Exploring Unconventional Approaches: Applications of Text Analysis in Economics

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Teona Shugliashvili
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With heartfelt gratitude to my beloved family,
a testament to perseverance for my son, and
a humble contribution to society.

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Preface

Employing unconventional methodologies, such as text analysis, has become increasingly essential in addressing economic challenges. Quantified textual data, including the frequency of newspaper coverage, sentiment, subject-specific topics, and tone-adjusted topic time series, enriches economic models. Textual analysis has been integrated across models of diverse economic indicators, reflecting a growing interest in leveraging unconventional data sources for economic research and confirming its empirical validity.

However, effectively harnessing text analysis techniques to complement existing methodologies and enhance timely, precise nowcasting and policy-relevant modelling in economics presents challenges. These include ensuring data quality and reliability, managing and reducing the volume and velocity of data, navigating with semantic ambiguity due to the inherent complexity of natural language, accurately integrating qualitative insights with quantitative data, and navigating algorithmic complexity in developing and refining hybrid economic models.

This dissertation aims to illustrate unconventional approaches for tackling economic challenges by effectively leveraging text-driven data and text analysis methodologies alongside statistical techniques. The dissertation addresses three crucial economic issues:

1. **Modelling exchange rate dynamics** is crucial for monetary policymakers as it directly impacts the transmission mechanism of monetary policy, affecting inflation, economic output, and employment through changes in import prices, export competitiveness, and overall demand conditions. Understanding exchange rate movements is essential for maintaining external balance and ensuring sustainable trade conditions. Policymakers also rely on exchange rate considerations within inflation targeting frameworks to adjust monetary policy in response to imported inflation. Moreover, exchange rate fluctuations can influence financial stability by affecting the balance sheets of firms, households, and financial institutions, necessitating proactive policy responses. Overall, comprehensive modeling of exchange rate dynamics provides critical insights for monetary policymakers to achieve their policy objectives effectively. Recent academic research has highlighted the influence of news on exchange rates, emphasizing the need for models and methodologies that can effectively integrate news dynamics into traditional macroeconomic frameworks.

   Another compelling reason why research on exchange rates in the context of text analysis is crucial is the significant challenges researchers face in accurately modeling exchange rates. In response, there has been a growing adoption of stochastic models, which accommodate the inherent randomness and unpredictability of exchange rate movements. Concurrently, efforts to enhance predictive accuracy have focused on integrating news-driven data into exchange rate models. However, many existing approaches are limited by their sole reliance on news data. By complementing textual data analysis with macroeconomic variables and advanced statistical techniques, researchers can uncover nuanced insights, thereby improving both the understanding and forecasting of exchange rate dynamics.

2. **Industry-level capital structure dynamics** are essential in economics because they impact investment decisions and economic growth. Excessive debt levels across an industry can hinder investment and pose systemic risks, necessitating careful monitoring by macroeconomists. Additionally, capital structure influences interest rates, investor sentiment, and resource allocation, underscoring its broader economic implications. Effective policy interventions are essential to align capital structure dynamics with macroeconomic objectives, such as fostering growth and ensuring financial stability. Hence, modeling capital structures, incorporating news-generated variables, and deriving policy implications are crucial endeavors in this realm.

3. **GDP nowcasting** is essential for making accurate decisions for highly effective fiscal and monetary policies. Accurate GDP nowcasts can benefit businesses in optimizing operational strategies, investors in investment decisions, financial institutions in risk management and resource allocation.

In this dissertation, two chapters integrate previously published or forthcoming academic content. Chapter 1 originated from my research paper, which underwent rigorous double-blinded peer review and was initially published in 2023 as "The Words Have Power: The Impact of News on Exchange Rates" Shugliashvili (2023*a*), with my sole authorship. A shortened version of this work was subsequently reviewed by the journal *Applied Economic Analysis*, which issued a decision of "acceptance with revision." This working paper has been further developed and refined for inclusion in this dissertation. Chapter 2 also underwent thorough double-blinded peer review and is published under the same title in the journal *Credit and Capital Markets*, with myself as the first author Shugliashvili et al. (2024).

Chapter 1 of this dissertation introduces our novel hybrid exchange rate model, news extended taylor model (NETM), which integrates the attention to U.S. dollar-related news topics and news-generated economic policy uncertainty indices into the Taylor rule model through a machine learning step to investigate their impact on EUR/USD and GBP/USD exchange rates. This statistically robust hybrid news-fundamentals-based VAR model offers insights into currency fluctuations.

In contrast to methodologies employed in the mainstream literature, we incorporate news-driven data in the form of attention measures to recent news. Additionally, while studies primarily derive text-driven variables from macroeconomic announcement titles, our research adopts a different approach by utilizing entire text bodies. These nuanced choices aim to provide a more comprehensive understanding of the interplay between news content and exchange rates.

Our findings reveal that U.S. Dollar-related news and economic uncertainty news account for 25-27% of long-term exchange rate variation. Combining news attention metrics with macroeconomic fundamentals enhances exchange rate identification, outperforming models that rely solely on the Taylor rule or news variables. This study provides valuable insights into exchange rate dynamics, benefiting governments, central banks, international trade entities, investors, financial markets participants, and academia.

The comprehensive findings, derived from both forecast error decomposition and impulse response analysis, robustly affirm the hypothesis that news plays a pivotal role in influencing exchange rates. The integration of news variables into prominent Taylor rule models significantly improves the accuracy of exchange rate identification.

Moreover, a substantial body of existing literature extensively explores the impact of variables such as stock prices, oil, economic growth, and international trade on exchange rates, which we have identified as the top five topics related to exchange rates.

Overall, our study advances the understanding of exchange rate dynamics and underscores the importance of integrating news data with traditional economic models for improved forecasting and policy formulation. By enriching news-based exchange rate literature and highlighting the significant role of news in market behavior, this research provides valuable insights for policymakers and market participants.

Chapter 2 of this dissertation identifies the determinants of industry-specific capital structures of German small and medium-sized companies by incorporating the news-generated economic policy uncertainty index alongside microeconomic and macroeconomic variables. The model's innovative design, which integrates a high-frequency news-driven economic policy uncertainty index and policy-related independent variables, allows this study to shed light on the effects of economic policy uncertainty and other fiscal policies on the financing decisions of SMEs and provide timely implications for policymakers.

This chapter investigates the financing decisions within German SMEs, examining firm-specific, macroeconomic, and news-related determinants. Utilizing a 10-year dataset encompassing 13,051 SMEs, we employ a dynamic panel data model with an unbiased Dynamic Panel Fractional (DPF) estimator to identify the key variables influencing the debt-to-equity ratio. The findings underscore the importance of factors such as the non-debt tax shield, firm size, interest rate spread, and the economic policy uncertainty index, the latter being a news-driven variable.

Our study finds that the capital structure decisions of German SMEs are influenced by firm-specific variables such as size and the non-debt tax shield, as well as industry effects and macroeconomic factors. While our empirical findings generally support the trade-off theory, some industries may deviate from this expectation due to industry-specific effects on leverage.

We observe a significant effect of the non-debt tax shield on German SMEs' capital structures across all industries, and the sign of the estimated effect changes depending on the industry. In manufacturing, retail, finance, and service industries, the non-debt tax shield is negatively related to leverage, aligning with the predictions of the trade-off theory. Consequently, policymakers can use a non-debt tax shield instead of other debt tax shields as a policy instrument to promote reinvestments and thus decrease the accumulated risk in SMEs from these industries. We find that, due to industry effects, the effect of the non-debt tax shield on leverage for agriculture, mining, construction, and transportation industries contradicts the expected sign according to trade-off theory. Industry-level analysis suggests selectively applying the policy instrument of the non-debt tax shield to certain industries. From our analysis of debt maturity structure, we also find that trade credit can serve as a policy tool for influencing debt maturity.

Furthermore, the industry-level analysis reveals that German SMEs are subject to the influence of market conditions. Results identify that the maturity risk premium (term spread) and economic policy uncertainty in the economy have a statistically important influence on the overall leverage of SMEs at the industry level.

This study draws several policy implications for German SMEs. Some of these recommendations are listed as follows:

- The incentives of a non-debt tax shield can be applied if higher debt financing of SMEs is needed, and the current debt-to-equity ratio (DE) is below the "healthy level of debt-to-equity ratio".

- Tax policies promoting higher non-debt tax shields (NDS) would increase the debt-to-equity ratio (DE) in the retail industry through a direct mechanism, and in the construction, manufacturing, transportation, and service industries through an indirect mechanism. The impact of changes in NDS on DE is ambiguous in the manufacturing industry.

- A higher term spread on government bonds boosts reinvestment by financial SMEs. An increase in the lagged term spread directly raises debt financing in the retail industry, while a rise in the industry mean of the lagged term spread drives up debt financing in manufacturing and transportation.

- In the period after an increase in economic uncertainty, SMEs' leverage is lower across industries.

- A single-period shock induces short-term adjustments in the capital structures of SMEs. The effects of such a shock dissipate after approximately eight months.

- The same policy for all industries is not optimal. Industries react to conditions diversely, and their reactions last for different time spans.

- To reduce borrowing costs and shorten the average maturity of SMEs' debt, policymakers can implement tax policies that encourage the use of trade credit.

Chapter 3 of this dissertation introduces a novel approach to GDP nowcasting. We commence by meticulously preprocessing 14 years of GDP-related news articles, employing a novel Boolean approach to filter out irrelevant past content and sentiments from texts. Subsequently, we apply NLP techniques to extract present-relevant information and integrate it as dynamic factors conditioning GDP dynamics. By effectively integrating unconventional textual news data with lagged traditional economic variables such as industrial production and exports, our approach achieves higher accuracy and lower RMSFE values in nowcasting compared to the best existing models for nowcasting German GDP, as well as to well-established variables traditionally used for GDP nowcasting. Our findings demonstrate that a dynamic factor model incorporating news-driven tone-adjusted topic frequency time series consistently outperforms the same model utilizing the widely used Ifo Business Climate Index in monthly GDP nowcasting. The RMSFEs of our text-driven model are significantly lower compared to those reported in the most effective recent papers on nowcasting and forecasting German GDP. This highlights the substantial value of unconventional data sources in economic forecasting and the power of our methodology, especially in creating text-driven variables, showcasing their potential to enhance accuracy and provide superior predictive insights.

The three chapters effectively illustrate the importance of using non-traditional textual data to explain economic indicators more precisely and effectively. Each chapter provides empirical evidence supporting the integration of news-generated variables in economic modelling and demonstrates how novel approaches reveal the impact of news on the economy. While these chapters share themes and concepts, each chapter is a self-contained and independent study.

1 Beyond Tradition: A Hybrid Model Unveiling News Impact on Exchange Rates

At the outset of this chapter, it is essential to acknowledge that the research presented here was previously disseminated as a research paper authored by myself and underwent a rigorous double-blinded peer review process. Specifically, the findings and analysis contained in this chapter were originally published in the working paper titled 'The Words Have Power: The Impact of News on Exchange Rates,' Shugliashvili (2023*a*), authored by Teona Shugliashvili and published in the FFA Working Papers journal in 2023. The paper is also accessible on SSRN (Shugliashvili, 2023*b*) and Ideas for broader visibility. As the sole author of the publication, I have diligently refined and expanded upon the content to offer a comprehensive examination of the research topic within the framework of this dissertation.

Abstract

This study investigates the influence of U.S. dollar-related news on EUR/USD and GBP/USD exchange rates using a novel hybrid news-fundamentals-based VAR model applied to 18 years of monthly data. Leveraging Latent Dirichlet Allocation (LDA) we identify the top 5 U.S. dollar-related news topics, quantify attention they receive over time using Shannon's entropy, and integrate these news-generated metrics with news-constructed economic uncertainty indices and Taylor rule fundamentals into the VAR model. Through impulse-response analysis and forecast error decomposition, we examine how exchange rates react to shocks from the identified U.S. Dollar-related news topics and economic uncertainty identified by the news.

Our findings reveal that U.S. Dollar-related news and economic uncertainty news account for 25-27% of long-term exchange rate variation. Combining news attention metrics with macroeconomic fundamentals enhances exchange rate identification, outperforming the models that rely solely on the Taylor rule or news variables. This study provides valuable insights into exchange rate dynamics, benefiting governments, central banks, international trade entities, investors, financial markets participants, and academia.

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Keywords: Foreign Exchange, U.S. Dollar, News Media, Machine Learning, Natural Language Processing (NLP)

1.1 Introduction

The relationship between exchange rates and macroeconomic factors has long been a focal point in economic literature, especially concerning the enduring challenge of the exchange rate disconnect.[1] This disconnect underscores the need to explore

[1]This phenomenon describes the weak or unexpected response of exchange rates to changes in macroeconomic fundamentals.

unconventional determinants of exchange rates that traditional fundamentals-based models may overlook.

Recent research highlights news as a crucial factor in exchange rate dynamics (Tadphale et al. (2023); Jabeen et al. (2022); Aquilante et al. (2022); Thorsrud (2020)). However, there is a noticeable gap in the literature concerning the joint influence of news and macroeconomic fundamentals on exchange rates. Most studies analyze these variables in isolation, omitting the interactive effects that could significantly impact exchange rate behaviour. While a few studies, such as Tadphale et al. (2023) and Zhang et al. (2005), have begun integrating these factors and find that hybrid models enriched by text analysis outperform models without news, their reliance on "black box" (Ribeiro et al., 2016) neural network-based machine learning models or scatter matrices lacks the transparency of probabilistic semantic analysis methods, like Latent Dirichlet Allocation. Furthermore, the number of papers utilizing such hybrid models is limited, with stochastic modelling of exchange rates (Haas et al. (2004), You and Liu (2020), among others) still prevailing in the literature.

