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Sentiment and Uncertainty Indices
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Abstract

This study introduces an approach for measuring sentiment and uncertainty indices in Colombia through text mining. Economic news from digital media, spanning March 2020 to September 2024, is analyzed using dictionary-based methods and predefined word lists. The constructed indices reflect major macroeconomic events, such as the phased reopening during the pandemic, the national strike in May 2021, and the decline in demand associated with elevated inflation. These indices function as leading indicators and exhibit statistically significant associations with high-frequency economic data. Incorporating news-based sentiment and uncertainty indices improves the precision of nowcasting Colombia's economic activity using a dynamic factor model. The results indicate that incorporating qualitative, forward-looking news with traditional data enhances the monitoring of short-term economic fluctuations and the identification of turning points.

JEL Classification Numbers: C53, C82, E27.

Keywords: sentiment, uncertainty, artificial intelligence, text analysis techniques, natural language processing, dynamic factor model.

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Índices de Sentimiento e Incertidumbre de las noticias económicas de Colombia

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Resumen

Este estudio presenta un método para medir el sentimiento y la incertidumbre económica en Colombia mediante técnicas de minería de texto. A partir de noticias publicadas entre marzo de 2020 y septiembre de 2024 y empleando metodologías de diccionario basadas en listas predefinidas de palabras positivas y negativas, se construyeron los índices de sentimiento e incertidumbre. Estos índices identificaron episodios macroeconómicos relevantes, como la reapertura gradual tras la pandemia, el Paro Nacional de 2021 y la desaceleración de la demanda en un entorno de elevada inflación. Los índices exhiben propiedades de series adelantadas y mantienen relaciones estadísticamente significativas con variables económicas de alta frecuencia. El análisis empírico muestra que su incorporación en modelos factoriales dinámicos mejora de manera sistemática la precisión en los pronósticos de la actividad económica. Los resultados muestran que la información cualitativa y prospectiva contenida en las noticias complementa los datos tradicionales y fortalece la capacidad para determinar dinámicas de corto plazo y anticipar puntos de inflexión de la actividad económica colombiana.

Códigos de Clasificación JEL: C53, C82, E27.

Palabras clave: sentimiento, incertidumbre, inteligencia artificial, técnicas de análisis de texto, procesamiento de lenguaje natural, modelo factorial dinámico.

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1. Introduction

Amid the unprecedented emergence of COVID-19 and heightened uncertainty, we recognized an urgent need to develop real-time indicators. Most of the official economic data is released with a delay of one or two months, generally based on surveys that require careful execution, processing, and dissemination. The rapid shifts in the economic conditions were prompting the production of new indicators to support effective decision-making.

Advances in technology have accelerated text analysis in economics and finance, enabling the computation of anticipated indices through the application of computational algorithms. We discovered multiple studies on the use of natural language processing (NLP) and artificial intelligence (AI) for strategic decision-making within sales and marketing. Across both physical stores and digital platforms, AI is increasingly used to analyze customers' behavior and assess satisfaction levels with products and services. The areas of research have been expanded through text mining analysis, driven by innovations in technology that systematize business processes, improve data handling, and enable automation across operations.

Given the rise of smart systems and improved data processing tools, we propose a novel approach to measuring economic sentiment and uncertainty in Colombia by applying text mining techniques to economic news. We explored the development of both metrics by leveraging opportunities in digital news. Information and communication technologies are the most widely used to ensure timely access to information about national and international events. This study covers only the period from March 2020 to September 2024; however, the indicators are currently updated monthly and released to technical staff promptly within 5 days of the month-end.

Using NLP, we estimated the Sentiment Index of Colombia (SENTreg), introducing a forward-looking measure to assess economic dynamics ahead of official releases. At the same time, we developed the Uncertainty Index (UNCERTreg), which captures risk perceptions of the state of the economy, offering greater opportunity than other similar indicators proposed for the country (International Monetary Fund and Fedesarrollo).

In our knowledge, this is the first time a sentiment indicator has been developed in Colombia based on economic news. The SENTreg displays a coherent trajectory, mirroring the trends observed in related economic metrics, such as the consumer confidence index compiled by Fedesarrollo. Our approach shows that aggregating textual information from Colombian regions can produce numerical indicators that closely align with actual economic performance, especially during extreme economic shocks. At the same time, our work contributes to the existing literature by applying text-mining techniques to construct regional-level indicators.

Regarding the Uncertainty Index, we found that domestic news provides deeper insights into internal tensions surrounding recent economic events. We extend the international literature on uncertainty metrics by addressing contexts beyond technical reports. The UNCERTreg exhibits greater sensitivity to local economic fluctuations than the World Uncertainty Index for Colombia developed by the International Monetary Fund. The indicator has gained increased relevance in the current period, driven by heightened local and global tensions.

Our empirical evidence shows that enriching dynamic-factor-based ARMAX nowcasting models with Sentiment and Uncertainty Indices extracted from economic news, consistently improves predictive performance relative to specifications based solely on traditional data. This result underscores the value of text-based information as a high-frequency complement to traditional macroeconomic indicators and the relevance of qualitative news signals in real-time monitoring.

The study is structured around the introduction and five additional sections. The next section presents the literature review accompanied by a discussion of the most relevant aspects of previous research. The third and fourth sections outline the data sources and the methodological approach used to develop the indices. The fifth section presents the main results for Colombia compared to other metrics. The following section presents the indices' capacity to predict economic activity through an econometric analysis. Finally, the last section concludes.

2. Literature review

Across Central Banks (CBs), the AI has been used in text mining analysis to find insights related to the transmission effectiveness of monetary policy, through the study of written language, style, and tone, contained in press releases or in the minutes of the Board of Directors meetings (Arango et al., 2017; Taborda, 2015; Shapiro et al., 2021). Recently, CBs have expanded their research to measure sentiment in technical reports and newspaper articles. Among the CBs studies, we found sentiment indices of Australia (Nguyen and La Cava, 2020), Chile (Cruz et al., 2020; Becerra et al., 2021), Spain (Moreno and González, 2020; Aguilar, 2020), the Netherlands (Borovkova et al., 2017), and the United Kingdom (Hubert et al., 2017; Nyman et al., 2018).

Regarding the text analysis of the technical reports, Moreno and González (2020) examined the linguistic tonality in the Financial Stability Reports (FSRs) published by the Central Bank of Spain between 2002 and 2019. Drawing on rigorous research, the authors built a dictionary of Spanish words with positive and negative tonalities. Using computational linguistic tools for text mining, they measured the sentiment implicit in the FSRs and, after their dissemination, extracted sentiment from articles related to the FSRs' publication. On the other hand, Aguilar et al. (2020) constructed a sentiment indicator for Spain from national print media articles, aiming to provide an alternative measure of confidence in economic activity. The authors noted that the indicator is useful for nowcasting gross domestic product (GDP) growth and offers advantages over the European Commission's sentiment index.

In the case of the CB of Chile, Cruz et al. (2020) studied sentiment measurement using the Business Perceptions Report (BPRs) on a quarterly basis. Their results showed a higher correlation with other indicators such as industrial confidence and economic expectations.

For the same institution, Becerra and Cruces (2021) developed a sentiment index based on FSRs, compiled semi-annually from 2004 to 2020. They found that a higher positive tone in the FSRs is associated with improvements in the economy and credit activity. The authors built a dictionary in Spanish with linguistic tonalities of central banking and financial stability based on the FSRs for sixty-four (64) countries, combined with the analysis in Moreno and González (2020) and Correa (2017).

The sentiment analysis of news has also been addressed by several scholars in the international literature. Shapiro et al. (2020) studied the sentiment from economic and financial news published between 1980 and 2015. They created their own English lexicon by analyzing word lists from previous research and Vader's computational tool, developed by Hutto and Gilbert (2014). Their results showed trends similar to the economic cycle and a strong correlation with the University of Michigan's consumer sentiment index, based on surveys. The authors also pointed out the importance of defining an appropriate vocabulary for the topic of interest in the study to leverage results from models trained to analyze structured sentences.

Text analysis has also been applied to examine the link between news coverage and changes in stock market returns. Calomiris and Mamaysky (2018) used news articles to identify signals of future gains or losses in returns and corresponding reductions or increases in risk. Their study addressed key issues in the construction of sentiment indicators and isolated information relevant to stock market movements across countries. Their evidence indicates systematic differences between developed and emerging economies, driven by variation in word frequency, atypical language, tonal patterns, and topic-specific wording related to commodities, government, firms, and credit.

García (2013) studied the sensitivity of asset prices to sentiment extracted from financial news published in The New York Times prior to market opening. The author identified a closer relationship in periods of recession. In the case of Shen et al. (2022), they constructed different time-series measures of sentiment from news published in the Global Data on Events Location and Tone database. The authors found that their model successfully predicted returns in China’s stock market.

Moreover, the study of anticipated indices constructed from news articles has advanced toward the development of measures of uncertainty. Baker et al. (2016) developed an Economic Policy Uncertainty Index for 12 countries based on an analysis of news published by the main media. The authors concluded that the increase in uncertainty suggests a reduction in consumption, production, employment, and investment as well as an increase in market volatility, in the face of changes in stance on fiscal, regulatory, and monetary measures and specific events such as elections, wars, and financial crises. Gil and Silva (2019) developed the Economic Policy Uncertainty Index of Colombia (2000:01-2022:05), based on the methodology proposed by the previous authors. The source of information comes from the economic and political sections of the newspaper "El Tiempo". Recently, Fedesarrollo (2024) published the Economic Policy Uncertainty Index (IPEC in Spanish), in which the selection criteria for articles in “El Tiempo” are limited to news about uncertainty surrounding Colombia’s economic policy.

The International Monetary Fund publishes the World Uncertainty Index (WUI) for 143 countries, including Colombia (Ahir et al., 2018). For comparative purposes, they use the country reports conducted by The Economist Intelligence Unit as the only source of information. The WUI captures the uncertainty surrounding political and economic factors; therefore, upward movements are associated with market volatility, increased risk, and lower growth. Other sources of uncertainty have recently been identified in Tweets, as in the study by Baker et al. (2021).

In most of the studies, the authors agreed on several fundamental aspects for measuring sentiment and uncertainty. Among the main ones are: i) text length serves as a valuable feature for filtering tonal variations and minimizing volatility in the results; ii) the indices anticipate economic trends and closely mirror confidence indices in their ability to capture both current and expected perceptions.; iii) researchers incorporate indices into forecasting / nowcasting models to enhance predictive accuracy; and iv) text analysis may contain relevant information for forecasting movements in financial variables.

3. Data

The Sentiment and Uncertainty Indices are derived from economic news in Colombia since the onset of the COVID-19 pandemic. For academic purposes, the criteria for selecting economic news were based on factual content, including relevant events, observable trends, and statistical evidence that describes or influences the country's economic variables. The economic narrative of the articles serves as the corpus for assessing sentiment and uncertainty derived from national and regional digital media[1]. (Annex 1).

Once the corpus was built around the topic of interest to be analyzed, each article was manually tagged with categories for economic activities and geographic areas in the country. The former were based on national accounts variables from a production perspective, and we also considered classifications for inflation, market labor, health, education, public services, and other activities not specified[2] (Annex 2). If the corpus contained an analysis grouped by several economic activities, it was labeled as a global context. Regarding the geographic areas where the economic event occurred, the tagging was disaggregated by cities and

[1] Not all digital media sources were available during the research period.
[2] For example: external debt, national and local budgets, foreign trade, tax reforms, sovereign risk, and foreign direct investment, among others.

departments across Colombia's seven regions[3], along with a national-level category[4] (Map 1). The regions were based on the Regional Centers for Economic Studies - Central Bank.

Map 1. Regional coverage of economic news in Colombia

Source: Authors' elaboration.

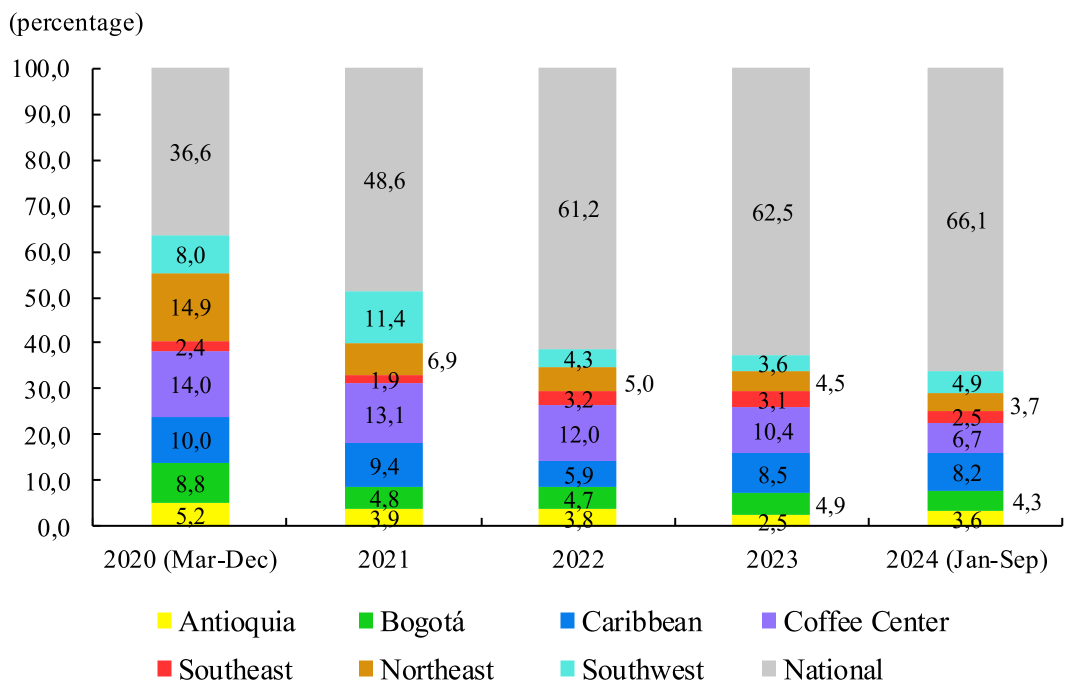
[3] Antioquia, Bogotá (Bogotá, Cundinamarca); Caribbean (Atlántico, Bolívar, Cesar, Córdoba, Magdalena, La Guajira, Sucre y San Andrés); Coffee Center (Caldas, Quindío, Risaralda; Tolima, Huila, Caquetá); Northeast (Santander, Norte de Santander, Boyacá); Southwest (Valle del Cauca, Nariño, Cauca); and Southeast (Amazonas, Casanare, Guainía, Guaviare, Meta, Vaupés, Vichada).

[4] National-level category applies when the corpus does not refer to a specific city, department, or region, or, conversely, refers to multiple territories from different regions.

Manual reading and tagging were carried out by a team of trained professionals to record information in a technological environment that supports real-time collaboration. The training was conducted through joint meetings and instructions provided in a user guide, with participants labeling the information according to the research's purposes. The operating manual outlines the definition of the corpus, its classifications, and the procedures for obtaining additional information, such as the article's publication date, web address, and the name of the media outlet. The articles were registered once released, without bias regarding the media, economic activity, or geographic coverage.

