ALGORITHMIC TRADING SYSTEM ON NASDAQ TWEETS

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***Abstract**: Behavioral Finance is demonstrating, daily, that investor sentiment is relevant in investment decisions. In this study, a big data algorithmic trading system was developed to predict the future of the Nasdaq Index, based on investor sentiment measured by tweets about FAANG Companies (Facebook, Apple, Amazon, Netflix and Alphabet´s Google). Tweets were qualified as good, bad or neutral using natural language processing. A positive tweet about a FAANG company opened a long position in the Nasdaq Index Futures, while a negative tweet opened a short position. Back testing carried out throughout October 2018 obtained positive returns. A one-hour hold was determined to be the optimum time period to maintain an open position in the market with a profit factor of 8 and a Sharpe ratio of 6,5. This study shows that investor sentiment is a relevant instrument in stock market analysis.*
***Keywords**: FAANG; Twitter; NASDAQ Index; algorithmic trading; investor sentiment.*
***JEL Classification**: B4, C5, D4, F1, E32, E44, E62, F21*

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Introduction

Emotions play an important role in decision making. The effects of mood on decision-making processes are analysed scientifically in psychological research (Etzioni, 1987). Good mood has a positive impact in decision-making resulting in faster and more efficient decisions (Forgas, 1998). In Finance, Behavioural Finance researches this phenomenon in the investment decision-making process by searching for patterns of stock market behaviour as a response to different stimuli. This line of research attempts to provide an alternative theory to the Efficient Market Hypothesis in which stock market prices are driven by new information and follow a random walk pattern. As a body of research, Behavioural Finance tries to demonstrate empirically, that the mood of investors is related to their financial market decisions and thus has an impact on asset returns.

Several external variables (weather, the lunar cycle, biorhythms, sport results, social beliefs and others) have been analysed by how they cause mood fluctuations in investors. Goldstein (1972), Sanders and Brizzolara (1982), and Keller et al. (2005) have demonstrated that, over the decades, good/bad weather is positively correlated with good/bad moods promoting optimistic/pessimistic sentiments. In the financial markets, sunny weather is associated with bullish stock markets sessions (Saunders, 1993; Hirshleifer & Shumway, 2003). The effects of the lunar cycle on mood also been studied. It has been demonstrated that higher hormone levels are associated with full moon phases (Cajochen et al, 2013; Coghlan, 2013) and that this effects traders' testosterone levels and contributes to positive stock market results (Coates & Helbert, 2008). Also, biorhythms, such as the January or Monday effect have been statistically proven to relate to mood and have been tested by Ariel (1990), Kamstra, Kramer and Levi (2003), and Yuan, Zheng and Zhu (2006). Sport results are another external variable that present links with mood as can been seen in Edmans, García and Norli (2007), Gallagher and O'Sullivan (2011) or Gómez and Prado (2014). Superstitions, horoscopes, fortune-tellers, black cats or witches, otherwise known as the social beliefs, also are related to investor mood and the stock market (Dowling & Lucey, 2005; Torgler, 2007). For example, Kolb & Rodriguez (1987) demonstrated that Friday 13th is associated with below-average returns on Fridays. Even air quality (Li & Peng, 2016) and holidays (Kaplanski & Levy, 2012) has been researched.

This evidence shows that investors' mood is linked to the behaviour of financial markets. The question now, is how to measure it. Early attempts used the dividends to profits ratio (Darling, 1955) and consumer confidence (Lemmon & Portniaguina, 2006), but the latest technical advances in big data have made it easier to source large amount of data about investors' moods from the Internet and social networks. The frequency of use of different words linked to investors' moods has been researched from different sources such as conventional media, social networks, Wikipedia and Twitter.

