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Sentiment Analysis as an Innovation in Inflation Forecasting in Romania

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Abstract: Romania faced the highest inflation rate in the European Union at the beginning of 2024, but progress has been made compared to that in 2023 due to the increasing interest rate. This inflation stemmed from a combination of global and domestic factors (global factors such as the Russia-Ukraine war, supply chain disruptions caused by the COVID-19 pandemic and war, rising commodity prices, domestic factors such as wage and pension increases, tax and charge hikes, and a strategy of gradual increase in the monetary policy interest rate). The National Bank of Romania (NBR) uses a combination of monetary policy instruments to target inflation and provides quarterly forecasts. However, under uncertain conditions, numerical forecasts are less reliable, and the inclusion of sentiment analysis in forecasts might lead to innovation in the field by improving the prediction accuracy. Sentiment analysis has become increasingly important in the field of economics, offering valuable insights and potentially improving economic forecasting and decision-making due to rapid technological progress. Sentiment analysis can identify potential changes in consumer behaviour and business decisions before they are translated into actual economic data, providing an early warning system for economic trends and potential crises. The methodological background relies on natural language processing to extract sentiment indices for large amounts of texts in Inflation Reports provided by NBR. Moreover, the sentiment indices calculated by IntelliDocker are incorporated into autoregressive distributed lag (ARDL) models to provide quarterly inflation forecasts. This type of econometric model has the advantage of addressing endogeneity. Moreover, the unemployment rate is considered an inflation predictor since tensions in the labour market might impact inflation. This paper contributes to empirical forecasting by proposing sentiment forecasts that are more accurate than NBR numerical forecasts corresponding to the 2006: Q1-2023: Q4 horizon. The new forecasting method might be used to make inflation predictions for the next quarters. More accurate forecasts would be valuable for businesses, the central bank, policymakers, and the general public. However, while sentiment analysis offers valuable insights, it is important to remember that human judgment and expertise remain essential for interpreting the data and making informed economic decisions.

Keywords: inflation; forecasts; sentiment index; natural language processing.

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1. Introduction. At the beginning of 2024, Romania recorded the highest annual inflation rate in the European Union, at 7.3% in January (Eurostat, 2024). This was significantly higher than the EU average of 3.1%. In February 2024, Romania's central bank, the National Bank of Romania (NBR), lowered its inflation expectations for the end of the year. They now predict inflation to be 4.7%, which is lower than their earlier forecast of 4.8%. The BNR also anticipates that inflation will decrease further to 3.5% by approximately 2025 (NBR, 2024). In this context, the necessity of providing the most accurate inflation forecasts for Romania to control inflation and reach the convergence criteria for joining the euro area should be a priority for policymakers and experts in forecasting.

Inflation forecasting presents interest for both individual businesses and for the economy as a whole. First, businesses can use inflation forecasts to anticipate changes in the market and plan their operations accordingly. This might involve adjusting prices, budgeting for expenses, or strategically negotiating contracts. By understanding expected inflation, businesses can make informed decisions that protect their profits. Accurate inflation forecasts can help businesses manage risks associated with rising prices. They can plan for higher input costs or adjust their pricing models to account for inflation. This proactive approach can minimize financial strain during inflationary periods. Second, central banks rely on inflation forecasts to set monetary policy, which aims to achieve stable economic growth and prices. Knowing the projected inflation rate allows them to adjust interest rates and other tools to keep inflation under control and within a target range. This helps maintain a healthy overall economic environment. Third, inflation forecasts also influence market expectations. By gauging what economists and central banks predict, businesses and consumers can make choices based on that future outlook. This can impact things such as investment decisions, wage negotiations, and household spending.

The goal of obtaining the most accurate predictions should take into account the national and international context. In times of political, social or economic crises, forecasts are significantly affected by uncertainty, and numerical forecasts based on quantitative methods might be unreliable. In this framework, the narratives that accompany the numerical predictions might provide important information on future inflation. However, these narratives should be expressed in a numerical form to allow us to make quantitative forecasts. The transition from text to numerical values is made through sentiment analysis, which is based on natural language processing. The sentiment indices that characterize the NBR opinions on future inflation are computed using official inflation reports. These indices are considered inputs in inflation rate forecasting methods. The use of sentiment analysis in making prognoses for quarterly inflation in Romania is justified by the uncertainty that characterizes the current international and internal framework. The identification of the best method for forecasting inflation in the next quarters should be based on the performance of historical predictions. The actual high inflation in Romania is explained by global and domestic factors. The main global determinants of current inflation in Romania are supply chain disruptions and energy crises. The pandemic caused blockages in global supply chains, making it more difficult and expensive to transport goods. This affected the availability and price of many products in Romania, contributing to inflation. Moreover, the war in Ukraine and other geopolitical tensions have led to a significant increase in global energy prices, affecting the cost of oil, natural gas, and electricity. Romania relies on energy imports, so the price increase has contributed to domestic inflation. Domestic factors refer to increased demand and monetary and fiscal policies. After the initial lockdowns, Romania experienced a strong recovery in consumer spending and investment. This increase in demand, combined with supply chain issues, led to price increases. Measures taken during the pandemic to stimulate the economy, such as increasing the money supply, have unintentionally contributed to inflationary pressures. Some government policies, such as recent VAT increases on certain goods and services, directly contribute to inflation. NBR experts' opinions on these issues might provide valuable information that could improve numerical forecasts of inflation. Therefore, the main objective of this paper is to propose better inflation forecasts compared to the numerical forecasts published by NBR. This objective is reached by considering the benefits of sentiment analysis in forecasting. As an important novelty for the scientific literature in empirical forecasting, this paper proposes a new method to build inflation sentiment forecasts in Romania on the 2006:Q1-2023:Q4 horizon that includes a sentiment index. The forecast accuracy evaluation allows us to identify the best forecasting method that will be used for future predictions of the inflation rate in Romania to improve the decision process at the microeconomic and macroeconomic levels.

