Revista Universo Contábil, ISSN 1809-3337
Blumenau, 2023, v. 19: e2023114, p. 01-20

doi:10.4270/ruc.2023114
Disponível em www.furb.br/universocontabil

ANÁLISE DA RELAÇÃO ENTRE HUMOR EXPRESSO NO TWITTER, RETORNO, VOLATILIDADE E VOLUME DE NEGOCIAÇÕES NO MERCADO ACIONÁRIO BRASILEIRO

ANALYSIS OF THE RELATIONSHIP BETWEEN MOOD EXPRESSED ON TWITTER, RETURN, VOLATILITY, AND TRADING VOLUME IN THE BRAZILIAN STOCK MARKET

ANÁLISIS DE LA RELACIÓN ENTRE HUMOR EXPRESADO EN TWITTER, RENTABILIDAD, VOLATILIDAD Y VOLUMEN NEGOCIADO EN LA BOLSA DE VALORES BRASILEÑA

Recebido em: 01-03-2022
Avaliado em: 07-02-2023
Reformulado em: 08-03-2023
Aceito para publicação em: 18-03-2024
Publicado em: 28-02-2025
Editor Responsável: Moacir Manoel Rodrigues Jr.

Lyss Paula de Oliveira[1]
César Augusto Tibúrcio Silva[2]

RESUMO

O objetivo do estudo é investigar a relação entre a variação do humor expresso no Twitter, retorno das ações, volatilidade e volume de negociações no mercado acionário brasileiro. A amostra foi composta por dados diários do humor expresso no Twitter e do Ibovespa. Esses dados foram analisados por meio de regressão quantílica, em que se investigou o impacto que a variação do humor expresso na plataforma tem no mercado de ações, em função do rápido e amplo alcance, do efeito de rede e do contágio emocional que a mídia gera. O tema é original, com crescente interesse por pesquisas que envolvem as mídias sociais, o sentimento expresso e a sua relação com a tomada de decisão no mercado de ações. O estudo evidenciou que a variação do humor tem relação negativa com o volume de negociações e positiva com a volatilidade do Ibovespa, ou seja, os investidores tendem a estar menos dispostos a negociar quando o humor está oscilando e que a sua variação contribui para o aumento da volatilidade das ações. Existe uma alteração inversa na movimentação dos retornos das ações, conforme o humor do Twitter varia. A relação é negativa quando a variação do humor é baixa e positiva quando é alta. Esses resultados contribuem com os envolvidos no mercado acionário ao evidenciar que o humor é um elemento que afeta o preço dos ativos, como investidores, analistas financeiros e, em especial, reguladores que têm mostrado interesse em monitorar a disseminação de informações financeiras nas mídias sociais, como a atuação de influenciadores digitais. O estudo também trouxe contribuições teóricas à literatura e à academia ao se discutir, de forma inovadora, um assunto em crescente desenvolvimento.

[1]Doutora em Ciências Contábeis pela Universidade de Brasília (UnB); ORCID: https://orcid.org/0000-0001-5285-4778; E-mail: lysspaula@gmail.com
[2]Doutor em Controladoria e Contabilidade pela Universidade de São Paulo (USP); Professor titular no Mestrado e Doutorado de Contabilidade (PPGCont) da Universidade de Brasília (UnB); ORCID: https://orcid.org/0000-0002-5717-9502; E-mail: cesaraugustotiburciosilva@gmail.com

Palavras-chave: Humor; Mercado de Ações; Twitter.

ABSTRACT
The study investigates the relationship between mood changes expressed on Twitter, stock returns, volatility, and trading volume in the Brazilian stock market. The sample consisted of daily data on moods expressed on Twitter and Ibovespa. These data were analyzed using quantile regression, in which the impact of the variation in mood expressed on the platform on the stock market was investigated due to the rapid and broad reach, the network effect, and the emotional contagion that the media generates. The theme is original, with a growing interest in social media research, expressed sentiment, and its relationship with decision-making in the stock market. The study showed that the variation in mood has a negative relationship with the trading volume and a positive relationship with the volatility of the Ibovespa; that is, investors tend to be less willing to trade when the mood is oscillating and that its variation contributes to the increase in stock volatility. There is an inverse change in the movement of stock returns as Twitter's mood changes. The relationship is negative when mood variation is low and positive when it is high. These results contribute to those involved in the stock market by showing that mood is an element that affects asset prices, such as investors, financial analysts, and, in particular, regulators who have shown interest in monitoring the dissemination of financial information on social media, such as the performance of digital influencers. The study also brought theoretical contributions to the literature and academia by innovatively discussing a subject that is in increasing development.

Keywords: Mood; Stock market; Twitter.

RESUMEN
El objetivo del estudio es investigar la relación entre los cambios de humor expresados en Twitter, los rendimientos de las acciones, la volatilidad y el volumen de negociación en el mercado de valores brasileño. La muestra consistió en datos diarios sobre el estado de ánimo expresado en Twitter y el Ibovespa. Estos datos se analizaron mediante una regresión cuantil, en la que se investigó el impacto que tiene en el mercado de valores la variación del estado de ánimo expresado en la plataforma, debido al rápido y amplio alcance, el efecto red y el contagio emocional que genera el medio. El tema es original, con un interés creciente en la investigación que involucra las redes sociales, el sentimiento expresado y su relación con la toma de decisiones en el mercado de valores. El estudio mostró que la variación en el estado de ánimo tiene una relación negativa con el volumen negociado y una relación positiva con la volatilidad del Ibovespa, o sea, los inversionistas tienden a estar menos dispuestos a operar cuando el estado de ánimo es oscilante y que su variación contribuye a la aumentar la volatilidad de las acciones. Hay un cambio inverso en el movimiento de los rendimientos de las acciones a medida que cambia el estado de ánimo de Twitter. La relación es negativa cuando la variación del estado de ánimo es baja y positiva cuando es alta. Estos resultados contribuyen a los involucrados en el mercado de valores al mostrar que el humor es un elemento que afecta los precios de los activos, como inversores, analistas financieros y, en particular, los reguladores que han mostrado interés en monitorear la difusión de información financiera en las redes sociales, como como la actuación de los influencers digitales. El estudio también trajo contribuciones teóricas a la literatura y la academia al discutir, de manera innovadora, un tema en creciente desarrollo.

Palabras-clave: Humor; Mercado de acciones; Twitter.

1 INTRODUCTION

This study investigates the relationship between mood changes expressed on Twitter, stock returns, volatility, and trading volume in the Brazilian stock market. Research on people's moods has grown in recent decades (e.g., Kramer et al., 2014; Mogilner et al., 2012; You et al., 2017; Zhang et al., 2018). The interest in understanding how people's moods change and their consequences on consumer relations, investment practices, interpersonal relationships, or other human behaviors arises to understand the individual's relationships with the world (Mogilner et al., 2012).

Mood is an adaptive component of social behavior (Fischer & Manstead, 2008; Ralph & Damasio, 2000), and there is a link between mood and decision-making (Loewenstein & Lerner, 2003; Loewenstein & Rick, 2008). The mood is considered an enduring emotional state (Dalgalarrondo, 2000; Owens & Maxmen, 1979), and emotional states, such as mood, are essential for all decisions (Damasio, 1994 apud Baddeley, 2018).

