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Predictive power of the sentiment of the Monetary Policy Council

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Abstract

This study explores the predictive power of the sentiment captured in the minutes of the Monetary Policy Council (MPC) meetings regarding the setting of the reference interest rate in Poland. It assesses its usefulness in forecasting the returns on financial markets. The sentiment is computed with the VADER analysis tool. The release of the MPC meeting minutes impacts stock and Treasury bond markets but appears to have negligible effect on the foreign exchange market. Adding the sentiment as a feature enhances the forecast accuracy of daily stock index returns and bond yield changes generated by the LSTM machine learning models.

Keywords: sentiment analysis, natural language processing, forecasting, machine learning, LSTM

JEL: C53, G17

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1. Introduction

Sentiment analysis is the computational study of people's opinions, moods, attitudes, and emotions expressed in recorded language that found application in various disciplines, including finance. The processing tools evolved from simple lexicons, with words assigned an integer value corresponding to their tone, namely -1 if negative, 0 if neutral, and 1 when positive, to advanced machine learning models using deep learning techniques. They are trained on large sets of human-labelled text data to recognise context and relationships among words, texts and language structures to compute a sentiment score for the examined textual information (Hilscher, Nabors, Raviv 2024).

The aim of the study is to verify the predictive power of the sentiment expressed in the minutes of the Monetary Policy Council (MPC) meetings when deciding on the reference rate of Narodowy Bank Polski (NBP). We check whether the release of these minutes, which occurs within one to three weeks after the MPC meetings, impacts financial markets. By this time, the interest rate decision itself is already absorbed by market participants. However, markets may still be affected by the release of the minutes, as they capture the MPC's outlook on the Polish economy.

The sentiment score is quantified with the VADER tool available in Python's Natural Language Toolkit (NLTK). We verify whether adding the sentiment score as a model feature improves the predictions of financial markets indicators. Specifically, we consider the daily returns on the WIG20 stock index, daily yield changes of Polish 10-year Treasury bonds and daily changes of the EUR/PLN exchange rate. Forecasting is done using the machine learning long short-term memory (LSTM) technique. We have chosen the LSTM as studies show that it tends to outperform other approaches in forecasting related to stock, bond and currency markets (Shao 2023; Kostyra 2024; Suimon et al. 2020; Lee, Chang, Hwang 2019).

This study contributes to existing literature of textual analysis and financial forecasting. It explores the impact of central bank's textual communication style and tone on financial markets. These relationships present an opportunity to increase trader's returns leading to improved market efficiency. It fills the gap with respect to the application of sentiment analysis in the Polish financial markets as few studies have been published, particularly in the forecasting context.

This article is organised as follows. In the second section, we review the literature on the sentiment analysis and its application in finance. The third section sets out the research question and the primary hypothesis. The fourth section outlines the natural language processing and forecasting methodologies. The fifth section describes the data. The sixth section provides the sentiment analysis and forecasting results. The seventh section concludes on the applicability of the results in financial forecasting.

2. Literature review

The literature on the sentiment analysis and its application in finance is rapidly growing. Here, we present a snapshot of studies focused on financial forecasting, including Polish markets.

He et al. (2024) verified the application of sentiment scores from stock news releases in the Apple stock forecasting with the LSTM technique. They used VADER and FinBERT sentiment tools for language processing. The study confirms that sentiment score could be a good predictor of stock prices, with FinBERT delivering slightly better results compared to VADER's.

Hilscher, Nabors and Raviv (2024), using the FinBERT library, analysed FOMC minutes and ECB press conferences and concluded that Fed and ECB sentiments moved together. They also found that central banks' sentiment could be used to predict policy interest rates and the Taylor rule.

Homsirikamol, Tangjitprom and Sethjinda (2021) analysed the sentiment expressed in the meeting minutes of the Bank of Thailand's Monetary Policy Committee derived through the VADER tool. They concluded the sentiment was consistent with the occurrence of key economic events both for expansion (positive sentiment) and slowdown (negative sentiment). Through the application of vector-autoregression, they also confirmed that the sentiment score served as a good predictor of long-term government bond yields. However, this was not confirmed for short-term bond yields and the SET stock index.