The economic repository from March 2020 to September 2024 consists of 59,648 news articles. According to the data, in 2020, the distribution of records by geographic area was greater in the regions (63,4%) (Figure 1). At the onset of the pandemic, we observed higher regional reporting levels, driven by the varied and unexpected economic disruptions caused by regional lockdown policies. On the other hand, in 2024, the record allocation shows a stronger emphasis on the national context (66,1%)

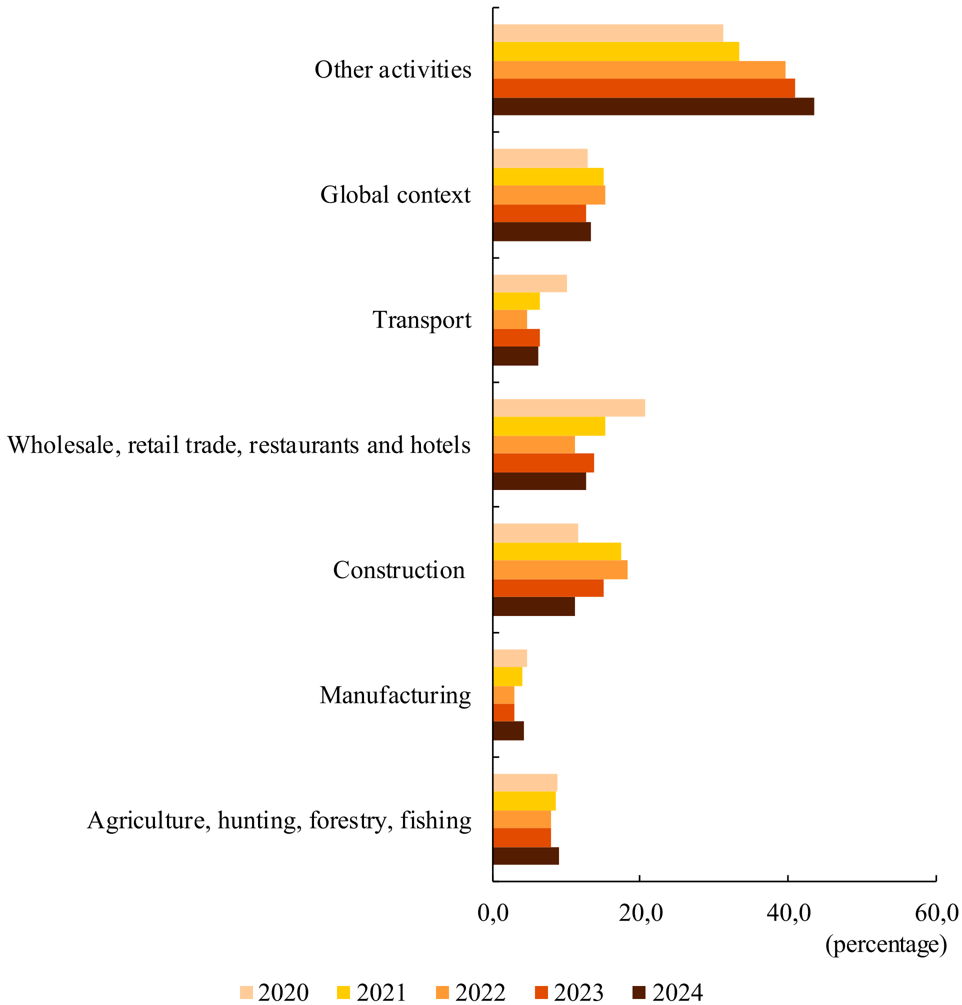
Figure 1: Geographical distribution of economic news



Source: Authors' calculations based on national and regional news.

Regarding the records broken down by economic activity, the distribution varied with the prevailing economic trends in each period (Figure 2). In 2020, one-fifth of the records focused on wholesale trade, retail trade, restaurants, and hotels. In the same year, transport recorded its highest share during the study period, largely due to the severe impact of Covid-19, which significantly restricted land and air passenger mobility. In the case of construction in 2021 and 2022, the records received greater coverage than in the commerce, transport, manufacturing, and agriculture categories. The construction sector in 2021 was primarily focused on recovering from the pandemic's disruptions. In contrast, 2022 was marked by global supply shortages, increased financing costs, and uncertainty surrounding new residential developments, driven by instability in housing subsidy programs.

Figure 2. Distribution of economic news by economic activity



Source: Authors' calculations based on national and regional news.

In the other activities category[5] the marked increase in the number of records since 2022 was mainly due to events related to rising inflation in the country, the depreciation of the Colombian peso against the U.S. dollar, and the tax reform of the new government (Figure 2). At the same time, international trade in goods was shaped by lingering post-pandemic supply chain disruptions, intensified by the geopolitical impact of Russia's invasion of

[5] Other activities include mining, financial system, telecommunications, health, education, public services, labor market, inflation, external trade, and other unspecified activities.

Ukraine. In 2023, the dataset captured key fiscal and macroeconomic developments, including adjustments to domestic gasoline prices to mitigate the deficit in the Fuel Price Stabilization Fund. It also highlighted concerns over oil production, uncertainty regarding structural reforms in pensions, healthcare, and labor, and indicators of weak domestic demand and declining consumer confidence. Meanwhile, in 2024, among the issues examined were the widening fiscal deficit, disruptions in the gas supply chain, and doubts regarding the viability of sustained healthcare funding.

4. Methodology

The indices were developed using text mining techniques, trained natural language processing models, and press articles from digital media. The corpus of economic news was identified through manual reading and labeling, according to the definitions and parameters described in the data section. Then we compiled all the unstructured text for analysis through computational methods. The programming language prepares the information into a cleaner format for analysis of its grammatical structure and for keyword recognition to perform sentiment and uncertainty analysis.

The Sentiment Index of Colombia (SENTreg) measures the optimistic, pessimistic, or neutral tone of economic news. The method used to estimate the sentiment indicator relies on the polarity detection by counting positive and negative words for each month (t), according to the standard measure:

$$Sentiment_t = \frac{\sum Positive_t - \sum Negative_t}{\sum Positive_t + \sum Negative_t} \qquad (1)$$

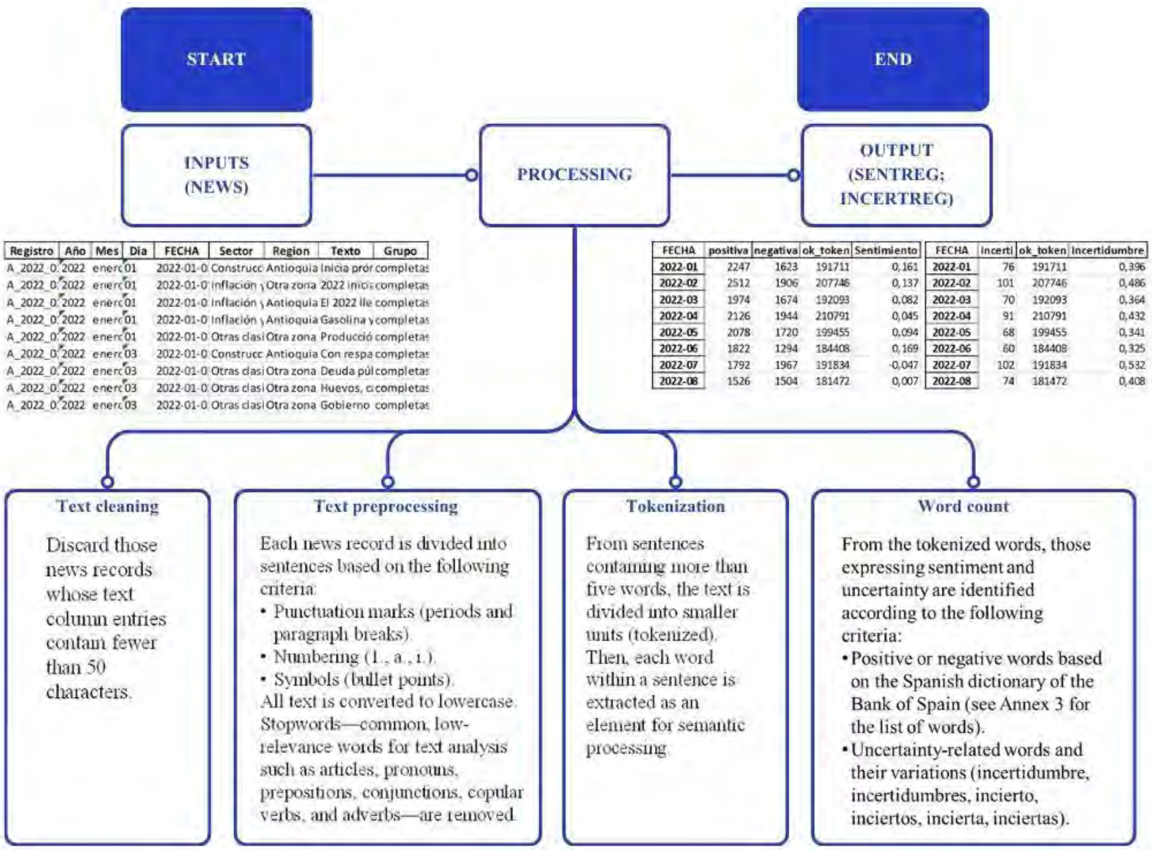
We use the predefined list of words with contrary emotions (positive-negative) developed by the Central Bank of Spain (Annex 3a and 3b). The dictionary was produced by a dedicated team of experts who conducted a rigorous linguistic analysis in the Financial Stability Reports (Moreno and González, 2020). The sentiment indicator ranges from -1 to 1, where values above 0 indicate positive economic sentiment and values below 0 indicate negative economic sentiment. The data is available four to five business days after the end of each month. The index's monthly computation schedule was designed to capture short-term economic fluctuations. Diagram 1 details the process of computing the Sentiment Index.

While developing the Sentiment Index for Colombia, we expanded our research to create an uncertainty indicator, using the same sources of information as inputs and the previously defined corpus. Unlike sentiment, where positive and negative words are counted, the Uncertainty Index (UNCERTreg) is estimated by counting the frequency of uncertainty (or the variant) in each month (t).

$$Uncertainty_t = \frac{\sum word \text{ “}uncertain\text{” } (or\ its\ variant)_t}{\sum words\ processed_t} \qquad (2)$$

The UNCERTreg is normalized by the total number of words processed, removing the stopwords (articles, prepositions, conjunctions, pronouns) and rescaled by multiplying by 1.000. In the face of uncertainty, a greater positive value is associated with higher levels of uncertainty and, otherwise, with lower uncertainty. Diagram 1 details the process of computing the Uncertainty Index.

Diagram 1. Construction of the Sentiment and Uncertainty Indices



Source: Authors' elaboration.

To contextualize the construction of Sentiment and Uncertainty Indices, it is essential to acknowledge the characteristics of news-based measures and the empirical considerations that arise when using textual data to approximate economic conditions. These features shape both the potential value of the indicators and the methodological challenges inherent in their interpretation, providing a conceptual foundation for evaluating their role as complementary inputs to traditional statistics.

Table 1 provides a structured comparison of the strengths and weaknesses of news-based economic sentiment and uncertainty indicators. It synthesizes the core attributes that make these measures valuable complements to traditional economic statistics, while also identifying the conceptual and empirical constraints that affect their reliability.

Table 1. Advantages and disadvantages of news-based sentiment and uncertainty indicators

Advantages	Disadvantages
Capture the qualitative component of the economic cycle, including business confidence, risk perception, sector-specific concerns, and investment climate.	**Dependence on media coverage**, reflect how events are reported rather than the underlying economic reality; coverage may exhibit agenda bias, uneven regional representation, and artificial spikes when non-economic events dominate headlines.
Provide high-frequency and timely information, with minimal publication lag relative to official statistics and a closer reflection of current economic conditions.	**Editorial and narrative biases**, stemming from political orientation, editorial lines, or newsroom routines, which may introduce systematic negativity and selective reporting.
Incorporate forward-looking and anticipatory information, covering themes related to public policies, macroeconomic tensions, external shocks, sector and regional disturbances, and political or institutional uncertainty.	**High short-term volatility and noise**, react to daily news intensity, generating sharp fluctuations unrelated to fundamentals, spikes from isolated events, and difficulties separating signal from noise without smoothing.
Increase sensitivity to shocks, responding quickly to events like protests, regulatory shocks, external crises, international conflicts, abrupt changes in global prices, political scandals.	**Dependence on dictionaries or classification models**, dictionaries may miss linguistic nuances, supervised models rely on labeled corpora, language evolves over time, and semantic ambiguity can lead to misclassification.
Complement—rather than replace—official data, adding informational value through new signals, qualitative content (sentiment, narratives, uncertainty, topic entropy), and anticipatory insights regarding potential future developments.	**Structural changes in news reporting,** driven by digitalization and social media, which can alter article length, increase opinion-based content, and introduce vocabulary shifts that undermine temporal comparability.
Improve the performance of forecasting models, helping to reduce forecast errors, particularly at short horizons, improve the detection of turning points, and augment real-sector factors with perception- and risk-based information.	**Limited coverage concentrated in national high-circulation newspapers**, may underrepresent regional dynamics, exclude less visible sectors, and overemphasize agents with greater media exposure.

Source: Authors' elaboration based on Barbaglia et al. (2023), Kaveh-Yazdy & Zarifzadeh (2023), Nguyen, La Cava (2020), and van Dalen (2017).

News-based sentiment and uncertainty measures offer timely, forward-looking insights that capture the qualitative and anticipatory aspects of economic behavior. In contrast, quantitative indicators of real activity are generally released with delays and reflect historical outcomes. The high frequency and responsiveness of news-based measures to emerging shocks make them valuable complementary tools for monitoring and forecasting or nowcasting economic conditions.

However, news-based sentiment and uncertainty measures are subject to several limitations. These include potential biases in media coverage, volatility in prevailing narratives, methodological dependence on specific dictionaries or classification models, and limited representativeness across different regions and sectors.