Emotional states, including mood, can be transferred to others through emotional contagion (Kramer et al., 2014; Xiaomei et al., 2018). Previous evidence suggests that networks can transfer prolonged moods (Fowler & Christakis, 2008). Kramer et al. (2014) show that emotional contagion of people's moods does not only spread in face-to-face conditions but that the effect provoked by social media influences the emotional state of other users, with large-scale emotional contagion occurring through this channel.

To understand the main factors behind the thoughts and emotions that affect people's moods today and interfere with their decision-making, using social media appears to be a logical resource, as they are part of the everyday aspects of modern life (Kujur & Singh, 2018). Social media channels (e.g., Twitter®) allow people to be more participatory, creating online communities and sharing information, ideas, personal messages, and other content (Chua & Banerjee, 2015), directly affecting people's behavior (Alter, 2018).

The Internet has recently changed the landscape of information generation, dissemination, and interaction (Li, Shen, Xue, & Zhang, 2017). The various forms of existing social media platforms provide unique data sets that would be very difficult or impossible to obtain without the Internet (Da et al., 2015; Zhang et al., 2018). Among the existing digital platforms, the study investigates the relationship between the variation in mood expressed by all Twitter users and the movement of the Brazilian stock market. Therefore, the investor sentiment analyzed here corresponds to the mood expressed on Twitter and is measured through the happiness index. Li et al. (2017) and Ruan et al. (2018) point out that the stock market is among the most commented topics on Twitter (tweets containing comments related to recommendations and rumors, posted by individual or institutional investors, news agencies, and in some cases, even regulators).

Online messages influence people's emotional experiences, affecting their behavior outside social media (Kramer et al., 2014). Since there is a link between mood and decision-making, and the mood expressed on social media is transmitted to other people through the network effect and emotional contagion, this feeling will also reach investors' behavior outside social media, impacting their decision-making related to trading in the stock market. By impacting investors' decision-making in the stock market, there will consequently be interference in the willingness to trade, increasing volatility, which can alter stock returns. Thus, this study assumes that the mood expressed on Twitter reaches investor sentiment and, therefore, interferes with the stock market.

Bond (2012) shows that even small effects can have significant aggregate consequences on social media, mainly due to its broad and rapid reach (Deng et al., 2018; Jung et al., 2018). Several studies show that there is a relationship between the mood expressed on Twitter and the movement of the stock market, reinforcing the use of mood expressed in this media as an indirect proxy for investor sentiment (Lee et al., 2020; Li et al., 2017; Naeem et al., 2020; Naeem et al., 2021; You et al., 2017; Zhang et al., 2018). The research gap to be filled in this study focuses mainly on analyzing the Brazilian market.

Twitter was considered a relevant social media for the study because the messages posted express people's moods, which influence and can be influenced by the media, personal relationships, and people's decisions, causing a network effect. Kraaijeveld and Smedt (2020) pointed out one of the reasons for the constant studies involving the stock market. Twitter is concerned that the platform can combine news and feelings due to greater access to online information. It also provides indicators to measure emotional states, such as mood and investor preferences (Naeem et al. (2021).

Thus, this study uses data from the Bovespa index regarding the daily opening values, trading volume, and volatility of the leading Brazilian stock exchange, B3, as well as daily data extracted from the Happiness Index calculated based on the content posted by users on Twitter, which is a proxy for measuring the variation in users' mood. Therefore, the research is limited to this social media, although it is possible to believe that the conclusions can be generalized. The data are analyzed from January 2009 to March 2021 using quantile regression.

The results show that trading volume negatively correlates with mood variations on Twitter, i.e., investors are less willing to trade stocks when their moods fluctuate considerably. Mood variations have an inverse relationship with stock returns. When mood variations are low, the relationship with stock returns is negative; when the variations are high, the relationship is positive. According to mood variations expressed by people, there is a distinct behavior in decision-making related to investments in the Brazilian stock market, as the literature has already discussed. More pronounced mood variations tend to increase returns, as investors take less analytical positions with higher moods, being more willing to trade. Finally, the evidence shows that the volatility of the Ibovespa has a positive relationship with mood variations, i.e., when mood variations on Twitter increase, volatility also tends to increase. The results confirm the hypotheses.

This study contributes to those involved in the capital markets by showing that people's mood is an element that affects the price of assets. Using a proxy extracted based on user-generated content on Twitter is relevant for investors, financial analysts, regulators, and other market stakeholders. From the regulators' point of view, the study contributes to the regulatory initiative promoted by the Securities and Exchange Commission, which has intensified monitoring of the dissemination of financial information on social media, both disclosed by companies and by digital influencers. The content disseminated can impact people's moods on digital platforms and interfere with the functioning of the market.

The results have implications for portfolio managers, as they make it possible to understand the link between mood and stock market behavior, helping with future portfolio management. In addition, the difference between the studies lies in their originality and approach to the subject, especially in the Brazilian scenario. The results also generate theoretical contributions to the literature on the sentiment expressed on social media and its relationship with investment decision-making and academia by discussing, innovatively, a subject that is increasingly under development.

2 THEORETICAL FRAMEWORK

Noisy signals in the market, such as investor sentiment, theoretically cause systematic risk and affect stock prices, deviating them from their fundamental values and making the market more volatile (Baker & Wurgler, 2007). Volatility links investor sentiment and stock returns, which drives stock market volatility (Stambaugh et al., 2012). Thus, as mentioned, this study assumes that the mood expressed on Twitter reaches investor sentiment.

According to Baddeley (2018), moods are more general phenomena, often experienced collectively. People in a good mood are likelier to use simple heuristics, relying on pre-existing knowledge and paying little attention to precise details. In contrast, when they are in a bad mood, they are more likely to pay more attention to precise details than existing knowledge (Schwarz, 2000 apud Baddeley, 2018). Baddeley (2018) generally recognizes that mood can greatly impact people's behavior, so people will not always make logical and reasonable calculations in their decision-making process.

In addition to historical stock performance in the stock market, investors' decisions can be affected by other information (Chen et al., 2014; Fang & Peress, 2009; Luo et al., 2013). According to Ruan et al. (2018), the mood reflected in social media has played an important role in investors' decision-making process, affecting the stock market; in this sense, the stock market is related to the public's mood. Previous studies reveal that cognitive bias is one of the leading causes of the gap between asset prices and their fundamental values (Kahneman & Tversky, 1979). This bias generates deviations in investors' rationality, which is defined as investor sentiment (Brown & Cliff, 2004). Sentiment is the excess of optimism or pessimism of investors; in this study, the mood expressed on Twitter is used as an indirect proxy for investor sentiment.

From this perspective, it is understood that people's mood is affected by both good news and bad news. News impacts mood, which impacts individuals' decisions. Social media can accentuate this scenario due to its rapid power to disseminate information and broad reach. Taking into account that social media can disseminate information more quickly and that users post their moods on the platforms daily, the potential for this emotional state generated by the user to reach is more significant and faster, affecting other individuals through an effect of emotional and network contagion (Kramer et al., 2014; Xiaomei et al., 2018).

