XLVI Encontro da ANPAD - EnANPAD 2022
On-line - 21 - 23 de set de 2022
2177-2576 versão online

Vox populi, vox Dei? Impacts of Fintwit's Sentiments on Brazilian Interest Rate using Machine Learning Forecasting Models

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Resumo

Selic rate is the Brazilian government's central monetary policy, and its forecasting is vital for all financial markets. Currently, economic players' expectations over Brazilian interest rate are mainly based on the Central Bank's Focus bulletin. However, Brazil is the fifth country with more Twitter accounts worldwide, and our community has an active and engaged financial group (Fintwit). We aim to analyze Fintwit's forecasting capability through sentiment analysis of its publications related to Selic rate, using three different machine learning models: Linear Regression, Support Vector Machines (SVM) and Recurrent Neural Networks. We evaluated over 75,956 publications during four 2021 meetings of the Monetary Policy Committee, and observed behaviors of Brazilian Fintwit: (i) the community becomes more active during the meetings; (ii) publications are more favorable during the two days of the meetings; (iii) postings are less favorable in the days after the meetings; (iv) the community splits itself more in the day of the second meeting and the day after. Overall, the models provided better outcomes when increased by publication's sentiments. Remarkably, the SVM was the best model among the three techniques. Therefore, there is evidence that the Fintwit contains relevant information for the market players' expectations formation over Selic rate.

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Abstract

Selic rate is the Brazilian government's central monetary policy, and its forecasting is vital for all financial markets. Currently, economic players' expectations over Brazilian interest rate are mainly based on the Central Bank's Focus bulletin. However, Brazil is the fifth country with more Twitter accounts worldwide, and our community has an active and engaged financial group (Fintwit). We aim to analyze Fintwit's forecasting capability through sentiment analysis of its publications related to Selic rate, using three different machine learning models: Linear Regression, Support Vector Machines (SVM) and Recurrent Neural Networks. We evaluated over 75,956 publications during four 2021 meetings of the Monetary Policy Committee, and observed behaviors of Brazilian Fintwit: (i) the community becomes more active during the meetings; (ii) publications are more favorable during the two days of the meetings; (iii) postings are less favorable in the days after the meetings; (iv) the community splits itself more in the day of the second meeting and the day after. Overall, the models provided better outcomes when increased by publication's sentiments. Remarkably, the SVM was the best model among the three techniques. Therefore, there is evidence that the Fintwit contains relevant information for the market players' expectations formation over Selic rate.

Keywords: Twitter; Selic rate; sentiment analysis; forecasting models; machine learning.

1. Introduction

The Selic rate, the most powerful instrument for the Brazilian Central Bank's (BCB) monetary policies, influences several economics fields, such as the interest rates practiced in the market, inflation control, and the prices and returns of financial instruments (Montes & Machado, 2014; Oreiro et al., 2012). So, the necessity of forecasting and forming expectations over the future values of this interest rate is essential to the financial market agents (Araújo et al., 2018; Maestri & Malaquias, 2017).

The interest rate term structure (Duarte et al., 2015) and the Focus bulletin (Guillén & Garcia, 2014) can be highlighted among the sources and techniques used to form the Brazilian interest rate expectation. While the first one is applied for long term interest rate curves extrapolations, the second one, published weekly by the BCB, contains a summary of the daily projections from more than 100 Brazilian institutions over critical indexes of the Brazilian economy, such as an inflation index (IPCA), the exchange rate, the GDP growth, and the Selic rate goal.

Different from the Focus, which only a restricted group of specialists from the leading financial institutions are part of, the Fintwit (noun derived from the combination of "finance" and "Twitter") is a broad and active community composed of investors, investment fund managers, anonymous profiles who discuss stocks, finance, politics, and investments (Kim & Kim, 2014; Souza, 2020). Apart from Twitter, this community can also be found in other social media such as Reddit, Instagram, and Facebook (Al-Nasseri & Menla Ali, 2018).

Comments published on Twitter, a platform that contain more than six thousand posts per second[i], became object of study of those who seek to analyze subjects such as finance, politics, and sports, extracting from the social media reactions, sentiments, and opinions from the agents (Bollen et al., 2011; Caetano et al., 2018; Grijalva et al., 2020).

The development of techniques to analyze textual contents allied with modern machine learning techniques resulted in forecasting models that input the population's sentiment and reaction over many events. These models, applied to finance, sometimes have financial indexes (interest rates, for example) as outputs (Yasir et al., 2020). Others aim to analyze the correlation between a stock return and its comments on Twitter (Tabari et al., 2019).

Umar et al. (2021) analyze the increase of GameStop's stock price in Jan/2021 caused by a non-institutional investors movement that started on the social media influenced the price stocks of the company. The evidence points that the sentiment presented in the Twitter publications could positively have impacted the stock's returns. The authors also suggest that regulators should keep an eye on the Fintwit since it could create inefficiency in the market, as happened in the GameStop case. Thus, social media publications present themselves as a new source of information to be accounted for before the investor's decision.

Decision-making and expectations formation from the Brazilian economic agents about the Selic rate are currently based in part on the Focus bulletin, as the report contains a summary of the forecasts of important market players about the Brazilian economy indices, such as inflation and the basic interest rate (Meurer & Lima, 2019). Furthermore, Brazil is the fifth country with the most Twitter users[ii] worldwide and has a broad and active Fintwit community. Thus, there is a large availability of data to analyze the population's feelings and reactions about changes in the rate that can help economic agents' decision-making. Moreover, given the Selic rate importance for the maintenance of one of the macroeconomic policies conductions pillars, added to its considerable variation throughout 2020 and 2021 (impart due to the COVID pandemic and its consequences) result in a prolific environment for modeling the community expectations formation over the Brazilian rate.

