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Social sentiment and exchange-specific liquidity at a Eurasian stock exchange outside of US market hours

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Abstract
We perform a neural network analysis of the impact of Russian retail investors´ sentiment on the stock price behavior of well-known American companies. We study American stocks in a situation of a time-segmentation of the stock market. A special feature of our analysis is the separate time trading mode, when trading is active at the SPB (formerly St. Petersburg) exchange and inactive at the US stock exchanges. Building on the unique local exchange data and original technique for constructing a neural network to identify the sentiment of messages from several Internet forums, we uncover the existence of behavioral anomalies in a non-English-speaking emerging market and analyze sentiment and attention metrics in social networks. We construct several sentiment metrics based on AI text analysis and use panel regression to identify their statistical significance under the selected hypotheses. The impact of sentiment is examined across the entire sample of US companies available to investors on the SPB exchange and a separate zooming is made at the top 10, 25, 50, and 100 stocks that are under special interest manifested by volume of discussions and trading volume. We also analyze the impact of sentiment on price reaction for individual popular stocks and by industry. We find that retail investors' sentiment exercises a statistically significant influence on price spikes. The stocks, most sensitive to sentiment, are healthcare and high tech.

Keywords Neural networks · Big data modeling · Investors sentiments · Foreign stock exchange · Liquidity

1 Introduction

Information efficiency is the basic paradigm of financial economics (Gomes & Gubareva, 2020). However, the channels for obtaining information and the degrees of investors´ awareness change over time, especially in what concerns financially non-literate traders. Numerous research papers take in account the

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important role of sentiment, visibility of the company and its leader (the cases of Elon Musk, Bill Gates) as well as emotional attachment of customers to the company's products and brands and reveal that these factors significantly impacts stock prices. Social sentiment and social networks also have been receiving a lot of attention by academy. For instance, Zhou et al., (2021), analyze the influence of Twitter on stock prices in the USA et al., Afzali and Martikainen (2021) address financial effects of social networks in European countries, while Bossman et al., (2023a, 2023b), and Ghosh et al., (2023), study the impact of investor sentiment, respectively on stocks of European Union countries and energy transition metals. Identifying the influence of investor sentiment on price behavior allows us to identify both, anomalies in the market and possible manipulations; see Mensi et al., (2023). Moreover, Teplova and Tomtosov (2021), Fedorova et al., (2022), and Teplova et al., (2022), applied AI methods to analyze texts in Russian language and analyze the influence of Russian social platforms and messengers on stock prices in the Moscow stock exchange. To the best of our knowledge, venue-confined liquidity problems are not addressed in the literature.

Another important open question—whether there are specifics for emerging markets in the situation of the social media revolution (Umar et al., 2021a, 2021b, 2021c; Peress and Schmidt, 2020). Existing literature exclusively focuses on the association between local investor sentiment and local stock market performance. Nonetheless, it is still an open question whether the community of local investors, who exchange messages in non-English languages, can influence the price changes of global stocks by their emotional mood.

News arrivals and access to information has long been acknowledged basic factors in financial economics to explain asset pricing. The neoclassical efficient market hypothesis (EMH) has been constantly tested and amended since the 1960s. A number of significant changes observed recently in public life has generated an increased role of sentiment (an emotional connotation for events, statements, forecasts, and assessments) in explaining retail investors' decision-making, forecasting of their investment choice, dynamic patterns of key financial assets, stemming from deviation of investors from rational thinking (Banerjee & Green, 2015). Spotting effects like naming and alphabetism and copycat effects of replicating portfolios of investment gurus and hedge funds are turning secondary against an emotional disposition for securities that arises across investment communities in social networks and messengers.

We outline three non-fundamental factors in asset pricing in financial markets which can result in both abnormal behavior of market microstructure properties and overall stock market crashes. These are (1) copycat effects (measured by trading volume, price response, inclusion in to a stock index or into a portfolio of hedge funds and other institutional investors, and news feed), (2) spotting effects (less volatile factors such as a remarkable ticker, company size, etc.), and (3) emotional loyalty (an emotional attachment to one or another asset formed unintentionally or a positive image of a company formed intentionally with various manipulation techniques over the opinions of the community members.

A huge rise in retail investors in financial markets in 2020–2021 resulted in an enhanced role of social networks which began to exercise an increased influence upon investor's decision-making and, ultimately, affect asset prices.

In works by Tetlock et al. (2008), Bollen et al. (2011), García (2013), the authors give a quantitative estimate the text content from online media with the analysis of text data and report that investors' sentiment affects asset dynamics. By analyzing Twitter massages, Bollen et al. (2011) constructed an indicator named "call sentiment" which was able to forecast daily volatility of the Dow Jones Index.

In terms of the activity of retail investors, the Russian market occupies an intermediate position between the United States and China (Lee et al., 2010). Covid-19 crisis and lockdowns leveraged investors' time and attracted them to the stock market amid low interest rates on the bond market and deposits.

In our study, we focus on the behavior of Russian investors in relation to American stocks, considering the specificity of the functioning of the Russian stock exchange, namely, on the situation of a time-segmentation of the stock market.

The SPB Exchange (known formerly as St. Petersburg Stock Exchange) is the main platform for trading in foreign securities for Russian investors (in 2021, the Moscow Exchange is trying to create competition for it, where investors can carry out settlements in the national currency). The peculiarity of the SPB Exchange is settlements in US dollars and the function of the global pre-market: 78% of transactions are executed within the Exchange itself. In 2021, transactions were concluded with over 1570 foreign shares and depositary receipts. The traditional monthly volume of transactions in the group of instruments "foreign securities" on the SPB Exchange at the end of 2021 is 29 billion USD, while over the period from January 2020 to August 2023 this figure equals to 15.6 billion USD. More than 10 million private Russian investors have accounts on the exchange (this is the number of unique clients). There are about 1 million active clients (10%). Interestingly, in some months (for example, June 2021), the volume of trades in foreign securities exceeded the volume of trades in Russian securities on the Moscow Exchange (a particular interest was associated with Virgin Galactic)—see Fig. 1. In order to demonstrate a relative importance of the SPB Exchange we indicate that during the period from January 2020 to August 2023, the overall volume of USD-denominated transaction totalizes 670,4 billion USD, which correspond to the average daily volume of 0.74 billion USD.

In 2021, SPB Exchange developed SPB100—the world's first stock index reflecting the interest of retail investors (SPB100 Index reflects the behavior of the average portfolio of retail investors, the top 10 of the SPB100 index in the fall of 2021 included the largest American companies, such as Apple, Amazon, AT&T, Boeing and Tesla, Chinese Alibaba, Baidu and Vipshop, as well as popular among retail investors Carnival and Virgin Galactic).

With the development of IT, machine learning, and neural networks capable of analyzing huge arrays of text messages by artificial intelligence techniques, there appeared a possibility to catch the tone of messages from a large volume of network discussions and, by classifying, to construct sentiment metrics (Jing et al., 2021). In our work, we use artificial intelligence techniques to reveal daily tonality of network messages (neutral, positive, negative) and to test a hypothesis about how this

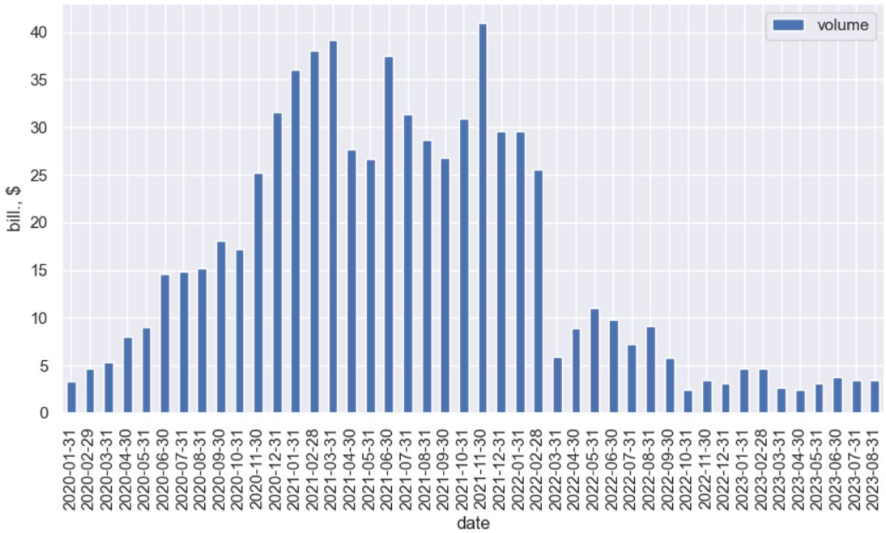

Fig. 1 The trading volumes at the SPB Exchange. Source: https://spbexchange.ru/ru/market-data/

tonality affects price behavior. Since American stocks are traded in different countries and, thus, in different time zones, we have chosen a time interval for venue-confined liquidity; i.e., when Russian investors have access to trading outside of US market hours, which allows us to test hypotheses in the situation of a time-segmentation of stock market.

We have coined the term venue-confined liquidity to refer to trading hours on the SPB Exchange. Due to differences in time zones, trading hours at the SPB Exchange are not synchronized with those at US exchanges. Consequently, liquidity of US stocks generated on the SPB Exchange may be mostly, if not entirely, conditioned by properties of market microstructure and market participants of this particular trading venue without being subject to outside liquidity spillovers. Hence, we come to use the term venue-confined liquidity.

The main objective of our study is to investigate the trading of American stocks at the SPB Exchange, focusing on whether sentiment exercises a statistically significant influence on price spikes. These stocks are hot discussion topics in virtual professional communities. Such discussions contribute to an emotional attachment of investment community members, which tend to emphasize positive properties of the US equities. The scope of our study is to reveal the phenomenon of venue-confined liquidly of US securities induced by retail investors' sentiments.

We point to three key factors that generate anomalies in financial markets (including the effect of meme stocks: (1) an arrival of a large number of retail investors to the stock market (partly due to the pandemic and lockdowns, partly because of ease of handling software applications to access brokerage accounts and decreased trading costs on internet trading platforms, and partly due to a downward move of real returns on high credit quality assets into the negative zone and a resulting need for investors to accept larger risk); (2) A fast proliferation of new information transmission channels (messengers, social networks) and vast possibilities for the formation of relatively segregated virtual communities with their own rules, authorities, a scope for self-fulfillment for their members through collective investment strategies; (3) A growing speed of communication, collection and processing data, strength of simulation studies conducted by market participants to determine profitable investment strategies which are not just based on fundamentals but encompass emotional perception.

The impact of sentiment is examined across the entire sample of US companies available to investors on the SPB exchange and a separate zooming is made at the top 10, 25, 50, and 100 stocks that are under special interest manifested by volume of discussions and trading volume (see Appendix 1).

Text messages are collected from Russian-speaking internet forums. Neural network techniques are used to classify messages and then econometric analysis is performed to detect an impact of the discussion tone and of other metrics of stock conspicuity for market investors on daily stock dynamics.

Our paper deals with over 1300 stocks of US companies, classified over 11 million messages by Russian retail investors, regressed over 200,000 econometric models with both individual and panel data, and checked the inferences' consistency by considering results from different perspectives. To train sentiment classification models, we used a dataset of over 35,000 messages from private investors collected on Russian stocks from the sites tinkoff pulse, mfd. To train the neural network models of the message classification problem, the marked-up dataset described above was used. The dataset was randomly divided into three parts with stratification: train, validation, and test datasets in the proportions of 0.7, 0.15, and 0.15, respectively. Train and validation datasets used in model fine-tuning. The test dataset was used in the final with models that showed the best results in training and validation, considering the selection of hyperparameters.

Based on the previous research works, which evidence diversity of market impact metrics, and in line with the best practices of econometric analysis, we formulate the three following hypothesis: (i) retail investors' sentiment exercises a statistically significant influence on price changes during the hours of venue-confined liquidity; (ii) retail investors' sentiment exercises a statistically significant non-linear influence; and (iii) retail investors' sentiment exercises industry specific influence on price dynamics. By testing these hypothesis we find that retail investors' sentiment exercises a statistically significant influence on price spikes.