In line with the discussion, Deng et al. (2018) state that the proliferation of social media platforms in recent years has removed most of the limits on where and when users post a message, and it is promising to explore the mood of these users on these media to predict social, political, and economic activities. The findings of Deng et al. (2018) reveal that the mood expressed on social media can be considered an indirect proxy for investor sentiment. Jia et al. (2020) reveal that the volume of tweets related to days with more or less happy events (affecting people's moods) spread on Twitter and are more likely to be seen repeatedly on social media, which may affect the willingness to trade in the stock market.

Sentiment analysis of social media is related to various events, such as public mood and political movements (Li & Li, 2013; Bond et al., 2012), measurement of customer satisfaction (Kang & Park, 2013), and prediction of movie sales (Rui & Liu, 2013). More data is available with more users joining social media; thus, many studies benefit from the trend. Among them, financial market analysis is one of the fields most investigated and has attracted much attention. From a market perspective, Kim and Kim (2014) and Da et al. (2015) constructed investor sentiment proxies from social media data and revealed that all social media have predictability for stock returns; Zhang et al. (2018) reveal that there are interdependencies between online activities on platforms and stock markets; and Bollen et al., (2011) extract sentiment from Twitter feeds and find that the constructed sentiment can predict daily directional changes in the closing prices of the Dow Jones Industrial Average with an accuracy of 86.7%.

As the influence of the trust network is used to weight tweets, the sentiment expressed on Twitter correlates with abnormal stock returns (Ruan et al., 2018). Ruan et al. (2018) aimed to identify the trust relationships among the most influential Twitter users, demonstrating that these users' results align even more closely with abnormal stock returns. Other studies indicate a relationship between stock returns and Twitter sentiment, which is only evident at extreme mood levels (You et al., 2017). This connection between Twitter sentiment and stock returns is more significant in American countries than in Middle Eastern and South African ones (Li et al., 2017; Zhang et al., 2018).

By dividing daily mood into quantiles, from days with lower to higher moods, Shen et al. (2018) show that the distortion of the higher mood subgroup is significantly greater than that of the other subgroup, with a close relationship between the dynamics of online moods and stock market performance (Shen et al., 2018). For Naeem et al. (2020), using indices that measure people's emotional states based on social media as a proxy for investor mood is useful to indicate future stock market volatility. In addition, the results of Naeem et al. (2020) generate insights into the influence of mood variations on investors' risk aversion in stock markets. At the same time, Chen et al. (2014) and Luo et al. (2013) reveal that negative moods on platforms can induce a drop in stock prices.

Overall, the evidence supports the claim that social media, including Twitter, are related to stock market movements. However, these findings need to be better understood, mainly because the studies cited generally use small data samples, in most cases from less than one year. This study expands the sample to understand whether the results are consistent over time.

3 DEVELOPMENT OF HYPOTHESES

Literature related to the stock market has long indicated that the formation of the perception of investing is not deliberate and can be influenced or facilitated by the mood at the time of choice (Alter et al., 2007; Bolte et al., 2003). From this perspective, the study assumes that the variation in mood expressed on Twitter is related to the volume of trading, the return, and the volatility of the Brazilian stock market. Three essential points lead to assuming this relationship:

i) i) emotional states affect people's decision-making (Alter et al., 2007; Baddeley, 2018; Bolte et al., 2003);
ii) emotional states, such as mood, can be transferred to other people through emotional contagion (Kramer et al., 2014; Xiaomei et al., 2018) and
iii) emotional contagion is transferred in person and through social media due to the network effect they generate and their broad reach (Deng et al., 2018; Jung et al., 2018).

Lee et al. (2020) present evidence that volatility increases when investors become more pessimistic and decreases when they become more optimistic. Based on the most recent discussions that social media affects investor sentiment, measured by mood expressed on Twitter, and that volatility is affected depending on whether investors are more optimistic or pessimistic, the study assumes that when mood variation is lower, Ibovespa volatility will be lower. When the variation is higher, volatility will also be higher. Thus, the first hypothesis of the study establishes that:

H1: Mood variations expressed on Twitter have a positive relationship with stock volatility.

As evidenced by Jia et al. (2020), the volume of tweets related to days with more or less happy events spreads on Twitter, influencing people's moods and potentially affecting their willingness to trade in the stock market. Alter et al. (2007), Bolte et al. (2003), and Topolinski and Strack (2009) argue that when a person is in a good mood, they tend to judge the situation positively. Some people in a more positive mood prefer to avoid calculations, making judgments more affective and relying more on heuristics (Baddeley, 2018; Bessa, 2016; Slovic et al., 2002; 2004). Mood affects judgment positively or negatively depending on whether the event, moment or situation is good or bad (Bessa, 2016). For example, Jordan and Kaas (2002) show that investment fund advertisements with emotional content reduce investors' risk perception. With this discussion as support, it is understood that mood variations can impact stock returns; however, this relationship is reversed depending on positive or negative moods. Based on these concepts, it is believed that lower mood variations will have a negative relationship with returns. In contrast, more extreme mood variations will have a positive relationship with returns, as they will positively affect people's judgment. Thus, the second hypothesis of the study establishes that:

H2: The variation in mood expressed on Twitter is related to the return on stocks. This relationship reverses from negative to positive, depending on whether the mood varies less or more.

Based on the same arguments presented in the second hypothesis of the study, it is believed that mood variation may also be related to the volume of negotiations, given that mood has a significant impact on people's behavior (Alter et al., 2007; Baddeley, 2018; Bessa, 2016; Bolte et al., 2003; Topolinski & Strack, 2009) and willingness to negotiate (Jia et al., 2020), it is believed that moods that fluctuate considerably will negatively impact individuals' willingness to negotiate. The third hypothesis of the study establishes that:

H3: Mood variations expressed on Twitter have a negative relationship with stock trading volume.

The assumptions presented in each of the hypotheses are based on the view that online messages influence people's emotional experiences, affecting their behavior outside social media (Kramer et al., 2014). Due to greater access to online information, Twitter provides indicators to measure emotional states, such as mood and investor preferences (Naeem et al. (2021).

4 METHODOLOGICAL PROCEDURES

4.1 The Proxy for Mood

The study uses information extracted from the Hedonometer Happiness Index as a proxy for users' moods and information captured from the Brazilian stock market. The Hedonometer Index is an indicator developed by Peter Dodds and Chris Danforth from the University of Vermont in the United States, which measures what the researchers call happiness daily through people's online expressions on Twitter. The calculation of the index includes the expressions of users in general, including investors and potential investors, following the study's premises that the mood expressed on Twitter affects the movement of the stock market due to the network effect and emotional contagion.

The data for this measurement were extracted by accessing the API (Application Programming Interface) of the system available on the hedonometer. When accessing the website hedonometer.org, in the "Data" tab, there is a step-by-step guide for extracting the data using Python programming. After extraction, the data was transferred from Python to a spreadsheet, where the database was built. Subsequently, the regression models and other statistics were analyzed using the Stata program, version 16. The study period was from January 2, 2009, to March 31, 2021.

The indicator's interest arose because it is based on content produced on Twitter, a digital platform with the potential to represent the universe surrounding the stock market. According to Li et al. (2017), this proxy has the advantage of being derived from hundreds of millions of potential investors and avoiding the endogenous problem of market variables. The index has been used in several recent studies involving investor sentiment measured via social media (Li et al., 2017; Naeem et al., 2020; Naeem et al., 2021; You et al., 2017; Zhang et al., 2018).

