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Social media and capital markets. An overview.

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Abstract

A growing body of research and practical applications employ social media data as a proxy for complex behavior of a society. This paper provides an overview of academic research related to link between the social media and capital markets. Its theoretical rationale is predominantly defined by behavioral finance. Behavioral finance augments standard model of efficient markets and considers less rational factors like investors' sentiment or public mood as influential for asset pricing or capital market volatility. In this context, social media is a novel tool which enables to collect the data about such less rational factors at the level of a society. The paper introduces social media data from technical and economic point of view. Further, it contributes to the theoretical construction of the transmission mechanism between social media and capital markets currently missing in the literature. Subsequently, the paper summarizes the main findings in this field and outline its future prospects.

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Keywords: social media; retail investors; information demand; sentiment; transmission mechanism

1. Introduction

Social media can be classed without dispute among the current phenomena in our society. Social media connects people from all over the world into one virtual community. The main goal of social media is the ability to accomplish an easier communication and content sharing. However, for the purpose of this paper another and any less fact is relevant. Social media is a great database of society's behavior. Data provided by social media, so called "big data", are becoming very popular and many practical applications as well as academic research have been accomplished in this field. The goal is clear, to better understand the behavior of a society.

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The purpose of this paper is an overview of the current state of the art in the research related to employment of social media big data in the field of capital markets. The main focus is to provide the inclusion in this growing research, summarize main findings and outline the future evolution of this field. The contribution of the paper is the theoretical proposal of the transmission mechanism from social networks to capital markets. Despite the growing research, there has been no clear definition of this relationship yet. The rest of the paper is structured as follows. The next section provides the reader with an understanding of social media, its forms and functioning. Further, it describes the basic definition of big data. These two chapters are quite technical, but very important if one would like to understand the challenges in the collection of data about society's behavior via social media. The third section presents the link between social media and capital markets from an economic point of view in the form of the transmission mechanism. The fourth section summarizes the contributions and findings of several important papers. Last section concludes and proposes the potential prospects of the further research.

2. Understanding of social media

From a technical point of view, social media are web-based or mobile technologies necessary for operating of highly interactive platforms where users create, modify and share user-generated content (Kietzmann et al., 2011). Boyd & Ellison (2008) use instead of the term "social media" the term "social network site" and characterize it also as a web-based services which allow for users to create public or semi-public profile and create a tree of connections with other users. Kaplan & Haenlein (2010) describe social media as internet-based applications that incorporate the ideas and technology of previous web structure like Web 2.0 but allow for individual users in the creation and exchange of web content.

Social media has evolved into many forms. Kaplan & Haenlein (2010) provide the classification scheme to sort social media in the systematic manner. However, for the purpose of this paper, this deeper classification is not relevant because the research related to capital markets uses predominantly the data from social media Facebook and Twitter. The choice of these two social media is most likely related to practical reasons like data availability, number of users or high popularity in the western world, because current research in this field examines US or advanced European capital markets. Deeper understanding of the social media functioning is provided in the paper of Kietzmann et al. (2011) who constructed a framework of seven social media building blocks. This framework describes the social media environment and social media audience in detail. For the purpose of this paper, building blocks "Sharing" and "Conversations" are the most important because they are the source of "big data". In other words, social media users lead conversations in many forms like Facebook "comments" or Twitter "tweets" and they are able to share them with others. Such a data can be collected and further analyzed. However, these two blocks are results of other blocks, in particular "Presence", "Identity", "Groups", "Relationships" and "Reputation". Their functionalities and explanation are shown in Kietzman et al. (2011).

The big data provided by social media are not the only source of data employed in the analysis related to capital markets. Several papers presented below employ data from search engine Google. To be specific, Google provides data about the volume of searches for given phrase so called Google queries. These search queries are considered in this paper also as a big data because its provide the insight about the interest of a society in the searched topic. From a technical point of view, the Google search engine is not a standard social media like Twitter and Facebook, but from a practical point of view this discrepancy is not relevant for the purpose of this paper. In general, Google provides data about society's behavior as well as the Twitter or Facebook.

2.1. Big data

Previous part introduces the definition of social media and search engine Google as a sources of big data related to applications on capital markets. However, big data require characterization of its own. Halevi & Moed (2012) defines big data as the large sets of data which cannot be processed by traditional management tools due to their size and complexity. Big data are high-volume, high-velocity and high-variety information that requires cost-effective and innovative approach to processing of data which release the opportunity for enhanced insight, decision making and process automation (Beyer & Laney, 2012; Gartner, 2015). The previous definitions need to be augmented in the line with the idea of this paper. To be specific, big data are large data sets related to the behavior of individuals and society.