Therefore, our objective is to analyze the predictive capability of the comment's sentiments from the financial environment published on Twitter about the Selic rate. To model this expectancy and to assess the forecasting capability of the Fintwit over the Selic rate, we collect comments related to the rate from Twitter's financial community, focusing it on publications made close to the Monetary Policy Committee (Copom) meetings during 2021 that determines the Brazilian free risk rate. The forecasting models and comparison will be made with three models: (i) Linear Regression (LR); (ii) Support Vector Machines, and; (iii) Recurrent Neural Networks. In order to evaluate the sentiment's inclusion effect, we estimate models with a few combinations: (i) considering as input the exchange rate and Ibovespa index (Brazilian stock market performance proxy), isolated and united, and; (ii) adding to the inputs the sentiment from Twitter comments to each one of the models. Thereby, we can measure the effects of publication sentiments information over the forecasting models.

2. Theoretical background and empirical literature

The international literature is prolific regarding models that forecast the future evolution of the interest rate. Among the methods presented in the literature, it can be highlighted those that make use of exponential functions as a functional form for the term structure of the interest rate as a function of time to maturity (Nelson & Siegel, 1987; Svensson, 1994). At Svensson (1994), the term structure has parameters that represent the level of the curve (or long term), the slope (or short term), the curvatures (or medium term) and parameters that determine the decay velocity of the medium-term components.

The term structure, used by insurers due to the regulatory requirement to perform the annual liability adequacy test (LAT), according to Circular Susep No. 517/2015, is used for the long-term prediction of discount rate behavior. The regulatory requirement, which obliges insurers to estimate the value of their discounted cash flow, led Franklin Jr. et al. (2012) to apply the curve proposed on Svensson (1994) for the Brazilian scenario. Given the LAT's regulatory requirement, the authors aim to contribute to companies in the Brazilian insurance market measure, by discounting their cash flows consistently, their obligations. Combining genetic algorithms and nonlinear optimization, they seek to find the best estimate for the Brazilian market curves parameters.

Brazilian economic agents' forecasting and expectations over the short-horizon Selic rate are based, in part, on the Focus report published by BCB. Additionally, the use of news and investor sentiment as a tool to aid decision-making is well explored in the literature (Da et al., 2011, 2015). The analysis of publications on social media has been used as a proxy for the population's feelings (Corea, 2016). Bukovina (2016) analyzes the state of art of social media big data use in capital markets fields. The author notes that posts made on Twitter have become the object of study to assess the impact and relationship between the emotional state of society and stock prices and the capital market.

In the literature, Twitter's feelings analysis is usually divided into three stages: (i) collection or mining; (ii) cleaning and formatting, and; (iii) analysis (Guo et al., 2016; Li, 2020). In the first stage, the texts to be analyzed are collected. In Twitter case, the platform has an API (application programming interface) that assists the extraction of comments made on social media. The second step is to format the captured text to be more easily processed, i.e., transform the text into vectors to exclude, for example, non-textual elements, such as links, unrecognized strings, and stop-words. Finally, the third step consists of textual analysis. At this stage, Guo et al. (2016) divide the textual analysis into two approaches: (i) Lexicon, and; (ii) Machine Learning (ML).

Lexicon's approach classifies the text according to the incidence of the word. Based on a previously defined dictionary, such as the Harvard General Inquirer (GI) word list, Loughran and McDonald's dictionary (Loughran & Mcdonald, 2016), and Henry Word List (Henry, 2008), in which words are separated by their semantics into positive and negative. The second approach uses machine learning techniques to classify and recognize textual patterns. In this approach, the database is usually separated into two groups: the first one training; and the second one for the unsupervised classification. In the literature of finance, *Naïve Bayes*, *Support Vector Machines* and *Neural Networks* are some Machine Learning techniques to be highlighted (Audrino et al., 2020; Holowczak et al., 2019; Rajakumar et al., 2019).

Holowczak et al. (2019) to predict the market response to changes in a company's auditor compared the following ML classifiers: (i) Ridge Classifier; (ii) k-Nearest Neighbor (kNN); (iii) Random Forest; (iv) Linear Support Vector Classifier (SVC) with L2 penalty, and; (v) Multinomial *Naïve Bayes* (MNB). The best accuracy index was obtained with the MNB classifier. Moreover, during the sensitivity test, the authors point out that, for the classifiers SVC, MNB, kNN, and Random Forest, changes in the tuning parameters do not show significant changes in their level of accuracy.

Through neural networks, Bollen et al. (2011) estimate Dow Jones Industrial Average (DJIA) future values. The authors aim to investigate whether measures of collective emotional state obtained by a broad database of publications made on Twitter are correlated with the DJIA index. Sentiments are measured in six dimensions (calm, alert, sure, vital, kind, and happy). Self-Organizing Fuzzy Neural Network (SOFNN) presents the best results for DJIA's future values estimate when added to the model a combination of the calm and happiness measurements. In addition, the authors verified that changes in feelings measurements coincided with variations in DJIA that occurred three to four days later.

Aligned with Bollen et al. (2011), McGurk et al. (2020) point to empirical evidence that the estimated indexes for the publication's sentiments are related to abnormal returns. They also observed that an increase in negative sentiment indexes is related to higher abnormal returns. Finally, the authors tested whether the inclusion of sentiment indices would improve the performance of forecast models. The conclusion was that using these sentiment's indexes improve the model's accuracy.

Social media publications have not been only the object of study in finance's academic research. Its use in political analysis papers can also be highlighted. Caetano et al. (2018) define, based on the sentiment analysis with Lexicon's approach to publications made during the 2016 U.S. elections, the political spectrum, and the level of homophily, a tendency to approach people with similar characteristics. The authors conclude that there is homophily in all scenarios analyzed and that the level of homophily increases when there are similar discourses and when connections on Twitter are reciprocal.

Also through Lexicon's approach, however, in the finance environment, Yasir et al. (2020) developed a DL model to estimate interest rates in the U.K., Turkey, China, Hong Kong, and Mexico. The model considers the exchange rate for the U.S. dollar and sentiments extracted from Twitter as input variables. Sentiment analysis was made about six global events, among them the 2012 U.S. elections and Brexit in 2016, and classified as positive, neutral, and negative with the help of the Henry Word List. To evaluate whether the inclusion of feelings improves the prediction, the authors compared the error presented in three different models (linear regression, SVM, and DL) of interest rate prediction. In conclusion, the deep learning model presented the best results and was more assertive when Twitter's feelings were considered.