Our study addresses this gap by combining hard (macroeconomic) and soft (textual) information in a unified framework, offering a comprehensive perspective on exchange rate determinants. Departing from traditional approaches, we apply a hybrid model that integrates machine learning-based text analysis, specifically using the probabilistic model Latent Dirichlet Allocation (LDA), with fundamentals-based modeling, enhancing the traditional Taylor rule with news-driven variables. This novel approach provides a more holistic view of exchange rate dynamics.

Our primary aim is to elucidate the impact of news shocks on exchange rates. In line with the speculative efficiency hypothesis and attention theory, we acknowledge the substantial influence of information flow on decision-making processes. Expanding on the research by Sadoghi (2018), we quantify information flow using the Shannon entropy of news. Employing news entropy as a measure addresses a notable gap in the literature, providing a nuanced perspective on the informational content of news and its implications for exchange rates. Furthermore, integrating textual news data as a measure of attention aligns with attention theory, underscoring the significant role of news attention in shaping market dynamics.

Diverging from previous studies that often focus on macroeconomic announcement titles or google trends, we utilize complete text bodies from news items in the extensive Nexis-Uni database. Our keyword-based search for 'U.S. Dollar' yields over 15 million news items. We select relevant news based on the specific criteria outlined in the data section, resulting in a dataset that captures U.S. Dollar-related news.

Our findings, revealed through forecast error decomposition and impulse response analysis, demonstrate a substantial and statistically significant impact of news shocks on exchange rates. These results align with established economic theories and empirical researches, emphasizing the influential role of news in models predicting exchange rates Kebe and Uhl (2024); Narayan et al. (2021); Ben Omrane et al. (2020); Edwards (1983).

In essence, our study not only integrates the news and macroeconomic fundamentals using comprehensive data and novel methodologies but also considers the crucial role of information flow. This alignment with the broader theoretical framework and empirical findings enables our model to enhance our understanding of exchange rate dynamics.

1.2 Literature Review

1.2.1 Theory and Studies on News Impact on Exchange Rates

The theoretical framework underpinning the impact of news on exchange rates is rooted in the speculative efficiency hypothesis and attention theory. These theories posit that agents integrate available news information into their decision-making processes. Currency pricing models corroborate this perspective, suggesting a direct influence of public news on exchange rates through trading, as shifts in demand transmit news shocks to currency prices. Seminal contributions by Edwards (1983) emphasize the significant impact of news, as unexplained behavior in future spot rates is linked to new information available to economic agents. In efficient markets, expectations are fully adjusted by new information, shaping exchange rate dynamics. Building on this foundation, subsequent works by Engel et al. (2006) and Devereux and Engel (2006) delve deeper into the impact of expectations on exchange rates, further reinforcing the theoretical perspective that news plays a pivotal role in shaping exchange rate dynamics.

Complementing these theories, the Efficient Market Hypothesis suggests that new information leads to a reestablishment of equilibrium. Furthermore, studies by Evans and Lyons (2008) and Love and Payne (2008) provide additional theoretical support, indicating that news can indirectly influence exchange rates through induced order flow and expectations. This theoretical foundation sets the stage for understanding the substantial role of news in shaping exchange rate dynamics.

Numerous recent studies have extensively explored the influence of news on exchange rates, shedding light on the intricate dynamics of currency markets. Tadphale et al. (2023) introduced a hybrid deep learning model integrating news sentiment and market indicators, elucidating the pivotal role of news in understanding exchange rate dynamics. In a different approach, Narayan et al. (2021) employed predictive regression models, demonstrating the predictive nature of economic news in forecasting the USD/GBP exchange rate. Examining mean and volatility spillovers of macro news headlines across 18 exchange rates over a decade, Caporale et al. (2018) identified linkages and causality-in-variances, particularly strengthening during times of crisis. Addressing the sensitivity of EUR/USD exchange rate volatility to macroeconomic news announcements at high frequencies, Ben Omrane et al. (2020) presented compelling evidence. Furthermore, a multitude of papers, including those by Jabeen et al. (2022); Kebe and Uhl (2024); Cheung et al. (2019); Yaganti and Manpuria (2018); Caruso et al. (2016); Clarida and Waldman (2008); Galati and Ho (2003); Almeida et al. (1998); Ito and Roley (1987), collectively emphasize the significant role of news as a driving force behind exchange rate movements. Notably, Evans and Lyons (2008) revealed that macro news accounts for a substantial portion, specifically 36%, of the total daily price variance in currency markets. Additionally, Peramunetilleke and Wong (2002) contributed evidence supporting the notion that news forecasts intraday currency exchange rates more accurately than random walk models. Taken together, these findings underscore the substantial contribution of news to explaining exchange rate volatility.

As emphasized by Ben Omrane et al. (2020), the influence of news on exchange rates varies depending on economic conditions. Unlike conventional news-based approaches, Tadphale et al. (2023) and Zhang et al. (2005) integrated macroeconomic fundamentals and financial indicators with news data to assess exchange rates. Tadphale et al. (2023) incorporated sentiment polarity scores from news, blogs, and social media, using a fine-tuned BERT model for financial sentiment analysis. These sentiment scores were combined with economic factors, including USDX price, gold price, and crude oil price, to build a recurrent neural network—specifically, an LSTM model—to forecast the USD/Indian Rupee exchange rate. Their findings show that this hybrid model outperforms traditional exchange rate forecasting models. Similarly, Zhang et al. (2005) preprocess news by classifying it into positive and negative categories and constructing a news index based on the number of "good" and "bad" news documents, classified through scatter matrices of feature vectors. They incorporated this news index alongside key economic indicators—such as US non-farm payrolls, US unemployment rate, US employment cost index, US durable goods orders, NAPM manufacturing and non-manufacturing indices, US advance retail sales, US industrial production, US CPI, Ifo index, Germany unemployment rate, Germany industrial production, INSEE industrial trends, Germany CPI, and EU 11 PPI—in rolling regressions. Both studies find that incorporating news data alongside market indicators improves exchange rate forecasting. Our study draws on this hybrid approach, integrating both news sentiment and macroeconomic fundamentals to offer a more holistic perspective on exchange rate dynamics. In contrast to these works, our approach does not rely on "black box" neural network-based models, such as LSTM or hardly interpretable BERT model (Bolukbasi et al., 2021). However, Unlike Tadphale et al. (2023), we exclude broader social media and blogs, as these channels pose a higher risk of fake news. Instead, our data sources come from more professional and reliable sources. Similar to Zhang et al. (2005), we apply news filtering to focus on exchange rate-specific information, though our set of economic variables differs from theirs. Additionally, while Zhang et al.'s variables vary by country, our economic variables are consistent across different countries in terms of their calculation.

1.2.2 Macroeconomic Fundamentals' Impact on Exchange Rates

Rossi (2013) identifies the Taylor rule as a leading framework for explaining exchange rate dynamics, while Byrne et al. (2016) highlights the superior predictive capability of time-varying, linear Taylor rule models over traditional fundamentals. Recent studies (You and Liu (2020); Cao et al. (2020); Molodtsova et al. (2011)) offer compelling evidence for the predictability of exchange rates through Taylor rule fundamentals, reinforcing its robustness. Various methodologies, including deep learning (Cao et al. (2020)), macroeconomic equilibrium models (Engel et al. (2007) and Engel and West (2004)), and robust semi-parametric interval forecasting (Wang and Wu (2012)), consistently showcase the effectiveness of Taylor rule fundamentals in forecasting exchange rates. Our model aligns with these findings by incorporating Taylor rule fundamentals to identify exchange rates.

1.3 Methodology

This section describes the methodology employed in the study, incorporating both hard and soft information within a Taylor framework. The inclusion of soft information involves topic modeling, a technique that analysis textual data.

1.3.1 Natural Language Processing

In the initial phase, we employ Natural Language Processing (NLP) techniques to preprocess the unstructured body text of news articles into a structured, machine-readable format. This includes tokenization, stopword elimination, stemming, and temporal tagging, which collectively facilitate the creation of the time-stamped text corpus, the input required for the Latent Dirichlet Allocation (LDA) algorithm.

1.3.2 Latent Dirichlet Allocation (LDA)

After pre-processing the text (removing stop words and standardizing terms), we transform the corpus into a **Document-Term Matrix (DTM)**. This matrix represents each document as a row and each unique term as a column, with entries capturing the frequency of each term within each document. The DTM allows us to identify patterns in term usage and forms the basis for identifying "topics" within the corpus using Latent Dirichlet Allocation (LDA) (Blei et al., 2003).

LDA assumes each document is a mixture of topics, with each topic represented by a specific distribution of words. The model iteratively assigns N terms to K topics based on co-occurrence patterns across D documents, automatically categorizing a large collection of news articles into manageable themes without manual labeling. Through this process, the model identifies clusters of frequently co-occurring words, which we interpret as themes relevant to economic events.

Key LDA Parameters and Margin of Discretion LDA calculates two main parameters:

- θ: The topic distribution for each document, representing the probability of each topic appearing within a document.
- φ: The term distribution for each topic, indicating the likelihood of each word within that topic.

Both parameters follow a Dirichlet distribution and sum to 1, ensuring that the estimates reflect relative importance within each document or topic.

The margin of discretion in applying LDA lies primarily in selecting the number of topics (K) and setting hyperparameters α and β, which control the distribution of topics across documents and terms within topics. Balancing these choices is essential for obtaining meaningful results: too few topics may overlook key nuances, while too many may produce overlapping or fragmented themes. In our study, we set $\alpha = 0.1$ and $\beta = 0.01$, values that yielded well-differentiated topics closely aligned with the thematic structure of economic news. This choice ensures relevant term clustering within topics and a focused topic distribution across documents. We conduct a subjective coherence check with expert oversight after generating topics with the highest coherence scores from the optimal range of 4 to 12 topics, resulting in 5 topics.

1.3.3 Quantifying the Attention

To measure attention to a news topic, we follow Sadoghi (2018) and estimate how much an economic agent can learn, on average, about that topic in a news document (Glasserman and Mamaysky, 2019). Higher entropy typically suggests more diverse or fluctuating information—likely due to increased reporting or varied topics, often corresponding with heightened market interest or attention. High entropy occurs when news is abundant or market activity is volatile, such as during major financial events. This is when the media and public are more attentive, reflecting higher interest. Low entropy, on the other hand, would imply lower variability in information—indicating a stable or calm period with fewer significant news stories or less public attention.

As described by Sadoghi (2018), the attention to a news topic can be quantified using Shannon entropy (Shannon, 1948) from the link probability between topic k and document d, with parameter θ, expressed as:

$$H(\theta_{kd}) = -P(\theta_{kd}) \cdot \log(P(\theta_{kd})). \tag{1.1}$$

We aggregate intra-day values of entropy $H(\theta_{kd})$ and create a daily index of the topic:

$$\bar{H}(\theta_{kt}) = \frac{\sum_{i=1}^{N_t} H(\theta_{ki})}{N_t}, \tag{1.2}$$

where N_t represents the number of documents in day t.

Researchers, such as Ishizaki and Inoue (2020) and Stosic et al. (2016), have applied Shannon entropy to analyze exchange rates data. We follow Sadoghi (2018), who employs the Shannon entropy measure for terms, as proposed by Glasserman and Mamaysky (2019), to gauge attention to Bitcoin in news media. We adopt Sadoghi (2018)'s methodology, quantifying informational flows related to news topics using Shannon's entropy.

Introducing entropy variables, which are less conventional, is further justified by the robustness check outlined in section A.7, titled 'Robustness Check of U.S. Dollar-Related News Variables'.

1.3.4 Vector Autoregressive Model

The main econometric model employed in this study to identify exchange rates is a VAR model. Our choice is based on the outcomes of the Engel-Granger procedure discussed in subsubsection A.4 "Selection of the Estimation Method" in the appendix, as well as the proven effectiveness of VAR models in identifying exchange rates Carriero et al. (2009), Yaganti and Manpuria (2018), particularly within the Taylor framework Chen et al. (2017), and Grossmann et al. (2014).

The structural form representation of a VAR model with orthogonal errors is:

$$B^{-1}\gamma_t = B^{-1}A_1\gamma_{t-1} + \ldots + B^{-1}A_p\gamma_{t-p} + B^{-1}u_t, \tag{1.3}$$

where γ represents a vector of endogenous variables, B denotes a lower triangular matrix with real, positive diagonal entries obtained through Cholesky decomposition of the variance-covariance matrix (Ω) of the error vector u_t ($BB^{-1} = \Omega$).

We applied a VAR model with 7 lags, selected via AIC, with residual normality confirmed by the Jarque-Bera test.