Our work represents a contribution to academic research along the three following directions: (1) for the first time, the sentiment specific influence of non-English-speaking retail investors on popular US stocks during periods of inactive trading in the US (time-segmented trading zone, venue-confined liquidity) are analyzed, (2) the possibilities of using AI methods for text data in Russian are shown, and (3) the influence of sentiment metrics on different price reactions was compared both for popular portfolios of different sizes (10, 25, 50, 100) and by industry. The most popular promotions are considered separately. To the best of our knowledge, there are no published works with similar analysis of the impact of sentiment on foreign stocks traded during the hours of venue-confined liquidity. Our research feels this gap.

The structure of the remaining part of the paper is as follows. Section 2 is dedicated to formulation of the research hypothesis, based on the survey of the previous research and the current state of the art. Section 3 addresses the objectives of the study, data description, and the methodology overview. Section 4 presents empirical results and discusses their implications. Section 5 concludes.

2 Research hypothesis formulation

2.1 State of the art: diversity of market impact metric

Based on the studied literature, we distinguish direct and indirect communication channels for market participants to generate the effect of emotional attachment. Direct communication channels encompass public communications of interested parties: (1) officially disclosed financial and non-financial company reports and reports by industry-specific agencies including opening statements and remarks, (2) comments and interviews by companies' senior officials and beneficiaries, (3) recommendations by independent and in-house investment analysts.

Indirect communication channels encompass: (1) media (conventional newspapers and magazines, and their e-versions, taking into account the tonality of articles; (2) chats in messengers and social networks (as channels for exchanging ideas and assessments of events by retail investors; (3) statements by high-profiles persons, show business celebrities, investment gurus, (4) indicators that track activities of professional financial market participants (a focus here is on the disclosure of the asset breakdown, which may signal a change in investment preferences).

A remarkable progress in internet technologies over the past years has led to a spectrum of research related to the impact of exchange trading specific internet forums and social networks on price behavior. A development of machine learning algorithms and artificial intelligence facilitated text mining and stock ranking not just according to conspicuity for investors (conventionally measured by frequency of mentions, search queries, etc.) but additionally capturing investors' attitude to a stock, the tone of discussion (sentiment).

Our paper extends the work by Schumaker et al. (2009), and Sadeghi and Beigy (2013) who, on the basis of text data, detect sentiment to assess new factors which may explain price dynamics and differences in returns. In a paper by Kumar and Ravi (2016), the authors, based on answers to a questionnaire about data mining in finance, conclude that about 70% of previous research works were carried out with the use of standard machine learning techniques such as decision tree, SVM, and regression analysis.

In recent years, the development of neural networks made it possible to extrapolate their usage to text data analysis. In a paper by Yoshihara et al. (2016), the authors report that the use of neural networks results in decreased frequency of binary classification errors by 7%. In order to forecast asset prices in the stock market with Twitter messages, Si et al. (2013) employ a non-parametric thematic model that incorporates continuous Dirichlet process mixture (CDPM) for time series.

Giannini, et al. (2019), based on a text analysis of Twitter discussions, shows that differences of opinion among investment community members significantly affect stock returns before financial results (for example, profits) have been published. Optimistic tonality in the media is an important factor to increase stock prices irrespectively of the companies' fundamental value that eventually results in financial bubbles.

2.2 Formulation of research hypothesis

Based on the surveyed-above previous research, which evidence diversity of market impact metrics, and in line with the best practices of econometric analysis, we arrive at the following hypothesis to formulate:

> Hypothesis 1. Retail investors' sentiment exercises a statistically significant influence on price changes during the hours of venue-confined liquidity; i.e., from the close of the previous day's trading session in the US to the end of the current trading session in Russia.

There are several metrics of market impact used in the work:

1. Price change from the previous close price to the next open price in the US
2. Difference between the open price and the highest price quoted on the SPB exchange (during hours of venue-confined liquidity)
3. Difference between the open price and the lowest price quoted on the SPB exchange (during hours of venue-confined liquidity)
4. Difference between the highest price and the lowest price quoted on the SPB exchange (during hours of venue-confined liquidity)

Our motivation for considering the above price change metrics is anchored in the analysis of price changes either to the opening of the next trading section or to the closure of the last trading session, as these price movements reveal the most rational actions of participants. On the other hand, a maximum growth of a stock price resulting in a price upside or a pronounced decay of a daily price resulting in a downside are manifestations of an emotional reaction. It is important for us to separate these two reactions—more emotional and less emotional, and to show the impact of discussions in instant messengers on these two price movements.

> Hypothesis 2. Retail investors' sentiment exercises a statistically significant no-linear influence.

The influence of sentiment is non-linear. Dealing with this question, we envisage to uncover whether the influence of stock discussions on the respective share prices is non-linear. For instance, we focus on providing empirical evidence regarding the influence of very strong positive/ negative emotions as well as of the absence of an explicitly expressed tonality of discussions. We gauge whether these factors are capable of generating considerable upward downward moves in stock prices. We also investigate whether positive discussions of moderate intensity, i.e., not very intensive interchange of messages conveying positive information about a stock, generate an upside in prices. In addition, we also study the influence of negative discussions on downsides in prices, including both moderate negative discussions and extreme sentiment expressions in order to gauge their influence on (sharp) trading movements. We posit that the coefficients of the non-linear sentiment variables for extreme price reaction must be positive, as arguably investors' trading behavior is expected to be susceptible to market sentiment and tone of discussion.

Hypothesis 3. Retail investors' sentiment exercises industry specific influence on price dynamics.

Industry differences across companies are important in explaining price dynamics by the sentiment of members of the investment community. Hypothesis 3 states that retail investors' sentiment plays an industry specific role in price dynamics of the companies from different sectors of economic activity.

Testing this hypothesis, we intend to check the inferences' consistency across different industry sectors. Hence, we run panel regressions for several sample of stocks from the healthcare, industrial, technology, and basic material sectors of economic activity, using not the totality of the available companies per sector, but the top 10, 25, 50, and 100 discussed stocks subsamples for each of the considered industries. We focus on stocks of companies with high market capitalization. We expect that some regression equations produce more significant or less significant results depending on the considered sector of economic activity.

3 Objectives of the study, data description, and methodology

We have analyzed over 1300 stocks of US companies, classified over 11 million messages by Russian retail investors, regressed over 200,000 econometric models with both individual and panel data, and checked the inferences' consistency by considering results from different perspectives. Python was used to accomplish these research tasks.

At the end of 2014, the SPB Exchange launched the trading of the 50 most liquid foreign stocks from the S&P 500 Index. Figure 1 shows trading volumes.

At the end of 2017, more than 500 foreign stocks were available for trading while in mid-2019 the number exceeded 1000. As of 2021, more than 1650 foreign stocks are traded on the SPB Exchange. Trading is carried out under the Russian jurisdiction.

The trading session schedule is shown in Fig. 2.

The trading session has several time periods which can contingently be split into:

- A period of venue-confined liquidity prior to trading in the US (from 7:00 to 14:30 (15:30*)) Moscow time;
- A period of trading in US stock markets (from 14:30 to 23:00 (00:00*) Moscow time.

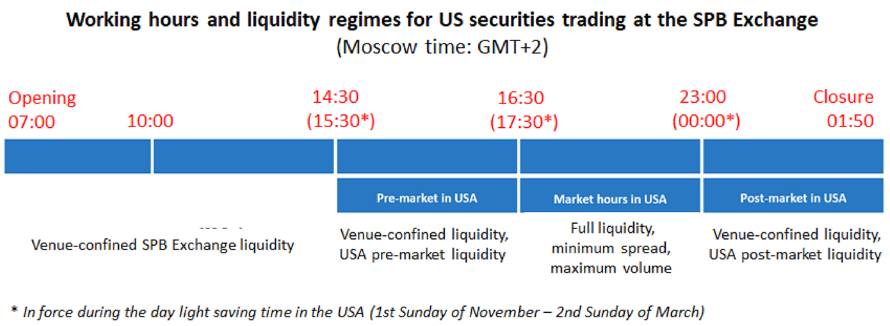

Fig. 2 The trading sessions at the SPB Exchange

Table 1 The descriptive statistics for tickers during venue-confined liquidity at SPB Exchange. Source: https://spbexchange.ru/market-data/totals/

	Open	High	Low	Close	Volume
Count	1,662,205	1,662,205	1,662,205	1,662,205	1,662,205
Mean	85.54215	85.71684	85.34633	85.53987	890.2491
Std	118.1074	118.3116	117.8887	118.105	12,090.61
Min	0.69	0.7	0.69	0.69	0.033333
Max	2460.98	2468.08	2460.98	2460.98	4,109,640

In the first half of the day, liquidity is formed by Russian market participants, algorithmic traders, and market makers. With the opening of the American market, the quotes of the leading American markets are added to the domestic venue-confined liquidity.

In our paper, we only consider the period of venue-confined liquidity on the SPB Exchange, as we seek to determine the influence of the sentiment of Russian-speaking retail investors on American stocks.

3.1 Quotes data

Quotes of foreign shares were taken directly from the SPB Exchange's website.[1] Trading period also takes place when trading is closed in the American market (a period of venue-confined liquidity). The time interval of quotes is 30 min, which is enough to build the aggregated intervals for testing hypotheses due to the inner trade period of SPB exchange.

In total, the quotes for more than 1300 stocks have been downloaded from January 2018 to February 2021. Splits were also considered for all stock quotes that occurred during this period.

The descriptive statistics for 30 min interval tickers in a period of venue-confined liquidity are shown in the Table 1.

[1] https://spbexchange.ru/ru/stocks/inostrannye.

Table 2 Descriptive statistics of messages downloaded from the forums

Statistics	ru.investing.com (1)	tinkoff pulse (2)
Number of American stocks discussed	1938	1398
Number of messages	1,171,086	10 822,684
Average number of messages per stock	604	7747
Median number of messages per stock	7	538
Number of unique authors	36,826	163,336
Average number of messages per author	31	66
Median number of messages per author	3	8
Median length of messages	47	49
Average length of messages	67	112

3.2 Sentiment messages

To download relevant messages by retail investors, we use web-scraping to find Internet forums with investment discussions. An Internet forum is a web-page in the HTML format with formatted text and various message attributes: the author's name, the content of the message, the date of publication. Often, there are other data in hidden attributes such as the unique message number, the unique author number, etc. All these attributes are necessary and important for further analysis.

The most popular forums among Russian retail investors include mfd (mfd.ru), tinkoff pulse (https://www.tinkoff.ru/invest/stocks), smart-lab (https://smart-lab.ru), investing.com (https://ru.investing.com). These are free virtual venues, with free registration. There Russian retail investors actively discuss financial markets with the major focus of discussion concern being on the Russian stock market.

American stocks had not been widely discussed until recently. In some Internet forums (mfd, smart-lab) the discussions are essentially episodic and centered on few securities. Therefore, these two sites are excluded from sources of messages.

We constrain our research to messages from two sites: investing.com and tinkoff pulse (tinkoff.ru/invest/pulse-social/). To collect data, special parser programs are written or each forum which download message archives for each American stock and save them in a special format designed for further processing. To write one's own parser programs, we use a combination of Python and Beautiful Soup as the most convenient and affordable option. For convenience, we will refer to ru.investing.com as the 1st site and to tinkoff pulse as the 2nd site.

As can be seen from Table 2, the number of discussed American stocks is significantly greater on the 1st site while the number of messages and unique authors is significantly greater on the 2nd site. This suggests that stocks are far more often discussed on the 2nd site than on the 1st one. A noticeable difference between the median and mean values suggests that most of the messages are concentrated on a few dozens of stocks.

The same conclusion can be drawn from the analysis of trades. For example, in June 2021, 25% of the total trading volume was generated by Virgin Galactic. This might rise a question whether the constructed indicators and the analysis of market impact will mostly reveal the influence of the common stock sentiment rather than a sentiment specific for a poorly discussed stock. A bias in the number of messages per author also points to a small group of active participants who generate a lot of messages. However, it would be incorrect to say that the opinion of such groups determines the overall emotional tonality since the number of their messages is much less than the total number of messages.

As for the message length, Table 2 shows that the median length is approximately the same in the two forums and does not exceed 50 characters, which indicates that messages are short. We consider this to be a positive aspect in data processing: short messages are exactly an opinion, frequently emotional, of a retail investor while long messages are usually a kind of review of a company or the market which is bereft of any emotional tonality. A bias in the average message length on the 2nd site indicates that there are much more messages containing analysts' reviews, reports, and opinions.

In Appendix 1, the aggregate distribution of the number of messages and unique authors per time are presented.

