Mendel University in Brno

MENDELU Working Papers

in Business and Economics

56/2015

Sentiment of a society and large-cap stock liquidity.

Jaroslav Bukovina

MENDELU Working Papers in Business and Economics
Research Centre
Faculty of Business and Economics
Mendel University in Brno
Zemědělská 1, 613 00 Brno
Czech Republic
http://vyzc.pef.mendelu.cz/en
+420 545 132 605

Citation

Bukovina, J. (2015). Sentiment of a society and large-cap stock liquidity. *MENDELU Working Papers in Business and Economics* 56/2015. Mendel University in Brno. Cited from: http://ideas.repec.org/s/men/wpaper.html

Abstract

Jaroslav Bukovina: **Sentiment of a society and large-cap stock liquidity.**

The impact of sentiment in the sample of small and young companies due to higher transaction and information costs is a generally agreed notion. On the contrary, such impact is less likely in the sample of large-cap stock companies. However, this paper goes beyond this notion and shows that we can study the influence of sentiment even at the level of large-cap companies due to the following reasons. Firstly, the paper is unique by employment of social media Facebook data as a proxy for the sentiment of a society related to the individual corporation. Such data have a potential to provide deeper insights in a society's behavior. Secondly, the author proposes the volume of trade or liquidity as a variable which incorporates sentiment in a society better than stock returns. Empirical results confirm this prediction. Overall, the paper shows the existence of the negative link between sentiment in the society and volume of trade at the level of large-cap corporations.

Key words

Sentiment of a society, liquidity, Facebook activity, quantile regression

JEL: G14, G19

Contacts

Jaroslav Bukovina, Department of Finance, Faculty of Business and Economics, Mendel University in Brno, Zemědělská 1, 613 00 Brno, Czech Republic, e-mail: jaroslav.bukovina@mendelu.cz.

Acknowledgements

I would like to thank to Svatopluk Kapounek and Petr Koráb for their helpful comments and criticism. I gratefully acknowledge the fund support of the Internal Grant Agency of PEF Mendelu, Grant No. PEF_DP_2015_003.

1 Introduction

The analysis of a society's behavior and its impact on capital markets belongs among rapidly growing fields of research. One of the reasons is technological development which makes new data available. Specifically, data mining methods (Pang & Lee, 2008; Liu, 2012) have been suggested for studying the society's behavior on the basis of news in the standard media and activities of people at social networks. These so-called "big data" are known as proxies for a society sentiment and an increasing number of papers (Sprenger & Welpe, 2010; Bollen et al., 2011; Mao et al., 2011; Oliveira et al., 2013) make use of such data to better explain the capital market or the stock price behavior. This research is based on a framework of behavioral finance which challenges the notion of efficient markets and considers factors like animal spirits, the mood of a society (Shiller, 1984; Prechter 1999, 2003; Nofsinger, 2005) or investor sentiment (Baker & Wurgler, 2007) to be important for market volatility.

This paper employs data from social media and the framework of behavioral finance but it puts a strong emphasis on the relationship between stock liquidity and sentiment and not on that between stock prices and sentiment. The choice of this relationship is based on a specific sample of companies analyzed in this paper. To be more specific, the paper studies the link between sentiment and large cap corporations so-called the blue-chip companies or the bond-like stocks. An analysis of this link is hard to be found in the scholarly literature because these are stable large companies which have a long history of providing information about earnings and dividends. Therefore, an estimation of the fundamental value is easy due to the availability of information in comparison to small, young and non-dividend paying companies which do not provide such rich data. Consequently, the influence of sentiment is likely to be less significant in a sample of bond-like stocks but it is likely to be disproportionately higher in small and young companies (Glushkov, 2005; Baker & Wurgler, 2006, 2007; Baker et al., 2012). However, this paper goes beyond this notion and shows that we can study the influence of sentiment even at the level of large-cap companies due to following reasons. Firstly, this paper employs unique data of Facebook activity which have a potential to better reflect the social mood or society's sentiment. Secondly, it recommends liquidity relating to blue-chip companies as a variable which better reflects social mood in comparison to stock prices. The empirical results below seem to confirm this hypothesis.

The second part of the paper describes the main theoretical framework which contains the research relating to stock liquidity, "transmission mechanism" from social media to retail investors and suitability of social media such as Facebook to be a proxy for the sentiment of a society. The third part presents the methodology and the data. The fourth part gives the results and the last part sums up the conclusions.

2 Literature Review

2.1 Market liquidity and sentiment

Stock liquidity is considered an important factor influencing stock returns. Amihud (2002) or Jones (2002) state that stock market liquidity predicts market returns. Pastor & Stambaugh (2003) or Acharya & Pedersen (2005) show that market liquidity variation is a priced risk factor. However, only a few studies analyze determinants of stock liquidity (Chordia et al., 2001, 2005; Breen et al., 2002) and even fewer ones consider sentiment to be a factor influencing market liquidity. Baker & Stein (2004) or Baker & Wurgler (2006, 2007) hypothesize about a link between sentiment and liquidity but provide no empirical testing. Only a recent study by Liu (2015) examines the relationship between sentiment and stock liquidity more deeply. This paper therefore enhances the insufficient research in this field and to the author's knowledge, it is the first one which employs the sentiment of the society proxied by the social media data in the context of market liquidity.