It has to be processed computationally due to its complexity. In the field of capital markets, data from social media Twitter, Facebook and search engine Google are applied to reveal the deeper insights, trends and associations between the society and capital markets.

The each above definition incorporate the issue of difficulty in a big data processing and it is the one of the most important points in the big data research. Social media data has to be downloaded, analyzed and transformed from qualitative into quantitative form. The "data-mining" and "machine learning" methods have been proposed to deeply analyze the big data and these methods evolved to autonomous fields of study. Detail, especially technical information about data-mining and machine learning are provided in the research of Pang & Lee (2008); Russel (2011), Liu (2012), Dařena & Žižka (2013). In the context of the paper, data from Twitter and Facebook need to be transformed from the qualitative nature to quantitative one by the above mentioned methods. These quantitative data can be later employed in an econometric modeling. An exception are data of Google queries and Facebooks's Gross National Happiness Index (FGNHI) publicly available in the standardized outcome. Google provides data in the quantitative form only, as the volume of a specific search phrase expressed as an index. Similarly, Facebook developed the FGNHI which provides the daily sentiment data for twenty international markets. This index consists of a number of anonymous positive and negative words employed in comments of people.

3. Economic rationale in social media big data applications

Social media big data captures the activity of individuals, interactions among them or more precisely the complex behavior of a society. Society's behavior and its relation to capital markets are a dominant part of analysis in the field of behavioral finance. Therefore, especially the behavioral finance framework serves as a main motivation for the employment of social media big data in the field of capital markets. In particular, behavioral finance challenges the notions of efficient markets and proposes the factors like animal spirits (Shiller, 1984), social mood (Nofsinger, 2005), investor sentiment (Baker & Wurgler, 2007) or psychological factors (Fenzl and Pelzmann, 2012) as a source of market volatility and anomalies. The previous research employed questionnaires (Case & Shiller, 2003) or derived sentiment proxy (Baker & Wurgler, 2007) to capture such factors. However, only social media bring the opportunity to collect detailed data about these factors at the aggregate level of a society. The next important contribution of behavioral finance research is the realistic assumption about the existence of investors with bounded rationality (De Long et al., 1990, Shleifer & Vishny, 1997, Barberis, Shleifer & Vishny, 1998). In the reality, these less rational investors are especially the retail (small or individual) investors. In the future, one can even assume the increasing number of retail investors due to technological development and growing number of trading platforms. These economic agents are a major part of the transmission mechanism from social media to capital markets. Their existence has two following economic interpretations in the current research.

3.1. Information demand

The first idea is based on the information demand of investors, so called investors' attention. In particular, retail investors use investment forums of social media or search engine Google as a publicly available source of information because they have limited sources and access to professional databases like Bloomberg or Thomson Reuters. This idea is presented in papers of Da et al. (2011), Vlastakis & Markellos (2012), Ding & Hou (2015) who employ the Google queries in their analysis. Information demand is also presented in Sprenger et al. (2014a, b), who propose the investment forums of Twitter as an alternative information source for retail investors. Investment forums on social media connect professional retail traders and they discuss the market or security fundamentals. The rationale of information demand is presented in Figure 1 which show simple transmission mechanism.