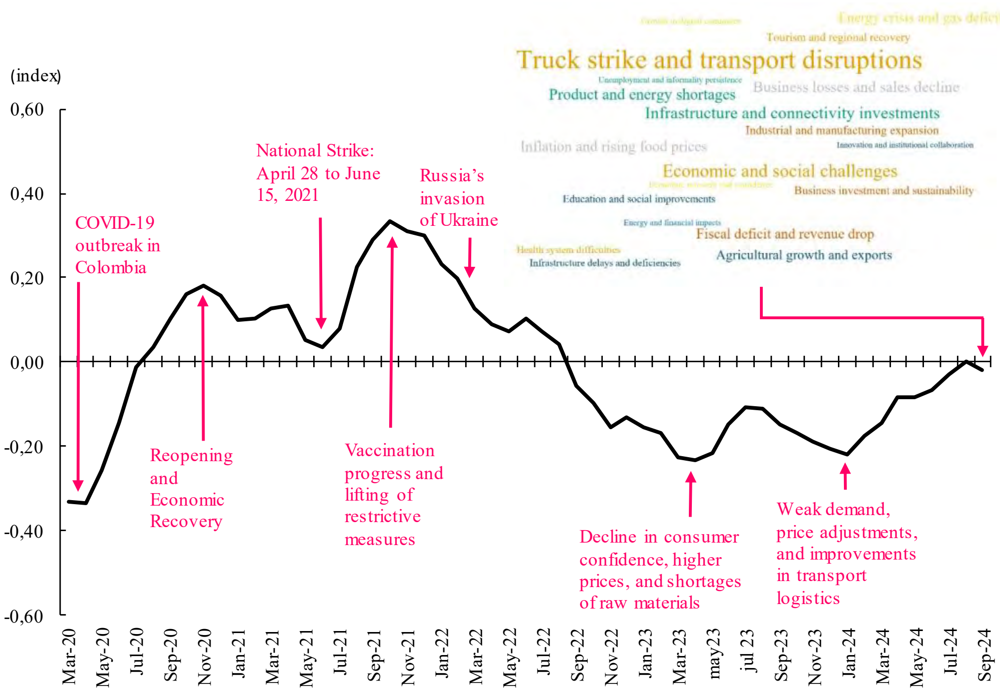
5. Sentiment and Uncertainty economic indices for Colombia

The following section presents the Sentiment Index of Colombia for the six regional territories[6]. For the Uncertainty Index, we introduce only the national aggregate[7]. Although this study examines data from March 2020 to September 2024, the indicators continue to be updated monthly and are typically released to technical staff within 5 business days after month-end.

5.1. Sentiment Index

Analyzing the time series of Colombia's Sentiment Index (SENTreg), we observe that shifts between optimistic and pessimistic tones closely align with economic events in each timeframe (Figure 3). In March 2020, the SENTreg showed an excessive level of pessimism emerged amid strict isolation measures and the initial impacts of the COVID-19 shock. Then the sentiment reached its peak of optimism in November 2020, driven by the easing of strict quarantine measures, the gradual reopening of markets, and the reactivation of the economy.

Figure 3. Regional Economic Sentiment Index for Colombia (SENTreg)
(quarterly moving average)

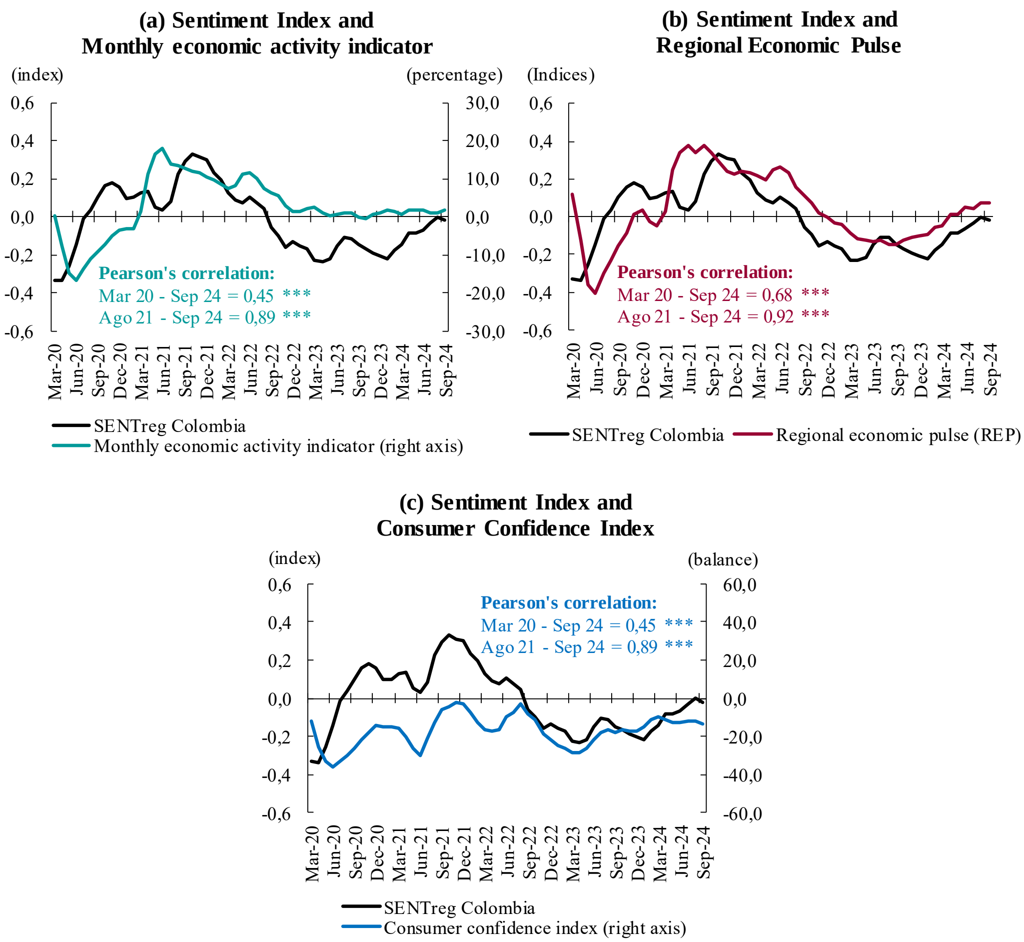


Source: Authors' calculations based on national and regional news.

[6] For the Southeast region, we do not present its results due to high and persistent volatility.
[7] The uncertainty measures for the regions attained zero consecutively in some periods.

In October 2021, optimism reached a peak as the vaccination plan continued to progress. This optimism followed heightened tensions caused by the national strike, which began in late April and persisted until June 2021. At the end of February 2022, Russia's invasion of Ukraine deepened concerns about supply chains, just as the world was emerging from the pandemic. During this time, oil prices rose, as did prices for durable goods and agricultural inputs. By September 2022, sentiment turned negative due to rising inflation and the depreciation of the Colombian peso against the dollar. From then on, pessimism persisted until the first half of 2024, reflecting the impact of high inflation, elevated transport costs, increasing fuel prices, and deteriorating consumer confidence, among other domestic factors (Figure 3). When SENTreg showed signs of improvement, this trend reversed in August and September 2024, due to a transporters' strike linked to diesel price increases.

Figure 4. Sentiment Index and key economic indicators

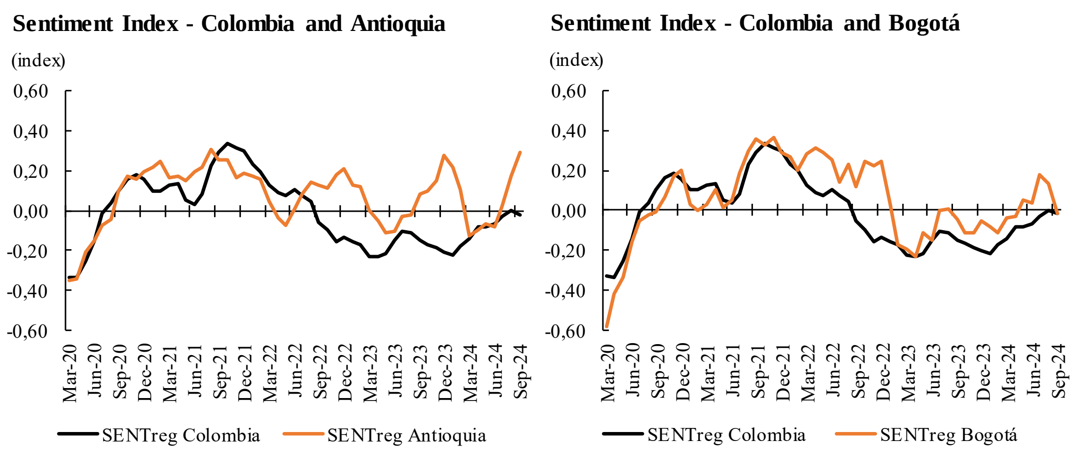


*** statistically significant correlations at the 1% significance level.
Note: the correlation is calculated for two periods. The first is from March 2020 to the current month, and the second is from August 2021 onward. The split accounts for a drop in correlation between April and July 2021, when the National Strike caused divergence across series. The Sentiment Index captured immediate reactions to news, while traditional economic indicators showed rebounds driven by the low COVID-19 comparison base.
Source: Authors' calculations based on news, (a) DANE, (b) Banco de la República, and (c) Fedesarrollo.

The SENTreg, compared to the Economic Monitoring Indicator (ISE in Spanish) measured by the National Administrative Department of Statistics (DANE in Spanish), exhibited some similarities in its trajectory, as did the Regional Economic Pulse (REP) indicator (Figure 4.A. and 4.B.). The REP, estimated by Banco de la República, is a monthly measure developed to monitor the dynamics of six economic activities at the regional and national levels[8]. The trends diverge from April to June 2021 during the national strike due to statistical effects in the ISE and the REP, explained by the low comparison basis caused by the pandemic, while the SENTreg reflected a negative tone in the current situation. On the other hand, the SENTreg, compared with the Consumer Confidence Index (CCI), built from surveys, showed co-movement in trends throughout the period (Figure 4.C.). The last relation aligns with literature, particularly the research by Cruz et al. (2020; 2022) and Shapiro et al. (2020). The correlations with the three time series improved without the national strike (Figure 4.A., 4.B., and 4.C.).

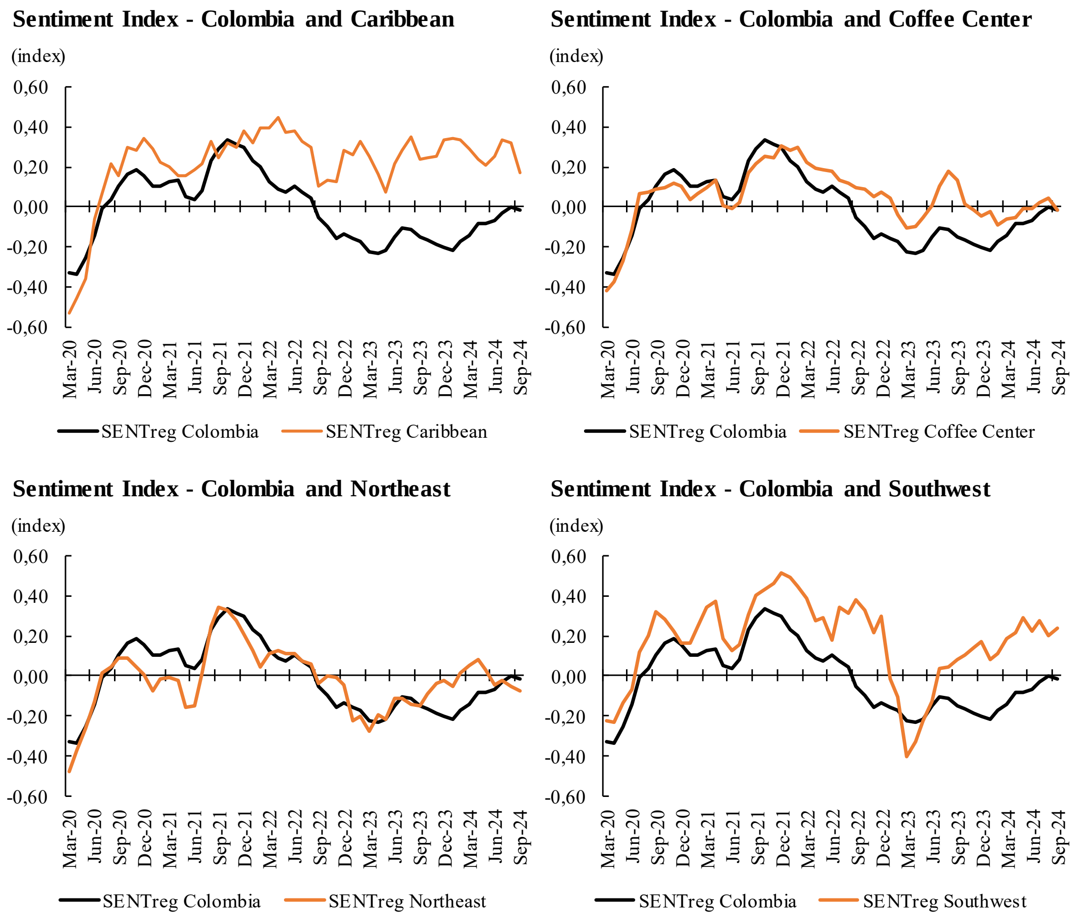
Sentiments by region largely mirrored SENTreg patterns, with periods of extreme shocks and some differences driven by local issues (Figure 5). Sentiment in Bogotá, the Caribbean, and the Northeast was more negatively affected by COVID-19 than in other regions. When restrictive quarantines ended, all regions saw increased positive sentiment, although recovery rates varied. Optimism slowed during the second wave of COVID-19 and the 2021 national strike, with differing impacts across regions.