Most of the previous papers on empirical inflation forecasts use econometric models such as dynamic stochastic general equilibrium (DSGE) models, autoregressive integrated moving average (ARIMA) models, and different extents of vector autoregressive (VAR) models (Petropoulos et al., 2022). However, these studies neglect the importance of sentiment analysis, which could provide important insights into the future evolution of inflation. Moreover, it is necessary to address the endogeneity issue in the econometric models that are applied. Given these gaps in the literature, this paper introduces as a novelty the combination of advantages of ARDL models that reduce endogeneity and sentiment indices that suggest in a quantitative form the opinion of NBR experts on the future evolution of inflation. Moreover, the sentiment indices are computed using natural language processing by taking advantage of recent artificial intelligence developments. In this context, the research question is related to the capacity of ARDL models, including the sentiment index, to provide more accurate forecasts than models that do not incorporate the results of sentiment analysis.

This paper asks this research question through a gradual path of scientific construction, which also reflects the structure of the paper. After this introduction, the article makes a deep presentation of the literature review following two directions of research: the concept of sentiment in various fields of research and sentiment analysis in forecasting. This paper continues with a description of the methodology and data as a preamble for the empirical findings, discussion and conclusion.

2. Literature Review. Computational exploration of the scholarly literature in the Web of Science revealed the existence of 1,111 scientific documents that included phrase sentiment analysis (sentiment* anal*) in their title and were correlated with topic forecasting (forecast*) (Figure 1).

The bibliometric visualization created using VOSviewer illustrates the intricate relationships and significance of various research themes in the field of sentiment analysis for forecasting, according to the Web of Science database.

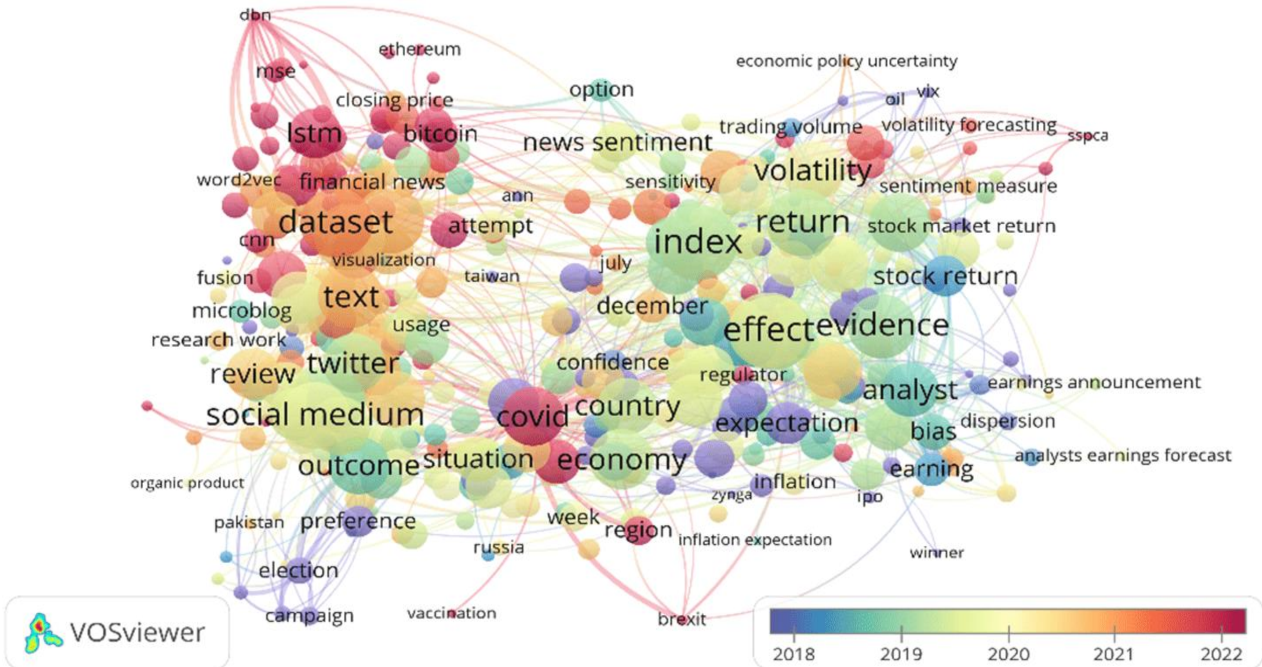

Figure 1. Mapping the intersection of sentiment analysis and forecasting in scholarly literature retrieved from the WoS database
Sources: developed by the authors based on VOSViewer v.1.6.15 software.

