UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

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Effectiveness of Sentiment Analysis in Predicting Ecuador's GDP Annual Growth Rate Using Newspaper Textual Data (2000-2024)

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RESUMEN

La crisis multifacética de Ecuador aumenta la necesidad de realizar pronósticos económicos oportunos para fundamentar la toma de decisiones. Las encuestas tradicionales de empresas y consumidores captan las expectativas económicas, pero están limitadas por la frecuencia de publicación mensual. Este trabajo mejora los pronósticos del crecimiento del PIB al integrar el análisis de sentimientos de los artículos de periódicos diarios. Analizando más de 240.000 artículos desde 2000 hasta 2024, se construyó cinco indicadores de sentimiento utilizando un algoritmo PLN personalizado que integra TextBlob, VADER y el modelo español de SpaCy. Estos indicadores se incorporan a un modelo econométrico LASSO-ARDL junto con controles macroeconómicos tradicionales e indicadores basados en encuestas. Las comprobaciones de robustez incluyen RMSE bootstrap junto a validación cruzada. Los resultados indican que el modelo enriquecido por sentimientos supera significativamente al punto de referencia basado en encuestas para los pronósticos del PIB a corto plazo (1 a 3 meses), con un RMSE más bajo y una mayor estabilidad. Sin embargo, esta ventaja disminuye en el largo plazo donde las diferencias del modelo se vuelven estadísticamente insignificantes. Esta investigación ofrece un marco escalable para integrar datos en tiempo real en las previsiones económicas, demostrando el valor de los modelos basados en sentimientos para capturar señales económicas de alta frecuencia y complementar los métodos tradicionales para abordar los desafíos económicos de Ecuador.

Palabras clave: Ecuador, análisis de sentimiento, pronosticación del PIB, LASSO-ARDL, información en tiempo real

ABSTRACT

Ecuador's multifaceted crisis heightens the need for timely economic forecasting to inform decision-making. Traditional Business and Consumer Surveys capture economic expectations but are limited by monthly release frequency. This study enhances GDP growth forecasting by integrating sentiment analysis from daily newspaper articles. Ana- lyzing over 240,000 articles from 2000 to 2024, I construct five sentiment indicators using a customized NLP algorithm integrating TextBlob, VADER, and SpaCy's Spanish model. These indicators are incorporated into a LASSO-ARDL econometric model alongside traditional macroeconomic controls and survey based indicators. Robustness checks include bootstrap RMSE and cross-validation. Results indicate the sentiment-enhanced model significantly outperforms the survey-based benchmark for short-term GDP forecasts (1–3 months), with lower RMSE and greater stability. However, this advantage diminishes over longer-term horizons where model differences become statistically insignificant. This research offers a scalable framework for integrating real-time data into economic forecasting, demonstrating the value of sentiment-based models in capturing high-frequency economic signals and complementing traditional methods to address Ecuador's economic challenges.

Key words: Ecuador, sentiment analysis, GDP forecasting, LASSO-ARDL, real-time data

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1 Introduction

Ecuador encompasses a history of significant challenges, currently facing a rising crime and insecurity crisis, deepening political polarization and economic struggles through a consistent growth in informal work; especially among the youth. Energy shortages and ongoing health system strain have added more complexity to daily life. In this volatile environment, policymakers and leaders in the private sector need precise insights into public perceptions and trends to make informed decisions and navigate uncertainty effectively.

Business and Consumer Surveys (BCSs) have been historically essential tools for policymakers and researchers to monitor and forecast the economy. These surveys provide broader insights in people's perception on the current and expected state of economic activity, which is particularly valuable given the often delayed release of macroeconomic indicators. By measuring people's perception on different areas—such as consumers' attitudes toward spending and purchasing, managers' expectations on the situation of the country's economy, expectations on construction and commerce performance—BCSs offer quantifiable information into various aspects of the economy. Prominent examples like the University of Michigan's Survey of Consumers and the European Union's BCS (Curtin and Dechaux, 2015) have shown the enhancement of the ability to forecast and nowcast economic variables more frequently, thereby aiding in more effective decision-making amid the country's uncertainties. However, because these surveys are typically released monthly, they may still not capture the granular effects of different sectors on the economy opportunely.

Sentiment analysis is a method used to determine the tone or emotional context of written or spoken language, often applied to understand public opinions and trends. By analyzing vast amounts of textual data, such as news articles, this approach identifies whether the content conveys positive, negative, or neutral sentiments. As a result, sentiment analysis algorithms can approximate qualitative subjective opinions to quantitative probability distributions for statistical research and inference. For example, if multiple news articles report rising concerns about inflation with phrases like "prices are soaring" or "economic hardship grows," sentiment analysis quantifies these expressions as negative economic sentiment giving them a numerical score. This process relies on natural language processing (NLP), a field of artificial intelligence, to interpret and classify textual data. Unlike traditional surveys that collect public opinion monthly or quarterly, sentiment analysis provides real-time insights by processing information available at a higher frequency [1], such as daily news updates.

Incorporating sentiment analysis offers a valuable approach to addressing Ecuador's complex social and economic challenges by leveraging real-time insights into public perceptions and market conditions (Barbaglia et al., 2024). This methodology enables researchers and decision makers to use the vast wealth of textual information to compute sentiment on any economic aspect at minimal cost, unlike traditional surveys with fixed, inflexible structures (Malandri et al., 2018). Furthermore, integrating sentiment analysis with flexible econometric models provides a powerful solution to the limitations of conventional forecasting methods, particularly for forecasting macroeconomic variables in a volatile economic environment.

Traditional attempts to forecast economic variables, such as Vector Autoregression (VAR) and standard time series analyses, have often faltered in Ecuador due to the country's unique

[1] It refers to the ability to collect and analyze data at short intervals, such as daily, whereas "low frequency" involves longer intervals, like monthly.

economic volatility, structural constraints, and susceptibility to external shocks like natural disasters, political instability, and fluctuating commodity prices. While dynamic equations systems may provide robust frameworks for analyzing economic dynamics, they frequently struggle with the inherent rigidity of predefined lag structures and their inability to adapt to rapid, unforeseen economic changes like the 2016 earthquake or the COVID-19 pandemic (IMF, 2019). In this context, sentiment analysis offers a critical alternative as it allows for the real-time capture of public and market perceptions, effectively bridging the lag in data availability that often characterizes traditional economic indicators. The use of sentiment analysis in financial news has also demonstrated predictive capabilities regarding economic activity and labor market decisions in various contexts, underscoring its relevance as a supplementary tool for economic modeling (van Binsbergen, 2023). Building on this foundation, the integration of sentiment analysis into Autoregressive Distributed Lag (ARDL) models provides a structured approach to harness real-time data for both short-term and long-term economic forecasting.

ARDL models are particularly well-suited for scenarios where variables exhibit different integration orders, allowing them to simultaneously incorporate stationary variables and those requiring differencing to achieve stationarity. This flexibility makes them ideal for analyzing sentiment indicators, which often display unique statistical behaviors due to their high-frequency nature and responsiveness to abrupt shifts in public opinion. By capturing both short-term dynamics and long-term relationships, ARDL models provide a nuanced framework for understanding how sentiment data interacts with economic outcomes, offering a robust tool for macroeconomic forecasting in volatile contexts. Their adaptability is especially critical in environments like Ecuador, where sudden political or economic shifts can have cascading effects on public sentiment and economic performance. By integrating sentiment indicators they not only complement traditional macroeconomic indicators but enhance their predictive capacity by providing a richer more dynamic dataset that reflects both the quantitative and qualitative facets of the economy. By bridging the gap between traditional econometrics and alternative data sources, sentiment-based ARDL models create a robust, scalable framework capable of addressing the unique forecasting challenges posed by Ecuador's economic landscape.

Building on the need for precise insights, the alternative measure of economic sentiment I explore in this paper hence seeks to capture the public's overall attitude toward specific aspects of the economy in order to forecast macroeconomic variables. My measure is derived from textual analysis of a large dataset of daily digitalized newspaper articles from different sectors, as news outlets offer a valuable source of information by reporting on economic and social events that influence economic decisions. By using sentiment analysis I aim to capture the information from sentiments into quantifiable indicators that allows me to asses their performance on forecasting. Specifically, I aim to evaluate the effectiveness of news-based sentiment analysis as a tool to predict GDP percentual growth rate in Ecuador using information from 2000 to 2024 digitalized newspapers at monthly frequency. For this purpose, I compared a sentiment-based model—incorporating news-derived sentiment scores and survey data—with a traditional model that uses only business and consumer confidence surveys information. I constructed sentiment indicators using over 240,000 news articles from Ecuador's main newspapers[2], totaling more than 12.5 million Spanish words. To perform sentiment analysis, I customized an NLP algorithm integrates TextBlob and

[2]'El Comercio','La Hora','Diario El Universo','Expreso','Metro','El Mercurio', among others

VADER (Valence Aware Dictionary and Sentiment Reasoner) Python libraries for textual data processing through SpaCy's large spanish news model to enhance sentiment analysis and adaptability to diverse contexts.

I implemented two ARDL models as econometric tools to analyze the long and short term effects. The first ARDL stands out as a benchmark model which integrated traditional macroeconomics controls with survey-based indicators, while the second model adds 5 customized sentiment indicators[3] after Lasso regularization (LASSO-ARDLS). This last step was crucial in order to enhance predictive accuracy by penalizing less informative predictors and preventing overfitting. To evaluate the model's predictive capacity I performed an in-sample and out-of-sample analyses with bootstrap analysis on RMSE, average rolling RMSE, cross-validation with varying lambda values, CUSUM, CUSUMSQ and the Diebold-Mariano test at different forecasting horizons to validate the robustness of the findings.

The results revealed that the LASSO-ARDLS model integrated with sentiment indicators significantly outperformed the benchmark ARDL model in short-term GDP forecasting for Ecuador, especially at horizons of 1 to 3 months. This superiority was demonstrated by lower Root Mean Square Error (RMSE) values in both bootstrap and rolling window analyses, and statistically significant Diebold-Mariano test results at short horizons. Besides, CUSUM and CUSUMSQ further confirmed the LASSO-ARDLS model's stability and robustness to shocks and structural changes. However, the performance advantage of the LASSO-ARDLS model diminished as the forecasting horizon extended beyond 6 months, with differences between the models becoming statistically insignificant. This suggested that while the sentiment-

[3]The indicators encompass the areas of `HEALTH,SOCIETY,ECONOMY,POLITICS,SECURITY`. For more information on the words used for the indicators classification please revise the section of annexes.

integrated model is particularly effective for short-term forecasting due to its adaptability and enhanced predictive power, its benefits over the benchmark model wane in the long term. Overall, sentiment integration is a well-suited alternative for stable short-term forecasting using news-based information, whereas the traditional framework trough structural surveys remains a competent option for long-term trend analysis. In addition, further validation trough a VAR framework showed the existence of bidirectional relations between sentiment and survey indicators. Although no direct causation was established, surveys demonstrated a significant additional explanatory power for sentiment variables, as shown by widespread statistical significance in Granger-causality tests. This interplay suggests that traditional surveys and sentiments are complementary, where surveys provide a structured representation for the long term analysis while sentiments seem to capture more reactive and short-term responses.

In essence, integrating sentiment analysis into GDP forecasting offers policymakers and business leaders a practical tool for navigating Ecuador's volatile economic landscape. This approach provides a framework for capturing real-time public perceptions and translating them into actionable insights. Compared to traditional methods, which are often limited by low frequency and delayed reporting, sentiment analysis allows for timely adjustments to policies and strategies. Whether allocating resources during economic downturns, anticipating the impact of fiscal policies, or understanding public reactions to major events, this framework offers an actionable tool to decision-makers with the precision and agility required to respond effectively to dynamic economic conditions.

2 Data

Due to the varied nature and sources of the required variables, I gathered publicly accessible data from various sources including the websites of the National Institute of Statistics and Census of Ecuador (INEC for its initials in Spanish) the Central Bank of Ecuador (CBE) and *Trading Economics* economic data provider. The dependent variable of this study is Ecuador's annual GDP growth rate, sourced from CBE's quarterly reports. To provide a comprehensive analysis of economic activity, I also included monthly data on national exports and remittances sent to Ecuador from abroad. To account for international influences, I incorporated the U.S. Federal Reserve's interest rate and West Texas Intermediate (WTI) crude oil prices, both obtained from the St. Louis Fed: Archival FRED (ALFRED). For structural information about economic expectations, I extracted data from the Economic Expectations Index (IEE) by the CBE.

These survey indicators represent the expectations from medium-high and high income companies on the key four sectors of the Ecuadorian economy trough an analytical bulletin detailing the results of the IEE from 2000 to 2024. The IEE captures the opinions of company directors in construction, commerce, manufacturing, and services regarding the current economic situation and future prospects of their companies. This index is derived from the Monthly Business Opinion Survey (EMOE for its initials in Spanish), which targets companies with the highest sales income in their economic sectors. Furthermore, the dataset also included the Consumer Confidence Index (ICC) from the CBE, which is a weighted average measuring households' perceptions of their economic situation, consumption patterns, and the country's economic condition over the previous month and the next three months. The

Ecuador Business Confidence Index (`BUSS_CONFIDENCE`) records the ease of doing business and expectations about the company's situation and the economy as a whole, serving as an indicator of the overall business climate. Eventually, the dataset included sentiment indicators for sectors of `HEALTH, ECONOMY, POLITICS, SECURITY,SOCIETY` built through the identification strategy described in the *sentiment identification* subsection.

To account for pivotal exogenous macroeconomic events, I identified and coded key recessionary periods and shocks in the last 14 years as dummy variables into the LASSO-ARDLS and ARDL benchmark model. I identified these periods based on news data from *Index-Mundi* news repository and Ecuador's Central Bank report of economic cycles for 2022 and 2023. By explicitly modeling these periods, the analysis ensured that the effects of these external shocks were appropriately isolated allowing the model(s) to better capture the underlying relationships between survey and sentiment indicators on the target variable in their respective frameworks. The periods included:

- Recession of 2015-2016 ("2015-01-01" to "2016-12-01")
- Earthquake of 2016 ("2016-04-01" to "2016-12-01")
- Fuel Subsidy Removal of 2019 ("2019-10-01" to "2019-11-01")
- COVID-19 Pandemic ("2020-03-01" to "2020-12-01")
- Post-Pandemic Recession ("2021-01-01" to "2021-12-01")

2.1 Descriptive statistics

The analysis of sentiment across different sectors in Ecuador depicted in Figure 1 shows the sentiment indicators of economic activity together with recessionary periods. I aggregated the information from daily frequency to monthly frequency by averaging the values within each month and standardize the measures to a normal distribution with mean 0 and variance 1 to make them comparable across indicators. Results revealed significant volatility, particularly during recessionary periods, and brought out the intricate interplay between various domains of public perception.

The *health sector* exhibits pronounced fluctuations, with significant peaks and troughs in sentiment, especially during times of economic downturn. The COVID-19 pandemic marked a drastic drop in health-related sentiment, reflecting heightened public concern over the healthcare system's capacity to handle the crisis. Recovery in this sector appears sluggish, with the effects of the pandemic extending into the post-pandemic recession of 2021. This delayed recovery indicated deep-seated public anxiety over systemic issues and demonstrated the sector's high reactivity to external shocks. The *Economic sentiment* trends displayed consistent oscillations but are sharply impacted by major downturns such as the recession of 2015–2016, the lifting of fuel subsidies in 2019, and the pandemic-related disruptions in 2020. During the 2015–2016 recession, economic sentiment suffered a prolonged decline, showcasing a slow and gradual recovery that underscores the depth of economic instability during that period. The 2019 fuel subsidy policy further exacerbated economic concerns, leading to one of the steepest declines in sentiment. Further in time, even as economic sentiment begins to stabilize post-pandemic, it did not recover to pre-crisis levels, reflecting lingering structural

Figure 1: Time series of the standardized news-based sentiment indicators for different sectors. The sentiment is averaged within each month and sampled at a daily frequency. The shaded areas represent the recession established from IndexMundi information.

challenges and the lasting impact of recessionary periods on public perception.

The *societal sentiment* is characterized by frequent fluctuations closely aligned with crises that impact social structures. The 2016 earthquake caused a steep decline in societal sentiment as the immediate social and infrastructural repercussions dominated public discourse. Similarly, the pandemic brought sustained negativity, reflecting extensive social disruptions caused by lockdowns, unemployment, and strained community networks. Interestingly, societal sentiment demonstrates quicker rebounds compared to the health and economy sectors, possibly due to an inherent adaptability to changes in social narratives and resilience in the face of social challenges. The *security sentiment* maintained relative stability over time, with significant declines occurring primarily during acute crises. Interestingly, the lifting of fuel subsidies in 2019 caused a minimal drop in security sentiment, likely to public uncertainty of the consequences of the strike on social security and governmental capacity to manage the ensuing protests. The pandemic also saw a notable decline, pointing to heightened perceptions of insecurity during periods of societal strain. However, recovery in this sector tends to be faster, as security-related concerns often normalize once immediate crises subside.

The *political sentiment* displayed interesting relations with other indicators as seemingly both a driver of and responder to shifts. Periods of economic and social turmoil correspond with sharp declines in political sentiment, highlighting public dissatisfaction with governmental policies and their perceived inadequacy in addressing crises (Peter Starke, 2024; Center, 2019; Méda, 2024). Political sentiment showed delayed improvement after the 2015–2016 recession but stabilized more quickly following the pandemic, due to government efforts in managing recovery measures. This mixed recovery pattern underscores the critical role of effective governance in shaping public perception during and after crises.

The interconnectedness of these sectors becomes particularly evident during recessionary periods and crises. On general, the recession of 2015–2016 had a profound impact on sentiment across all sectors. Economic sentiment saw a sustained decline with slow recovery, indicating the deep and lasting nature of this downturn. Health and societal sentiments also declined, albeit less severely, pointing to the interconnected effects of economic instability on public health and social cohesion. Security and political sentiments demonstrated more resilience during this period, reflecting a degree of stability in these domains despite economic struggles. Similarly, the 2016 earthquake primarily affected societal and security sentiments, with marked dips in public perception tied to the disaster's immediate social and safety consequences. While economic and political sentiments also declined during this period, the impact was less drastic, as the earthquake's effect on broader economic and policy narratives was more contained. Recovery from this event was relatively rapid compared to other crises, reflecting the resilience of societal narratives and effective disaster response measures.