The index is formulated randomly from approximately 10,000 words related to feelings in Twitter posts. When constructing the index, the developers created it for several languages, such as Arabic, English, and Portuguese. In all languages in which the indicator was created, the words that make up the index were evaluated by participants who helped define those that denote more or less happiness. Despite having been developed by North American researchers, the index is suitable for Brazilian data since the evaluation of the words for the Portuguese language was done by native Brazilians who live in Brazil during the construction of the data.

The index developers selected these Brazilians through the Amazon Mechanical Turk® platform. The scores assigned to each word range from zero to ten, assuming that words closer to zero are negative and closer to ten are positive. Pre-tests were also conducted; some words were selected, and some participants were asked to rate their happiness with each term. The happiness index values essentially coincided with the scores obtained in the pre-test. The word selection process relies on the "true-false" system, which seeks to detect the use of terms that contain irony, so when a positive word (happy) is written together with a negative word (less happy), this term is discarded from the index analysis and vice-versa.

4.2 Variables and Empirical Model

Data related to the capital market, such as volatility and trading volume, were collected for the study. All data of interest are daily. The Ibovespa was selected as the market index; the data is available in the Economática® database and Investing.com website.

The model developed in the study was a quantile regression model. Analysis along the quantiles allows for a better understanding of the effect of mood variation and the dependent variables under study. According to Fávero and Belfiore (2020), quantile regression has advantages over linear regression because it allows the entire conditional distribution of the dependent variable to be characterized since different parameter estimates are obtained for different quantiles, which allows for a better interpretation of the behavior of the dependent variable in the face of changes in the independent variables at the most diverse points of the distribution. Quantile regression helps analyze market movements in the distribution of quantiles better.

There is an expectation, supported by empirical evidence from Shen et al. (2018) and You et al. (2017), that there will be a different effect on the study's dependent variables when there is a fluctuation in the mood expressed on Twitter. Regressors X are estimated to have different impacts across the distribution of Y values.

Mood variation was used to measure the relationships between mood, Ibovespa volatility, stock returns, and trading volume. Since volatility measures stability, which measures the oscillations of the variable, it will be possible to see whether or not there are changes in the selected market variables as people's mood fluctuates.

The daily return of the Ibovespa is calculated according to the equation (1):

$$Ret\_Ibov = (VA_t - VA_{t-1}) / VA_{t-1} \tag{1}$$

Where VA_t is the daily opening value of the Ibovespa portfolio, and VA_{t-1} is the opening value on the previous day. The opening value was chosen to capture the investor's mood during the twenty-four hours of a day instead of capturing only the period in which the market is open for trading.

The daily volatility of the Ibovespa and the mood variations are calculated according to the RiskMetrics equation. The average between the mood of the previous day and the current day was considered a starting point to calculate the mood variations, seeking to analyze whether the mood of day 1 impacts the market movement on day 2.

RiskMetrics is a methodology developed by the North American bank JP Morgan (1994), applied to calculate volatility and correlation and was used in the study, given the difficulty in obtaining the daily calculation of the Ibovespa volatility in the analyzed databases. Christoffersen (2001) highlights some advantages of the model: it tracks changes in variance so that there is consistency with the observed returns, with more recent returns being more relevant than more distant returns; the model contains only one unknown parameter and when calculated for many assets, a similar result was found among the assets; and there is a need to retain little data to calculate the variance. As this author highlights, RiskMetrics is a special case of the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, which is a model for situations of volatility in the prices of financial assets. RiskMetrics is calculated as follows (2):

$$Volatility = (0{,}94\, x\, \sigma^2) + (0{,}06\, Return^2) \tag{2}$$

The models for the regressions are those shown in equations (3), (4) and (5):

$$Vol\_Ibov_t = \beta 0_t + \beta 1 Var\_Mood_t + \varepsilon \tag{3}$$

Where:

Vol_Ibov: variable obtained according to the RiskMetrics calculation based on Ibovespa data.

Var_Mood: calculated according to the RiskMetrics equation based on Hedonometer Daily Happiness Index data.

The model presented in equation (3) tests hypothesis 1 of the study.

$$Stock\_Ret_t = \beta 0_t + \beta 1 Var\_Mood_t + \varepsilon \tag{4}$$

Where:

Stock_Ret: variable obtained by calculating equation (1).

The model of equation (4) tests hypothesis 2 of the study.

$$Vol\_Neg_t = \beta 0_t + \beta 1 Var\_Mood_t + \varepsilon \tag{5}$$

Where:

Vol_Neg: calculated based on the daily trading volume of the Ibovespa.

The model of equation (5) tests hypothesis 3 of the study.

The study sought to analyze the daily effect of mood on the Brazilian stock market; the results are presented in section 5.

5 PRESENTATION AND DISCUSSION OF RESULTS

Table 1 shows the descriptive statistics of the variables, aiming to understand better the characteristics of the data from the sample under study.

Table 1
Descriptive Statistics

Variables	Note	Average	S.D.	Minimum	25th percentile	Median	75th percentile	Maximum
Mood	3000	6.42	0.12	6.01	6.35	6.43	6.50	6.86
Stock Returns	3000	0.001	0.02	-0.15	-0.01	0.001	0.01	0.14
Volume Negotiations	3000	4.01	2.52	0.42	2.45	3.43	4.58	21.77
Ibovespa Volatility	3000	0.001	0.01	0.001	0.001	0.001	0.001	0.01
Mood Variations	3000	0.001	0.001	0.001	0.001	0.001	0.001	0.01

Note: The table contains descriptive statistics of the variables.

Among the stratified observations, it is possible to identify that there is a large oscillation in market variables, daily stock returns, and trading volume. For example, the return on the stocks that make up the Ibovespa varies between -15% and 14%; this is a common characteristic in financial markets of emerging and less mature countries, such as Brazil, since the oscillations tend to be greater in these markets (Shen et al., 2018). On the other hand, the mood expressed on Twitter presents a smaller oscillation throughout the sample, even having a very close mean and median; that is, the mood does not change so abruptly over the time studied. Considering the data presented in Table 1, it is possible to observe that the mood variable, expressed on Twitter's social media, is more focused on a good than a bad mood; on average, the social media mood is 6.42.

This first analysis of descriptive statistics shows that quantile regression presents advantages for discussing the results, mainly due to the presence of outliers in the last quintile of the sample for the variables Ibovespa volatility and trading volume. A correlation analysis (not tabulated) and the VIF test were also performed, which showed no highly correlated variables, avoiding multicollinearity problems. From this point on, analyzing the regressions allows a better understanding of the relationship between the variables.