Figure 5. National and regional economic sentiment indices (SENTreg)
(quarterly moving average)



[8] The Regional Economic Pulse indicators and their report draw on surveys of business owners and managers who assess the annual dynamics of their economic activity, complemented by available statistical information. The report is produced by the Regional Economies Section of the Technical and Economic Information Department at Banco de la República. Available at: https://suameca.banrep.gov.co/estadisticas-economicas/informacionSerie/500031/economia_regional_pulso_economico_regional_por_regiones

Figure 5. *Cont.*

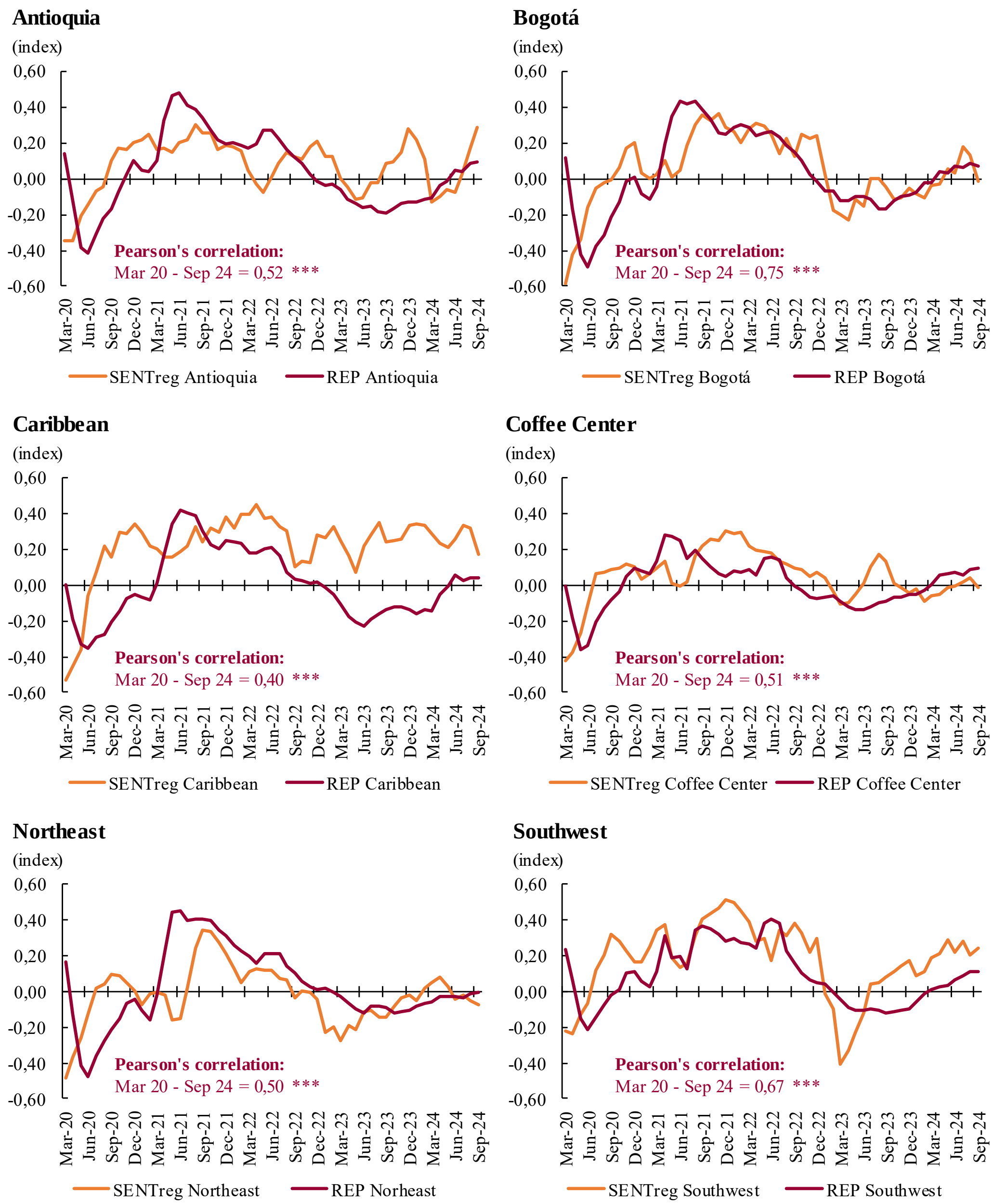


Source: Authors' calculations based on national and regional news.

The strike particularly affected Bogotá, the Coffee Center, Northwest, and Southwest, where sentiment indices captured the impact of severe blockades, production was halted, essential goods could not be transported, and both internal and external trade suffered interruptions. A gradual return to normality led to higher optimism, especially in the Caribbean, where sentiment remained positive through 2024. In contrast, the Northeast recorded mainly negative sentiment from September 2022 through January 2024.

The regional sentiment indices, compared with the REP, showed similar trends, particularly in Bogotá, the Coffee Center, the Northeast, and the Southwest (Figure 6). The REP indicator is calculated for the same regions of the sentiment. The trends can differ based on methodological factors; for example, in April 2021, positive results in the REP were influenced by a low comparison base, while the Sentiment Index captured the negative impact of the national strike in real-time. Despite methodological differences, in most regions the sentiment indices reflected the downward trend in the economy, as measured by the REP, since the second semester of 2022. In contrast, the Caribbean maintained positive sentiment, unlike its REP, marking an exceptional deviation from the rest.

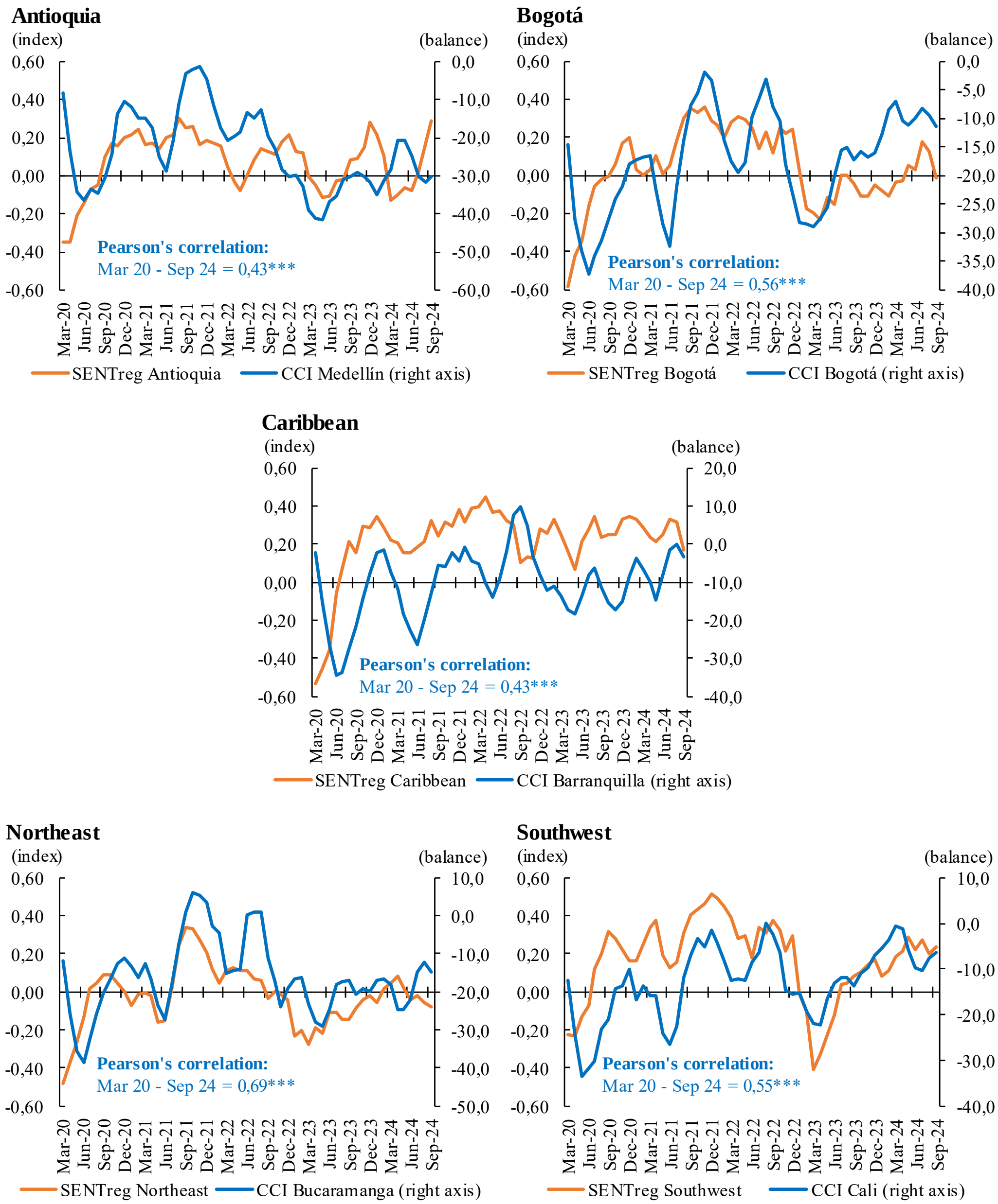
Figure 6. Sentiment Index (SENTreg) and Regional Economic Pulse (REP)
(quarterly moving average)



*** statistically significant correlations at the 1% significance level.
Source: Authors' calculations based on national and regional news and Banco de la República.

Among the survey-based indicators analyzed, the CCI from Fedesarrollo showed the highest correspondence with regional sentiment trends (Figure 7). The CCI measures consumer confidence in the current and future economic outlook. The confidence index is calculated for Bogotá, Medellín, Cali, Barranquilla, and Bucaramanga. The similarity in trends between the CCI and the sentiment indices stems from both metrics capturing behavioral factors that influence economic decision-making. In fact, both reflect economic agents' perceptions and expectations related to macroeconomic conditions and economic behavior. Empirical evidence in the literature, such as Baker et al. (2016) and Shapiro et al. (2020), shows that news-based sentiment indices move closely with confidence indices, especially during economic crises. Thus, both indices can provide important, timely information to central banks and policymakers to assess economic trends and anticipate downturns or recoveries.

Figure 7. Sentiment Index (SENTreg) and Consumer Confidence Index (CCI)
(quarterly moving average)

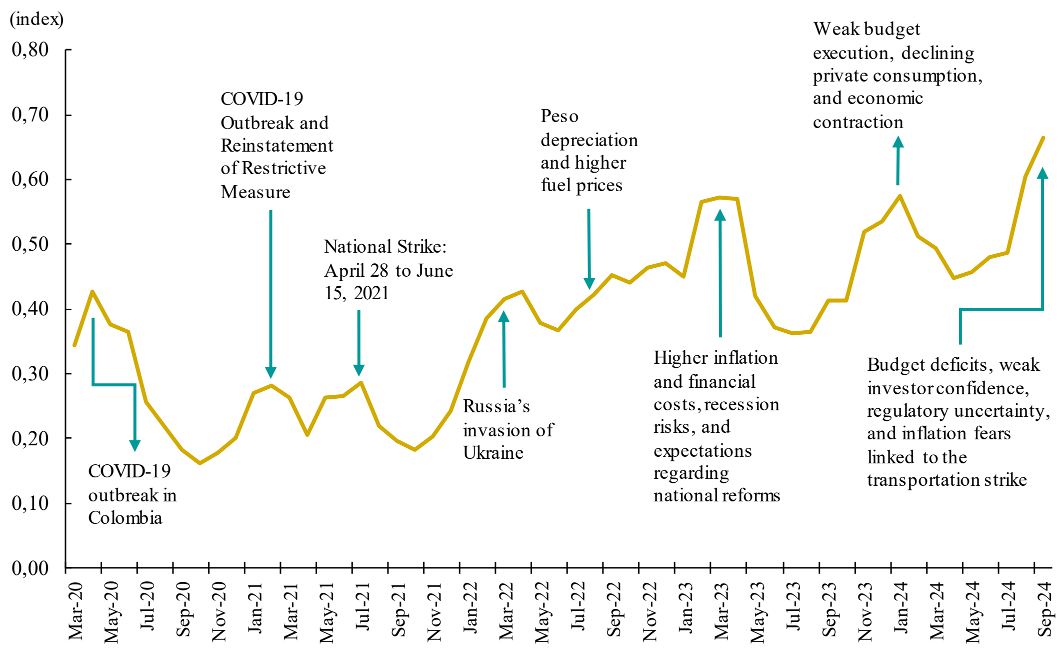


*** statistically significant correlations at the 1% significance level.
Source: Authors' calculations based on national and regional news and Fedesarrollo.

5.2. Uncertainty Index

The Uncertainty Index of Colombia (UNCERTreg) shows fluctuations in risk perceptions across events throughout the study period (Figure 8). Among some specific events of higher uncertainty were the appearance of Covid-19 in the country (March 2020), the outbreaks of contagion, and the return to quarantines (January 2021), the national strike (May 2021), the war in Ukraine (February 2022), the devaluation of the Colombian peso against the U.S. dollar, and the beginning of increases in fuel tariffs (July 2022), peak of inflation levels (March 2023). By the end of the study period, UNCERTreg exhibited heightened responsiveness to short-term volatility, particularly during episodes of economic stress.

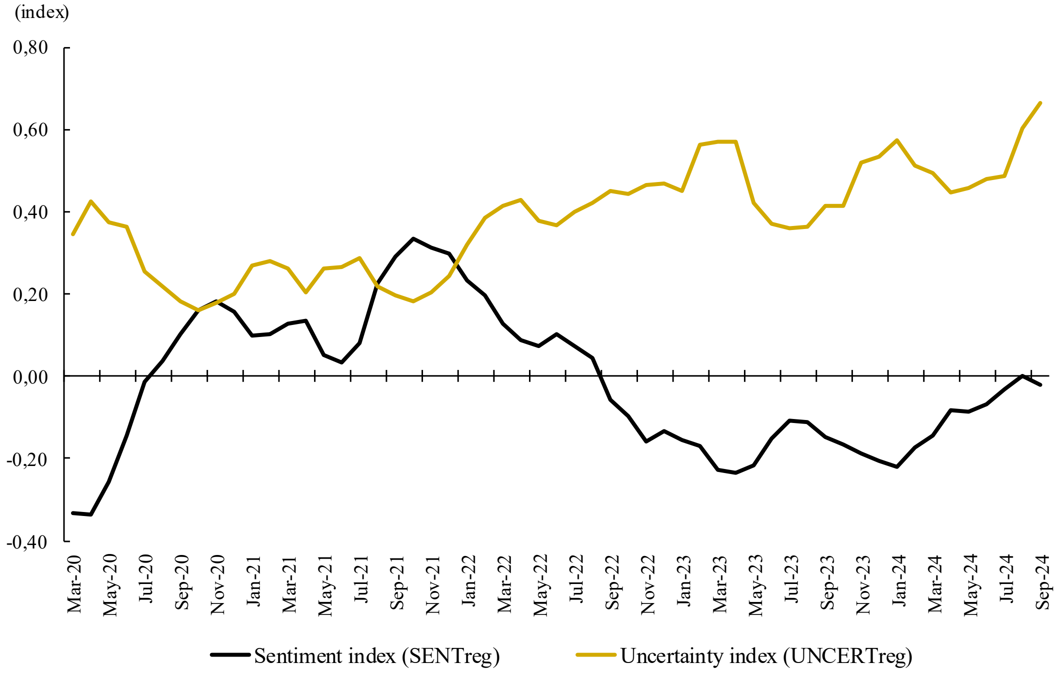
Figure 8. Regional Economic Uncertainty Index for Colombia (UNCERTreg)
(quarterly moving average)



Source: Authors' calculations based on national and regional news.

The trajectories of the SENTreg and the UNCERTreg show mirror behavior, with both trends converging during periods of increasing positive sentiment and lower uncertainty (Figure 9). On the other hand, contrary movements in the indices reflect negative sentiment and higher levels of uncertainty. Some specific events stand out when both trends widen, such as the beginning of the pandemic (April 2020), the national strike (May 2021), the beginning of the war in Ukraine (February 2022), and the rise of inflation and depreciation of the local currency (July 2022), among others.

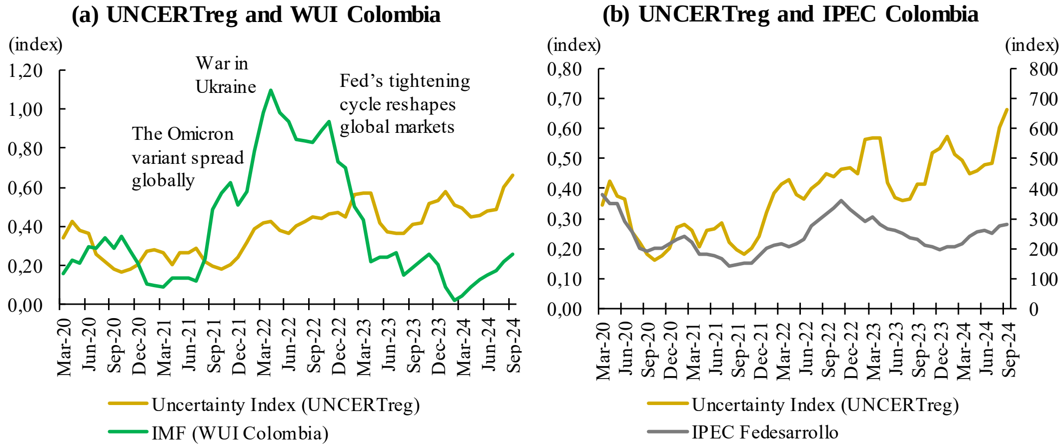
Figure 9. Regional Economic Sentiment and Uncertainty Indices for Colombia
(quarterly moving average)



Source: Authors' calculations based on national and regional news.