Among the Brazilian publications of finance that concern the analysis of feelings of the Twitter community, Souza (2020) seeks to analyze the effect of investor sentiment on returns and volume traded in the Brazilian stock market. Sentiments are assigned via Google Cloud Natural Language API, which ranks the publication between -1, extremely pessimistic, and +1, extremely optimistic. Among the results presented, it is noteworthy that the more positive is the investor's sentiment, the higher is IBOVESPA's return. However, the author points out that the relationship is positive in a contemporary way, but when the gap of the past sentiment is larger, the lower the current return. For the author, the behavior is elucidated within the idea that good news about specific stocks drives increases in their returns. However, after the period of euphoria, prices tend to return to the initial level.

Finally, to broader the discussion, explore the sentiment analysis gap in the Brazilian financial literature, and following Souza (2020) and Yasir et al. (2020), we will use techniques for assigning sentiments to Twitter publications and the Selic rate forecasting capacity of the Linear Regression, SVM and RNN models. Also, we will evaluate and compare scenarios where the Fintwit publications sentiments are included among the inputs. The following section presents how the databases were obtained and the theoretical framework for the mathematical models.

3. Methodology and Database

This section will be covering the techniques that will enable the treatment of the central question of this work: to evaluate whether the inclusion of Fintwit feelings improves the Selic rate forecasting models. The section is divided into two parts: the first, in light of Souza (2020) work, we will address how the data were obtained and the publication sentiments attribution; the second, aligned with Sciacovelli (2020) and Yasir et al. (2020), we will present the mathematical models used for Selic rate forecasting.

3.1. Database and Sentiment Assignment

Both Selic rate historical series[iii] and the exchange rate historical series, it was used the PTAX rate[iv], were obtained from the website of the Brazilian Central Bank (BCB). The IBOV index closing value was obtained on *Yahoo!Finance*[v] website. The comments extraction from Twitter was made through the official platform's API and Python software, finally the publications were treated using the R software. The following filters were used in the search for publications: (i) publications in Portuguese; (ii) publications made in the interval of five days before, and three after the Copom meetings in Jun/2021, Aug/2021, Sep/2021 and Oct/2021 (totaling 44 calendar days), and; (iii) publications containing the terms: Selic, Copom and inflation.

Sentiment attribution will be performed by the Google Cloud Natural Language API, a natural language processor that classifies the text feeling between -1, extremely pessimistic, and +1, extremely optimistic. It is noteworthy that the tool distinguishes emotions, however, it does not specify it: i.e., feelings such as sadness and irritability are considered negative, while happiness, for example, is considered positive. In addition to the attribution of feeling, the tool also measures the overall emotion strength magnitude. The magnitude is not normalized and can have values between 0 and +∞. Each expression of emotion within the text contributes to its magnitude. In this paper we will consider the classification between -1 and 1 of the text sentiments.

3.2. Mathematical Models

3.2.1. Linear Regression (LR)

LR assumes that there is a linear relationship between two variables $(x_i, y_i)_{i\,=\,1,\dots,n}$ where the first one is the independent variable and the second one is dependent. Thus, one can describe such linear dependence by:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i, \tag{1}$$

with the usual assumptions for random errors. The most common form to estimate the parameters is by minimizing the sum of squared errors. If $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 \hat{x}_i$, then one can define the error as the difference between the observed value y_i and the calculated value $\hat{y}_i$. Thus, if $\varepsilon_i = y_i - \hat{y}_i$, then:

$$\sum_{i=1}^{n} {\varepsilon_i}^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} (y_i - \hat{\beta}_0 + \hat{\beta}_1 \hat{x}_i)^2 \tag{2}$$

The estimators of the parameters that minimize (2) are given by:

$$\begin{gathered} \hat{\beta}_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, \\ \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \end{gathered} \tag{3}$$

where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ e $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$.

3.2.2. Support Vector Machines (SVM)

Aligned with Sciacovelli (2020), Yasir et al. (2020) and Hastie et al. (2006), SVM can be seen as an adaptation of the Maximal Margin Classifier (MMC) classification tool. The objective of MMC is to find the hyperplane of maximum margin (or optimal separation), i.e., the one with the largest minimum distance for training observations. Once this step is accomplished, one can classify the observation depending on which side of the hyperplane it is on. Finally, the support vectors are defined as those that are closest to the separation hyperplane, influencing their position and orientation.

On the other way of the MMC, whose objective is to find the hyperplane that most departs the observations to classify them, the SVM seeks to find a function that approximates the sample data. For the SVM, the data pairs will be described $(x_i, y_i)_{i=1,\dots,n}$ and to map them in a larger space, a function $\phi : \mathbb{R}^n \rightarrow \mathbb{R}^N$ is taken, with $N > n$. So, being $\boldsymbol{w}$ the weight vector, the prediction function is:

$$f(x) = \boldsymbol{w}\phi(x) - b \tag{4}$$

Finally, a tolerance ϵ is taken, and is defined by ξ the distance between the margin defined by the tolerance ϵ to a point above the hyperplane, and by ξ^* the same distance to a point below the hyperplane. The variables ϵ and ξ are known as slack variables. Thus, to find the function that best suits the data one must solve the conditioned optimization problem defined in (6):

$$\min\left(\frac{1}{2}\|\boldsymbol{w}\|^2 + c\sum_{i=0}^{N}\left(\xi_i + \xi^*{}_i\right)\right) \tag{5}$$

$$subject\ to \begin{cases} y_i - \boldsymbol{w}\phi(x_i) - b \leq \epsilon + \xi_i \\ \boldsymbol{w}\phi(x_i) + b - y_i \leq \epsilon + \xi_i^*, \\ \xi_i, \xi_i^* \geq 0 \end{cases} \tag{6}$$

in which constant c acts as a regulator for simplicity and generalization of the model, since the constant penalizes the presence observations that are outside the margin defined by the tolerance ϵ.