Chong et al. (2022) constructed simple sentiment indices based on finance lexicons that count the number of positive and negative words or use the sentiment score assigned to words to calculate the average sentiment. Their study found that news sentiment calculated with these indices had a reliable predictive ability for private investment growth in Malaysia for short forecast horizons.

Cajner et al. (2024) verified the accuracy of various sentiment measurement methods (ranging from dictionary-based to modern deep learning methods) and their usefulness in forecasting US industrial production. The authors found that deep learning techniques such as FinBERT outperformed other methods in sentiment classification. They confirmed that the sentiment score derived from survey responses provided by manufacturing firms served as a good predictor of industrial production in the US.

Lee, Chang and Hwang (2019) compared various auto-regressive and machine learning techniques in predicting the USD/AUD exchange rates and analysed the impact of news sentiment quantified with the SnowNLP. They found that the LSTM model performed best with historic exchange rates and sentiment scores as features. It slightly outperformed the LSTM without the sentiment. Other models without sentiment (ARIMA, SARIMA, SLP) performed far worse compared to both LSTM models.

Marszal (2022) used the VADER library to quantify the financial market sentiment expressed in news headlines sourced from Refinitiv. The sentiment scores were consistent with major global events, such as the outbreak of the COVID-19 pandemic, the development of the COVID vaccine, monetary and fiscal stimulus packages, and the US presidential election. The author verified the relationships between the news sentiment and financial market prices and identified moderate correlations between sentiment scores and the DXY index, the EUR/USD exchange rate, and gold.

Polak (2021) investigated the impact of news sentiment on the banking stock index at the Warsaw Stock Exchange. Sentiment was derived using the Polish Sentiment Dictionary. Using machine learning classifiers such as various decision tree-based methods, SVC, KNN, Naive Bayes, he concluded that news sentiment had no predictive power for the direction of the stock index changes.

Wojarnik (2022) examined the impact of news sentiment on the energy companies listed at the Warsaw Stock Exchange. Sentiment was derived with the MS Azure Sentiment Analysis API service. Using the machine learning DNNClassifier of the TensorFlow library, he concluded that news sentiment did not improve the forecasts of stock returns for energy companies.

Overall, studies tend to confirm the predictive power of sentiment when used in financial forecasting as an explanatory variable. However, specifically for Poland, it was shown that the financial news sentiment did not improve the predictions of stock price changes.

3. Research question and primary hypothesis

The question we attempt to answer is whether the sentiment expressed in the minutes from the meetings at which the MPC decides on the NBP interest rates is useful in financial markets forecasting. The primary hypothesis is that the inclusion of the sentiment score as a feature in the model forecasting daily returns on financial markets increases the accuracy of the predictions. The reason behind this hypothesis is that the released minutes provide insight into the decision process of the Council, which takes a prospective view of the Polish economy when setting the level of interest rates. Therefore, the sentiment of the MPC meetings minutes could indicate the evolution of market prices. This is consistent with the Efficient Markets Hypothesis (Fama 1965a), according to which markets should react to the arrival of new information.

4. Methodology

4.1. Processing of natural language

The Valence Aware Dictionary and sEntiment Reasoner (VADER) was originally developed by Hutto and Gilbert (2014) to measure sentiments expressed in social media, however, it proved to be a very popular and effective tool used to analyse the sentiment of financial information as evidenced in the literature. It is a lexicon and rule-based sentiment analysis tool, which was developed in following stages:

Lexicon construction. The VADER lexicon was created by aggregating a large number of sentiment-rated words from existing sentiment word-banks, and by manually adding words and phrases commonly used in social media.

Human evaluation. Words and phrases were rated on a scale from -4 (extremely negative) to +4 (extremely positive), with 0 as a neutral rating, by human raters. This allowed for sentiment grading as opposed to trinary classification, i.e. 1 (positive), 0 (neutral) and -1 (negative). The lexicon was further refined through a series of validations.

Heuristic rules. VADER incorporates heuristic rules to manage grammatical and syntactical nuances. These rules reflect the impact of punctuation (exclamation points), capitalization ('GREAT' vs. 'great'), intensifiers ('extremely good' vs. 'good'), contrastive conjunction (shifting the meaning by using words such as 'but' or 'yet'), and negations ('not good').

Compound score calculation. For the examined piece of text, VADER computes a compound normalised score, with values between -1 (most negative) and +1 (most positive).