1.4 News Extended Exchange Rate Model

1.4.1 Taylor Rule Model

In this paper, we employ the Taylor rule-based model for exchange rate forecasting, known to outperform other exchange rate models (Rossi (2013)). Extending the standard Taylor rule by incorporating the real exchange rate (Taylor (1993)), we follow a linear specification proposed by Molodtsova and Papell (2009):

$$i_t^* = \mu + \phi(\pi_t - \pi_t^* + \eta y_t) + \delta q. \tag{1.4}$$

This equation transforms into the exchange rate formula:

$$\Delta \log(s_{t+1}) = \omega - \omega_\pi \pi_t + \omega_{\tilde{\pi}}\tilde{\pi}_t - \omega_y y_t + \omega_{\tilde{y}}\tilde{y}_t + \omega_i \tilde{i_t} - \omega_i i_{t-1} + \omega_{\tilde{i}} \widetilde{i_{t-1}} + \eta_t, \tag{1.5}$$

where s is the nominal exchange rate, π_t is the inflation rate, y_t is the output gap calculated based on the Industrial Production Index (IPI), i_t is the interest rate, and foreign variables are denoted by tildes. Our choice of the linear specification of VAR model aligns with the findings of Burns and Moosa (2015), supporting its effectiveness in forecasting exchange rates.

1.4.2 News-Extended Taylor Model (NETM)

We extend the Taylor rule model with a topic modelling step and develop the News-Extended Taylor Model (NETM), integrating monthly averages of topic entropies and economic uncertainty indices derived from news data. The model is represented by the following system of equations (Equations 1.6–1.9):

$$B_0\gamma_t = C_0 + B_1\gamma_{t-1} + B_2\gamma_{t-2} + ... + B_p\gamma_{t-p} + \eta_t, \tag{1.6}$$

where B_0 is the $k \times k$ identity matrix, and C_0 is a $k \times 1$ vector of constants. B_j for $j = 1, \ldots, p$ are $k \times k$ coefficient matrices, η_t is a vector of uncorrelated structural shocks with zero mean and a contemporaneous covariance matrix that is positive semidefinite, and γ_t is a vector with $k = 14$ elements, representing variables of the model:

$$\gamma_t = \begin{bmatrix} \log(s_t) \\ \log(\pi_t) \\ \log(\tilde{\pi}_t) \\ \log(y_t) \\ \log(\tilde{y}_t) \\ \log(i_t) \\ \log(\tilde{i}_t) \\ \log(M2) \\ \log(\tilde{M}2) \\ \log(a_{1,t}) \\ \log(a_{2,t}) \\ \log(a_{3,t}) \\ \log(a_{4,t}) \\ \log(a_{5,t}) \\ \log(e_t) \\ \log(\tilde{e}_t) \end{bmatrix} \tag{1.7}$$

where s_t represents the nominal exchange rate, π_t is inflation, y_t is the GDP gap (measured by the industrial production index), i_t is the interest rate, e_t refers to the news-based economic uncertainty index, and the corresponding variables for the foreign country ($\tilde{\pi}_t$, $\tilde{y}_t$, $\tilde{i}_t$, $\tilde{e}_t$) are denoted by tildes. $a_{j,t}$ denotes attention to news topic j for $j = 1, 2, 3, 4, 5$.

The monthly attention to the topics $a_{j,t}$ is computed from the time series of each LDA-identified topic j as follows:

$$a_{j,m} = \frac{\sum_{d=1}^{N_d} \overline{H}(\theta_{ki})}{N_d}, \tag{1.8}$$

where $a_{j,m}$ represents the attention to topic j in month m, N_d is the number of days in the month, and the daily entropy $\overline{H}(\theta_{ki})$ is calculated as:

$$\overline{H}(\theta_{ki}) = \frac{\sum_{i=1}^{N_t} H(\theta_{ki})}{N_t}, \tag{1.9}$$

in this context, θ_{ki} represents the Shannon entropy of the i^{th} news item (article) on a given day, and N_t is the number of news items on that day.

Averaging entropies monthly is reasonable in our study because daily positive and negative entropies balance each other, reflecting similar responses to both types of news. This approach provides a stable measure of news impact, smoothing short-term noise and volatility for a clearer understanding of underlying trends. While capturing very short-term exchange rate reactions may interest some researchers, constructing a daily non-mixed-frequency model is impractical due to the lack of Taylor rule variables at higher frequencies. Therefore, we persist in using monthly data.

The robustness tests for the News-Extended Taylor Model are detailed in section A.7, titled 'Model Specification Robustness'. These tests include assessments of various aspects, such as the VAR model stability test, residual analysis (normality, heteroskedasticity, and serial correlation tests), Granger and instantaneous causality tests, comparisons of our model to Taylor rule models excluding news variables, comparisons to news models excluding macroeconomic variables, and evaluation of explanatory power of our model for the U.S. money market rate.

1.5 Data

This study integrates two types of data: soft data, comprising unstructured textual information available at an intraday frequency, and hard data, consisting of monthly macroeconomic indicators.

The dataset spans from 2000 to 2018, excluding the pandemic years 2019–2023, to mitigate bias from abnormal exchange rate reactions during this high-risk period. The pre-2000 period is omitted due to limited availability of news data and the instability of the EURO currency during its first year after introduction in 1999. The data is recorded on a monthly frequency.

Soft Data: We collect textual data from news articles related to the U.S. Dollar using the extensive Nexis-Uni Database, containing over 84 billion public records. The Nexis Uni database comprises news and other content carefully curated with strict editorial standards directly sourced from over 17,000 reputable licensed publishers, helping to ensure that our data is as free as possible from misinformation and fake news. Employing the keyword "U.S. Dollar" for our search, we identify over 15 million non-duplicate news items from reputable online publishers. Our data cleaning process verifies the presence of "U.S. Dollar" in the title, ensures repeated mentions in the opening paragraph, and automatically identifies "U.S. Dollar" as the subject by Nexis-Uni. Furthermore, the news-constructed economic uncertainty (EPU) index, obtained from the official website of the index, comprises quantified newspaper data about policy-induced economic uncertainty, temporary tax code provision, and expectation fallacy of experts about economic variables Baker et al. (2024).

Hard Data: Our analysis relies on standard macroeconomic indicators commonly employed in Taylor rule models. These indicators comprise the industrial production index (IPI) as a proxy for GDP, seasonally adjusted consumer price index (CPI) for measuring inflation, M2 for measuring money supply and the money market rate as an indicator of short-term interest rates. Data for the IPI, CPI and M2 are sourced from Datastream for reliability and consistency. For the UK, the latest seasonally adjusted CPI data series from the British Office for National Statistics (CPIH INDEX 00: ALL ITEMS 2015=100) is utilized. Following the methodology of Molodtsova and Papell (2009), the GDP gap is calculated by assessing the percentage deviation of the industrial production index from its trend, obtained through Hodrick-Prescott filtering. Additionally, money market rates are directly sourced from local central banks, and exchange rates are retrieved from the Federal Reserve Bank of St. Louis database.

We analyze data for the world's top-traded major currencies, namely the U.S. Dollar (USD), Euro (EUR), and Pound Sterling (GBP).

The dataset Shugliashvili (2024) used in this study is publicly available on the Harvard Dataverse.[2] Descriptive statistics for model variables are shown in Table A.1, and news entropy time series are displayed in Figure A.1, both located in the appendix.

1.6 Results and Discussion

This section unveils the five key topics associated with the U.S. Dollar, as identified through Latent Dirichlet Allocation (LDA). We then conduct forecast error decompositions for EUR/USD and GBP/USD exchange rates and explore how exchange rates respond to news shocks.

1.6.1 News-Derived Topics Related to the U.S. Dollar

Constructing the LDA model from extensive news data, we pinpoint the top 5 topics most relevant to exchange rates:

Topic 1: Stock Market News[3]
Main terms: commodities, commercial bank, oil market, stock exchange, taxation, shareholders.

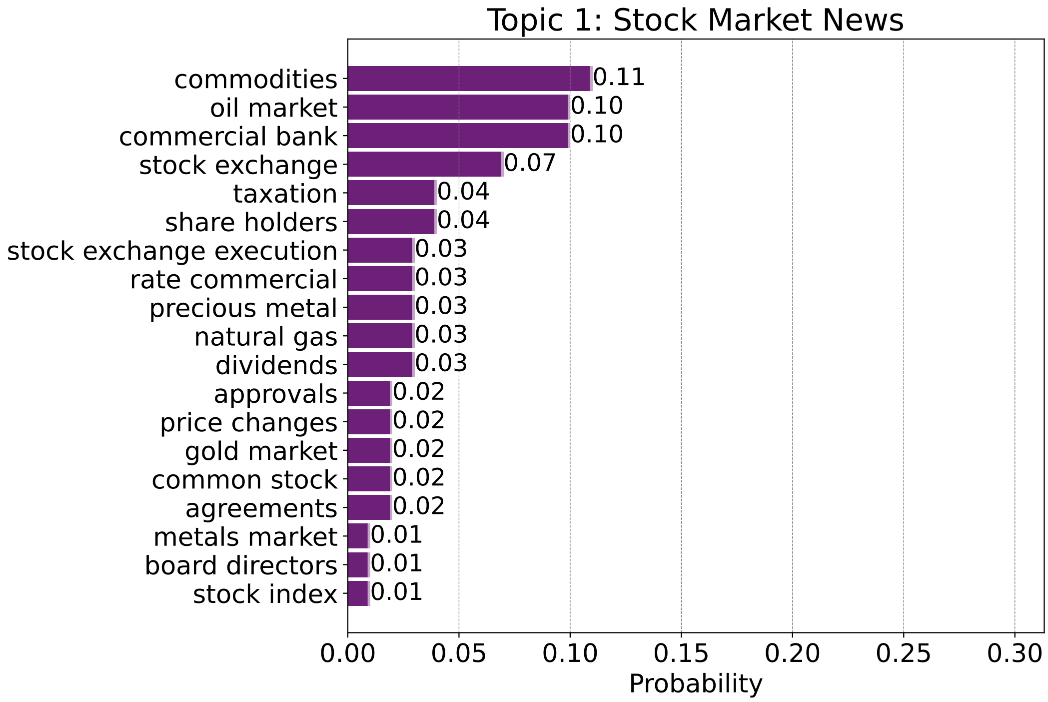
Topic 2: Economic Development News
Main terms: monetary policy, economic policy, inflation, public policy, eurozone, economic growth.

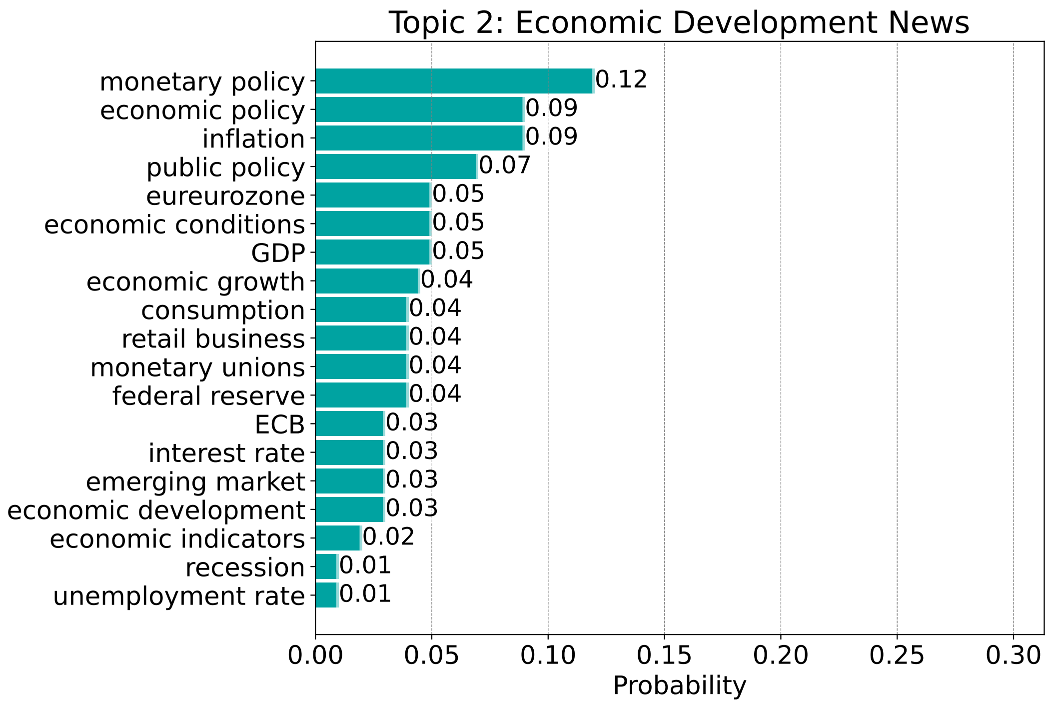
Topic 3: FED News
Main terms: central bank, interest rates, bond, exchange market, stock index, market price.