The rationale of the link between sentiment and liquidity is based on the framework of behavioral finance, especially on the existence of noise traders or less rational investors. This paper hypothesizes that portfolios of little investors also contain large-cap stocks. This is based on the following argumentation. First, the information costs are lower. Blue-chip companies provide richer information in contrast to small or new companies, and retail investors have limited resources to perform a deep research. The second reason is the existence of biases like the availability bias (Tversky & Kahneman, 1973) or the familiarity bias (Barber & Odean, 2011). Simply said, large-cap companies are well known in the society due to their intense marketing activities and a high media attention. Therefore, investors can be prone to add them to portfolios because they feel more familiar with them. The last reason is the lower transaction costs expressed as the lower bid-ask spread due to higher liquidity. To sum up, I put forward a hypothesis that even large-cap stocks can be influenced by social activities, especially by the activities of noise traders or retail investors. Quite an extensive research (Barberis & Thaler, 2003; Baker & Wurgler, 2007; Barber & Odean, 2011) implies that these "less-rational" groups of investors are prone to behave according to social mood, sentiment and various biases. In addition, even rational investors can contribute to the impact of sentiment. One can profit from the activities of noise traders because of predicting them in advance. Such an in advance trading may shift stock prices even further from the fundamental levels (De Long et al. 1990). In addition, we need to keep in mind that the volume of trade achieved by retail investors is considerably smaller in comparison to that achieved by the big institutional ones. In liquid markets, particularly, the price of stocks is given to small investors by the market and they are not able to influence it due to their small volumes. On the contrary, liquidity may reflect even marginal changes in volumes caused by trading of individual investors and this paper recommends liquidity as a suitable variable which incorporates the sentiment of the society towards large-cap companies.

2.2 The transmission mechanism from sentiment of a society to stock liquidity

The link between society's behavior and stock prices was previously studied by Da et al. (2011) and Ding & Hou (2015) who examine the retail investors' attention based on the search volume index data (SVI) provided by Google. Their argumentation is based on the demand of retail investors for information about stock prices while looking for them with the Google web browser.

The argument of this paper is based on a reaction of the society to information about a specific company. The reaction of the society is represented by the Facebook activity because every well-known company has a Facebook profile where users, the so-called "followers", react to the information provided by the company or other users. Large-cap companies have millions of followers and the paper considers them to be representatives of the society expressing the current perception of a particular company. Such information as the perception of the society or the social mood can be misunderstood as signals by retail investors or noise-traders because they are less rational. The consequent trading influences the volume of trade.

2.3 Facebook activity as a proxy for sentiment

Kietzmann et al. (2011) explain the main building blocks of social media. In the context of this paper, the most important building block is "Relationship". Basically, it describes the association between the firm and an individual user. This relationship starts with the single user, who click on the "like" button on the Facebook profile of a company. The "Like" of the user express his/her preferences to be in a relationship with the company and share/receive information from other users or that particular company. The preferences of users to be in a relationship with the company are shaped by many factors like marketing and the brand name of the company, or factors like the social status of users. This paper does not study them but the author considers the formation of users' preferences to be a random process. The next important fact to be considered is that the Facebook users are ordinary people who represent the current perception of the company in the society. There is no financial or investing forum where users discuss the current stock price movements, company fundamentals or trading recommendations. People only express (by "likes" or comments) what they dis/like about the information shared by the company or other users. Therefore, the social activities on the Facebook can be described with the term "sentiment". In a model construction, it is assumed as an exogenous variable without a relation to the stock market. Of course, the situation like a new product release can influence the stock price as well as Facebook activity. In the model, such a situation is controlled by the variable news, which represents the specific news for every single company during the studied period.

3 Methodology

The methodology of this paper involves the quantile regression in the environment of panel data. The panel quantile regression (Koenker, 2004; Galvao, 2008; Lamarche, 2010) has been applied due to the following reasons. The primary advantage, in a comparison to standard regression, is the ability to explore the full spectrum of the conditional quantile, not only mean estimates. Therefore, it shows different variations in the behavior of modelled variables. This method increases the robustness of results because the data of stock returns can contain extreme values or a non-Gaussian distribution. This method can decrease the impact of outliers and the existence of fat-tailed error distribution. The employment of quantile regression in the environment of panel data is often a challenging issue. However, in this paper, the author applies a simple pooled quantile regression because the data do not contain unobserved (fixed) effects as they were transformed to the first differences which wipe out the fixed effects. This transformation accounts for a serial correlation in the data and it is a condition for employing the pooled quantile regression as well. The general model for the given quantile $0 < \tau < 1$ is defined as follows:

$$Quant_{\tau}(y_{it}|x_{it}) = \alpha(\tau) + x_{it}\beta(\tau);\ i = 1, \dots, N; t = 1, \dots, T; \tag{1}$$

where y_{it} is a dependent variable, α is an intercept, x_{it} is a regressor and β its estimate for the given quantile. Both the intercept and the slope depend on the quantile τ.