A thorough examination of the visualization highlights an interdisciplinary research area bridging finance, computer science, and data analysis. Central concepts such as "COVID," "economy," "volatility," and "stock return" emerge as focal points, indicating a concentration on economic indicators and the reaction of markets, particularly in relation to social media platforms such as Twitter. During the preparation of this work the author(s) used ChatGTP4 in order to comment Figure 1. The key observations include the following:

- Temporal Markers (examples: "COVID," "July," "December"): These markers reflect a research dynamic that is in sync with events influencing market volatility, notably the COVID-19 pandemic.
- Focus on Financial Markets (examples: "stock return," "volatility," "index"): A considerable part of the research targets the analysis of financial markets, with a special focus on stock prices, returns, and market indices. The terms "volatility" and "volatility forecasting" suggest the use of sentiment analysis to forecast market movements.
- Sentiment Analysis Methodologies (examples: "LSTM," "CNN," "word2vec"): The presence of such terms indicates the adoption of sophisticated machine learning technologies in sentiment analysis.

- Cryptocurrencies (examples: "Bitcoin," "Ethereum"): The mentions of Bitcoin and Ethereum show an exploration of how public sentiment affects volatile cryptocurrency markets.
- Data Sources (examples: "Twitter," "Social Medium," and "Financial News"): The prominence of these sources indicates a reliance on social media and financial news platforms as primary data inputs for sentiment analysis.
- Gradient Bar and Timeline (bottom right): This feature maps the chronological development of the field from 2018 to 2022, with colour gradations marking the individual years, revealing the field's evolution and the emerging trends and interests.
- Network Interconnections: The connecting lines between terms represent their co-occurrence within the same body of literature, suggesting thematic links and collaborative efforts across different disciplines.

In sum, visualization emphasizes the integration of sentiment analysis into economic forecasting, harnessing real-time data from a multitude of digital platforms to anticipate and interpret market dynamics. This integration further highlights the growing importance of nontraditional data sources and sophisticated analytical methods in economic research.

2.1. Literature review that explains the usefulness of sentiment analysis in forecasts

2.1.1. Definition of sentiment

From a historical perspective, in regard to econometric modelling, one can appeal to sentiment use either as a parameter or as a variable, all under the umbrella of sentometrics, as a novel research area with substantial potential for future development in forecasting (Simionescu, 2022; Algaba et al., 2020).

The academic literature on ′sentiment′, ′tonality′ or ′tone′ (Eugster & Uhl, 2024; Sharpe et al., 2023; Bajo & Raimondo, 2017), depending on the field in which they are used, underlines a predominant feature of the concept that is also relevant for the economic context. In this respect, “sentiment” is defined as an attitude that one entity (e.g., individuals, media outlets, corporations, governmental bodies, sectors, and market environments) holds towards another, manifested through various communicative forms, that can be quantified and expressed qualitatively via textual, auditory, and visual channels (Algaba et al., 2020). In regard to other domains, such as linguistics, Taboada (2016) refers to sentiment as a positive or negative subjective point of view, while in social sciences, it is regarded as a mood that describes the status associated with a specific spatial and temporal context (Evans & Aceves, 2016).

From a psychological perspective, sentiment is viewed as a manifestation of an individual's beliefs and desires (Munezero et al., 2014). Van de Kauter et al. (2015) differentiate between explicit sentiment, which conveys subjective private states, and implicit sentiment, which conveys factual information. Shapiro et al. (2018) described emotions using two dimensions: valence (the degree of positivity) and arousal (the level of intensity). Scholars indicate that in terms of accounting, finance and politics, sentiment serves as a synonym for tone and measures uncertainty, positivity or negativity, which characterize the news associated with a specific topic (Bajo & Raimondo, 2017; Grimmer & Stewart, 2013). Feldman et al. (2010) define tone as the optimism or pessimism conveyed in qualitative verbal disclosures, and Henry (2008) characterizes tone in earnings press releases as the impact of communication. In constructing a news-based coincident index of business cycles, Thorsrud (2018) employs tone as a synonym for sentiment, identifying it by assessing whether news articles are positive or negative.

Additionally, according to Algaba et al. (2020), sentiment data have the potential to aid in solving or understanding various problems that utilize econometrics across multiple disciplines, including economics, finance, accounting, marketing, psychology, and computer science. The impact of sentiment data on decision-making at both the macroeconomic and microeconomic levels is analysed by economists, and according to Angeletos et al. (2018), market expectations are directly impacted by sentiments that act as external shocks. Within this background, Angeletos & La'O (2013) linked market results with expectations via sentiments, and sentiment indices derived from text analysis were employed to gauge expectations or to assess various shocks in an economy (Algaba et al., 2020). Needless to say, sentiment analysis is considered a milestone in behavioural economics, and it is usually linked to sentiments felt by the investor (Kearney & Liu, 2014) and consumer confidence (Ludvigson, 2004). Because macroeconomic forecasts are directly connected with sentiments, Casey & Owen (2013) highlight that future economic trends are anticipated by consumer expectations, while global market returns can be predicted by a sentiment index associated with media information (Kräussl & Mirgorodskaya, 2017).