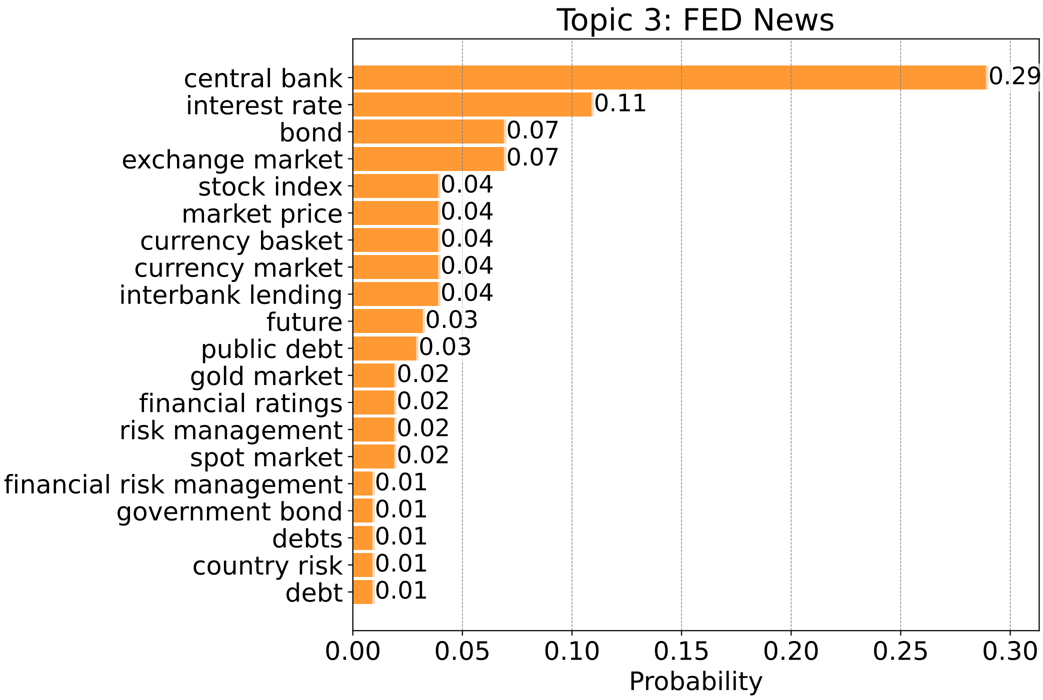
Topic 4: Microeconomic News
Main terms: income tax, company earnings, balance sheet, financial results, capital expenditure, financial performance report.

Topic 5: International Trade News
Main terms: exchange port trade, import trade, public finance, output demand, agency treasury, budgets.

[2] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/0IIZJO
[3] These topic titles are provided for reference and serve as notations within this paper.


Topic 1: Stock Market News
commodities 0.11
oil market 0.10
commercial bank 0.10
stock exchange 0.07
taxation 0.04
share holders 0.04
stock exchange execution 0.03
rate commercial 0.03
precious metal 0.03
natural gas 0.03
dividends 0.03
approvals 0.02
price changes 0.02
gold market 0.02
common stock 0.02
agreements 0.02
metals market 0.01
board directors 0.01
stock index 0.01
0.00 0.05 0.10 0.15 0.20 0.25 0.30
Probability


Topic 2: Economic Development News
monetary policy 0.12
economic policy 0.09
inflation 0.09
public policy 0.07
eureurozone 0.05
economic conditions 0.05
GDP 0.05
economic growth 0.04
consumption 0.04
retail business 0.04
monetary unions 0.04
federal reserve 0.04
ECB 0.03
interest rate 0.03
emerging market 0.03
economic development 0.03
economic indicators 0.02
recession 0.01
unemployment rate 0.01
0.00 0.05 0.10 0.15 0.20 0.25 0.30
Probability


Topic 3: FED News
central bank
interest rate
bond
exchange market
stock index
market price
currency basket
currency market
interbank lending
future
public debt
gold market
financial ratings
risk management
spot market
financial risk management
government bond
debts
country risk
debt
0.29
0.11
0.07
0.07
0.04
0.04
0.04
0.04
0.04
0.03
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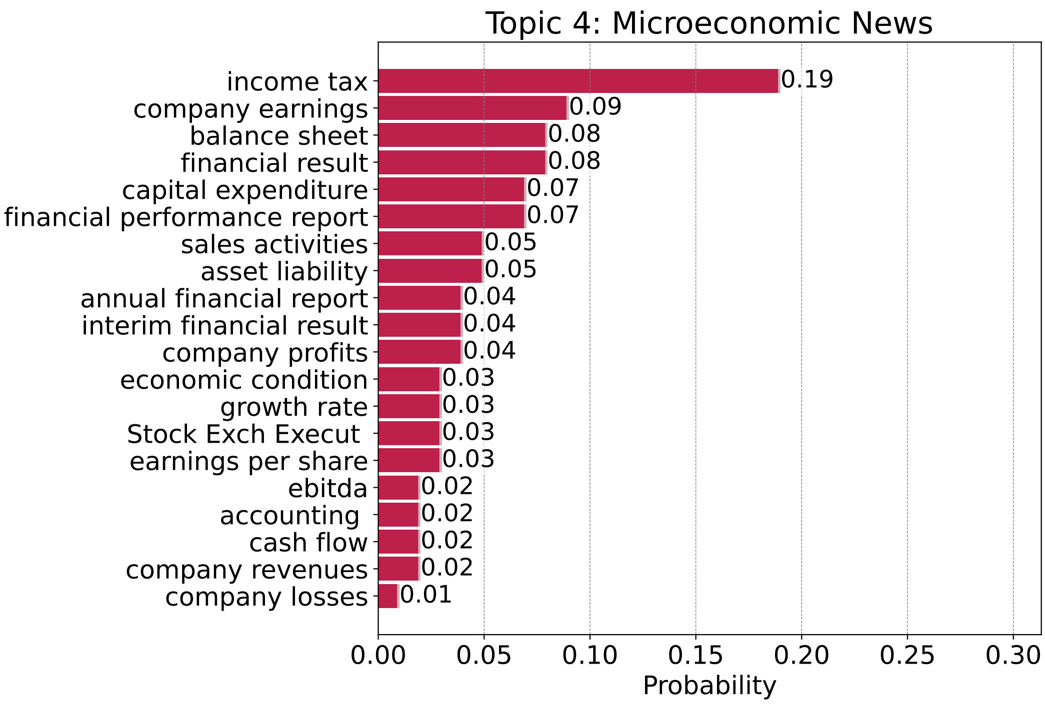
Probability


Topic 4: Microeconomic News
income tax
company earnings
balance sheet
financial result
capital expenditure
financial performance report
sales activities
asset liability
annual financial report
interim financial result
company profits
economic condition
growth rate
Stock Exch Execut
earnings per share
ebitda
accounting
cash flow
company revenues
company losses
0.19
0.09
0.08
0.08
0.07
0.07
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Probability

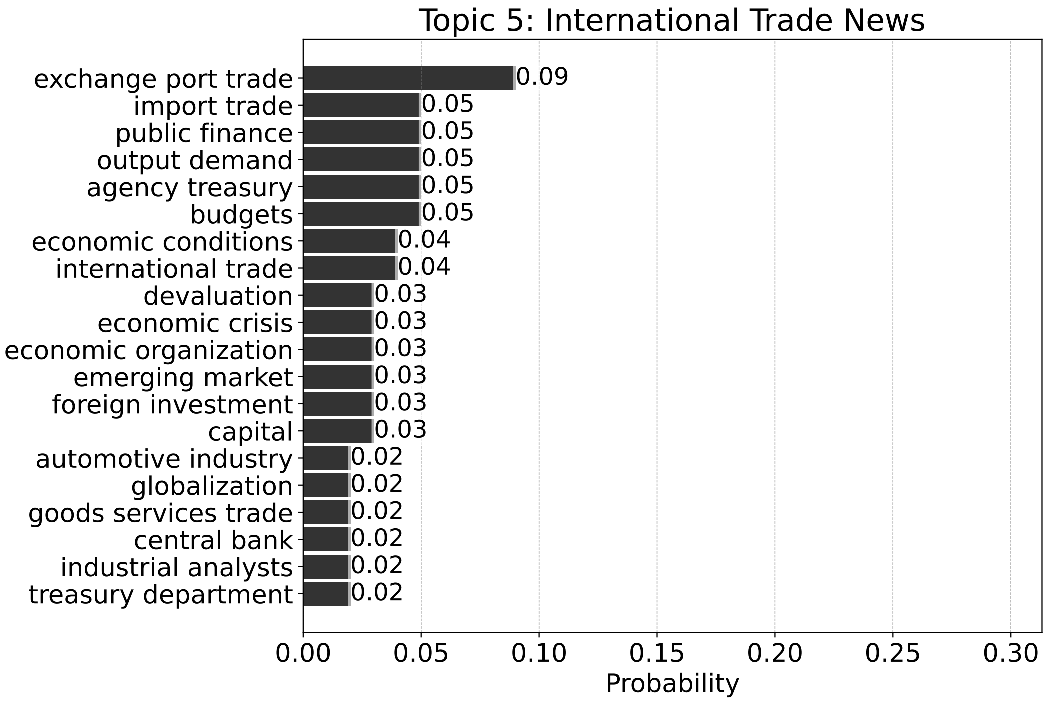


Figure 1.1: Probability distributions of top terms in each topic.

Note: The figure represents the likelihood of the top terms appearing in each respective topic.

The probability distributions of the top terms in each topic are illustrated in Figure 3.4. The first topic, "Stock Market News," includes information about commodities, oil markets, gas, stock exchange, and precious metal markets, representing the underlying assets of commodity futures and indices. The second topic, "Economic Development News," delves into information regarding inflation, economic policy, monetary policy, economic growth, GDP, consumption, federal reserves, and unemployment. The third topic, "FED News," covers details about central banks, interest rates, bonds, currency markets, public debt, and government bonds. The fourth topic, "Microeconomic News," explores aspects like company profits, sales, financial performance, and cash flows. Finally, the fifth topic, "International Trade News," includes information on import, foreign investment, goods and services trade, and globalization.

The evolution of monthly attention to these topics is presented in Figure A.1 of the appendix.

1.6.2 Forecast Error Decomposition

Figure 1.2 illustrates the results of the Forecast Error Decomposition (FEVD) for the GBP/USD exchange rate. The numerical values depicted denote the percentage of the forecast error in the GBP/USD exchange rate attributed to the innovation in each variable across various horizons, ranging from 0 to 47 (spanning four years). Detailed numerical data for the FEVD for GBP/USD is provided in Table A.2 in the appendix.

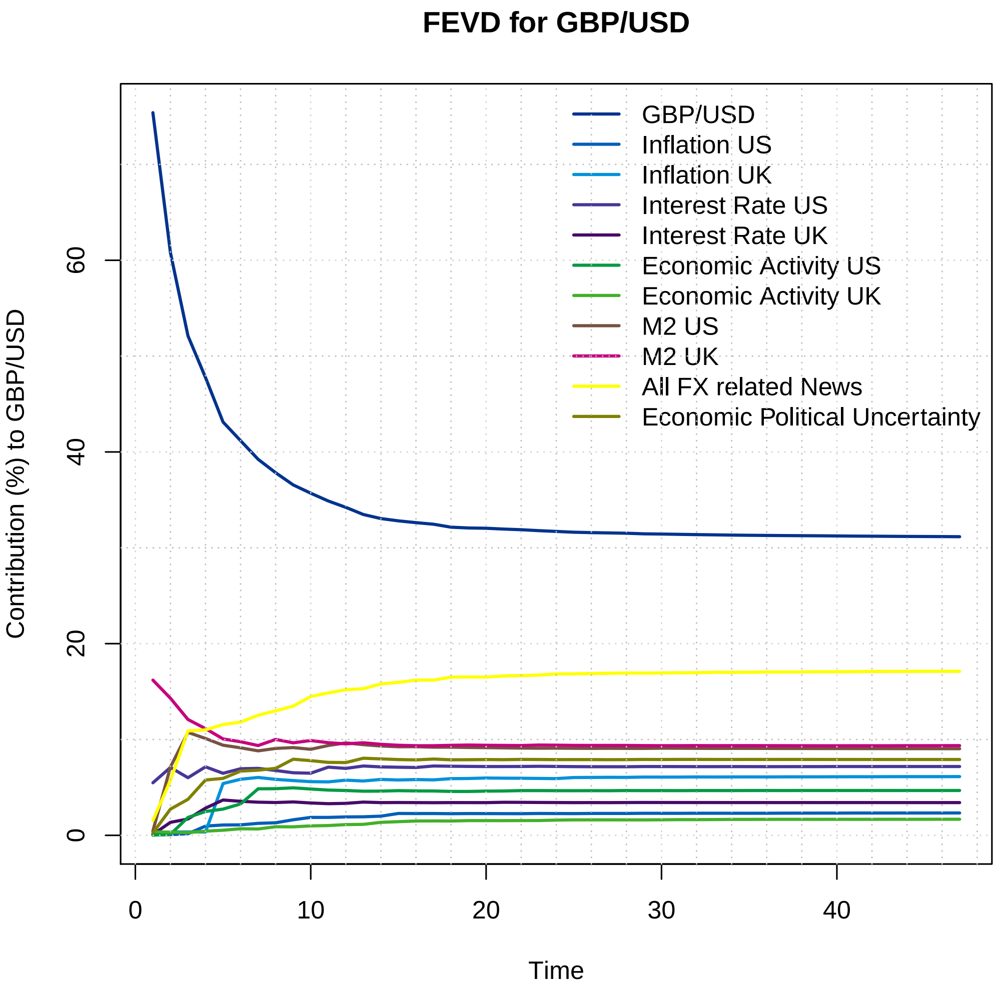


Figure 1.2: FEVD for GBP/USD
The figure illustrates the percentage of forecast error in the GBP/USD exchange rate attributed to innovations in itself or other variables. The x-axis represents months.

Figure 1.2 illustrates the stabilization of contribution percentages to the GBP/USD forecast error after 2 years. In the long run, U.S. Dollar-related news innovations account for 17% of the forecast error variation. Both M2 in the UK and US contribute 9% to the variability of GBP/USD, while the political uncertainty index derived from policy-related news adds 8%. Contributions from economic activity, inflation, and interest rate variables to the GBP/USD forecast error remain below 8%. These findings, along with the stabilization of the contribution percentages to the GBP/USD forecast error over time, underscore the significant influence of news on exchange rates.