The VADER tool is available in Python's Natural Language Toolkit, which was created by Bird, Loper and Klein (2001), and covers symbolic and statistical natural language processing.

4.2. Forecasting

Random walk (RW) was first applied to capture stock dynamics by Bachelier (1900). It was further developed and formalised by Pearson (1905), who coined the term random walk. Its application in finance was popularized by Fama (1965b) and Malkiel (1973). The method serves as the benchmark, and its naive interpretation supposes that 'nothing changes' over the forecasting horizon. The dynamics of a random variable (x_t) are assumed to be:

$$x_t = x_{t-1} + \varepsilon_t \tag{1}$$

where $E(\varepsilon_t) = 0$.

Long Short-Term Memory (LSTM) is a machine learning technique proposed by Hochreiter and Schmidhuber (1997). We follow the specification as presented by Sak, Senior and Beaufays (2014). The LSTM is a type of recurrent neural network technique, which feeds the network activations from a previous time step as inputs to the network to influence predictions at the current time step. These activations are stored in the internal states of the network, which can hold long-term temporal information. The LSTM has units called memory blocks in the recurrent hidden layer. The memory blocks contain memory cells with self-connections storing the temporal state of the network in addition to special multiplicative units called gates to control the flow of information. Each memory block contains an input gate, output gate and a forget gate. The input gate controls the flow of input activations into the memory cell. The output gate controls the output flow of cell activations into the rest of the network. The forget gate scales the internal state of the cell before adding it as input to the cell through the self-recurrent connection of the cell, therefore adaptively forgetting information.

The LSTM model maps an input $x = (x_1, ..., x_{T-P})$ to an output $y = (y_{1+P}, ..., y_T)$ by computing the network unit activations. It uses the following equations iteratively from $t = 1$ to T:

$$i_t = \sigma\left(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i\right) \tag{2}$$

$$f_t = \sigma\left(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f\right) \tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g\left(W_{cx}x_t + W_{cm}m_{t-1} + b_c\right) \tag{4}$$

$$o_t = \sigma\left(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o\right) \tag{5}$$

$$m_t = o_t \odot h(c_t), \quad y_t = \phi\left(W_{ym}m_t + b_y\right) \tag{6}$$

where:

x_t – input vector to LSTM unit,
y_t – output vector of LSTM unit,
i_t – input/update gate's activation vector,
f_t – forget gate's activation vector,
o_t – output gate's activation vector,
b_i – input gate's bias vector,
c_t – cell input activation vector,
m_t – cell output activation vector,
$\odot$ – Hadamard product (element-wise product),
σ – sigmoid function,

g – cell input activation function (hyperbolic tangent),
h – cell output activation functions (hyperbolic tangent),
ϕ – network output activation (softmax),
W – weight matrices.

5. Data and pre-processing

5.1. Timeframe

We chose the 2022–2024 period as the intention is to focus on more recent data. This period is marked by a rapid post-pandemic rebound of the GDP growth in Poland that occurred in 2022 and first half of 2023, and its slowdown in the second half of 2023. In 2024, GDP growth experienced modest acceleration. The beginning of the analysed period was also characterised by rising inflation, which settled into double-digit territory between August 2022 and August 2023, peaking in March. It was slowly declining over the remaining period, yet it persisted above the NBP inflation target. Since NBP is responsible for the value of the Polish currency, the MPC reacted to changing GDP growth and inflation rates by adjusting the level of interest rates. The selection of this timeframe also allows our forecasting models to be trained on data which include a series of increases, decreases and no changes of the reference interest rate.

5.2. Minutes of the Monetary Policy Council meetings

While the minutes of the Monetary Policy Council meetings are only one of the means of the central bank communication on the monetary policy (*Monetary Policy Guidelines*, *Reports on Monetary Policy*, *Inflation Reports*, MPC press releases on interest rate decision meetings) they possess all the following key attributes that make them especially useful in measuring the impact of the central bank's sentiment on the markets:

Monthly frequency. The MPC meetings' minutes and press releases occur monthly except for August, when the Council does not meet. *Inflation Reports* are produced three times a year. *Monetary Policy Guidelines* and *Reports on Monetary Policy* are published annually. Since the intention is to observe the impact on financial markets, a higher frequency is preferable.