Despite a large number of stocks which are mentioned in discussion threads in the forums and the total number of messages for the stocks, most of the discussions are concentrated on a small group of stocks. These discussions will set the overall emotional tonality during the analysis. Moreover, individual indicators of emotional tonality will not be indicative for most of the stocks because of rare messages.

To classify messages by emotional tonality, we use machine learning with the supervised learning ("learning with a teacher") approach. Therefore, the general objective is divided into four tasks: preparation of a training sample, adjustment of algorithms (neural network models), preparation of data for classification, and classification of messages. The selected model performed labelling within the data sample; the results are presented in Appendix 2 (Table 19).

3.3 Training dataset

To train sentiment classification models, we used a dataset of over 35,000 messages from private investors collected on Russian stocks from the sites tinkoff pulse, mfd. In this case, it does not matter what actions are discussed in the messages, since their emotional tone is important to us. But at the same time, we cannot use any other sentiment datasets to train such models, because of the specific slang when discussing the action. These messages were manually classified into three classes (each message has only one class): positive, neutral and negative, with the numbers 2, 1, and 0.

For example, if a message has a label of 1, it means that it contains a market-neutral emotional tone. The messages were marked up by HSE undergraduate and graduate students with the support of the HSE Center for Financial Research and Data Analysis (https://fmlab.hse.ru/). The manual classification was used without resorting to any algorithms due to the specificity of messages and slang. This procedure assured a fair expert judgement regarding the correctness of the classification.

As a result, 6367 positive messages, 9130 negative messages, and 20,000 neutral messages were classified.

3.4 Selection neural network model for classifying sentiment of messages

Over the past few years, natural language processing (NLP) techniques have been largely improved. NLP is a field of mathematical linguistics focused on the development of models that understand a human language. A breakthrough occurred in 2018 when new approaches were advanced for building and instructing neural networks for NLP purposes, and new models were offered that largely surpassed existing solutions. This breakthrough was called NLP's Image Net moment,[2] in analogy with a jump in the development of computer vision applications.

Vector representations, pre-trained on large volumes of unlabeled data using such algorithms as word2vec and Glove,[3] were employed to initialize the first layer of the neural network while the remaining layers were used for training within specific applications. At that time, this was a standard approach to accomplish NLP objectives. However, there is a problem that the rest of the model must still be trained from scratch and is required to learn both to overcome the problem of multiple meanings of words and to recognize meaningful sequence of word which is a key to understanding any language.

Over the past few years, NLP techniques have improved significantly. In 2018, there is a paradigm shift, consisting in the transition from a simply initiating the first layer to training the entire model and further training the last layer of the neural network model for a specific application. Ultimately, this approach was adopted for solutions that became the basis for further breakthrough developments: semi-supervised sequence learning (Clark et al., 2018), Transformer (Wolf et al., 2020), ELMo (Peters et al., 2018), ULMFiT, (Howard & Ruder, 2019), GPT (Xie et al., 2020). These approaches make it possible to pre-train neural network language models on large volumes of data and carry out further fine-tuning for specific applications. At the end of 2018, Google Inc. introduced the BERT language model[4] with open source code and an option to integrate models that had been already pre-trained on large volumes of text data. This allowed independent developers to use a ready-made powerful model for their own architecture to accomplish NLP objectives thus avoiding a waste of time and effort for the resource-intensive process of pre-training on large volumes of text data.

As for the results, the model successfully surpassed the leaders in GLUE tests in NLP tasks at that time, including in the binary text classification test (SST-2) in Fig. 3.

[2] https://ruder.io/nlp-imagenet.

[3] https://nlp.stanford.edu/projects/glove.

[4] https://ai.googleblog.com/2018/11/open-sourcing-bert-state-of-art-pre.html.

Rank	Model	Score	CoLA	SST-2	MRPC	STS-B	QQP	MNLI-m	QNLI	RTE
1	BERT: 24-layers, 1024-hidden, 16-heads	80.4	60.5	94.9	85.4/89.3	87.6/86.5	89.3/72.1	86.7	91.1	70.1
2	Singletask Pretrain Transfromer	72.8	45.4	91.3	75.7/82.3	82.0/80.0	88.5/70.3	82.1	88.1	56
3	BiLSTM+ELMo+Attn	70.5	36	90.4	77.9/84.9	75.1/73.3	84.7/64.8	76.4	79.9	56.8

Fig. 3 Bert test results of NLP tasks and comparison with past leaders (https://huggingface.co/bert-base-multilingual-cased; https://huggingface.co/facebook/mbart-large-cc25). Source: https://blog.research.google/2018/11/open-sourcing-bert-state-of-art-pre.html

Based on the conclusions above and considering accessibility, we decided to use the pre-trained mBERTbase[5] and mBARTlarge[6] models as the main models. The prefix "m" in the model names means multilingual.

3.5 The architecture and description of the main models and baseline

The mBERT large (model 1)—a multi-layer bidirectional Transformer encoder, pre-trained model with 24 layers, 1024 hidden and total 340 M parameters, described in Devlin et al. (2019). Model was pretrained on the 104 languages with the largest Wikipedias.[7]

The mBART large (model 2)—a sequence-to-sequence denoising auto-encoder, described in Liu et al. (2020). The model has 12 encoder and 12 decoder layers, with model dimension of 1024 on 16 heads and total about 680 M parameters. Model was pretrained on a subset of 25 languages (CC25)—extracted from the Common Crawl (CC) (Conneau et al., 2020; Wenzek et al., 2019).[8]

For NLP classification task we change head on top of the encoders of both model by a line output layer with output size of 3 (we have three classes of our training dataset: positive, negative and neutral, as we mentioned above).

For baseline we choose basic, well-proven at classification tasks machine learning algorithms LinearSVC[9] (Linear Support Vector Classification, model 3) and RandomForestClassifier[10] (model 4).

3.6 Methodology and results of fine-tuning NN

To train the models of the message classification problem, the marked-up dataset described above was used. The dataset was randomly divided into three parts with stratification: train, validation, and test datasets in the proportions of 0.7, 0.15, and 0.15, respectively. Train and validation datasets used in model fine-tuning. The test dataset was used in the final with models that showed the best results in training and validation, considering the selection of hyperparameters.

5 https://huggingface.co/bert-base-multilingual-cased.

6 https://huggingface.co/facebook/mbart-large-cc25.

7 https://github.com/google-research/bert/blob/master/multilingual.md#list-of-languages.

8 https://commoncrawl.org/.

9 https://scikit-learn.org/stable/modules/svm.html#svm-classification.

10 https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html.

Table 3 Hyperparameters of models and their possible values

Parameter	Options or range
Batch size	8, 16, 32
Dropout rate	0.05, 0.1, 0.2, 0.25
Epochs	6
Learning rate	2e−5, 1e−5, 3e−5

As a metric of classification quality, we used f1-macro score,[11] which takes into consideration the imbalance of classes.

Preprocessing. Data preprocessing included the removal of links, stop words (except for "not" (Russian “не” pronounced as “nie”)), reduction to lower case. For models 1 and 2 the input data was tokenized using WordPiece and models vocabularies(with over 100 k tokens for mBert and 200 k tokens for mBart). For models 3 and 4, the input data was TF-IDF transform (with unigrams) processing messages with the Sklearn framework.[12]

Tools. We use the HuggingFace transformers framework[13] on Python to fine-tune model 1 and 2 for classification task. This framework is good because it is already optimized for specific NLP tasks, in particular, the classification task, for working with pretrained neural network models of the transformer types. For model 3 and 4 the Sklearn[14] framework was used to train and test the algorithms.

Hyperparameters. For models 1 and 2, we applied hyperparameters that are used in the transformers framework to classify messages by default: optimizer—AdamW, loss function—CrossEntropyLoss). As well as some of the hyperparameters (dropout rate, epochs, batch size, learning rate) discussed in Wysocki et. al. (2019). Since the model is already pre-trained and has a certain architecture, we did not change some of the hyperparameters. As a result, Table 3 shows hyperparameters and their possible values for tuning.

Learning rate—is an important parameter whose value allows you to avoid Catastrophic forgetting McCloskey and Cohen (1989). The optimal value for models like BERT is 2e-5 as investigated in Sun et al. (2019).

We stopped on the number of epoch equal to 6, since, as a rule, after the 5th epoch, the quality indicators of the trained model on the validation sample were submitted (and on the contrary, they grew on the training sample), which indicated that the model was overtrained. After each epoch, the model is validated, and intermediate weights are saved. As a result, the model that showed the best result in one of the epochs is selected.

11 https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html.

12 https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html.

13 https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html.

14 https://scikit-learn.org/stable/index.html.

Table 4 The results of hyperparameters search

Parameter	Model 1	Model 2
Batch size	32	32
Dropout rate	0.1	0.2
Epochs	34	4
Learning rate	2e−5	1e−5
F1 macro (validation)	0.65	0.67
F1 macro (test)	0.63	0.66

Table 5 Sensitivity analysis of best model (model 2)

Parameter	Value	F1 macro
Baseline	baseline	0.6
Loss function	CrossEntropyLoss[a]	0.67
	NLLLOSS[b]	0.65
Batch size	32	0.67
	16	0.6
Learning rate	1e-5	0.67
	1e-4	0.62

[a] https://pytorch.org/docs/stable/generated/torch.nn.CrossEntropyLoss.html

[b] https://pytorch.org/docs/stable/generated/torch.nn.NLLLoss.html

Since we are limited in computing power and large models are used for classification, it was decided to stop at the list of hyperparameters listed above and use the rest by default. The use of a more extended list of hyperparameters will be implemented in future studies, and the results of the current one is quite satisfactory to us.

For best hyperparameters search in models 1 and 2 we used the Optuna framework[15] with transformers Trainer API.[16] The results of hyperparameters search and quality metrics on the validation and test datasets of models are shown in the Table 4.

Finally, considering the results presented in Table 4 (also Tables 19 and 20), the model 2 was chosen for message classification.

Sensitivity analysis. We evaluated sensitivity of the model 2 performance in classification task with factors that played important role in model fine-tuning process. For each scenario we only changed one hyperparameter and keeping else the same, as discussed in Nguyen and Ślepaczuk (2022).

The most important factors are loss function, batch size, learning rate as discussed in Michańków et al. (2022). The results of sensitivity analysis are shown in Table 5.

As shown in Table 5, changing factors affect the classification quality of the model and in some cases, the quality drops to the baseline level, that is, the models

[15] https://optuna.org/.

[16] https://huggingface.co/docs/transformers/hpo_train.

have the worst ability to classify messages by sentiment. As a result, sentiment indicators constructed on the basis of classified messages by such models are of no interest to us as exogenous variables in panel regressions.

We constructed sentiment indicators using messages classified by Models 5 and 6 from Table 5. These models showed a worse classification result on the test sample than our best model 2. As a result, when testing hypothesis 1, the results of panel regressions turned out to be weaker, both in terms of the lower coefficient of the explained variance R^2, and in terms of the insignificance of some equations or exogenous variables. The results are shown in Table 21 of Appendix 2 and represent a robustness check for the tested models.

3.7 Classified data

The details of sentiment statistics, including message labeling as well as monthly, weekly, and daily numbers of positive and negative messages, may be consulted in Appendix 3. Overall, we have classified about 11 million messages from the two forums. Approximately 20% of them are classified as either positive or negative while 60% are neutral.

Hypothesis testing was performed on the data in period from the beginning of 2018 to February 2021, as this period is featured with the highest concentration of messages. Also, due to an explosive growth of messages in 2020 in the 2nd forum, a significant portion of the messages falls on 2020 and further on.

3.8 Data preparation for hypothesis testing

Prior to the analysis, we check compatibility of time periods for exogenous and endogenous variables for each hypothesis. We consider an annual transition to winter time in the US and a subsequent shift in the starting time of the trading period in the US premarket and an increase in the trading period with venue-confined liquidity on the SPB Exchange. Messages that are published during non-trading days (weekends, holidays, etc.) are also considered. For this purpose, a period is understood as a time interval from a certain time (depending on the hypothesis) of the last trading day to a certain time of the current trading day with possible inclusion of non-trading days.

The dependent variable is the log of the price change over the period $rets_{i,[t-1,t]} = \ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right)$ where $P_{i,t-1}, P_{i,t}$ denote the price of the stock i. Since not all the sample stocks have been traded since the beginning of 2018 their values are replaced with zeros. In case of missing prices, the previous value fills the gap. For price change metrics, the maximum and minimum prices per day are considered.