3.1 Data

The paper examines 47 publicly traded companies that are among the 100 biggest companies in the world measured by the market capitalization. The examined period is 12 months. The sample of 47 companies is given by a benchmark which represents the amount of "likes" on the Facebook profile of a company. This benchmark is a median value. Three companies are not included in the analysis due to changes in their profiles and an insufficient amount of data. The number of "likes" represents the relative number of followers (people who follow the activities of individual firms) and the "like" of a user in a company's profile expresses his/her attitude thus forming a relationship between him/her and the company. The benchmark diminishes the danger that social activity at Facebook reflect only activities of a few thousands of followers, which would not be a proper representation of the society. The companies in the studied samples have millions of followers. Four companies are traded in Europe, one in Asia and 43 companies can be found on the US market.

The data of financial variables (stock returns, the trading volume and the news volume) have been collected from the Yahoo! Finance. The news data represent the media coverage of the dominant part of the market because the Yahoo! Finance summarizes on its web the company news from several sources like Bloomberg, Thomson Reuters or Forbes, to mention only a few. The data of the Capital Market Index are provided by Google Finance. The Capital Market Index (CPMKTS) covers approximately 9,500 instruments, not only securities but also the fixed income and the money market. It is applied to the model as a representation of the US economy instead of the stock index like the S&P 500 because the analyzed sample represents the dominant variation and the weight of the S&P 500. The data of the Facebook activity were downloaded from Fanpage Karma[1]. These data represent only the volume of activity and not the qualitative distinction between positive and negative activity. Therefore the data transformation from the qualitative values to the quantitative ones as proposed by Kapounek & Lacina (2011) was not employed. The original data are daily values that are transformed to logarithms and then to first differences. The missing data of the market variables during weekends and holidays have been calculated by linear interpolation. The studied data are in the balanced panel with 16,243 daily observations.

3.2 Model

This paper provides estimates of two models. The first model (Model I.) is considered to be the main model of this paper. The dependent variable in the first model is the volume of trade. The second model employs daily stock returns as a dependent variable. The second model (Model II.) and its results are shown in the appendix. The objective of these two models is to recommend liquidity as a variable which will better reflect the sentiment of the society relating to large-cap companies in comparison to stock price.

3.2.1 Model I.

$$liq_{it} = \alpha + liq_{it-1} + ind_{it} + news_{it} + sent_{it} + d_{1,\dots,5} + D_{1,\dots,12} + \varepsilon_{it}, \tag{2}$$

where liq_{it} is the liquidity or the volume of trade relating to a specific company, α is the model constant, liq_{it-1} is the lagged volume of trade, ind_{it} is the Capital Market Index applied to a sample of US companies - for European and Asian companies this variable covers the national stock indexes, $news_{it}$ covers the daily amount of news about the given company, $sent_{it}$ represents the Facebook activity relating to a particular firm, dummies $d_{1,\dots,5}$ represent the level of the company

[1] FanPage Karma website is available at http://www.fanpagekarma.com/

communication on the Facebook (how active is company on its Facebook profile). Levels[2] are defined as: *"lazy", "occasional", "regular", "often", "lot",* where *"lazy"* means almost no activity and *"lot"* means an excessive activity. Dummies $D_{1,\ldots,12}$ represent unobserved time effects, one dummy being for one month, and ε_{it} is an error term.

In the model construction, the author follows the theory that blue-chip companies should predominantly reflect the fundamentals. However, as daily data are used in the analysis, the standard fundamentals data like earnings or dividends are not available. On the contrary, sentiment is considered as a short run factor, and therefore intraday or daily data are appropriate. Therefore, the author applies the lagged volume of trade (liq_{it}) which incorporates all past information, especially most recent changes in the fundamentals and investor behavior. Variable ind_{it} is the Capital Market Index (CPMKTS) as a representantive of the US economy, and for the European and Asian markets the national stock indices have been applied. Therefore, variable ind_{it} represents the current economic condition of the country, which is a very important fundamental. Variable $news_{it}$ covers the daily amount of news relating to the given firm. It also covers fundamentals like earning report releases, but its primary objective is to control the impact of information which can influence the stock price as well as Facebook activity. For example, the release of a new iPhone would influence investors and their investment decisions about the Apple stocks, and people on the Facebook will definitely talk about this release as well. The variable of interest, $sent_{it}$, covers the sentiment of the society. Five dummies ($d_{1,\ldots,5}$) capture the potential impact of a company's behavior on activities of users of a Facebook profile. In general, it can be understood as the level of marketing activities. This variable can provide some answers to the company's success in influencing users. Variables $D_{1,\ldots,12}$ are time dummies which cover potential unobserved changes relating to the studied sample during the analyzed period.