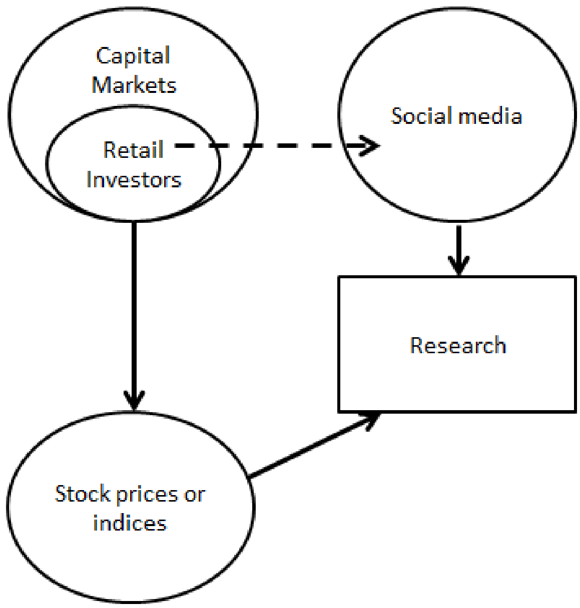

Fig. 1. Transmission mechanism – Information demand

Transmission mechanism begins with capital markets and retail investors are a part of it. Retail investors, due to limited resources, use social media investment forums or the search engine Google as the main information source. We can assume only a partial reflection of information demand in social media data, which is shown by the dashed arrow from retail investors to social media in Figure 1. Further, capital market aggregate activity, which includes also trading of retail investors, "defines" the value of stock prices or stock indices. It is shown by the solid arrow. Subsequently, research in this area employs the data from capital markets and social media to better understand this relationship. Important parts of the transmission mechanism are in circles. "Research" is in the rectangle, to distinguish it from the main parts of the transmission mechanism.

3.2. Sentiment

The second point of view is based on a reaction of society to existing information. To be specific, social media enables to create, share and respond to existing information. Such a combination of reactions is a valuable source of data mostly about opinions, emotions or social mood shared by the social media audience. Such an audience consists especially of ordinary people who share their opinions, mood or emotions about the concrete information. The good example is a corporate website on Facebook where ordinary people share their opinions related to the individual company. In financial literature such information like opinions, moods, emotions can be described by term sentiment. A set of irrelevant information not related to company fundamentals. Rich research (Kumar & Lee, 2006; Baker & Wurgler, 2007; Barber & Odean, 2011) implies that less-rational groups of investors are prone to behave according to sentiment. This idea is shown in the papers of Bollen et al. (2011), Mao et al. (2011) who study the Twitter data or Karabulut (2013), Siganos et al. (2014) and Bukovina (2015) who employs the data of Facebook. Figure 2 shows this transmission mechanism.

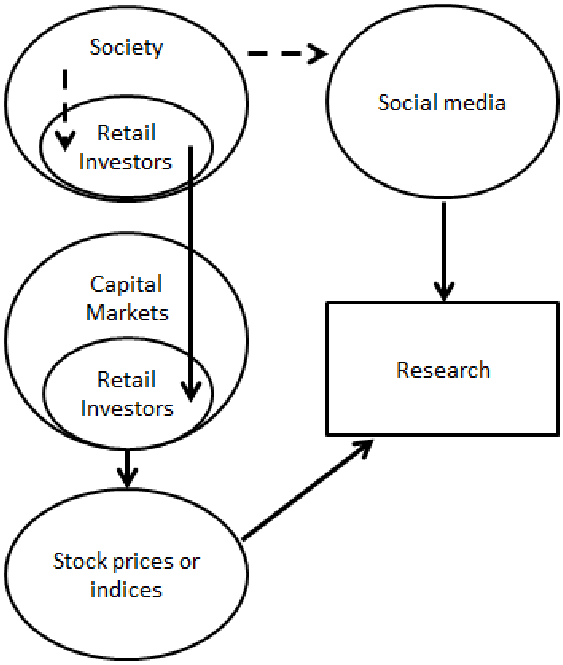

Fig. 2. Transmission mechanism – Sentiment of a society

At its beginning there is the society and retail investors are a part of it. In the society, sentiment forms randomly due to many factors which cannot be predicted. Retail investors as a part of a society can be at least partially influenced by sentiment. They are aware of the fundamentals (signal), but the sentiment (noise) can be also the deciding factor. In the Figure 2, it is presented by dashed line because we cannot assume the influence of sentiment only. Similarly, we can assume only a partial reflection of society's sentiment in social media. The next part of transmission mechanism is capital market and since retail investors are a part of it, there can be also the impact of sentiment. Subsequently, the total trading of institutional and retail investors is reflected in the stock price and if retail investors are influenced by sentiment, also the stock price can reflect it.

The most important contribution of this chapter is the understanding that social media is only a tool how to technically capture the data about the behavior of a society. However, what really matters is the behavior of a society, an existence of retail investors and their influence to capital markets.

4. Main empirical findings

The aim of this chapter is to document the main empirical findings about the link between behavior of society tracked by social media and capital markets. Currently, there are many papers which employ the social media data but do not focus on a better understanding of the capital market behavior. An example of such research is technically focused papers, which try to propose the new or advanced data-mining methods and they test it on a link between social media and capital markets. Therefore, this chapter contains only the papers which follow the economic rationale and transmission mechanism proposed above. This chapter has three parts based on the name of social media data which is employed as the main source of data.