To map the base in a non-linear manner, a Kernel function should be used. Using Lagrange multipliers, we have:

$$\begin{gathered} max\left(-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\alpha_i - \alpha_j^*\right)\left(\alpha_j - \alpha_i^*\right)K(x_i,x_j) - \epsilon\sum_{i=1}^{N}\left(\alpha_i + \alpha_j^*\right) + \sum_{i=1}^{N} y_i\left(\alpha_i - \alpha_j^*\right)\right) \\ subject\ to \begin{cases} \sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0 \\ \alpha_i, \alpha_i^* \in [0,c] \end{cases} \end{gathered} \tag{7}$$

in which α_i and α_i^* are the Lagrange multipliers and K, the Kernel function. Thus, the objective function is given by:

$$f(x) = \sum_{j=1}^{N}(\alpha_i - \alpha_i^*)K\left(x_i, x_j\right) + b \tag{8}$$

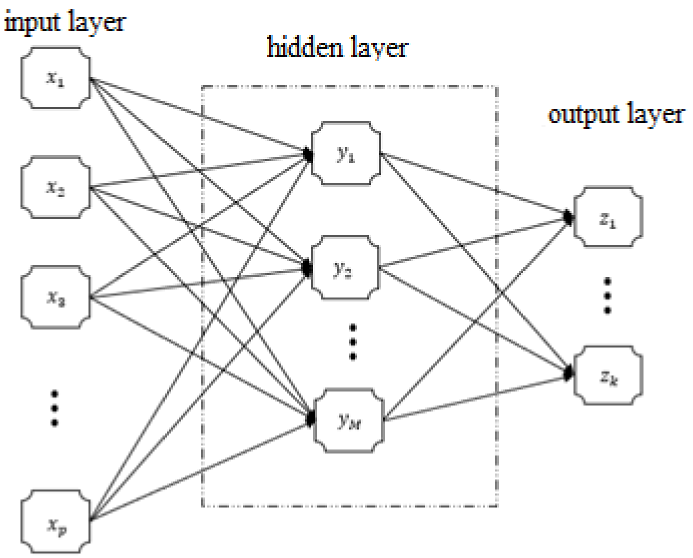
We will use the Gaussian radial kernel function which is described by:

$$K\left(x_i, x_j\right) = \exp\left(-\frac{\|x_i - x_j\|}{2\sigma^2}\right) \tag{9}$$

3.2.3. Deep Learning (DL)

Aligned with Aggarwal (2018), a neural network can be defined as a set of algorithms that, through processes that mimic the interactions between neurons, seek to find relationships between variables in a data set. Among the architectures normally employed, we can highlight the feed-forward neural network (FNN) and a variation of it: the recurrent neural network (RNN). FNN, also known as a multilayer neural network, presents an architecture that considers one or more hidden layers that rely on inputs obtained by a previous layer of neurons. Figure 1 shows the schematization of a neural network with hidden layers.

Figure 1 - Schematization of an FNN.



Source: own elaboration.

In Figure 1, $x = (x_1, .., x_p)^T$ represents the input variables, $z = (z_{z1}, .., z_k)^T$ the output ones and $y = (y_1, .., y_M)^T$ the unobservable ones that compose the hidden layer. Weights are assigned by $\alpha_j = (\alpha_{j1}, .., \alpha_{jp})^T$, $j = 1, \dots, M$ and $\beta_k = (\beta_{k1}, .., \beta_{kM})^T$. Thus, the neural network schematized in Figure 1 is described by Equations (10) and (11):

$$Y_j = h(\alpha_{0j} + \alpha_j^T X), \qquad j = 1, \dots, M, \tag{10}$$

$$Z_j = g(\beta_{0k} + \beta_k^T Y), \qquad k = 1, \dots, K. \tag{11}$$

where the functions $h(\cdot)$ e $g(\cdot)$ are the activation functions. The most commonly used activation functions are: (i) logistic function; (ii) hyperbolic tangent function; (iii) ReLU (rectified linear unit) function, and; (IV) Leaky ReLU function.

When using the activation functions are obtained in place of Equations (10) and (11) the following expression that is equivalent to the output of the neural network:

$$f(x, w) = \varphi\left(\sum_{j=0}^{M-1} \omega_j \phi_j(x)\right) \tag{12}$$

where $\phi_j, j = 0, \dots, M-1$ are functions dependent on the assigned activation function, $\varphi(\cdot)$, which in the case of regression (K = 1) is the identity function. In the end, ω_j is the weight vector.

After defining the neural network output by Equation 12, in the feedforward process the following activation is usually considered:

$$a_k = \sum_{i=0}^{p} \omega_{ji}^{(1)} x_i, \; j = 1, \dots, M \tag{13}$$

which includes the bias $\omega_{j0}^{(1)}$ over the weight vectors $w_j^{(1)} = \left(\omega_{j0}^{(1)}, \omega_{j1}^{(1)}, \dots, \omega_{jp}^{(1)}\right)^T$, with $x_0 = 1$. The index (i) in the exponent of the weight vector indicates the i-th neural network layer.

After that, each activation a_j is transformed through the function $h(\cdot)$ activation initially chosen, obtaining:

$$y_j = h(a_j) \tag{14}$$

The activation of the output is considered:

$$a_k = \sum_{j=0}^{M} \omega_{kj}^{(2)} y_j,\ k = 1, \ldots, K \tag{15}$$

which again includes the bias $\omega_{j0}^{(2)}$ over the weights vector w.