Diversity of views. The MPC minutes reflect the discussion on economic conditions in Poland and the vote on proposed changes to the reference interest rates. They capture a variety of opinions, not just synthesised consensus, which is presented in the press releases. As a result, the sentiment of the minutes is representative of the whole Council.

Interest rate decisions. The MPC minutes and press releases convey information on interest rate decisions. The NBP interest rate is the key instrument of the monetary policy that has a direct and tangible impact on the banking system and the economy. Since the minutes are published one to three weeks after the meetings, the actual decisions on interest rates are already absorbed by the markets. This enables us to disaggregate the market impact of the interest rate changes from the sentiment changes. The MPC press releases are published on the same day the MPC decision meetings end.

On the other hand, *Reports on Monetary Policy* summarise interest rate decisions taken within a year, while *Monetary Policy Guidelines* define the NBP interest rates.

Document format. The MPC minutes, press releases and *Monetary Policy Guidelines* are pure textual information in a compact form, which makes them easily accessible. *Inflation Reports* and *Reports on Monetary Policy* rely heavily on graphs and tables. This non-textual information does not feed to the sentiment score. They are also long form documents that require more analysis by market participants.

Overall, for this particular exercise, only the MPC minutes and press releases appear to be the most relevant. As explained above, the minutes are preferable. We collected their English language versions from the NBP website. The text of the minutes is tokenised and lemmatised using the NLTK library.

5.3. Financial data

We gathered daily financial market indicators from Investing.com, specifically: WIG20 prices, yields on Polish Treasury 10-year bonds, and EUR/PLN exchange rates from the period 2022–2024. Figure 1 presents the time series of daily changes in these indicators calculated with the formula below:

$$x_t = \ln\left(\frac{MI_t}{MI_{t-1}}\right) \tag{7}$$

where MI – market indicator, i.e. stock index price, Treasury bond yield, foreign exchange rate.

Figure 1
Daily changes of financial market indicators

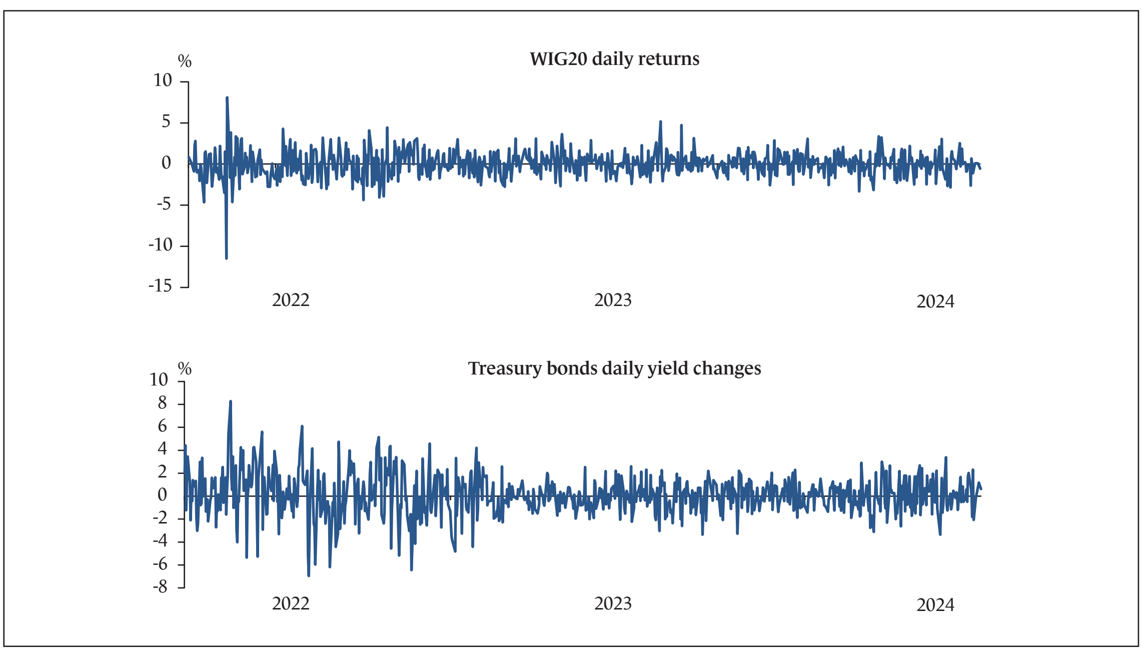
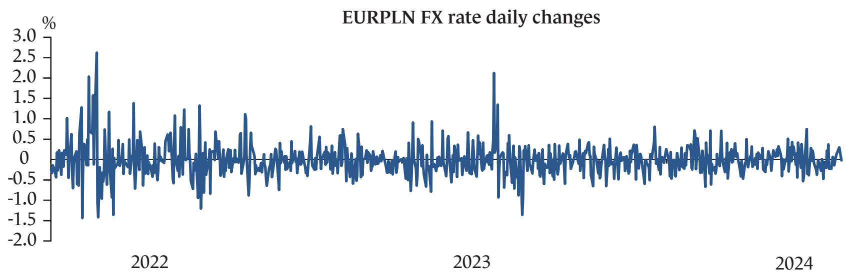