The fuel subsidy policy change in 2019 caused one of the sharpest declines in sentiment across sectors. Economic, societal, and health sentiments were particularly affected, reflecting widespread public dissatisfaction with the policy's immediate impact on living costs and social stability. Political sentiment also suffered as public perceptions of governance and accountability seems to have been deteriorated. Recovery from this period was uneven, with societal and security sentiments rebounding faster, while economic and political perceptions remained subdued, highlighting the enduring impact of economic policies on public sentiment.

The pandemic emerged as the most synchronized crisis, with all sectors showing sharp declines in sentiment. Health and societal sentiments were the most heavily impacted, reflecting concerns over healthcare system strain, lockdowns, and social isolation. Economic sentiment also suffered a steep decline, mirroring the global economic fallout of the pandemic. Political sentiment dipped sharply, indicating public dissatisfaction with governmental responses. Recovery across sectors was slow, particularly for health and economy, highlighting the pandemic's deep and multifaceted impact on public perceptions and the prolonged effects of recessionary periods. During the post-pandemic recession, economic sentiment remained subdued revealing lingering structural challenges. Other sectors, including health and society, began to show signs of stabilization, with gradual recovery in public perceptions. Political sentiment showed some improvement, reflecting renewed public confidence in recovery measures. Security sentiment, which had normalized after the pandemic, remained stable during this period, indicating reduced societal volatility.

Volatility across sectors varies significantly, with health, economy, and politics showing the highest reactivity to external shocks. These sectors are deeply intertwined, as economic downturns often cascade into health crises and political instability (WEF, 2023). Security and societal sentiments are relatively stable, with more rapid recovery patterns, suggesting a certain resilience to acute shocks. The interconnectedness of these sectors is particularly evident during crises, where economic disruptions consistently affect societal perceptions, and health crises amplify security and political concerns (Fathi, 2022). Political sentiment, in turn, seems to shape and is shaped by economic and social dynamics, demonstrating its central role in public discourse during periods of instability. In addition, recovery patterns highlight differences in resilience across sectors. Security and societal sentiments tend to stabilize quickly, reflecting the public's ability to adapt to changes in social and security narratives. In contrast, health and economic sentiments exhibit prolonged recovery periods, indicating the lasting impacts of structural challenges and the complexities involved in restoring public confidence in these areas. Political sentiment recovery is mixed as it often depends the effectiveness of governance and policy responses to crises.

The time series results from the sentiment indicators suggest a series of co-movement in sentiment across different sections. To analyze this commonality, Figure 2 displays correlation estimates between different sentiment indicators calculated at a monthly frequency. The most significant correlation is observed between Economy and Politics, indicating a moderately strong positive relationship. This reflects how economic conditions influence public perceptions of political governance and policy effectiveness. Furthermore, the correlation between Economy and Health highlights a positive relationship, albeit less pronounced than that between economy and politics. Economic perception seem to have a direct effect on public health sentiment, as recessions can strain healthcare systems, reduce access to medical services, and exacerbate public concerns about health.

The correlation between Health and Politics reflects a weaker yet still positive relationship displaying how public sentiment toward healthcare systems is still influenced by political decision-making, especially during health crises. While the sentiment related to Security exhibits weak correlations with most other sectors, with the exception of a slightly negative correlation with Politics. The lack of strong associations suggests that security sentiment is relatively insulated from broader public perceptions of economic, health, or political conditions. Besides, the sentiment for Society shows weak positive correlations with other sectors, such as Politics and Economy. These weak correlations suggest that societal sentiment, which reflects social cohesion and community resilience, is only marginally influenced by economic or political conditions. Instead, societal sentiment may be driven by broader cultural and social factors, such as community solidarity or generosity.

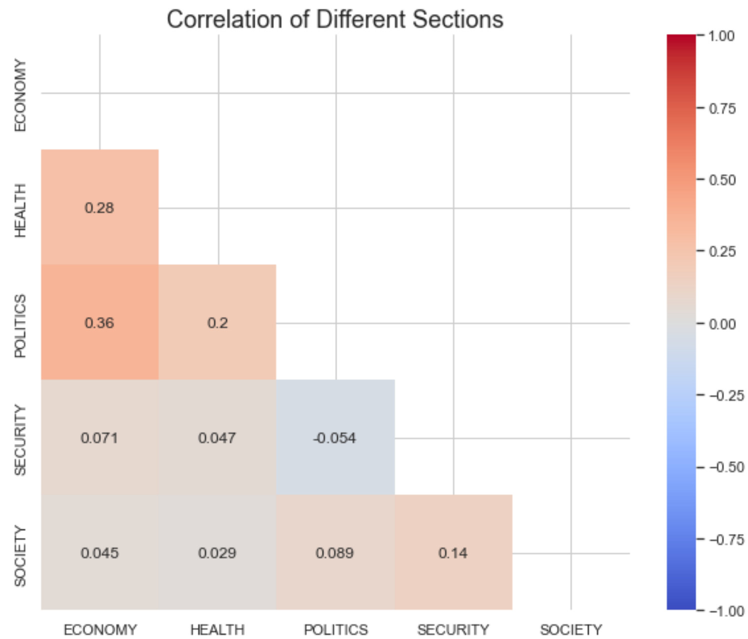

Figure 2: Correlation estimates on the sentiment indicators across sections. Redder colors indicate a large correlation in aboslute value.

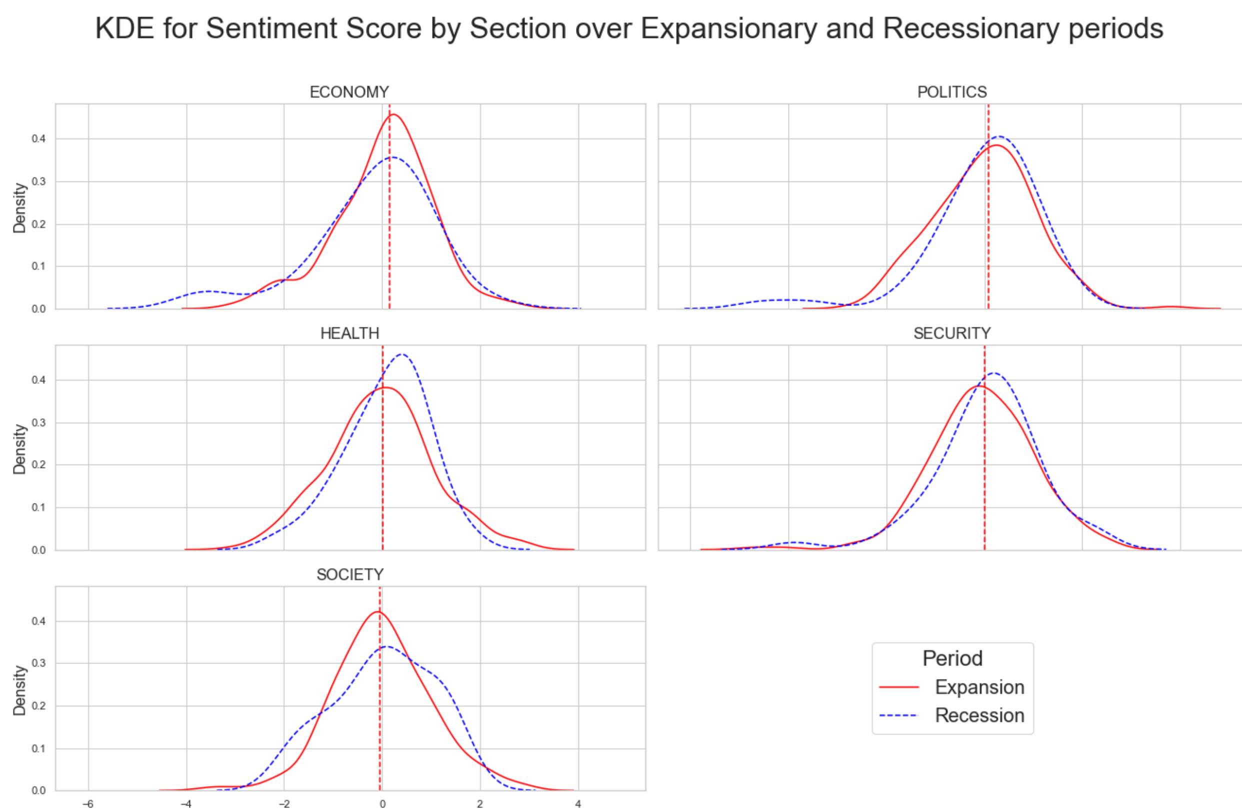

Figure 3: Kernel density estimates of the standardized sentiment indicators during expansions and recessions by section. The dotted red vertical line shows the mean of the ditribution.

The dependence of the scaled sentiment scores on the business cycle is apparent in Figure 3, which displays the behavior of the estimates of the indicators during expansionary and recessionary periods. By examining sentiment distributions across key sectors during these periods, I aimed to gain critical insights into how economic cycles influence public perceptions through Kernel Density Estimation (KDE) plots. These plots reveal how sentiments varied in magnitude, spread, and recovery patterns during times of stability and crisis across different sectors.

I observed that economic sentiment exhibited the most pronounced decline during recessions, with the recessionary KDE curve shifting significantly leftward. This shift depicted the severity of negative perceptions during economic downturns, while the broader spread reflected heightened variability and uncertainty among the public. A significant proportion of sentiment scores fell below the mean value depicted by the dotted red line, emphasizing the profound impact of economic instability on public confidence. The sector's slow recovery further highlighted the lasting scars that economic crises leave on public perception, making it one of the most sensitive domains during downturns.

In contrast, I found that political sentiment showed a more modest leftward shift during recessions compared to economic sentiment. The overlap between expansionary and recessionary distributions indicated that while recessions negatively impacted perceptions of governance, these effects were less severe and more contained. The symmetry of the curve suggested that political sentiment stabilized more quickly, as the public's focus shifted toward governance solutions during crises. Nonetheless, sharp dips in sentiment during significant economic and social crises highlighted the importance of effective government responses in maintaining public confidence during challenging times.

The health sector displayed a marked decline in sentiment during recessions, with a significant leftward shift and a notable concentration in the negative range. Health-related crises, such as the COVID-19 pandemic, amplified public anxieties, particularly when healthcare systems faced strain. The wider spread of the recessionary curve suggested sustained public concerns and heightened variability in perceptions. The slow recovery of health sentiment indicated systemic challenges in restoring public confidence, underscoring the importance of addressing public health concerns comprehensively during and after economic crises.

I observed that security sentiment, unlike other sectors, exhibited minimal leftward shift during recessions, with significant overlap between expansionary and recessionary distributions. This stability reflected the public's relatively consistent perception of security, even amid economic and social disruptions. While security sentiment experienced occasional declines during acute crises like protests or pandemics, it normalized quickly once stability returned. The narrower spread during recessions further highlighted its resilience, making it one of the least volatile sectors.

Societal sentiment displayed a more interesting multimodal structure during recessions, mainly due to a complex and heterogeneous public discourse. This suggests that societal sentiment does not respond uniformly to economic downturns; instead, it reflects a blend of narratives shaped by various factors such as media coverage, cultural resilience, and differing socio-economic experiences. A more nuanced analysis from a VAR framework[4] suggested a bidirectional relationship between macroeconomic survey indicators and societal sentiment, creating a dynamic interplay that could drive or stabilize public perceptions. During re-

[4]See annexes section for the specifications of the model construction and further analysis on Granger-causality and instantaneous causality.

cessions, I observed that this bidirectional influence may explain the fragmentation seen in the KDE. Declining consumer and business confidence likely contributed to the dominant negative narrative—the main bump in the leftward shift of the KDE. The coexistence of multiple sentiment clusters, as evidenced by the secondary bumps in the KDE, could reflect polarized public discourse, where societal concerns are both influenced by and further exacerbate declining economic expectations.

The interconnectedness of the sentiment indicators became especially pronounced during recessions, where the ripple effects of economic downturns were reflected in both sentiment distributions and Granger-causality relationships. The Granger-causality results provided evidence of these interdependencies, showing that economic sentiment acted as a critical driver cascading into other domains and creating a dynamic feedback loop that amplified societal sentiment fragmentation and instability. According to the Granger-causality results, economic expectations (e.g., consumer confidence and sectoral indicators like manufacturing and services) strongly Granger-caused sentiments in health, politics, security, and societal discussions. This suggested that declining economic conditions set off a chain reaction, affecting how other sectors were perceived and discussed. For instance, rising unemployment or financial strain may lead to heightened anxiety about healthcare availability or the adequacy of social security service to satisfy people's health demands.

Moreover, I observed that political sentiment played a pivotal role in this interconnected web as both a driver and a reflection of the dynamics during recessions. The Granger-causality results highlighted that political sentiment strongly Granger-caused and was Granger-caused by economic, health, and societal sentiment. This bidirectional relationship underscored the centrality of politics in shaping and responding to public discourse during instability. For instance, political decisions regarding fiscal policy, healthcare reforms, or public security measures directly influenced how the public perceived the economic and social landscape. At the same time, political sentiment was shaped by how effectively governments managed these crises, often becoming a focal point for blame or praise.

I found that recovery patterns further illustrated differences in resilience across sectors. Security and societal sentiments stabilized quickly, reflecting the public's ability to adapt to changes in social and security narratives. In contrast, health and economic sentiments exhibited prolonged recovery periods, underscoring the structural challenges in these areas. Political sentiment recovery varied depending on governance effectiveness, highlighting the critical role of policymaking in restoring public confidence. Economic and health sentiments seemed to be highly sensitive and slow to recover, emphasizing the profound and lasting impact of economic crises on public perceptions in these domains. Political sentiment's stability depended on effective governance during crises, while security and societal sentiments demonstrated resilience by stabilizing more rapidly due to the public's adaptability. The fact of recognizing these dynamics is crucial for policymakers aiming to address public concerns and foster recovery during and after economic downturns.

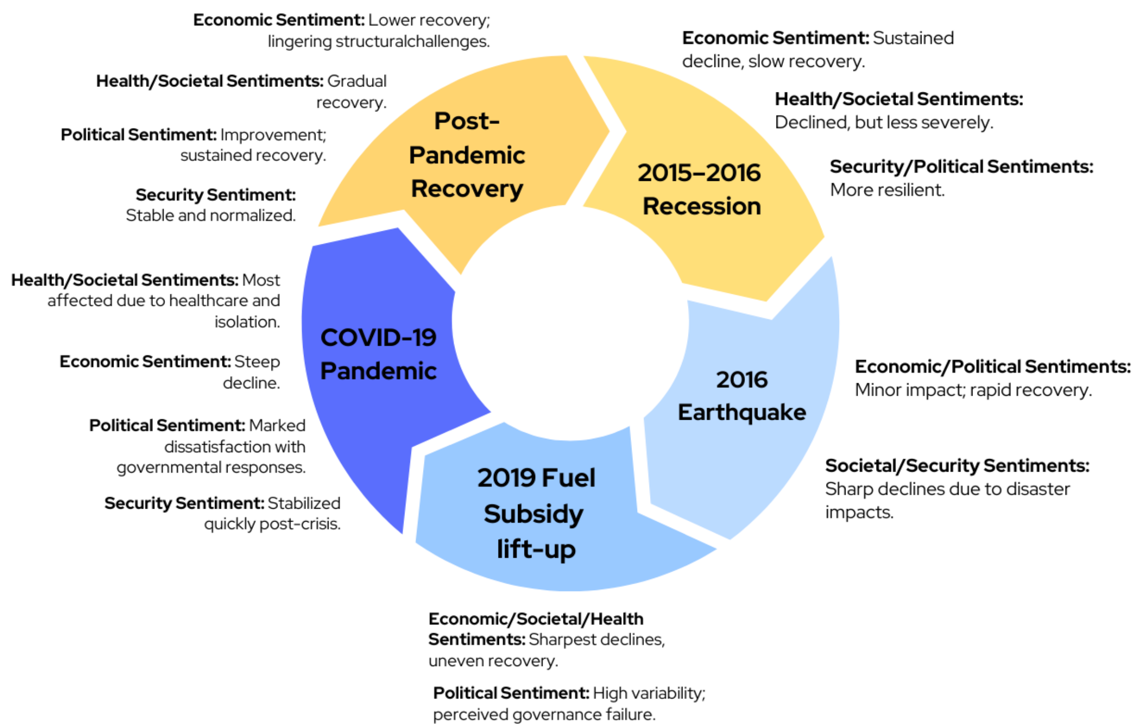

Figure 4: Effects of major crises on different sentiments and their recovery patterns.

3 Methodology

3.1 Sentiment identification strategy

To structure and analyze sentiment indicators, I used articles from the main newspapers companies like *El Comercio, La Hora, Diario El Universo, Expreso, Metro, El Mercurio*, among others from year 2000 to 2024. I identified five key sectors historically prone to systemic instability in the Ecuadorian economy: `ECONOMY`, `POLITICS`, `HEALTH`, `SOCIETY`, `SECURITY`. To categorize the newspaper extracts into these sectors, I applied a customized function that uses a predefined dictionary [5] to perform the classification task, extracts that couldn't be fitted in any of these categories were labeled as "OTHER."

The function takes a text input and first checks wether the text is null or an empty string after trimming any leading or trailing spaces. If the text is empty, the function returns the label "OTHER", otherwise it converts the text to lowercase to ensure consistency in processing. By using SpaCy's functions for language processing I analyzed each classified phrase for unrecognized characters (e.g @#$) and replace them to a word based on its most direct semantical root[6]. After that, the function initializes a dictionary called match_counts with keys representing the defined sectors and values set to zero. For each sector, the function counts the number of occurrences of predefined keywords associated with that sector within the text, then the counts are updated in the dictionary accordingly. These keywords are specific terms indicative of the sector's content. After processing all sectors, the function identifies the category with the highest keyword match count. If the highest count is greater than zero, it returns that category as the label for the text; otherwise it returns "OTHER."

Next, I looped through each newspaper datasets from 2000 to 2024, dynamically generating the identification labels. For each generated label, the function stored the processed identifier of the news extract variable in a new column called *section.* This process effectively categorized the text data across multiple yearly dataframes. Finally, I extracted the identified sections from all the processed dataframes and compiled them into a new dataset. This dataset included the time index (dates), serial code of the news from the source dataset of the news extract, the assigned sector (section), and the news extract itself. This organized

[5] Check *NLP Dictionary* subsection in Annexes section for more details
[6] Revise the *SpaCy large news model* subsection in methodology for further details.

dataset served as the foundation for the subsequent sentiment analysis.