The activations described in Equation (15) undergo a transformation by a second activation function, usually logistics, resulting in the outputs Z_k from the neural network:

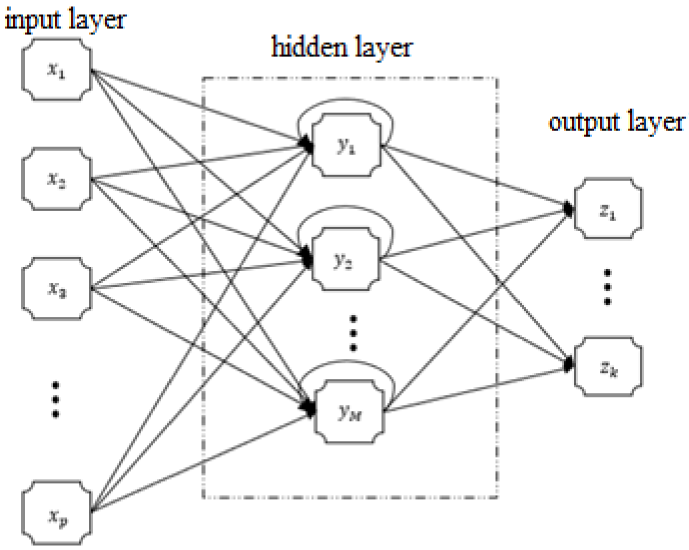
$$Z_k = g(a_k). \tag{16}$$

In the case of regression problems $Z_k = a_k$. Finally, by combining equations (12), (15) and (16) one would obtain:

$$f_k(x, w) = g\left(\sum_{j=0}^{M} \omega_{kj}^{(2)}\, h\left(\sum_{i=0}^{p} \omega_{ji}^{(1)} x_i\right)\right). \tag{17}$$

RNN differs from FNN since it presents the possibility of neuron connections forming cycles, to consider as input not only the variables initially presented, but also what they have experienced over time. Thus, RNN also incorporate a self-regressive memory, which results in the understanding that there is information in the sequence in which the data is presented to the model. Figure 2 shows the schematization of a recurrent neural network.

Figure 2 - Schematization of an RNN.



Source: own elaboration.

4. Results

4.1. Descriptive Statistics and Preliminary Analysis

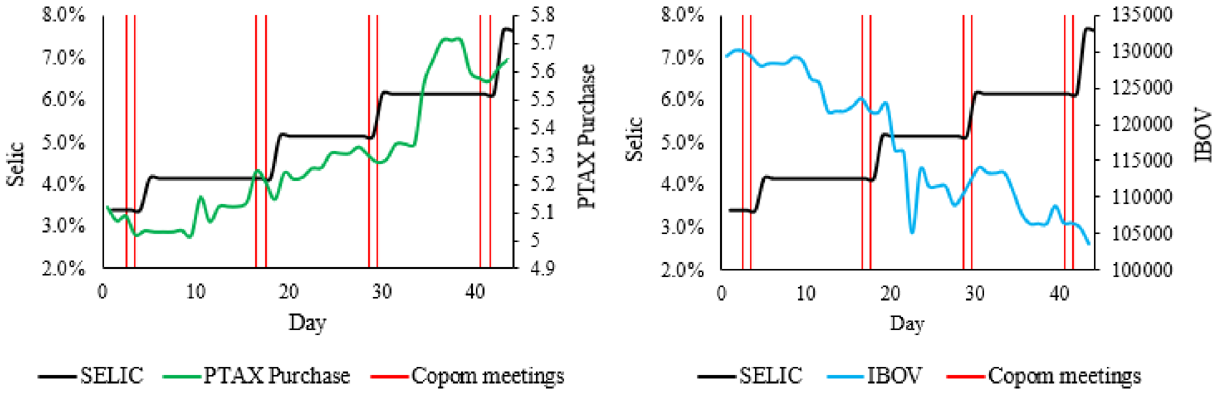
In light of Sciacovelli (2020) and Yasir et al. (2020) works, in which the authors seek to measure and evaluate the impact of the inclusion of Twitter sentiments in interest rate forecasting models, having as an input variable the exchange rate for the U.S. dollar, our study seeks to measure the same impact for the Brazilian picture.

Apart from the exchange rate for the U.S. dollar (PTAX Purchase) as an entry variable, the Ibovespa index (IBOV) will be tested as a control variable as well. IBOV is an index of the Brazilian stock market that expresses the average performance of a hypothetical portfolio with the main stocks traded on the market. It is a proxy for the feelings of economic agents about the financial performance of the largest companies in Brazil.

It is necessary, before analyzing the performance of the model, to evaluate the input variables that will be considered, they are: (i) PTAX Purchase; (ii) IBOV, and; (iii) Average daily sentiment of Twitter posts, as well as the output variable, the Selic rate. The feelings of the Twitter publications will be further analyzed in section 4.2, while the others will be evaluated in this section.

In Figure 3, we show the evolution of the variables over the 44 days observed. For continuity purposes, the exchange rate and IBOV's values on weekends were considered equal to those observed on the preceding Friday.

Figure 3 – Selic, PTAX Purchase and IBOV evolution.



Source: own elaboration.

From the Figure 3, we see that the scenario of free Brazilian risk-free interest rate presents an increase, as does the exchange rate; it is also perceived that IBOV comes in the opposite direction.

Once presented, we must evaluate the stationarity hypothesis of the time series through the Augmented Dickey-Fuller (ADF) test. For all cases, we used the variables in log-returns. Table 1 contains the test results.

Table 1 – ADF's test result

Variable	p-value
Selic	0.01
PTAX Purchase	0.01
IBOV	0.01

Source: own elaboration.

With the results, we can reject all the null hypotheses that there is a unit root. It is concluded, then, that time series are all stationary.

4.2. Analysis of Twitter Posts

Before presenting the results of the publications analyses, it is necessary to present how the filtering and cleaning of this data was done. As pointed out in section 3, the capture of the publications was made based on three terms: (i) Selic; (ii) Copom, and; (iii) inflation, in the interval of five days before and three after each one of the four Copom meetings in 2021 considered. It needs to be highlighted that the June meeting, called in Brazilian as the “super

Wednesday", counted, in addition to the meeting of the Brazilian committee, with the meeting of the Federal Reserve, in which the U.S. interest rate were defined. Additionally, it was necessary to remove duplicate posts and clear the contents of publications, i.e., removal of special characters such as emojis (small images used to express an idea), duplicate spacings and links.

Table 2 provides five examples of publications and the level of sentiment attributed to them by the API.