Table 2
Quantile Regression Ibovespa Volatility

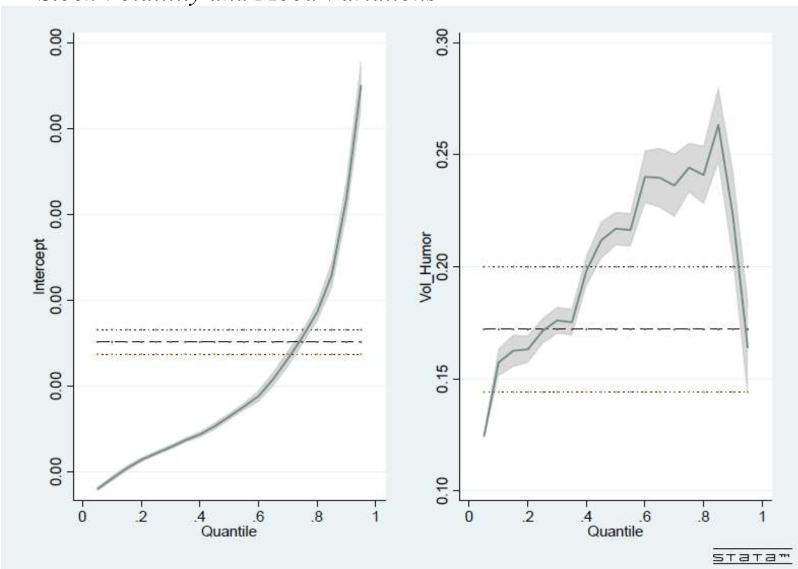
Dependent Variable[a]		**Ibovespa Volatility**				
Independent Variable[b]		Q 0.10	Q 0.30	Q 0.50	Q 0.70	Q 0.90
Mood Variations	**Coef.**	0.157	0.176	0.217	0.236	0.223
	t	56.81***	66.75***	51.03***	28.63***	9.77***
Constant	**Coef.**	0.001	0.001	0.001	0.001	0.001
	t	65.32***	95.94***	75.94***	55.10***	36.06***
Pseudo R^2		0.0385	0.0504	0.0637	0.0751	0.0941
No. of obs.				3000		

Note: Contains the estimated coefficients for the generated data. The model contains the quantile regression for the study variable, and the Qs indicate the quantiles (or percentiles) from 10 to 90. [a] The dependent variable is the daily volatility of the Ibovespa. [b] The independent variable is the mood variation, measured by the Hedonometer happiness index. *** indicates statistically significant at 0.01.

Table 2 presents the regression results between the volatility of Ibovespa stocks and the mood expressed on Twitter. The results show that mood variation is positively related to Ibovespa volatility, being statistically significant with 99% confidence; that is, when mood variation increases, the volatility of Ibovespa stocks tends to increase as well. This evidence

confirms the study's first hypothesis: that mood expressed on Twitter has a positive relationship with stock volatility.

Figure 1
Stock Volatility and Mood Variations



The study results show that when the mood variation expressed on Twitter rises, the volatility of Ibovespa stocks also tends to rise. This evidence corroborates the claim by Naeem et al. (2020) that using indexes that measure people's emotional states based on social media as a proxy for investor mood can be useful in indicating future stock market volatility.

An additional test was performed using ordinary least squares (OLS) regression. The results did not differ substantially from those presented in Table 2 (the same premise was adopted for the data in Tables 3 and 4). When observing Figure 1, it is possible to see that modeling using quantile regression added to the results since, with it, the mean of each quantile follows the behavior of the data better compared to the conditional mean of the OLS modeling.

Table 3
Quantile Regression Stock Returns

Dependent Variable[a]		Stock Returns				
Independent Variable[b]		Q 0.10	Q 0.30	Q 0.50	Q 0.70	Q 0.90
Mood Variations	**Coef.**	-4.065	-1.584	1.433	3.154	6.053
	t	-3.91***	-2.35**	2.25**	4.72***	6.01***
Constant	**Coef.**	-0.017	-0.006	0.001	0.007	0.018
	t	-32.44***	-18.06***	1.83*	20.45***	35.53***
Pseudo R^2		0.0045	0.0008	0.0006	0.0031	0.0156
No of Obs.				3000		

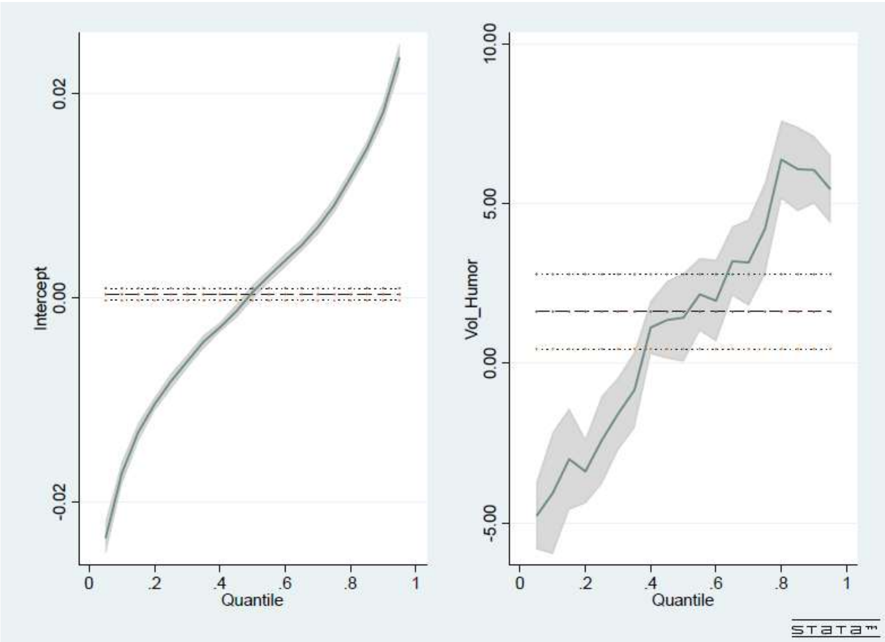
Note: This file contains the estimated coefficients for the generated data. The model contains the quantile regression for the study variable, and the Qs indicate the quantiles (or percentiles) from 10 to 90. [a] The dependent variable is the daily return of Ibovespa stocks, and [b] the independent variable is the mood variation. ***, **, and * indicate statistical significance with 0.01, 0.05, and 0.10, respectively.

The results presented in Table 3 show that mood variation is related to stock returns. When mood variation is lower or higher, it impacts stock returns, similar to the findings of Li et al. (2017), You et al. (2017), and Zhang et al. (2018). Based on this evidence, the study's second hypothesis is also **confirmed**.

Unlike the results between mood variation and Ibovespa volatility, the coefficients between mood and stock returns are inverted in some of the quantiles presented. The statistical coefficients generated in the regression reveal that lower mood variation negatively impacts stock returns, while higher mood variation positively impacts stock returns.

This evidence suggests that the discussion promoted by Baddeley (2018), Bessa (2016), and Slovic et al. (2002; 2004) can be associated with the study's results. The authors state that people's mood affects their decision-making differently in lower or higher moods. That is, mood variations from lower to higher or vice versa affect the willingness to trade, which impacts stock returns.

Figure 2
Stock Returns and Mood Variations



Based on the graph shown in Figure 2, it can be seen that, for the stock return variable and the variation in Twitter mood, the choice of quantile regression was also appropriate, better conditioning the extreme data of the sample throughout the entire data distribution.

Similar to the results found by You et al. (2017), the evidence presented for the Brazilian market shows a relationship between the mood expressed on Twitter and stock returns. However, this relationship depends on the fluctuations in the mood expressed on social media, being statistically significant and with distinct behaviors (coefficients that are inverted) when the mood variation is lower (quantile 0.10) or higher (quantiles 0.50, 0.70, and 0.90). Still, regarding stock returns, it is worth noting that the results found are in line with the evidence presented by both Li et al. (2017) and Zhang et al. (2018), whose studies demonstrate that the relationship between the mood expressed on Twitter and stock returns is accentuated in Latin American countries.

