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Abstract. We analyze the possibility of improving the prediction of stock market indicators by adding information about public mood expressed in Twitter posts. To estimate public mood, we analysed frequencies of 175 emotional markers - words, emoticons, acronyms and abbreviations - in more than two billion tweets collected via Twitter API over a period from 13.02.2013 to 22.04.2015. We explored the Granger causality relations between stock market returns of S&P500, DJIA, Apple, Google, Facebook, Pfizer and Exxon Mobil and emotional markers frequencies. We found that 17 emotional markers out of 175 are Granger causes of changes in returns without reverse effect. These frequencies were tested by Bayes Information Criteria to determine whether they provide additional information to the baseline ARMAX-GARCH model. We found Twitter data can provide additional information and managed to improve prediction as compared to a model based solely on emotional markers.

Keywords: Twitter, mood, emotional markers, stock market, volatility

1 Introduction

Mood, emotions and decision making are closely connected. Modeling decision making process [1] report that psychological states invoked by reading stories can affect the evaluation of risk level. Positive moods lead individuals to make more optimistic choices and, vice versa, negative moods lead to pessimistic choices, see [2], [3].

Positive and negative moods influence the decision making process by invoking different heuristics. For example, individuals in positive mood tend to spend less time on decision making by referring more rarely to already reviewed alternatives and ignoring information they believe is irrelevant according to [4].

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[5] expresses the idea that general level of optimism/pessimism in society can be connected with economic activity. Nofsinger also supposes that the stock market itself can be a direct measure of social mood. Following Nofsinger, we will regard the economy not as a physical system, but as a complex system of human interactions, in which moods and irrationalities can play a significant role. This point can be supported by observing the informational cascades phenomenon in the stock market.

Regarding the stock market and Twitter as two possible measures of social mood, we can assume their correlation and the possibility of using analyses of moods expressed in tweets to increase prediction accuracy for stock market indicators.

Experiments in psychology and behavioral economics show how moods and emotions influence decision making [6], [7], [8]. The role of moods and emotions in decision making grows in situations of uncertainty incidental to the stock market. Behavioral researchers found a trader's decision to demonstrate a wide set of human cognitive biases and influence of emotional factors [9], [10]. Publicly expressed emotions in Facebook and Twitter draw attention of many researchers [11], [12], [13]. A relation between Facebook's Gross National Happiness Index and 20 international markets is shown in [14]. They also demonstrated that negative sentiments are related to increases in trading volumes and return volatility. We propose to use an alternative measure of sentiment based on posts published by user marked their location in US in Twitter.

Noteworthy is that people tend to often use abbreviations and emoticons in Twitter, so we extended the list of words with such signs and termed them emotional markers.

Another important question we raise in our research is whether frequencies of emotional posts from Twitter add information according to the Bayes Information Criteria, see, for example, [15]. In their detailed review of methods and models applied in textual sentiment analysis in the financial field [16] note that volatility models have rarely been used. For example in recent paper by Nofer and Hinz the returns are modelled by a linear regression without taking into account autoregressive and conditional heteroskedasticity effects [12]. In our research we tested the hypothesis that Twitter could provide additional information to increase the fit of the ARMAX-GARCH econometric model. We expected information about Twitter users' sentiment to be a significant regressor in complex ARMAX-GARCH models for S&P500 index. ARMAX-GARCH model was chosen as one of the most widespread models in time series analysis, which allow autocorrelation and heteroskedasticity to be taken into account [17].

Over the last five years social media and sentiment analysis have drawn attention of many researchers in economics. According to [16], most of 38 studies run in this area in 2004-2013 were concerned with the usage of news articles, annual reports, earnings press or other financial-related information and only one dealt with information from Internet messages. On the one hand, the approach based on financial data looks more relevant, but it may fail to recognize faked or historical news as was the case in 2013 [18], [19]. We also expect public moods and emotions to provide additional information and influence investors' response to certain news and events.

Although in several preprints [11], [20], [21], [22] the authors report that Twitter mood could be used to enhance the quality of stock market forecasts, the validity of the conclusions made by the authors remains doubtful. Regretfully, in the first preprints concerned with this topic there was either a short (less than 40 days) out-of-sample testing period or the authors only compared the results of using moods to a simple econometric model. In our research we extended the out-of-sample period to 100 days and applied a more complicated ARMAX-GARCH model.

Assuming that some words, abbreviations and emoticons can be more related to emotions, we verified the hypothesis that emotional marker frequencies can be indicators of stock prices movement.

The rest of the article is organized as follows. Section 2 describes the methods employed in the research, Sect. 3 describes the data and their preprocessing, Sect. 4 contains the results and Sect. 5 concludes.