3.2 ARDL models

Autoregressive Distributed Lag (ARDL) models are a class of econometric models designed to capture both the short-run dynamics and long-run equilibrium relationships between variables. They are flexible in that they incorporate lags of both the dependent variable and explanatory variables, allowing the careful examination of how current outcomes relate not only to current predictors but also to past values of both the outcome and predictor variables. ARDL models are particularly useful when studying both short-term and long-term trends because they separate out immediate adjustments from deeper, more persistent relationships. In the short run, transitory shocks may cause variables to deviate from their long-term path; ARDL models can pinpoint how quickly and through which channels the system returns to equilibrium. Over the long term, ARDL models help identify stable, long-run coefficients that indicate the underlying relationship between variables, ensuring that analysts understand the fundamental linkages that persist over time, even after short-term fluctuations wash out.

The proposed ARDL framework offered distinct advantages over alternative methods commonly used in the academic literature, particularly for the case of Ecuador's economic forecasting. Traditional methods, like Vector Autoregressive (VAR) models or Vector Error Correction Models (VECM), are popular for capturing relationships between macroeconomic variables but are often ill-suited to handle mixed-frequency data and high-dimensional datasets like those involving sentiment indicators. VAR and VECM also require all variables to share the same integration order, which limits their flexibility when incorporating sentiment data that might behave differently from traditional economic variables (Pennington et al., 2014). Additionally, the rigidity of these models in the presence of structural breaks, such as those caused by the 2016 earthquake or the COVID-19 pandemic in Ecuador, often leads to reduced forecast accuracy.

In contrast, machine learning models, such as neural networks or ensemble methods, are increasingly applied in forecasting tasks due to their ability to capture complex, non-linear relationships. However, these models often lack interpretability and require large volumes of data to perform well, making them less practical for countries like Ecuador where historical datasets may be limited in scope and frequency. Unlike black-box machine learning methods, the ARDL models retain the interpretability of traditional econometric techniques while leveraging the benefits of feature selection to enhance forecasting accuracy. For instance, neural networks tend to overfit when used with small or medium-sized datasets, while LASSO-ARDLS' regularization in contrast ensures that only the most relevant predictors are included, reducing noise and improving generalization (Medeiros and Mendes, 2017).

3.3 Forecasting Models

My goal is to understand both short-term and long-term relationships between the annual percentual growth rate of GDP and multiple explanatory variables. The baseline specification considered is:

$$y_t = \beta_t \mathbf{X}_t + \eta_t \mathbf{S}_{t-j} + \delta_t \mathbf{D}_t + \theta_t \mathbf{Z}'_{t-j} + \varepsilon_t,$$

where:

- y_t represents GDP annual growth rate at time t.
- X_t indicates different control variables and survey indicators.
- Z'_{t-j} is a vector of the lagged control variables, survey indicators and GDP annual growth rate.
- S_{t-j} is a sentiment indicators vector from digitalized newspapers from 2000-2024 with their respective lags. These sentiments aim to track the flow of information available to forecasters up to time t.
- D_t a set of dummy variables that account for structural changes, such as recessions, natural disasters, and pandemics.
- β_t, ϕ_t, γ_t, δ_t, θ_j are the parameters to be estimated.
- $\varepsilon_t$is the forecast error for the monthly release of GDP growth based on the information available at time t.

The model formula is dynamically constructed in the statistical software R to integrate all the key components described above. It is implemented in two formats: one that focuses solely on the effects of survey variables as a benchmark (ARDL) and another that incorporates both survey and sentiment variables (ARDLS). Using the `dynlm` package in R, the ARDL benchmark model seamlessly include autoregressive terms, contemporaneous and lagged explanatory variables, real-time sentiment indicators, and structural breaks through dummy variables. This structure provides a robust framework for estimating short-term dynamics while capturing long-term relationships.

Due to the high variability obtained from the sentiment information, it was necessary to implement a regularization process to estimate the parameters of the ARDLS model. To address this challenge, I used LASSO regularization into the ARDLS framework as it enhances model selection and estimation accuracy, particularly in the presence of numerous predictors. Medeiros and Mendes (2017) showed the usefulness of this regularization process by estimating stationary ARDL models with GARCH (Generalized Autoregressive Conditional Heteroskedasticity) errors trough LASSO penalization. Their study demonstrated that adaptive LASSO effectively identifies relevant variables with a probability converging to one, achieving oracle efficiency. That is the estimator's distribution aligned with that of an oracle-assisted least squares estimator, which assumes prior knowledge of the relevant variables (Medeiros and Mendes, 2017). The authors also illustrated that the LASSO estimator could serve as a basis for constructing initial weights in the adaptive LASSO procedure, thereby enhancing the model's performance in finite samples.

Moreover, Yukang et al.(2022) displayed the usefulness of LASSO regularization when addressing the challenge of modeling and forecasting economic variables in a globalized context, where interdependencies among regions and high-dimensional datasets complicate traditional econometric approaches. In their study, the researchers proposed a Time-Varying Parameter Global Vector Autoregressive (TVP-GVAR) model integrated with machine learning techniques, including the aforementioned LASSO-type regularization. Their results shows how the LASSO-enhanced TVP-GVAR outperformed traditional GVAR and other econometric models in forecasting accuracy. The time-varying parameters captured the dynamic relationships between variables more effectively than static models. Furthermore, by selecting a subset of significant predictors, the model offered clearer insights into the economic drivers and their evolving impacts over time. Ultimately, the model's ability to identify **key economic interdependencies** provided valuable insights for policymakers, particularly in understanding how global shocks propagate across regions.

Based on this evidence, I estimated the coefficients on the ARDLS model by penalizing the absolute magnitude of regression coefficients through LASSO regularization to effectively select the most significant regressors while shrinking irrelevant coefficients to zero. In return, this allowed the model to improve its robustness and generalizability by simplifying the model and reducing noise from the high-dimensional sentiment data trough the regularization parameter (λ). This parameter was optimized using cross-validation to ensure a balance between complexity and predictive accuracy[7].

3.4 Denton method for temporal disaggregation of time series

The Denton method is a widely used technique for temporal disaggregation, designed to convert low-frequency data into high-frequency data while preserving the original series' consistency. In context of this study, the goal was to disaggregate quarterly GDP growth rates, remittances, and exports into monthly series using the monthly Consumer Confidence Indicator (CCI), denoted as `CONS_CONFIDENCE` in the dataset, as the guiding variable. The process estimates smooth and accurate monthly series for these variables, consistent

[7]The annexes section contains a graphic comparison for the model fit before and after LASSO regularization.

with observed quarterly growth rates. Essentially, the method minimizes distortions in the proportional relationship between the high-frequency indicator and the target series to ensure the smoothness of the series (Sax and Steiner, 2013). As a result, the disaggregated monthly series maintained consistency with quarterly data while incorporating meaningful high-frequency variations suggested by the CCI. The process was implemented through the following procedure.

1. **Input Data:**

   - Quarterly-frequency time serie(s), Q_t, represent the low-frequency serie(s) to disaggregate.
   - Monthly Consumer Confidence Index (CCI), M_t, acts as the high-frequency indicator correlated with Q_t.

2. **Proportionality Assumption:** The monthly GDP growth rates (M_i) are assumed to be proportional to the monthly CCI values (x_i):

$$M_i = w_i \cdot x_i$$

   where w_i is a scaling factor.

3. **Constraints:** The disaggregated monthly series must satisfy the following condition:

$$\sum_{i \in t} M_i = Q_t$$

   for each quarter t, ensuring the monthly series sums to the quarterly data.

4. **Optimization Criterion:** The Denton method minimizes the variation in the monthly growth rate estimates relative to the indicator (CCI):

$$\min \sum_{i=2}^{n} \left(\frac{M_i}{x_i} - \frac{M_{i-1}}{x_{i-1}} \right)^2$$

   This ensures a smooth monthly series that aligns with the CCI pattern.

5. **Solution Process:**

   - Start with an initial estimate for M_i proportional to x_i:

$$M_i^{(0)} = \frac{Q_t}{\sum_{i \in t} x_i} \cdot x_i$$

   - Adjust iteratively to satisfy the constraints while minimizing the objective function.

6. **Output:** The final series (M_i) are consistent with quarterly data and reflect the intra-quarter variability indicated by the CCI.

The Denton method, integrated with the ARDL framework, further underscores this approach's suitability by harmonizing mixed-frequency data—a frequent challenge in economic forecasting for developing countries. Unlike dynamic factor models, which are often used for similar purposes, the Denton method maintains a smooth and consistent relationship between high and low frequency data without imposing rigid assumptions about the underlying processes (Denton, 1971). This adaptability is critical for Ecuador, where macroeconomic indicators like GDP and remittances are typically reported quarterly but sentiment information are available much more higher frequencies. In this context, the quarterly GDP annual growth rate, exports and remittances were disaggregated into a monthly series using the monthly indicator of Consumer Confidence Index as the high-frequency movement guide for the disaggregation process. By combining Denton method's data harmonization capabilities with the robust regularization of LASSO, the proposed approach not only captures short and long term dynamics but also ensures stability in the presence of high-frequency text-derived sentiment data, addressing the unique forecasting challenges posed by Ecuador's volatile economic environment.

3.5 Natural Language Processing Algorithms

Natural Language Processing (NLP) is an interdisciplinary field that combines linguistics and computer science to apply mathematical and computational methods to natural language. Its applications are diverse, encompassing text-to-speech conversion, automatic translation, text correction, information retrieval, and many other areas (Lukauskas et al., 2022). NLP is widely used by various companies for these tasks and others, including sentiment analysis.

Traditionally, sentiment analysis has relied on statistical methods that calculate indices based on the frequency of certain words or phrases within a text corpus (Buckman et al., 2020). These frequency-based approaches, often referred to as bag-of-words models, consider each word independently without accounting for context or linguistic nuances. While effective to some extent, these methods can miss subtleties such as sarcasm, negations, or the influence of surrounding words, potentially leading to less accurate sentiment assessments.

Lexicon-based sentiment analysis algorithms on the other hand offer a more holistic view by incorporating dictionaries of sentiment-laden words along with rules that consider context and grammatical structures. Tools like VADER (Valence Aware Dictionary and Sentiment Reasoner), TextBlob or FiGAS aim to combine heuristics to evaluate the intensity and polarity of sentiments expressed in text extracts. This approach allows for integrating higher variation when performing statistical analysis on social phenomena, as it accounts for modifiers, intensifiers, and negations that affect the sentiment conveyed (Hutto and Gilbert, 2014). Moreover, lexicon-based methods are transparent and interpretable since they rely on predefined sentiment scores assigned to words and phrases. They are particularly effective in domains where labeled training data is scarce or when the goal is to understand specific language patterns contributing to overall sentiment. However, they require regular updates to the lexicon to stay current with evolving language use, slang, and domain-specific terminology.

The results from lexicon-based sentiment analysis can enrich and sharpen economic analysis, such as in forecasting economic and financial variables. Sentiment derived from news is especially useful when predicting macroeconomic variables, as it allows the state of the economy to be monitored in real-time—unlike official releases of macroeconomic data that are seldom available and often significantly delayed (Einav and Levin, 2014). Consoli et al. (2022) suggest that understanding human sentiments can provide better and clearer insights into market dynamics in economic analysis. Consequently, improving forecasting models performance and providing more accurate results that serve as the basis for more informed economic and financial decisions (Chang et al., 2016; Malandri et al., 2018).

3.5.1 Valence Aware Dictionary and Sentiment Reasoner

Developed by C.J. Hutto and Eric Gilbert in 2014, VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool specifically designed for text from online platforms such as tweets, comments, and web page reviews. It combines a comprehensive sentiment lexicon with heuristic rules to evaluate the intensity of emotions conveyed in text. Since VADER is lexicon-based, it does not require training on labeled datasets, saving time and resources. Additionally, VADER's lexicon is customizable, allowing users to add or modify words and their associated sentiment scores to tailor it to specific domains or applications. Although primarily designed for English, VADER's methodology can be adapted for other languages by integrating it with external statistical models trained in the desired language.

At the heart of VADER lies its sentiment lexicon, a carefully curated list of words, phrases, and symbols annotated with sentiment scores. Each word or phrase in the lexicon is assigned a valence score that reflects its emotional intensity. Key aspects of the sentiment lexicon include:

- Annotated Scores: Words like "happy" and "excellent" are assigned positive scores (e.g., +2.1, +3.0), while words like "sad" and "terrible" receive negative scores (e.g., -2.0 -3.5). Neutral words have a score close to 0.

- Coverage of Informal Language: The lexicon includes slang, emoticons, abbreviations, and colloquial expressions such as "lol," "meh," or ":)", ensuring compatibility with informal text like tweets and digital media posts.

- Intensifiers and Modifiers: Words like "very" and "extremely" amplify the sentiment intensity of adjacent words, while negations like "not" or "barely" reduce or invert sentiment.

After processing the text using its lexicon and rules, VADER computes sentiment scores. These scores are presented in four categories:

- Positive: The proportion of the text that conveys positive sentiment.
- Negative: The proportion of the text that conveys negative sentiment.
- Neutral: The proportion of the text that is neutral or lacks strong sentiment.
- Compound Score: A normalized, weighted composite score that combines positive, negative, and neutral sentiments into a single value ranging from -1 (most negative) to +1 (most positive).

Sentiment analysis offers meaningful insights into how public opinions and narratives drive financial markets, consumer behavior, and investor decisions. Due to its adaptability and versatility, VADER has been increasingly utilized to analyze sentiment across different domains. For instance, Soni et al.(2023) demonstrated the immediate impact of news headlines on a company's stock performance using NLP. By comparing traditional machine learning algorithms with VADER sentiment analysis, they found that the VADER-based approach provided superior accuracy in predicting stock market trends, offering a more reliable tool for investors and businesses navigating the highly volatile financial landscape (Soni and Mathur, 2023).

Similarly, Rutkowska et al.(2024) explored sentiment analysis in central bank communications by assessing sentiments using four different lexicon dictionaries. Through a series of analyses—including lexicon content comparison, performance tests for highly positive and negative messages, and statistical tests of dictionary alignment and correlation—they concluded that the choice of dictionary significantly impacts the detection of central bank intentions (Rutkowska and Szyszko, 2024). Their findings suggested that applying dictionary methods, such as those used in VADER, to assess policy release sentiments in small open economies can effectively capture and analyze whether the intended messages by central authorities are properly conveyed to the public.

In the political realm, VADER has been extensively used to study public opinion, campaign strategies, and policymaker communication. Its ability to process short, informal texts makes it an effective tool for analyzing sentiment in political discourse. Researchers have leveraged VADER to evaluate the impact of politicians' social media activity on public sentiment and electoral outcomes. For instance, Ali et al. (2022) conducted a large-scale sentiment analysis of 7.6 million tweets pertaining to the 2020 U.S. Presidential Election using VADER. Their novel approach included identifying tweets and user accounts that were later deleted or suspended, allowing them to observe sentiments across accessible, deleted, and suspended tweets and accounts. They discovered that deleted tweets posted after Election Day were more favorable toward Joe Biden, while those leading up to Election Day were more positive about Donald Trump. Additionally, older Twitter accounts tended to post more positive tweets about Joe Biden (Ali et al., 2022). This study underscores the importance of conducting sentiment analysis on all posts captured in real time, including those now inaccessible, to determine the true sentiments surrounding significant political events.

Collectively, these applications of VADER at the intersection of economics and political sentiment highlight its innovative and powerful utility. By exploring sentiments in central bank communications and analyzing tweets and addresses by government officials to assess public sentiment surrounding fiscal policies, VADER provides actionable insights into the interplay between political rhetoric and economic decision-making. These applications reveal how sentiment extracted via VADER can inform researchers and policymakers about public reactions to fiscal and monetary policies, offering valuable tools for shaping effective communication strategies and making informed decisions in both economic and political spheres.

3.5.2 TextBlob

TextBlob is a Python library for processing textual data for sentiment analysis by leveraging pre-trained models and a lexicon-based approach. It processes text at the sentence level, breaking the input into sentences and analyzing each one independently. This allows it to handle variations in sentiment across a text document, providing a more granular analysis (Loria, 2018). For instance, if one sentence is positive and another is negative, the tool calculates separate scores for each and then averages them to produce an overall sentiment for the entire document. This methodology helps to capture mixed sentiments in texts like reviews or news articles. A key advantage of TextBlob is its simplicity and integration into natural language processing workflows. Unlike more advanced deep learning models, TextBlob requires no training or additional setup.

Regarding score calculations, TextBlob assigns a sentiment polarity score to text through the polarity ranges from -1 (negative sentiment) to +1 (positive sentiment), and a subjectivity score ranging from 0 (objective) to 1 (subjective). This dual scoring system allows TextBlob to capture not only the overall sentiment but also the degree of personal opinion versus factual content in the text. These scores are calculated by evaluating individual words and phrases in the text against a predefined lexicon of sentiment-bearing terms. The underlying sentiment lexicon in TextBlob contains words with predefined polarity and subjectivity values (Loria, 2018). For example, words like "great" or "terrible" have strong positive or negative polarity values, respectively. TextBlob aggregates these individual word scores across the text, adjusting them based on linguistic features such as negations ("not good" flips polarity) or modifiers ("very good" amplifies positivity). This approach ensures that sentiment analysis accounts for contextual nuances rather than relying solely on traditional word-level scores. Besides, TextBlob works directly in the users setup making it accessible for developers and analysts who need quick and reliable sentiment analysis. While its lexicon-based approach may lack the sophistication of a neural network-based models, it remains effective for many use cases, particularly for straightforward or well-structured text data.

TextBlob's utility extends to multilingual sentiment analysis, including Spanish, thanks to its support for language translation and processing through the integration of external libraries like Google Translate. This capability is particularly useful for Spanish sentiment analysis in cases where no native Spanish lexicon is available, as TextBlob can translate Spanish text into English before performing sentiment analysis using its English lexicon (Unipython, 2019). While this introduces some dependency on translation accuracy, it provides a straightforward solution for handling Spanish texts, enabling sentiment analysis even when no specialized tools for Spanish are available. Furthermore, TextBlob's simplicity and adaptability make it a practical choice for preprocessing Spanish text before applying more advanced or domain-specific models. It can perform basic tasks such as tokenization, part-of-speech tagging, and noun phrase extraction for Spanish, helping to prepare data for downstream tasks.