Figure A.2 in the appendix presents a comprehensive overview of aggregated contributions from macroeconomic variables, news, and GBP/USD's own shocks to the exchange rate. Over the long term, shock to the news variables contribute 25% to GBP/USD variability, while macroeconomic variables represent the largest share at 43%. The remaining 32% of GBP/USD forecast error is attributed to exchange rate variability. These findings underscore the substantial role of news in exchange rate variability, particularly beyond the two-year mark. Moreover, in the long run, 68% of GBP/USD variability is associated with exogenous variables of our model, namely Taylor rule variables, and news variables, highlighting the model's significant explanatory power for the exchange rate.

Before stabilizing, the contribution of GBP/USD innovation to its own variation steadily declines over the initial two years. Within six months, it decreases to 41%, further dropping to 32% by the end of two years. Simultaneously, exogenous macroeconomic and news variables increasingly influence the GBP/USD exchange rate, with news variables explaining up to 23% of its variability after one year. By the end of the first year, external factors account for 66% of the observed variability in the GBP/USD exchange rate. By the end of two years, the exogenous variables account for 68% of the variability in GBP/USD. Aggregating the impact of all news variables, as shown in Figure A.2 in the appendix, reveals that news (U.S. dollar-related news and Economic Uncertainty Indices) accounts for 24.6% of the variation in GBP/USD after two years. In parallel, macroeconomic variables contribute 43,6% to the forecast error variance of GBP/USD over the same timeframe (see Figure A.2 in the appendix). The contributions stabilize after two years and reach fixed values after 41 periods, indicating that exogenous factors predominantly drive the exchange rate in the long run (up to 69%), of which 25% is attributed to news variables.

The forecast error decomposition of GBP/USD shown in Figure 1.2 highlights that U.S. dollar-related news innovations are the primary contributors to the forecast error in the GBP/USD exchange rate, surpassing the impacts of non-aggregated exogenous variables. Following U.S. dollar-related news, M2 shocks, economic uncertainty shocks (also derived from news), economic activity shocks, and inflation shocks have the most significant impact on the GBP/USD exchange rate among the exogenous shocks, and this pattern persists for all periods starting from the sixth month.

In Figure 1.3, we illustrate the breakdown of FX news contributions to the variance of GBP/USD forecast error, showing the contributions from each U.S. dollar-related news topic.

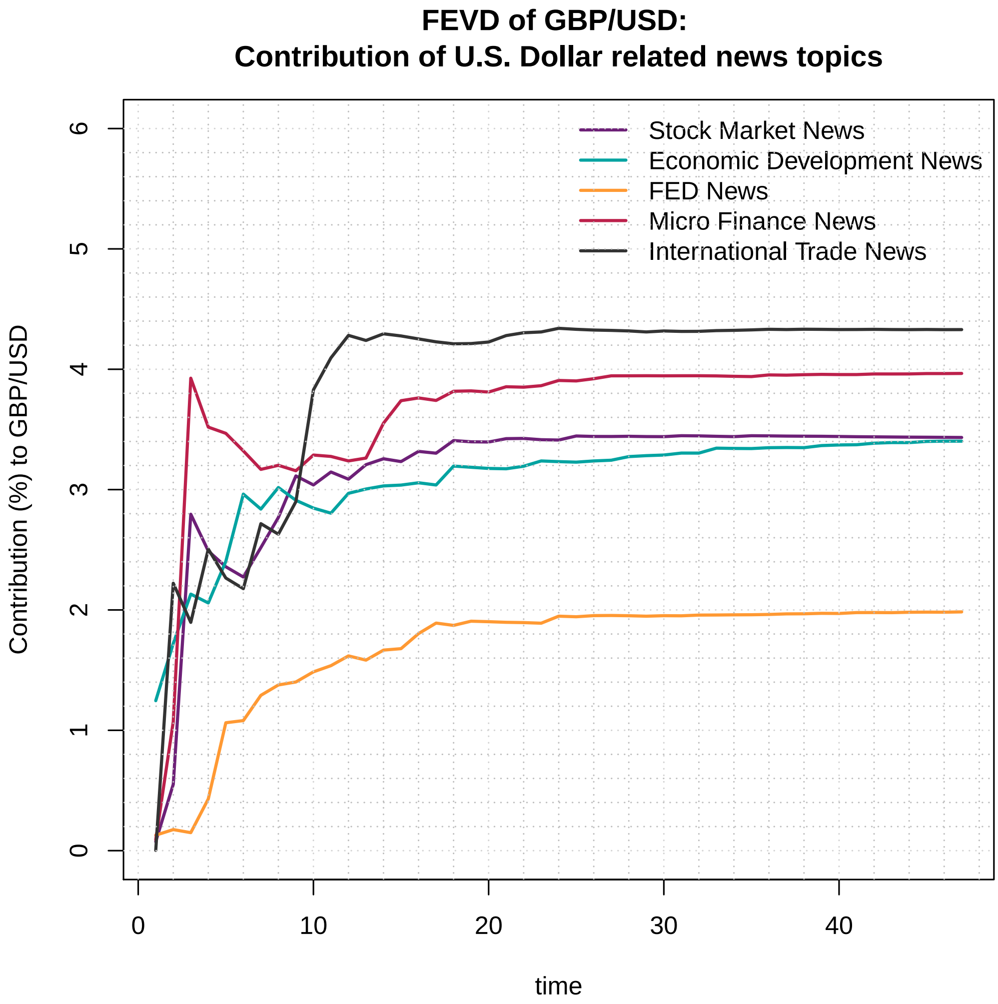


Figure 1.3: Contribution of U.S. dollar-related news to GBP/USD variations

In Figure 1.3 we observe that after a two-year period, U.S. dollar-related news contributes approximately 17% to the shock in GBP/USD. This contribution is distributed across various news topics as follows: international trade news explains 4.2% of GBP/USD variability, microeconomic news contributes 4%, stock market news attributes 3.4%, economic development news accounts for 3.2%, and FED news contributes 2%.

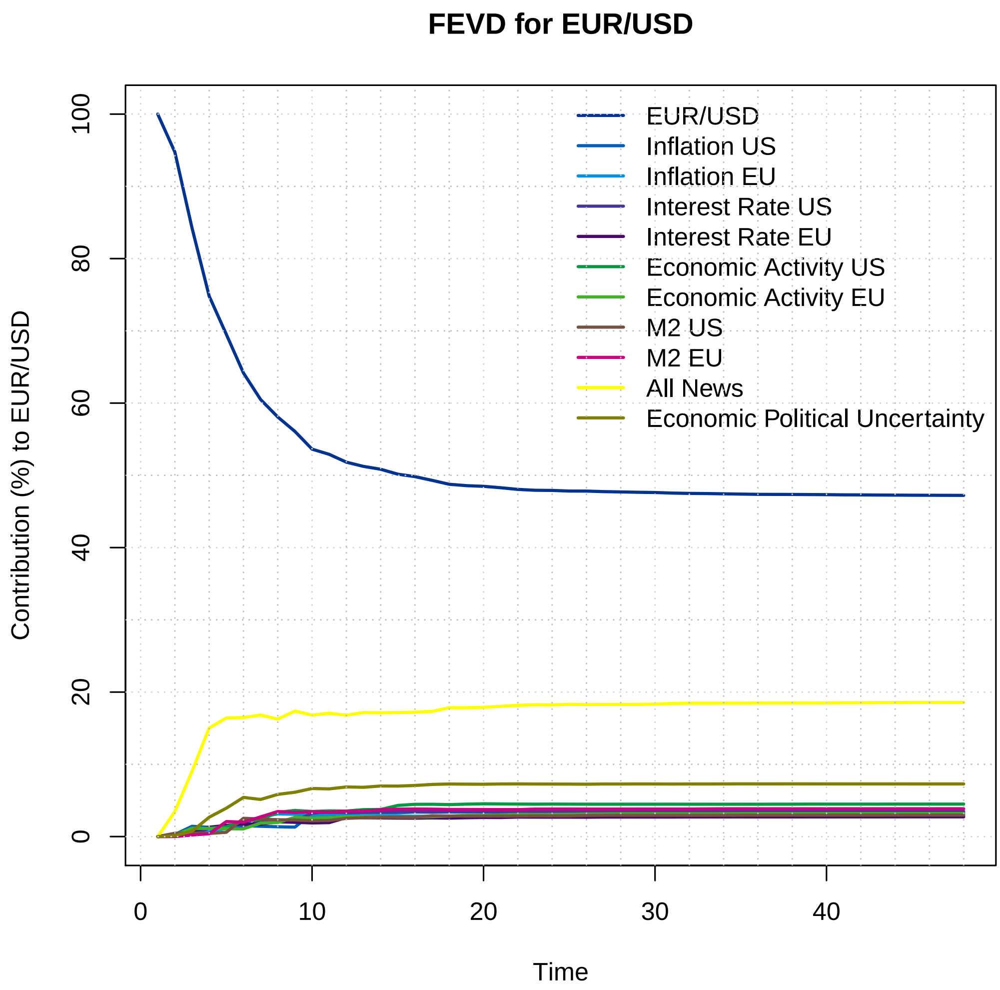


Figure 1.4: FEVD for EUR/USD
The figure illustrates the FEVD for the EUR/USD exchange rate. The reported numbers represent the percentage of the forecast error in the EUR/USD exchange rate attributable to innovation in itself or other variables.

Figure 1.4 presents the results of the forecast error variance decomposition for the EUR/USD exchange rate. The corresponding numerical values are provided in Table A.3 in the appendix. Over a two-year horizon, U.S. dollar-related news explains 18% of the EUR/USD forecast errors, while economic policy uncertainty indices contribute 8%. Thus, over this period, news variables collectively (U.S. dollar-related news and economic uncertainty indices) account for up to 26% of the exchange rate variation. M2 in the US accounts for 4.2% of the variability, followed by MMR in Europe, IPI in the US and Europe, inflation, M2 in Europe, and economic activities in the US and Europe. Similar to the case of GBP/USD, a significant portion of the variability in EUR/USD can be attributed to news shocks.

Upon aggregating the impact of all news variables, as illustrated in Figure A.2 in the appendix, it becomes apparent that news accounts for 27% of the EUR/USD variation after a 2-year period. Similarly, when summing up all macroeconomic variables, they contribute to 30% of the forecast error variance of the EUR/USD after the same period (refer to Figure A.2 in the appendix).This indicates that exogenous variables primarily influence the exchange rate in the long run, explaining 57% of its variation.

In the short run, over the initial two years, the intrinsic impact on EUR/USD steadily diminishes, following a pattern similar to that observed for GBP/USD. Within six months, this self-explanatory contribution decreases to 65%, further dropping to 47% after one year. Subsequently, exogenous model variables progressively influence EUR/USD dynamics.

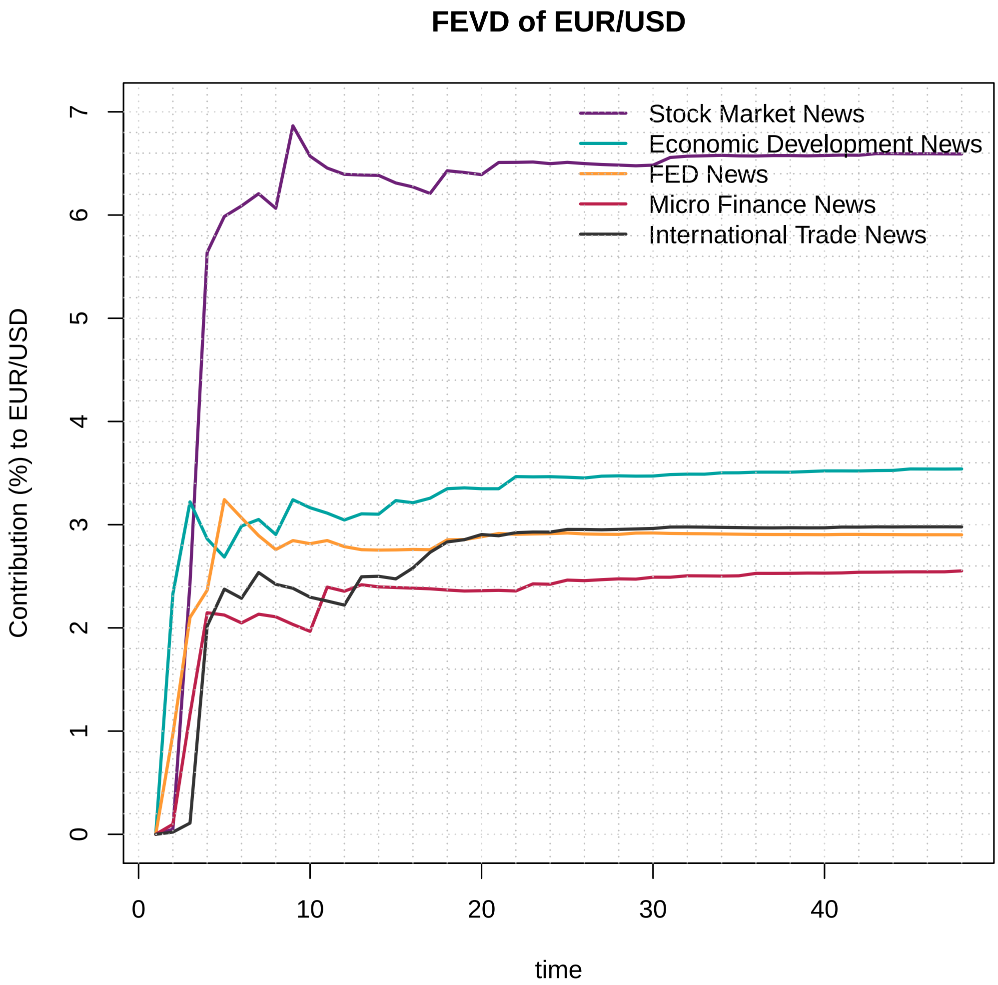


Figure 1.5: Contribution of U.S. dollar-related news to EUR/USD variations

Figure 1.5 illustrates how US.Dollar-related news contributes to the forecast error variance of EUR/USD, breaking down the contributions from each news topic. The order of influence on the EUR/USD exchange rate is as follows: stock market news, economic development news, international trade news, FED news, and microfinance news. The 18% contribution to EUR/USD variability after two years breaks down into the following news topics: stock market news explains 6.7%, economic development news explains 3.6%, international trade news 3.2%, FED news 2.7%, and microfinance news contributes around 1.7%.