4 Results

The lagged value of volume of trade (liq_{it-1}) is significant as it may be expected due to a dynamic nature of this relationship. The variable of Capital market index (ind_{it}) is significant with negative impact. In general, this index represents market liquidity levels and current high levels show the "ease" in the markets. Therefore, the negative sign can be explained as the transfer of investors from large-cap and less risky stocks to more risky and profitable instruments. An interesting result is provided by variable $news_{it}$, which is significant only in Q10-Q50. In addition, Figure 1. clearly shows that Q10-Q50 are the estimates with positive impact and quantiles from Q60 to Q90 are in negative levels but not significant. The variable of interest $news_{it}$ is statistically significant with negative impact in every quantile. In reality it means the decrease in the volume of trade due to negative sentiment of society related to the specific company/ies. The value of the coefficient is marginal, therefore the impact is very small but this result supports the fact that the volume of trade provided by retail investors is small. Dummy variables of a company's activities on Facebook ($d_{1,\ldots,5}$) are in most cases insignificant. Therefore, there is no clear pattern relevant to generalization of results about the company's influence of the perception of users. Time effects dummy variables ($D_{1,\ldots,12}$) are insignificant as well and they are not shown in Table 1.

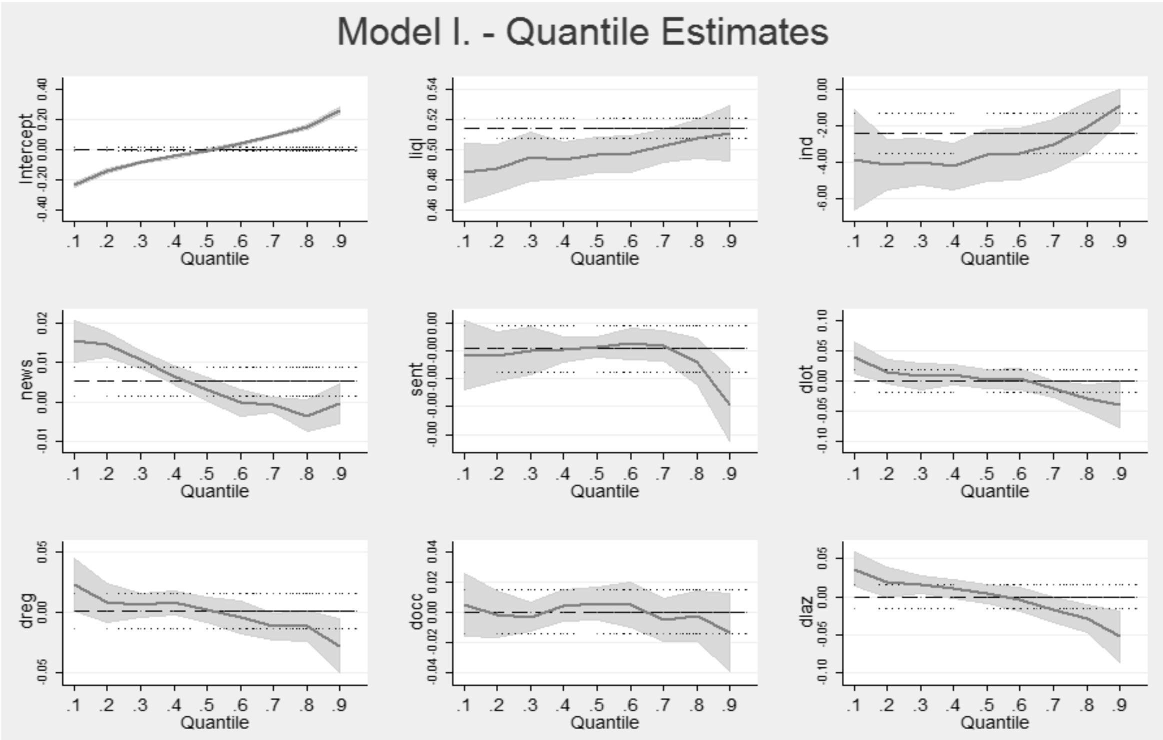

Figure 1. Quantile estimates of Model I.

Source: The author's estimates. Computed by Stata.
Notes: Figure 1 is divided into 9 charts (intercept and 8 regressors). Each chart has the following parts: The horizontal line shows the quantiles τ ranging from 0.1 to 0.9. The vertical scale indicates the covariate effect and includes the name of a variable according to Model I. The dashed line in the middle and two dotted lines represent conventional 90 percent confidence interval for the standard least square estimate. The dark gray line represents the quantile regression estimates and the gray area is the confidence interval of estimates.