The sentiment variables given in Table 6 stand as exogenous variables. Each variable, unless specified differently, is computed for the period [t-1, t].

Table 19 in Appendix shows more wide scores and models on test dataset with tuned hyperparameters in model 1 and 2. Table 19 also shows the results of baseline classification.

Table 6 Sentiment variables used in the research

Variable	Description
ln_pos	Log of the sum of positive messages of stocks
ln_pos_sq	Log of the squared sum of positive messages of stocks
ln_neg	Log of the sum of negative messages of stocks
ln_neg_sq	Log of the squared sum of negative messages of stocks
ln_pos_30dmean_scale	Log of the sum of positive messages of stocks normalized by the 30-day average value. It reflects the dynamics of positive mood (fading in, fading out)
ln_neg_30dmean_scale	Log of the sum of negative messages of stocks normalized by the 30-day average value. It reflects the dynamics of negative mood (fading in, fading out)
Badj	Indicator (25) of stocks
*_scale	Variables from which the medians were removed and scales the data according to the quantile range (defaults to IQR: Interquartile Range). The IQR is the range between the 1st quartile (25th quantile) and the 3rd quartile (75th quantile). These variables are similar to the ones given above but logarithmization is replaced with standardization. Their names contain scale instead of ln

The sentiment variables used in the construction of individual regressions for individual companies are shown in the tables of Appendix 4.

The *Badj* variable reflects an excess of positive messages over the negative ones, adjusted by the log of the sum of these messages for the considered period. For an individual stock, the variable is computed in a similar manner based on messages only relevant to this stock.

$$Badj = \left[\frac{pos_t - neg_t}{pos_t + neg_t}\right] \times \ln\left(1 + pos_t + neg_t\right) \tag{1}$$

Various combinations of the variables are used in regression equations (both individual and panel). In the correlation analysis, the emphasis is on the Spearman's correlation coefficient (9) since it is less affected by outliers.

We use panel regression with fixed and random effects in the analysis of panel data. The inferences' consistency is checked by considering various stock allocations: top 10, 25, and 50 discussed stocks, stocks from most widely discussed industry, stocks of companies with certain a market capitalization range.

As can be seen from Table 22 in Appendix, there is a large bias towards neutral messages, which we also observed in the training sample.

4 Empirical results: hypothesis testing outcomes

4.1 Hypothesis 1: statistically significant impact of sentiment on price out of trading hours

Hypothesis 1. Retail investors' sentiment exercises a statistically significant influence on price changes during the hours of venue-confined liquidity; i.e.,

Table 7 The descriptive statistics of gap to the highest price aggregated variables

	Count	Mean	Std	Min	Max
rets	281,502	0.006	1.00	−1.34	2.07
ln_pos	281,502	6.421	1.869	2.773	10.04
ln_neg	281,502	6.436	1.904	2.89	10.267
ln_pos_sq	281,502	12.831	3.75	5.421	20.081
ln_neg_sq	281,502	12.872	3.80	5.78	20.534
pos_scale	281,502	0	1.00	−0.668	5.223
neg_scale	281,502	0	1.00	−0.664	6.279
pos_scale_sq	281,502	0	1.00	−1.545	12.034
neg_scale_sq	281,502	0	1.00	−1.357	15.947
ln_pos_30dmean_scale	281,502	0.733	0.176	0.23	1.497
ln_neg_30dmean_scale	281,502	0.73	0.187	0.174	1.533
all_scale	281,502	0	1.00	−0.769	9.452
Badj	281,502	−0.085	0.514	−2.033	1.687

from the close of the previous day's trading session in the US (23:00 in summer, 00:00 in winter) to the end of the current trading session in Russia (14:30 in summer, 15:30 in winter). The influence of sentiment is only seen in extreme price changes (upward or downward spikes), but is not significant for traditional daily returns metrics.

For traditional yield metrics the stock price changes are computed as $r_{t-1,t} = \ln\left(close_t\right) - \ln(close_{t-1})$, where $close_t$ denotes the close of the current trading session with venue-confined liquidity and $close_{t-1}$ denotes the close of the previous US trading session. A similar procedure is also employed when we analyze the price changes towards the closure of the last trading section or towards the opening of the current trading section.

However, if our econometric calculations did not show statistical significance or sufficient explanatory power, we do not provide results for either individual stocks or cross-sectional panels. For the vast majority of the provided results the important indicator of regression analysis, which is the amount of explained variance, namely R^2, is above 0,1, which we consider as acceptable lower limit, as it means that we are able to associate at least 10% of variation to the metrics of retail investors sentiment.

4.2 Gap to the highest price

Stock price changes are computed as $rets_t = \left(\max(price_t\right) - open_t)scaled$, where $open_t$ denotes the open of the current trading session with venue-confined liquidity and $\max\left(price_t\right)$ denotes the highest price of the current trading session. Sentiment variables calculated as sum from the end of previous trading session with venue-confined liquidity to the open of the current. Based on the first hypothesis, which

Table 8 Panel regression across all sample stocks (3 models). Top 100 and top 25 (3 models)

	All tickers			Top 100 tickers			Top 25 tickers		
	−1	−2	−3	−1	−2	−3	−1	−2	−3
nobs	281,520	281,520	281,520	36,800	36,800	36,800	9200	9200	9200
Rsq-overall	0.0018	0.007	0.0014	0.1410	0.0546	0.1651	0.1666	0.1351	0.1553
f-pvalue	0	0	0	0	0	0	0	0	0
all_scale			0.0268*** (18.3580)			0.0363*** (54.6510)			0.1502*** (19.6974)
neg_scale		0.0182*** (13.1113)			0.0139*** (30.0079)			0.1286*** (17.9855)	
pos_scale	0.0619*** (20.6026)			0.0574*** (47.3730)			0.1518*** (20.6823)		

was not confirmed, to the opening of the premarket, prices tend to the starting price of trading in America, so our goal is to check price deviations within the trading session, which can later be used for short-term trading operations.

The descriptive statistics of gap to the highest price aggregated variables are shown in Table 7.

Herein we investigate what causes an upside in the price dynamics.

As can be seen from Table 8, testing the hypothesis on the entire sample of US stocks that are traded on the St. Petersburg stock exchange does not show a significant influence of sentiment. However, the narrowing of the sample to 100, and then to 25, most popular securities, significantly changes the conclusions. From Table 8 we can conclude that the sentiment affects the price upside during the day. Moreover, positive discussions and recommendations generate a larger surge in price.

4.3 Gap between max and min prices: extreme price reaction (price volatility)

Another stock price change metric is calculated as $rets_t = \left(max(price_t) - min(price_t)\right)_{scaled}$, where $\max\left(price_t\right), \min\left(price_t\right)$ denote the highest and the lowest price of the current trading session, respectively. Scaled implies the standardization procedure as described in formula (7).

Sentiment exercises a significant influence on price change during hours of venue-confined liquidity from the open of the current day's trading session (10:00) to close of the current trading session (till 14:30 in summer, 15:30 in winter).

The descriptive statistics of gap between max and min price aggregated variables are shown in Table 9. Sentiment variables are equal to those listed in Table 7.

Table 9 The descriptive statistics of gap to the highest price aggregated variables

	Count	Mean	Std	Min	Max
rets	281,502	0.023	1.00	−2.67	4.38

Table 10 Panel regression across top 10 stocks—extreme price reaction

	(1)	(2)	(3)	(8)
nobs	3680	3680	3680	3680
Rsq-overall	0.1918	0.1999	0.1975	0.0285
f-pvalue	0.0000	0.0000	0.0000	0.0000
Badj				−0.2885*** (−5.3560)
all_scale			0.4221*** (6.4454)	
neg_scale		0.4247*** (6.4811)		
neg_scale_sq				
pos_scale	0.4160*** (6.3704)			
pos_scale_sq				

Table 11 Panel regression across top 25 stocks (4 models)—gap to the highest price

	(1)	(2)	(3)	(4)
nobs	9200	9200	9200	9200
Rsq-overall	0.1651	0.1461	0.177	0.2173
f-pvalue	0.0000	0.0000	0.0000	0.0000
neg_scale		0.1696*** (14.0199)	−0.1672*** (−6.3267)	0.1262** (3.4910)
neg_scale_sq		−0.0008*** (−4.1204)		−0.0047*** (−11.4804)
pos_scale	0.1316*** (10.4264)		0.3203*** (11.5961)	0.0247 (0.6439)
pos_scale_sq	0.0004** (2.0165)			0.0048*** (10.7816)

The results of testing the four models are shown in Table 10. They do not reject our hypothesis that sentiment has an impact on price dynamics.

The variable responsible for the relative prevalence of positive discussions (Badj) is not significant for all sample but, as per Table 10, it is statistically important for the top-10 stocks subsample (see Fig. 7 in Appendix).

Based on the sample of the top 10 most discussed stocks, an interesting result is obtained—the variable responsible for the relative prevalence of positive discussions (Badj) turns out to be significant with a negative sign. In addition, we find that positive discussions smooth out price volatility in widely discussed stocks.

Analysis of jumps in stock prices is shown in Appendix 4.

4.4 Hypothesis 2: the influence of sentiment is non-linear

Dealing with this question, we find that the influence of discussions is non-linear; see Tables 11, 12, and 13. For instance, we provide empirical evidence that solely very strong positive emotions or the absence of an explicitly expressed tonality of discussions is capable of generating considerable upward surges in stock prices. Positive discussions of moderate intensity do not generate an upside in prices. In respect to negative discussions, downsides in prices, on the contrary, are generated by moderate negative. In what concerns negative discussions, the extreme sentiment areas do not cause strong price changes (perhaps investors perceive massive criticism as a kind of artificiality of the situation and abstain from sharp trading movements).

Sentiment exercises a significant influence on price change during hours of venue-confined liquidity from the open of the current day's trading session (10:00) to the highest price of the current trading session (till 14:30 in summer, 15:30 in winter).

Estimates of regression coefficients are significant at the 1% level of significance.

Wrapping up our findings regarding Hypothesis 2, we state that both, negligible number of messages and extremely elevated volume of messages do not generate any considerable downside in price. For positive emotions, the situation is different,

Table 12 Panel regression across top 50 stocks (5 models)—gap to the highest price

	(1)	(2)	(3)	(4)	(5)
nobs	18,400	18,400	18,400	18,400	18,400
Rsq-overall	0.1383	0.1155	0.1104	0.2841	0.0009
f-pvalue	0.0000	0.0000	0.0000	0.0000	0.0277
Badj					−0.0514** (−2.2021)
neg_scale		0.0015* (1.6934)	0.0062*** (6.3205)	−0.0452*** (−26.5484)	
neg_scale_sq		0.0000*** (9.2246)		0.0001*** (36.7011)	
pos_scale	0.0641*** (25.7271)		0.0106** (2.9368)	0.1650*** (32.8536)	
pos_scale_sq	−0.0001*** (−14.2910)			−0.0002*** (−38.5900)	

Table 13 Panel regression across top 10—gap to the highest price

	(1)	(2)	(3)	(4)	(5)
nobs	3680	3680	3680	3680	3680
Rsq-overall	0.1318	0.1322	0.128	0.1352	0.0084
f-pvalue	0.0000	0.0000	0.0000	0.0000	0.0005
Badj					−0.1403** (−3.4770)
neg_scale		0.2029*** (25.8180)	0.0645*** (18.0961)	0.1173*** (16.2195)	
neg_scale_sq		−0.0918*** (−11.6561)		−0.0555*** (−7.2841)	
pos_scale	0.2119*** (29.0020)		0.0877*** (22.9304)	0.1544*** (22.7307)	
pos_scale_sq	−0.0925*** (−12.3690)			−0.0752*** (−10.3257)	

Table 14 Panel regression across top 10 stocks, 4 models—gap to the highest price

	(1)	(2)	(3)	(4)
nobs	3680	3680	3680	3680
Rsq-overall	0.1085	0.1239	0.1267	0.0106
f-pvalue	0.0000	0.0000	0.0000	0.0129
Badj				−0.0043** (−2.4867)
ln_30dmean_neg_scale			0.0183*** (5.2568)	
ln_30dmean_pos_scale		0.0182*** (5.1714)		
ln_neg	0.0097** (3.1968)			
ln_neg_sq	−0.0035** (−2.1903)			
ln_pos	0.0124** (2.9056)			
ln_pos_sq	−0.0058** (−2.5677)			

however it is evidenced only for the narrow sample of the top 25 securities; see Table 11.