Analyzing the UNCERTreg versus the IMF's WUI for Colombia, it appears that the former shows an upward trend since November 2021, reaching higher levels of uncertainty in September 2024, well above those observed during the pandemic (Figure 10). In Colombia's WUI, uncertainty rose with the initial spread of the Omicron variant, and was subsequently exacerbated by the global turmoil resulting from the war in Ukraine. Then Colombia's WUI showed lower levels of uncertainty since April 2023, diverging from the UNCERTreg's path. The differences are mainly explained in the corpus, as Colombia's WUI relies on the EIU's technical reports, written in English. On the other hand, analyzing UNCERTreg and the IPEC highlights the growing gap since December 2021, primarily due to differences in the criteria used to select articles for the corpus of study and in the number of media sources (Figure 11).

Figure 10. Uncertainty Index and other measures of uncertainty in Colombia
(quarterly moving average)



Note: World Uncertainty Index (WUI) for Colombia, International Monetary Fund (IMF). Computed by counting the percent of the word "uncertain" (or its variant) in the Economist Intelligence Unit country reports. Índice de Incertidumbre de la Política Económica en Colombia (IPEC), Fedesarrollo. Constructed by counting words related to political or economic uncertainty in news articles from El Tiempo newspaper. Source: Authors' calculations based on national and regional news, IMF, and Fedesarrollo.

6. Using Sentiment and Uncertainty Indices in nowcasting

Economic nowcasting traditionally depends on quantitative and official indicators derived from real-sector activity. However, these measures often fail to capture the qualitative and forward-looking dimensions of economic behavior reflected in public discourse and business sentiment as conveyed through news media. The integration of text-based indicators, such as the Sentiment and Uncertainty Indices, facilitates assessing whether information embedded in economic news offers additional insights into short-term dynamics beyond those available from conventional data sources.

Recent literature demonstrates that news-based sentiment and uncertainty indicators improve real-time assessments of economic activity. Algaba et al. (2020) highlight that a central aspect of employing qualitative sentiment and uncertainty measures in econometric analysis is their ongoing validation, particularly through the evaluation of out-of-sample statistical and economic performance of model-based predictions.

Multiple studies support these findings. Barbaglia et al. (2023, 2024) and Aprigliano et al. (2023) demonstrate that sentiment measures derived from newspaper text improve short-term forecasts of GDP and industrial production relative to models that rely exclusively on traditional data. Algaba et al. (2021), Ashwin et al. (2024), and Okuneva (2024) report systematic improvements in nowcasting accuracy when text-derived indicators are integrated with conventional macroeconomic predictors. Kalamara et al. (2022) find that including newspaper text in macroeconomic forecasting models significantly improves prediction accuracy. Chen et al. (2023) show that textual features from extensive financial news corpora improve the detection and prediction of financial crises using machine learning techniques. Sharpe et al. (2023) demonstrate that narrative-based sentiment offers substantial incremental predictive power for U.S. macroeconomic forecasts beyond standard time-series indicators. Zheng et al. (2024) further find that combining textual information with traditional macroeconomic data within a mixed-frequency nowcasting framework yields superior performance.

This section evaluates the relevance of SENTreg and UNCERTreg as complementary inputs for nowcasting economic activity. The aim is to determine whether sentiment and uncertainty-based information improve the predictive accuracy of standard models when integrated with traditional indicators. More specifically, the analysis examines the incremental value of incorporating newspaper sentiment indicators in a formal nowcasting horse race between models using only baseline indicators and those augmented with Sentiment and Uncertainty Indices. The results seek to establish the extent to which these indices serve as early, high-frequency measures that capture real-time perceptions of economic conditions and reinforce empirical nowcasting frameworks.

6.1. Nowcasting setup

The evaluation of whether news-based sentiment and uncertainty indicators improve real-time estimates of Colombia's economic activity employs a four-stage procedure based on dynamic factor models and ARMAX specifications[9]. This process is summarized in Diagram 2. The analysis considers both the monthly ISE and quarterly GDP using two information sets that reflect varying degrees of data timeliness. The first set includes "3-day" supply-side indicators, which are traditionally used to monitor activity and provide a three-day lead over official releases. The second set consists of "13-day" supply-side indicators, primarily survey-based or alternative high-frequency proxies, offering a 13-day informational advantage. A comprehensive list of the selected time series is provided in Annex 4.

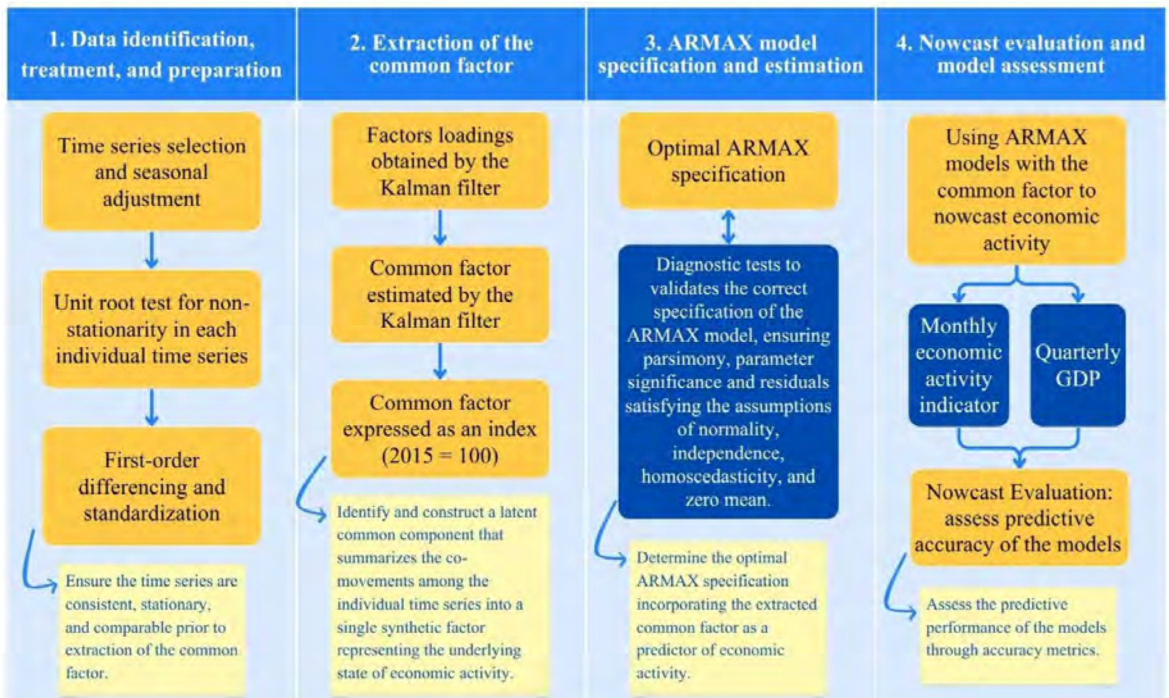
This design with two data sets ensures that the estimated predictive contributions of Sentiment and Uncertainty Indices are not tied to a specific informational structure. Confronting text-based indices with datasets of varying timeliness and information strength allows testing whether their value-added persists across heterogeneous nowcasting contexts. If improvements in nowcasting accuracy remain robust across both settings, the contribution of sentiment and uncertainty can be interpreted as systematic and broadly applicable. This approach is consistent with recent evidence showing that the effectiveness of text-derived indicators depends on the informational structure of the underlying data used in the models (Barbaglia et al., 2024; Zheng et al., 2024; Kalamara et al., 2022).

In the first stage, the time series in each set are seasonally adjusted, tested for unit roots, differenced when necessary, and standardized to ensure comparability. The second stage

[9] For a detailed discussion of dynamic factor models, see Stock and Watson (2011), and for their application to tracking Colombia's economic activity, see Cote-Barón et al. (2023).

extracts latent common factors from each information set using a Kalman-filter representation of a dynamic factor model. For further methodological details, see Stock and Watson (2002) and Vidal et al. (2017). Six-monthly factors are obtained: three from the 3-day set (baseline, baseline + sentiment, baseline + sentiment + uncertainty) and three analogues from the 13-day set. Each factor is rescaled to an index with 2015 as the base year, mirroring the official scaling of the ISE and GDP series.

Diagram 2. Workflow for extracting a common factor and evaluating its nowcasting performance using ARMAX models



Source: Authors' elaboration.

The third stage embeds these common-factor indices into ARMAX models used to nowcast monthly and quarterly activity[10]. Four optimal ARMAX specifications are selected, two based on the 3-day factors and two based on the 13-day factors, each estimated for both the ISE and GDP. Outlier dummies, temporary change (TC), and additive outlier (AO) were included when statistically significant. Model selection follows a rigorous multi-criterion approach based on AIC, BIC, and HQ rankings, complemented by diagnostic checks ensuring parameter significance, white-noise residuals, and compliance with normality, homoscedasticity, and independence assumptions.

The fourth stage evaluates the models' out-of-sample performance over a 21-month, 7-quarter horizon. Predictive accuracy is assessed through absolute metrics (RMSE, MAE,

[10] Because all variables are rendered stationary before estimation, the appropriate specification is ARMAX rather than ARIMAX.

MSE), relative metrics (MAOE, RMSPE, CSP), error-diagnostic measures (Theil's U and U2), and systematic bias indicators (MFE, MPE)[11]. Finally, differences in predictive performance between models using only baseline time series and those complemented with sentiment and uncertainty are formally tested using the Diebold–Mariano and Harvey, Leybourne, and Newbold tests. This framework provides a comprehensive evaluation of the incremental nowcasting value of news-based sentiment and uncertainty measures for the Colombian economy.

6.2. Common factor and nowcasting models

The application of the Kalman filter in this analysis is justified by its optimization properties, which facilitate the integration of unbalanced time-series datasets. As highlighted by Foroni et al. (2013), Doz et al. (2011), Bańbura and Modugno (2010), and Jungbacker and Koopman (2009), the Kalman filter utilizes the complete information set, even when faced with ragged-edge observations and incomplete cross-sections. This capability is particularly important in real-time contexts and large-scale dynamic factor models. Accordingly, the common factor is initialized in January 2005 to coincide with the starting points of the monthly ISE and quarterly GDP series, using 2015 as the reference year. This approach ensures that the Sentiment and Uncertainty Indices are incorporated into a common factor with a time-series length identical to that of the target variables, despite their shorter historical records. The predictive value of these indices is thus assessed relative to benchmark indicators with substantially longer histories. Consequently, the resulting nowcast assessment is more coherent and reliable than alternative approaches that would directly incorporate the Sentiment and Uncertainty Indices, which would be limited by the shorter duration of these series.

Table 2 reports the contributions of each variable to the common factor extracted via the Kalman filter under three model specifications: Baseline, Baseline plus Sentiment, and Baseline plus Sentiment and Uncertainty, for both 3-day and 13-day information sets. The factor loadings indicate that the Sentiment and Uncertainty Indices make significant contributions to the latent common factor that summarizes economic activity. The Sentiment Index displays positive and economically meaningful loadings across both information sets, suggesting that improvements in news-based sentiment are associated with expansions in the underlying economic cycle. Conversely, the Uncertainty Index consistently exhibits negative loadings, consistent with theoretical expectations that higher uncertainty suppresses investment, production, hiring, and overall economic momentum, and therefore moves inversely with the latent factor representing economic activity.

[11] The nowcasting accuracy metrics are defined as follows: root-mean-square error (RMSE); mean absolute error (MAE); mean squared error (MSE); mean absolute percentage error (MAPE); root-mean-squared percentage error (RMSPE); correct-sign prediction (CSP); Theil's U and U2 inequality coefficients; mean forecast error (MFE); and mean percentage error (MPE).

Table 2. Factor loadings of the time series contributing to the common factor

Time series used to nowcast Colombia's economic activity with a 3-day lead				
Series name	Description	Factor loadings by Kalman filter		
		Baseline	Baseline + Sentiment	Baseline + Sentiment + Uncertainty
a1	Supply of the agricultural sector	1,0	0,9	1,0
a2	Milk collection	0,5	0,5	0,5
b1	Mining and quarrying	5,4	5,3	5,4
c1	Manufacturing	9,2	9,0	9,2
de1	Electricity, gas, and water supply	6,2	6,0	6,1
f1	Gray cement	10,1	9,9	10,0
f2	Ready-Mixed Concrete	8,0	7,8	7,9
g1	Wholesale and retail trade	7,9	7,7	7,8
g2	New vehicle sales	8,5	8,3	8,4
h1	Land transport	7,3	7,1	7,3
h2	Freight transport	4,9	4,8	4,9
i1	Accommodation	3,6	3,5	3,5
k1	Financial system disbursements	3,6	3,5	3,6
l1	New residential sales	7,8	7,6	7,7
o1	Public administration and defence	2,2	2,1	2,1
r1	Social and cultural activities	3,4	3,3	3,4
ss1	Service activities	3,9	3,8	3,9
xi	Tax revenue	1,9	1,8	1,8
per	Regional Economic Pulse	4,6	4,5	4,6
se1	Sentiment index		2,4	2,5
in1	Uncertainty index			-1,8

Time series used to nowcast Colombia's economic activity with a 13-day lead				
Series name	Description	Factor loadings by Kalman filter		
		Baseline	Baseline + Sentiment	Baseline + Sentiment + Uncertainty
a1	Supply of the agricultural sector	1,6	1,6	1,6
a2	Milk collection	0,7	0,6	0,7
b2	Mining exports	4,1	4,0	4,0
c1	Leading indicator of industry	9,1	8,8	9,1
c3	Cardboard Box Index	5,5	5,3	5,5
d1	Electricity demand	4,5	4,3	4,4
f1	Gray cement	11,6	11,2	11,4
g1	Credit and debit card spending	6,1	5,9	6,1
g2	New vehicle sales	10,1	9,6	9,9
h1	Land transport	9,3	9,0	9,3
h2	Freight transport	6,5	6,3	6,5
k1	Financial system disbursements	4,7	4,5	4,7
l1	New residential sales	9,8	9,5	9,7
o1	Public administration and defence	2,7	2,6	2,6
mnrs1	Service activities	4,9	4,7	4,8
xi	Tax revenue	2,3	2,2	2,2
per	Regional Economic Pulse	6,5	6,3	6,5
se1	Sentiment index		3,5	3,6
in1	Uncertainty index			-2,5

Note: the factor loadings were normalized to sum to 100. Source: Authors' calculations.