Table 2 – Publications and the sentiment level assigned examples

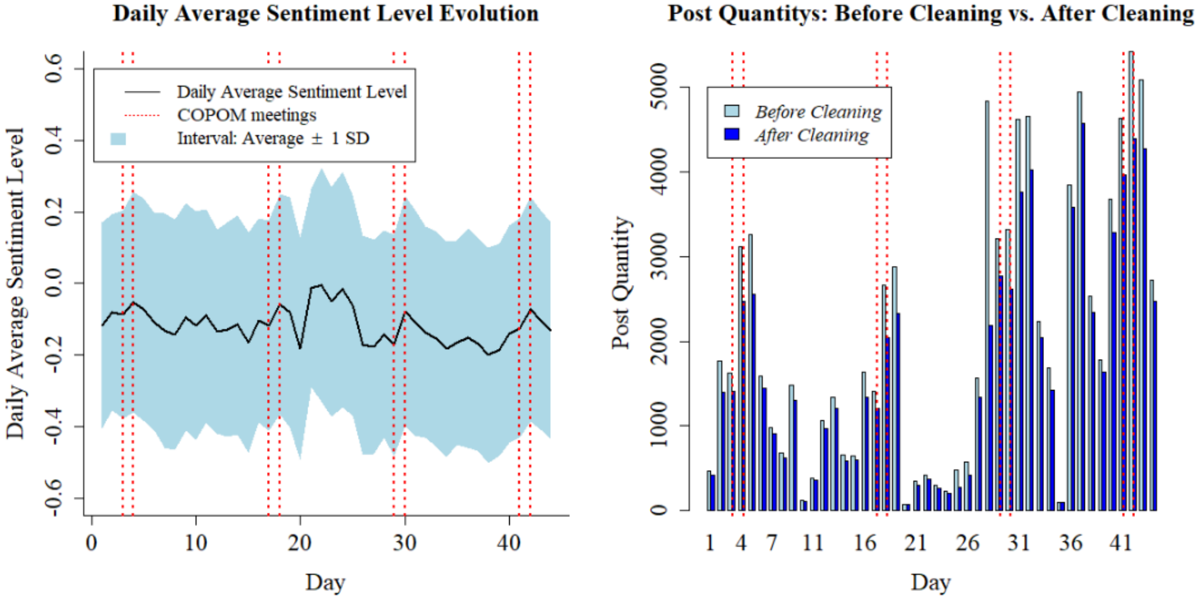
Publication	Assigned Sentiment
The management considers this as an "extremely negative reaction to the #SELIC increase, since the large part of the fund quote holders had only saw rate level decreases"	-0.7
Don't agree with the Copom. It had a good diagnosis, but it made a mistake on the medicine prescription. And it could be worst.	-0.5
Already expected by the market this result confirms the committee tendency on balance the interest rates to fight the inflation.	0
Selic under the 4.25% forecasted for the year. Now we're just missing the exchange rate under R$5.00.	0.5
Along with the Selic increase comes happiness	0.9

Note: the API's evaluation was made in Portuguese. Here we presented only some examples. Source: own elaboration.

Table 2 shows the API's ability to assign coherent levels to publications as in the detection of positive satisfaction with the increase in Selic rate (two last lines), as well as in the capture of negative comments (first two publications).

Figure 4 shows the evolution of the average daily sentiment (with an interval of 1 standard deviation) and the evolution of the number of publications captured and the final amount after filtering and cleaning.

Figure 4 – Daily Average Sentiment and Posting Amounts Evolution.



Source: own elaboration.

The left panel of Figure 4 shows three general common trends that were somewhat repeated in the framework of the four meetings observed: (i) the publications' sentiment becomes more negative in the following of the meetings; (ii) the feeling is more positive during meetings, and; (iii) the standard deviation of the average sentiment level is higher in the day of the second meeting and the day after. The second meeting is where the decision about the Selic rate is disclosed. On average, publications are slightly negative, and the standard deviation is 0.3. These data will be presented and further explored in more detail in Table 3.

The right-hand side panel in Figure 4 points out that the number of posts increases during the meetings, consequently increasing the number of filtered publications. A total of 91,084 publications were captured, 15,128 publications were filtered out, leaving a sample of 75,956 publications to be evaluated by the API.

Table 3 – Daily Average Sentiment Descriptive Statistics

Meeting	Date	Daily Average	Δ %	Standard Deviation	Δ %
July	14/Jun/2021	-0.08047	-	0.27461	-
	15/Jun/2021*	-0.08722	8%	0.29096	6%
	16/Jun/2021*	-0.05218	-40%	0.30722	6%
	17/Jun/2021	-0.07312	40%	0.31132	1%
	18/Jun/2021	-0.10867	49%	0.30398	-2%
August	02/Aug/2021	-0.10381	-	0.28583	-
	03/Aug/2021*	-0.11787	14%	0.29407	3%
	04/Aug/2021*	-0.05914	-50%	0.30788	5%
	05/Aug/2021	-0.08115	37%	0.32252	5%
	06/Aug/2021	-0.18261	125%	0.31010	-4%
September	20/Sep/2021	-0.14176	-	0.28925	-
	21/Sep/2021*	-0.17227	22%	0.31053	7%
	22/Sep/2021*	-0.07783	-55%	0.32072	3%
	23/Sep/2021	-0.10945	41%	0.31500	-2%
	24/Sep/2021	-0.13602	24%	0.29530	-6%
October	25/Oct/2021	-0.14146	-	0.30397	-
	26/Oct/2021*	-0.12495	-12%	0.30714	1%
	27/Oct/2021*	-0.07171	-43%	0.31365	2%
	28/Oct/2021	-0.10210	42%	0.30720	-2%
	29/Oct/2021	-0.13258	30%	0.30297	-1%

Note: Copom meeting dates are highlighted by an asterisk. Source: own elaboration.

The three trends mentioned before are even more evident when observing Table 3. It can be noted that, in general, when compared to the previous day of the meetings, the sentiment level on the date of the meetings becomes more positive and turns more negative in the two days that follow it. The most abrupt variation resulted in a more negative sentiment occurred from the August meeting, from the first day after the meeting to the subsequent, the daily sentiment level average turned 125% more negative. The most abrupt variation that results in a more positive feeling occurred between the first and second meeting of September, in which the sentiment level was 55% more positive.