Across the subsamples of the top 50 stocks analyzed in Table 12 as well as the full sample of stocks, positive non-linearity manifests itself as follows: the more positive emotions are expressed, the less the price reaction. Also, there is no price reaction (upside) even with a minimum number of positive discussions.

A similar conclusion holds in respect of the influence of negative messages on downsides in prices. Excessive emotions do not generate a corresponding price reaction.

Table 13 displays the results of panel regression across the subsample of the most intensely discussed stocks. These stocks accumulate the maximum number of messages. Estimates of regression coefficients reveal a significant impact at the 1 and 5% level of significance. Overall, the results are not much different from the previous ones.

Sentiment variables normalized by the 30-day average value (Table 14) are also statistically significant and this suggests that an increase in positive tonality in stock discussions encourages purchases.

Substitution of the price change in Hypothesis 2 with the gap to the highest price does not alter the general conclusion: statistically significant contribution of sentiment into price dynamics is not rejected. In fact, this approach to assess price dynamics more accentuates the role of sentiment. The proportion of the explained variance does not exceed 16% in individual regressions with additional testing procedures. Linear dependency between the sentiment variables and price gaps is sufficiently strong; the distribution is positively skewed; the correlation coefficient does not exceed 35% on average. We also detect industries where stock returns are most sensitive to sentiment: consumers, high tech, healthcare. This possibly reflects the

Table 15 Panel regression across top 10 stocks – extreme volatility

	(1)	(2)	(3)	(4)
nobs	3680	3680	3680	3680
Rsq-overall	0.1961	0.2017	0.2004	0.2048
f-pvalue	0.0000	0.0000	0.0000	0.0000
neg_scale		0.3555** (2.9790)	0.5579** (3.4791)	0.9100** (3.7294)
neg_scale_sq		0.0798 (0.9244)		−0.3163** (−2.4451)
pos_scale	0.3102** (2.4614)		−0.1349 (−0.8835)	−0.5529** (−2.2403)
pos_scale_sq	0.1226 (1.3124)			0.3870** (2.3619)

impact of the overall distress and restrictive measures imposed in 2020 due to the Covid-19 pandemic (Gubareva, 2021; Gubareva et al., 2021; Umar et al., 2021a).

The coefficients of the non-linear sentiment variables for Extreme Price Reaction are positive, indicating that investors' trading behavior is susceptible to market sentiment and tone of discussion. The most negative or positive sentiments of members of investment communities lead to significant price volatility, see Table 15. Sentiment variables normalized by the 30-day average value are also statistically significant and this suggests that an increase in positive tonality in stock discussions encourages purchases.

Table 15 displays the results of panel regression across the sample of 10 stocks most intensely discussed. These stocks accumulate the maximum number of messages.

4.5 Hypothesis 3: the influence of sentiment differs across sectors of economic activity

Hypothesis 3 states that Retail investors' sentiment exercises industry specific influence on price dynamics, implying that industry differences across companies are important in explaining price dynamics by the sentiment of members of the investment community.

As in the previous results, we focus on two indicators of price change: price deviation from the opening of trading section and the maximum range of price variations.

To check the inferences' consistency, we run panel regressions for: a sample of stocks with statistically significant estimates of regression coefficients identified in individual regressions; a sample of stocks from to the healthcare industry (as the industry with the largest number of stocks most intensely discussed); a sample of stocks of companies with high market capitalization. The results are not much different from the previous ones: some regression equations produce more insignificant or, on the contrary, significant estimates of regression coefficients; but, overall, there are no significant contradictions as for the main conclusions.

In Table 16, we present the results for the healthcare industry, considering a subset of the 50 most talked about stocks, selected from all the companies in this sector

Table 16 Panel regression across top 50 Healthcare industry stocks – gap to the highest price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
nobs	18,400	18,400	18,400	18,400	18,400	18,400	18,400
Rsq-overall	0.1264	0.1657	0.1425	0.14	0.197	0.1829	0.3504
f-pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
all_scale			0.0152*** (21.7478)				
neg_scale		0.0084*** (24.0014)			−0.0023** (−2.3549)	0.0200*** (15.6924)	−0.0366*** (−15.0594)
neg_scale_sq					0.0000*** (11.6962)		0.0001*** (26.1210)
pos_scale	0.0271*** (20.0149)			0.0449*** (13.9109)		−0.0448*** (−9.3980)	0.1306*** (16.3438)
pos_scale_sq				−0.0000*** (−6.0296)			−0.0002*** (−24.5245)

Table 17 Panel regression across top 50 Industrial stocks – gap to the highest price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
nobs	18,400	18,400	18,400	18,400	18,400	18,400	18,400
Rsq-overall	0.365	0.3685	0.3683	0.3771	0.3727	0.3701	0.3794
f-pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
all_scale			0.2738*** (37.9323)				
neg_scale		0.2637*** (37.9369)			0.1987*** (14.0269)	0.1959*** (5.2422)	0.1444** (2.4138)
neg_scale_sq					0.0007*** (5.3820)		−0.0037** (−2.3456)
pos_scale	0.3088*** (37.4523)			0.1990*** (13.1005)		0.0814* (1.8453)	0.0609 (0.9062)
pos_scale_sq				0.0015*** (8.5942)			0.0072** (2.7935)

Table 18 Panel regression across top 50 Technology stocks – gap to the highest price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
nobs	18,400	18,400	18,400	18,400	18,400	18,400	18,400
Rsq-overall	0.3661	0.3229	0.3599	0.3718	0.3285	0.3743	0.3936
f-pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Badj							
all_scale			0.0773*** (57.8091)				
neg_scale		0.1392*** (52.7583)			0.1812*** (25.8097)	−0.1016*** (−9.2445)	−0.1941*** (−8.2249)
neg_scale_sq					−0.0001*** (−6.3412)		0.0000 (0.4975)
pos_scale	0.1473*** (58.4862)			0.1924*** (26.1956)		0.2453*** (22.6467)	0.4404*** (16.3464)
pos_scale_sq				−0.0001*** (−6.4639)			−0.0003*** (−6.9645)

of economic activity. The results for two more sectors, namely Industrials and Technology stocks are shown in Tables 17 and 18, respectively. It is also worth mentioning that for the basic materials industry (1650 observations) no statistical dependence was found.

Table 16 , 17 and 18 show the results for the top 50 most talked about Healthcare, Industrial and Technology stocks, respectively. These results allow us to draw an important conclusion that sectoral differences are significant, thus not rejecting the Hypothesis 3. This result, once again, confirms that the influence of positive and negative sentiment is different.

In Appendix 4 we can see regression results for individual stocks and for different sectors. We run 50,237 regressions, out of which 15,735 regressions turn out to have produce insignificant F-statistics, 15,804 regressions have conditional number > 20 and 7707 regressions have insignificant estimates of regression coefficients. The breakdowns by sectors, by industries and by sentiment variables are as follows: by sector, there prevail consumers, high tech, industrials, and healthcare; by industry there prevail software development and biotechnology; by sentiment variables, aggregate variables seem to slightly surpass individual variables, but the difference is not large; by market capitalization, there prevail companies with a medium market capitalization. It can also be seen that negative tonality produces more statistically significant equations than positive tonality, which indirectly indicates a greater impact of negative messages on investors' decision-making. This result is in line with Caporale et al. (2016).

5 Conclusion

We perform neural network analysis of the impact of retail investors sentiment on the stock price behavior of well-known American companies in a situation when, due to the time-zone difference, trading is active at the Russian SPB (formerly St. Petersburg) exchange and inactive at the US stock exchanges. Based on a unique Russian data, we reveal the existence of behavioral anomalies in a non-English emerging market and analyze sentiment and attention in social networks. We develop an original technique for constructing a neural network to identify the sentiment of messages further advancing the rejection of the "bag of words" approach.

In the present paper, we address this specific issue by looking at US stocks that are available for investment to Russian investors. It is worth mentioning that Russian investors, when making decisions under the venue-confined liquidity conditions, rely on two types of information. First, local investors take into account the results of trades in US stocks on their original exchange. Second, they consider opinions of other investors, which are expressed locally outside of US market hours. Our research continues the direction of Lia et al. (2017) paper, which employs Twitter data to address the behavior of Chinese investors regarding Chinese companies that are listed on the US stock exchanges.

Our research sheds additional light on "home bias" puzzle, which is a well-documented phenomenon in the US stock market (Ivkovic et al., 2008) when investors in the US are far more optimistic about domestic stocks than about foreign equities, thereby leading to the tendency to substantially overweight domestic stocks when constructing investment portfolios. We do not confirm the existence of the "home bias" at the SPB stock exchange in Russia.

Hypotheses we tested with different metrics of price change are not rejected. Our tests have shown that the acceptance of the hypothesis depends on the price metric. The three metrics do not reject the hypothesis about the importance of sentiment in explaining price dynamics—price upside during the day (gap to the highest price), price downside during the day (gap to the lowest price), and the price dispersion.

All our test results, based on the three above mentioned metrics, do not reject three hypotheses: (1) both positive and negative discussions affect the price movement during the period of internal venue-confined liquidity (when America is sleeping), (2) the influence of retail investors´ sentiment on stock price is non-linear, and (3) there is industry specificity in the sentiment influence on the behavior of stock prices.

The most pronounced statistical dependencies are observed when selecting from 25 to 100 most discussed shares, and not the entire sample of shares available to Russian investors. The results are presented for the top 10, 25, 50 and 100 stocks subsamples.

A lack of discussion and too much sentiment have less effect on price action than a moderate intensity of discussions. The general increase in discussions leads to a price change.

The moderate intensity of discussions during the trading session, as opposite to an intensive fulminant interchange of opinions, has the greatest impact on price jumps towards extreme either maximum, or minimum values. Extreme price drops can be explained by the increase in negative discussions in social networks.

It can be assumed that both macro dynamics and other news are reflected in the discussions. Community members, when expressing their thoughts and describing actions, justify their emotions by how America traded yesterday or how Asia opened up and what impact a particular Asian opening will have on the prices of US shares during the next trading section.

In addition, the employed metrics for calculating price dynamics in sectoral consideration show that whose companies exhibit the highest sensitivity to sentiment include high tech, and healthcare, followed by consumer and industrial sector stocks. This possibly reflects the impact of the overall distress and restrictive measures imposed in 2020 due to the Covid-19 pandemic.

It is worth noting that our results allow for detecting possible manipulations, and hence, alert the regulators on the need for to carefully monitor the situation during the hours of the venue-confined liquidity. It is made possible as studying the influence of investor sentiment on price behavior allows us to identify both, anomalies in the market and possible market manipulations. We also emphasize the possibility of building trading strategies based on the sentiment of private investors. Moreover, for regulators, a signal of possible market manipulation and pump-and-dump transactions may help them to proceed with a timely intervention and prevent adverse effects on retail investors. This is especially true in a current situation when trading volumes has decreased since March 2022 due to Russia-Ukraine military conflict (Bossman & Gubareva, 2023; Kumar et al., 2023).

In what concerns the limitations of our study, we mention the fact that we only consider the influence of sentiment factors on stock prices. However, we believe that investigating sentiment in messengers may provide other sources of information, potentially relevant for investors and their decision-making. In addition, it is worth outlining that there exist time-interval limitations related to the selection of our dataset, as we are looking solely at a bounded period from January 2018 to February 2022.

Considering the already highlighted limitations, inherent to our research, it makes a sense to delineate future directions for further investigation in this scientific domain. In the future, this study could be developed into several price forecast algorithms as well as could be incorporated in the design of portfolio construction strategies. Notwithstanding an already considerable coverage of the sentiment-related factors in the present research, the future development of this investigation line could advance through the further expansion of the range of sentiment factors, allowing for creation of a more complete body of knowledge regarding the influence of sentiment on investors´ trading attitudes.

And last but not least, our results are potentially useful for investors, brokers, dealers, local exchange operators, and stock market regulators. As such, further research in these field is highly desirable as the performance of stock markets and individual stocks may profoundly impact the well-being of societies as well as financial stability around the globe.