Table 1: Quantile estimates of Model I.

liq_{it}	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
liq_{it-1}	.4844*** (49.28)	.4864*** (56.16)	.4947*** (54.34)	.4931*** (62.64)	.4963*** (25.53)	.4965*** (68.77)	.5022*** (76.84)	.5069*** (63.87)	.5104*** (62.71)
ind_{it}	-3.789*** (-3.23)	-4.108*** (-5.67)	-4.036*** (-5.86)	-4.299*** (-6.87)	-3.757*** (-5.85)	-3.777*** (-5.55)	-3.394*** (-5.65)	-2.224*** (-2.91)	-1.073* (-1.71)
$news_{it}$	.0152*** (6.10)	.0146*** (7.12)	.0106*** (5.75)	.0067*** (4.54)	.0032* (1.94)	.0001 (.02)	-.0006 (-.37)	-.0035* (-1.77)	.0002 (.06)
$sent_{it}$	-.0012* (-1.94)	-.0012*** (-2.64)	-.0010** (-2.35)	-.0009*** (-2.94)	-.0009*** (-2.68)	-.0008* (-1.96).	-.0008** (-2.24)	-.0014*** (-2.93)	-.0031*** (-4.06)
d_{lot}	.0375** (2.53)	.0148 (1.46)	.0092 (1.20)	.0117 (1.46)	.0022 (.00)	.0036 (.42)	-.0142 (-1.61)	-.0304*** (-2.67)	-.0388** (-2.50)
d_{reg}	.0225** (2.30)	.0079 (.85)	.0072 (1.17)	.0073 (1.70)	.0016 (.00)	-.0035 (-.46)	-.0133 (-1.56)	-.0118 (-1.18)	-.0289** (-2.15)
d_{occ}	.0039 (.35)	-.0009 (-.10)	-.0016 (-.27)	.0042 (.63)	.0056 (.00)	.0056 (.74)	-.0056 (-.64)	-.0025 (-.26)	-.0136 (-1.02)
d_{laz}	.0345*** (3.2)	.0201* (1.96)	.0166 (2.76)	.0096 (1.43)	.0036 (.00)	-.0025 (-.32)	-.0186** (-2.11)	-.0278*** (-2.67)	-.0527*** (-3.76)
cons	-.2369*** (-23.39)	-.1457*** (-16.83)	-.0889*** (-17.53)	-.0484*** (-8.00)	-.0076 (.00)	.0343*** (4.94)	.0893*** (11.24)	.1471*** (16.12)	.2543*** (20.14)
Pseudo R^2	.37	.34	.32	.31	.31	.32	.34	.36	.39

Source: The author's estimates. Computed by Stata.
Notes: 500 bootstrap replications have been applied. The significance level: ***/**/* of coefficients is 1/5/10%, respectively. The values of t-statistics are in parentheses. The number of observations is 16,243.

5 Discussion

As mentioned in the literature review, the only study which deeply analyzes the relationship between liquidity and sentiment is Liu (2015) which shows that investor sentiment increases stock market liquidity. The results of this paper are in opposition to Liu (2015) because a higher level of Facebook activity is accompanied with a decrease in the volume of trade. The author considers these differences to result from a discrepancy in the used methodologies. Liu (2015) employs a broader sentiment index relating to the stock market. On the contrary, this study is aimed at a firm level data sample containing only large-cap companies.

The negative relationship between the sentiment of society and liquidity given in the above results is in line with papers by Kahneman & Tversky, (1979), De Bondt & Thaler, (1985), Tetlock (2007), Tetlock et al. (2008) and Da et al. (2011) who suggest negative events to be more influential. Therefore, we can assume the sentiment of society represented by Facebook activity forms at higher levels when users discuss the negative issues related to the specific company or when negative information has a bigger impact.

The results of this paper agree with a paper by Baker & Wurgler (2007) who argue that in the case of large-cap or blue-chip companies the impact of sentiment is likely to be less influential. According to Model I., $sent_{it}$ is significant in every quantile but the value of the coefficient is marginal. In addition, the Model II., shown in the appendix, presents the influence of $sent_{it}$for stock prices to be significant only in Q10.

Both models of the paper provide interesting results related to variables $news_{it}$ and $sent_{it}$. This is a unique combination of variables ($news_{it}$ and $sent_{it}$) in one model because the previous research studied these factors independently. Hayo & Kutan (2002), Green (2004) and Parker (2007) study media coverage and their impact on capital markets only. On the contrary, Bollen et al. (2011), Sprenger & Welpe (2011) or Oliveira et al. (2013) are focused on sentiment or social mood of society proxied by social media only. This paper shows that the variable $news_{it}$ is related to positive impact on liquidity based on Model I and on stock prices based on Model II. On the contrary, $sent_{it}$ shows the negative influence only. These differences are a motivation for further research focusing on a better understanding the differences in the formation of perception of the society influenced by media coverage and social activities.

The main contribution of the above mentioned results is the argument that the research of sentiment in capital markets predominantly focused on prices should be extended to other market variables as well. To be more specific, despite the non-existence of a link between sentiment and stock prices, liquidity is a plausible variable which shows the existence of a social mood or sentiment of society in relation to blue-chip companies. However, this argument has to be understood also in the opposite manner. Despite the social media potential, the information about the behavior of society does not provide better insights. Therefore, investors trying to better estimate the future stock price should treat the social media data more carefully at least in the sample of large-cap companies. Such argumentation is in contrast to papers like Bollen et al. (2011) or Oliveira et al. (2013) who suggest the social media to be a new sentiment indicator helpful for explaning stock prices or capital market movements. However, further research in this field is still needed due to limitations of this paper, e.g. employing the Facebook activity data expressed as quantity and not as quality. New insights even in the sample of large-cap companies can be provided by the qualitative distinction between positive and negative activities in the society. Valuable research would be definitely accomplished on a bigger sample of companies employing data from social media. However, such research is challenging due to insufficient activities of users in relation to smaller companies. The employment of more social media sources is a possible solution for such a challenge.