2.1.2. Sentiment analysis in forecasts

For a long time, economists have been exploring the influence of sentiment on economic decision-making. Understanding how sentiment data relate to decision-making, both at the micro and macro levels, remains crucial in economic theory (Algaba et al., 2020). In this context, sentiment analysis in forecasts is believed to be more accurate than the use of traditional models (Eugster & Uhl, 2024). Sentiment analysis employs mathematical techniques and textual data to assess whether a given text has a positive or negative tone (Zhang et al., 2018; Hussein, 2018). Additionally, the text can be analysed differently by determining its positivity or negativity and identifying the text's mood. This application of natural language processing enables the automation of various tasks and enhances the speed of data analysis (Lukauskas et al., 2022).

This study highlights the usefulness of sentiment analysis in forecasts, with sentiment being an inherent variable that cannot be quantified directly (Simionescu, 2022). There are three known methods for measuring sentiment, as indicated in the scientific literature: indices derived from qualitative assessments, survey questionnaires, and official reports such as Thomson Reuters MarketPsych Indices (Algaba et al., 2020). If these indices computed using text are compared with survey-based indices, they seem to offer a range of advantages, such as greater flexibility, the ability to perform backtesting, fewer chances of release delays, and the use of simpler methods for constructing the sentiment index (Simionescu, 2022).

The sentiment variables are also incorporated into regression models to enhance the forecasting accuracy. Studies indicate that forecasts improve when sentiments from media data are included, which affects trading volumes and stock returns (Tetlock, 2007; Jegadeesh & Wu, 2013; Kearney & Liu, 2014). Ardia et al. (2019) refined economic growth forecasts for the US by integrating sentiment values using sparse regressions. Additionally, Ardia et al. (2021) developed an R package called 'sentometrics' for calculating sentiment scores and making predictions based on aggregate sentiment, including predicting the CBOE Volatility Index. In addition, this specialized software is not error-free and may capture irrelevant details from the text. Despite technological advances, human analysis of sentiment indices often results in fewer errors. As digital text availability grows, converting qualitative data into indices has become commonplace in economics, enhancing fields such as macroeconomic forecasting and trading based on specific algorithms (Shapiro et al., 2020).

Considering macroeconomic analyses, textual narratives often follow forecasts for key indicators such as inflation, output, and unemployment, providing more insights. Clements & Reade (2020) underline the value of narratives in capturing critical information not available in numerical data, enhancing forecast accuracy, signalling future economic trends absent in quantitative forecasts, and offering insights into forecast uncertainty. Such narratives assist policymakers in adjusting their strategies (Castle et al., 2017). Moreover, narratives are frequently analysed to understand the effects of national bank communications on inflation expectations, monetary policy, and the real economy (Clements & Reade, 2020). For instance, Hansen & McMahon (2016) examined how Federal Open Market Committee (FOMC) communications influence expectations of monetary policy and economic growth. Romer & Romer (2008) utilized FOMC narratives to explore connections between GreenBook and FOMC prognoses in relation to monetary policy. Stekler & Symington (2016) assessed qualitative forecasts by analysing FOMC meeting minutes for insights into the Great Recession. They innovated by scoring qualitative statements to create an index and using text analysis to extract key information from qualitative forecasts. Despite anticipating the recession, the FOMC did not anticipate it early. These prognoses were compared to those from the SPF and Greenbook. Ericsson (2016) later used these indices, refining them with historical data to develop new indices.

Our paper diverges from previous studies such as those of Clements & Reade (2020) and Jones et al. (2020) by examining whether sentiment indices can be integrated with quantitative prognoses to enhance accuracy. Moreover, Shapiro et al. (2020) highlighted the predictive strength of sentiment forecasts. Unlike prior research focusing on the Bank of England's inflation forecasts, we utilize inflation prognoses starting from quarterly reports from the National Bank of Romania (NBR). Our analysis uses text to compute sentiment indices, which, as Di Fatta et al. (2015) suggest, should be carefully adapted to the specific context, emphasizing the use of adverbs and adjectives. Recognizing the limitations of automatic sentiment analysis, which often neglects the depth of context, we manually calculate sentiment indices. This manual approach aims to better predict future inflation trends and identify key factors influencing inflation.

Other papers have typically used automated methods to compute these sentiment indices, employing language tools such as dictionary methodologies for topic modelling. In addition, Clements & Reade (2020) applied this dictionary direction, focusing on in/decrements, a method we adopted in our study. Other research has constructed sentiment indices using newspaper texts—for instance, Garcia (2013) utilized NYT articles for financial analyses; on the other hand, Baker et al. (2016) analysed ten newspapers to create an index indicating economic policy uncertainty, and Fraiberger (2016) used Reuters articles to predict stock market returns and risks. Additionally, Nyman et al. (2021) forecasted financial system distress using newspaper data, Thorsrud (2020) enhanced GDP nowcasts with business newspaper sentiment in Norway, and Bortoli et al. (2018) obtained better short-term output prognoses using sentiment data from the *Le Monde* newspaper.