For Spanish sentiment analysis, it can also be combined with custom lexicons or rule-based enhancements to address language-specific nuances through other language processing models. This flexibility, coupled with its ease of use, makes TextBlob a versatile tool for researchers and developers working with Spanish-language sentiment analysis. Overall, TextBlob is a valuable tool for standard sentiment analysis tasks where interpretability and simplicity are priorities. Despite its strengths, TextBlob has limitations as it relies heavily on its predefined lexicon, making it less effective for domain-specific texts or slang-heavy language that might not be well-represented in the lexicon (Unipython, 2019). Additionally, TextBlob struggles with complex linguistic constructs like sarcasm or context-dependent sentiment(s).[8]

3.5.3 SpaCy large news model

The SpaCy large news model is a robust and pre-trained natural language processing (NLP) model designed to process and analyze text, particularly within the domain of news and general information. Built on a combination of machine learning techniques and linguistic rules, this model enables users to extract meaningful insights from large text datasets. Its architecture, pre-training, and processing pipeline make it a powerful tool for handling the complexities of natural language. At its core, the SpaCy large news model leverages a deep learning framework based on transformers or convolutional neural networks (CNNs) to encode semantic and syntactic features of text. Pre-trained on large corpora of news articles and other general-domain text, the model captures linguistic patterns, context, and relation-

[8]To account for deeper understanding and adaptability I integrated it with VADER interface to obtain a more suitable solution for the context specific scenario of the news articles.

ships within text (Honnibal and Montani, 2020). This pre-training allows it to generalize effectively across various news-related tasks, such as named entity recognition (NER), dependency parsing, and part-of-speech (POS) tagging, which are foundational to understanding text structure and meaning.

One of the standout features of the SpaCy large news model is its ability to perform named entity recognition (NER). This task involves identifying proper nouns, dates, monetary values, and other specific entities within a text. Due to its pre-trained on news-related data, the model is able to recognize entities commonly encountered in journalistic contexts, such as locations, organizations, and political figures. This capability is particularly useful in analyzing large-scale news datasets, extracting relevant information, and structuring it for further use in applications like sentiment analysis.

Additionally, the model's pipeline consists of several key components, each contributing to the processing and analysis of text. Tokenization is the first step, where the text is broken down into individual tokens, such as words or punctuation marks, while preserving language-specific rules, such as contractions or compound words to ensure accurate downstream analysis. After tokenization, POS tagging assigns grammatical roles (e.g., nouns, verbs) to each token while dependency parsing identifies syntactic relationships between tokens, such as subject-verb-object structures (Pennington et al., 2014). These tools enable the model to map grammatical and logical relationships within a sentence.

Another key aspect of the model is its use of vector embeddings to capture semantic meaning. SpaCy employs word embeddings, such as GloVe or transformers-based embeddings, to represent words as dense numerical vectors in high-dimensional space. These embeddings encode the relationships between words based on their context in the training data. For instance, the model understands that "bank" in the context of "river bank" differs from "bank" in "financial institution." This semantic understanding enhances its ability to disambiguate words and phrases in diverse contexts, making it a versatile tool for analyzing nuanced language.

The SpaCy large news model is also highly customizable and efficient, which makes it suitable for a wide range of NLP tasks. Users can fine-tune the model on domain-specific corpora, such as financial or scientific articles, to improve its performance in specialized contexts. Additionally, the model is optimized for speed and scalability, enabling it to process large text datasets quickly. This efficiency makes it particularly valuable in news analytics, where real-time or near-real-time processing of vast quantities of data is often required. The combination of pre-trained knowledge, linguistic capabilities, and adaptability ensures that the SpaCy large news model remains a go-to solution for comprehensive text analysis in the news domain (Vaswani et al., 2017). Moreover, SpaCy contains specialized text cleaning and normalization functions required for pre-processing the data before running sentiment analysis on the text extracts.

3.6 Text cleaning protocol

Text cleaning and normalization are essential processes in Natural Language Processing (NLP) to handle irregular or non-standard inputs. Words like $enc@m\$ass$, which include unusual characters, present challenges for models and must be transformed into a more understandable and structured form. The cleaning process typically involves identifying and removing unwanted elements, ensuring uniformity, and approximating meaningful content.

This transformation relies on regular expressions (*regex* function) and other techniques to clean and normalize text systematically. The four key steps involved in this process are described below.

The first step involves identifying and removing non-alphanumeric characters. Consider the case of the word *enc@m$ass* that contain symbols like @ and $, which are neither letters nor numbers and provide no semantic value in most contexts. These characters can be detected using a regex pattern such as $[^{a} - zA - Z0 - 9]$, which matches anything that is not a letter or number. Replacing these characters with an empty string or a space effectively removes them, leaving only the core alphanumeric components. In the case of *enc@m$ass*, this step results in the cleaned string **encmass**. By eliminating extraneous symbols, this step ensures that the word is stripped of noise while retaining its semantic essence.

Once non-alphanumeric characters are removed, the second step involves ensuring case uniformity. Natural language often includes a mix of uppercase and lowercase letters, but for most NLP tasks, treating words in a case-sensitive manner is unnecessary and can introduce inconsistencies. Converting all letters to lowercase guarantees that words like *Enc@m$ass* and *enc@m$ass* are processed identically, yielding encmass after cleaning. This normalization step is straightforward yet crucial, as it helps standardize text for downstream processing, reducing the number of unique tokens in the data.

The third step addresses the presence of multiple consecutive non-alphanumeric characters, often found in informal text from social media or user-generated content. If such characters are detected, they are either consolidated into a single space or removed entirely to produce a more readable and structured result. Once cleaned, the algorithm approximates the word to a valid dictionary term or a more recognizable form. For instance, while the

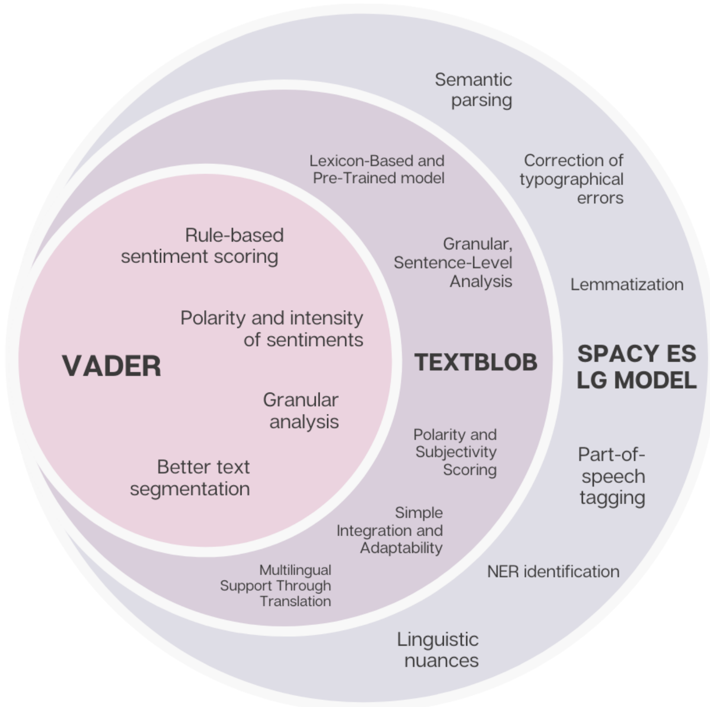

Figure 5: Integration of VADER, TextBlob and SpaCy ES LG Model to analyze textual data comprehensively.

string encmass is free of noise, it may not correspond to a valid word. Using techniques like Levenshtein Distance or phonetic algorithms, the cleaned word is compared to a lexicon to identify the closest match, such as **encompass**. These methods assess string similarity or phonetic alignment, helping to recover the intended word and correcting typographical errors or unconventional spellings.

Additionally, leveraging the ChatGPT 4.0 API, I added an extra layer that ensured the cleaned text was logical, grammatically correct, and semantically consistent when applied to the newspapers datasets while considering its identifier in the variable 'section'. If the text fails this contextual check, the cleaning process is restarted before proceeding to analyze the next phrase.

3.7 Limitations

Despite numerous advantages, the integration of news-based sentiment analysis into GDP forecasting also has several limitations that warrant careful consideration. A primary concern lies in the inherent subjectivity of sentiment analysis, where news content is shaped by editorial policies, biases, and agendas, which can influence the tone and framing of articles. As a result, sentiment indicators derived from such data may not fully reflect a fully objective state of public opinion or economic conditions. For example, during politically charged events, media outlets with differing political leanings might portray economic developments in contrasting lights introducing noise or bias into the sentiment analysis process.

Additionally, NLP algorithms, while powerful, are not immune to inner biases. Pre-trained models such as VADER or TextBlob rely on lexicons and rules that may not adequately account for regional linguistic nuances or evolving language patterns such as idiomatic expressions and colloquialisms. In return,they may misinterpret the message of the analyzed texts potentially skewing sentiment scores by unknown degrees depending on the intensity of the sentiment. Even advanced models, while more context-aware, require significant fine-tuning to accurately process the subtleties of local language and discourse. These limitations highlight the need for continuous refinement of NLP tools to ensure that they capture sentiments accurately and meaningfully in context-specific scenarios. In addition, the overreliance on high-frequency textual data, which while providing timely insights, can also amplify short-term noise or anomalies, is another factor to be considered. Events that generate intense but fleeting public reactions, like controversial political statements or short-lived market fluctuations, might disproportionately influence sentiment indicators. This can lead to overestimation of their impact on GDP forecasts, especially in highly dynamic periods. Without robust mechanisms to filter or contextualize such outliers, there is a risk of producing forecasts that are overly reactive to changes in transient sentiment.

Finally, the proposed LASSO-ARDL framework, while effective for short-term forecasting, demonstrated diminishing returns for longer horizons. This limitation comes from the fact that the influence of sentiment-based indicators weakens over time as structural economic trends and traditional macroeconomic variables become more dominant. Although this does not diminish the utility of the approach for short-term applications, it underscores the need for complementary methods to enhance long-term predictive power. Addressing these limitations thus requires further methodological refinements, such as incorporating additional data sources, fine-tuning NLP models for local contexts, and developing hybrid forecasting frameworks that balance short-term responsiveness with long-term stability.

4 Results

4.1 In-sample analysis

This section discusses a comparative analysis between the benchmark model ARDL model and the LASSO-regularized ARDL (LASSO-ARDLS) model with sentiment indicators for an in-sample scenario. Results reveal significant differences in their forecasting performance and stability over time, based on several statistical metrics including the Iterated Root Mean Square Error (RMSE), Diebold-Mariano (DM) test results, and stability tests such as the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ).

In essence, results displayed a clear advantage of the LASSO-ARDL model in short-term GDP forecasting, particularly in terms of Root Mean Square Error (RMSE), a critical metric for assessing prediction accuracy. For instance, the model's RMSE for 1-month forecasts is considerably lower than that of the benchmark ARDL model, indicating that it can provide more precise predictions of Ecuador's GDP fluctuations within this short horizon. To put this into perspective, if policymakers rely on GDP forecasts to plan fiscal adjustments a lower RMSE translates to fewer deviations between expected and actual outcomes reducing the likelihood of overestimating or underestimating economic performance. This is particularly important for Ecuador, where accurate forecasts are essential for managing debt obligations and social spending amidst volatile commodity markets.

Figure 4 showcases iterated RMSE values for both models showing noticeable spikes that likely correspond to periods of economic shocks or structural changes in the underlying dataset. In terms of general performance, the ARDL model exhibits significant volatility in RMSE values, with higher pronounced spikes indicating periods where the model struggles to capture sudden changes in the data. The average RMSE for the ARDL model is 1.3831, suggesting a relatively higher prediction error overall. In contrast, the LASSO-ARDLS model demonstrates a more stable RMSE trajectory, with fewer extreme variations. Its average RMSE is 0.9122, notably lower than that of the ARDL model. This lower RMSE indicates that the LASSO-ARDLS model provides more accurate forecasts on average. This stability can be attributed to the LASSO regularization technique which seems to effectively mitigate overfitting by penalizing the absolute size of the regression coefficients, thus simplifying the model and enhancing its ability to generalize to new data.

Forecasting Horizon	DM Coefficient	p-value
1 month	1.3874	0.0027
3 months	1.0928	0.0250
6 months	0.8215	0.0699
12 months	0.6423	0.1078
24 months	0.5246	0.1688

Table 1: Diebold-Mariano Test Results for LASSO-ARDLS Model at Different Forecasting Horizons (In-Sample). DM statistic is set as errors ardl, errors lasso

The practical significance of these improvements becomes evident when considering real-world economic scenarios. For example, during the COVID-19 pandemic, rapid changes in economic activity required timely and accurate forecasts to allocate emergency funds effectively. A sentiment-enhanced LASSO-ARDL model, with its lower RMSE and ability to incorporate real-time public perceptions from news, could have provided early indications of economic downturns or recovery trends. This timeliness showcases a useful tool for policymakers to preemptively address challenges such as unemployment spikes or disruptions in public services, which traditional models might detect only after substantial delays.

Additionally, the LASSO-ARDL model's lower RMSE indicates its robustness in capturing the nuanced effects of high-frequency data like sentiment indicators. During the 2019 removal of fuel subsidies in Ecuador, widespread public dissent was reflected in media sentiment, which traditional economic variables might not immediately capture. A model with a lower RMSE ensures that such immediate public reactions are effectively translated into actionable insights. This responsiveness is particularly valuable in Ecuador's context, where political and economic instability often amplify the importance of short-term decision-making.

Table 1 presents the Diebold-Mariano (DM) test results for forecasting horizons of 1, 3,

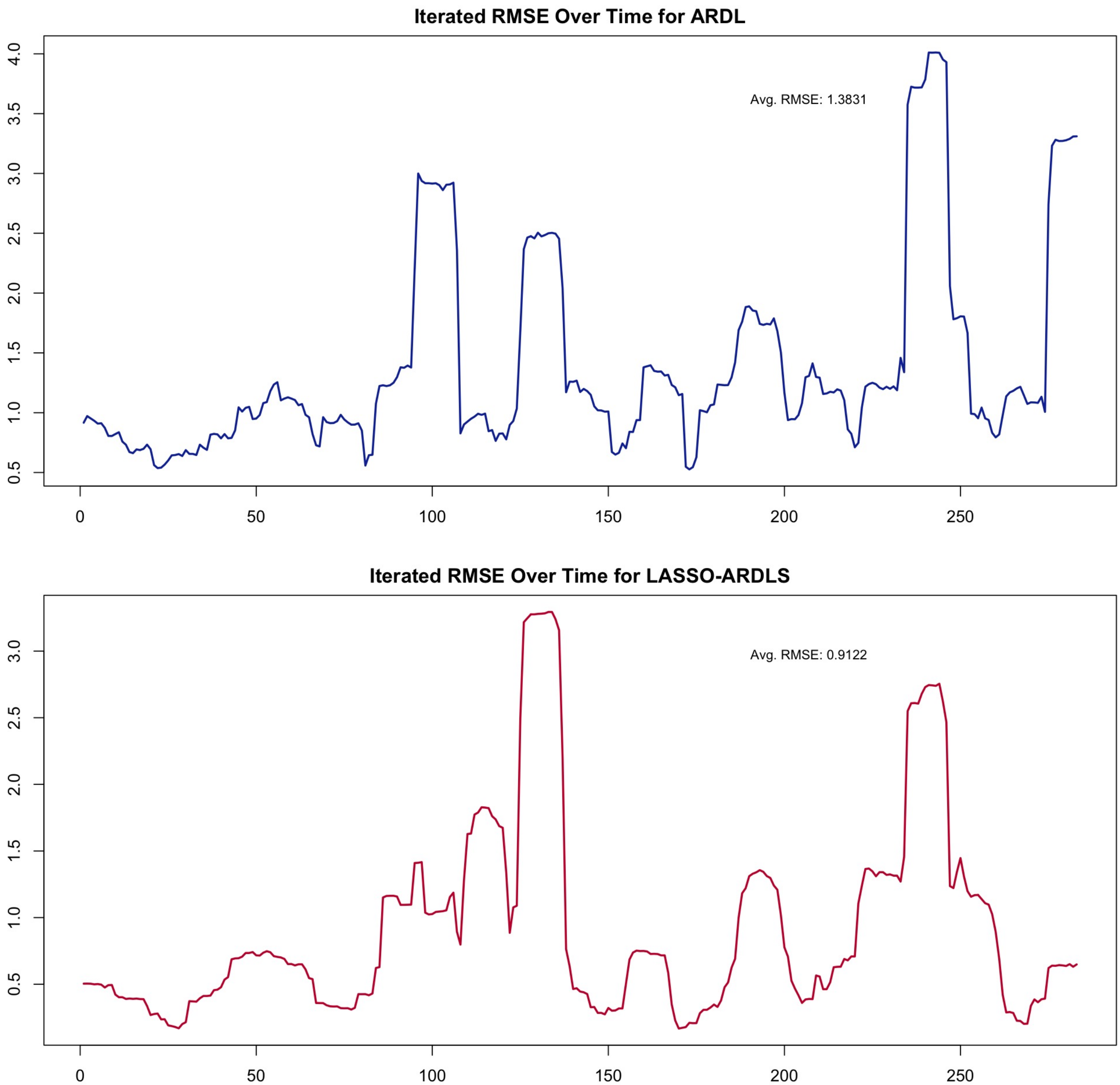

Figure 6: Comparison of iterated RMSE over time for ARDL and LASSO-ARDLS models.

6, 12, and 24 months to compare the models predictive accuracy in these horizons. The DM test yields statistically significant p-values of 0.0027 and 0.0250 for the 1-month and 3-month horizons, respectively. These low p-values indicate that the differences in forecasting accuracy between the two models are statistically significant at 5% level. Nonetheless, as the forecasting horizon extends the statistical significance diminishes as shown by the 6-month, 12-month, and 24-month horizons p-values, where ultimately there is no statistically significat difference between the forecasting ability of the models. This trend suggests that while the LASSO-ARDLS model has a clear advantage in the short term, its superiority diminishes over longer forecasting horizons as both models' display a similar ability to capture long-term trends, making their performances converge over time.

In terms of stability and robustness, the CUSUM and CUSUMSQ tests in Figure 5 shows that the cumulative sum of residuals remains within the critical bounds, indicating structural stability in each model specifications. However, a closer inspection reveals that the LASSO-ARDLS model displays smaller and more stable deviations compared to the ARDL model, highlighting its robustness to shocks or parameter shifts. The CUSUMSQ test results reinforce this observation, as it depicts greater variability in the ARDL model, particularly during periods of volatility. In contrast, the LASSO-ARDLS model appears less sensitive to variance changes, making it a more robust choice under dynamic conditions.