6 Conclusion

The paper studies the link between sentiment of the society and large-cap companies. Further, it contributes to the research of the behavior of society based on social media data. The results show that stock prices of large-cap companies do not reflect the influence of sentiment. However, this result was expected because large-cap companies should be driven close to fundamental values by rational arbitrageurs who are not responsive to factors like social mood. Therefore, this paper hypothesizes that liquidity or volume of trade are plausible variables which incorporate the impact of sentiment due to retail investors‘ trading. Retail investors by nature hold low volumes of capital and this is the reason why the reflection of their trading in stock prices is not much likely. Empirical testing confirms this prediction and shows sentiment to be significant but with a negative impact. However, this result is in line with the research by Kahneman & Tversky (1979), De Bondt & Thaler (1985), Tetlock (2007), Tetlock et al. (2008), Da et al. (2011) who show a bigger impact of negative events. In summary, the paper argues that research concerning sentiment and capital markets should also be extended to other market variables than stock prices. However, despite the potential of social media data, investors should primarily treat liquidity at the level of blue-chip companies when looking for a source providing information about the behavior of the society.

References

Acharya, V. V. and Pedersen, H. L., 2005: Asset pricing with liquidity risk, Journal of Financial Economics, vol. 77, no. 2005, pp. 375-410.

Amihud, Y., 2002: Illiquidity and stock returns: Cross-section and time-series effects, Journal of Financial Markets, vol. 5, no. 1, pp. 31-56.

Baker, M. and Stein, J., 2004: Market liquidity as a sentiment indicator. Journal of Financial Markets, vol. 7, no. 2004, pp. 271–299.

Baker, M. and Stein, J., 2006: Investor sentiment and the cross-section of stock returns. Journal of Finance, vol. 61, no. 4, pp. 1645–1680.

Baker, M. and Wurgler, J., 2007: Investor Sentiment in the Stock Market. National Bureau of Economic Research. Working Paper 13189, pp. 1-38.

Baker, M. Wurgler, J. and YUAN, Y., 2012: Global, local and contagious investor sentiment. Journal of Financial Economics, vol. 104, No. 2, pp. 272-287.

Barber, B. M. and Odean, T., 2011: The Behavior of Individual Investors (September 7, 2011). Available at SSRN: http://ssrn.com/abstract=1872211.

Barberis, N. and Thaler, H.R., 2003: A Survey of Behavioral Finance. in Handbook of the Economics of Finance,. Eds G. Constantinides, M, Harris, and R. Stultz, North-Holland, Amsterdam, pp. 1051-1119.

Breen, W. J., Laurie, S. H. and Korajczyk, A. R., 2002: Predicting equity liquidity, Management Science, vol. 48, no. 4, pp. 470-483.

Bollen, J., Mao, H. and Zeng, X-J., 2011: Twitter mood predicts the stock market. Journal of Computational Science, Vol. 2, No. 1, pp. 1-8.

Chordia, T., Roll, R. and Subrahmanyam, A., 2001: Market liquidity and trading activity, Journal of Finance, Vol. 56, No. 2 pp. 501-530.

Chordia, T., Roll, R. and Subrahmanyam, A., 2005: An empirical analysis of stock and bond market liquidity, Review of Financial Studies, Vol. 28, No. 1, pp. 85-129.

Da, Z., Engelberg, J. and Gao, P., 2011: In search of attention. Journal of Finance, Vol. 66, No. 5, pp. 1461–1499.

DeBondt, W.F. M. and Thaler, R. H., 1985: Does the Stock Market Overreact?. Journal of Finance, Vol. 40 No. 3, pp. 557-581.

DeLong, J. B., Shleifer, A., Summers, H. L. and Waldmann, J. R., 1990: Positive Feedback Investment Strategies and Destabilizing Rational Speculation. The Journal of Finance Vol. 65, No. 2, pp. 379-395.

Ding, R. and Hou, W., 2015: Retail investor attention and stock liquidity. Journal of International Financial Markets, Institutions & Money. Vol. 7, No. 2015, pp. 22-26.

Green, T. C., 2004: Economic News and the Impact of Trading on Bond Prices. The Journal of Finance. Vol. 59, No. 3, pp. 1201-1233.

Hayo, B. and KUTAN, A., 2002: The impact of News, Oil Prices, and International Spillovers on Russian Financial Markets. Finance 0209001, EconWPA.

Galvao, A., 2008: Quantile regression for dynamic panel data with fixed effects. Working paper, University of Illinois. Urbana-Champaign.