Regarding to conventional media, Gidofalvi y Elkan (2001) used financial news to predict short term movements of stock prices. Tetlock (2007) showed how the pessimism of a daily column in the Wall Street Journal predicted a downward movement in market prices. García (2013) concluded that two columns of financial news from The New York Times allowed one to measure investor sentiment and its effect on stock movements, especially during recessions. Alanyali, Moat and Preis (2013) found a positive correlation between the daily number of mentions of a company in the Financial Times and the volume of daily transactions of the company's shares. García-Medina, Junior, Bañuelos and Martínez-Argüello (2018) concluded that there is a strong relationship between news in The New York Times and the movements of forty world indexes.

In the case of social networks, Gerow and Keane (2011) analysed the frequency of words, Batra and Daudpota (2018) used the social networking site StockTwits where they found an accuracy of 76.65% in stock prediction. Related to Wikipedia, Moat, Curme, Avakian, Kenett, Stantly and Preis (2013) suggested that its articles may give early signs of stock markets moves and Xu and Zhang (2013) found that it improved the information environment of the financial market and moderated the timing of managers' voluntary disclosure of bad news about companies and, also, investors´ negative reaction to bad news.

Finally, Twitter was found to be another source for sentiment analysis. Twitter has about 325 million monthly active users worldwide (Statista, 2019) and they send 500 million tweets per day (Internet live stats, 2019). It has become one of the most used databases of sentiment analysis activities. It is considered a rich opinion mining data source because of its efficacy of sentiment analysis of tweets (Pak & Paroubek, 2010). Over the last few years, several papers have been published in different areas. In the case of Finance, research has been done to extract indicators from the opinions expressed in tweets to forecast the performance of: financial markets (Bollen, Mao & Zeng, 2011; Zhang, Li, Shen & Teglio, 2016; Cowlessur, Annappa, Sree, Gupta & Velaga, 2019), cryptocurrencies (Abraham, Higdon, Nelson & Ibarra, 2018), of trading volumes for stocks in the NASDAQ (Bordino et al.,2012), Dow Jones´ stocks (Ranco, Aleksovski, Caldarelli, Grčar, & Mozetič, 2015), S&P 500 stocks (Ruan, Durresi & Alfantoukh, 2018) and Spanish stocks (Gómez, Medrano y Gallego, 2017). This research revealed that Twitter analytics is a useful tool for the prediction of financial markets.

This paper proposes to use Twitter sentiment about FAANG stocks in order to predict changes in a financial Index, in this case the Nasdaq Index. FAANG is an acronym given to the five most important technology companies: the social media network Facebook, the multinational technology company Apple, the online megastore Amazon, the streaming service Netflix and the multinational conglomerate Alphabet´s Google. These companies are listed on the NASDAQ and they have been a favourite investment over the past decade for their high returns, because of the transformation of their sector and the way they have acquired customers. Apple and Amazon were worth $1 trillion in 2018 (Sheetz, November 20, 2018) and FAANG as a group reached 27% of the capitalization of the Nasdaq Index (Kochkodin, May 4, 2018). Despite their financial relevance, little academic research has been done regarding their performance and predicting their stock price movements. To our knowledge, this paper is the first attempt to investigate the relationship between investors mood captured from tweets about FAANG and the Nasdaq index value. Only Skehin, Crane & Bezbradica (2018) have tried to forecast day ahead price movements of FAANG stocks, but using ARIMA, LTSM networks and wavelets.

Following this introduction, section 2 provides the hypothesis, section 3 presents the research methodology used, section 4 describes how the data was collected, section 5 shows the results and, finally, section 6 summarizes the conclusions.

Hypothesis and methodology

This study will analyse the effect of the sentiment of tweets, that include the ticker of FAANG companies, on changes in the value of the Nasdaq index. The first assumption is that a positive (negative) sentiment in Twitter will mean optimism (pessimism) and therefore a positive (negative) impact on the Nasdaq index. Therefore, a long (short) investment after a positive (negative) tweet about a FAANG company will generate positive returns by investing in the Nasdaq Index Futures. The hypothesis to test is:

- H_0: A positive (negative) sentiment in Twitter means optimism (pessimism) and therefore positive (negative) returns.

If the hypothesis is validated, the next factor to analyse is the length of time a tweet is effective in moving the market and generating positive returns.