Both indices exhibit greater magnitudes in the 13-day dataset, indicating that text-derived indicators become more informative when combined with richer data environments that include survey-based or qualitative variables. This finding aligns with recent research demonstrating that the predictive value of textual measures is contingent on the structure and timeliness of the accompanying data (Barbaglia et al., 2024; Zheng et al., 2024; Kalamara et al., 2022). Collectively, these results demonstrate that Sentiment and Uncertainty Indices offer complementary signals that enhance the informational content of the common factor.

The selection of the optimal ARMAX specifications for nowcasting Colombia's monthly ISE and quarterly GDP using the 3-day and 13-day information sets is summarized in Annex 5a and 5b. Following a model-selection strategy consistent with Xie (2023), the specifications highlighted in green jointly minimize the AIC, BIC, and HQ criteria and pass all diagnostic checks, including parameter significance, absence of serial correlation, residual normality, homoscedasticity, zero-mean errors, and i.i.d. structure.

The selected ARMAX (4,2) (0,0) and ARMAX (2,0) (0,0) specifications for the monthly ISE and quarterly GDP, using the 3-day and 13-day information sets, respectively, constitute statistically robust, well-identified, and dynamically consistent models appropriate for nowcasting Colombia's economic activity. Importantly, the fact that the optimal ARMAX order is the same for the ISE and for quarterly GDP within each information set reinforces internal coherence: the underlying dynamics of the common factor extracted from each dataset remain stable across monthly and quarterly frequencies. Overall, the selected ARMAX models provide a rigorous econometric foundation for evaluating whether Sentiment and Uncertainty Indices enhance predictive accuracy. The selected specifications balance parsimony, statistical soundness, and forecasting relevance, ensuring that the nowcast results reflect genuine informational improvements rather than model-selection artifacts.

6.3. Out-of-sample accuracy

Figure 11 presents the out-of-sample nowcast evaluation for ARMAX models, using forecasts from January 2023 to September 2024. The analysis follows best practices in nowcast-accuracy research, emphasizing comprehensive model evaluation through absolute, relative, and error-structure metrics as detailed by Buturac (2022).

The empirical evaluation of the nowcasting models reveals three main findings about the influence of news-based sentiment and uncertainty indices. First, most metrics show that including SENTreg and UNCERTreg improves predictive accuracy compared to models without these indices. These improvements are reflected in absolute accuracy measures (RMSE, MAE, MSE) as well as in relative accuracy statistics (MAPE, RMSPE). This indicates that the observed gains reflect real reductions in forecast errors, not just differences in scale.

Second, models using the 13-day information set show the greatest improvements. These models consistently post the lowest errors in both absolute (RMSE, MAE, MSE) and relative (MAPE, RMSPE) terms, along with reduced systematic bias (MFE, MPE). This suggests that

Sentiment and Uncertainty Indices offer more value when predictors are more timely or forward-looking. This result is consistent with previous studies of text-enhanced nowcasting. Supporting this finding, recent research shows that text-based indicators are most effective when used with survey-based 'soft' data, rather than relying only on 'hard' macroeconomic indicators. For example, Bortoli et al. (2018) found that a media-based sentiment index significantly improved French GDP forecasts relative to both pure autoregressive models and AR models supplemented with the Insee Business Climate indicator. Likewise, Aprigliano et al. (2023) found that text- and survey-based indicators are highly complementary, while van Dijk and de Winter (2023) showed that news-based topics often add information not present in official hard data releases.

Third, the results for quarterly GDP are less consistent across the different evaluation metrics. While some indicators improve when sentiment and uncertainty are added, others change only slightly or even worsen. Such mixed results are typical in quarterly nowcasting, where lower data frequency, more aggregation, and fewer observations reduce the added value of qualitative indicators. This pattern aligns with the literature, which shows that text-based measures perform better at higher frequencies (Ashwin et al., 2024; Algaba et al., 2021).

Notably, models with Sentiment and Uncertainty Indices achieve higher correct-sign percentages, showing a greater ability to identify turning points and short-term cycles. This aligns with evidence from Ashwin et al. (2024), Kalamara et al. (2022), and Thorsrud (2016), who found that text-based indicators improve nowcasting by adding forward-looking and real-time signals. Additionally, Theil’s U and U2 coefficients, which measure forecast accuracy relative to simple models, usually approach or fall below 1 for models with Sentiment and Uncertainty Indices. This means these models have better error structures compared to basic benchmarks.

Overall, the evidence suggests that Sentiment and Uncertainty Indices add meaningful predictive value, especially when used with timely, richer data and when nowcasting higher-frequency activity such as monthly ISE. Though the improvements are not always consistent, especially for quarterly GDP, the overall pattern supports using news-based indicators as high-frequency sources that complement traditional predictors in real-time.

Figure 11. Nowcasting evaluations for the ARMAX models

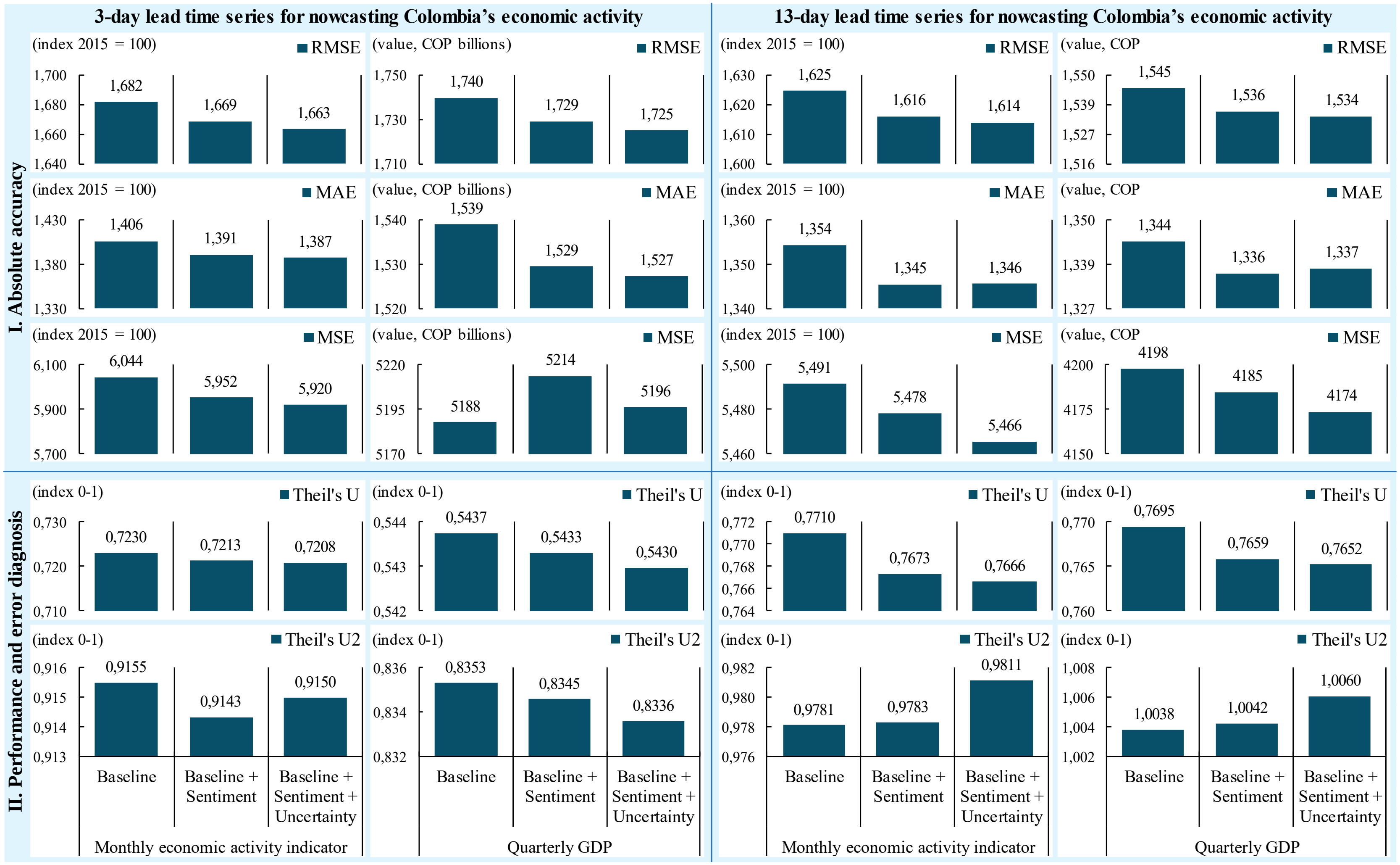
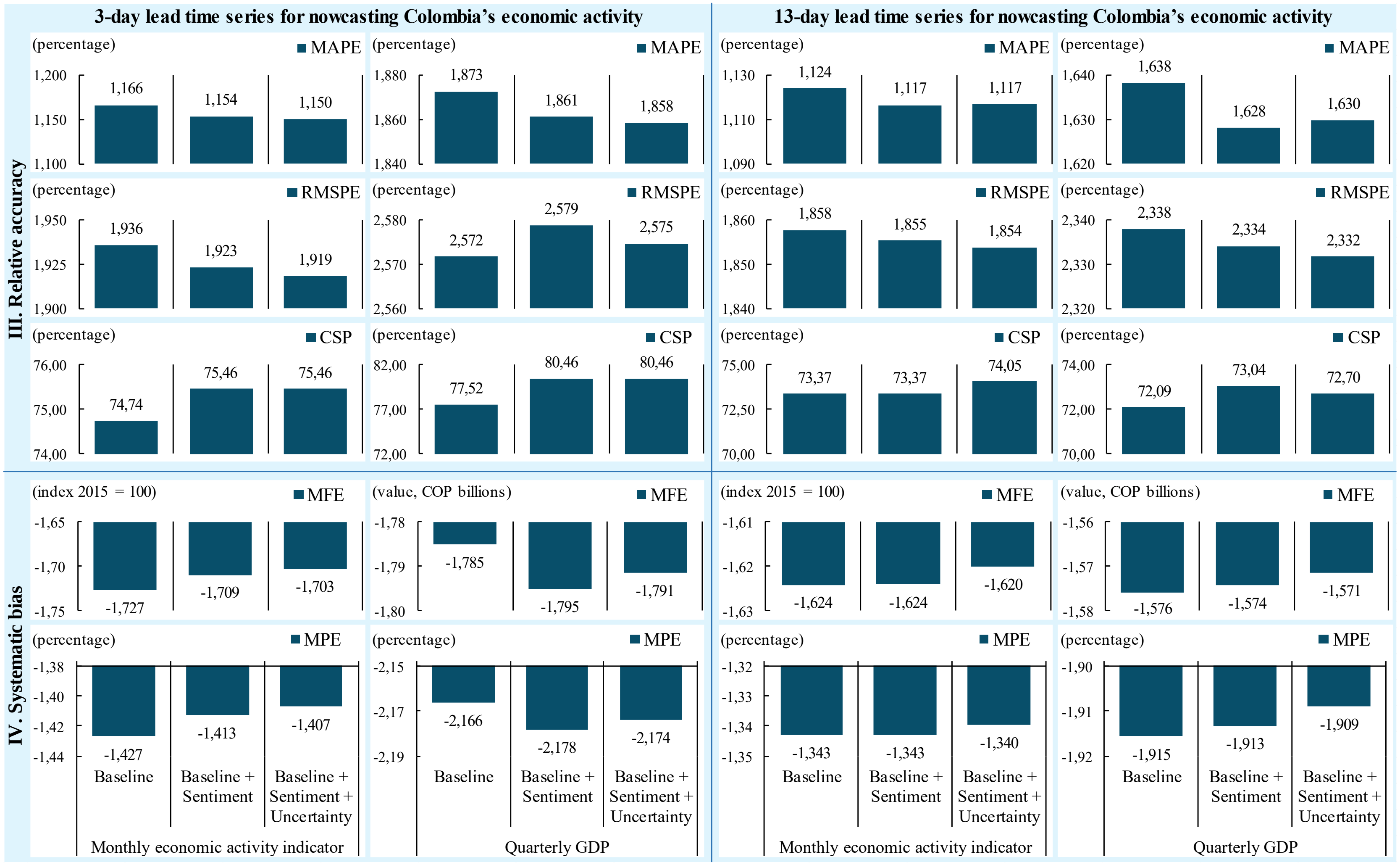


Figure 11. *Cont.*



Source: Authors' calculations.

6.4. Nowcast comparison test

To rigorously compare ARMAX forecasting models, it is important to assess whether observed differences in accuracy are statistically significant. While accuracy metrics such as RMSE, MAE, MAPE, and Theil's U suggest improvements when Sentiment and Uncertainty Indices are included, these metrics alone do not establish predictive gains. Therefore, formal statistical comparison tests are necessary. As shown in Table 3, these tests frequently reject the null hypothesis of equal accuracy at the 5% significance level. This indicates that ARMAX models enhanced with Sentiment and Uncertainty Indices consistently outperform the baseline, confirming that news-based indicators provide statistically meaningful improvements in predictive performance.

The Diebold-Mariano (DM) and Harvey, Leybourne, and Newbold (HLN) tests play a key role in validating these findings. The DM test is commonly used to compare forecasting models, but it may be less reliable with small sample sizes, a common issue in real-time nowcasting (Harvey et al., 1997). The HLN adjustment addresses this limitation by correcting the variance of the loss differential, thus improving reliability in cases with limited data. Using both tests strengthens the evaluation framework and increases confidence that the observed advantages of enhanced models are not artifacts of small-sample bias. In summary, Table 3 demonstrates that augmenting models with sentiment and uncertainty information yields predictive gains beyond those of traditional economic indicators, with statistical significance.