The contribution of **Stock Market News** to exchange rate fluctuations, 3.4% for GBP/USD and 6.7% for EUR/USD, indicates that attention to shifts in global financial markets—particularly those driven by commodities like oil and precious metals—significantly affects both currency pairs. Similarly, the contribution of **Economic Development News**, 3.2% for GBP/USD and 3.6% for EUR/USD, underscores the role of U.S. Dollar-related information concerning inflation, monetary policy, economic policy, GDP, consumption, and economic growth in determining exchange rates. The **FED News** contribution, at 2.0% for GBP/USD and 2.7% for EUR/USD, highlights the impact of Federal Reserve policy news, including interest rate changes and forward guidance, on the strength of the U.S. dollar, which, in turn, influences both currency pairs. Attention to FED news, such as information on market expectations regarding U.S. interest rates or potential "economic tightening," further shapes investor behaviour, currency demand, and exchange rate movements.

Meanwhile, **Microeconomic News**, contributing 4.0% to GBP/USD and 4.6% to EUR/USD, emphasizes the impact of sector-specific and corporate factors—such as corporate earnings, tax policies, and financial performance—on currency flows and market sentiment. The contribution of **International Trade News**, 4.2% for GBP/USD and 3.2% for EUR/USD, pinpoints the influence of trade balances, foreign investment flows, and economic output in the U.S., Eurozone, and U.K. on the relative value of both currency pairs. Lastly, the **Economic Policy Uncertainty Index (EPU)** highlights the significance of broader economic conditions, with the U.S. EPU contributing 4.7% to GBP/USD and 4.0% to EUR/USD, the U.K. EPU contributing 3.2% to GBP/USD, and the EU EPU contributing 3.9% to EUR/USD, reflecting the substantial impact of economic uncertainty on currency values.

To sum up, U.S.-related news drives significant and stable variability in both EUR/USD (27%) and GBP/USD (25%) after two years since the shock, underscoring the role of U.S. economic developments, policies, and uncertainty in shaping these currency pairs.The findings also demonstrate consistent stability across different samples. A parallel analysis was conducted for both exchange pairs, excluding the financial crisis period (July 2007–March 2009). The model remained stable with explained variance showing minimal fluctuation, with the exogenous variables accounting for 60% of the variability in EUR/USD and 68% in GBP/USD.

Comprehending the relative impact of variables on exchange rate fluctuations offers invaluable insights for policymakers, analysts, and stakeholders. This understanding empowers policymakers to formulate effective strategies for stabilizing exchange rates, while enabling analysts to refine their forecasting models for informed investment decisions. Furthermore, our FEVD analysis sheds light on how news captures critical factors overlooked by conventional models, bolstering the robustness of our findings against potential biases.

1.6.3 Impulse-Response Analysis

The cumulative generalized impulse-response functions, as illustrated in Figures 5 to 9 in the appendix, underscore the statistically significant impacts of U.S. Dollar-related news topics on exchange rates. Particularly noteworthy is the consistent positivity observed in the responses of GBP/USD and EUR/USD to news pertaining to stock market activities, economic development, and international trade over the four years following the initial shock. Conversely, the responses to microeconomic fluctuations and news related to the Federal Reserve (FED) exhibit negative trends or fluctuating signs over time.

In contrast, the cumulative generalized impulse-response functions depicting the relationship between exchange rates and macroeconomic fundamentals, presented in Figure A.9 in the appendix, reveal statistically significant yet modest impacts, with predominantly insignificant signs.

Furthermore, the impulse-response analysis suggests that heightened attention to economic development news corresponds with an appreciation of exchange rates against the USD during the initial three quarters. Conversely, intensified focus on FED policies and microeconomic factors can result in statistically significant depreciations of exchange rates against the USD in specific post-shock periods.

It is worth noting that the comparison between generalized cumulative impulse response functions and Forecast Error Variance Decompositions (FEVDs) consistently highlights significant impulse responses for news topics that contribute most to the error variance in exchange rates during certain months post-shock.

Our impulse response analysis provides valuable insights for policymakers, financial institutions, and investors. Policymakers can tailor monetary policies in response to economic developments and news events, while financial institutions can refine risk management strategies. Investors can enhance decision-making regarding currency trading and asset allocation, leading to improved investment outcomes.

1.6.4 Discussion

Our comprehensive findings, derived from both forecast error decomposition and impulse response analysis, robustly affirm the hypothesis that news plays a pivotal role in influencing exchange rates. The integration of news variables into prominent Taylor rule models significantly improves the accuracy of exchange rate predictions.

These results align with established economic theories, including attention theory, the efficient market hypothesis, and currency pricing models, all of which posit the impact of news on exchange rates. Existing literature further corroborates our findings, with studies by Tadphale et al. (2023), Aquilante et al. (2022), Jabeen et al. (2022), Cheung et al. (2019), Caruso et al. (2016), Clarida and Waldman (2008), Galati and Ho (2003), Almeida et al. (1998), and Edwards (1983) consistently highlighting the substantial influence of news on exchange rates.

Moreover, a substantial body of existing literature extensively explores the impact of variables such as stock prices (Rehman and Chisti (2020)), oil (Siddiqui et al. (2023)), economic growth (Ridhwan et al. (2024)), and international trade (Lal et al. (2023)) on exchange rates, which we have identified as the top five topics related to exchange rates.

In contrast to methodologies employed in studies such as Narayan et al. (2021), Ben Omrane et al. (2020), and Caporale et al. (2018), which primarily focus on macroeconomic announcement titles, our research adopts a distinct approach by utilizing entire text bodies. This nuanced choice aims to provide a more comprehensive understanding of the interplay between news content and exchange rates. Despite the difference in data type, our findings align with theirs, contributing to the growing consensus that news exerts a substantial influence on exchange rates.

Despite demonstrating the impact of news on exchange rates, our model presents several considerations that warrant further attention: exploring alternative topic modelling techniques and information theory metrics could improve robustness. Using models beyond VAR may also enhance results. Another concern is that the period before 2002 was a transitional phase for the introduction of the euro, which may unduly affect the results. A dataset beginning in 2002, when the Euro became fully operational, yields normally distributed residuals and improves FEVDs, explaining 69% of EUR/USD variations. Despite the shortened timeframe, this dataset potentially offers more precise insights. Furthermore, incorporating additional news related to the GBP and Euro could further enrich the dataset. Currently, the model uses the industrial production index (IPI) as a GDP proxy; however, alternatives like news-based or survey-based monthly GDP estimates could offer better accuracy, though employing the survey-based data may be a discussion issue. Additionally, wide credible intervals in some Impulse Response Functions (IRFs) highlight significant uncertainty. Thus, the main practical implication is that economic agents should use U.S. Dollar-related news as an additional tool for risk monitoring and integrate it into advanced exchange rate models. However, the magnitude of the exchange rate's response to specific news varies with the news content, emphasizing the need for further linguistic and analytical analysis of news with heightened attention to enhance understanding and precision.

Looking ahead, future research avenues could explore further topic subsetting, distinguishing between positive and negative news, and incorporating additional macroeconomic variables or media news sources to enhance model explanatory power. Additionally, exploring regime-switching models may offer insights into exchange rate behavior during extraordinary periods.

1.7 Conclusion

This study assesses the influence of news on exchange rates by extending the Taylor rule model with U.S. Dollar-related news and economic policy uncertainty-related news. Our findings reveal that news significantly impacts exchange rates, contributing to 22%-24% of short-run and 25%-27% of long-run exchange rate variability.

Impulse-response analyses highlight the positive impact of economic development news on EUR/USD and GBP/USD exchange rates for approximately three quarters post-shock. Notably, economic development news led to an increase in EUR/USD and GBP/USD exchange rates, resulting in a decline in the U.S. Dollar value against EUR and GBP. Additionally, stock market news positively affected EUR/USD in the initial months, while FED news caused EUR/USD depreciation in the first quarter post-shock. Conversely, microeconomic news led to GBP/USD depreciation in the first quarter, while international trade news resulted in GBP/USD appreciation in the second quarter post-shock.

Our study's contribution lies in the application of a hybrid model, News-Extended Taylor Model (NETM), which integrates text analysis and economic fundamentals. This research enhances the news-based exchange rate modelling literature by incorporating news attention metrics—quantified through analysis of entire news bodies—alongside macroeconomic variables. Our findings underscore the valuable insights provided by soft information from news in understanding exchange rate movements. Furthermore, shocks in attention toward identified news topics play a relevant role in exchange rate dynamics, with "Casual Topics" offering potential explanations for market changes.

Overall, our study contributes to advancing the understanding of exchange rate dynamics and underscores the importance of integrating news data with traditional economic models for improved forecasting and policy formulation.

2 Capital Structure Determinants in German SMEs: Panel Analysis and Policy Recommendations

At the outset of this chapter, it is essential to state that the research presented here was recently published as a scientific paper in the journal Credit and Capital Markets, with myself as the first author (Shugliashvili et al. (2024)). This chapter is based on joint work with Prof. Dr. Pirveli, Assoc. Prof. Munjishvili and Assoc. Prof. Deari.

Abstract

This study investigates the financing decisions within German SMEs, examining firm-specific, macroeconomic, and news-related determinants. Utilizing a 10-year dataset encompassing 13,051 SMEs, we employ a dynamic panel data model with an unbiased Dynamic Panel Fractional (DPF) estimator to identify the key variables influencing the debt-to-equity ratio. The findings underscore the importance of factors such as the non-debt tax shield, firm size, interest rate spread, and the economic policy uncertainty index.

The study's findings propose the following policy implications:

1. Policy initiatives targeting firm size and non-debt tax shields affect SME leverage.
2. Policies addressing the term spread and economic uncertainty influence debt levels across various industries in Germany.
3. Industry-specific SME policies are advisable, due to the significant industry effects on German SME leverage.
4. External shocks exert short-term effects on the capital structures of German SMEs, as they adjust their leverage within an eight-month period.

Keywords: SME policy, capital structure, SMEs, financing decisions, leverage, panel data.

2.1 Introduction

Due to the key economic role of SMEs around the globe (OECD, 2017), the analysis of the capital structure of small- and medium-sized enterprises has attained an increasing importance worldwide (Kumar et al., 2020). Also in Germany, SMEs are vital for the economy; they comprise 99.6% of the country's businesses and made an impressive contribution of 54.4% and 47.4% to the country's GDP in 2019 and 2022, respectively. This underscores the importance of researching the capital structure of German SMEs. Furthermore, deriving policy implications from the leverage decisions of German SMEs is crucial, as it is debated that policy could be improved to support SMEs' capital investments, and SBA fact sheets document that state aid and access to finance for German SMEs are just at the EU average.

The academic debate on capital structure has been ongoing since Modigliani and Miller (1958). The theories—trade-offs, pecking order, and agency costs theory—assist decision-makers. Despite this, authors such as Brealey et al. (2019) and Yapa Abeywardhana (2017) list capital structure issues as unanswered topics.

Empirical research on SMEs' capital structure often yields contradictory results, with studies examining various firm-specific variables as determinants. Yapa Abeywardhana (2017) and Forte et al. (2013) highlight this inconsistency. Omitted variable bias may contribute to this contradiction by distorting the coefficients of these variables. To address this issue, some studies have focused on macroeconomic determinants such as economic uncertainty (Zhang et al., 2015; Graham et al., 2015) or industry effects (MacKay and Phillips, 2005; Hatfield et al., 1994). While these studies have identified significant effects of industry and macroeconomic uncertainty on the capital structure, they often overlook considering these factors together, potentially leading to contradictory findings. Although research has examined the capital structure of German SMEs (Hall et al., 2004; Schäfer et al., 2004; Iqbal and Kume, 2014), there's a gap in simultaneously analyzing microeconomic, macroeconomic, and industry effects within German SME data, leaving room for the omitted variable problem. Biased estimates could also contribute to contradictory results in empirical research on leverage, and we do observe many biased estimates used in capital structure literature.

Clear policy recommendations on SMEs' leverage are essential to prevent financial crises (Geanakoplos, 2010), maintain accounting standards (Pirveli, 2015), and foster financial market development. However, stating clear implications of research findings is necessary for informing policymakers (Antoniou et al., 2008). While some scholars, like Yu (2000), propose policy implications, recommendations often lack specificity and context, particularly for German SMEs. Bridging this gap is crucial for informed decision-making and tailored policy formulation.

As discussed above, the capital structure literature reveals several gaps, including inaccuracies in leverage models due to omitted macroeconomic variables and industry effects, biased estimates of SMEs' leverage, and a lack of practical implications for policymakers. Our study seeks to address these gaps.