The first task is to analyse tweets that include the ticker of a FAANG company. This task is made possible thanks to Senseitrade. This is an app for smartphones that lets anyone to invest in the stock market, with very low commissions and in a very flexible way. Moreover, this app generates value information about each stock traded. For example, this app analyses any tweet of the stocks listed with natural language process (NLP) assigning a value to each tweet[4]:

- 1 if the sentiment of the tweet is positive.
- -1 if the sentiment of the tweet is negative.
- 0 if there are no significant sentiment in the tweet

Senseitrade's information was the starting point to validate the hypothesis H_0. To connect sentiment to trading, an algorithmic trading system developed by Trading Motion was used. Trading Motion is a platform for automated trading strategies that has been operating in the market since 2002. Currently, this platform is connected to 36 brokers all over the world. Clients of these brokers can open a managed account and activate or deactivate any of the available trading systems. The platform opens for clients, in an unattended way, long or short positions, in the corresponding futures market, according to investment signals issued by the trading systems[5].

The trading system developed for this study followed this workflow:

(1) Senseitrade reads the Twitter feed and analyses the sentiment of each tweet.
(2) When a tweet mentioning any FAANG company appears, the algorithmic trading system opens a long position if the sentiment is positive (1) or a short position if the sentiment is negative (-1).
(3) If a position is open, then there are three options:

[4] For more information visit: https://usa.senseitrade.com/
[5] For more information visit: https://www.tradingmotion.com/

(a) If there are no more tweets, the position is automatically closed after “X” minutes.
(b) If a new tweet appears with the same sentiment, the duration of the trade is extended by another “X” minutes.
(c) If a new tweet appears with an opposing sentiment, the position is closed.

(4) This trading system can be optimized according to three parameters:
(a) The “X” number of minutes the position is open in the market.
(b) A trailing stop loss
(c) A take profit limit

For validating H_0, the algorithmic trading system must be profitable, so all the following conditions must be fulfilled by the back testing of the system:

(1) The profit and loss result must be positive (P&L)
(2) Profit factor (win amount divided loss amount) must be higher than 1
(3) Winning sessions must be greater than 50%

Validating this hypothesis means that:

- Investors’ mood measured by Twitter sentiment is a valid tool to create investment alerts.
- Considering that the signals are about the FAANG companies and that the system operates on the Nasdaq index, we assume a certain drag effect from the FAANG to the rest of the components.
- The efficient market hypothesis and its assumption of investors rationality is questioned.

The optimization of the “X” number of minutes a position is open by searching for the maximum P&L result provides an indication of the time that a tweet has impact on the investor community and its effect on investors’ mood.

Data

A sample of 16.118 tweets was provided by Senseitrade. This was an aleatory sample of tweets that mention the ticker, or the hashtag of any stock listed in the market. The earliest tweets were dated 2014 and the latest ones were dated November 2018. From this sample, the tweets selected for back testing were the ones that fulfilled two conditions:

(1) Tweets that had the ticker of a FAANG company

(2) Sentiments of 1 or -1

According to these criteria, 95 tweets were selected from the sample set. The first tweet of the selection was issued in October 16th2018 and the last one was issued in November 7th2018. The highest number of tweets of FAANG companies was issued during so called "Black October" a period of volatility and uncertainty (Egan, October 31, 2018).

Nasdaq Index quotes were provided by Trading Motion using one-minute bars.

Results

Different back testing was run for different open position time periods in steps of 30 minutes. The results of the back testing are summarized in the Table 1 whereas the detail of the sessions traded by the system is shown in Table 2.