2 Methodology

2.1 Emotional Markers

One of the simplest and most intuitive way of textual analysis is word counting [23], so we use the frequencies of words from a specially drawn up list instead of combining them into one or several mood indexes[3]. The results obtained reveal a high correlation between words expressed in Twitter and the S&P500 index, but those correlations did not always ensure that information was added to the ARMAX-GARCH model.

We compile our list of emotional markers using a Brief Mood Introspection Scale with 8 scales and 2 adjectives representing each mood as the starting point in creating dictionaries [24]. We extend this list with all the synonyms of the adjectives selected from the WordNet dictionary [25]. For example, we measure the presence of an energetic state in tweets by the occurrence of the following words: animate, animated, athletic, brisk, chipper, emphatic, enterprising, exuberant, fresh, lusty, passionate, robust, sprightly, spry, strenuous, strong, tireless, trenchant, warming party, honor, and vote. We also add the possibility of recognizing derived words, such as "happyyy" or "happpppppyyyyyyy" and count them using regular expressions.

We do not include negations, because after analyzing a testing sample of 9000 tweets we found that negations were not common. For example, the testing sample with 51 words "happy" contains the negation "not happy" only once. The same is the case with "but" and sentences expressing desires, e. g. "wanna

[3] A similar approach is used by [22]. They analyze frequencies of several words (e.g. "worry", "hope", "fear" etc.) and find high correlation between the frequencies of emotional posts and S&P500, DJIA, and VIX indexes.

be happy". The probable reason for that is the small number of words allowed for a Twitter message (140 words).

[26] show that emoticons[4] have a very good classification power and that accuracy of emoticon-based sentiment classification exceeds 90% for tweets with emoticons. Impressed by this result we extend our list with emoticons used in [27]. It should be mentioned that we distinguish different types of smiles. For example, ":)", ":-)", and ":D" are not synonyms.

Importantly, that Twitter lexicon contains a lot of abbreviations and slang words, such as "LOL", "WTH"[5]. At the final stage we add abbreviations expressing emotional states from [28].

Our list of emotional markers contains totally 175 items. We count the number of posts with each emotional marker per day and consider it as emotional marker frequencies. Before that all the tweets are transferred to the lower case. The frequencies are included in (4) and (5) as additional regressors.

2.2 Granger Causality

We examined the predictive causality[6] relations between sentiment and log returns, using the idea of the Granger test (see, for instance, [29]). Following the methodology described in [30], we estimate (1) and (2).

$$R_t = a_0 + \sum_{i=1}^{L} \alpha_i R_{t-i} + \sum_{j=1}^{L} \beta_j X_{t-j} + \varepsilon_t, \tag{1}$$

$$X_t = \widetilde{a_0} + \sum_{i=1}^{L} \widetilde{\alpha_i} X_{t-i} + \sum_{j=1}^{L} \widetilde{\beta_j} R_{t-j} + \widetilde{\varepsilon_t}, \tag{2}$$

where R_t is asset's returns, X_t — emotional marker, a_0, α_i, β_j and their tilde counterparts are parameters, ϵ_t and $\widetilde{\epsilon_t}$ are uncorrelated error terms. We found the optimal lag of each sentiment series X_t by varying the L parameter from 1 to 30, whereas in the works undertaken the lags for Granger test do not commonly exceed 7 days [11, 22].

The estimation of (1) and (2) allows us to select those emotional markers which Granger-cause returns and simultaneously are not Granger-caused by them. In fact we leave only those markers for which (1) is significant and (2) is insignificant on 5% level according to F-test. Thereby we prevent the reverse causality problem, described in [31].

[4] Emoticon means "emotional icon" and usually denotes some combination of printed symbols expressing person's feelings or mood.

[5] "laughing out loud" and "what the hell"

[6] "True causality" relations is rather a philosophical question, here we explore the relations of preceding one time series to another, which are useful in establishing the predictability.

2.3 ARMAX-GARCH Model and Model Testing

To examine the impact of Twitter mood on the returns of stocks and stock market indexes, this study uses the well-known ARMAX-GARCH model, controlling for autocorrelation and conditional heteroskedasticity, see, for example, [32]. The resulting ARMAX(p,q)-GARCH(r,m) model can be written as in (3).

$$x_t = E(x_t|\mathcal{F}_{t-1}) + y_t, \tag{3}$$

where $E(x_t|\mathcal{F}_{t-1})$ is a conditional mean of daily return x_t at time t conditional on all available at $t-1$ information F_{t-1}, y_t are innovations. Returns x_t are calculated as a logarithm of today price divided by yesterday price: $x_t = log(\frac{P_t}{P_{t-1}})$. Conditional mean $E(x_t|\mathcal{F}_{t-1})$ is modelled as ARMA(p,q), (4).

$$E(x_t|\mathcal{F}_{t-1}) = a_0 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j} + \sum_{k=1}^{n} \gamma_k X_{k,t}, \tag{4}$$

where parameter α_i and β_j are the ith-order autoregressive (AR) and jth-order moving average (MA) terms respectively; parameter γ_k measures the impact of additional regressor X_k on the index return. In our research emotional marker frequencies play a role of the additional regressors X_k.