Table 3. Comparison of nowcasting accuracy

3-day lead time series for nowcasting Colombia's economic activity
Monthly economic activity indicator

Model 1	Model 2	DM Statistic	DM p-value	DM Result	DM Decision (5%)	HLN Statistic	HLN p-value	HLN Result	HLN Decision (5%)
		Diebold-Mariano (DM) Test				Harvey, Leybourne, and Newbold (HLN) test			
Baseline	Baseline + Sentiment	14,08	0,0000	p-value < α DM > 0	Reject H_0 → Model 2 better	15,66	0,0000	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline	Baseline + Sentiment + Uncertainty	9,05	0,0000	p-value < α DM > 0	Reject H_0 → Model 2 better	10,07	0,0000	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline + Sentiment	Baseline + Sentiment + Uncertainty	3,25	0,0012	p-value < α DM > 0	Reject H_0 → Model 2 better	3,62	0,0017	p-value < α HLN > 0	Reject H_0 → Model 2 better

3-day lead time series for nowcasting Colombia's economic activity
Quarterly GDP

Model 1	Model 2	DM Statistic	DM p-value	DM Result	DM Decision (5%)	HLN Statistic	HLN p-value	HLN Result	HLN Decision (5%)
		Diebold-Mariano (DM) Test				Harvey, Leybourne, and Newbold (HLN) test			
Baseline	Baseline + Sentiment	13,46	0,0000	p-value < α DM > 0	Reject H_0 → Model 2 better	14,98	0,0000	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline	Baseline + Sentiment + Uncertainty	8,84	0,0000	p-value < α DM > 0	Reject H_0 → Model 2 better	9,84	0,0000	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline + Sentiment	Baseline + Sentiment + Uncertainty	3,15	0,0016	p-value < α DM > 0	Reject H_0 → Model 2 better	3,51	0,0022	p-value < α HLN > 0	Reject H_0 → Model 2 better

13-day lead time series for nowcasting Colombia's economic activity
Monthly economic activity indicator

Model 1	Model 2	DM Statistic	DM p-value	DM Result	DM Decision (5%)	HLN Statistic	HLN p-value	HLN Result	HLN Decision (5%)
		Diebold-Mariano (DM) Test				Harvey, Leybourne, and Newbold (HLN) test			
Baseline	Baseline + Sentiment	5,16	0,0000	p-value < α DM > 0	Reject H_0 → Model 2 better	5,74	0,0000	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline	Baseline + Sentiment + Uncertainty	2,30	0,0213	p-value < α DM > 0	Reject H_0 → Model 2 better	2,56	0,0186	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline + Sentiment	Baseline + Sentiment + Uncertainty	0,07	0,9446	p-value > α	Fail to reject H_0	0,08	0,9391	p-value > α	Fail to reject H_0

13-day lead time series for nowcasting Colombia's economic activity
Quarterly GDP

Model 1	Model 2	DM Statistic	DM p-value	DM Result	DM Decision (5%)	HLN Statistic	HLN p-value	HLN Result	HLN Decision (5%)
		Diebold-Mariano (DM) Test				Harvey, Leybourne, and Newbold (HLN) test			
Baseline	Baseline + Sentiment	5,92	0,0000	p-value < α DM > 0	Reject H_0 → Model 2 better	6,58	0,0000	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline	Baseline + Sentiment + Uncertainty	2,62	0,0089	p-value < α DM > 0	Reject H_0 → Model 2 better	2,91	0,0086	p-value < α HLN > 0	Reject H_0 → Model 2 better
Baseline + Sentiment	Baseline + Sentiment + Uncertainty	0,07	0,9476	p-value > α	Fail to reject H_0	0,07	0,9424	p-value > α	Fail to reject H_0

Note: α = 0,05. Null hypothesis H0: models have equal predictive accuracy. A positive DM / HLN statistic indicates Model 1 yields a larger mean squared forecast error than Model 2.
Source: Authors' calculations.

Conclusions

This study introduces two new indices for Colombia, the Sentiment Index and the Uncertainty Index, that track economic perceptions and risks through real-time press analysis. The Sentiment Index reflects optimism or pessimism in response to major events. The Uncertainty Index captures perceptions of economic risks. Both indices have predictive value for economic trends.

This research establishes Colombia's first national news-based economic sentiment indicator, which converts regional qualitative narratives into quantitative indices through adaptable statistical methods. These indices yield timely, actionable insights, equipping central banks and policymakers to assess economic conditions and forecast downturns or recoveries.

International evidence shows that sentiment indices align with survey-based confidence measures and key economic metrics, especially during shocks. Consequently, Colombia's Sentiment Index is essential for tracking economic changes and forecasting downturns or recoveries.

Integrating news-based Sentiment and Uncertainty Indices into nowcasting frameworks significantly improves Colombia's short-term economic predictions. These improvements are consistently confirmed by statistical evidence across all prediction metrics.

Integrating forward-looking news data into traditional models improves the detection of emerging economic trends and turning points. This enhances real-time monitoring and predictive power for policymakers, and the approach can be tested for robustness across sectors, regions, topics and textual sources.

Advances in data analytics and artificial intelligence are enabling researchers to develop sentiment and uncertainty indices that provide timely tools for monetary policymakers. This includes designing a Colombia-specific dictionary based on relevant linguistic patterns in academic and technical content for the Central Bank.

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Annexes

Annex 1. National and regional digital media

90 minutos	El Heraldo	Meridiano Regional
Al Poniente	El Isleño	Mi Diario
Archipielago Press	El Norte	Mi Oriente
BC Noticias	El nuevo siglo	Nación Paisa
Boyaca7dias	El País	NotiBarranquilla
Cali Buenas Noticias	El Pereriano	Noticias Caracol
Canal RED+	El Quindiano	Noticias del Meta
Caracol Radio	El Rionegrero	Noticias Ya
Cesar Noticias	El Suroeste	Noticiero del Llano
Contexto Ganadero	El Tiempo	Noticiero Macarena
Diario de Occidente	El Universal	Onda Opita
Diario del Cauca	Extrategia Medios	OPA Noticias
Diario del Cesar	Forbes Colombia	Pasto Extra
Diario del Huila	Guajira News	Periódico del Meta
Diario del Norte	Hora 13 noticias	Portafolio
Diario del Sur	Hoy diario del Magdalena	Portal portuario
Diario El Nuevo Día	HSB Noticias	RCN Radio
Diario La Economía	La Crónica del Quindío	RíoNoticias
Diario La Libertad	La FM	Risaralda Hoy
Diario La Nación	La Gran Noticia	Semana
Diarioriente	La Guajira	Soy de Buenaventura
Eje21.com	La Nota Económica	Ultimahoraboyaca
El Colombiano	La República	Valora Analitik
El Diario (Pereira)	Las Chivas del Llano	Vanguardia
El Diario del Llano	Llano Al Mundo	Villavonoticias
El Espectador	Llano Siete Días	Vive el meta

Source: Authors' elaboration.

Annex 2. Economic activities

Agriculture
Manufacturing
Construction
Wholesale, retail trade, restaurants and hotels
Transport
Financial and insurance activities
Mining
Accommodation and food services activities
Tourism
Telecommunications
Education
Health
Public Services
Market Labor
Inflation
Arts, entertainment, and recreation activities
Global Context
Other Activity

Source: Authors' elaboration.

Annex 3a. List of positive words from the Moreno and González dictionary (2020)

absorbidas	buenos	mejoraron	reequilibrando
abundancia	calma	mejorase	reequilibrar
abundante	calmar	mejores	reforzado
acomodaticia	capaces	mejoría	reforzándolo
acomodaticias	capaz	mejorías	reforzará
acomodaticio	cómoda	mejoró	reforzaron
afiance	contención	mitiga	reforzó
afianzado	desendeudamiento	mitigaban	remontado
afianzamiento	dinamismo	mitigado	renovado
afianzando	dinamizador	mitigar	resisten
ágil	disfrutan	mitigaron	resistido
alcista	eficaces	normalidad	restablecer
alcistas	eficaz	normalizado	restableciendo
aliviadas	eficiente	normalizados	restablecimiento
aliviado	eficientes	normalizando	restaurar
aliviando	equilibrada	normalizándose	revalorizaba
aliviar	equilibrado	normalizar	revalorizaciones
aliviará	excelente	normalizó	revalorizado
aliviaron	excelentes	oportunidades	revalorizaron
alivio	expandió	optimismo	revalorizarse
amortigua	expansiva	ordenada	revalorizó
amortiguación	favorable	ordenado	revitalización
amortiguador	favorablemente	positiva	revitalizar
amortiguan	favorables	positivamente	robusta
amortiguar	favorece	positivas	robustas
amortiguarlos	favorecen	positivo	robusto
amortiguarse	favorecido	positivos	robustos
apoyada	favorecieron	progreso	saneada
asentarse	fortaleciéndose	progresos	saneado
atenuación	fortalecimiento	propicias	saneados
atenuados	fortaleció	propicio	sanearon
beneficiándose	fortaleza	reaccionado	satisfactoria
beneficiar	fortalezas	reactivación	satisfactoriamente
beneficiara	ganancia	reactivándose	sólida
beneficiarán	ganó	reafirmando	sólidas
beneficiarían	holgada	recuperación	solidez
beneficiaron	holgadamente	recuperado	sólido
beneficiarse	holgadas	recuperan	solvente
beneficien	holgado	recuperando	solventes
beneficioso	holgados	recuperándose	sostenibles
benigna	mejora	recuperar	suaves
benignas	mejorada	recuperara	suavizarán
benigno	mejorado	recuperaron	superada
benignos	mejoran	recuperarse	sustenta
bienestar	mejorando	recuperase	tranquilidad
buen	mejorándose	recuperen	vigorosamente
buenas	mejorar	recuperó	vigoroso

Source: Moreno and González (2020).

Annex 3b. List of negative words from the Moreno and González dictionary (2020)

abrupta	contagiadas	deterioradas	gravemente	perjudiciales	restaron
abruptas	contagiado	deteriorado	graves	perjuicios	restringiendo
abrupto	contagiaron	deteriorando	guerra	persistencia	resurgido
abruptos	contagie	deteriorándose	impactará	persistente	resurgimiento
abusivo	contagio	deteriorar	inadecuados	persistentes	retraimiento
acentuaban	contagió	deteriorarse	incapaces	persistieron	retrasa
acentuadas	contracción	deteriorase	incapaz	perturbaciones	retroceder
acusados	contracciones	deterioro	incertidumbre	perversos	retrocedieron
adversa	contractiva	deterioró	incertidumbres	pesimismo	retrocedió
adversas	contrae	difícil	incierta	pesimista	retroceso
adverso	contraerse	difíciles	inciertas	pobre	retrocesos
adversos	contrajo	dificulta	incierto	precipicio	revés
afrontan	contraproducentes	dificultad	inciertos	prematura	secuelas
afrontarían	contrayendo	dificultada	inconveniente	preocupación	sensible
agotamiento	contrayéndose	dificultades	indefinición	preocupaciones	serias
agravada	convulso	dificultado	indeseado	preocupado	serio
agravado	costosa	dificultando	ineficiencia	preocupados	serios
agravamiento	costosas	dificultándose	ineficiencias	preocupante	severa
agravando	costoso	dificultar	inestabilidad	preocupantes	severas
agravar	costosos	dificultaría	inestable	presión	severo
agravará	crisis	dificultarían	inestables	presiona	sobrecalentamiento
agravarían	cruda	disfunción	insostenible	presionaban	sombras
agravó	dañar	disfunciones	insuficiencia	presionada	súbita
agudas	dañaría	drástica	insuficiente	presionadas	sufren
agudizado	daño	drásticas	insuficientes	presionado	sufrida
agudizamiento	débil	drásticos	intervenida	presionados	sufridas
agudizara	débiles	dudas	intervenidas	presionan	sufrido
agudizaran	debilidad	empeora	intervenir	presionando	sufridos
agudizaron	debilidades	empeorado	invalidar	presionar	sufriendo
agudizó	debilita	empeoramiento	inviabilidad	presionará	sufrieran
agudo	debilitada	empeoramientos	inviable	presionaría	sufrieron
agudos	debilitado	empeoran	inviables	presionaron	sufrió
altibajos	debilitamiento	empeorando	irregular	presiones	sufrirán
amenaza	debilitan	empeorar	lamentablemente	problemas	suspensión
amenazados	debilitar	empeoró	lastrada	problemática	temor
amenazan	debilitó	endurecido	lastradas	problemáticas	temores
amenazar	débilmente	endureciéndose	lastrado	quebrar	tensión
amenazas	decepcionante	endurecimiento	lastrar	quebró	tensiona
anómala	decepcionantes	endurecimientos	lastre	quiebra	tensionaban
arrastrado	decepcionaron	erosión	lastró	quiebras	tensionado
asimétricos	deficiencias	erosionado	lenta	ralentice	tensionamiento
ataque	deficiente	erosionar	lento	ralentiza	tensionando
ataques	deficitaria	escalada	mal	ralentización	tensionaron
atonía	delicada	escándalos	mala	ralentizar	tensiones
atravesando	depresión	escasísima	malas	ralentizara	titubeante
atraviesan	deprimidos	estallar	merma	ralentizarse	traumática
bache	deprimirían	estallido	miedo	ralentizó	truncada
brusca	desaceleración	estancada	negativa	rebaja	turbulencia
bruscas	desastres	estrangulamiento	negativamente	rebajadas	turbulencias
brusco	desconfianza	estrangulamientos	negativas	rebrote	urgencia
bruscos	desencadenamiento	evaporarse	negativo	recaída	virulencia
colapsados	desequilibrada	excesivo	negativos	recalentamiento	volátil
colapso	desequilibrio	excesivos	obstáculo	recesión	vulnerabilidad
complejidades	desequilibrios	falta	oscilaciones	recesivas	vulnerabilidades
complejo	desestabilizadores	fatiga	padece	recrudecían	vulnerable
complica	desfavorable	frágil	padecían	recrudecidos	vulnerables
complicaciones	desfavorablemente	frágiles	pánicos	recrudecieron	
complicada	desfavorables	fragilidad	peligro	recrudecimiento	
complicadas	destrucción	fragilidades	peligros	recrudeció	
complicado	destruyendo	fragmentación	penalizado	rémora	
complicados	desvaneciendo	frenazo	peores	rescatadas	
complicando	deteriora	frustró	pérdida	rescatar	
complicar	deterioraban	grave	perjudica	resentido	
complicarían	deteriorada	gravedad	perjudicadas	resentirse	

Source: Moreno and González (2020).