Table 1

Back testing summary

	Open position time					
Performance summary	**30'**	**60'**	**90'**	**120'**	**150'**	**180'**
Net P&L	5037,00 $	9240,09 $	6507,09 $	4635,09 $	521,09 $	-1460,91 $
Gross P&L	6690,00 $	10570,00 $	7765,00 $	5785,00 $	1635,00 $	-455,00 $
Profit factor	4,88	8,08	3,11	2,00	1,05	0,87
Sharpe ratio	6,60	6,47	4,48	3,00	0,44	-0,33
Slippage per side	-0,50	-0,50	-0,50	-0,50	-0,50	-0,50
Commission per side	8,00 $	8,00 $	8,00 $	8,00 $	8,00 $	8,00 $
Annual ROI	523,79 %	1235,40 %	304,50 %	144,60 %	9,75 %	-19,53 %
Mathematical expectation	72,72	142,84	110,93	90,39	26,37	-8,13

The detail of the sessions traded by the system is shown in Table 2.

Table 2
Back testing sessions detail

	Open position time					
Session analysis	**30'**	**60'**	**90'**	**120'**	**150'**	**180'**
Analyzed sessions	30	30	30	30	30	30
Sessions in market	14	14	14	14	14	14
Winning sessions	11	11	9	8	7	7
Winning sessions (%)	78,6%	78,6%	64,3%	57,1%	50,0%	50,0%
Winning sessions profit	6336,28 $	10544,28 $	9590,00 $	9264,00 $	10331,00 $	10149,00 $
Winning sessions average	576,03 $	958,57 $	1065,56 $	1158,00 $	1475,86 $	1449,86 $
Losing sessions	3	3	5	6	7	7
Losing sessions profit	-1299,28 $	-1304,19 $	-3082,91 $	-4628,91 $	-9809,91 $	-11609,91 $
Losing sessions average	-433,09 $	-434,73 $	-616,58 $	-771,48 $	-1401,42 $	-1658,56 $
Worst drawdown	-926,28 $	-680,19 $	-1679,00 $	-3024,00 $	-7073,91 $	-9902,91 $
Worst drawdown date	23/10/18	23/10/18	29/10/18	29/10/18	29/10/18	29/10/18
Best session	1161,00 $	3048,00 $	3239,00 $	2190,00 $	2497,00 $	2527,00 $
Best session date	31/10/18	26/10/18	26/10/18	26/10/18	30/10/18	30/10/18
Worst session	-895,28 $	-680,19 $	-1643,00 $	-2988,00 $	-4933,00 $	-6618,00 $
Worst session date	23/10/18	23/10/18	29/10/18	29/10/18	29/10/18	29/10/18

Table 1 shows that only strategies for 180 minutes open position time were not profitable. The optimum open position time was 60 minutes because this is the period that generated the highest P&L result and the highest profit factor. The best winning sessions were for 30- and 60-minute back tests. All these figures validate H_0.

Figures 1, 2 and 3 show how the main performance metrics (Net P&L, Profit factor and Sharpe ratio) were optimized for an open position time of 60 minutes and that open position times beyond that, resulted in deteriorating performance.