Glushkow, D., 2005: Sentiment Betas. Unpublished working paper. University of Texas. Austin.

Jones, M. C., 2002: A century of stock market liquidity and trading costs. Working paper, Columbia University. Available at SSRN: http://ssrn.com/abstract=313681

Kahneman, D. and Tversky, A., 1979: Prospect theory: An Analysis of decisions under risk. Econometrica, Vol. 47, No. 2, pp. 313-327.

Kapounek, S. and Lacina, L., 2011: Inflation perceptions and anticipations in the old Eurozone members states. Prague economic papers. Vol. 2, No. 2011, pp. 120-139.

Kietzmann, H. J., Hermkens, K., McCarthy, P. I. and Silvestre, S. B., 2011: Social media? Get serious! Understanding the functional building blocks of social media. Business Horizons, Vol. 54, No. 3, pp. 241-251.

Koenker, R., 2004: Quantile regression for longitudinal data. Journal of Multivariate Analysis. Vol. 91, No. 1, pp. 74–89.

Lamarche, C., 2010: Robust penalized quantile regression estimation for panel data. Journal of Econometrics 157, No. 2010, pp. 396–408.

Liu, B., 2012: Sentiment Analysis and Opinion Mining. Morgan & Claypoll Publishers.

Liu, S., 2015: Investor Sentiment and Stock Market Liquidity. Journal of Behavioral Finance. Vol. 16, No. 1, pp. 51-67.

Mao, H., Counts, S. and Bollen, J., 2011: Predicting financial markets: Comparing survey, news, twitter and search engine data. arXiv preprint arXiv:1112.1051 (2011).

Nofsinger, R. J., 2005: Social Mood and Financial Economics. Journal of Behavioral Finance. Vol. 6, No. 3, pp. 144-160.

Oliveira, N., Cortez, P. and Nelson, A., 2013: On the Predictability of Stock Market Behavior Using StockTwits Sentiment and Posting Volume. Progress in Artificial Intelligence, Lecture Notes in Computer Science, Vol. 8154, pp. 355-365.

Pang, B. and LEE, L., 2008: Opinion mining and sentiment analysis. Foundation and Trends in Informational Retrieval. Vol. 2. No. 1-2, pp. 1-135.

Parler, C. J., 2007: The impact of economic news on financial markets. Munich Personal RePEc Archive. Online at: http://mpra.ub.uni-muenchen.de/2675/. pp. 1-62.

Pastor, L. and Stambaugh, F. R., 2003: Liquidity Risk and Expected Stock Returns. The Journal of Political Economy. Vol. 111, No. 3, pp. 642 – 685.

Prechter, R. R., 1999: The Wawe Principle of Human Social Behavior and the New Science of Socionomics, Gaineswille, GA: New Classic Library.

Prechter, R. R., 2003: Pioneering Studies in Socionomics, Gaineswill, GA: New Classic Library.

Shiller, J. R., 1984: Stock prices and Social dynamics. Brookings Papers on Economic Activity, Vol. 2, No. 1984, pp. 457-510.

Sprenger, T. and Welpe, I., 2010: Tweets and trades: The information content of stock microblogs. Social Science Research Network Working Paper Series, pp. 1–89.

Tetlock, P. C., 2007: Giving content to investor sentiment: The role of media in the stock market. Journal of Finance, Vol. 62, No. 3, pp. 1139-1168.

Tetlock, P. C., Saar-Tsechansky, M. and Macskassy, S., 2008: More than words: Quantifiying language to measure firms fundamentals. Journal of Finance, Vol. 63: 1437-1467.

Tversky, A. and Kahneman, D., 1973: Availability: A heuristic for judging frequency and probability. Cognitive Psychology. Vol. 5, No. 2, pp. 207-232.

Appendix

Model II.

$$ret_{it} = \alpha + ret_{it-1} + ind_{it} + liq_{it} + news_{it} + sent_{it} + d_{1,\dots,5} + D_{1,\dots,14} + \varepsilon_{it}, \quad (3)$$

ret_{it} is the daily stock return, α is the model constant, ret_{it-1} is the lagged return, $\mathrm{ind_{it}}$ is Capital market index (CPMKTS), $\mathrm{liq_{it}}$ is the volume of trade, $\mathrm{news_{it}}$ is the media coverage for the given firm (daily amount of news), $\mathrm{sent_{it}}$ is the sentiment of society relating to the given company, dummies $d_{1,\dots,5}$ represent the level of the company communication on Facebook (whether the company is active on its Facebook profile). The levels are defined as: *"lazy", "occasional", "regular", "often", "lot"*. Where *"lazy"* represents almost no activity, *"lot"* means an excessive activity. Dummies $D_{1,\dots,12}$ represent unobserved time effects, one dummy for one month, and $\varepsilon_{\mathrm{it}}$ is an error term.

