social networks (number of followers or investing approach) vary their market influence (Irvine and Giannini, 2012; Li and Hendler, 2013; Sprenger et al., 2014).

This research analyzed the differences between the influence of technical and non-technical investors by means of social network activity, specifically StockTwits.com, on market risk. Its goal is to analyze if the type of investor makes a difference to the impact StockTwits.com activity has, and what variables derived from the investor profile have an individual influence over the risk perceived in the market. With this aim, we have used a logit and a probit model, which can analyze the individual influence that some predictors have applied to a categorical variable. The analysis has taken into account variables related to the profiles of social network users such as experience in making investments, the number of followers and the holding period. In order to differentiate the type of investor another characteristic was considered: the investment approach. In this way, we have classified

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the users into two categories: those who use technical analysis and those who use other types of analysis such as fundamental analysis, momentum analysis or value analysis. Furthermore, the message sentiment was considered too because its influence on the stock market is tested. The sample was made up of daily data regarding messages posted by investors on StockTwits.com from 2009–2015. In short, the aim of this study is to contribute towards understanding the effect that social networks have on the stock market, and specifically to understand if social network messages have more or less influence on it depending on the investor type.

The paper is structured as follows. In Section 2, the theoretical background is presented. Section 3 describes the data and the analysis method. Section 4 presents and discusses the results of the model put forward. Finally, in Section 5 there is a conclusion and guidelines for future research are suggested.

2. Theoretical background

Nowadays there are two different schools in finance. Firstly, there is the traditional school made up of those researchers who consider markets efficient, which follows Fama (1970). Secondly, there is the behavioral school, which includes those researchers who think that investors sometimes act irrationally, and that this behavior leads to certain anomalies in the market. Fama refers to efficient market when the "prices always fully reflect available information" (Fama, 1970 1), so agents always behave rationally. According to this theory, information is an important element, since there are three levels of efficiency based on the information available, weak-form efficiency, semi-strong-form efficiency and strong-form efficiency. In weak-form efficiency, the information available is just past prices or returns, so it is not possible to predict future prices by looking at past prices. Semi-strong-form efficiency implies that all public information is available and prices adjust to new information quickly. In strong-form efficiency, prices reflect all information, so any investor or group has monopolistic access to any important information. Some authors criticize these assumptions suggesting that markets are inefficient because they underreact and overreact to information (Shiller, 1979, 1981; De Bondt and Thaler, 1985), and some investors are not completely rational (Barberis and Thaler, 2002). These investors are known as noise traders (De Long et al., 1990) and they are significant because the risk noise traders pose can force rational investors to liquidate their positions prematurely, which may cause them potential losses (Barberis and Thaler, 2002). In this way, some researchers have realized that a few psychological theories could be used to explain investor behavior, which is why behavioral finance emerged as a discipline in this field of knowledge. Then, behavioral finance argues that some deviations in asset prices from their fundamental value are brought about by the presence of investors who are not fully rational (Barberis and Thaler, 2002). Therefore, the pedagogical goals of behavioral finance are to identify the mistakes that are commonly made by investors and analyze how to avoid them, and to identify which strategies maximize market returns (Subrahmanyam, 2008).

Behavioral finance states that psychological factors can affect the decisions investors make, with sentiment being one of these. Investor sentiment can be defined as how investors form beliefs (Barberis et al., 1998). Over time, several ways to measure investor sentiment have appeared; for example, the measures extracted from the Closed-End Fund Discount (CEFD) (Qiu and Welch, 2004); or the Equity Market Sentiment Index (EMSI) (Bandopadhyaya and Jones, 2006). Other known way to measure investor sentiment is the index elaborated by Baker and Wurgler (2006) based on six proxies: the Closed-End Fund Discount, the NYSE share turnover, the number of and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. With the rise of the Internet and more specifically, of social media, new ways to measure sentiment have appeared. Some social networks offer the possibility of indicating the mood or the sentiment at the time the user posts the message. In this sense, the user can use emoticons (Logunov and Panchenko, 2011; Gilbert and Karahalios, 2010) or words, such as bullish to express a positive sentiment, or bearish or fear to express a negative one (Oliveira et al., 2013; Zhang et al., 2011, 2012). Due to advances in the area of language analysis, some researchers have also used sentiment analysis software for extracting the sentiment of the messages posted by social network users (Antweiler and Frank, 2004; Tetlock, 2007; Bollen et al., 2011; Oh and Sheng, 2011; Chekanskiy, 2012; Piñeiro Chousa et al., 2016; Makrehchi et al., 2013; Sprenger et al., 2014).

We have used the sentiment analysis software of Standford University, Standford CoreNLP Natural Language Processing Toolkit (Manning et al., 2014) for extracting sentiment from microblogging messages. This software analyzes the sentiment found in each word in a sentence, and calculates the overall sentiment of the sentence as a whole. We have chosen this software because it is widely used by the NLP researchers and because it uses the Recursive Neural Tensor Networks that obtains 80.7% accuracy on sentiment prediction. This software also captures negation at positive and negative sentences accurately (Socher et al., 2013). This sentiment is a Likert scale where the lowest score is −2, which means very negative sentiment, and the highest score is 2, which is very positive sentiment, with 0 being neutral sentiment.

Considering the relationship between social media sentiment and stock market activity, it is true that in several previous studies no evidence was found of the relationship between the sentiment extracted from microblogging messages and stock market returns and movements (Logunov and Panchenko, 2011; Oliveira et al., 2013). This could possibly be due to the sentiment extraction method because these authors did not use sentiment analysis software. However, it is also true that other authors have proved that sentiment extracted from microblogging messages can help to predict stock market returns and movements. For example, Oh and Sheng (2011) found that microblogging sentiment contains valuable information for investment decision-making and about the influence of irrational investors on market prices. Furthermore, there is the study of Rao and Srivastava (2012), who created a system that could maximize directional accuracy forecasts in portfolio adjustments, and elaborated a simple hedging strategy based on trade signals from Twitter including sentiment. Additionally, there is the study of Ruiz et al. (2012), who analyzed the correlation of stock market events with several features on Twitter, and who attempted to elaborate a trading strategy based on sentiment analysis.

Therefore, some investors are not rational and are influenced by internal and external factors, so it is possible that different types of investors behave differently. For example, institutional investor sentiment is more rational than that of individual investors (Verma and Verma, 2008) because the responses of institutional investor sentiment to a greater number of risk factors of a greater magnitude suggest that the expectations of the institutional investors are more rational than the individuals' expectations. In this way, if social networks are taken into account, it would be wise to consider that the profile of the investors is also an important variable that can be of significance in the relationship between social networks and stock markets. In the user's profile, there is important information to consider, such as their number of followers or their number of retweets that can be useful for measuring the impact or the influence a certain user has (Irvine and Giannini, 2012; Sprenger et al., 2014). For this reason, in this study several variables related to the profiles of social network users have been taken into account. For example, their experience in investment, considering three levels: novel, intermediate and expert; the number of followers, and