Appendix 1: Messages statistics

As can be seen in Fig. 4, the 1st forum has a much longer message history, but the number of messages itself is not large. In the 2nd forum, messages start to appear in 2019 and in 2020 an explosive growth is observed. That year, the distress associated with the Covid-19 virus emerged: to some extent it explains a growing interest in stock markets in general, and in American stocks, in particular. Therefore, we suppose that the data will mainly reflect investors' mood as of 2020 and as of the beginning of 2021. The considered period does not exceed 3 years.

Figure 5 displays the breakdown of the number of messages per month. It can be seen that in the 1st forum, a strong growth starts at the end of 2020, and in the 2nd forum, it starts in the beginning of the second quarter of 2020. Most likely, this reflects both an increased interest in discussion from retail investors and promotion campaigns the developers of the sites.

Figure 6 displays the distribution of the number of unique authors per month. An interesting point is that in the 1st forum, a significant growth begins in the middle of 2020 while in the 2nd forum a two-fold increase is observed from March to April 2020, just at the time of the largest drop in market indices due to the Covid-19 pandemic.

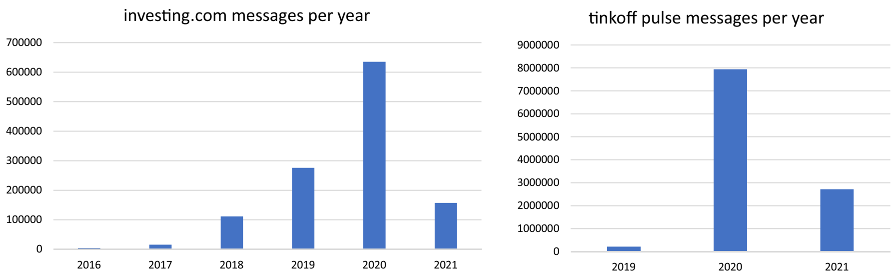

Fig. 4 Number of messages per year

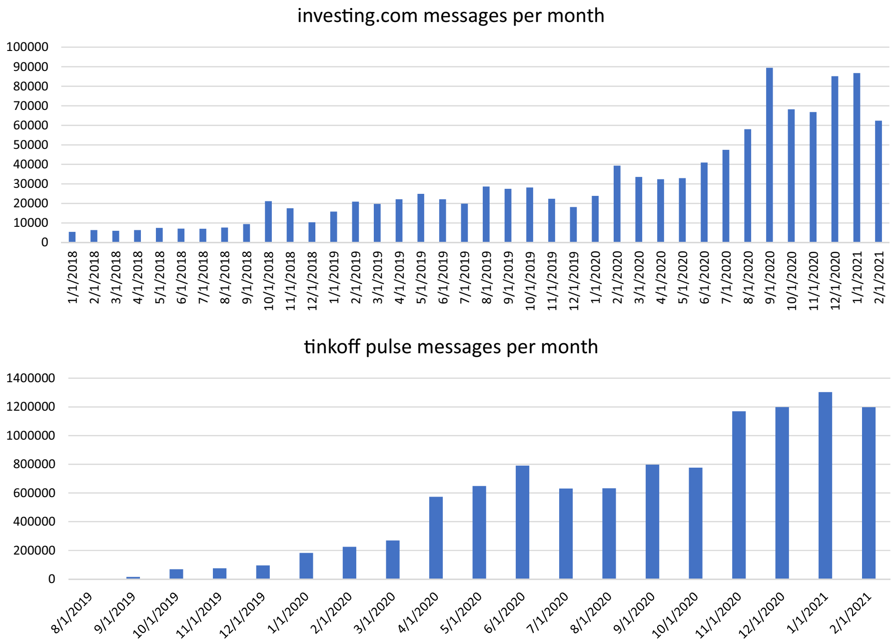

Fig. 5 Number of messages per month

Figure 7 displays the statistics of the number of messages for the top 10 discussed stocks in each of the two forums (tinkoff.ru and investing.com). As can be seen, the leader is Tesla Inc. Actually, this may indirectly describe the type of

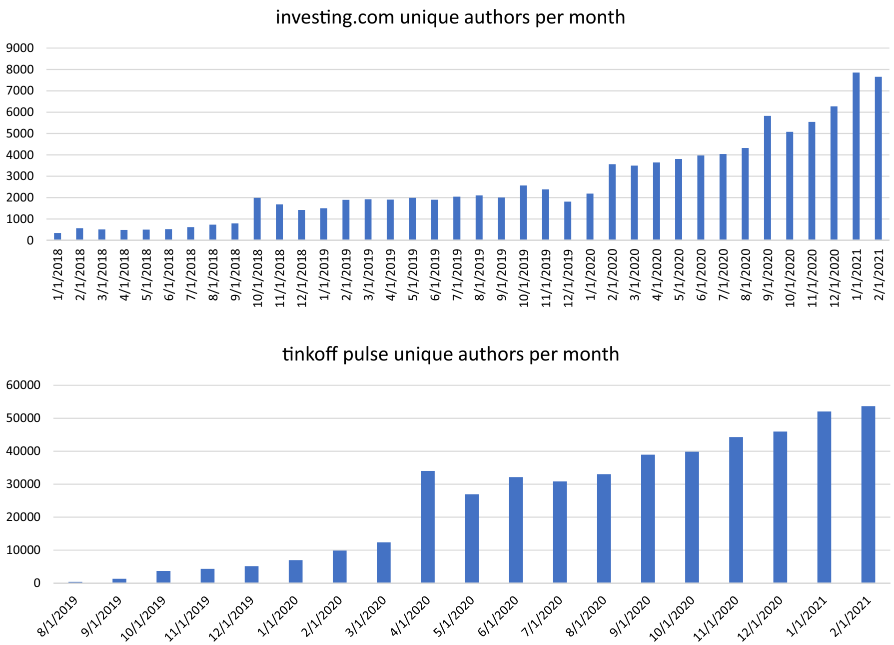

Fig. 6 Distribution of the number of unique authors per month

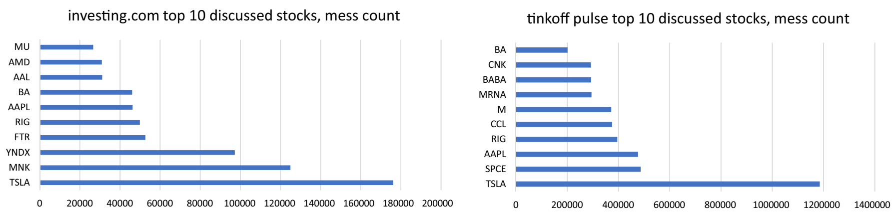

Fig. 7 Top 10 discussed stocks

investors under consideration: most likely they are young people under the age of 35 with a rather aggressive attitude toward risk. Conservative investors are unlikely to be interested in such a volatile stock.

Appendix 2: Network models. Test results of trained neural network models

Table 19 shows more wide scores and models on test dataset with tuned hyperparameters in model 1 and 2. The table also shows the results of baseline classification.

As we can see on table above, model 2 shows best score in test dataset.

Another test is aimed at demonstrating an understanding of the possibility of classifying messages with implicit semantic connection, where only by understanding the whole meaning of the sentence, and not its specific words, will it help to classify messages correctly. Table 20 below shows the test result (0—negative, 1—neutral, 2—positive).

As, it could be seen from Table 20 the base algorithms did a poor job of handling such tasks.

The result of sensitive analysis by obtained models from Table 5 is shown in Table 21. We tested hypothesis 1, gap to the highest price. Here, model 2—our model with best classification score (Table 19). Models 5 and 6 with worse results from SA (Table 5).

In the Table above we can see, that explained variance is lower and equations or exogenous variables are insignificant in comparing with our model 2, showing best results.

Table 19 Results of models testing

Class	Model 1	Model 2	Model 3	Model 4
f1 macro	0.63	0.66	0.59	0.6
Precision				
Negative	0.64	0.67	0.6	0.62
Neutral	0.61	0.65	0.62	0.61
Positive	0.62	0.66	0.55	0.56
Recall				
Negative	0.65	0.64	0.55	0.52
Neutral	0.62	0.68	0.65	0.73
Positive	0.59	0.65	0.57	0.54

Table 20 Results of additional testing

#	Message	Model 1	Model 2	Model 3	Model 4
1	Stocks did not rise, they fell	0	0	2	2
2	Stocks did not fall, they rose	2	2	0	0
3	Stocks could go up, but they went down	0	0	1	2
4	Stocks could have fallen, but they have risen	2	2	0	0
5	Stocks look good but are actually bad	1	0	2	1

Table 21 Results of NN sensitivity analysis

	Model 2		Model 5		Model 6	
	(1)	(2)	(3)	(4)	(5)	(6)
nobs	18,400	18,400	18,400	18,400	18,400	18,400
Rsq-overall	0.1383	0.1155	0.0901	0.0802	0	0
f-pvalue	0.0000	0.0000	0.0000	0.0000	0.2166	0.6579
neg_scale		0.0015* (1.6934)		0.2341*** (7.4522)		0.1469 (0.8042)
neg_scale_sq		0.0000*** (9.2246)		0.0301 (0.8250)		−0.0038 (−0.298)
pos_scale	0.0641*** (25.7271)		0.1789*** (12.9124)		0.2173 (1.3095)	
pos_scale_sq	−0.0001*** (−14.2910)		0.0017*** (10.2706)		−0.0084 (−0.8502)	

Appendix 3: Sentiment statistics

As can be seen from Table 22, there is a large bias towards neutral messages, which we also observed in the training sample.

The graphs in Fig. 8 show the distribution of positive and negative messages for each forum per month, as well as in the period February—March 2020.

As can be seen from Fig. 9, approximately from February 2020, negative messages begin to prevail due to the proliferation of Covid-19.

Figure 10 displays weekly distributions for the period January-April 2020. This period is featured by the largest decline of the US stock market. The graph reveals the dominance of negative messages. Figure 9 displays daily numbers of positive and negative messages.

As can be seen from Fig. 10, since the end of February 2020, there clearly have been observed much more negative messages. Also, significant peaks are observed

Table 22 Message labelling in the two forums

	investing.com (1)	tinkoff pulse (2)
Number of stocks	1925	1397
Number of positive messages	269,233	1,844,072
Number of negative messages	274,325	1,966,566
Number of neutral messages	550,794	6,009,923

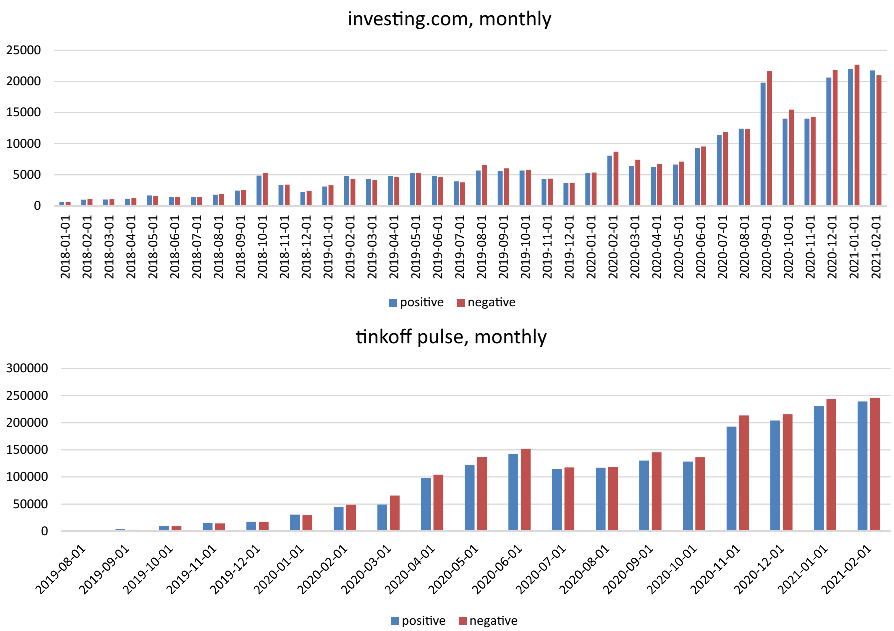

Fig. 8 Distribution of positive and negative messages per month

Fig. 9 Weekly numbers of positive and negative messages

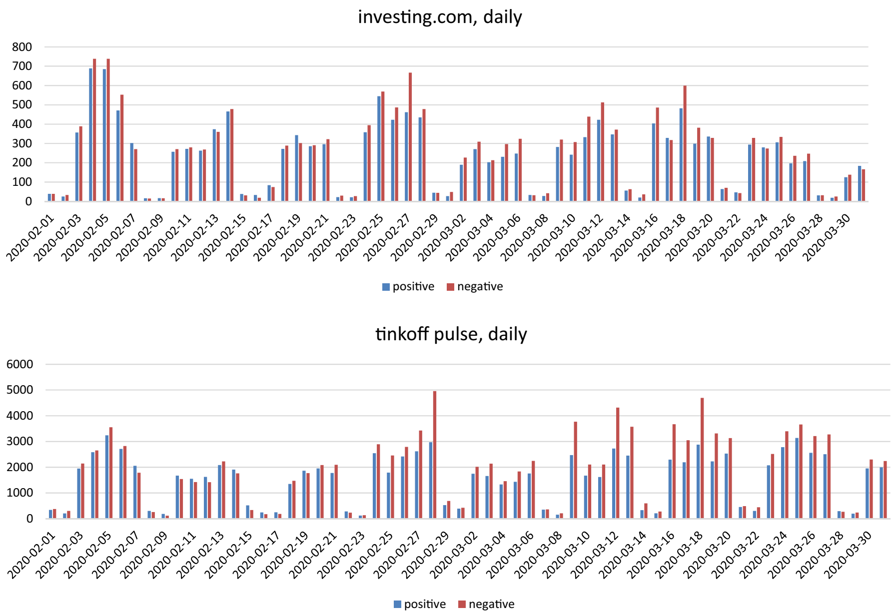

Fig. 10 Daily number of positive and negative messages

which coincide with significant drops in the S&P 500 Index. Notably, the discussion activity is extremely low over weekends, but we still need to take it into account for the analysis. In the 1st forum, there are, on average, 400 daily messages of both tonalities per day; in the 2nd forum there are about 2000 daily messages on average.