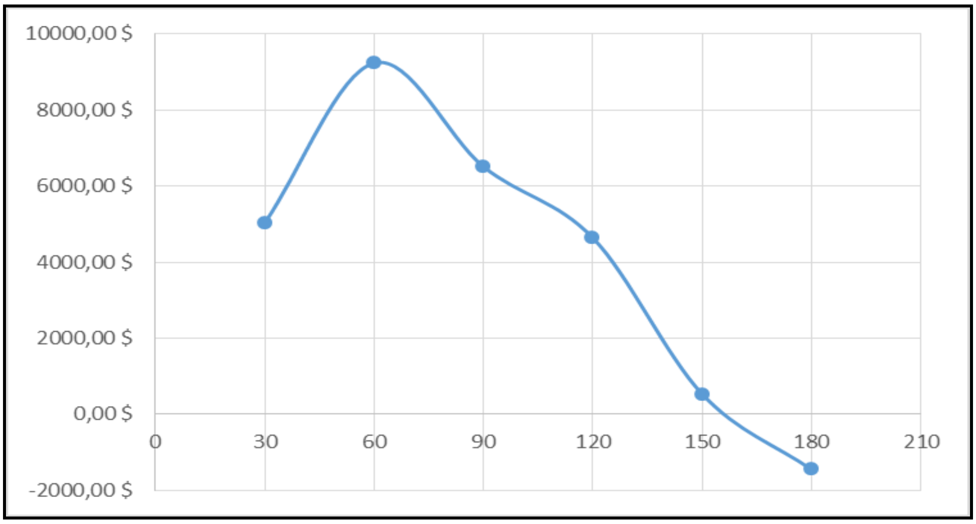

Fig. 1. Back testing Net P&L

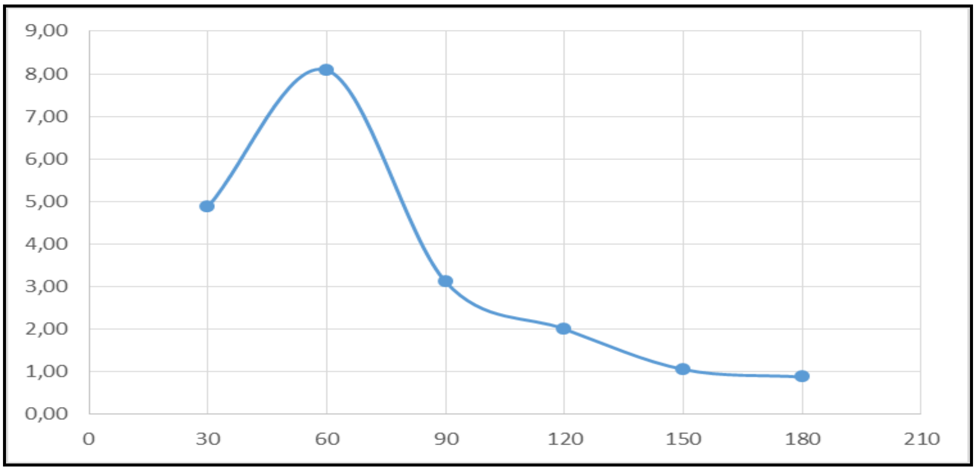

Fig. 2. Back testing profit factor

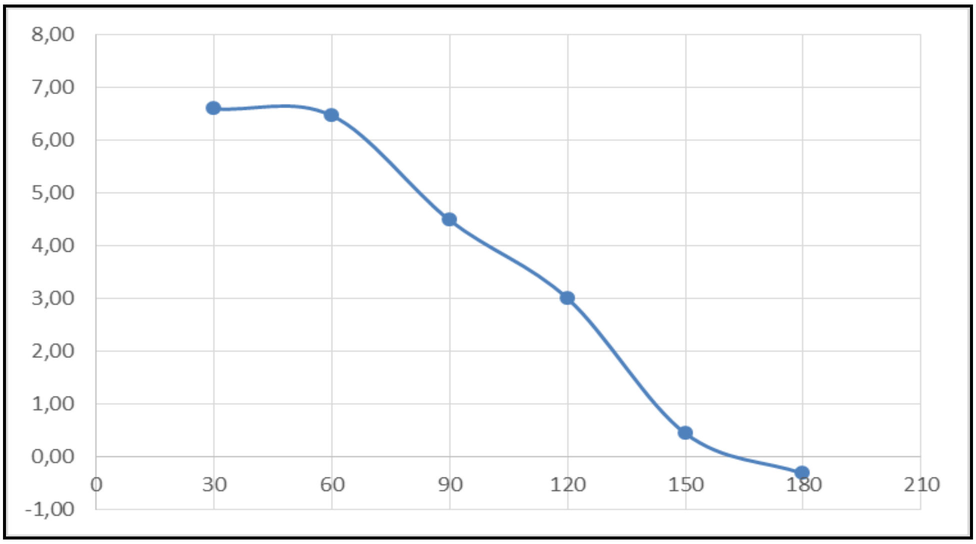

Fig 3. Back testing Sharpe ratio

The net and gross P&L time chart evolution for the 60 minutes open position time back test is shown in graph 4, plotted against the evolution of the Nasdaq index for that period.