Annex 4. Time series selected to nowcast Colombia's economic activity

Time series used to predict Colombia's economic activity with a three-day lead						
Series name	**Description**	**Period from**	**Lag in days**	**Unit of measurement**	**Unit-Root Correction (First Diff.)**	**Source**
a1	Supply of the agricultural sector	Jan-13	3	Metric tons	Yes	DANE - Sipsa
a2	Milk collection	Jan-08	35	Liters	Yes	Minagricultura - USP
b1	Mining and quarrying	Jan-14	45	Index 2018=100	Yes	DANE - IPI
c1	Manufacturing	Jan-04	45	Index 2018=100	Yes	DANE - EMM, Emmet
de1	Electricity, gas, and water supply	Jan-14	45	Index 2018=100	Yes	DANE - IPI
f1	Gray cement	Jan-04	31	Metric tons	Yes	DANE - ECG
f2	Ready-Mixed Concrete	Jan-11	45	Cubic meters	Yes	DANE - EC
g1	Wholesale and retail trade	Jan-04	45	Index 2019=100	Yes	DANE - EMCM, EMC
g2	New vehicle sales	Jul-08	31	Units	Yes	Asonac, Fenalco-ANDI
h1	Land transport	Jan-04	30	Number of vehicles	Yes	ANI
h2	Freight transport	Jan-15	15	Metric tons	Yes	Mintransporte
i1	Accommodation	Jan-19	45	Percentage	Yes	DANE - EMA
k1	Financial system disbursements	Jan-04	30	Millions of pesos deflated with CPI excluding foods	Yes	Superfinanciera
l1	New home sales	Jan-10	23	Units	Yes	Camacol
o1	Public administration and defence	Jan-15	30	Thousands of employed in public administration activity	Yes	DANE - GEIH
r1	Social and cultural activities	Jan-18	45	Pesos deflated with CPI excluding foods	Yes	Coljuegos
ss1	Service activities	Jan-17	45	Index 2014=100	Yes	DANE - EMS
xi	Tax revenue	Jan-04	23	Millions of pesos deflated with CPI excluding foods	Yes	DIAN
per	Regional Economic Pulse	Jan-12	20	Indicator with values between -1 and 1	Stationary	Banco de la República
se1	Sentiment index	Mar-20	5	Indicator with values between -1 and 1	Yes	Banco de la República
in1	Uncertainty index	Mar-20	5	Indicator with values > 0	Yes	Banco de la República
Time series used to predict Colombia's economic activity with a thirteen-day lead						
Series name	**Description**	**Period from**	**Lag in days**	**Unit of measurement**	**Unit-Root Correction (First Diff.)**	**Source**
a1	Supply of the agricultural sector	Jan-13	3	Metric tons	Yes	DANE - Sipsa
a2	Milk collection	Jan-08	35	Liters	Yes	Minagricultura - USP
b2	Mining exports	Jan-04	35	Metric tons	Yes	DANE - Exportaciones
c1	Leading indicator of industry	Jan-15	15	Index 2018=100	Yes	Banco de la República
c3	Cardboard Box Index	Jan-11	20	Index jan-2018=100	Yes	Banco de la República
d1	Electricity demand	Jan-05	3	Gigawatt-hours	Yes	SIEL - UPME
f1	Gray cement	Jan-04	31	Metric tons	Yes	DANE - ECG
g1	Credit and debit card spending	Jan-17	31	Index 2021=100	Yes	Banco de la República
g2	New vehicle sales	Jul-08	31	Units	Yes	Asonac, Fenalco-ANDI
h1	Land transport	Jan-04	30	Number of vehicles	Yes	ANI
h2	Freight transport	Jan-15	15	Metric tons	Yes	Mintransporte
k1	Financial system disbursements	Jan-04	30	Millions of pesos deflated with CPI excluding foods	Yes	Superfinanciera
l1	New home sales	Jan-10	23	Units	Yes	Camacol
o1	Public administration and defence	Jan-15	30	Thousands of employed in public administration activity	Yes	DANE - GEIH
mnrs1	Service activities	Jan-15	30	Thousands of employed in service activities	Yes	DANE - GEIH
xi	Tax revenue	Jan-04	23	Millions of pesos deflated with CPI excluding foods	Yes	DIAN
per	Regional Economic Pulse	Jan-12	20	Indicator with values between -1 and 1	Stationary	Banco de la República
se1	Sentiment index	Mar-20	5	Indicator with values between -1 and 1	Yes	Banco de la República
in1	Uncertainty index	Mar-20	5	Indicator with values > 0	Yes	Banco de la República

Departamento Administrativo Nacional de Estadística (DANE). Sistema de información de precios (SIPSA). Ministerio de Agricultura y Desarrollo Rural (Minagricultura). Unidad de Seguimiento de Precios (USP). Índice de Producción Industrial (IPI). Encuesta mensual manufacturera (EMM). Encuesta mensual manufacturera con enfoque territorial (Emmet). Estadísticas de Cemento Gris (ECG). Estadísticas de Concreto Premezclado (EC). Encuesta mensual de comercio al por menor y comercio de vehículos (EMCM). Encuesta Mensual de Comercio (EMC). Asociación Nacional Concesionarios Colmotores (Asonac). Federación Nacional de Comerciantes Empresarios (Fenalco). Asociación Nacional de Industriales (ANDI). Agencia Nacional de Infraestructura (ANI). Ministerio de Transporte (Mintransporte). Encuesta Mensual de Alojamiento (EMA). Superintendencia Financiera de Colombia (Superfinanciera). Cámara Colombiana de la Construcción (Camacol). Gran Encuesta Integrada de Hogares (GEIH). Empresa Industrial y Comercial del Estado Administradora del Monopolio Rentístico de los Juegos de Suerte y Azar (Coljuegos). Encuesta mensual de servicios (EMS). Dirección de Impuestos y Aduanas Nacionales (DIAN). Sistema de Información Eléctrico Colombiano (SIEL). Unidad de Planeación Minero Energética (UPME).

Note: the time series included in each dataset were selected based on their correlation with the disaggregated ISE across 12 economic activities, ensuring that at least one indicator captures GDP activity from the supply side. The selection also required that the series were sufficiently long and published in a timely manner.
Source: Authors' elaboration.

Annex 5a. Optimal ARMAX model specification

ARMAX Model Order (1)	Model selection criteria (2)	AIC (3)	BIC (4)	HQ (5)	Log-Likelihood (6)	Adjusted R-squared (7)	All AR–MA Coeffs Sig. (8)	Ljung-Box - p-value < 0.05 (9)	Jarque-Bera (10)	Test - ARCH (11)	Residual Mean Test (12)	BDS test p-values (13)
3-day lead time series for forecasting Colombia's monthly economic activity indicator												
Best-fitting ARMAX [ranking AIC(3) SIC(3) HQ(4)] includes 5 AO and 3 TC												
ARMAX (2,3)(0,0)	AIC	-6,6583	-6,4235	-6,5636	801,6785	0,7930	Yes	3	JB-Norm	ARCH-OK	Mean = 0	**
ARMAX (2,0)(0,0)	AIC	-6,6362	-6,4454	-6,5593	796,0723	0,7840	Yes	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (4,2)(0,0)	AIC	-6,6544	-6,4049	-6,5538	802,2179	0,7958	Yes	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,1)(0,0)	SIC	-6,6324	-6,4269	-6,5495	796,6187	0,7840	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (3,0)(0,0)	SIC	-6,6306	-6,4251	-6,5477	796,4072	0,7836	No	0	JB-Norm	ARCH-OK	Mean = 0	**
ARMAX (2,0)(1,0)	SIC	-6,6277	-6,4223	-6,5449	796,0734	0,7830	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (3,4)(0,0)	HQ	-6,6458	-6,3816	-6,5393	802,2029	0,7920	No	3	JB-Norm	ARCH-OK	Mean = 0	*
ARMAX (2,3)(1,1)	HQ	-6,6589	-6,3947	-6,5524	803,7499	0,8027	Yes	6	JB-Norm	ARCH-OK	Mean = 0	*
ARMAX (2,4)(0,0)	HQ	-6,6514	-6,4019	-6,5508	801,8610	0,7924	No	3	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (3,3)(0,0)	HQ	-6,6510	-6,4015	-6,5504	801,8147	0,7923	No	3	JB-Norm	ARCH-OK	Mean = 0	***
3-day lead time series for forecasting Colombia's quarterly GDP												
Best-fitting ARMAX [ranking AIC(3) SIC(3) HQ(4)] includes 5 AO and 2 TC												
ARMAX (2,3)(0,0)	AIC	-6,5235	-6,3033	-6,4347	784,7690	0,7712	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,0)(0,0)	AIC	-6,5289	-6,3528	-6,4579	782,4111	0,7696	Yes	0	JB-Norm	ARCH-OK	Mean = 0	**
ARMAX (4,2)(0,0)	AIC	-6,5612	-6,3263	-6,4665	790,2176	0,7823	Yes	0	JB-Norm	ARCH-OK	Mean = 0	*
ARMAX (2,1)(0,0)	SIC	-6,5372	-6,3464	-6,4602	784,3848	0,7725	Yes	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (3,0)(0,0)	SIC	-6,5350	-6,3442	-6,4581	784,1277	0,7720	No	0	JB-Norm	ARCH-OK	Mean = 0	**
ARMAX (2,0)(1,0)	SIC	-6,5205	-6,3297	-6,4436	782,4224	0,7686	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (3,4)(0,0)	HQ	-6,5076	-6,2580	-6,4070	784,8918	0,7694	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,3)(1,1)	HQ	-6,5081	-6,2586	-6,4075	784,9587	0,7697	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,4)(0,0)	HQ	-6,5150	-6,2802	-6,4204	784,7747	0,7702	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (3,3)(0,0)	HQ	-6,5150	-6,2802	-6,4204	784,7718	0,7702	No	0	JB-Norm	ARCH-OK	Mean = 0	**

Note: (AO) Additive Outlier. (TC) Temporary Change. (1) ARMA model with the lowest selection criterion value. (2) Ranking of best-fitting ARMA models based on AIC, BIC, and HQ. (3) Akaike Information Criterion. (4) Schwarz or Bayesian Information Criterion. (5) Hannan–Quinn Criterion. (6) log-likelihood value. (7) Adjusted R-squared value. (8) Yes, if all AR and MA parameters are significant at 5%, otherwise No. (9) The Ljung–Box Q-statistic is a test used to detect autocorrelation in model residuals. Number of lags (1–36) with p-value < 0.05. (10) The Jarque–Bera test evaluates whether the residuals of a model are normally distributed, JB-Norm if p-value > 0.05, otherwise Not JB-Norm. (11) The ARCH test checks whether residuals have constant variance at lag 1, ARCH-OK if p-value > 0.05, otherwise ARCH-Het. (12) The Mean Test checks if the residuals' average is statistically zero, Mean = 0 if p-value > 0.05, otherwise Mean ≠ 0. (13) The Brock–Dechert–Scheinkman (BDS) test assesses whether the residuals are truly random, independent, and identically distributed (i.i.d.). *, **, *** indicate that the residuals are independent and exhibit no nonlinear dependence when the lowest p-value across dimensions 2–6 lies within the 1–5%, 5–10%, and above 10% ranges, respectively; otherwise, the residuals are classified as non-i.i.d.

Annex 5b. Optimal ARMAX model specification

ARIMAX Model Order (1)	Model selection criteria (2)	AIC (3)	BIC (4)	HQ (5)	Log-Likelihood (6)	Adjusted R-squared (7)	All AR–MA Coeffs Sig. (8)	Ljung-Box - p-value < 0.05 (9)	Jarque-Bera (10)	Test - ARCH (11)	Residual Mean Test (12)	BDS test p-values (13)
13-day lead time series for forecasting Colombia's monthly economic activity indicator												
Best-fitting ARMAX [ranking AIC(3) SIC(3) HQ(4)] includes 5 AO and 3 TC												
ARMAX (6,2)(0,0)	AIC	-6,6636	-6,3848	-6,5512	805,3098	0,7987	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (4,3)(1,1)	AIC	-6,6267	-6,3331	-6,5083	801,9458	0,7966	No	1	JB-Norm	ARCH-OK	Mean = 0	**
ARMAX (4,2)(1,1)	AIC	-6,6301	-6,3512	-6,5177	801,3499	0,7957	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,0)(0,0)	SIC	-6,6456	-6,4548	-6,5687	797,1773	0,7860	Yes	0	JB-Norm	ARCH-OK	Mean = 0	**
ARMAX (2,1)(0,0)	SIC	-6,6433	-6,4378	-6,5605	797,9127	0,7864	No	0	JB-Norm	ARCH-OK	Mean = 0	**
ARMAX (3,0)(0,0)	SIC	-6,6411	-6,4356	-6,5583	797,6532	0,7859	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,3)(0,0)	HQ	-6,6614	-6,4265	-6,5667	802,0415	0,7936	Yes	3	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,3)(1,1)	HQ	-6,6427	-6,3785	-6,5362	801,8420	0,7982	No	0	JB-Norm	ARCH-OK	Mean = 0	*
ARMAX (4,0)(0,0)	HQ	-6,6434	-6,4233	-6,5547	798,9255	0,7873	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,0)(1,0)	HQ	-6,6372	-6,4317	-6,5543	797,1859	0,7850	No	0	JB-Norm	ARCH-OK	Mean = 0	*
13-day lead time series for forecasting Colombia's quarterly GDP												
Best-fitting ARMAX [ranking AIC(3) SIC(3) HQ(4)] includes 5 AO and 2 TC												
ARMAX (6,2)(0,0)	AIC	-6,5868	-6,3226	-6,4803	795,2467	0,7894	No	2	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (4,3)(1,1)	AIC	-6,5785	-6,2996	-6,4661	795,2645	0,7887	No	3	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (4,2)(1,1)	AIC	-6,5857	-6,3215	-6,4792	795,1104	0,7916	Yes	2	JB-Norm	ARCH-OK	Mean = 0	non-i.i.d.
ARMAX (2,0)(0,0)	SIC	-6,5714	-6,3952	-6,5004	787,4195	0,7792	Yes	0	JB-Norm	ARCH-OK	Mean = 0	*
ARMAX (2,1)(0,0)	SIC	-6,5778	-6,3870	-6,5009	789,1837	0,7816	No	0	JB-Norm	ARCH-OK	Mean = 0	non-i.i.d.
ARMAX (3,0)(0,0)	SIC	-6,5758	-6,3850	-6,4989	788,9501	0,7811	No	0	JB-Norm	ARCH-OK	Mean = 0	*
ARMAX (2,3)(0,0)	HQ	-6,5655	-6,3453	-6,4767	789,7234	0,7806	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (2,3)(1,1)	HQ	-6,5498	-6,3003	-6,4492	789,8734	0,7815	No	0	JB-Norm	ARCH-OK	Mean = 0	***
ARMAX (4,0)(0,0)	HQ	-6,5710	-6,3655	-6,4882	789,3809	0,7810	No	0	JB-Norm	ARCH-OK	Mean = 0	*
ARMAX (2,0)(1,0)	HQ	-6,5631	-6,3723	-6,4862	787,4422	0,7783	No	0	JB-Norm	ARCH-OK	Mean = 0	non-i.i.d.

Note: (AO) Additive Outlier. (TC) Temporary Change. (1) ARMA model with the lowest selection criterion value. (2) Ranking of best-fitting ARMA models based on AIC, BIC, and HQ. (3) Akaike Information Criterion. (4) Schwarz or Bayesian Information Criterion. (5) Hannan–Quinn Criterion. (6) log-likelihood value. (7) Adjusted R-squared value. (8) Yes, if all AR and MA parameters are significant at 5%, otherwise No. (9) The Ljung–Box Q-statistic is a test used to detect autocorrelation in model residuals. Number of lags (1–36) with p-value < 0.05. (10) The Jarque–Bera test evaluates whether the residuals of a model are normally distributed, JB-Norm if p-value > 0.05, otherwise Not JB-Norm. (11) The ARCH test checks whether residuals have constant variance at lag 1, ARCH-OK if p-value > 0.05, otherwise ARCH-Het. (12) The Mean Test checks if the residuals' average is statistically zero, Mean = 0 if p-value > 0.05, otherwise Mean ≠ 0. (13) The Brock–Dechert–Scheinkman (BDS) test assesses whether the residuals are truly random, independent, and identically distributed (i.i.d.). *, **, *** indicate that the residuals are independent and exhibit no nonlinear dependence when the lowest p-value across dimensions 2–6 lies within the 1–5%, 5–10%, and above 10% ranges, respectively; otherwise, the residuals are classified as non-i.i.d.
Source: Authors' calculations.