Innovations y_t are modeled as GARCH(r,m), (5).

$$\begin{gathered} y_t = \sigma_t \cdot \eta_t,\ \eta_t \sim f(\theta), \\ \sigma_t^2 = c_0 + \sum_{i=1}^{r} \kappa_i \epsilon_{t-i}^2 + \sum_{j=1}^{m} \mu_j \sigma_{t-j}^2, \end{gathered} \tag{5}$$

where parameters κ_i and μ_j account for ARCH and GARCH effects of ith and jth orders respectively; σ_t^2 — volatility, η_t — error term, distributed according to some distribution f with parameter set θ It is also possible to add Twitter mood X_k to GARCH equation in order to measure the influence of Twitter mood on volatility.

Traditional specifications of ARMAX-GARCH imply normal or Student-t distribution of the error term. These distributions is that they cannot capture asymmetry in returns distribution. In order to eliminate this drawback, we implemented the skewed normal and skewed Student's distributions for error term. The distributions are modeled as special cases of generalized hyperbolic distribution by [33]. We also estimate ARMAX-GARCH with normal errors as a benchmark.

We choose the parameters p, q, r and m by means of Bayesian information criteria (BIC) — the best specification corresponds to the minimal BIC. Estimation is carried out by means of *rugarch* package by [34]. We employ Vuong test for comparing models. Our choice is caused by the fact that this test can be used for non-nested models in contrast to traditional likelihood ratio test. The null hypothesis implies the equal goodness of fit for the comparing models. Since the observations in financial time series are not typically independent we use heteroskedasticity and autocorrelation consistent version of Vuong test [35].

We use the mean squared error (MSE) and directional accuracy (DAC) as measures of out-of-sample performance. The latter shows the percentage of matches between returns and their forecast.

3 Data Description

The data about eight assets, including S&P500 and DJIA indexes; Apple, Facebook, Google, JP Morgan Chase, Pfizer and Exxon Mobil stocks are obtained from [36]. The period under consideration spanned 521 trading days and lasts from February 13, 2013 to April 22, 2015.

By making use of Twitter API, we downloaded 2,349,036,300 tweets over the considered period. It's in average 3,098,992 tweets per day. The only restriction made on downloaded posts is that they should be published by people located in US. All the tweets were sorted by days and analyzed automatically in the created JAVA application. For each day we calculated frequencies of posts with each item from the emotional markers list, described in Sect. 2.1, and normalize them by the number of tweets downloaded on each day.

Most of the frequencies exhibited non-stationary behavior. On the other hand, some frequencies (approximately 10% out of all) are difference stationary, i. e. have a unit root, which is confirmed by the augmented Dickey-Fuller test [37].

If non-stationary regressors present in the ARMAX-GARCH model, then conventional statistical measures, such as t-statistics or R-squared, are inapplicable [38]. The non-stationary emotional markers' frequencies are brought to stationary series by means of either detrending (for trend stationary series) or taking the first difference (for difference stationary series). The repeated ADF test rejects non-stationarity in all cases.

The whole data set was divided into two subsamples: for in-sample and out-of-sample testing. We choose to use 100 days period for out-of-sample testing, what gives approximatly 400 days to find a model with a optimal fit. It is worth to mention that each emotional marker has its own optimal L parameter in (1) and (2), meaning the time lag on which Granger causality takes place. Therefore unique subsample, cut due to L, corresponds to each emotional marker and estimation of baseline model for an asset is conducted on these subsamples.

4 Empirical Results

Firstly we evaluate the causality relations between emotional markers and returns by Granger test as explained in Sect. 2.2. Secondly we define three groups of assets: indexes, emotion sensitive stocks and emotion insensitive stocks. The groups include S&P500 and DJIA; Apple, Facebook and Google; JP Morgan Chase, Pfizer and Exxon Mobil correspondingly. For each group two ARMAX-GARCH models are estimated: a sentiment model, which contains emotional marker in the mean equation (4), and a baseline model without additional regressor in the mean equation.