Figure 1, cont'd



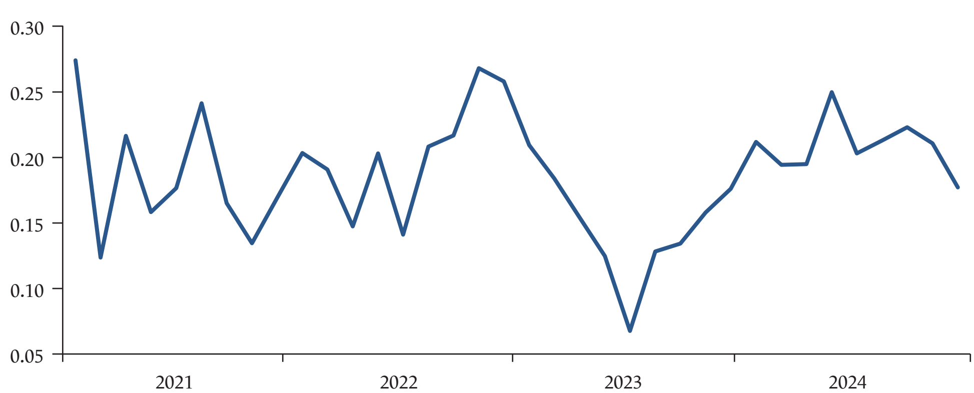
Source: own calculations.

6. Results

6.1. Sentiment against the economic backdrop in Poland

In Figure 2, we plot the sentiment scores of the MPC meeting minutes obtained via the VADER tool. The sentiment in the examined period remains positive, with an average and standard deviation of 0.19 and 0.04 respectively. Below, we explain the global and local extrema of the sentiment score time series by reviewing the respective minutes.

Figure 2
Sentiment score derived from the minutes of the Monetary Policy Council meetings



Source: own calculations.

The highest sentiment (0.27) occurred in December 2021 (minutes released in January 2022) due to the post-pandemic recovery, with GDP growth exceeding expectations. Through 2022 and the first quarter of 2023, the sentiment oscillated around 0.18. It peaked again in April 2023, almost reaching 0.27 due to decreased inflationary pressures and low unemployment. In the following months, it kept declining, hitting its lowest point of 0.07 in October 2023. This was likely caused by the sharp drop of economic growth in Germany, the decrease in bank lending and persistently high inflation. It was also a period of elevated uncertainty due to national parliamentary elections just days away, with topics like VAT rate changes on energy and food dominating the public debate. The sentiment began to slowly recover thereafter due to the improving economy with low unemployment and declining inflation.

6.2. Sentiment as a predictor of the market behaviour

We build two sets of forecasting LSTM models for each market (stock, bond, foreign exchange), six models in total. In the first set (LSTM1NoSent), an input vector contains just a single explanatory variable, namely a one-day lagged output variable for each market. In the second (LSTM2wSent), there are two variables. Apart from the lagged output variable, we also include the sentiment score. Daily time series of following variables are used as model inputs for each market respectively: WIG20 returns, changes in 10-year Polish Treasury bonds yields, and changes in EUR/PLN exchange rates. We construct a daily time series of sentiment scores, such that the sentiment score is updated when the MPC minutes are released, and the score remains unchanged until the release of the next minutes.