In contrast to the abovementioned studies, this research employs specific reports from the National Bank of Romania to propose necessary sentiment indices, considering that national bank forecasters' opinions are more reliable than those sourced from newspapers. This approach is supported by studies such as Baciu (2015) and Simionescu (2020), which suggest that inflation forecasts from the central bank are better than those derived from regressions or expert expectations. Sentiment indices serve as inputs for machine learning-based forecasting models to predict inflation rates. This study is pioneering in combining a sentiment approach with machine learning methods for inflation prediction. The development of this type of analysis has been driven by the capacity to analyse human sentiments from large data volumes, involving interactions between PCs and humans, finding relevant information, and analysing data from multiple sources (Cambria et al., 2017).

A comprehensive review by Wang et al. (2022a, 2022b) on the calculations of sentiment indices demonstrated the utility of both unimodal and multimodal data from physiological and physical sources. This paper highlights the value of data derived from physiological and physical contexts. Additionally, this type of analysis is explored using graph neural models on dependency trees (Liang et al., 2022).Further advancements in sentiment analysis involve neurosymbolic AI, which merges rule-based AI with sophisticated deep learning, providing more accurate forecasts with less data than traditional methods (Susskind et al., 2021).

3. Methods and research methods.

3.1. Sentiment Analysis Methodology

NLP is used to compute the sentiment index to suggest the future evolution of inflation. Sentiment analysis is a natural language technique and a game changer for extracting valuable insights from text data. It empowers researchers, business professionals, and political analysts alike to quantify and interpret emotions expressed within vast amounts of text. Sentiment analysis is employed to determine the polarity of the content: positive, negative, or neutral. Sentiment analysis uses document classification and recurrent neural networks (RNNs), machine learning algorithms. The indices are computed based on the positive/negative/neutral values of the words in the text.

The text is analysed by scoring each word as positive, negative, or neutral. Positive words get a thumbs up (1 point), negative words get a thumbs down (-1 point), and neutral words get a shrug (0 points). We sum all these scores and normalize the scores to obtain values between 0 and 1. A similar method was employed by Clements & Reade (2020), who also used increments and decrements; however, in this study, we automatically computed the values of sentiment indices by using IntelliDocker. Moreover, the method proposed by Clements & Reade (2020) is based on a limited number of words (3000 words), while our approach for computing the sentiment index is based on all the words in the dictionary of the Romanian language.

3.2. Context Splitter Function

The context splitter function is used to conduct sentiment analysis. This function cuts text into meaningful pieces, considering the relationships between words. This is helpful for tasks such as summarizing, analysing, or translating languages, where understanding the flow of ideas matters.

This method employs advanced techniques to identify significant text chunks. It might consider:

- Sentence endings: Splitting at sentence breaks ensures that each segment holds a complete thought.
- word roles: Analysing the grammatical function of words helps identify cohesive phrases and clauses.
- entity recognition: Recognizing entities such as people, places, and organizations helps pinpoint the focus of each segment.
- Machine learning: Training models to recognize context based on various features can be powerful for complex or nuanced text.

3.3. Data collection and analysis

In this study, *inflation reports* released by the central bank are used to collect inflation forecasts with quarterly frequency corresponding to the quarter in which the reports are published (NBR, 2024). Moreover, these reports are also used to collect data on registered inflation in the previous quarters and to analyse the abstracts in the *Inflation Outlook section* of these reports and to compute sentiment indices. The inflation reports are released in February, May, August and November of each year in the 2006: Q1-2023: Q4 period and correspond to the middle month of each quarter. The analysed abstracts play the role of narratives that are used to calculate sentiment indices (the sentiment index is denoted by *si*).

3.4. Application to ARDL Models

The computed sentiment index (*si*) plays the role of an explanatory variable in various representations of the autoregressive distributed lag (ARDL) models that are used as inflation forecasting methods.

$$inflation_t = \alpha_1 + \beta_1 \cdot inflation_{t-1} + \gamma_1 \cdot si_t + \varepsilon_{1t} \quad (1)$$
$$ln(inflation_t) = \alpha_2 + \beta_2 \cdot ln\,(inflation_{t-1}) + \delta_1 \cdot ln\,(u_t) + \varepsilon_{2t} \quad (2)$$
$$ln(inflation_t) = \alpha_3 + \beta_3 \cdot \ln\,(inflation_{t-1}) + \gamma_2 \cdot si_t + \delta_2 \cdot ln\,(u_t) + \varepsilon_{3t} \quad (3)$$

where inflation is the quarterly inflation rate recorded in actual period *t*; *si* is the sentiment index; and *u* is unemployment; $\alpha_1, \alpha_2, \alpha_3, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \delta_1, \delta_2$ – parameters; $\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}$ – errors; *t* – time index.

The specifications of the ARDL models allow us to anticipate inflation in the current quarter using the NBR report released in that quarter and previous quarterly inflation. The forecasting method that determines the most accurate predictions can be used for future inflation forecasts.

4. Results. The values of the sentiment indices are computed using IntelliDocker, and ARDL models are built to construct sentiment forecasts. These models explain the actual inflation rate based on the sentiment index. Before making the estimations based on quarterly time series, the stationarity is checked for variables in the models: the actual inflation rate, the sentiment index and the unemployment rate. The data for the unemployment rate are provided by the National Institute of Statistics for the period 2006: Q1-2023: Q4. The descriptive statistics are reported in Table 1.