Table 4
Quantile Regression Trading Volume

Dependent Variable[a]		Trading Volume				
Independent Variable[b]		Q 0.10	Q 0.30	Q 0.50	Q 0.70	Q 0.90
Mood Variations	**Coef.**	-212.615	-490.463	-457.598	-398.778	-674.355
	t	-4.22***	-7.48***	-6.90***	-4.14***	-3.16***
Constant	**Coef.**	1.726	2.754	3.468	4.323	7.399
	t	67.20***	82.45***	102.59***	88.09***	26.98***
Pseudo R^2		0.0059	0.0133	0.0098	0.0070	0.0055
No of Obs.				3000		

This file contains the estimated coefficients for the generated data. The model contains the quantile regression for the study variable, and the Qs indicate the quantiles (or percentiles) from 10 to 90. [a] The dependent variable is the daily trading volume of Ibovespa stocks, and [b] the independent variable is the mood variations. *** indicates statistical significance at 0.01.

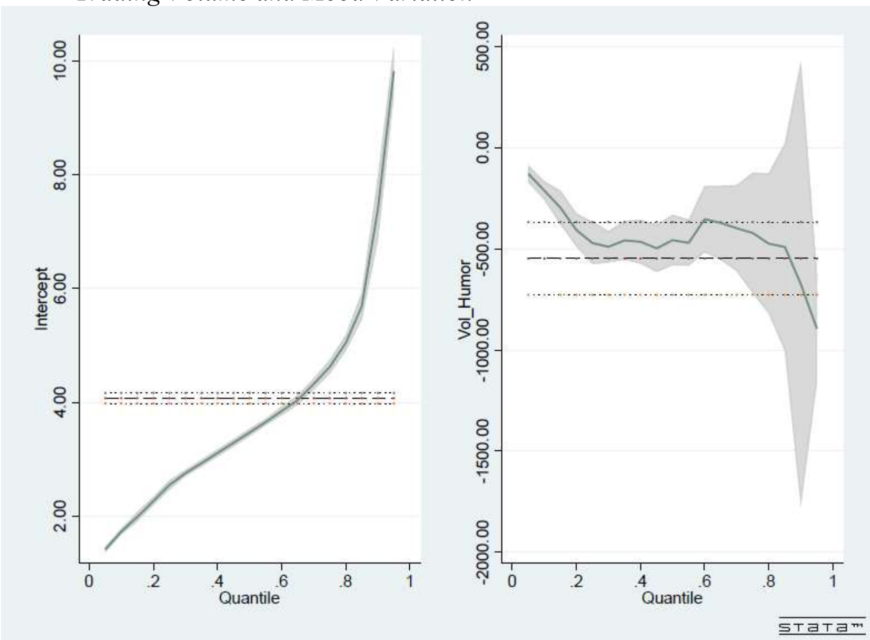
According to the results presented in Table 4, it is possible to demonstrate that mood variation is also related to the trading volume of the shares that make up the Ibovespa. The relationship between the mood expressed on Twitter and the trading volume is statistically significant, with 99% confidence in all quantiles analyzed, which allows us to **confirm** the third hypothesis of the study.

Mood variation is negatively related to stock trading volume (negative statistical coefficient in all quantiles), i.e., the more the mood expressed on Twitter fluctuates, the lower the trading volume tends to be. The literature supports this evidence, showing that mood is an emotional state that generally impacts people's decision-making and is a relevant component (Fischer & Manstead, 2008; Ralph & Damasio, 2000).

One of this study's most robust results was the relationship between mood variation and trading volume. The relationship between the variables is negative and statistically significant in all regression quantiles. This result aligns with empirical evidence that the volume of tweets on days with more or less happy events spreads and influences people's mood, which can affect the willingness to trade in the stock market (Jia et al., 2020).

Based on the graph shown in Figure 3, it can be seen that, for the variable trading volume of the shares that make up the Ibovespa and the mood variation, the choice of quantile regression also proved to be adequate, better involving the extreme data of the sample throughout the data distribution.

Figure 3
Trading Volume and Mood Variation



After analyzing the study's main regressions, tests were performed, separating the sample by day of the week. These tests were performed to understand whether the mood expressed on Twitter may have different behavior depending on the day of the week. The results are presented in Tables 5, 6, and 7.

Table 5
MLR Regression Ibovespa Volatility by Day of the Week

Dependent Variable[a]		**Ibovespa Volatility**				
Independent Variable[b]		Monday	Tuesday	Wednesday	Thursday	Friday
Mood Variations	**Coef.**	0.167	0.176	0.180	0.193	0.155
	t	5.46***	5.37***	5.24***	5.22***	5.76***
Constant	**Coef.**	0.001	0.001	0.001	0.001	0.001
	t	15.28***	15.35***	15.48***	15.05***	16.11***
Adjusted R^2		0.0462	0.0446	0.0416	0.0421	0.0514
F statistic		29.84***	28.89***	27.47***	27.29***	33.21***
No. of Obs.		596	599	611	599	595

Note: This table contains the estimated coefficients for the generated data. The model contains the OLS regression (pooled) for the study variable. The model variables are the same as in Table 2. *** indicates statistical significance at 0.01.

The results show that mood variation is positively related to Ibovespa volatility on all days of the week, and this relationship is statistically significant with 99% confidence. However, when the data are separated by day of the week, these variables have no distinct behavior.

Table 6
OLS Regression Stock Returns by Day of the Week

Dependent Variable[a]		Stock Returns				
Independent Variable[b]		Monday	Tuesday	Wednesday	Thursday	Friday
Mood Variations	**Coef.**	4.014	-1.012	-0.318	-1.767	4.974
	t	3.38***	-0.68	-0.24	-1.22	4.07***
Constant	**Coef.**	0.001	-0.001	0.001	0.001	-0.001
	t	0.49	-0.38	1.66*	1.43	-0.07
Adjusted R^2		0.0172	0.0009	0.0016	0.0008	0.0255
F statistic		11.40***	0.46	0.06	1.48	16.55***
No. of Obs.		596	599	611	599	595

Note: This table contains the estimated coefficients for the generated data. The model contains the OLS regression (pooled) for the study variable. The model variables are the same as in Table 3. *** and * indicate statistically significant at 0.01 and 0.1, respectively.

Table 6 shows a distinct mood swing on Monday and Friday, positively affecting the return of Ibovespa stocks on these days. Although the statistical coefficients of mood variation were negative for Tuesdays, Wednesdays, and Thursdays, signaling a possible change in this feeling, the variable was not statistically significant.