Our paper relates to four interconnected strands of literature: the microeconomic modeling of SMEs' capital structure, the impact of macroeconomic and industry factors on leverage decisions, panel data estimation methodologies, and literature on leverage policy recommendations.

In this article, we propose a model to identify the debt-to-equity ratios in German SMEs, analyzing their response to firm-specific, macroeconomic, and industry shocks. We aim to provide policy recommendations relevant to the capital structure for German SMEs at both the business entity and industry levels. To derive policy insights, this paper unlike mainstream literature, and like Reddy et al. (2022), simultaneously tests for macroeconomic impact and industry effects. We aggregate SMEs' data from the firm level to the industry level for comprehensive analysis.

Additionally, we assess the expected policy outcomes by examining the duration of SMEs' response to policy changes. This evaluation involves analyzing industry and firm-level adjustment speeds of the capital structure using the dynamic panel fractional estimator (DPF), known for its precision in assessing capital adjustment speed (Elsas and Florysiak, 2015).

The study reveals several key findings: 1) capital structure responds to a non-debt tax shield, suggesting it is reasonable in Germany to apply tax policy incentives related to the non-debt tax shield. 2) As company size is significant capital structure determinant, policymakers can target policy incentives towards smaller firms. 3) German SMEs leverage is subject to statistically significant industry effects, indicating that different industries make leverage decisions differently. 4) capital structure is sensitive to macro variables such as the term spread and uncertainty index, with SMEs in several industries tending to take on more debt during periods of economic uncertainty. 5) SMEs adjust their capital structures within eight months, the effects of a one-time external shock last for the same duration.

The primary contribution of this paper lies in its provision of comprehensive evidence regarding German SMEs' capital structure decisions, offering valuable insights relevant for policymakers.

The rest of this paper is structured as follows: Section 2 reviews existing literature on microeconomic and macroeconomic factors influencing capital structure. Section 3 covers data sources, methodology, and estimation techniques. Section 4 presents empirical findings from our analysis of German SMEs and discusses implications. Finally, Section 5 concludes with policy recommendations.

2.2 Background Literature

Since the seminal work of Modigliani and Miller (1958) in the capital structure literature, researchers have devoted significant effort to identifying factors that explain firms' borrowing behavior (Lussuamo and Serrasqueiro, 2021). A considerable branch of the literature researches capital structures of SMEs. Reddy et al. (2022), and Degryse et al. (2012) explored industry effects on SMEs' capital structure, while Daskalakis and Tsota (2023) and Pan et al. (2019) explored macroeconomic effects on SMEs. Additionally, Pham and Hrdý (2023) and others (Iqbal and Kume, 2014; Procenca et al., 2014; Balios et al., 2016; Daskalakis et al., 2017; Matias and Serrasqueiro, 2017; Öhman and Yazdanfar, 2017; Yazdanfar et al., 2019) examined the impact of firm-specific variables on capital structure.

Studies document that leverage is strongly affected by the firm-specific characteristics and economic conditions. Firm-specific determinants suggested in the literature are size (Daskalakis et al., 2014; Balios et al., 2016), Non-debt tax shield (De Miguel and Pindado, 2001; Ramlall, 2009), net trade credit (Nilsen, 2002; Seifert et al., 2013), tangibility (Antoniou et al., 2008; De Jong et al., 2008), profitability (Camara, 2012), economic conditions suggested in the literature are term-spread (Bauer et al., 2018), inflation (Falato et al., 2018), and economic policy uncertainty index (Zhang et al., 2015; Lee et al., 2017) generated from news.

To draw policy implications, we focus on specific factors: interest rate spread (influenced by monetary policy), NDS (influenced by fiscal policy), the Economic Policy Uncertainty Index (influenced by economic policy), and stable company-specific variables like size and last period's leverage. This targeted approach enhances our ability to draw policy implications from capital structure dynamics.

2.2.1 Firm-specific variables

Non-debt tax shield

DeAngelo and Masulis (1980) were among the pioneering researchers who investigated the impact of corporate taxes, personal taxes, and non-debt tax shields on capital structure. Their seminal model proposed that tax deductions related to depreciation and investment tax credits serve as substitutes for the tax benefits associated with debt financing. Consequently, firms with substantial non-debt tax shields, particularly those benefiting from tax deductions for depreciation, tend to rely less on debt in their capital structures (Titman and Wessels, 1988). This suggests that firms with significant non-debt tax shields may not feel as compelled to increase their debt levels to leverage the tax deductibility of interest payments (Rubio and Sogorb, 2011).

Trade-off theory hypothesizes significant effects of taxes on capital structure as it considers tax savings to be benefits of leverage. Trade-off theory hypothesizes that there is a negative relationship between leverage and non-debt tax shield.

In prior studies, an inverse relationship between debt levels and non-debt tax shields has been consistently observed. Pham and Hrdý (2023) found this relationship among the Visegrad group SMEs, Antoniou et al. (2008) in Germany, Japan, and the UK, Czerwonka and Jaworski (2021) in Central and Eastern Europe SMEs and De Miguel and Pindado (2001) in Spanish firms. Korajczyk and Levy (2003) concluded that firms benefiting from greater non-debt tax shields tend to have lower leverage, a finding supported by Ozkan (2001) and Fama and French (2002).

In contrast, certain studies in the literature have identified a positive relationship between non-debt tax shields and leverage. For example, Ramlall (2009) suggested such a relationship in cases involving both long and short-term loans and debt. Ramlall (2009)'s calculation of the non-debt tax shield as depreciation divided by earnings before interest and tax might have contributed to this finding.

Most recently, Shaik et al. (2022) state that for Indian non-bank financial companies, they do not find explanatory power of non-debt tax shield as a determinant of capital structure.

In our study, we use the non-debt tax shield (calculated as depreciation divided by total assets, following Moradi and Paulet (2019)) as a proxy of the current tax deductions associated with capital equipment, following DeAngelo and Masulis (1980), who suggest that current tax deductions are partially captured by the non-debt tax shield.

Firm size

Research has demonstrated that firm size significantly influences capital structure decisions, potentially reflecting its impact on both diversification and financial distress risk. According to the trade-off theory, larger firms tend to have lower financial distress costs and fewer information asymmetries (such as more stable collateral assets and better transparency), making them more inclined to use leverage (Titman and Wessels, 1988). For larger firms, fixed direct bankruptcy costs constitute a smaller portion of the firm's value, leading to relatively lower costs of leverage (Titman and Wessels, 1988). Additionally, larger firms face a lower probability of bankruptcy, enabling them to accommodate higher debt capacity (Rajan and Zingales, 1995), thus reinforcing their demand for debt.

According to pecking order theory, larger firms are more transparent to investors, so the problems of information asymmetry will be less severe (De Haas and Peeters, 2006). These firms will have a higher chance of receiving external financing, either through bank debt or by issuing bonds or equity. As positive accounting theory suggests, larger firms are likely to make less risky investments Pirveli (2020). Correspondingly, larger firms can obtain more bank credit, whereas smaller firms are forced to rely on internal financing (De Haas and Peeters, 2006). Thus, larger firms tend to operate with more leverage because they are more transparent, have lower asset volatility, or have better access to public debt markets (Flannery and Rangan, 2006; Ilie et al., 2019).

Large firms typically have higher leverage due to their better access to financial markets, more stable cash flows, and reduced financial distress (Rubio and Sogorb, 2011). Additionally, Chung (1993) suggests that larger firms may face lower agency costs related to asset substitution and underinvestment, further supporting their higher leverage. Conversely, smaller firms often maintain lower leverage ratios, as they face heightened risks of liquidation during financial distress, illustrating a positive correlation between firm size and leverage Ozkan (2001).

Empirical research frequently highlights disparities in capital structure decisions between SMEs and large firms. For example, Jõeveer (2013) finds that SMEs' decisions in Western Europe are not governed by the same variables influencing leverage decisions in large firms. Similarly, Korajczyk and Levy (2003) demonstrate that capital structure decisions differ between financially constrained and less financially constrained firms in the U.S.

The pecking order theory suggests that firms with greater internal resources are more likely to use debt financing before issuing equity. As a result, larger firms, which typically have more internal funds and better access to external financing, may exhibit higher leverage. Procenca et al. (2014) found a positive link between size and leverage in Portuguese SMEs, a trend supported by Artikis et al. (2007), Sheikh and Wang (2011), Daskalakis et al. (2014), Balios et al. (2016), and Daskalakis and Psillaki (2008). Similarly, Czerwonka and Jaworski (2021) analyzed SME data from Central and Eastern Europe and also reported similar findings. In the same vein, Yazdanfar et al. (2019) observed a positive correlation between size and short-term debt in Swedish SMEs, with a negative correlation for long-term debt.

In our study, we focus exclusively on SMEs and hypothesize that their capital structure decisions differ from those of larger firms. Specifically, we examine how differences in SMEs' sizes influence their capital structures by analyzing the impact of firm size on their debt-to-equity ratio.

2.2.2 Macroeconomic variables and industry effects

Firms do not operate in a vacuum. Thus, when examining capital structure decisions, managers have to consider not only the state of the firm but also market conditions

Antoniou et al. (2008). Many studies have provided empirical evidence that market conditions influence the capital structures of large, listed firms. SMEs also react to market and economic conditions Daskalakis and Tsota (2023); Rubio and Sogorb (2011); Daskalakis et al. (2017). Mokhova and Zinecker (2014) analyzed panel data from 7 European countries and applied Pearson correlation analysis to show significant effects of economic conditions on corporate capital structure decisions in Europe. Camara (2012) studied a sample of U.S. local and international firms and argued that economic conditions influence capital structures. Cook and Tang (2010) also demonstrate that economic conditions influence the speed of capital structure adjustment.

Which economic conditions would influence a manager's decision to take on debt or issue obligations presently, or refrain from doing so? We can follow the trade-off theory and address the question as follows: Since managers are concerned about borrowing costs, it is essential that macroeconomic conditions influencing debt financing decisions capture: 1) the current comparative cost of acquiring debt or issuing obligations (relative to other periods), 2) expectations regarding future borrowing expenses, as well as uncertainties about the future. We incorporate solely macroeconomic variables into the model that meet these criteria.

The interest rate spread, which reflects the difference between short-term and long-term interest rates, is a key macroeconomic indicator influencing borrowing costs in the market. When the market is perceived as risky, investors demand higher interest rates for lending money, causing short-term rates to rise relative to the yields of long-term risk-free bonds such as 10-year government bonds. This results in a smaller term spread, indicating higher borrowing costs for firms. Consequently, financial managers may be less inclined to opt for debt financing due to the increased cost of short-term borrowing in a risky market environment.

Moreover, the interest rate spread is a macroeconomic financial indicator that implies expectations about future borrowing costs. The interest rate spread serves as a predictor of future interest rate changes or, in general, the course of the economy Bernanke (1990). Thus, the interest rate is a macroeconomic variable that satisfies both criteria we have formulated above.

Economic policy uncertainty significantly influences financial managers' decisions regarding debt issuance by signaling unassessed risks. This uncertainty, which reflects expected risks at the country level, directly impacts the cost of debt financing. Given its substantial influence on borrowing costs and financial decision-making, economic policy uncertainty is a crucial macroeconomic variable to include in our model.

In this study, we concentrate on investigating the influence of economic policy uncertainty and term spread on the leverage of German SMEs. These factors are chosen based on meeting the specified criteria and are supported in the literature. By doing so, we aim to examine the effects of market conditions on the leverage ratios of German SMEs. We acknowledge that the macroeconomic effects may not be equally strong for every firm, as firms exhibit differences in various aspects (as confirmed by the Hausmann test for our data). Nonetheless, we anticipate that the macroeconomic effects will exert a significant influence at the industry level.

Interest rate spread

Recent literature highlights the significance of the interest rate spread (or term spread) as a crucial macroeconomic determinant of capital structure decisions. The influence of the interest rate spread on leverage is explained as follows: the interest rate spread reflects expectations about changes in capital costs and signals future economic performance Bauer et al. (2018), and managers incorporate these expectations into capital structure decisions. Korajczyk and Levy (2003) argued that the term spread serves as a signal of economic performance and expected growth opportunities, thus influencing firm leverage.

Korajczyk and Levy (2003) observed firms that altered their capital structure and revealed that the term spread has a statistically significant negative relation with the debt-to-equity ratio as well as with the long-term debt-to-equity ratio in financially constrained firms.

We aim to assess whether a higher term spread correlates with lower leverage in German SMEs and whether this relationship is statistically significant. Our hypothesis posits that the interest rate spread is a crucial determinant of capital structure for German SMEs.

Economic policy uncertainty index

There are several theoretical channels through which economic policy uncertainty influences firms' capital structure decisions. Zhang et al. (2015) describe two channels through which economic uncertainty influences leverage by changing financing costs: 1) economic uncertainty leads to a deteriorated external financing environment, resulting in lower leverage; 2) Economic uncertainty leads to information asymmetry between borrowers and creditors, increasing default risk, and consequently lowering leverage.