Appendix 4: Analysis of jumps in stock prices

From the descriptive statistics, it follows that the average price change does not exceed 0.6% while standard deviation amounts to 1.5%.

The distributions of pair correlations between stock returns and the positive and negative tonality of messages, both at an aggregate and individual level are

Table 23 Sentiment variables for each separate stock analysis

ln_pos	Log of the sum of positive messages over all stocks
ln_pos_sq	Log of the squared sum of positive messages over all stocks
ln_neg	Log of the sum of negative messages over all stocks
ln_neg_sq	Log of the squared sum of negative messages over all stocks
ln_pos_lag1	Log of the sum of positive messages over all stocks over the preceding period (lagged variable)
ln_neg_lag1	Log of the sum of negative messages over all stocks over the preceding period (lagged variable)
ln_all	Log of the sum of positive and negative messages over all stocks
ln_all_sq	Log of the squared sum of positive and negative messages over all stocks
ln_pos_30dmean_scale	Log of the sum of positive messages over all stocks normalized by the 30-day average value. It reflects the dynamics of positive mood (fading in, fading out)
ln_neg_30dmean_scale	Log of the sum of negative messages over all stocks normalized by the 30-day average value. It reflects the dynamics of negative mood (fading in, fading out)
ticker_ln_pos	Log of the sum of positive messages for a stock
ticker_ln_neg	Log of the sum of negative messages for a stock
ticker_ln_pos_sq	Log of the squared sum of positive messages for a stock
ticker_ln_neg_sq	Log of the squared sum of negative messages for a stock
ticker_ln_pos_lag1	Log of the sum of positive messages for a stock over the preceding period (lagged variable)
ticker_ln_neg_lag1	Log of the sum of negative messages for a stock over the preceding period (lagged variable)
ticker_ln_all	Log of the sum of positive and negative messages for a stock
ticker_ln_all_sq	Log of the squared sum of positive and negative messages for a stock
ticker_ln_pos_30dmean_scale	Log of the sum of positive messages for a stock normalized by the 30-day average value
ticker_ln_neg_30dmean_scale	Log of the sum of negative messages for a stock normalized by the 30-day average value
ticker_Badj	Indicator (25) for a stock
Standardized indicators $x_{scale} = \frac{x-med}{IQR}$	
*_scale	Variables from which the medians were removed and scales the data according to the quantile range (defaults to IQR: Interquartile Range). The IQR is the range between the 1st quartile (25th quantile) and the 3rd quartile (75th quantile). These variables are similar to the ones given above but logarithmization is replaced with standardization. Their names contain scale instead of ln

presented in Fig. 11. These distributions are much different from those obtained in testing the previous hypotheses.

As can be seen, at an aggregate level, the distribution is skewed to the right from zero which points to a positive linear association between a change in prices and a change in the overall sentiment. When assessed at an individual level, the

Table 24 Descriptive statistics for selected aggregate variables

	Count	Mean	Std	Min	Max
rets	281,502	0.006	1.00	0	2.07
pos	281,502	2614.508	3892.636	15	22,932
neg	281,502	2767.975	4144.43	17	28,774
ln_pos	281,502	6.421	1.869	2.773	10.04
ln_neg	281,502	6.436	1.904	2.89	10.267
ln_pos_sq	281,502	12.831	3.75	5.421	20.081
pos_scale	281,502	0	1.00	−0.668	5.223
neg_scale	281,502	0	1.00	−0.664	6.279
ln_pos_30dmean_scale	281,502	0.733	0.176	0.23	1.497
ln_neg_30dmean_scale	281,502	0.73	0.187	0.174	1.533
Badj	281,502	−0.085	0.514	−2.033	1.687

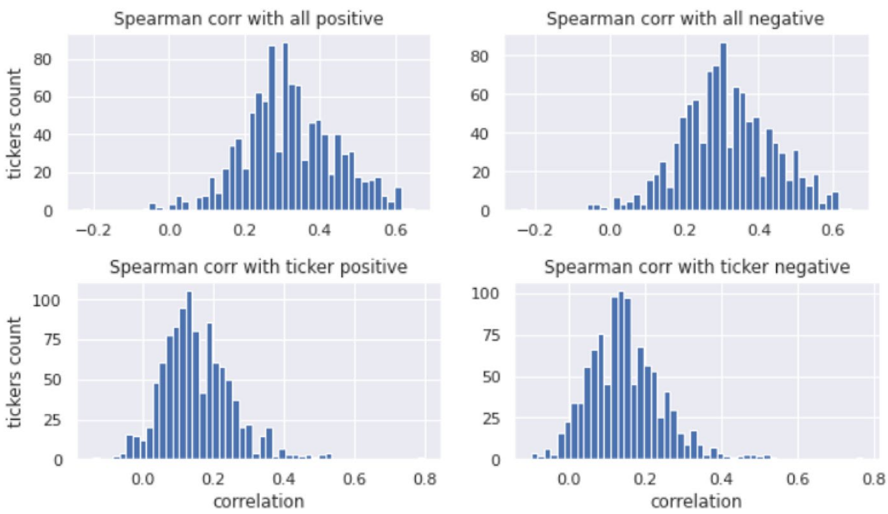

Fig. 11 Pair correlations between the variables and stock gaps

conclusion is different: the majority of correlation values only slightly deviate from zero (although more than in Hypothesis 1 and 2) but there is a heavy right tail that reflects the presence of individual association between the sentiment variables and specific stocks.

Regression results for individual stocks

In total, we run 50,237 regressions, out of which 15,735 regressions turn out to have produce insignificant F-statistics, 15,804 regressions have conditional number > 20 and 7707 regressions have insignificant estimates of regression coefficients. The remaining regressions have the following breakdown: 1365 regressions have significance ranging

Table 25 Breakdowns of statistically significant regressions

Name	Count	Name	Count
Top 10 by sector		Top 10 by industry	
Consumer cyclical	1694	Software—infrastructure	322
Technology	1385	Software—application	300
Industrials	1328	Biotechnology	258
Healthcare	1312	Specialty industrial machinery	220
Financial services	971	Medical devices	220
Consumer defensive	744	Oil & gas E&P	217
Energy	617	Banks—regional	203
Communication services	482	Restaurants	201
Real estate	397	Aerospace & defense	200
Basic materials	385	Internet content & information	189
Top 10 by sentiment variables		Top 10 by capitalization	
const + neg_scale	949	Medium	6448
const + all_scale	945	High	1769
const + pos_scale	939	Low	1409
const + pos_scale + pos_scale_sq	655		
const + all_scale + all_scale_sq	625		
const + Badj	610		
const + neg_scale + neg_scale_sq	579		
const + ticker_ln_all	539		
const + ticker_ln_pos	480		
const + ticker_ln_pos_30dmean_scale	459		

from 0.01 to 0.05; and 9626 regressions have coefficient p-values < 0.01. This is quite an impressive result, which is much better than those ones obtained in testing hypotheses with consideration of the standard price change, which takes into account the closing and opening prices of trading (Tables 23, 24 versus Tables 25, 26).

The breakdowns by sectors, by industries and by sentiment variables are as follows: by sector, there prevail consumers, high tech, industrials, and healthcare; by industry there prevail software development and biotechnology; by sentiment variables, aggregate variables seem to slightly surpass individual variables, but the difference is not large; by market capitalization, there prevail companies with a medium market capitalization. It can also be seen that negative tonality produces more statistically significant equations than positive tonality, which indirectly indicates a greater impact of negative messages on investors' decision-making. This result is in line with Caporale, et al. (2016).

Table 26 displays top 10 stocks by the determination coefficient, whose regression equation produced satisfactory results when additionally tested for heteroskedasticity (White, Breusch-Pagan) and autocorrelation (Breusch-Godfrey). These regressions mostly produce statistically significant coefficients for positive and negative messages, both at an aggregate and individual level. There are also statistically significant regression coefficients of squared variables which indicate the presence of a nonlinear

Table 26 Regression models for individual stocks

Ticker	f-pvalue	R-sq	params	Values	p-value
AJRD	≤0.01	0.677	const + pos_scale + ticker_pos_scale + pos_scale_sq + ticker_pos_scale_sq	0.0066, 0.0043, −0.0029, −0.0028, 0.0117	≤0.01, ≤0.01, ≤0.01, ≤0.01, ≤0.01
GVA	≤0.01	0.164	const + all_scale + all_scale_sq	0.0098, 0.0163, −0.007	≤0.01, ≤0.01, ≤0.01
GVA	≤0.01	0.164	const + pos_scale + pos_scale_sq	0.0097, 0.0168, −0.0075	≤0.01, ≤0.01, ≤0.01
GVA	≤0.01	0.163	const + neg_scale + neg_scale_sq	0.0098, 0.0158, −0.0067	≤0.01, ≤0.01, ≤0.01
SPB@US	≤0.01	0.156	const + neg_scale + ticker_neg_scale	0.0007, 0.0016, 0.0005	≤0.01, ≤0.01, ≤0.01
KNX	≤0.01	0.149	const + neg_scale + neg_scale_sq	0.0024, 0.0035, −0.0015	≤0.01, ≤0.01, ≤0.01
RGR	≤0.01	0.147	const + pos_scale + pos_scale_sq	0.0028, 0.0051, −0.003	≤0.01, ≤0.01, ≤0.01
RGR	≤0.01	0.146	const + all_scale + all_scale_sq	0.0028, 0.0049, −0.0028	≤0.01, ≤0.01, ≤0.01
RGR	≤0.01	0.144	const + neg_scale + neg_scale_sq	0.0028, 0.0047, −0.0026	≤0.01, ≤0.01, ≤0.01
NLOK	≤0.01	0.14	const + ticker_pos_scale	0.0096, 0.0062	≤0.01, ≤0.01

relationship between emotional tonality and price changes. The coefficients have a negative sign, which is consistent with the conclusions for the previous hypotheses.

Appendix 5: Analysis of downside in stock prices during one trading session

Gap to the lowest price

Sentiment exercises a significant influence on price change during hours of venue-confined liquidity from the open of the current day's trading session (10:00) to the lowest price of the current trading session (till 14:30 in summer, 15:30 in winter).

Stock price changes are computed as $rets_t = \ln\left(min(price_t)\right) - \ln(open_t)$, where $open_t$ denotes the open of the current trading session with venue-confined liquidity and $\min\left(price_t\right)$ denotes the lowest price of the current trading session.

Sample descriptive statistics for selected aggregate variables are given in Table 27 (average gap over all stocks).