Table 7
OLS Regression Trading Volume by Day of the Week

Dependent Variable[a]		Trading Volume				
Independent Variable[b] and Controls [c]		Monday	Tuesday	Wednesday	Thursday	Friday
Mood Variations	**Coef.**	-459.809	-525.937	-602.412	-660.013	-529.073
	t	-2.29**	-2.63***	-2.81***	-2.84***	-2.83***
Constant	**Coef.**	3.696	4.071	4.257	4.190	4.130
	t	34.20***	40.35***	42.07***	40.08**	38.55***
Adjusted R^2		0.0071	0.0098	0.0112	0.0116	0.0117
F statistic		5.25**	6.94***	7.92***	8.04***	8.02***
No. of Obs.		596	599	611	599	595

Note: This table contains the estimated coefficients for the generated data. The model contains the OLS regression (pooled) for the study variable. The model variables are the same as in Table 4. ** and *** indicate statistically significant at 0.05 and 0.01, respectively.

The results in Table 7 do not differ from those presented in Table 4, i.e., mood variation is negatively related to the volume of stock trading on all days of the week. The analysis of the interquartile range (IQR), performed using Bloxplot graphs, did not show the existence of extreme outliers.

The study found that mood expressed on social media is related to market variables such as stock volatility, return, and trading volume, as previously shown (Chen et al., 2014; Luo et al., 2013; Naeem et al., 2020; Ruan et al., 2018; Shen et al., 2018). These results demonstrate that the emotional and network contagion effect generated by Twitter reaches the Brazilian stock market, as Kramer et al. (2014) and Xiaomei et al. (2018) have already discussed.

The evidence presented is consistent with the mood expressed on Twitter, which is related to the movements of the Brazilian stock market. Furthermore, the results allowed a more robust analysis of these relationships, filling a gap that previous studies had left, using data samples with a long time interval, and demonstrating that the existing relationships between the mood expressed on Twitter and the Brazilian stock market are long-lasting.

5.1 Additional tests

Additional tests were performed to understand whether quantile regression was the best-proposed model and to check the consistency of the results. The regression parameter test showed that the standard errors were smaller in quantile regressions than in OLS, i.e., there is better estimation precision around the quantiles in these variables. In addition, the Wald test, which was used to test the statistical differences in means between quantiles, strongly rejected the null hypothesis that the means in all quantiles are equal to zero for volatility, stock returns, and trading volume.

Additional tests were also performed with 1, 2, and 3 days of delay for the mood variable, seeking to understand whether the effect of the mood expressed on Twitter on the day lasts longer. The untabulated results showed that, in general, the effect of mood variation does not last over the days, especially for the volatility of the Ibovespa and the return on stocks. The effect of the mood variation lag was statistically significant for some of the quantiles analyzed in the trading volume.

Another test involved creating dummy variables for days of the week within the observation sample. These tests differ from those presented in Tables 5, 6, and 7, in which the tests were performed with regressions since the quantile modeling was maintained with the total sample in the additional tests. The results showed that on Monday, there was a lower disposition to negotiate (statistically significant negative coefficients). The results also revealed a higher volume of negotiations driven by mood changes on Wednesdays.

Finally, a test of difference in means was performed for each day of the week concerning all the study variables (mood, mood variation, mood t-1, mood t-2, mood t-3, Ibovespa volatility, stock returns, and trading volume). Only Friday's mood had a significantly and statistically different mean from the other days of the week.

6 FINAL CONSIDERATIONS

The study investigates the relationship between mood changes on Twitter and events in the Brazilian stock market, specifically volatility, stock returns, and trading volume. A happiness proxy developed by researchers at the University of Vermont was used to measure mood. Market parameters were constructed based on the Ibovespa index.

The results indicate that stock volatility, Ibovespa return, and trading volume are significantly related to mood variations expressed on Twitter. Volatility is positively related to mood variations, and trading volume is negatively related, which suggests that investors are less willing to trade when moods vary greatly. The relationship between mood variations and stock returns is reversed throughout the analysis, being negative when mood variations are low and positive when they are high. These results confirm the study's hypotheses.

The study's evidence contributes to those involved in the Brazilian stock market, as it reveals that mood is an element that affects asset prices, especially investors, financial analysts, and regulators. In addition, the study presents an original approach to the topic, especially for the Brazilian scenario, which can contribute to developing other research related to the subject.

Several additional tests were applied to confirm the results presented, such as tests with days of delay for the mood variable and tests with dummies for the days of the week. Although additional tests were applied, the study has limitations related to the proxy used to represent the mood and new proxies may be constructed that can better capture investor sentiment. As a suggestion for future research, we believe it is relevant to study other mood measures to understand better the moment when mood changes and its implications for the stock market. Studies in this scope can better elucidate the relationship between mood and the market.

REFERENCES

Alter, A. (2018). *Irresistível*. Objetiva. ISBN: 978-8547000585.

Alter, A. L., Oppenheimer, D. M., Eppley, N., & Eyre, R. N. (2007). Overcoming institution: Metacognitive difficulty activates analytic reasoning. *Journal of Experimental Psychology General*, 136 (4), 569-576. https://doi.org/10.1037/0096-3445.136.4.569

Baddeley, M. (2018). *Behavioural economics and finance (English Edition)*. 2nd, Routledge. ISBN: 978-041-579-218-9 (Ebook).

Baker, M., Wurgler, J. (2007). Investor sentiment in the stock market. *J. Econ. Perspect*. 21 (2), 129–151.

Bessa, H. A. (2016). *A hierarquia de preferência do consumidor em decisões de investimento financeiro*. Tese de Doutorado, Universidade de São Paulo, São Paulo, SP, Brasil.

Bollen, J., Mao, H., Zeng, X. (2011). Twitter's mood predicts the stock market. *J. Comput. Sci.* 2 (1), 1–8.

Bolte, A., Goschke, T., Kuhl, J. (2003). Emotion and intuition: effects of positive and negative mood on implicit judgments of semantic coherence. *Psychological Science*, 14 (5), 416-421. https://doi.org/10.1111/1467-9280.01456

Bond, R. M., Farris, C. J., Jones, J. J., Kramer, A. D. I., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature*, 489 (7415), 295–298. https://doi.org/10.1038/nature11421

Brown, G., & Cliff, M. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, 11 (1), 1–27. https://doi.org/10.1016/j.jempfin.2002.12.001

Chen, H., De, P., Hu, Y., & Hwang B. H. (2014). Wisdom of crowds: the value of stock opinions transmitted through social media, *Review of Financial Studies*, *27*(5), 1367–1403. https://doi.org/10.1093/rfs/hhu001

Christoffersen, P. F. (2001). *Elements of financial risk management.* 1a. ed. Amsterdam: Academic Press.

Chua, A.Y., & Banerjee, S. (2015). Marketing via social networking sites: a study of brand-post popularity for brands in Singapore. *Proceedings of the International Multi-conference of Engineers and Computer Scientists*, 1 (18-20), pp. 1–6.

Da, Z., Engelberg, J., Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Rev. Financ. Stud*. 28 (1), 1–32. https://doi.org/10.1093/rfs/hhu072

Dalgalarrondo, P. (2000). *A afetividade e suas alterações*. Psicopatologia e semiologia dos transtornos mentais. Porto Alegre: Editora Artes Médicas Sul.

Deng, S., Huang, Z., Sinha, A. P., & Zhao, H. (2018). The interaction between microblog sentiment and stock returns: An empirical examination. *MIS Quarterly: Management Information Systems*, *42*(3), 895–918.