Model	**Average RMSE**
In-Sample ARDL	1.3831
In-Sample LASSO-ARDLS	0.9122
Out-of-Sample ARDL	11.4027
Out-of-Sample LASSO-ARDLS	0.0368

Table 2: Average RMSE for ARDL and LASSO-ARDLS models

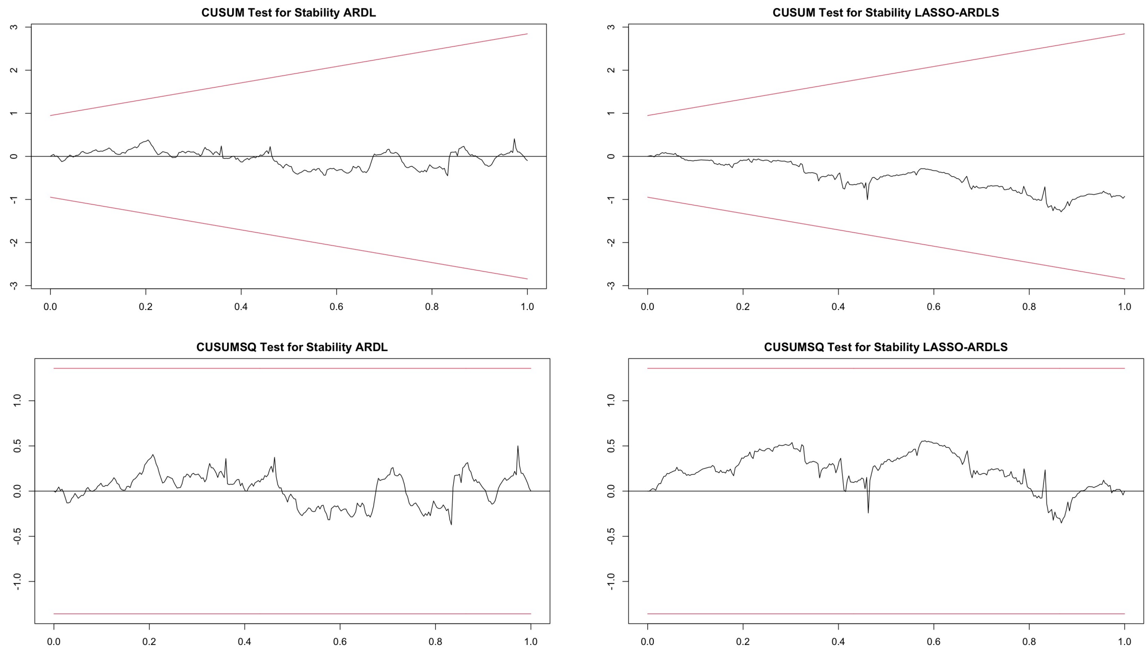

Figure 7: Comparison of CUSUM and CUSUMSQ tests for stability of ARDL and LASSO-ARDLS models (in-sample).

Altogether, the statistical evidence shows that the LASSO-ARDLS model is better suited for short-term forecasting, where it demonstrates superior accuracy and stability based on its lower RMSE, significant DM test results at shorter horizons and robust performance under the CUSUM and CUSUMSQ tests. Moreover, the LASSO-ARDLS model's robustness to structural shifts suggests it may still offer an edge under dynamic scenarios. These findings not only highlight the statistical robustness of the sentiment integrated model but also underscore its practical value for addressing real-world challenges in economic forecasting. By providing more accurate short-term forecasts, this approach presents a scalable framework for policymakers and businesses stakeholders to make informed decisions. Thus, the integration of sentiment analysis with traditional econometric methods offers a forward-looking solution to the limitations of conventional models, especially in rapidly changing and data-limited environments like Ecuador. Nonetheless, for longer horizons the differences between the two models become less pronounced suggesting that the information of sentiment indicators dilute over time.

4.2 Out-sample analysis

Forecasting Horizon	**DM Coefficient**	**p-value**
1 month	3.0868	0.0029
3 months	2.2811	0.0270
6 months	1.8350	0.0599
12 months	1.6247	0.1078
24 months	1.3874	0.1788

Table 3: Diebold-Mariano Test for LASSO-ARDLS Model at Different Forecasting Horizons (Out-Sample). DM statistic is set as errors ardl, errors lasso

This section evaluates the results of the performance analysis for the LASSO-ARDLS model in comparison to the benchmark model ARDL. The analysis was conducted using various robustness checks such as Bootstrap RMSE, Average Rolling RMSE, cross-validation with varying lambda values, and the Diebold-Mariano (DM) test at different forecasting horizons on the validation portion of the dataset.

Firstly, the model achieved a Bootstrap RMSE mean of 1.512247 with a standard deviation of 0. This zero standard deviation across bootstrap samples indicates exceptional stability, suggesting that the model performs consistently on different subsets of test data. Such consistency is a strong indicator of the model's robustness, as it implies that its predictive accuracy does not vary when trained and tested on different random samples. When using a 60-month rolling window, the model's Average Rolling RMSE reprted a value of 0.874, significantly lower than the bootstrap RMSE. This reduction suggests that the model adapts well to temporal shifts, maintaining high accuracy across different time segments. The ability to adjust to changes over time is crucial in time series forecasting, as it demonstrates the model's capacity to handle evolving patterns in the data.

A cross-validation analysis with rolling forecasting origin resampling was performed to evaluate the effect of varying lambda values, ranging from 0.001 to 0.096, on the model's performance. It was observed that as lambda increased, the RMSE and Mean Absolute Error (MAE) decreased, while the R-squared value improved. The optimal lambda was identified at 0.096, where the model achieved the lowest RMSE of 1.751 and an R-squared of 0.248. This means that approximately 24.8% of the variance in the target variable is explained by the model at this lambda value. The improvement in performance metrics with increasing lambda highlights the effectiveness of Lasso regularization in enhancing the model's predictive power by penalizing less informative predictors and preventing overfitting.

Coefficients in Table 2 shows the results from the Diebold-Mariano test further supporting the model's performance. At the 1-month forecasting horizon, the DM coefficient was 3.0868 with a p-value of 0.0029, indicating a statistically significant improvement over the ARDL model at the 1% level. For the 3-month horizon, the DM coefficient was 2.2811 with a p-value of 0.0270, showing significance at the 5% level. At the 6-month horizon, results reflected marginal significance at the 10% level. However, for the 12-month and 24-month horizons, the improvements were not statistically significant.

These results highlight that the LASSO-ARDLS model significantly outperforms the ARDL benchmark for short-term forecasting horizons of 1 to 3 months. As the horizon extends beyond 6 months, the performance advantage diminishes and becomes statistically insignificant. This suggests the model is particularly well-suited for short-term forecasting, while its advantage in long-term forecasts may be limited. Overall, the LASSO-ARDLS model demonstrates strong out-of-sample accuracy and robustness, as shown by the consistent Bootstrap RMSE and low rolling RMSE indicating stable performance across diverse data segments, supporting its reliability for forecasting. The low RMSE values across cross-validation and rolling windows confirm the model's capacity to generalize well to new data, which is essential for making accurate predictions on unseen datasets. Furthermore, the observed improvements in R-squared and reductions in RMSE with increasing lambda underscore the benefits of regularization in model tuning. By effectively balancing predictive accuracy and generalizability, the integration of sentiment indicators model is well-suited for stable and accurate forecasting in time series applications.

5 Discussion

The results of my study highlight the critical role of sentiment analysis in understanding how economic cycles influence public perceptions across various domains. The normalized sentiment scores show a strong dependence on the business cycle, evident from sharp declines during recessions and varied recoveries across sectors. For example, economic sentiment exhibited the most significant leftward shift in recessionary periods in the KDE plots, indicating intensified negative perceptions and heightened public uncertainty during downturns. This finding aligns with Barbaglia et al.(2024), who demonstrated that economic sentiment, measured through news-based indicators, is pro-cyclical and highly sensitive to macroeconomic conditions. As such, both studies emphasize the value of sentiment as an early signal of economic distress and as a tool for forecasting key economic indicators.

The results from my analysis also underscore the role of political sentiment during periods of instability. Political sentiment showed resilience compared to economic sentiment, stabilizing more quickly during crises. Similarly, Barbaglia et al. (2024) found a bidirectional interaction between political and economic sentiment, with news coverage on monetary policy and governance decisions significantly predicting GDP growth in countries like Spain and Italy (Barbaglia et al., 2024). This relationship highlights the central role of politics in shaping economic expectations. Lukauskas et al.(2022) observed a similar pattern during the outbreak of war and the COVID-19 pandemic in Lithuania in 2019 showing that negative political sentiment during crises strongly influences consumer satisfaction and economic forecasts.

The health sector experienced a significant decline in sentiment during economic downturns, with slow recovery patterns indicating systemic challenges. The COVID-19 pandemic exacerbated this effect, highlighting public anxiety about the adequacy of healthcare systems during crises. This mirrors the results of Barbaglia et al.(2024), who noted that while health-related sentiment was not directly incorporated into their GDP forecasting models, it indirectly influenced overall public confidence and macroeconomic sentiment. Furthermore, the findings of Lukauskas et al.(2022) reinforce this perspective by showing that alternative data sources, such as healthcare-related sentiment, can improve forecasts of economic indicators like unemployment and consumer satisfaction during periods of public health stress (Lukauskas et al., 2022).

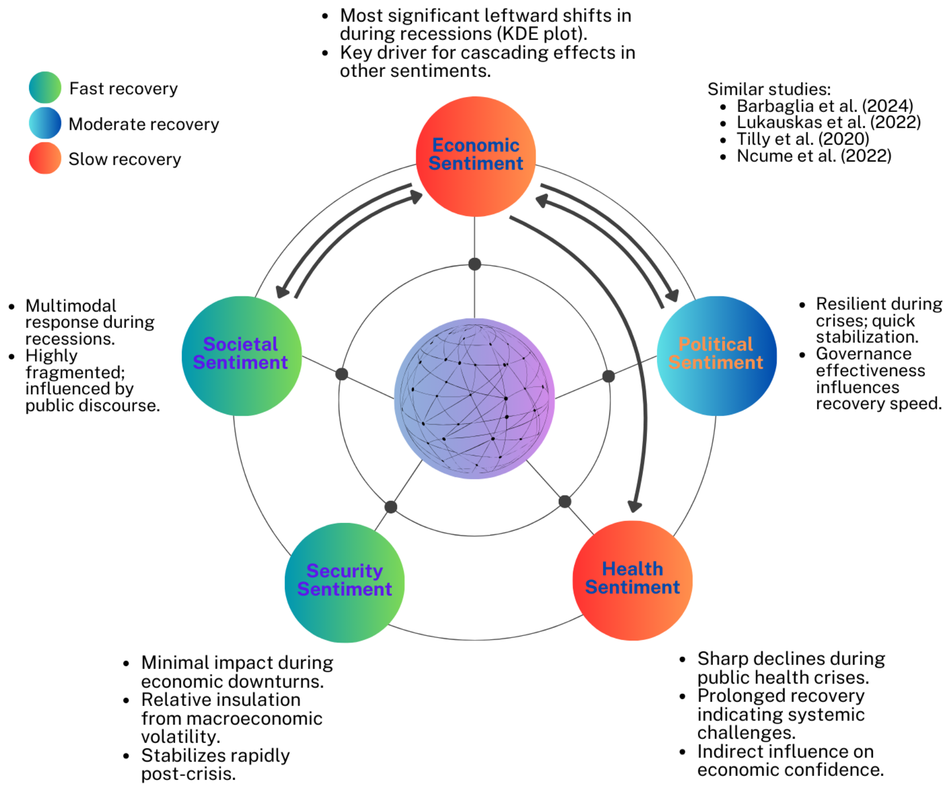

Figure 8: Cascading effects of sentiment dynamics across the five sentiment indicators. Arrows indicate directional influences between sections. Recovery speeds are color-coded.

Sectoral resilience varied, with security and societal sentiments stabilizing more quickly than economic and health sentiments. Results from my study displayed minimal leftward shifts in security sentiment during crises, reflecting its relative insulation from broader economic volatility. However, Barbaglia et al.(2024) highlight that financial sector sentiment, a component of security sentiment in their framework, showed marked declines during double-dip recessions but significantly contributed to short-term GDP predictions in countries like Germany and the United Kingdom. This suggests that while security sentiment may appear stable overall, specific components like financial security can reveal acute vulnerabilities during crises.

Furthermore, results from my study reveal that societal sentiment acts as both a reactive and proactive force in the economic landscape. These findings align with Barbaglia et al.(2024) and Lukauskas et al.(2022) regarding the interplay between societal sentiment and macroeconomic indicators throughout the business cycle. During recessions, societal sentiment shifts significantly leftward, reflecting intensified negativity as consumer confidence and business expectations deteriorate. However, the bidirectional influence identified through the VAR framework suggests a more complex interaction: societal sentiment not only responds to economic realities but also reshapes expectations captured in traditional surveys. Lukauskas et al.(2022) corroborate the relevance of societal sentiment in economic forecasting, highlighting how societal discourse improves predictive accuracy for consumer satisfaction and inflation. In my case, societal negativity during recessions appears to amplify economic pessimism by impacting consumer and business confidence. In expansionary periods, this dynamic reverses; societal optimism enhances survey-based economic expectations, fostering a virtuous cycle of confidence and growth. This understanding highlights that sentiments can both destabilize and stabilize the economy, depending on the business cycle phase.

One key distinction of my study is the explicit identification of a feedback loop between societal sentiment and macroeconomic indicators. While Barbaglia et al.(2024) focused on sentiment's predictive power for GDP, particularly through financial and monetary policy indicators, my findings suggest that societal sentiment is equally important for economic forecasting especially in understanding public confidence and cohesion. During recessions, declining societal sentiment magnifies the impact of poor business expectations and consumer confidence, contributing to the broader economic downturn. This contrasts with Barbaglia's emphasis on the direct influence of financial sentiment on GDP forecasts as my results indicate that for the case of Ecuador societal sentiment operates on a more diffuse but equally critical level influencing and being influenced by broader economic sentiment.

Additionally, news media and public discourse play a significant role during economic cycles. As societal sentiment shifts during recessions, public discourse often focuses on unemployment, inequality, and instability, magnifying the negative feedback loop between societal sentiment and economic expectations. Conversely, in expansionary periods, public discourse pivots to themes of progress and opportunity, reinforcing positive consumer and business confidence. This interaction between societal narratives and economic sentiment, observed in both this study and that of Lukauskas et al.(2022), underscores the importance of real-time monitoring of societal sentiment to capture nuances in public confidence during economic transitions.

For policymakers, these findings highlight opportunities to manage sentiments during different phases of the business cycle. In recessions, targeted interventions to address social concerns—such as social policies, economic relief measures, or public messaging—could disrupt the negative feedback loop between societal sentiment and macroeconomic confidence. During expansions, fostering societal optimism through proactive communication and emphasizing progress can sustain the virtuous cycle of growth and confidence. This dual strategy aligns with Barbaglia's recommendation to integrate sentiment measures into economic monitoring frameworks, demonstrating their capacity to predict economic trends but also shaping them by influencing public perception and behavior.

6 Conclusions and Recommendations

The integration of sentiment analysis into GDP forecasting models demonstrated significant potential for improving short-term economic predictions, especially in volatile changing environments like Ecuador. Leveraging news-based sentiment indicators alongside traditional survey data highlighted the usefulness of capturing high-frequency economic signals to provide actionable insights as shown by LASSO-ARDLS model superior performance for short-term horizons. This approach not only complements traditional macroeconomic indicators but also addresses their limitations, offering a scalable and adaptive framework for economic forecasting and underscoring the value of incorporating real-time data. However, the diminishing performance advantage at longer forecasting horizons suggests a need for further refinement in integrating sentiment indicators for sustained long-term accuracy.

A key contribution of this approach is its adaptability to sudden changes and structural shocks, such as the COVID-19 pandemic or the 2019 fuel subsidy crisis, which heavily impacted Ecuador's economy. While traditional economic indicators capture the aftermath of such events, sentiment-based indicators offer immediate insights enhancing the responsiveness of forecasting models. This study underscored the potential of these indicators to improve economic planning, resource allocation, and policy responses. Furthermore, integrating sentiment analysis is an actionable tool for researchers to quantify qualitative aspects of the economy, thus enriching the depth and context of economic analysis. These findings pave the way for more dynamic and responsive forecasting tools that align with the fragile and strained context of Ecuador's economy.

Moreover, the sectoral analysis of sentiment indicators reveals crucial insights into the interconnectedness of public perceptions across the different domains in the economy. Recessions are marked by sharp declines in sentiment across all sectors, with recovery patterns varying significantly showing the complex interplay between structural challenges and public confidence. For policymakers and businesses stakeholders, these findings feature the importance of timely interventions and strategic communication to manage public perceptions and enhance economic resilience. By bridging the gap between traditional forecasting tools and alternative data sources, this research provides a robust framework for addressing economic uncertainty and fostering informed decision-making in Ecuador's challenging economic landscape.

Looking forward, future studies may explore the application of advanced machine learning techniques, such as BERT (Bidirectional Encoder Representations from Transformers) models to enhance the extraction of sentiment indicators from textual data. BERT's ability to understand context and nuances in language at higher level would likely improve the accuracy of sentiment scores, particularly for a context with such complex narratives like Ecuador. Moreover, developing NLP models tailored specifically for Ecuadorian Spanish would significantly enhance the analysis of local news and public discourse as Ecuadorian Spanish includes unique regional idioms, expressions, and slang, which pre-trained models for general Spanish may not adequately capture. Customizing models to account for these linguistic nuances would greatly ensure more precise sentiment analysis and deeper insights into local economic conditions.

In addition to technical advancements, future research could expand the scope of sentiment analysis to explore its applications in other domains, such as sectoral forecasting or social policy evaluation. For instance, sentiment indicators could be applied to predict sector-specific outcomes such as trends in tourism, agriculture, or remittances, which are critical to Ecuador's economy. Furthermore, exploring the interplay between sentiment indicators and long-term economic trends could provide a more comprehensive understanding of their impact. These efforts would not only refine the methodological framework presented here but also solidify sentiment analysis as a cornerstone of economic forecasting in diverse contexts.