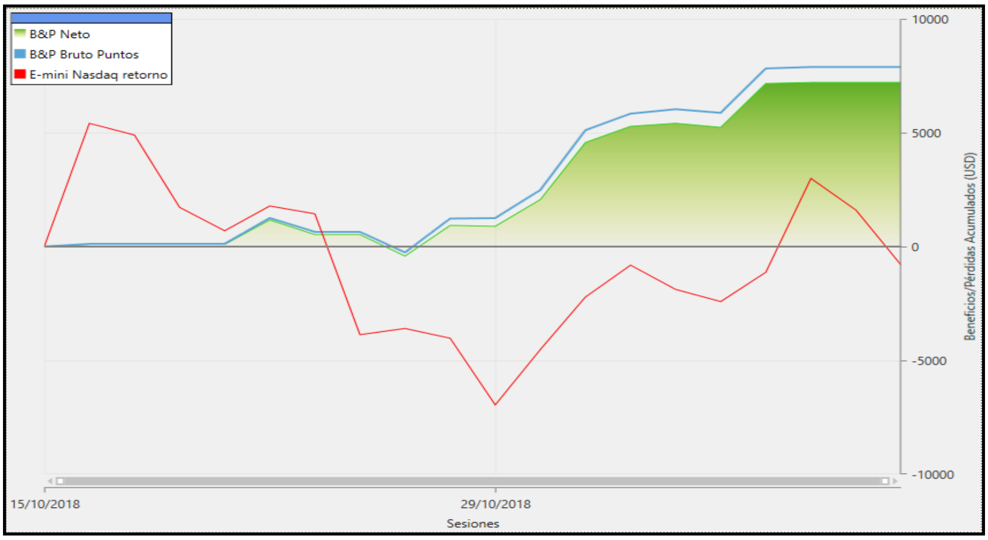

Fig. 4.P&L time chart for 60 minutes open position time back test

Discussion, conclusion and implications

Algorithmic trading is not new and for years research has been conducted to develop algorithms to beat the market in both bullish and bearish environments. However, previous research was linked to traditional forms of investment based mainly on technical analysis.

This study shows a new way of investing that could be considered "alternative" for two reasons. Firstly, it aims to obtain positive returns in absolute terms in both bearish and bullish environments by trading long and short positions in the futures market. Secondly, investment decisions are based exclusively on investor sentiment and therefore it is an alternative as it finds a new analysis context that is different from more traditional technical and fundamental analysis.

Neuroeconomics is demonstrating that emotional character of investment decisions is much more relevant than the classical investment themes authors considered in the last century. Their models proposed rationality as one of the main assumptions of the efficient market theory. This study shows that an investment strategy (which does not consider a single price, or financial data of listed companies) based exclusively on investor sentiment is profitable and shows that investor sentiment affects investment decisions and that its emotional component is relevant.

Another conclusion of this study is its shows the ability of Twitter to reflect investors' sentiment. It then follows that, this social network and the messages circulating through it, qualified by natural language processing algorithms, are representative of investors' mood and therefore an instrument to be considered in stock market analysis. In addition, the back testing carried out revealed the ephemeral nature of emotions, observing that, the optimum time that a tweet has an impact on investors, is just one hour.

The main limitation of this study is inherent in the methodology that utilized a limited sample set of 95 tweets over a period of two months of trading. It is evident that the next step, before the commercialization of this big data algorithmic trading system based on investor sentiment, is to run the system performing a prospective analysis over a relevant time period to develop a track record that will consolidate the results of this study.

References

Abraham, J., Higdon, D., Nelson, J., & Ibarra, J. 2018. Cryptocurrency price prediction using tweet volumes and sentiment analysis. SMU Data Science Review, 1(3), 1.

Alanyali, M., Moat, H. S., & Preis, T. 2013. Quantifying the relationship between financial news and the stock market. Scientific reports, 3, 3578.

Ariel, R. A. 1990. High stock returns before holidays: existence and evidence on possible causes. Journal of Finance, 45, 1611–1626.