Additionally, the third trend indicated above is also observed: the sentiment level standard deviation is higher on the day of the second meeting and the next day. When observing the meeting of Aug/2021, for example, it is noted that from the first meeting to the second there is an increase of 5% in the standard deviation, and from the second meeting to the next day there is another increase of 5%. The increase in the standard deviation indicates greater divergence in the Fintwit opinions.

Finally, four general trends can be extracted from this section: (i) Fintwit becomes, naturally, more active during Copom meetings when looking to the terms: Selic, Copom, and inflation; (ii) publications become more positive during the two-day meeting; (iii) posts become more negative in the days following the meetings, and; (iv) Fintwit is generally more divided on the day of the second meeting and the day after it.

4.3 Sentiment level inclusion impact on the models

Sciacovelli (2020) and Yasir et al. (2020) results point to models' improvement when added, among the input variables, the sentiment level captured from Twitter publications. Thus, in this section we evaluate the impact of the inclusion of twitter sentiments in three models: (i) Linear Regression; (ii) Support Vector Machines; and (iii) Recurrent Neural Network (RNN). Six combinations of input variables will be evaluated for each model: (i) PTAX Purchase; (ii) IBOV; (iii) PTAX Purchase + IBOV; (iv) PTAX Purchase+ Sentiments; (v) IBOV + Sentiments Level; (vi) PTAX Purchase + IBOV + Sentiments Level.

To compare the models, we will use two error measures widely used in the literature: (i) root mean square error (RSME), and; (ii) mean absolute error (MAE) described by Equations 18 and 19, respectively.

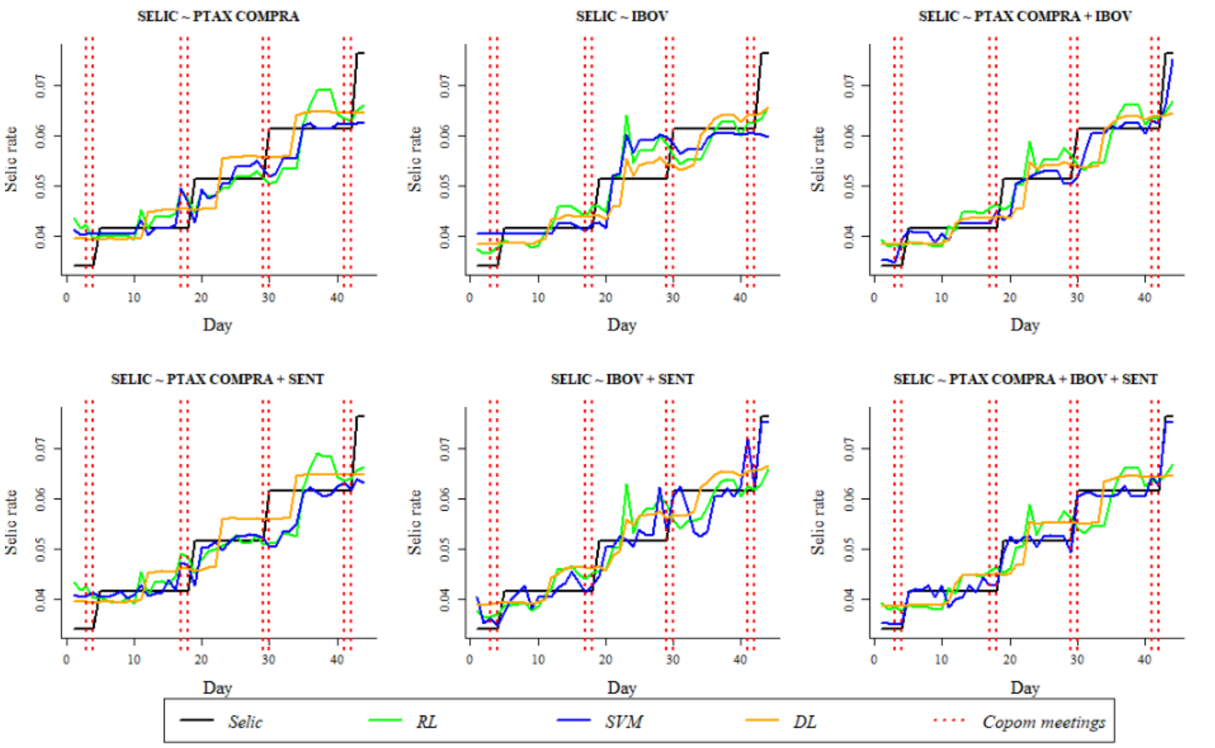
$$RSME = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \tag{18}$$

$$MAE = \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{n} \tag{19}$$

where, y_i is the observed value and $\hat{y}_i$ is the model predicted value.

Figure 5 shows the comparison of the 44 actual values of the Selic rate with the predicted values of each of the models, for each of the six combinations of input.

Figure 5 – Selic rate and forecasting models' daily evolution



Source: own elaboration.

Figure 5 shows that the inclusion of sentiment levels tends to improve the models. The effect of their inclusion can be clearly seen in the interval between the first and second meeting, when comparing the model that counts only with the PTAX and the one that use the exchange rate and with the sentiment level of the publications as inputs. The models seem to perform better in the scenario that relies on feelings than in the scenario where it does not. In particular, the SVM appears to have its best performance when considering all three as input to the model.

Table 4 provides the error measurements for each model and combination of input variables. Table 5 shows the percentage variations of error measures when comparing the models, with and without the inclusion of Twitter's sentiments.

Table 4 – Models' errors

	RMSE			MAE		
Models	**LR**	**SVM**	**RNN**	**LR**	**SVM**	**RNN**
Selic ~ PTAX Purchase	0.00557	0.00500	0.00481	0.00440	0.00346	0.00391
Selic ~ IBOV	0.00514	0.00568	0.00466	0.00415	0.00402	0.00389
Selic ~ PTAX Purchase + IBOV	0.00482	0.00315	0.00470	0.00418	0.00204	0.00386
Selic ~ PTAX Purchase + SENT	0.00553	0.00502	0.00480	0.00435	0.00327	0.00438
Selic ~ IBOV + SENT	0.00509	0.00378	0.00454	0.00414	0.00254	0.00416
Selic ~ PTAX Purchase + IBOV + SENT	0.00482	0.00132	0.00463	0.00418	0.00115	0.00412

Source: own elaboration.