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7 Anexxes

7.1 VAR-X Model with Dummy Variables as Exogenous Factors

In order to determine a broader and more precise relation between the sentiment variables and the percentual annual growth rate of GDP at monthly frequency, the following section describes a VAR model with exogenous variables (VAR-X). For this case, such role is fulfilled by the dummy variables in $\mathbf{D}_t$. These variables capture specific external conditions regarding key recessionary events in the last 10 years of Ecuadorian history that affect the dependent variable and other endogenous variables in $\mathbf{Z}_t$, but are not influenced by the dynamics of $\mathbf{Z}_t$. The matrix $\mathbf{B}$ quantifies the impact of these exogenous factors on the system.

The VAR-X model estimates the parameters $\mathbf{A}_i$ and $\mathbf{B}$ by maximizing the likelihood of observing $\mathbf{Z}_t$ given the lag structure determined by the AIC coefficient and the exogenous effects of the dummy variables.

Thus, the dataset is defined as:

$$\mathbf{Z} = [\mathbf{Y}, \mathbf{X}_{\text{controls}}, \mathbf{X}_{\text{survey}}, \mathbf{X}_{\text{sentiment}}]$$

where:

- $\mathbf{Y}$ is the dependent variable,
- $\mathbf{X}_{\text{controls}}$ represents the matrix of control variables,
- $\mathbf{X}_{\text{survey}}$ represents the matrix of survey variables,
- $\mathbf{X}_{\text{sentiment}}$ represents the matrix of sentiment variables.

The combined dataset $\mathbf{Z}$ is used as the endogenous variable set for the VAR model.

To determine the optimal lag order p, I applied the Akaike Information Criterion (AIC) across models with lag orders from 1 to a specified maximum $p_{\max}$. The lag p is chosen to minimize the AIC, calculated as follows:

$$p = \arg \min_{k \leq p_{\max}} \text{AIC}(k)$$

where

$$\text{AIC}(k) = -2 \ln(L) + 2k$$

and L is the likelihood of the model at lag k.

After selecting the optimal lag order p, I specified the final VAR-X model in matrix form as:

$$\mathbf{Z}_t = \mathbf{A}(L)\mathbf{Z}_t + \mathbf{B}\mathbf{D}_t + \mathbf{u}_t$$

where:

$$\mathbf{A}(L) = \mathbf{I} - \sum_{i=1}^{p} \mathbf{A}_i L^i$$

and:

- $\mathbf{Z}_t$ is the vector of endogenous variables at time t,
- $\mathbf{A}(L)$ is the lag polynomial of coefficient matrices, with $\mathbf{A}_i$ representing the coefficients for each lag i,
- $\mathbf{D}_t$ is the vector of exogenous variables, specifically the dummy variables in this model,

- $\mathbf{B}$ is the matrix of coefficients for the exogenous variables $\mathbf{D}_t$,

- $\mathbf{u}_t$ is a vector of residuals at time t, assumed to follow a white noise process.

This representation captures the dynamic relationships among endogenous variables $\mathbf{Z}_t$ while accounting for the influence of exogenous factors $\mathbf{D}_t$ through the matrix $\mathbf{B}$.

7.2 Granger-causality patterns analysis

Cause	Effect	F-Test	P-Value (Granger)	Chi-Square	P-Value (Inst.)
CONS_CONFIDENCE	ECONOMY	1.56787	0.00002	62.80371	0.0000
CONS_CONFIDENCE	POLITICS	1.56787	0.00002	62.80371	0.0000
CONS_CONFIDENCE	HEALTH	1.56787	0.00002	62.80371	0.0000
CONS_CONFIDENCE	SECURITY	1.56787	0.00002	62.80371	0.0000
CONS_CONFIDENCE	SOCIETY	1.56787	0.00002	62.80371	0.0000
BUSS_CONFIDENCE	ECONOMY	1.05127	0.32037	125.24297	0.0000
BUSS_CONFIDENCE	POLITICS	1.05127	0.32037	125.24297	0.0000
BUSS_CONFIDENCE	HEALTH	1.05127	0.32037	125.24297	0.0000
BUSS_CONFIDENCE	SECURITY	1.05127	0.32037	125.24297	0.0000
BUSS_CONFIDENCE	SOCIETY	1.05127	0.32037	125.24297	0.0000
MANUF_EXP	ECONOMY	1.55227	0.00002	134.56653	0.0000
MANUF_EXP	POLITICS	1.55227	0.00002	134.56653	0.0000
MANUF_EXP	HEALTH	1.55227	0.00002	134.56653	0.0000
MANUF_EXP	SECURITY	1.55227	0.00002	134.56653	0.0000
MANUF_EXP	SOCIETY	1.55227	0.00002	134.56653	0.0000
SERVICES_EXP	ECONOMY	1.47435	0.00018	138.34552	0.0000
SERVICES_EXP	POLITICS	1.47435	0.00018	138.34552	0.0000
SERVICES_EXP	HEALTH	1.47435	0.00018	138.34552	0.0000
SERVICES_EXP	SECURITY	1.47435	0.00018	138.34552	0.0000
SERVICES_EXP	SOCIETY	1.47435	0.00018	138.34552	0.0000
CONSTRUC_EXP	ECONOMY	1.30508	0.00778	102.88846	0.0000
CONSTRUC_EXP	POLITICS	1.30508	0.00778	102.88846	0.0000
CONSTRUC_EXP	HEALTH	1.30508	0.00778	102.88846	0.0000
CONSTRUC_EXP	SECURITY	1.30508	0.00778	102.88846	0.0000
CONSTRUC_EXP	SOCIETY	1.30508	0.00778	102.88846	0.0000
ECON_EXP	ECONOMY	1.60664	0.00001	140.24323	0.0000
ECON_EXP	POLITICS	1.60664	0.00001	140.24323	0.0000
ECON_EXP	HEALTH	1.60664	0.00001	140.24323	0.0000
ECON_EXP	SECURITY	1.60664	0.00001	140.24323	0.0000
ECON_EXP	SOCIETY	1.60664	0.00001	140.24323	0.0000

Table 4: Granger-causality analysis results for surveys-to-sentiments

The analysis reveals that survey indicators generally have substantial explanatory power

Cause	Effect	F-Test	P-Value (Granger)	Chi-Square	P-Value (Inst.)
ECONOMY	CONS_CONFIDENCE	1.14376	0.11231	47.47917	0.0000
ECONOMY	BUSS_CONFIDENCE	1.14376	0.11231	47.47917	0.0000
ECONOMY	MANUF_EXP	1.14376	0.11231	47.47917	0.0000
ECONOMY	SERVICES_EXP	1.14376	0.11231	47.47917	0.0000
ECONOMY	CONSTRUC_EXP	1.14376	0.11231	47.47917	0.0000
ECONOMY	ECON_EXP	1.14376	0.11231	47.47917	0.0000
POLITICS	CONS_CONFIDENCE	1.35815	0.00262	54.56292	0.0000
POLITICS	BUSS_CONFIDENCE	1.35815	0.00262	54.56292	0.0000
POLITICS	MANUF_EXP	1.35815	0.00262	54.56292	0.0000
POLITICS	SERVICES_EXP	1.35815	0.00262	54.56292	0.0000
POLITICS	CONSTRUC_EXP	1.35815	0.00262	54.56292	0.0000
POLITICS	ECON_EXP	1.35815	0.00262	54.56292	0.0000
HEALTH	CONS_CONFIDENCE	1.34979	0.00313	29.41676	0.0142
HEALTH	BUSS_CONFIDENCE	1.34979	0.00313	29.41676	0.0142
HEALTH	MANUF_EXP	1.34979	0.00313	29.41676	0.0142
HEALTH	SERVICES_EXP	1.34979	0.00313	29.41676	0.0142
HEALTH	CONSTRUC_EXP	1.34979	0.00313	29.41676	0.0142
HEALTH	ECON_EXP	1.34979	0.00313	29.41676	0.0142
SECURITY	CONS_CONFIDENCE	1.38184	0.00157	51.53013	0.0000
SECURITY	BUSS_CONFIDENCE	1.38184	0.00157	51.53013	0.0000
SECURITY	MANUF_EXP	1.38184	0.00157	51.53013	0.0000
SECURITY	SERVICES_EXP	1.38184	0.00157	51.53013	0.0000
SECURITY	CONSTRUC_EXP	1.38184	0.00157	51.53013	0.0000
SECURITY	ECON_EXP	1.38184	0.00157	51.53013	0.0000
SOCIETY	CONS_CONFIDENCE	1.43798	0.00043	64.27585	0.0000
SOCIETY	BUSS_CONFIDENCE	1.43798	0.00043	64.27585	0.0000
SOCIETY	MANUF_EXP	1.43798	0.00043	64.27585	0.0000
SOCIETY	SERVICES_EXP	1.43798	0.00043	64.27585	0.0000
SOCIETY	CONSTRUC_EXP	1.43798	0.00043	64.27585	0.0000
SOCIETY	ECON_EXP	1.43798	0.00043	64.27585	0.0000

Table 5: Granger-causality analysis results for sentiment-to-surveys

for sentiment variables, as evidenced by the widespread statistical significance (p-value < 0.05) of Granger-causality results for survey-to-sentiment relationships. Specifically, Consumer Confidence (`CONS_CONFIDENCE`) exhibits significant Granger-causality for all sentiment variables—including `ECONOMY`, `POLITICS`, `HEALTH`, `SECURITY`, and `SOCIETY`—with extremely low p-values (e.g., < 0.00002). This suggests that changes in consumer confidence strongly influence public sentiment across various domains, highlighting the importance of consumer perceptions in shaping societal narratives.

Similarly, Manufacturing Expectations (`MANUF_EXP`) demonstrate consistent Granger-causality across all sentiment variables, depicting the influence of sector-specific economic expectations on broader public sentiment. The significant p-values associated with `MANUF_EXP` indicate that manufacturing sector outlooks are reliable predictors of changes in public sentiment. Services Expectations (`SERVICES_EXP`) also show significant causality for most sentiment variables, indicating the relevance of service-sector perceptions in driving sentiments related to the economy, politics, and society.

In addition to Granger-causality, the instantaneous causality tests (Chi-squared) highlight strong contemporaneous relationships between surveys and sentiments. For instance, the Chi-squared statistic for `CONS_CONFIDENCE` and various sentiments is highly significant (p-value < 0.00001), suggesting mutual influence within the same time frame. Also, it indicates that surveys capture real-time public perceptions, which closely align with sentiment dynamics.

The strong explanatory power of survey indicators reflects their structured nature. Surveys, by design, aggregate information on consumer, business, and sector-specific expectations, making them reliable predictors of public sentiments. They effectively act as leading indicators, capturing economic and social realities that shape broader sentiment trends. In contrast, the analysis shows fewer significant relationships when sentiments are tested as causes of survey indicators. While some sentiment variables exhibit explanatory power for specific surveys, the overall impact is less pronounced. For example, Economic Sentiment (`ECONOMY`) shows moderate explanatory power for survey indicators like `CONS_CONFIDENCE` and `BUSS_CONFIDENCE`, but the p-values are less compelling compared to the reverse relationship. Political Sentiment (`POLITICS`) demonstrates Granger-causality for surveys such as `MANUF_EXP` and `SERVICES_EXP`; however, the strength and scope of these relationships are limited compared to survey-to-sentiment causality.

While Granger-causality is weaker in this direction, the instantaneous causality results remain highly significant (p-value < 0.05) across most relationships. This suggests that sentiments and surveys are contemporaneously related, even if sentiments alone do not consistently lead changes in survey indicators. The weaker explanatory power of sentiments may stem from their reactive nature as sentiments are often shaped by external shocks, social narratives, and underlying economic conditions, which are more systematically captured in survey indicators. Consequently, sentiments seem to follow survey results rather than driving them.

Comparing the explanatory power of survey-to-sentiment and sentiment-to-survey relationships reveals a clear dominance of survey indicators. Surveys such as `CONS_CONFIDENCE`, `MANUF_EXP`, and `SERVICES_EXP` consistently exhibit strong Granger-causality for sentiment variables, providing structured insights into public expectations and making them reliable predictors of sentiment trends. On the other hand, sentiment variables have limited Granger-causality for survey indicators, suggesting that sentiments are more likely to reflect, rather than drive, changes in public perceptions captured by surveys. Both surveys and sentiments exhibit significant instantaneous causality, highlighting their mutual influence within the same time frame and indicating a close interconnection with real-time feedback between the two.

These findings have important implications. From a policy perspective, they underscore the value of survey indicators as tools for policymakers and analysts. By monitoring survey data, stakeholders can anticipate shifts in public sentiment and design interventions to address emerging concerns. Sector-specific surveys, such as those focusing on manufacturing expectations, can provide early warnings of sentiment shifts in related areas like societal or political perceptions.

The results also highlight the interdependence of economic, social, and political factors. Surveys provide a structured representation of these dynamics, while sentiments capture more nuanced, reactive responses. Together, they offer complementary insights into the state of public perceptions. The significant instantaneous causality between surveys and sentiments emphasizes their mutual influence and interdependence.

In essence, the Granger-causality analysis demonstrates that survey indicators generally have greater explanatory power for sentiment variables than the reverse. Surveys seem to act as leading indicators, reflecting structured assessments of public and sector-specific expectations that shape broader sentiment trends. In contrast, sentiments are more reactive and limited in their ability to predict changes in survey results. These findings emphasize the importance of leveraging survey data for forecasting and policy-making while recognizing the reactive and complementary role of sentiments in understanding public perceptions.

Variable	**F-Test**	**df1, df2**	**p-value**
ECONOMY	1.1438	165, 1616	0.1123
POLITICS	1.3581	165, 1616	0.0026
HEALTH	1.3498	165, 1616	0.0031
SECURITY	1.3818	165, 1616	0.0016
SOCIETY	1.4380	165, 1616	0.0004

Table 6: Granger Causality Test Results for Sentiments-to-GDP annual growth rate (%) et al.

The results from Table 6 reveal that certain sentiment variables significantly predict GDP annual growth rates, highlighting the impact of societal perceptions on economic outcomes. Interestingly, `ECONOMY` sentiment does not show statistical significance in predicting GDP growth (F-Test: 1.1438, p-value: 0.1123). This may be because traditional economic indicators already capture much of its explanatory power, or due to potential multicollinearity with other variables obscuring its independent effect.

These results highlight the importance of non-economic factors—such as societal, security, political, and health sentiments—in driving GDP growth. Public perceptions of stability, governance, and well-being are intricately connected to economic performance. Monitoring these sentiments provides valuable insights for forecasting economic trends and designing policy interventions.

From a policy perspective, enhancing public confidence in governance, security, and societal well-being can foster an environment conducive to growth, even without significant changes in traditional economic indicators. By quantifying and analyzing people's sentiment policymakers may catch early signals of potential shifts in economic performance. It's important to note that while Granger-causality indicates predictive relationships, it does not imply true causation. The associations identified should be interpreted as indicative rather than definitive causal mechanisms. Further research is suggested to explore the underlying drivers of these relationships, specially for a system as volatile as Ecuador.

7.3 Tables

Variable	**Coefficient**
GDP_AN_GWTH_lag2	-0.0698
GDP_AN_GWTH_lag3	-0.0213
WTI_PRICES	0.0549
EXPORTS	0.2786
REMITTANCES	-0.2649
WTI_PRICES_lag1	-0.1481
WTI_PRICES_lag5	0.0580
WTI_PRICES_lag11	0.0037
REMITTANCES_lag1	0.0344
REMITTANCES_lag9	0.0384
CONS_CONFIDENCE_lag1	-1.6114
CONS_CONFIDENCE_lag3	4.6834
CONS_CONFIDENCE_lag4	0.2263
CONS_CONFIDENCE_lag9	0.9159
BUSS_CONFIDENCE_lag10	0.1911
MANUF_EXP_lag4	0.2203
MANUF_EXP_lag5	-0.2391
SERVICES_EXP_lag10	0.0204
CONSTRUC_EXP_lag4	-1.1912
CONSTRUC_EXP_lag8	-0.4232
ECON_EXP_lag3	0.8452
ECON_EXP_lag9	0.3743
POLITICS	-0.0729
ECONOMY_lag6	0.0415
ECONOMY_lag7	-0.0811
ECONOMY_lag8	0.1068
POLITICS_lag1	0.0292
POLITICS_lag5	0.0135
POLITICS_lag7	-0.0005
SECURITY_lag1	0.0760
SECURITY_lag3	-0.0040
SECURITY_lag5	0.0257
SECURITY_lag7	0.0963
SOCIETY_lag5	-0.0504
SOCIETY_lag6	0.0149
Recession_2015_2016	-0.0408
Pandemic_2020	-0.4773
Post_Pandemic_Rec	0.2036

Table 7: Non-zero coefficients for LASSO-ARDLS with $\lambda = 0.0781$

7.4 NLP dictionary

ECONOMY

- Economy, trade, business, entrepreneurial, labor, productive sector, company, market, human resources, innovation, expectations, hydrocarbons, trade agreement, stock market, market trends, Ecuador shrimp industry potential, strategic sector, exports, work, surplus, deficit, investment, bank, credit, financial, fund, mercantile, capital, economic, debt, profits, losses, investor, import, export, real estate, currency, foreign exchange, remittances, tariff, customs duty, fiscal, microcredit, money, budget, subsidy, recession, inflation, GDP, tax, income, finances, costs, economic shutdown, industrial, funds, profit, banking, competitiveness, subsidy, circular economy, financing, foreign investment, central banking, investment funds.

SOCIETY

- Society, citizen security, community, conjuncture, culture, interculturality, education, national assembly, state institution, issues, science, current events, news, events, opinion, national, global panorama, countries, firefighters, service, community, family, citizenship, neighbors, residential, neighborhood, event, social, church, NGO, volunteer, municipality, festival, campaign, foundation, social program, community project, social development, youth, disability, inclusion, assistance, city, civil, organization, neighbor, environment, daily life, cultural, history, solidarity, party, families, communities, celebration, union, immigration, integration, coexistence, gender equality, human rights, social inclusion, collective.

HEALTH

- Health, pandemic, coronavirus, health situation, pandemic effects, health crisis, global fight against the pandemic, public health, diseases, pharmaceuticals, medicines, Ecuadorian Social Security Institute (IESS), vaccination, hospital, clinic, treatment, patient, epidemic, doctor, nurse, illness, contagion, symptoms, medicine, surgery, consultation, cancer, prevention, healthcare, emergencies, health system, nutrition, therapy, psychology, cardiology, well-being, hygiene, care, rehabilitation, pharmacy, care, mental health, hospitalization, diagnosis, medical services, medical emergencies, biosecurity.