Batra, R., & Daudpota, S.M. 2018. Integrating StockTwits with sentiment analysis for better prediction of stock price movement. International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), International Conference on IEEE, 1-5.

Bollen, J., Mao, H. & Zeng, X. 2011.Twitter mood predicts the stock market. Journal of Computer Science, 2, 1–8.

Bordino I, Battiston S, Caldarelli G, Cristelli M, Ukkonen A, Weber I. 2012. Web Search Queries Can Predict Stock Market Volumes. PLoS ONE, 7(7), e40014.

Cajochen, C., Altanay-Ekici, S., Münch, M., Frey, S., Knoblauch, V., & Wirz-Justice, A. 2013. Evidence that the lunar cycle influences human sleep. Current Biology, 23 (15), 1485-1488

Coates, J. M., & Herbert, J. 2008. Endogenous steroids and financial risk taking on a London Trading floor. Proceedings of the National Academy of Sciences of the United States of America, 105(16), 6167-6172.

Coghlan, A. 2013. Full moon could be to blame for a poor night's sleep. New Scientist, 219 (2928), 12. doi: http://dx.doi.org/10.1016/S0262-4079(13)61911-9

Dowling, M., & Lucey, B. M. 2005. Weather, biorhythms, beliefs and stock returns – some preliminary Irish evidence. International Review of Financial Analysis, 14, 337–355.

Egan, M. (October 31, 2018): October was a horrible month for stocks. CNN Business. Avaible at: https://edition.cnn.com/2018/10/31/investing/stocks-markets-october/index.html

Edmans, A., García, D., & Norli, O. 2007. Sports sentiment and stock returns. The Journal of Finance, 62(4), 1967-1998.

Etzioni, A. 1987. The moral dimension: Toward a new economics. New York: The Free Press.

Forgas, J. P. 1998. On being happy and mistaken: Mood effects on the fundamental attribution error. Journal of Personality and Social Psychology, 75, 318–331.

Gallagher, J., O'Sullivan, D. & Murphy, M. 2013. Maladaptive Sleep Beliefs and Sleep Hygiene Are better Predictors of Insomnia Than Type D Personality, 10th Annual Psychology, Health and Medicine Conference.

García, D. Sentiment during recessions. 2013. The Journal of Finance, 68(3), 1267-1300.

García-Medina, A., Junior, L. S., Bañuelos, E. U., & Martínez-Argüello, A. M. 2018. Correlations and flow of information between the New York Times and stock markets. Physica A: Statistical Mechanics and its Applications, 502, 403-415.

Gerow, A., & Keane, M. T. 2011. Mining the Web for the voice of the herd to spot stock market bubbles. Paper presented at the International Joint Conference of Artificial Inteligence. Barcelona, Spain.

Gidofalvi, G., & Elkan, C. 2001. Using news articles to predict stock price movements. Department of Computer Science and Engineering, University of California, San Diego.

Goldstein, K. M. Weather. 1972. Mood, and Internal-External Control. Perceptual and Motor Skills, 35(3), 786–786.

Gómez, R., y Prado, C. 2014. Sentimiento del inversor, selecciones nacionales de fútbol y su influencia sobre sus índices nacionales. Revista Europea de Dirección y Economía de la Empresa, 23(3), 99-114.

Gómez-Martínez, R., Medrano-García, M.L. & Gallego-Vázquez, J.A. 2017. Twitter Investment Alerts for Ibex35 Securities. Perspectiva Empresarial, 4(1), 61-71.

Hirshleifer, D., & Shumway, T. 2003. Good day sunshine: Stock returns and the weather. The Journal of Finance, 58(3), 1009-1032.

Internet live stats. Twitter Usage Statistics, 2019. Avaible online at: http://www.internetlivestats.com/twitter-statistics/

Kamstra, M. J., Kramer, L. A., & Levi, M. D. 2003. Winter blues: A SAD stock market cycle. American Economic Review, 93(1), 324-343.