Regression results for individual stocks

In total, we run 50,237 regressions, out of which 15,588 regressions turn out to have produce insignificant F-statistics, 15,674 regressions have conditional

Table 27 Descriptive statistics for selected aggregate variables

	Count	Mean	Std	Min	Max
rets	281,502	−0.006	0.014	−3.764	0
pos	281,502	2614.508	3892.636	15	22,932
neg	281,502	2767.975	4144.43	17	28,774
ln_pos	281,502	6.421	1.869	2.773	10.04
ln_neg	281,502	6.436	1.904	2.89	10.267
ln_pos_sq	281,502	12.831	3.75	5.421	20.081
pos_scale	281,502	0	1.001	−0.668	5.223
neg_scale	281,502	0	1.001	−0.664	6.279
ln_pos_30dmean_scale	757	0.733	0.176	0.23	1.497
ln_neg_30dmean_scale	757	0.73	0.187	0.174	1.533
Badj	786	−0.085	0.514	−2.033	1.687

Table 28 Instances of the highest and lowest pair correlation values for top stocks

Ticker	Spearman corr	Ticker	Spearman corr	Ticker	Spearman corr	Ticker	Spearman corr
With variable ln_pos				With variable ln_neg			
Top negative		Top positive		Top negative		Top positive	
QDEL	−0.66	TEL	0.21	QDEL	−0.67	TEL	0.21
PBF	−0.65	ZYNE	0.15	PBF	−0.66	ZYNE	0.15
SHI	−0.62	GWW	0.12	SHI	−0.62	GWW	0.11
PLCE	−0.61	AGIO	0.09	PLCE	−0.62	CB	0.09
TAK	−0.61	FLWS	0.09	AMCX	−0.61	ES	0.08
AMCX	−0.6	CB	0.09	ATRO	−0.6	AGIO	0.07
CRS	−0.6	ANGI	0.08	TDS	−0.6	FLWS	0.07
TDS	−0.6	ES	0.08	CRS	−0.6	EVH	0.06
Ticker	Spearman corr	Ticker	Spearman corr	Ticker	Spearman corr	Ticker	Spearman corr
With variable ticker_ln_pos				With variable ticker_ln_neg			
Top negative		Top positive		Top negative		Top positive	
PBF	−0.67	FRPT	0.09	PBF	−0.67	AX	0.12
MSTR	−0.66	ONTO	0.08	MSTR	−0.65	ONTO	0.06
SPR	−0.63	MTD	0.06	SPR	−0.61	FRPT	0.05
CHEF	−0.59	FCN	0.06	CHEF	−0.59	ZYNE	0.05
QDEL	−0.57	CRL	0.05	QDEL	−0.55	OI	0.05
SAVE	−0.56	OI	0.05	RRGB	−0.55	TYL	0.05
CNK	−0.55	ZYNE	0.05	OXY	−0.55	EYE	0.04
RRGB	−0.54	IT	0.05	RDS.A	−0.55	FLT	0.04

number > 20 and 7540 regressions have insignificant estimates of regression coefficients. The remaining regressions have the following breakdown: 1629 regressions have significance ranging from 0.01 to 0.05; and 9806 regressions have coefficient

Table 29 Regression models for 10 individual stocks

Ticker	f-pvalue	R-sq	params	Values	p-value
CORT	≤0.01	0.252	const + ticker_pos_scale	−0.0095, −0.0042	≤0.01, ≤0.01
CORT	≤0.01	0.252	const + ticker_all_scale	−0.0095, −0.0042	≤0.01, ≤0.01
HUBG	≤0.01	0.182	const + neg_scale + ticker_neg_scale + neg_scale_sq + ticker_neg_scale_sq	−0.001, −0.0026, 0.0017, 0.0018, −0.0038	≤0.01, ≤0.01, ≤0.01, ≤0.01, ≤0.01
CHEF	≤0.01	0.164	const + pos_scale + ticker_pos_scale + pos_scale_sq + ticker_pos_scale_sq	−0.0105, −0.0174, −0.0204, 0.0111, 0.0133	≤0.01, ≤0.01, ≤0.01, ≤0.01, ≤0.01
CHEF	≤0.01	0.154	const + ticker_all_scale + ticker_all_scale_sq	−0.0173, −0.0252, 0.0162	≤0.01, ≤0.01, ≤0.01
CHEF	≤0.01	0.144	const + ticker_pos_scale + ticker_pos_scale_sq	−0.0177, −0.0246, 0.0162	≤0.01, ≤0.01, ≤0.01
SMPL	≤0.01	0.125	const + pos_scale + ticker_pos_scale + pos_scale_sq + ticker_pos_scale_sq	−0.0046, −0.0092, −0.0054, 0.006, 0.0041	≤0.01, ≤0.01, ≤0.01, ≤0.01, ≤0.01
CSII	≤0.01	0.122	const + ticker_ln_pos	−0.0044, −0.0093	≤0.01, ≤0.01
CHEF	≤0.01	0.118	const + neg_scale + ticker_neg_scale	−0.0158, −0.0062, −0.0091	≤0.01, ≤0.01, ≤0.01
MLCO	≤0.01	0.117	const + pos_scale + pos_scale_sq	−0.0081, −0.0124, 0.0096	≤0.01, ≤0.01, ≤0.01

Table 30 Panel regression across top 10 stocks—downside price dynamics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
nobs	7860	7860	7860	7860	7860	7860	7860	7860	7860	7860
Rsq-overall	0.1267	0.1291	0.1283	0.1242	0.125	0.129	0.1239	0.1306	0.1396	0.0188
f-pvalue	≤0.01	≤0.01	≤0.01	≤0.01	≤0.01	≤0.01	≤0.01	≤0.01	≤0.01	≤0.01
Badj										0.0059** (3.8533)
ln_30dmean_neg_scale									−0.0200*** (−6.2735)	
ln_30dmean_pos_scale								−0.0195*** (−5.9661)		
ln_all			−0.0035*** (−11.6592)							
ln_neg		−0.0038*** (−10.9641)			−0.0204** (−3.4748)	−0.0041*** (−5.2389)	−0.0135** (−3.4308)			
ln_neg_sq					0.0082** (2.9233)		0.0044** (2.5080)			
ln_pos	−0.0038*** (−10.5247)			−0.0186** (−3.0790)		0.0003 (0.4921)	−0.0150** (−3.1735)			
ln_pos_sq				0.0073** (2.5212)			0.0079** (3.2525)			

p-values < 0.01. This is quite an impressive result which is much better than those ones obtained in testing the previous two hypotheses (Table 28).

The breakdowns by sectors, by industries and by sentiment variables are as follows: by sector, there prevail consumers, high tech, industrials, and healthcare; by industry there prevail software development and biotechnology; by sentiment variables, aggregate variables seem to slightly surpass individual variables, but the difference is not large; by market capitalization, there prevail companies with a medium market capitalization.

Table 29 displays top 10 stocks by the determination coefficient, whose regression equation produced satisfactory results when additionally tested for heteroskedasticity (White, Breusch–Pagan) and autocorrelation (Breusch–Godfrey). These regressions mostly produce statistically significant coefficients for positive and negative messages, both at an aggregate and individual level. There are also statistically significant regression coefficients of squared variables which indicate the presence of a nonlinear relationship between emotional tonality and price changes.

Table 30 displays the results of panel regression across the sample of 10 stocks most intensely discussed. These stocks accumulate the maximum number of messages. Compared *to the gap to the highest price*, the overall coefficient of determination is lower. Estimates of regression coefficients also reveal a significant impact at the 1 and 5% level of significance. Overall, the results are not much different from the previous ones (gap *to the highest price).*

Appendix 6: Price volatility within one trading section under the influence of discussions in social networks. Descriptive statistics and individual effects.

From the descriptive statistics, it follows that the average price change does not exceed − 0.6% while standard deviation amounts to 1.4% (Table 31).

Table 31 Descriptive statistics for selected aggregate variables

	Count	Mean	Std	Min	Max
rets	281,502	0	1	− 3.005	27.953
pos	281,502	2614.508	3892.636	15	22,932
neg	281,502	2767.975	4144.43	17	28,774
ln_pos	281,502	6.421	1.869	2.773	10.04
ln_neg	281,502	6.436	1.904	2.89	10.267
ln_pos_sq	281,502	12.831	3.75	5.421	20.081
pos_scale	281,502	0	1.001	− 0.668	5.223
neg_scale	281,502	0	1.001	− 0.664	6.279
ln_pos_30dmean_scale	281,502	0.733	0.176	0.23	1.497
ln_neg_30dmean_scale	281,502	0.73	0.187	0.174	1.533
Badj	281,502	− 0.085	0.514	− 2.033	1.687

Regression results for individual stocks

In total, we run 50,237 regressions, out of which 9062 regressions turn out to have produce insignificant F-statistics, 16,632 regressions have conditional number > 20 and 16,553 regressions have insignificant estimates of regression coefficients. The remaining regressions have the following breakdown: 1956 regressions have significance ranging from 0.01 to 0.05; and 6034 regressions have coefficient p-values < 0.01. These results are also similar to the two previous ones.

The breakdowns by sectors, by industries and by sentiment variables are as follows (Table 32): by sector, there prevail consumers, high tech, industrials, and healthcare; by industry there prevail software development and biotechnology. By sentiment variables the results are more striking as they differ from the ones obtained previously. The leading position is occupied by the sum of negative messages over all stocks normalized by the 30-day average value which points to a large impact produced by negative emotional tonality. This is in line with Caporale et al. (2016). By market capitalization, there prevail companies with a medium market capitalization.

Table 33 displays top 10 stocks by the determination coefficient whose regression equation produced satisfactory results when additionally tested for heteroskedasticity

Table 32 Breakdowns of statistically significant regressions

Name	Count	Name	Count
Top 10 by sector		Top 10 by industry	
Technology	1097	Biotechnology	330
Consumer cyclical	1078	Software—application	282
Healthcare	981	Software—infrastructure	267
Industrials	813	Aerospace & defense	158
Consumer defensive	473	Semiconductors	143
Financial services	431	Internet content & information	136
Communication services	357	Restaurants	131
Energy	317	Medical devices	131
Basic materials	208	Specialty industrial machinery	118
Real estate	147	Diagnostics & research	117
Top 10 by sentiment variables		Top 10 by capitalization	
const + ln_neg_30dmean_scale	521	Medium	3858
const + neg_scale	496	Low	1263
const + all_scale	489	High	913
const + pos_scale	482		
const + ticker_ln_all	416		
const + ln_pos_30dmean_scale	371		
const + ticker_ln_pos	351		
const + pos_scale + pos_scale_sq	319		
const + ticker_ln_neg	315		
const + ticker_ln_pos_30dmean_scale	311		

Table 33 Regression models for individual stocks

Ticker	f-pvalue	R-sq	params	Values	p-value
MSGN	≤0.01	0.357	const + neg_scale	−0.3511, 0.5453	≤0.01, ≤0.01
MSGN	≤0.01	0.353	const + all_scale	−0.3509, 0.5436	≤0.01, ≤0.01
CORT	≤0.01	0.299	const + neg_scale + neg_scale_sq	−0.5617, 0.8341, −0.2806	≤0.01, ≤0.01, ≤0.01
CORT	≤0.01	0.298	const + all_scale + all_scale_sq	−0.5657, 0.8456, −0.2866	≤0.01, ≤0.01, ≤0.01
CORT	≤0.01	0.295	const + pos_scale + pos_scale_sq	−0.5654, 0.855, −0.2959	≤0.01, ≤0.01, ≤0.01
CORT	≤0.01	0.278	const + neg_scale	−0.4339, 0.5009	≤0.01, ≤0.01
SPB@US	≤0.01	0.277	const + neg_scale + ticker_neg_scale	−0.3673, 0.4098, 0.1814	≤0.01, ≤0.01, ≤0.01
PCRX	≤0.01	0.254	const + neg_scale	−0.4147, 0.4788	≤0.01, ≤0.01
SONO	≤0.01	0.252	const + neg_scale + ticker_neg_scale	−0.391, 0.4002, 0.145	≤0.01, ≤0.01, ≤0.01
PCRX	≤0.01	0.249	const + all_scale	−0.4125, 0.4753	≤0.01, ≤0.01

(White, Breusch–Pagan) and autocorrelation (Breusch–Godfrey). These regressions mostly produce statistically significant coefficients for negative messages, both at an aggregate and individual level. There are also statistically significant regression coefficients of squared variables which indicate the presence of a nonlinear relationship between emotional tonality and price changes.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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