The estimation of (1) and (2) results in 17 emotional markers. We excluded emotional markers which appeared very seldom and had many zeros.

Almost each asset is Granger caused by *gloom*, except from JPM and PFE. *Hope* and *bad* are Granger-valid for the half of assets, however they don't occur among emotion sensitive assets. The other markers have frequencies two or one and can be considered as specific for some asset. For example, PFE is Granger caused by *cancer*, XOM — by *richer*.

We explored different specifications of the ARMAX-GARCH model with p, q, r and m, ranging from zero to three (except r, which cannot be smaller than one).

4.1 In-sample

Firstly, we study the exploratory power of the emotional markers in financial time series modeling.

The group of indexes consist of S&P500 and DJIA has three common emotional markers: *hope*, *bad* and *gloom*. The dynamics of DJIA is also affected by *alas*. Although, *alas* provide additional information by AIC and HQIC criteria, but not according to a BIC. The emotional marker *bad* add information to models with normal and skewed Student distributions. Specifications which provide better fitting according to BIC in most cases have skewed normal distribution for error term. It's worth mentioning that indexes have no GARCH-effects in this specifications, because m parameter is equal to zero for the optimal models.

The coefficients in the optimal models are significant on 5% level. Although, emotional marker *gloom* have a positive effect on the dynamics of the both indexes', it affects DJIA almost ten times stronger than S&P500, see Table 1. *alas* has substantial negative impact on DJIA log returns.

The next group of assets, that we call emotional sensitive stocks, includes AAPL, FB and GOOG. The group has more Granger-valid emotional markers than the previous one, for example, *awful*, *fear*, *frighten* and already mentioned *bad* and *gloom*.

For emotional sensitive stocks sentiment models with skewed normal distribution again performs better than baseline models. Normal distribution is also presents among optimal specifications. Skewed Student's distribution is included in optimal specifications only for *ok*[7] marker for AAPL stock returns. Vuong test supports the alternative hypothesis that sentiment models has better fit than baseline ones, Table 1.

Emotional markers associated with fear, i.e. *fear* itself and *frighten* exhibit strong negative impact on returns. The same behavior is demonstrated by *awful*. Interestingly that *ok* also has negative effect but the size of the effect is much smaller than for *fear* marker.

Looking forward to marker has substantial positive impact on AAPL and GOOG stocks' returns. *bad* that is likewise among AAPL and GOOG Granger-valid markers has minor positive effect on returns in specifications with normal

[7] *ok* means "only kidding".

and skewed normal errors. *gloom* being common for all stocks in the considered group is insignificant on 5% level in optimal specifications.

As for the last group of emotion insensitive stocks normal and skewed normal distributions similarly demonstrate better fit, verified by Vuong test. Already mentioned *hope* and *frighten* have significant positive and negative impact correspondingly. For Exxon *hope* turns out to be insignificant on 5% level.

We found that emotion insensitive stocks have specific emotional markers, discovered by Granger test (1) and (2). They are *cancer* for Pfizer, *br*[8] for JP Morgan and *richer* for Exxon Mobil. Although *cancer* marker is insignificant it helps to improve the predictive power comparing to the baseline model. JP Morgan's specific marker slightly decreases the returns. As opposed *richer* is one of the strongest determinants of Exxon's returns growth. The other important emotional markers for XOM are positively affecting *gloom* and *dark* and negatively affecting *sad*.

Our hypothesis is that emotion sensitive group of stocks is more affected by emotional markers than emotion insensitive group. The results evidence that stocks in both groups are influenced by emotional markers. Although, the tweets we analyze are not restricted to those that regard to the economy, business climate, world affairs, specific businesses and, for example, includes tweets by teenagers talking about regular things or events, we found that suggested sentiment measurement do add information to ARMAX-GARCH model. One of the possible ways to further research in this area is to organize filtering of downloaded messages to measure sentiments of a more inclusive group, based on context published in their posts (business or economics related).

Table 1. Summary for sentiment models which significantly outperform baseline

	Asset	DJI	SNP	AAPL	JPM
Baseline model parameters	Distribution	snorm	sstd	sstd	sstd
	p,q,r,m	0,0,3,0	2,1,1,1	0,0,3,0	0,0,1,0
Sentiment model parameters	Distribution	snorm	sstd	sstd	sstd
	p,q,r,m	2,3,1,1	2,2,1,1	3,2,1,0	3,2,1,0
	Emotional marker	gloom	gloom	ok	hope
	Coefficient	0.634*	0.065*	-0.016	0.053*
	Lag	8	8	29	8
BIC	Baseline	-7.309	-7.192	-5.750	-6.030
	Sentiment	-7.314	-7.203	-5.764	-6.031
AIC	Baseline	-7.397	-7.280	-5.811	-6.079
	Sentiment	-7.421	-7.310	-5.875	-6.138
Vuong test		1.042*	0.407*	0.885*	0.053*

* means significant on 1% level.

p,q,r,m are corresponding parameters in (4) and (5).