The period January 2022 – June 2024 is used to train the LSTM models and period July 2024 – December 2024 to backtest the results. Forecasts are produced daily for the next day (1-step ahead). The model is using a 2.5-year sliding window approach for training. Each day, new daily data are added to the training set while the oldest data are removed.

Table 1

RMSFE of predictions generated with LSTM models

Model	WIG20	PL Treasury	EUR/PLN
		Benchmark: random walk	
RW	1.89885	2.10053	0.39057
LSTM1NoSent	49.8%***	59.9%***	53.9%***
LSTM2wSent	48.7%***	59.1%***	54.1%***
		Benchmark: LSTM1NoSent	
LSTM1NoSent	0.94472	1.25791	0.21049
LSTM2wSent	97.9%***	98.7%***	101.5%*

Notes: RMSFE of daily returns on the WIG20 index, daily yield change on 10-year Polish government bonds, daily changes in EUR/PLN exchange rate. RMSFE for forecasting models are expressed as the percentage of the benchmark. The Diebold--Mariano test verifies forecast accuracy against the benchmark with null hypothesis that the forecast accuracy of models is the same as the benchmark's.

Asterisks ***, ** and * denote the rejection of the null at 1%, 5% and 10% significance level, respectively.

Source: own calculations.

Table 1 presents the root mean squared forecast errors (RMSFEs). They are complemented with the outcomes of Diebold and Mariano (1995) test to verify the accuracy of these forecasts against the forecasts generated by the benchmark model. We scale the RMSFE of each forecasting model with the benchmark's RMSFE.

All LSTM models consistently beat the RW as their RMSFEs are lower. These results are statistically significant, as confirmed by the outcome of the Diebold-Mariano test. The addition of sentiment as a model feature leads to different outcomes in prediction accuracy depending on the market. Forecasts of stock index returns and bond yield changes become more accurate, RMSFE drops by 2.1% and 1.3% respectively, and these improvements are statistically significant. However, for the foreign exchange market, there is a slight deterioration in the forecast accuracy. The RMSFE increases by 1.5%, but this difference is statistically insignificant.

7. Discussion and conclusions

This study investigates the impact of the sentiment of the Monetary Policy Council on financial markets in Poland. The MPC meets to discuss the state of the Polish economy and set nominal interest rates. The MPC minutes present the points raised by various members of the Council, articulate their reasoning, and point to the data that support their opinions on the economic situation in Poland and developing trends. Therefore, sentiment scores are expected to convey information about the MPC's outlook on the economy. The release of the MPC meeting minutes can be regarded as the arrival of new information to which financial markets should react according to the Efficient Market Hypothesis (Fama 1965a). This impact could be exploited in forecasting the changes in market indicators.

The sentiment score of the MPC meeting minutes proves to be useful in financial forecasting with the LSTM machine learning model. Its inclusion as a model feature improves the accuracy of the daily forecasts of index stock returns (WIG20) and yield changes on long-term (10-year) Polish Treasury bonds, confirming the hypothesis for equity and debt markets. The magnitude of prediction improvement is higher for the stock market. Exchange rate (EUR/PLN) predictions are somewhat worse once the sentiment is included, yet differences are statistically insignificant. Therefore, we reject the hypothesis for the currency market. This result might be attributed to the much higher liquidity of the currency market compared to Polish stock and bond markets. We can conclude that capital and debt markets are impacted by the sentiment expressed in the MPC discussion. This outcome also supports the argument that communication style matters and could be used as a tool to facilitate monetary policy goals.

The general caveat needs to be noted that our conclusions are based on relationships identified in the specific timeframe. These relationships can change over time, hence the experiment outcomes may no longer hold. The sentiment could also shift, when the composition of the MPC changes, all other things being equal, in particular, with the appointment of a new NBP Governor, who runs the meetings, sets the overall tone and has a deciding vote. Another caveat relates to the choice we made regarding the language version. Since the MPC discussion is in Polish, the English language version of the minutes may express somewhat different sentiment compared to the Polish language version as some nuances may be lost. However, this was motivated by the choice of the sentiment tool, which was built for the English language as well as by the significant share of foreign investors in the markets' turnover.[1] These investors are likely to use the English versions of the minutes.