Table 1. Descriptive statistics

Statistics	Inflation rate	Unemployment rate
Mean	4.92%	6.73%
Median	4.82%	6.10%
Maximum	16.37%	9.3%
Minimum	-1.70%	3.70%
Std. dev.	3.78%	1.78%
Skewness	1.00	0.05
Kurtosis	4.29	1.51
Jarque-Bera stat. (p value in brackets)	17.03 (0.0002)	6.67 (0.03)
No. of observations	72	72

Sources: developed by the authors.

The maximum inflation rate in Romania corresponding to hyperinflation (16.37%) was registered in the last quarter of 2022 (Eurostat, 2024). The ongoing war in Ukraine significantly impacted global energy and food prices. Like many countries, Romania imports these commodities, making them more expensive domestically. Disruptions caused by the pandemic will continue to affect the supplies of various goods by 2022. This limited supply, coupled with high global demand, pushed prices upwards in Romania. The highest disinflation was recorded in Romania in the third quarter of 2019 due to the depletion of excess consumer demand.

The highest quarterly unemployment rate in Romania was recorded in the first quarter of 2010, in the context of the economic recession that occurred at that time. Consumer confidence weakens during recessions, and people tend to spend less. This can lead to businesses having lower sales and potentially resorting to layoffs. On the other hand, the unemployment rate reached its lowest level in the second quarter of 2008, when the Romanian economy was in a period of economic boom. First, the Romanian economy grew rapidly in 2008, with a GDP growth rate of 7.1% (NBR, 2024). This growth created new jobs and opportunities, leading to a decrease in unemployment. Second, foreign and domestic investment in Romania was high in 2008. This investment helped to create new businesses and expand existing ones, which further contributed to job creation. Third, the Romanian government implemented policies that made it easier for businesses to operate in the country. This made Romania an attractive destination for investment and helped to create jobs.

The normal distribution hypothesis is not supported at the 5% significance level according to the Jarque–Bera test. However, at the 1% significance level, normality is checked for the unemployment rate data series. The series are seasonally adjusted, and the augmented Dickey-Fuller (ADF) test is applied to check for unit roots. The results are presented in Table 2. Except for the sentiment index (*si*) data series, which is stationary at the 1% significance level, the rest of the time series are stationary only at the first difference at the same significance level.

Table 2. The results of the ADF test

Variable	Data series	Equation	ADF stat.	p value	Conclusion
inflation	data in the second difference	no trend	-6.801	<0.01	no unit root
	data in the first difference	no intercept	-7.593	<0.01	no unit root
	data in level		-1.608	0.101	unit root
u	data in the second difference	no trend	-8.572	<0.01	no unit root
	data in the first difference	no intercept	-7.125	<0.01	no unit root
	data in level		-0.420	0.5280	unit root
si	data in the second difference	no trend	-6.620	<0.01	no unit root
	data in the first difference	no intercept	-14.305	<0.01	no unit root
	data in level	intercept	-7.670	<0.01	no unit root
ln(inflation)	data in the second difference		-6.862	<0.01	no unit root
	data in the first difference		-5.882	<0.01	no unit root
	data in level		-0.614	0.4471	unit root
ln(u)	data in the second difference		-12.414	<0.01	no unit root
	data in the first difference		-6.866	<0.01	no unit root
	data in level		-0.306	0.5718	unit root
ln(si)	data in the second difference		-8.531	<0.01	no unit root
	data in the first difference		-14.311	<0.01	no unit root
	data in level		-1.175	0.2169	unit root

Sources: developed by the authors.

The results of the estimations for the ARDL models used to construct the sentiment forecasts are presented in Table 3. The multicollinearity issue is alleviated in the model that includes the unemployment rate by considering the natural logarithm of the data. There is no significant correlation between the actual inflation rate and the sentiment index (coef. of correlation=0.223, p value=0.556).

Table 3. The results of the estimations for the ARDL models

Variable	Coefficients (p values in brackets)		
Model	M1	M2	M3
inflation in the previous period	0.796 (<0.01)	-	-
si	-5.220 (0.0315)	-	-
ln(inflation in the previous period)	-	0.822 (<0.01)	0.768 (<0.01)
ln(u)	-	0.114 (0.0758)	-0.038 (0.0865)
ln(si)	-	-	-0.793 (0.0304)
Constant	4.138 (0.0105)	-	-0.041 (0.936)
White test: stat. (p value in bracket)	1.668 (0.8928)	0.392 (0.531)	0.956 (0.3281)
Breusch-Godfrey Serial Correlation LM Test for lag=1: stat. (p value in bracket)	0.338 (0.5608)	0.350 (0.5540)	2.171 (0.1406)
Breusch-Godfrey Serial Correlation LM Test for lag=2: stat. (p value in bracket)	0.618 (0.7341)	1.445 (0.4855)	2.228 (0.3282)
Jarque-Bera test: stat. (p value in bracket)	31.599 (<0.01)	28.792 (<0.01)	51.088 (<0.01)
Ramsey Reset Test	1.249 (0.2677)	1.269 (0.2641)	0.761 (0.3863)

Sources: developed by the authors.