[8] *br* means "best regards".

4.2 Out-of-sample

100 observations are retained to evaluate the out-of-sample performance of emotional markers. We calculate MSE and DAC (refer to Sect. 2.3 for details) as measures of emotional markers' predictive power.

The optimal models for index group demonstrate less successive predictive performance, comparing to baseline models. *hope* marker is an exception, providing smaller MSE for both indexes. In addition *hope* and *bad* markers with normal and skewed Student's errors allow to increase directional accuracy of DJIA and S&P500 returns to 58% and 54% correspondingly.

Directional accuracy for emotional sensitive group of assets is higher than for the index group even in BIC selected models. The obtained DAC for optimal models starts from 50% and peaks on 63% for *frighten* marker.

It should be noted that k[9] being insignificant on 5% level yield outstanding out-of-sample results with smaller MSE and DAC equal to 57%–58%. It confirms our suggestion of that the emotional markers which provide poor in-sample performance can be successfully used in prediction models.

Models directional accuracy in the last group of emotional insensitive stocks varies from 47% to 56%. The same distributions, namely normal and skewed normal, provide enhanced prediction comparing to baseline models. Emotional markers which contribute to the out-of-sample performance most are *br* for JPM, *cancer* for PFE and *richer*, *hope* and *dark* for XOM.

Models which exhibit poorer performance in-sample demonstrate promising out-of-sample results. We consider this as a motivation to find optimal specifications by some predictive criteria, such as MSE or DAC, to obtain models with increased predictive power.

It's important to add that emotional markers being included in volatility equation (5) are insignificant on any reasonable significance level. We also controlled the mean equation for day effects and found no evidence of their presence or their impact on the prediction ability.

5 Conclusion

We started our research with a question: can Twitter data bring additional information to the ARMAX-GARCH model? Being positive the answer is based on the thoroughly elaborated methodology (see Sect. 2 for more details), which includes collecting and preprocessing Twitter posts, applying some textual analysis to the tweets, defining the Granger causality relations and implementing the output to the ARMAX-GARCH modeling. We wish to make the textual analysis stage transparent and simple, thus we use parsimonious word count technique to create so called emotional markers, which subsequently are used as the determinants of the log returns dynamics in the ARMAX-GARCH model. We form three groups of assets, namely indexes, emotion sensitive stocks and emotion insensitive stocks.

[9] k is short for "ok".

Studying the explanatory power of constructed models we show that emotional markers demonstrate smaller BIC and provide significant positive increment to the likelihood function subject to Vuong test. In order to capture higher order effects of returns, such as skewness associated with the third moment of returns' distribution, we implement skewed versions of normal and Student's distributions for errors. In some cases, including Facebook, Google and JP Morgan, the third moment effects turn out to be insignificant so normal distribution also works well for these stocks.

We find evidence of that such emotions as fear and sorrow, represented by markers *fear*, *frighten* and *alas*, have substantial negative impact on the dynamics of both stocks and indexes. Negative influence of sorrow is also confirmed by *sad* for XOM. *Looking forward to* marker which corresponds to anticipation has substantial positive impact on stocks' returns from emotional sensitive group. The analysis of emotion insensitive group reveals the existence of specific emotional markers for the members of this group. Being negligible in the exploratory sense they allow to increase the predictive ability of the ARMAX-GARCH model.

We expect that the relationship between emotional markers and returns can change over time. Firstly, it could happen because of some fundamental factors. In a period of financial stability, for example, emotions may play a smaller role than during a downturn. And vice versa, the market response to similar financial news may be different depending on the mood prevailing in society.

Secondly, the behavior of stock market players could change if they would take in account information from emotional markers. Since we detect two kinds of emotional markers (see 4.2) — those, which explain the returns well, and those, which predict the returns, we expect that the changes in investors' behavior should be based on the emotional markers of the second kind. On the other hand "explaining" emotional markers should not change the behavior of stock market players, because they seem to be an intrinsic characteristic of the market and are unlikely to generate profitable trading strategy.

In our further research we plan to move in two directions. Firstly, we will distinguish periods when the stock market is emotional driven and news driven. Secondly, we will monitor Twitter posts to see if there will be significant changes in emotional marker frequencies, which could be a sign of manipulation.

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