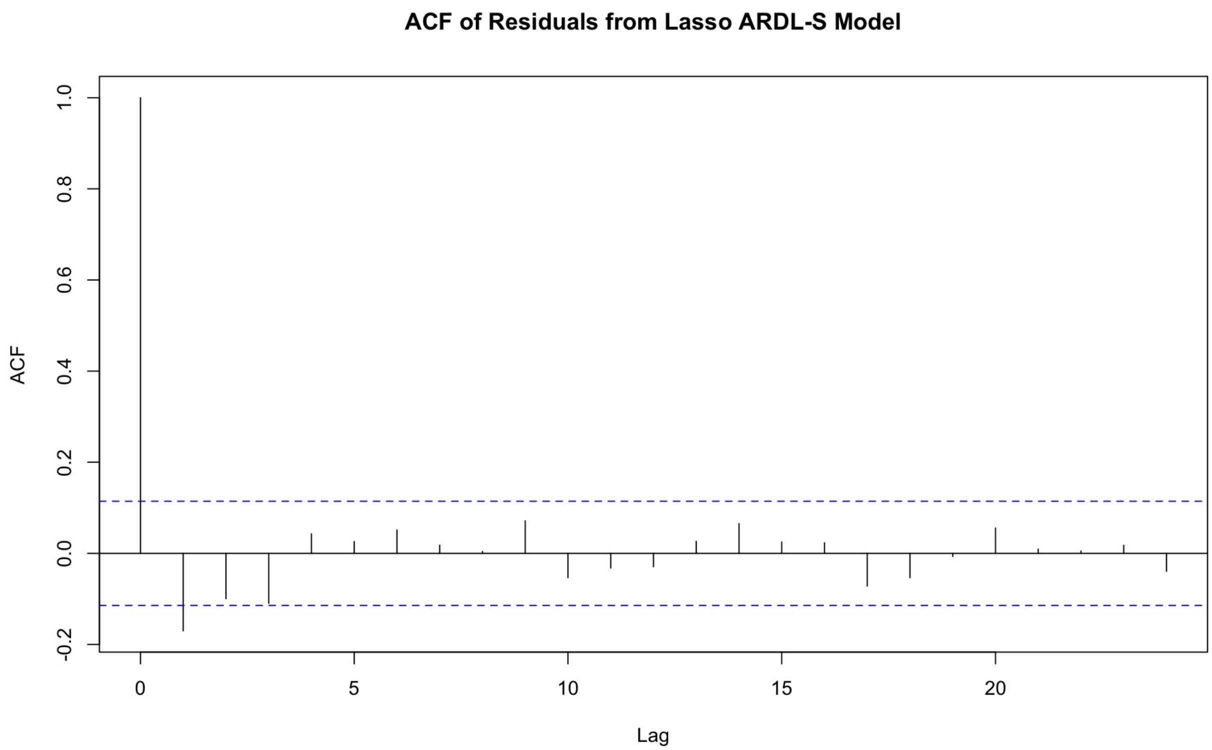
SECURITY

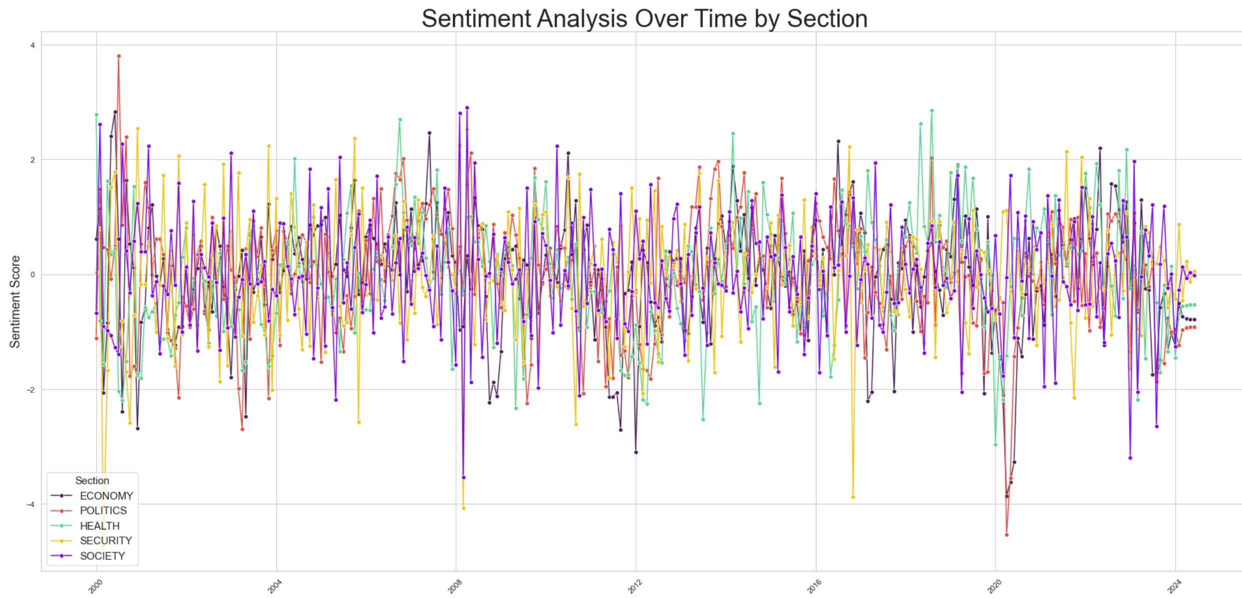
- Security, insecurity, crime, violence, prison crisis, street danger, murders, organized crime, criminal gangs, emergency, defense, civil, police, military, murder, robberies, kidnapping, criminal, armed forces, guard, justice, court, prosecutor's office, prison, penalty, jail, terrorism, armed, conflict, safe, fire, accident, surveillance, investigation, forensic analysis, patrolling, suspect, crime, operation, escort, national security, self-defense, guard, patrol, weapon, confiscation, pursuit, jurisdiction, civil protection, cybercrime, arms trafficking, public security, security operations, fraud.

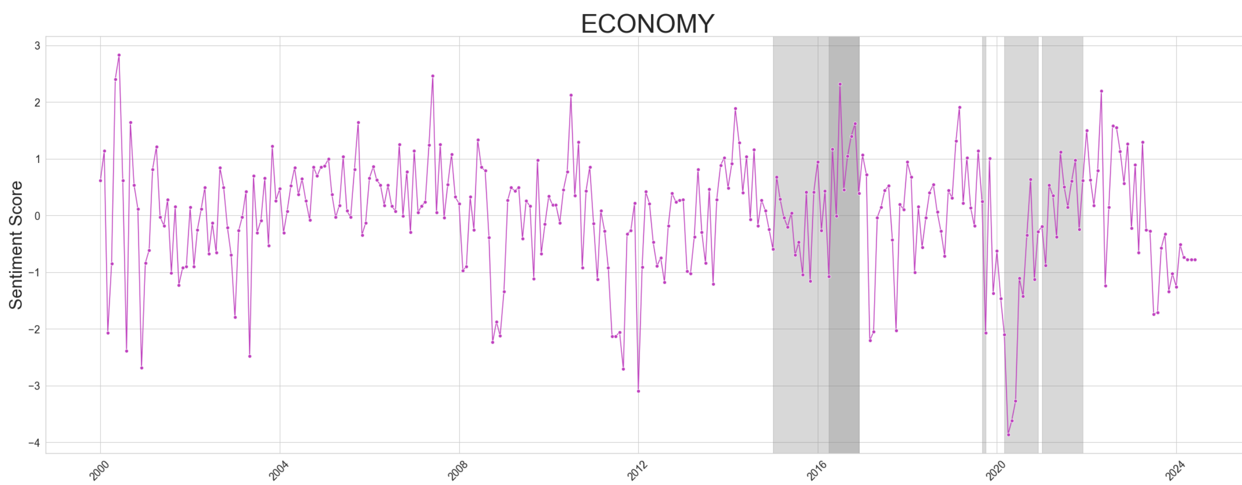
POLITICS

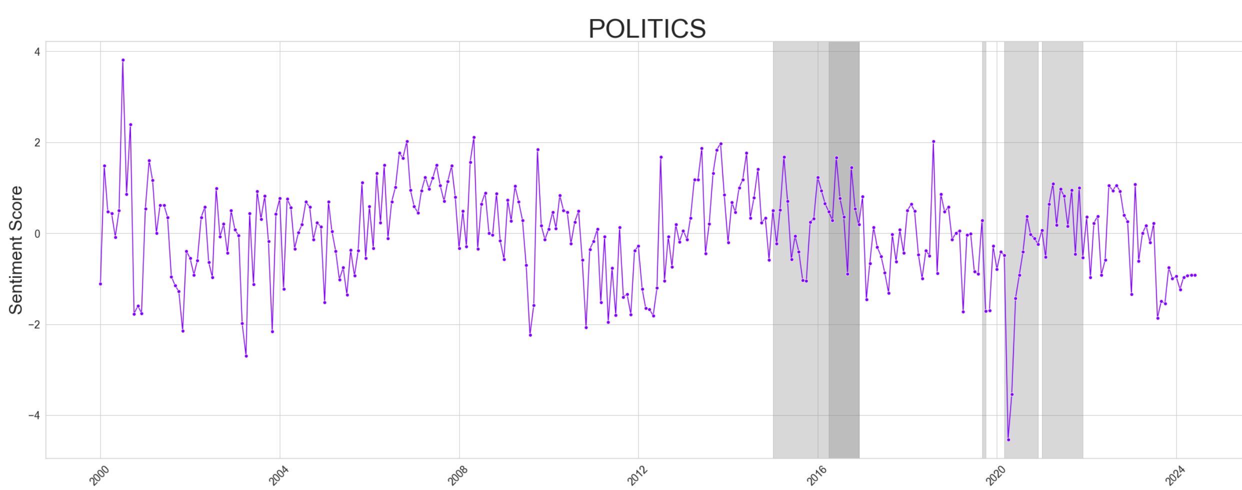
- Politics, political conjuncture, government change, elections, election results, political activity, presidential candidates, years, council, presidential elections, government, consensus, parties, politicians, austerity measures, Internal Revenue Service (SRI), congress, regulatory agency, ombudsman, state, minister, president, deputy, mayor, regime, legislative, reform, opposition, parliament, ministry, legislation, constitution, democracy, bill, board, administration, council, vice president, campaign, alliance, deputies, senator, governorship, candidate, representative, election, municipality, jurisdiction, senate, mandate, political alliances, coalition, diplomacy, geopolitics, public policies, civil rights, electoral system.

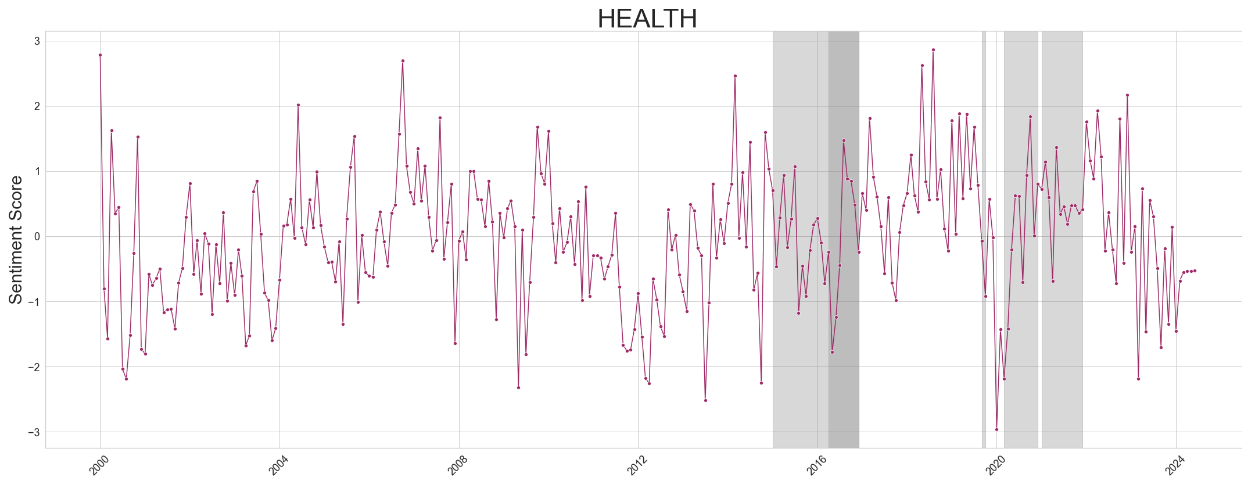
7.5 Graphs


ACF of Residuals from Lasso ARDL-S Model
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
5
10
15
20
Lag


Sentiment Analysis Over Time by Section
Sentiment Score
Section
ECONOMY
POLITICS
HEALTH
SECURITY
SOCIETY
2000
2004
2008
2012
2016
2020
2024


ECONOMY
Sentiment Score
2000
2004
2008
2012
2016
2020
2024


POLITICS
Sentiment Score
2000
2004
2008
2012
2016
2020
2024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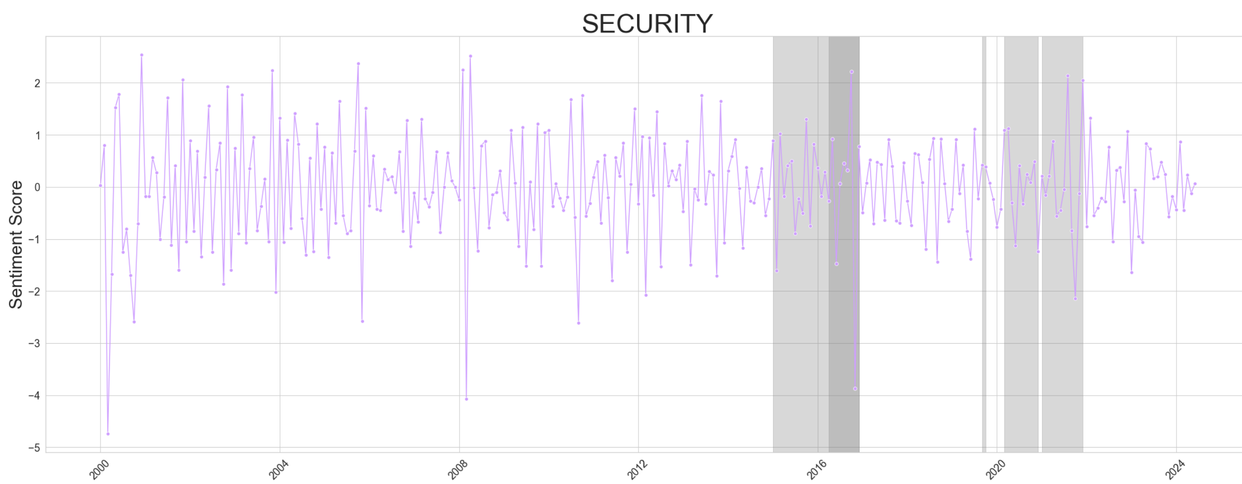
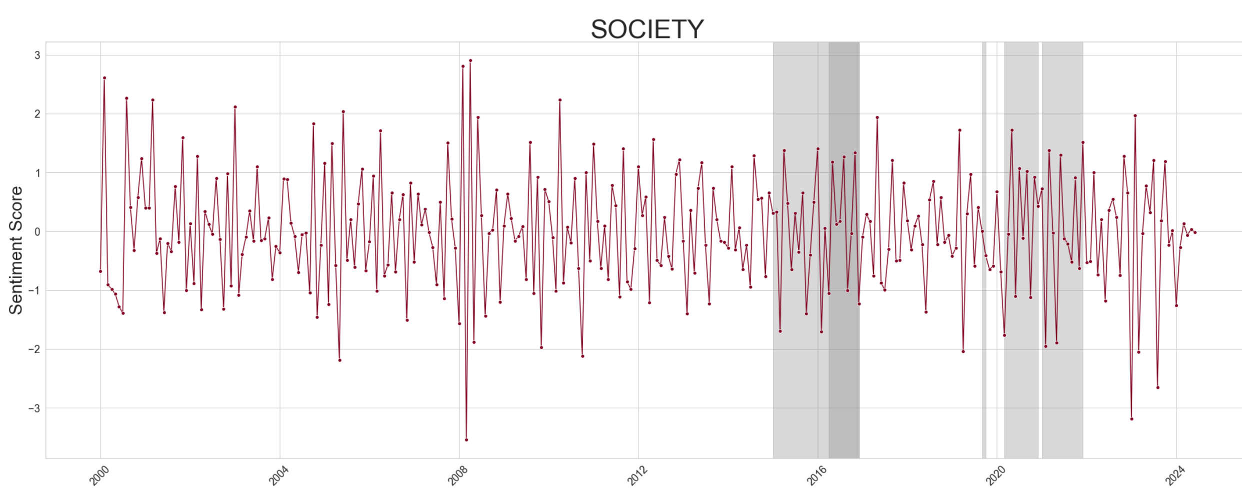
Sentiment Score
3
2
1
0
−1
−2
−3
2000
2004
2008
2012
2016
2020
2024


SECURITY
Sentiment Score
2
1
0
−1
−2
−3
−4
−5
2000
2004
2008
2012
2016
2020
2024


SOCIETY
Sentiment Score
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2
1
0
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−2
−3
2000
2004
2008
2012
2016
2020
2024