These ARDL models are used to make inflation forecasts, and their accuracy is compared with that of NBR forecasts. Two types of these predictions based on ARDL models are employed to construct sentiment forecasts. Moreover, combined predictions between NBR numerical prognoses and other expectations are built using traditional combination schemes. The forecast accuracy is evaluated not only for numerical NBR forecasts but also for sentiment prognoses and combined predictions based on traditional combination schemes. The results in Table 4 suggest that sentiment forecasts based on the ARDL model that uses the sentiment index and unemployment rate as explanatory variables are the most accurate according to all accuracy measures. These sentiment predictions and those based only on the sentiment index are more accurate than numerical NBR forecasts. Combined predictions did not improve the NBR or sentiment forecasts, but combined predictions based on the ARDL model with the sentiment index and unemployment as explanatory variables and NBR predictions under optimal and inverse schemes were better than other predictions in terms of the mean absolute percentage error.

Table 4. Prognosis accuracy for Romanian inflation rate predictions (2006: Q1-2023: Q4)

Predictions	Mean error	Mean abs. error	Root mean abs. error	U1 coef.	U2 coef.	Mean abs. percentage error
NBR forecasts	0.005	0.725	1.954	0.114	0.29	0.196
Sentiment predictions based on ARDL model and sentiment indices (sf1)	0.004	0.343	1.924	0.064	0.23	0.157
Sentiment predictions based on ARDL model, sentiment indices and unemployment (sf2)	-0.004	0.219	1.147	0.022	0.174	-0.052
Forecasts based on ARDL model	-0.943	1.1	2.145	0.568	0.375	-1.033
Combined forecasts based on NBR forecasts and sf1, optimal weights	0.011	1.354	2.933	0.164	0.93	0.352
Combined forecasts based on NBR forecasts and sf1, inverse weights	0.0089	0.983	2.414	0.128	0.595	0.246
Combined forecasts based on NBR forecasts and sf1, equal weights	0.008	0.957	2.344	0.127	0.571	0.24
Combined forecasts based on NBR forecasts and sf2, optimal weights	0.085	0.301	0.447	0.233	0.426	0.047
Combined forecasts based on NBR forecasts and sf2, inverse weights	0.062	0.266	0.398	0.131	0.718	0.027
Combined forecasts based on NBR forecasts and sf2, equal weights	0.056	0.258	0.389	0.200	0.348	0.020

Sources: developed by the authors.

Overall, the empirical findings suggest that sentiment indices based on experts' expectations play an important role in making accurate predictions of the quarterly inflation rate in Romania. The proposed method that determined the best forecasts might be used for making future quarterly inflation forecasts for 2024 and 2025.

5. Discussion. The research hypothesis related to the capacity of ARDL models, including the sentiment index, to provide more accurate forecasts than other models is validated in this study. The results are in line with those of Simionescu (2022), who reported that models using signals based on Fourier transform and the sentiment index as inputs in machine learning techniques outperformed methods that do not consider sentiment analysis in predicting inflation in Romania. However, for Lithuania, Lukauskas et al. (2022) showed that inflation predictions improve when only negative sentiments are incorporated. Sentiment forecasts based on the ARDL model, incorporating both the sentiment index and unemployment rate, consistently achieved the highest accuracy across various metrics. This suggests that incorporating sentiment analysis into inflation forecasting models can significantly improve their accuracy compared to relying solely on traditional numerical methods used by the NBR.

Combining different forecasting methods did not generally improve the accuracy of NBR or sentiment forecasts. However, combining the ARDL sentiment model with NBR predictions under specific schemes (optimal and inverse) showed some promise in terms of the mean absolute percentage error. Further research is needed to explore more effective combination strategies. Another solution would be to consider the combination of forecasts based on ARDL models with those based on machine learning techniques. Folgieri et al. (2018) showed that artificial neural networks based on sentiment analysis improved tourism arrival forecasts in Croatia.

These findings provide strong evidence that incorporating sentiment analysis into inflation forecasting models can significantly improve their accuracy. This finding is in line with existing research suggesting that public sentiment can be a valuable indicator of future economic trends. This study contributes to our understanding of inflation forecasting in Romania by demonstrating the potential of sentiment analysis as a powerful tool for enhancing the accuracy and effectiveness of inflation prediction models. It is important to acknowledge that the study's findings might be specific to the Romanian context and the chosen sentiment analysis approach. Further research is needed to validate these findings in other countries and with different sentiment analysis methods.

6. Conclusions. Macroeconomic forecasting, the art of predicting future economic trends, has traditionally relied on complex statistical models and historical data. While these methods have served us well, the increasingly interconnected and volatile global economy demands more. This is where innovation is shaking things up in the realm of forecasting. Sentiment analysis represents one of the innovations in forecasting. Public mood can significantly impact economic behaviour. By analysing the sentiment expressed in social media, news articles, surveys, and scientific reports, forecasters can gauge consumer confidence, risk perception, and potential shifts in spending patterns. This injects valuable "emotional intelligence" into the models.