The outcomes of this study can be helpful for money managers in financial markets analysis and predictions as well as stress scenario formulation.

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[1] The share of the foreign investors on the Warsaw Stock Exchange reached 70% at the end of 2024 (https://www.gpw.pl/analizy). Foreign investors also hold 13% of the Polish Treasury bonds (https://www.gov.pl/web/finanse/struktura-inwestorow) at the end of 2024.

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Moc predykcyjna sentymentu Rady Polityki Pieniężnej

Streszczenie

Rozwój metod procesowania języka pozwala na kwantyfikację sentymentu zawartego w komunikatach. Powstało wiele bibliotek językowych umożliwiających przetworzenie tekstu pisanego i uzyskanie zestandaryzowanej wartości sentymentu w przedziale od -1 do 1, gdzie -1 oznacza maksymalnie negatywny sentyment, 0 neutralny, a 1 maksymalnie pozytywny. W finansach często badany jest sentyment informacji udostępnianych w serwisach finansowych, jak również komunikatów banku centralnego. Wyniki tych analiz mogą zostać wykorzystane do prognozowania cen akcji, stóp procentowych, kursów walutowych itd.

Celem artykułu jest zbadanie mocy predykcyjnej sentymentu Rady Polityki Pieniężnej (RPP) w prognozowaniu finansowym. Stawiamy pytanie, czy sentyment zawarty w protokołach z posiedzeń RPP dotyczących ustalania poziomu stóp procentowych Narodowego Banku Polskiego (NBP), jest użyteczny w prognozowaniu na rynkach finansowych.

W artykule weryfikujemy następującą hipotezę: uwzględnienie zmiennej sentymentu z posiedzeń Rady Polityki Pieniężnej w modelu predykcyjnym poprawia dokładność generowanych prognoz dziennych zmian wskaźników rynków finansowych.

Za pomocą biblioteki VADER dokonujemy pomiaru sentymentu protokołów z posiedzeń Rady Polityki Pieniężnej w angielskiej wersji językowej, opublikowanych w latach 2022–2024, i konstruujemy szereg czasowy. Następnie prognozujemy dzienne zwroty z indeksu giełdowego WIG20, zmiany stóp dochodowości polskich obligacji skarbowych i zmiany kursu walutowego EUR/PLN. Prognozy są dokonane w dwóch wariantach. W pierwszym prognozujemy dzienne zmiany wskaźników (zwroty z indeksu akcyjnego, zmiany stóp dochodowości oraz kursu walutowego) tylko na podstawie ich historycznej wartości. W wariancie drugim dodajemy sentyment jako zmienną objaśniającą. Modele predykcyjne oparto na technikach długo- i krótkookresowej pamięci (LSTM) oraz błądzenia losowego, który służy jako benchmark.

Przeprowadzone badanie potwierdziło postawioną hipotezę w stosunku do dwóch z trzech rozważanych rynków finansowych. Sentyment protokołów z posiedzeń Rady Polityki Pieniężnej użyty jako zmienna objaśniająca w modelu prognostycznym prowadzi do poprawy dokładności prognoz dziennych zwrotów z indeksu giełdowego WIG20 oraz zmian stóp dochodowości polskich długookresowych obligacji skarbowych. Nie poprawia natomiast trafności prognoz zmian kursu walutowego EUR/PLN.

Analiza sentymentu dostarcza wartościowych informacji, które pozwalają lepiej zrozumieć badane zjawiska oraz pomagają w ich prognozowaniu. Sentyment protokołów z posiedzeń Rady Polityki Pieniężnej jest użyteczną zmienną, która może wspomóc podejmowanie decyzji o zakupie lub sprzedaży akcji oraz obligacji, a także formułowanie scenariuszy testów warunków skrajnych.

Zidentyfikowane zależności mogą się zmieniać z upływem czasu, a zatem przedstawione wyniki mogą nie mieć zastosowania w przyszłości, zwłaszcza w przypadku zmiany Prezesa NBP lub składu Rady. Kolejnym ograniczeniem jest wykorzystanie protokołów w angielskiej wersji językowej, mimo że dyskusja na posiedzeniach odbywa się w języku polskim.

Słowa kluczowe: analiza sentymentu, przetwarzanie języka naturalnego, prognozowanie, uczenie maszynowe, LSTM