Kaplanski, G., & Levy, H. 2012. The holiday and yom kippur war sentiment effects: the Tel Aviv Stock Exchange (TASE). Quantitative Finance, 12(8), 1283-1298.

Keller, M. C., Fredrickson, B. L., Ybarra, O., Côté, S., Johnson, K., Mikels, J., Conway, A. and Wager, T. 2005. A Warm Heart and a Clear Head: The Contingent Effects of Weather on Mood and Cognition. Psychological Science, 16(9), 724–731.

Kochkodin, B. May 4, 2018. FAANG Stocks Swallow Up More of the Nasdaq Than Ever Before. Bloomberg, Markets. Avaible online at: https://www.bloomberg.com/news/articles/2018-05-04/faang-stocks-swallow-up-more-of-the-nasdaq-than-ever-before

Kolb, R. W., & Rodriguez, R. J. 1987. Friday the thirteenth: Part VII – A note. Journal of Finance, 42(5), 1385-1387.

Lemmon, M., & Portniguina, E. 2006. Consumer confidence and asset prices: Some empirical evidence. The Review of Financial Studies, 19(4), 1499-1529.

Li, Q., & Peng, C. H. 2016. The stock market effect of air pollution: evidence from China. Applied Economics, 48(36), 3442-3461.

Moat, H. S., Curme, C., Avakian, A., Kenett, D. Y., Stanley, H. E., & Preis, T. 2013. Quantifying Wikipedia usage patterns before stock market moves. Scientific reports, 3, 1801.

Pak, A., & Paroubek, P. 2010. Twitter as a corpus for sentiment analysis and opinion mining. In Proceedings of the 7th international conference language resources and evaluation (LREC '10). European Language Resources Association ELRA.

Ranco, G., Aleksovski, D., Caldarelli, G., Grčar, M., & Mozetič, I. 2015. The effects of Twitter sentiment on stock price returns. PloS one, 10(9), e0138441.

Ruan, Y., Durresi, A., & Alfantoukh, L. 2018. Using Twitter trust network for stock market analysis. Knowledge-Based Systems, 145, 207-218.

Sanders, J. L., & Brizzolara, M. S. 1982. Relationships between mood and weather. Journal of General Psychology, 107, 157–158.

Saunders Jr., E. M. 1993. Stock prices and Wall Street weather. The American Economic Review, 83, 1337–1345.

Sheetz, M. November 20, 2018. Tech's 'FAANG' stocks have lost more than $1 trillion and counting from highs amid tech rout. CNBC, Markets. Avaible online at: https://www.cnbc.com/2018/11/20/techs-popular-faang-stocks-have-lost-945-billion-and-counting-from-highs-amid-tech-rout.html

Shu, H. C. 2010. Investor mood and financial Markets. Journal of Economic Behavior & Organization, 76, 267-282.

Skehin, T., Crane, M., & Bezbradica, M. December, 2018. Day ahead forecasting of FAANG stocks using ARIMA, LSTM networks and wavelets. CEUR Workshop Proceedings.

Statista. Number of monthly active Twitter users worldwide from 1st quarter 2010 to 3rd quarter 2018 (in millions). 2019. Avaible online at: https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/

Tetlock, P. C. 2007. Giving content to investor sentiment: The role of media in the stock market. The Journal of Finance, 62(3), 1139-1168.

Torgler, B. 2007. Determinants of superstition. Journal of Socio-Economics, 36(5), 713-733.

Xu, S. X., & Zhang, X. 2013. Impact of Wikipedia on market information environment: Evidence on management disclosure and investor reaction. Mis Quarterly, 1043-1068.

Yuan, K., Zheng, L., & Zhu, Q. 2006. Are investors moonstruck? Lunar phases and stock returns. Journal of Empirical Finance, 13(1), 1-23.

Zhang, W., Li, X., Shen, D., & Teglio, A. 2016. Daily happiness and stock returns: Some international evidence. Physica A: Statistical Mechanics and its Applications, 460, 201-209.