Fang, L., & Peress, J. (2009). Media Coverage and the Cross-section of Stock Returns. *The Journal of Finance*, LXIV (5), 2023-20-52. https://doi.org/10.1111/j.1540-6261.2009.01493.x

Fávero, L. P, & Belfiore, P. (2020). *Manual de análise de dados*. 1. Ed. Rio de Janeiro: Gen/LTC.

Fischer, A. H., & Manstead, A. S. (2008). *Social functions of emotion*. In: Handbook of Emotions, 3, 456–468.

Fowler, J. H, & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*, 337, 23–37. https://doi.org/10.1136/bmj.a2338

Jia, W., Redigolo, G., Shu, S. & Zhao, J. (2020). Can social media distort price discovery? Evidence from merger rumors. *Journal of Accounting and Economics*. https://doi.org/10.1016/j.jacceco.2020.101334

Jordan. J. & Kaas, K. P. (2002). Advertising in the mutual fund business: The Role of judgmental heuristics in private investors' evaluation of risk and return. *Journal of Financial Services Marketing*, 7 (2), 129-140. https://doi.org/10.1057/palgrave.fsm.4770079

JP Morgan (1994), "RiskMetrics Technical Documents", 1st edition, New York.

Jung, M. J., Naughton, J. P., Tahoun, A., & Wang, C. (2018). Do firms strategically disseminate? Evidence from corporate use of social media. *The Accounting Review*. https://doi.org/10.2308/accr-51906

Kahneman, D., & Tversky, A. (1979). Prospect theory: an Analysis of decision under risk. *Econometrica*, 47, 263-291. https://doi.org/10.2307/1914185

Kang, D., & Park, Y. (2013). Review-based measurement of customer satisfaction in mobile service: sentiment analysis and VIKOR approach. *Expert Systems with Applications*, 41, 1041-1050. https://doi.org/10.1016/j.eswa.2013.07.101

Kim, S.-H., Kim, D. (2014). Investor sentiment from internet message postings and the predictability of stock returns. *J. Econ. Behav. Org*. 107, 708–729. https://doi.org/10.1016/j.jebo.2014.04.015

Kraaijeveld, O., & Smedt, J. D. (2020). The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. Journal of International Financial Markets, Institutions, and Money, 65, 101188. https://doi.org/10.1016/j.intfin.2020.101188

Kramer, A. D. I., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *PNAS*, 111 (24). https://doi.org/10.1073/pnas.1320040111

Kujur, F., & Singh, S. (2018). Emotions as a predictor for consumer engagement in YouTube advertisement. *Journal of Advances in Management Research*, 15 (2), 184-197. https://doi.org/10.1108/JAMR-05-2017-0065

Lee, C. C., Chen, M. P., & Peng, Y. T. (2020). Tourism development and happiness: International evidence. *Tourism Economics*. https://doi.org/10.1177/1354816620921574

Li, Y. M., & Li, T. Y. (2013). Deriving market intelligence from microblogs, Decision Support Systems, 55, 206–217. http://dx.doi.org/10.1016/j.dss.2013.01.023

Li, X., Shen, D., Xue, M. & Zhang, W. (2017). Daily happiness and stock returns: The case of a Chinese company listed in the United States. *Economic Modelling*, 64, 496-501. http://dx.doi.org/10.1016/j.econmod.2017.03.002

Loewenstein, G., & Lerner, J.S. (2003). *The Role of affect in decision making.* In: Davidson, R., Scherer, K., Goldsmith, H. (Eds.), Handbook of affective science. New York: Oxford University Press.

Loewenstein, G., & Rick, S. (2008). *The Role of emotion in economic behavior*. In: Lewis, M., Haviland-Jones, J.M., L., F.B. (Eds.), Handbook of emotions. The Guildford Press, 138–156.

Luo, X., Zhang, J., & Duan, W. (2013). Social media and firm equity value. *Information Systems Research*, 24 (1), 146–163. http://dx.doi.org/10.1287/isre.1120.0462

Mogilner, C., Aaker, J., & Kamvar, S. D. (2012). How happiness affects choice. *Journal of Consumer Research*, 39, 429-443. https://doi.org/10.1086/663774

Naeem, M. A., Farid, S., Balli, F., & Shahzad, S. J. H. (2020). Can happiness predict future volatility in the stock Market? *Research in International Business and Finance*, 54, 101298. https://doi.org/10.1016/j.ribaf.2020.101298

Naeem, M. A., Mbarki, I., & Shahzad, S. J. H. (2021). Predictive Role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. *International Review of Economics and Finance*, pp. 73, 496-514. https://doi.org/10.1016/j.iref.2021.01.008

Owens, H., & Maxmen, J. S. (1979). Mood and affect: a semantic confusion. *The American Journal of Psychiatry*, 136 (1), 97–9. https://doi.org/10.1176/ajp.136.1.97

Ralph, A., & Damasio, A. R. (2000). The interaction of affect and cognition: A neurobiological perspective. Handbook of affect and social cognition. Routledge.

Ruan, Y., Durresi, A., & Alfantoukh, L. (2018). Using Twitter trust network for stock market analysis. *Knowledge-Based Systems*, 1–12. https://doi.org/10.1016/j.knosys.2018.01.016

Rui, H., Liu, Y., & Whinston, A. (2013). Whose and what chatter matters? The effect of tweets on movie sales. *Decision Support Systems*, 55 (2013) 863–870. http://dx.doi.org/10.1016/j.dss.2012.12.022

Shen, D., Liu, L., & Zhang, Y. (2018). Quantifying the cross-sectional relationship between online sentiment and the skewness of stock returns. *Physica A*, 490, 928-934. http://dx.doi.org/10.1016/j.physa.2017.08.036

Slovic, P., Finucane, M., Peters, E., & MacGregor, D. G. (2002). The Affect Heuristic. *In: Heuristic and Biases: the psychology of intuitive judgment*. 397-420.

Slovic, P., Finucane, M., Peters, E., & MacGregor, D. G. (2004). Risk as analysis and risk as feeling: some thoughts about affect, reason, risk, and rationality: *Risk Analysis*, 24 (2), 311-322. https://doi.org/10.1111/j.0272-4332.2004.00433.x

Stambaugh, R.F., Yu, J., Yuan, Y. (2012). The short of it: investor sentiment and anomalies. *J. financ. Econ*, 104 (2), 288–302. https://doi.org/10.1016/j.jfineco.2011.12.001

Topolinski, S., & Strack, F. (2009). The analysis of intuition: processing fluency and affect in judgments of semantic coherence. *Psychology Press*, 23 (8), 1465-1503. https://doi.org/10.1080/02699930802420745

Xiaomei, Z., Jing. Y., Jianpei, Z., & Hongyu, H. (2018). Microblog sentiment analysis with weak dependency connections. *Knowledge-Based Systems*, 142, 170–180. https://doi.org/10.1016/j.knosys.2017.11.035

You, W., Guo, Y., & Peng, C. (2017). Twitter's daily happiness sentiment and the predictability of stock returns. *Finance Research Letters*, 23, 58-64. http://dx.doi.org/10.1016/j.frl.2017.07.018

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). Twitter's daily happiness sentiment and international stock returns: Evidence from linear and nonlinear causality tests. *Journal of Behavioral and Experimental Finance*, pp. 18, 50–53. https://doi.org/10.1016/j.jbef.2018.01.005