Table 5 – Percentage change in the inclusion of sentiments

	RMSE			MAE		
Models' Inputs	**LR**	**SVM**	**RNN**	**LR**	**SVM**	**RNN**
PTAX *vs.* PTAX + SENT	-0.72%	0.40%	-0.21%	-1.14%	-5.49%	12.02%
IBOV *vs.* IBOV + SENT	-0.97%	-33.45%	-2.58%	-0.24%	-36.82%	6.94%
PTAX + IBOV *vs.* PTAX + IBOV + SENT	0.00%	-58.10%	-1.49%	0.00%	-43.63%	6.74%

Source: own elaboration.

Table 5 shows increments that are understood as worsening the errors measures and reductions, indicated as negative percentage variations, improvements. It is observed that the inclusion of feelings improves, in general, the measures of error. The results presented are in line with the works of Sciacovelli (2020) and Yasir et al. (2020).

The model that presented the smallest error measures was the SVM, especially when all three input variables were considered simultaneously. In this scenario, there was a significant reduction of 58.10% in RMSE and 43.63% in MAE. In addition to this improvement, it is observed that the SVM presented better performance when the sentiment level was added to the IBOV as input variables. The reduction in RMSE was 33.45% and the mean absolute error presented an attenuation of 36.82%.

When evaluating the RMSE, the sentiment inclusion improved expressively the errors measures errors in all scenarios. The only exceptions were in RL when considered PTAX + IBOV, in which there was no significant change in the error; and in the SVM when considered only PTAX, in which there was an increase of 0.40% in RMSE. By looking at the MAE, the SVM improved performance in all scenarios. On the other hand, RL did not improve only when PTAX + IBOV was considered, and RNN worsened its performance in all scenarios.

The worsening of RNN models performance, under the MAE measure, also occurred in Yasir et al. (2020) when the Turkish interest rate is analyzed. Considering the sentiments of Publications related to Brexit, MAE increase was of 125%, going from 0.406 to 0.914. A similar effect was observed in the Chinese interest rate when was added to the model to the sentiments related to welcoming refugees, MAE went from 0.102 without the sentiment level to 0.185 with it, an increase of 81%.

SVM model improvement was also observed in Sciacovelli (2020). When analyzing the models for the British interest rate, the author points to an improvement of 75% and 70% for the RMSE and the MAE respectively when added in the model the feelings of publications related to the Irish elections. In addition, the worsening of the MAE was also observed for the neural networks model when it was added to the model for the UK interest rate sentiments related to the Irish elections.

Unlike the results brought by Sciacovelli (2020) and Yasir et al. (2020), in which neural network models performed best, the model that best performed for Brazil was the SVM. However, it is necessary to consider that the sample size may be determinant. Yasir et al. (2020) has between 200 and 500 days observed, depending on the country analyzed; Sciacovelli (2020) analyzed information from 2013 to 2019. Our study, despite having used 75,956 publications, was distributed in only 44 days. Ajiboye et al. (2015) state that neural networks estimated with smaller database usually have higher levels of error than those obtained with larger database. Our results obtained by SVM are consistent, since not only do they have the lowest values of projection error metrics as they are the faster ones to respond to abrupt variations from interest rate level changes.

5. Final Remarks

The definition of the Selic rate is fundamental for the Brazilian economy, as well as the formation of its expectations. In light of the works of Sciacovelli (2020) and Yasir et al. (2020), our work aimed to analyze the impact of the Twitter financial community publications sentiment level inclusion over three different predictive models: (i) Linear Regression; (ii) Support Vector Machines; and (iii) Neural Networks. Different combinations of input variables were considered in the models:(i) PTAX Purchase; (ii) IBOV; (iii) PTAX Purchase + IBOV; (iv) PTAX Purchase + Sentiment Level; (v) IBOV + Sentiment Level; (vi) PTAX Purchase + IBOV + Sentiment Level.

From the analysis of the Fintwit publication sentiments, we could identify four patterns of the community behaviors in the periods of Copom meetings that decided on the Brazilian interest rate: (i) Fintwit becomes, as expected, more active during Copom meetings when the terms: *Selic*, *Copom*, and; *inflation*; (ii) publications become more positive during the two-day meeting; (iii) posts become more negative in the days following the meetings, and; (iv) Fintwit is generally more divided on the day of the second meeting and the day after it.

The models' outputs are close to the results observed in Sciacovelli (2020) and Yasir et al. (2020). After all, the sentiment level observed in twitter posts inclusion improves the measures of error. SVM presented the best fit, and lowest values for root mean square error and the mean absolute error, besides the most substantial improvements when the publication sentiments were added. When the publications sentiments were inserted in the model that used the PTAX Purchase and the IBOV as input variables, there was a RMSE significant reduction of 58.10% and of 43.63% in the MAE. Moreover, the SVM also improved when the sentiment levels were added to IBOV as inputs. The reduction in RSME was 33.45% and the MAE reduction was 36.82%.

However, unlike the two previous studies, the best model for the Brazilian interest rate was the SVM instead of the neural networks. One possible explanation for the neural networks low performance lies in the size of the base analyzed in our work. Here, although we used 75,956 publications, they are distributed in only 44 days, constituting the main limitation of the work. After all, as argued by Ajiboye et al. (2015), neural networks estimated from the smaller database tend to present higher errors.

Finally, we highlight the four Fintwit behaviors that could be abstracted from the publication sentiment level analysis and the model's performance improvement, particularly the SVM when, among the input variables, used with the sentiment levels of Twitter publications.

It is pointed out, then, to evidence that Fintwit's feelings contain relevant information to be considered for models, decisions, and formations of expectations about the Brazilian risk-free rate. Future studies are suggested to use other predictive models (e.g., time series analysis) and other social media (e.g., Facebook, LinkedIn).

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