4.1. Facebook

The paper of Karabulut (2013) employs the Facebook's Gross National Happiness index (FGNHI) as a direct indicator of investor sentiment and its result shows the ability of FGNHI to predict changes in the aggregate US market daily returns. This result is significant even when controlled by past stock market volatility, daily economic conditions or the turn-of-the-year effect. Karabulut (2013) argues these results are consistent with the noise trader models because the positive impact of sentiment is fully reversed during the following two trading weeks. Siganos et al. (2014) provides the international evidence within the 20 markets between the daily sentiment and trading based on FGNHI data as well. Their main findings show positive contemporaneous relation to stock market returns. In addition, they suggest a causality from sentiment to stock market because sentiment on Sunday affects the Monday stock returns. Siganos et al. (2014) explain their results based on a theory of behavioral finance proposed by DeLong et al. (1990) that sentiment has an impact when retail investors are plentiful and there is the existence of limits in arbitrage. Karabulut (2003) and Siganos et al. (2014) focus on the effect of investor sentiment in the aggregate market. Bukovina (2015) is focused on a micro level because he studies the impact of sentiment on the sample of the US blue-chip companies. He employs the data from Facebook websites of individual corporations and considers them as a sentiment of a society related to the specific company. His main findings suggest the existence of peaks in Facebook sentiment with negative impact on stock returns. Bukovina (2015) offers the explanation about the more bolder negative sentiment in comparison to positive one based on the loss aversion theory (Kahneman & Tversky, 1979).

4.2. Twitter

One of the most famous papers in this field is Bollen et al. (2011) who derive the social mood from Twitter feeds and find the correlation as well as causality in Granger's sense in the stock market. The public sentiment has been extracted from approximately 10 millions of tweets posted by 2.7 millions of users. The representation of the market is Dow Jones Industrial Average (DJIA) in their study. Moreover, Bolen et al. (2011) define the 6 dimensions of social mood and the dimension "Calm" significantly improves the prediction of DJIA. Sprenger et al. (2014a, b) study the Twitter microblogging forums related to stock markets. Sprenger et al. (2014a) argue these forums contain news about stock prices and market only, without the noise which is likely included in the general Twitter feed as is the case of Bollen et al. (2011). Sprenger et al. (2014a) are focused on the level of individual stocks because they analyze roughly 250 000 stock-related tweets on a daily basis. Their findings show the associations between tweet sentiment, stock returns and trading volume. Moreover, they show that the microblogging community can recognize the "extraordinary" users who consistently share the high-quality investment advice. Similarly, Sprenger et al. (2014b) study the company events via Twitter microblogging forums. They identify good and bad news in a sample of more than 400 000 stock-related tweets. Therefore, they are able to capture the market reaction to news as well as to the sentiment due to the qualitative distinction of news. Their findings show the different behavior of capital market according to categories of company events. In particular, categories like "Mergers & Acquisitions" or "Earnings" use to be a surprise for market participants in comparison to categories like "Joint Venture" or "Development" that rarely move the prices. Moreover, their results show that positive news are often leaked and incorporated into stock prices before the official announcement. In opposite, the negative news are predominantly surprising related to occurrence of an event within the day of occurrence.

4.3. Google

One of the first papers which examines Google data is Da et al. (2011) who propose the Google search queries of stock tickers as a new direct measure of investor attention. They accomplished the analysis in a sample of Russell 3000 stocks. According to their findings, the increased volume of searches for the studied sample of stocks predicts higher stock prices during the next 2 weeks and eventual price reversal follows within the year. In addition, it predicts company's IPO high first-day return and long-term underperformance. Da et al. (2011) explain their results according to Barber and Odean (2008) argument that retail investors increased attention increases the buying pressure on prices. Da et al. (2011) consider Google queries the proxy for investor attention. Joseph et al. (2012) consider the online ticker searches as a proxy for investor sentiment. Further, they suggest that a ticker search represents more likely a "buy" decision because an investor who considers a "sell" already has the relevant information. Joseph et al. (2012) accomplish the analysis in a sample of S&P 500 companies formed in portfolios based on search intensity, returns from volatility and dual-sorted portfolios (combination of search intensity and volatility). Their findings are very similar to Da et al. (2011) because the previous search intensity forecasts abnormal returns and higher trading volumes. Ding and Hou (2015) conduct study in the sample of S&P 500 as Joseph et al. (2012) but with focus on the stock liquidity. Their results show that increased investor attention leads to a reduced relative bid-ask spread and the higher turnover rate. An explanation of their results is based on the "investor recognition hypothesis" (Grullon et al. 2004; Fang and Peress, 2009) which says that stocks with higher attention are more "recognized" and subsequently more liquid.