Even though predicting inflation perfectly is difficult, forecasts provide a valuable glimpse into the expected future economic landscape. This allows businesses and policymakers to make informed decisions that can promote financial stability and economic well-being. Inflation forecasting is crucial in Romania, which should continue to control this phenomenon during the postpandemic period. Currently, Romania's high inflation is a complex issue with both international and domestic roots. By addressing these roots, the Romanian government and central bank can work towards bringing inflation under control and achieving price stability. However, accurate inflation forecasts are necessary to properly manage this hot issue for the Romanian economy.

This paper provides new insights into inflation forecasting by considering experts' opinions in the form of sentiment indices to anticipate Romanian inflation (horizon 2006: Q1-2023: Q4). Specifically, the sentiment forecasts based on the ARDL model, which uses the sentiment index and unemployment rate as explanatory variables, are more accurate than the NBR numerical predictions. However, the combinations of NBR predictions and these sentiment forecasts are not superior in terms of accuracy.

This paper offers novel insights into inflation forecasting by incorporating sentiment analysis in the form of sentiment indices to predict Romanian inflation over a long period (2006: Q1-2023: Q4). The study's key contributions are as follows:

- Demonstrating the superiority of sentiment-based forecasts: Sentiment forecasts based on an ARDL model utilizing both the sentiment index and unemployment rate as explanatory variables consistently outperform traditional numerical forecasts employed by the NBR. This finding highlights the potential of sentiment analysis to significantly improve inflation forecasting accuracy.
- Validating the importance of sentiment data: Even sentiment forecasts based solely on the sentiment index prove more accurate than NBR's numerical predictions. This emphasizes the crucial role of sentiment data in capturing public perception and its potential influence on inflation dynamics.
- Providing nuanced insights into combination strategies: While combined predictions generally do not improve upon individual NBR or sentiment forecasts, specific combinations involving the ARDL sentiment model and NBR predictions under optimal and inverse schemes show promise. This suggests the need for further research to explore more effective combination strategies for enhancing forecasting accuracy.
- Advancing understanding of Romanian inflation: This study contributes significantly to our understanding of inflation forecasting in Romania by demonstrating the power of sentiment analysis as a valuable tool for improving the accuracy and effectiveness of inflation prediction models.

This research is limited to a single method for constructing sentiment indices based only on NBR inflation reports. Moreover, combined forecasts are constructed using only traditional schemes. Therefore, future studies will consider more methods for constructing sentiment indices and other types of techniques for combining forecasts.

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Сентимент-аналіз як інноваційний інструмент прогнозування інфляції в Румунії

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На початку 2024 року Румунія зіткнулася з найвищим рівнем інфляції в Європейському Союзі. Проте порівняно з 2023 роком було досягнуто певного прогресу завдяки підвищенню відсоткової ставки. Інфляція виникла через

дію як глобальних, так і внутрішніх факторів: глобальні фактори включають війну Росії проти України, збої в ланцюгах постачання, спричинені пандемією COVID-19, а також зростання цін на сировину; внутрішні фактори включають підвищення заробітних плат і пенсій, підвищення податків і зборів та стратегію поступового підвищення ставки грошово-кредитної політики. Національний банк Румунії (НБР) використовує інструменти грошово-кредитної політики для таргетування інфляції та надає щоквартальні прогнози. Однак за умов невизначеності числові прогнози менш надійні. Використання сентимент-аналізу як інноваційного інструменту при прогнозуванні дозволяє підвищити рівень точності прогнозів. Авторами наголошено, що сентимент-аналіз стає все більш важливим у галузі економіки, пропонуючи цінні інсайти та потенційно покращуючи економічне прогнозування і прийняття рішень завдяки швидкому технологічному прогресу. Сентимент-аналіз дозволяє виявити потенційні зміни в поведінці споживачів і бізнес-рішеннях до того, як вони будуть відображені в реальних економічних даних, забезпечуючи систему раннього попередження про економічні тенденції та потенційні кризи. Методологічна основа дослідження заснована на обробці природної мови для витягування індексів сентименту з великих обсягів текстів в Інфляційних звітах, наданих НБР. Крім того, індекси сентименту, розраховані за допомогою IntelliDocker, включені в авторегресійні моделі з розподіленим лагом (ARDL) для надання щоквартальних прогнозів інфляції. Цей тип економетричної моделі має перевагу у вирішенні проблеми ендогенності. Крім того, рівень безробіття розглядається як предиктор інфляції, оскільки напруженість на ринку праці може впливати на інфляцію. Ця стаття робить внесок у емпіричне прогнозування, пропонуючи прогнози сентименту, які є більш точними, ніж числові прогнози НБР за період з першого кварталу 2006 року до четвертого кварталу 2023 року. Новий метод може використовуватися для прогнозування інфляції на наступні квартали. Точніші прогнози будуть цінними для бізнесу, центрального банку, політиків та широкої громадськості. Однак, хоча сентимент-аналіз надає цінні інсайти, важливо пам'ятати, що людське судження та експертиза залишаються важливими для інтерпретації даних та прийняття обґрунтованих економічних рішень.
Ключові слова: інфляція; прогноз; індекс сентименту; обробка природної мови.