This model is based on the same motivation as Model I. The lagged return (ret_{it-1}) is employed due to the nature of dynamic relationships on capital markets. Further, blue-chip companies are driven predominantly by fundamentals at the level of companies or the economy as well. However, an analysis of the short run period requires proxies for fundamentals like volume of trade (liq_{it}) at the level of a company, and market indices (ind_{it}) at the level of the economy. The variable $\mathrm{news_{it}}$ covers the daily amount of news concernig a given firm. This variable covers also fundamentals like earning report releases but its primary objective is to control for the impact of information which can influence the stock price as well as Facebook activity. The variable of interest, $sent_{it}$ covers the sentiment of the society. Five dummies ($d_{1,\dots,5}$) capture the potential impact of a company's behavior on activities of users on its Facebook profile. In general, it can be understood as a level of marketing activity. This variable can show answers about the company's influence of users' perception. Variables $D_{1,\dots,12}$ are time dummies which cover potential unobserved changes concerning the studied sample during the analyzed period.

Results

Table 2. represents the results of Model II. There is a dominant and positive impact of lagged return and Capital Market Liquidity Index as expected. The impact of liquidity on stock prices is significant for all quantiles except the Q60 but there is a problem with the negative sign of this estimate for Q10-Q50 which does not correspond with the theory. However, Q70-Q90 show a correct positive sign. The advantage of quantile regression is shown in relation to the variable $news_{it}$ because it is significant for every quantile except the Q40 and Q50. Therefore the standard OLS would show this variable as insignificant at the median level. The main variable of interest sentiment represented by

Facebook activity is significant only at Q10 with a positive sign. Dummy variables ($d_{1,\dots,5}$) which represent the activities of the company on the Facebook are predominantly negative in all quantiles and coefficients are very similar for all 5 dummies. Therefore, we cannot argue that different levels of a company's activities have an impact on its stock prices in different ways. Dummy variables responsible for time effects are statistically significant in no quantile and they have been removed from the model.

Table 2. Quantile estimates of Model II.

ret_{it}	**Q10**	**Q20**	**Q30**	**Q40**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
ret_{it-1}	.4184*** (13.08)	.4078*** (17.46)	.4007*** (22.76)	.4021*** (23.13)	.4015*** (24.39)	.4069*** (25.11)	.4076*** (29.62)	.4085*** (27.35)	.4235*** (22.55)
ind_{it}	.7132*** (12.01)	.7286*** (16.40)	.7595*** (21.37)	.7447*** (20.95)	.7231*** (22.17)	.6942*** (21.68)	.6813*** (22.40)	.6780*** (20.01)	.6628*** (18.06)
liq_{it}	-.0032*** (-4.47)	-.0023*** (-5.76)	-.0016*** (-5.50)	-.0009*** (-3.84)	-.0003** (-1.97)	.0001 (.71)	.0005** (2.56)	.0002**** (3.23)	.0020*** (3.63)
$news_{it}$	.0005*** (4.18)	.0004*** (4.75)	.0001*** (3.14)	.0001 (1.01)	-.0001 (-1.17)	-.0001** (-2.20)	-.0002*** (-4.24)	-.0008*** (-3.73)	-.0004*** (-3.07)
$sent_{it}$	.0001** (2.12)	.0001 (1.27)	-.0001 (-0.04)	.0001 (.83)	.0001 (0.66)	-.0001 (-.10)	-.0001 (-1.43)	-.0001 (-1.20)	-.0004 (1.37)
d_{oft}	-.0016** (-2.41)	-.0009* (-2.53)	-.0008*** (-2.97)	-.0005*** (-2.61)	-.0004*** (-2.75)	-.0003 (-.94)	.0001 (.25)	.00001 (.34)	.0007 (1.41)
d_{reg}	-.0034 (-0.73)	-.0003 (-1.10)	-.0004** (-2.35)	-.0004*** (-2.63)	-.0005*** (-3.53)	-.0007*** (-3.81)	-.0008*** (-4.96)	-.0008*** (-3.53)	-.0005 (-1.38)
d_{occ}	-.0015*** (-3.49)	-0008*** (-3.16)	-.0001** (-3.24)	-.0005*** (-3.17)	-.0005*** (-2.88)	-.0003 (-1.51)	-.0002 (-1.20)	.0005 (1.01)	.0013*** (3.72)
d_{laz}	-.0077 (-1.60)	-.0005* (-1.74)	-.0005** (-2.40)	-.0003* (-1.87)	-.0003*** (-1.96)	-.0001 (-.48)	-.0001 (-.54)	.0002 (.78)	.0013*** (3.55)
cons	-.0063*** (-15.51)	-.0034*** (14.04)	-.0017*** (-9.65)	-.0006*** (-4.67)	.0005*** (3.19)	.0015*** (8.07)	.0026*** (16.49)	.0047*** (17.92)	.0064*** (21.39)
Pseudo R^2	.29	.29	.27	.26	.25	.26	.27	.29	.30

Source: The author's estimates. Computed by Stata.
Notes: 500 bootstrap replications have been applied. The significance level: ***/**/* of coefficients is 1/5/10%, respectively. The values of t-statistics are in parentheses. The number of observations is 16,243.