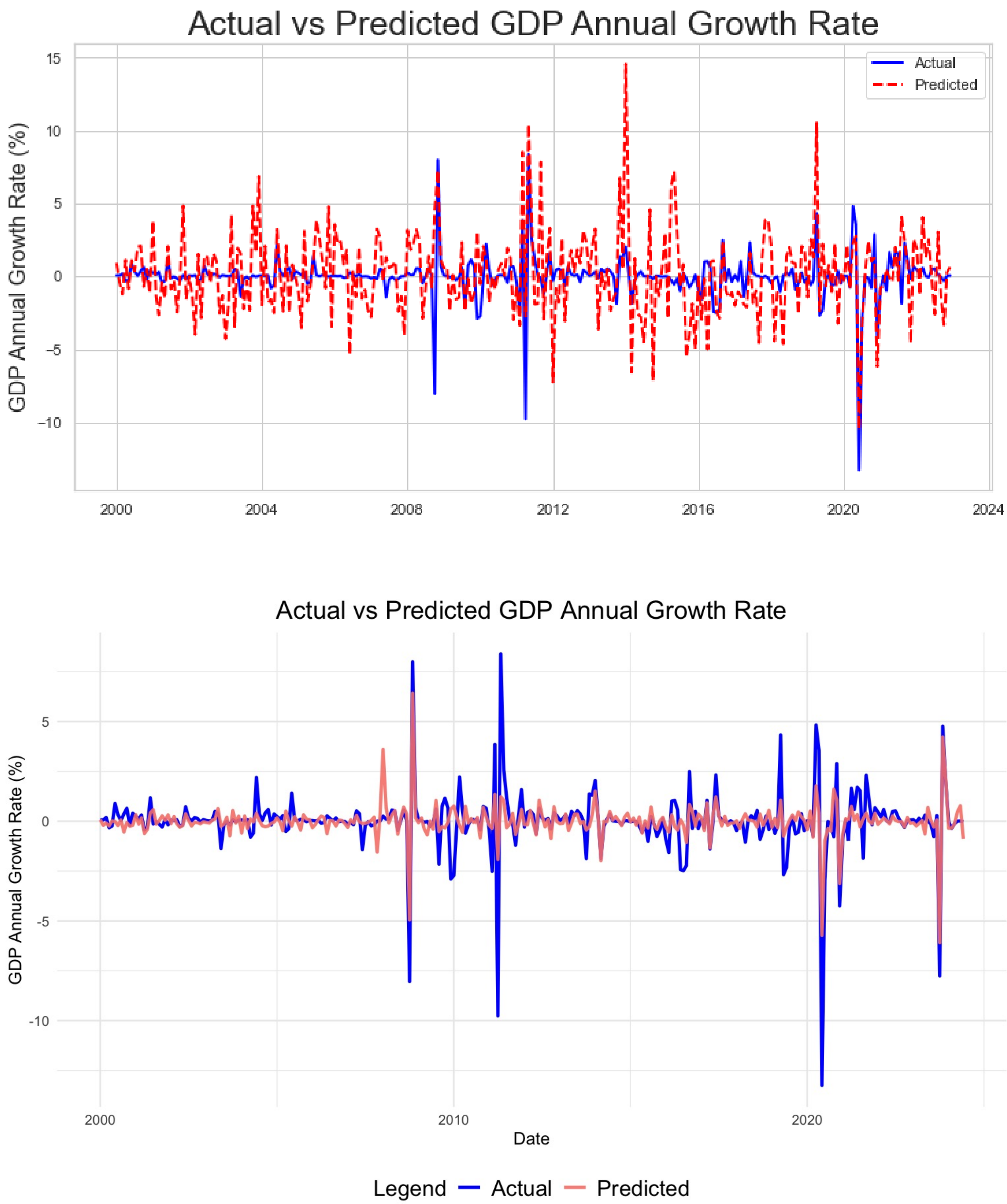
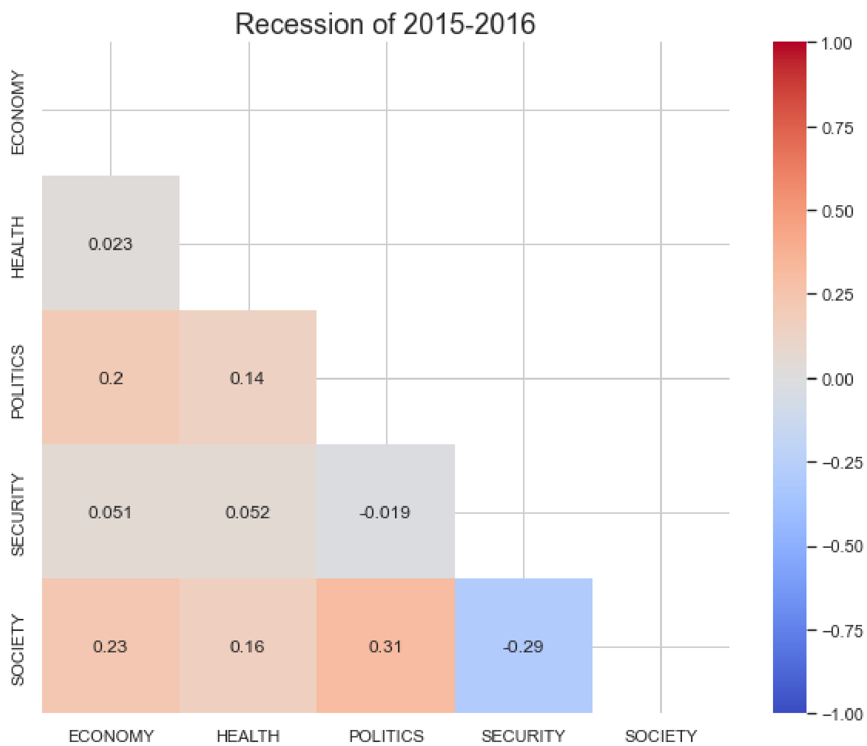
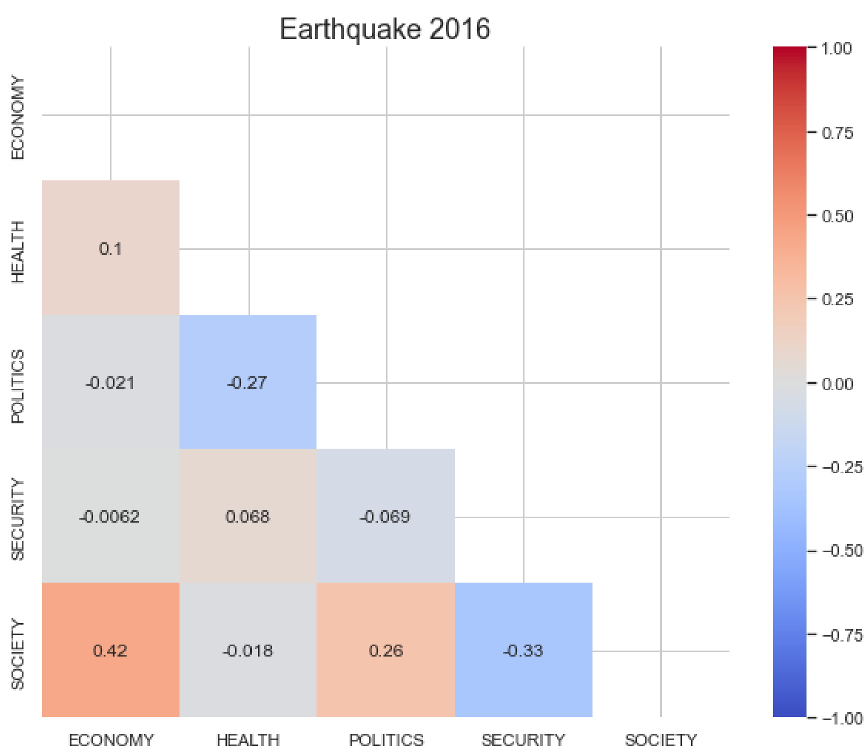


Figure 9: ARDLS fitted results before (upper graph) and after LASSO regularization (below).


Recession of 2015-2016
ECONOMY
HEALTH
POLITICS
SECURITY
SOCIETY
0.023
0.2
0.14
0.051
0.052
-0.019
0.23
0.16
0.31
-0.29
ECONOMY
HEALTH
POLITICS
SECURITY
SOCIETY
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Earthquake 2016
ECONOMY
HEALTH
POLITICS
SECURITY
SOCIETY
0.1
-0.021
-0.27
-0.0062
0.068
-0.069
0.42
-0.018
0.26
-0.33
ECONOMY
HEALTH
POLITICS
SECURITY
SOCIETY
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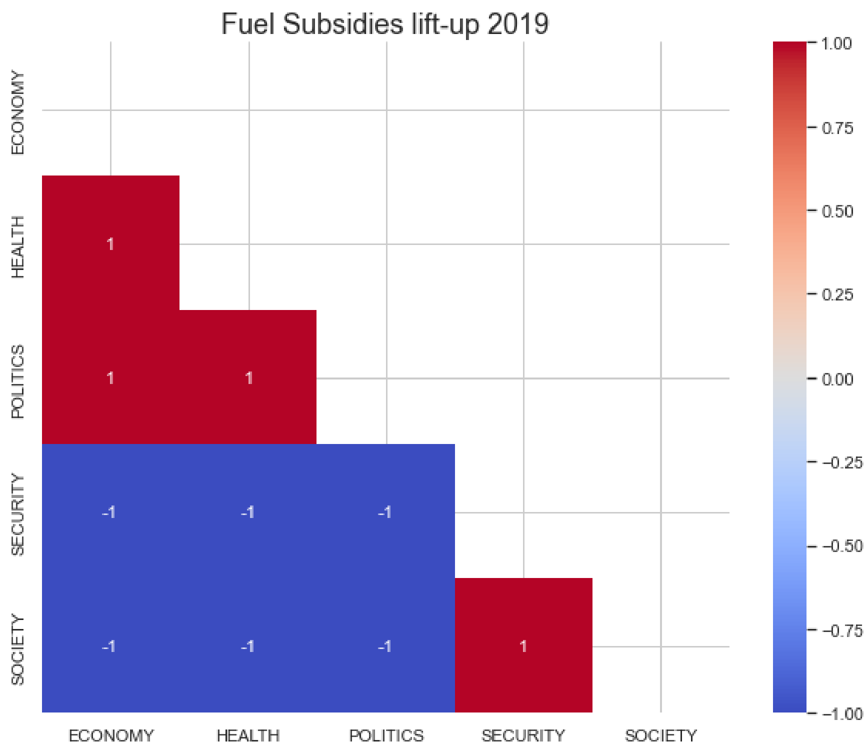
−0.75
−1.00


Fuel Subsidies lift-up 2019
ECONOMY
HEALTH
POLITICS
SECURITY
SOCIETY
1
1
1
-1
-1
-1
-1
-1
-1
1
1.00
0.75
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0.25
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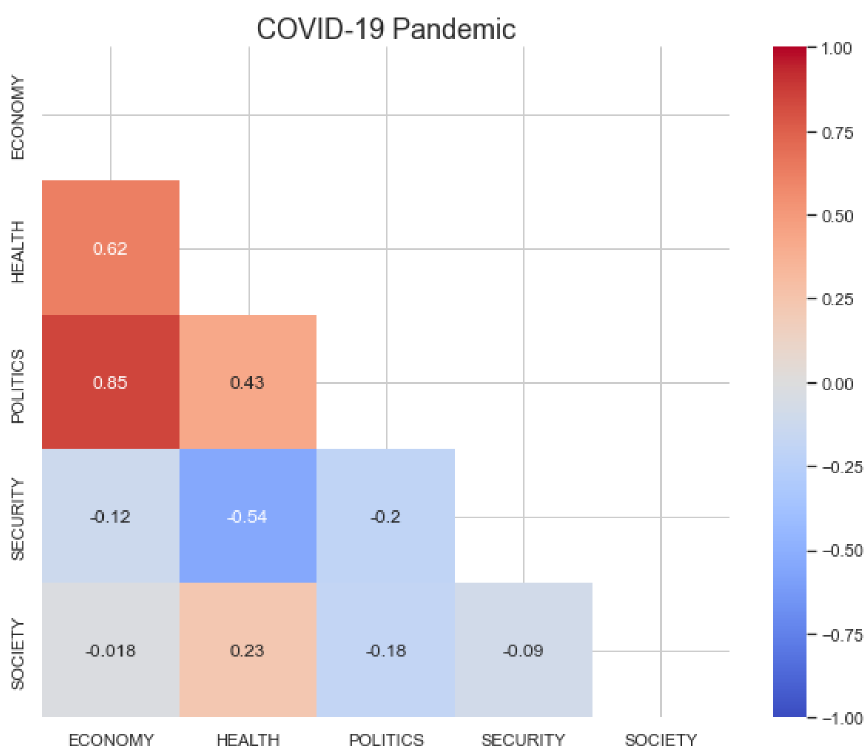
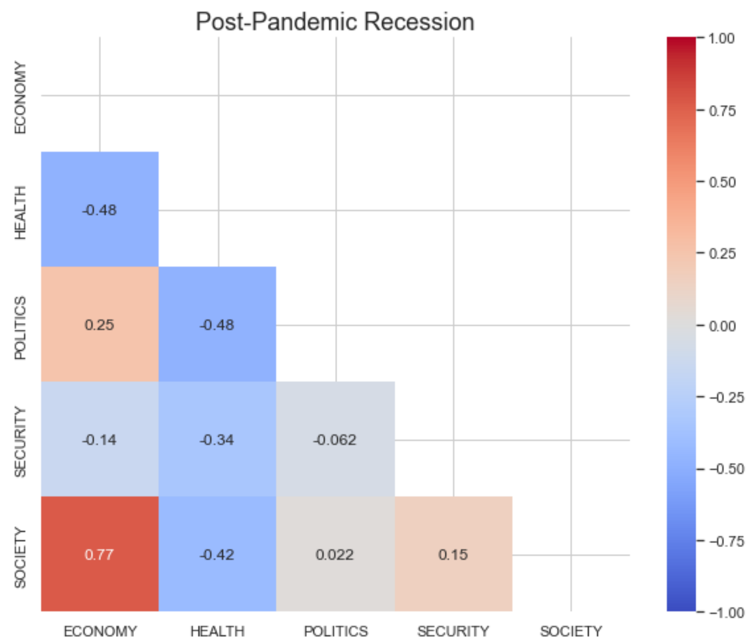
−0.75
−1.00


COVID-19 Pandemic
ECONOMY
HEALTH
POLITICS
SECURITY
SOCIETY
0.62
0.85
0.43
-0.12
-0.54
-0.2
-0.018
0.23
-0.18
-0.09
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Post-Pandemic Recession
ECONOMY
HEALTH
POLITICS
SECURITY
SOCIETY
-0.48
0.25
-0.48
-0.14
-0.34
-0.062
0.77
-0.42
0.022
0.15
1.00
0.75
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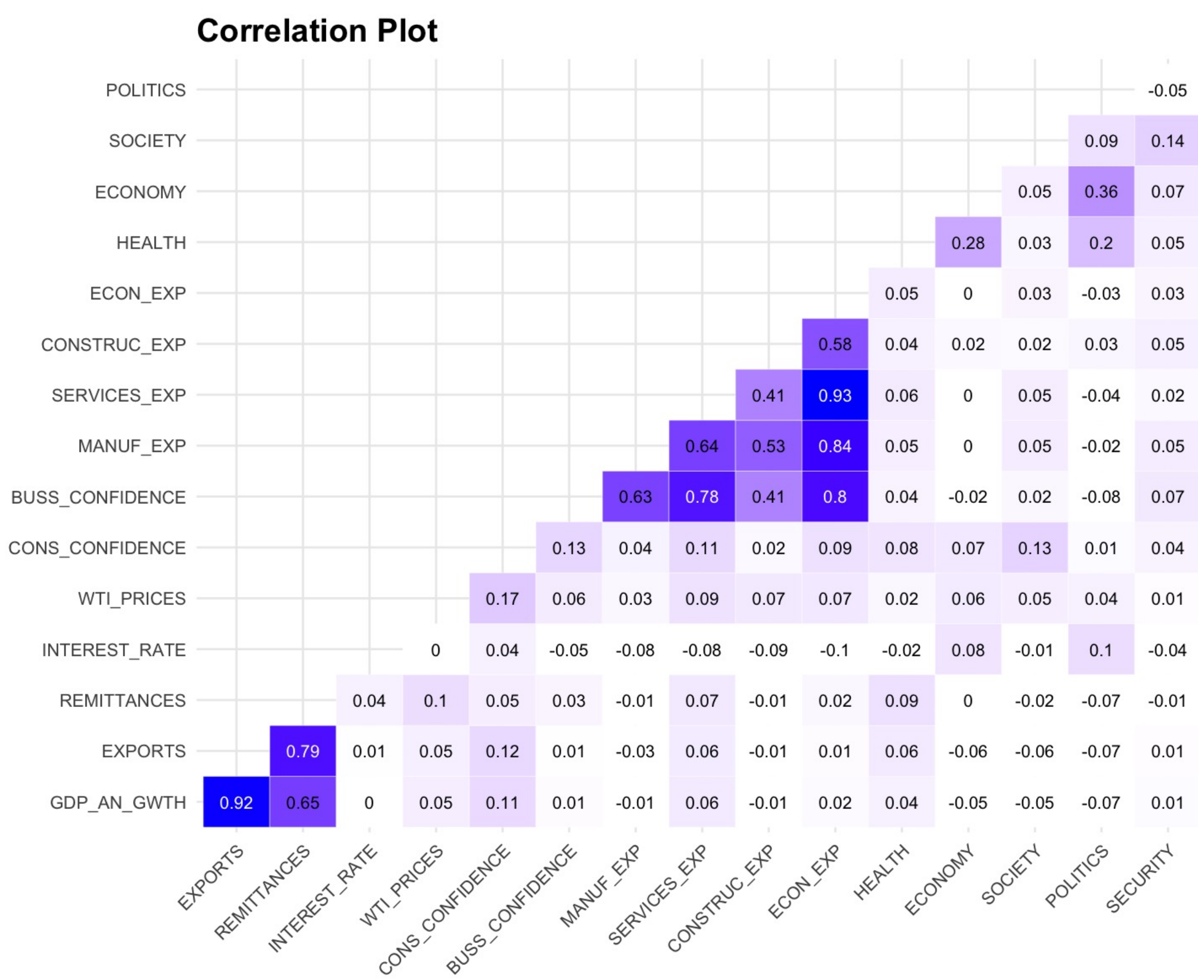
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Correlation Plot
POLITICS
SOCIETY
ECONOMY
HEALTH
ECON_EXP
CONSTRUC_EXP
SERVICES_EXP
MANUF_EXP
BUSS_CONFIDENCE
CONS_CONFIDENCE
WTI_PRICES
INTEREST_RATE
REMITTANCES
EXPORTS
GDP_AN_GWTH
EXPORTS
REMITTANCES
INTEREST_RATE
WTI_PRICES
CONS_CONFIDENCE
BUSS_CONFIDENCE
MANUF_EXP
SERVICES_EXP
CONSTRUC_EXP
ECON_EXP
HEALTH
ECONOMY
SOCIETY
POLITICS
SECURITY