Previous papers are focused on the trading of less-rational investors in the line with ideas of behavioral finance. However, Vozlyublennaia (2014) propose the reverse argument that higher investors' attention is related to higher market efficiency and not to a higher noise and consequently lower market efficiency as is presented in Da et al. (2011). Vozlyublennaia (2014) argues with the theory proposed by Grossman and Stiglitz (1980) who suggest that more information or greater number of informed investors leads to "better" prices because they incorporate more information. Vozlyublennaia (2014) finds that presence of attention diminishes the predictability of returns. In other words, it means the higher market efficiency. Vozlyublennaia (2014) also argues that retail investors probably do not use the Google as a tool for searching for information about individual companies. This argument reflects the reality that retail investors have more options to invest in broader portfolios than in individual stocks due to information and transaction costs. Therefore, Vozlyublennaia (2014) studies the investors' attention represented by Google queries and broad market indices like Dow Jones Industrial Average, S&P 500, NASDAQ which accounts for large, medium and small companies respectively. Further, she studies investors' attention to gold and oil via the Chicago Board Options Exchange Gold Index and West Texas Intermediate crude oil index, respectively. Vozlyublennaia's (2014) results show affirmative evidence that retail investors can create occasional fluctuation but not permanent shifts. Overall, this evidence supports the existence of more efficient market due to the increased attention of investors. Vlastakis and Markellos (2012) studies the information supply and demand and its relationship to stock market. They argue that information demand can be properly analyzed via Google data as never before. Their argument is based on Grossman and Stiglitz (1980) paper as in the study Vozlyublennaia (2014) but they do not literary suggest that higher information demand relates to more efficient markets. Still, they provide the interesting analysis focused on 30 of the largest stocks listed on the New York Stock Exchange (NYSE), NASDAQ and on aggregate market represented by S&P 500. Their findings show the contemporary and dynamic link between demand and supply. On top of that, information demand is significantly related to historical volatility and trading volume at the level of individual stock and to the aggregate market as well.

5. Discussion

To the best author knowledge, the previous chapter presents all existing papers which examine the link between social media and capital markets based on theoretical argumentation and the transmission mechanism proposed above. All presented papers "agree" about the existence of less rational investors who bears the information demand or sentiment with subsequent reflection in their trading. The only disagreement is, if information demand reflects either a noise information (Da et al. 2011, Joseph et al. 2012, Ding & Hou, 2015) or more efficient markets (Vozlyublennaia, 2014). The dominant part of previous papers employs either Google queries or Facebook happiness index FGNHI. It is an expected outcome, since these data are easily available without the employment of data-mining methods. From a methodology point of view, Google queries and FGNHI index data should be more valuable because we can "compare" findings in different studies and discuss its robustness. It is due to the standardized nature of data. On the other side, the employment of qualitative data in the form of Facebook comments or Twitter tweets, processed by data-mining methods, can provide a deeper insight into a behavior of a society. However, Mao et al. (2011) imply that the final findings rely on a unique, particular combination of data sets and specific sentiment tracking tools. Similarly, Sprenger et al. (2014a) encourage the research about the role of information weighting and diffusion of information in social media because picking the right tweets remains just as difficult as making the right trades. This situation can be considered as an opportunity for future research. Another opportunity is the employment of several social media at once as a source of sentiment or information demand because every above paper studies the single social media only. An exception in the current research is the paper of Mao et al. (2011) who employ Twitter feeds, Google queries and news headlines as the proxy for a sentiment in a society. Subsequently, they define several sentiment indicators and determine their predictive value over a range of financial indicators like Dow Jones Industrial Average price, trading volume, market volatility and the price of gold. They accomplished the analysis with weekly and daily data. For weekly data, their findings show the existence of Granger causality with employment of Google queries only. For daily data they find significant correlations over all sentiment indicators, but the Twitter data outperform the rest in the predictive power.

6. Conclusion

This paper provides an overview in the field of employment of social media big data on capital markets. It provides the brief description of social media and its functioning. The contribution of this paper is in the chapter "Economic rationale in social media big data applications", because it describes a logical sequence and the transmission mechanism from social media to capital markets based on the economic theory developed in the field of behavioral finance. Further, the paper presents the main findings of several papers and in the "Discussion", it outlines the future challenges and potential areas of research.

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