Recent empirical research has argued that economic and policy uncertainty influence capital structure decisions. Graham et al. (2015) detected that changes in economic uncertainty have influenced capital structures in the U.S. Zhang et al. (2015) documented the importance of policy uncertainty as a capital structure determinant and provided empirical evidence that firms lower their leverage in China during times of higher economic uncertainty.The recent study by Almustafa et al. (2023) found a significant impact of uncertainty, as measured by the Economic Policy Uncertainty (EPU) index, in their panel data analysis. Athari and Bahreini (2023) find that economic policy uncertainty (EPU) negatively impacts Western Union TL firms. Lee et al. (2017) reveal that in the U.S., economic uncertainty influences leverage decisions in the financial industry. Graham et al. (2015) confirm that in the U.S., economic uncertainty is negatively correlated with capital structures of all sizes of firms in unregulated industries. Pan et al. (2019) argue that political uncertainty has a significant negative impact on leverage. Tax changes are also incorporated into the political uncertainty index. Heider and Ljungqvist (2015) show that tax changes have a first-order effect on the capital structures of American companies. Motivated by this empirical evidence, we investigate the influence of the economic policy uncertainty index developed by Baker et al. (2016) on the overall leverages of German SMEs.

2.2.3 Industry effects

Several empirical studies investigate the industry effects on the capital structure of SMEs and demonstrate a statistically significant relationship. Degryse et al. (2012), based on their empirical research of small Dutch firms, conclude that compared to the manufacturing industry, all industries sustain different capital structures. By applying a fixed-effects model, they detect significant intra- and inter-industry effects on the capital structures of small enterprises. Serrasqueiro et al. (2011) analyze Portuguese SMEs that have been in the market for 7 years, comparing the capital structures of SMEs from the service sector to those from other sectors, and find that capital structure decisions of service SMEs differ from those of other firms. Hu (2019) finds that the direction of the impact of the non-debt tax shield on the capital structure of Chinese and British SMEs varies between capital-intensive and non-capital-intensive industries. Michaelas et al. (1999) empirically verify that small firms in the United Kingdom are subject to industry effects. Hall et al. (2000) study 3500 British unlisted SMEs and identify important industry effects on SMEs' leverage ratios. We follow the suggestion in these studies and check for industry effects in German SMEs. However, we do not test industry effects in isolation from the macroeconomic effects. Instead, we incorporate industry and macroeconomic effects together in one model. Similar to Reddy et al. (2022), who incorporate industry-specific and macroeconomic factors into a unified model. While Reddy's study covered 10 European countries and included SMEs and listed companies, our focus is on German SMEs, exploring the interplay between industry and macroeconomic effects on leverage.

2.3 Data and methods

2.3.1 The data and description of variables

In our study, we utilize panel data from the Amadeus database, provided by Bureau van Dijk Electroniques Van Dijk (2017). This balanced dataset spans a decade preceding the 2015 Investment Tax Act reform in Germany, covering the years from 2004 to 2014.

The 2015 Investment Tax Act reform is highly relevant for financing decisions. The reform introduced significant changes to the taxation of investment income. The reform aimed to stimulate investment by: 1) cutting the tax rate to a flat 25% on dividends and capital gains, abandoning the collection of the solidarity surcharge; 2) exempting accumulation units of investment funds (which reinvest income rather than distributing it to investors) from taxation; and 3) simplifying reporting requirements for investors.

We specifically focus on the pre-reform period. Our decision to analyze only this period is strategic and methodologically sound. Economic agents may respond differently to pre-reform, reform, and crisis periods. Combining these periods in the analysis could mask or distort the heterogeneity of responses, leading to misleading conclusions and blurred results. By focusing solely on the pre-reform period, we aim to provide a clear understanding of pre-existing financing decision behaviors, unaffected by the reform. This approach allows us to explore the nuances of financing decisions leading up to the reform without the potential confounding effects of subsequent policy changes.

The dataset utilized in this research consists of financial data from small and medium-sized German firms. These firms, totaling 27,889, are classified as SMEs, with up to 250 employees and revenue of up to 50 million Euros.

In the original unbalanced raw data from the Amadeus database, 34% of the dataset contains missing observations. To address this issue, we employ two approaches. First, we drop the year for the firm if any relevant variable observation is missing for that year-firm combination. This results in a cleaned, database with 72,921 observations from 14,597 firms. Second, we use the trimming technique to remove anomalous observations that fall outside the theoretical ranges of the variables. For example, we remove observations where total fixed assets exceed total assets or sales are negative. Additionally, we exclude the top 3% of debt-to-equity ratios to eliminate outliers that may skew the analysis, capping the maximum debt-to-equity ratio at 13.459. As a result of these procedures, we retain data for 13,051 SMEs and 70,734 observations, having removed 2,187 outliers from the original 72,921 observations.

Table 2.1 outlines the variables utilized in this study. The second column displays the abbreviations of the variables listed in the first column, while the third column presents the formulas used to calculate each variable.

The primary dependent variable, debt-to-equity ratio (DE), is computed as total debt divided by total equity. In various studies, proxies for capital structure, whether expressed in book or market values or a combination thereof, are used. Book leverage, representing the ratio of total book debt to total assets, is commonly employed as a measure of capital structure. For instance, De Miguel and Pindado (2001) and Fama and French (2002) both use the book value of the debt-to-equity ratio assessed by total book debt to total assets, as a measure of leverage. In our study, we adopt the same approach, considering the debt-to-equity ratio as a measure for leverage. It's important to note that for the industry model, we calculate the time-series industry means of debt-to-equity ratios (Mean DE) for each industry, as we are interested in the overall effects on industry debt-to-equity ratio caused by the explanatory variables of the model.

The descriptive statistics of the dependent variable are presented in the first section of Table 2.1. The subsequent sections of Table 2.1 outline the independent variables, comprising firm-specific, macroeconomic and news-driven factors. Firm-specific factors incorporated in the model encompass size and non-debt tax shield, while the aggregated models feature macroeconomic variable term spread and news-generated economic policy uncertainty index. Size is derived from the logarithm of sales, while the non-debt tax shield is calculated as depreciation and amortization divided by total assets.

Firm characteristics are obtained from the Bureau van Dijk's Amadeus database, and computations are conducted by the researchers. The data for calculating the term spread are sourced from the OECD database.

Table 2.1: Definition of Variables

Variable	Abbreviation	Calculation
Dependent Variable		
Debt-to-equity ratio	DE	Total debt divided by total equity
Independent Variables - Firm-specific Variables		
Non-debt tax shield	NDS	Depreciation and amortization divided by total assets
Size	S	Natural logarithm of sales
Independent Variables - Macroeconomic Variables		
Term spread	Term Spread	10-year long-term government bond yield minus yearly short-term interest rate
Independent Variables - News-Driven Variables		
Uncertainty index	Uncertainty Index	Economic Policy Uncertainty index of Germany

The term spread is calculated as the annual 10-year government bond yield minus the annual short-term interest rate.

We utilize the news-driven **Economic Policy Uncertainty (EPU) index** developed by Baker et al. (2016) for Germany. The EPU index comprises three key components designed to capture uncertainty:

1. **Quantified newspaper reports on economic uncertainty**: Monthly counts X_{it} of relevant articles containing specific terms related to economic uncertainty are obtained from leading newspapers such as Frankfurter Allgemeine Zeitung (FAZ) and Süddeutsche Zeitung (SZ) for each month t.

2. **Temporary tax code provisions**: This component tracks mentions in newspapers related to temporary changes or provisions in tax codes.

3. **Expert misperceptions about economic variables**: This includes misperceptions about economic variables such as the consumer price index and government spending, as inferred from newspaper articles.

Each component of the EPU index undergoes the following steps for construction:

1. **Data Collection**: Monthly counts of articles that mention specific terms related to the component of the Economic Policy Uncertainty (EPU) index X_{it} are gathered from selected newspapers for each component.

2. **Scaling**: Calculate the total number of articles N_{it} for each newspaper and month. Scale the raw counts X_{it} by dividing by N_{it} to obtain scaled series Y_{it}:

$$Y_{it} = \frac{X_{it}}{N_{it}}. \tag{2.1}$$

3. **Standardization**: Compute the standard deviation σ_i of Y_{it} for each newspaper i:

$$\sigma_i = \sqrt{\frac{1}{T}\sum_t (Y_{it} - \bar{Y}_i)^2}. \tag{2.2}$$

Standardize Y_{it} by dividing by σ_i to obtain standardized series Z_{it}:

$$Z_{it} = \frac{Y_{it}}{\sigma_i}. \tag{2.3}$$

4. **Normalization**: Normalize Z_{it} to have a mean value of 100 over the historical period T:

$$EPU_{it} = Z_{it} \cdot \frac{100}{\mu},$$

where μ is the mean of Z_{it} across all months t and newspapers i.

The normalized series EPU_{it} from each component are combined using a simple average into a single composite index for each time period t, forming the Economic Policy Uncertainty (EPU) index. This composite index captures fluctuations in policy-related economic uncertainty over time and across different newspapers. Detailed calculation methodologies and datasets for the Economic Policy Uncertainty (EPU) index are publicly available at http://www.policyuncertainty.com/methodology.html and http://www.policyuncertainty.com/europe_monthly.html.

We conducted an in-depth analysis focusing on the long-term debt-to-equity ratio (LTDE) to derive clearer policy recommendations. LTDE is calculated by dividing long-term debt by total equity.

Table 2.1 displays descriptive statistics of the model variables after removing outliers, including mean, standard deviation, minimum, maximum, and the number of observations.

Table 2.2: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Dependent Variable				
Debt-to-equity ratio (DE)	1.087	1.924	0	13.459
Independent Variables - Firm-specific Variables				
Non-debt tax shield (NDS)	0.045	0.044	0.000	0.991
Size (S)	9.951	1.115	0.000	17.111
Independent Variables - Macroeconomic Variable				
Term spread (Term Spread)	0.007	0.016	-0.028	0.024
Independent Variables - News Variable				
Economic policy uncertainty index	135.471	37.945	81.349	191.285

Note: The descriptive statistics presented in this table are derived from the final database, which excludes outliers, comprising 70,734 observations.

The debt-to-equity ratio is frequently 0 in 18,216 observations, indicating that more than 25% of firms have no debt. This may suggest limited access to financing for some German SMEs, or it could imply that these firms benefit from subsidies for innovative projects or rely on trade credit for funding.

The dynamic perspective, illustrated in Figure 2.1, shows that the overall yearly means of the debt-to-equity ratio were increasing before 2008. In 2010, the ratio reached its peak and dropped down again in 2011. In 2014, there was a sharp decline in the overall debt financing of SMEs. Notably, during the years 2008 and 2010, which coincide with the global financial crisis, the overall debt financing consistently remained above 8%.

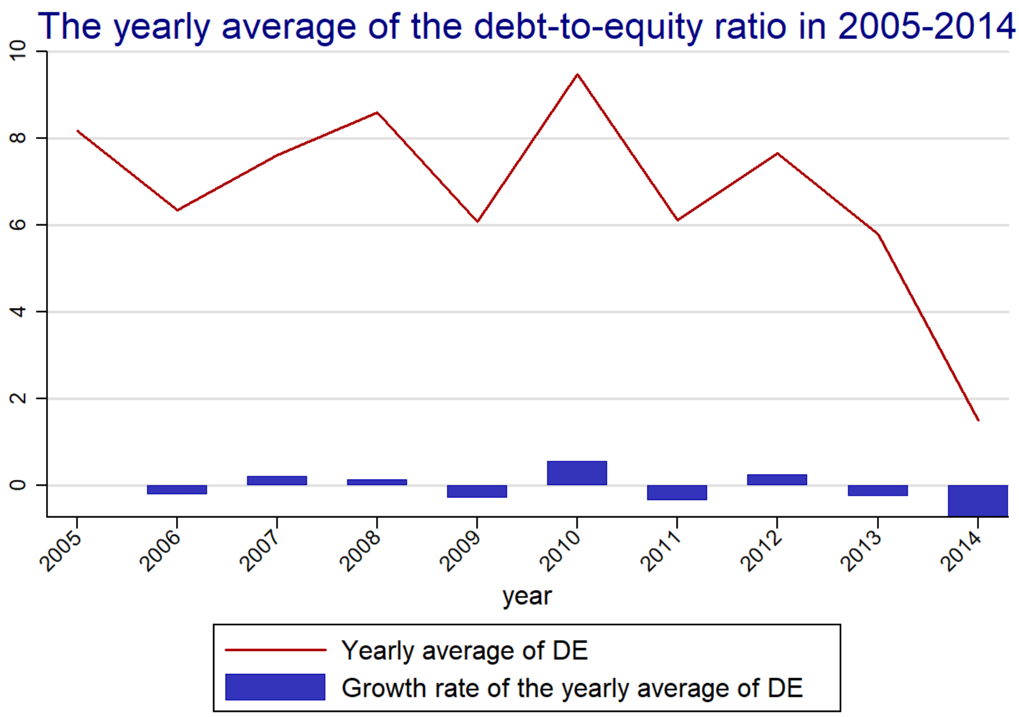


Figure 2.1:
Overall yearly mean of the debt-to-equity ratio of SMEs in Germany
The figure illustrates the dynamics of overall yearly mean of the debt-to-equity ratio of SMEs in Germany before deleting outliers.

To understand the factors behind these changes, we analyze the trend lines of debt-to-equity ratios across industries (refer to Figure 2.2).

Overall, as depicted in Figure 2.2, the construction and finance industries exhibit notably higher average leverage compared to other sectors. In 2009, the sharp decrease in SMEs' debt financing in the construction industry contributed to the overall decline in SMEs' debt financing in Germany (compare Figure 2.1), reflecting increased risk aversion due to the crisis. In 2008, the increase of leverage in construction, finance and service industries increased the yearly average of leverage in Germany (as seen on Figure 2.1). In 2010, the increase of leverage in construction, transportation and finance industries increased the yearly average of leverage in Germany.

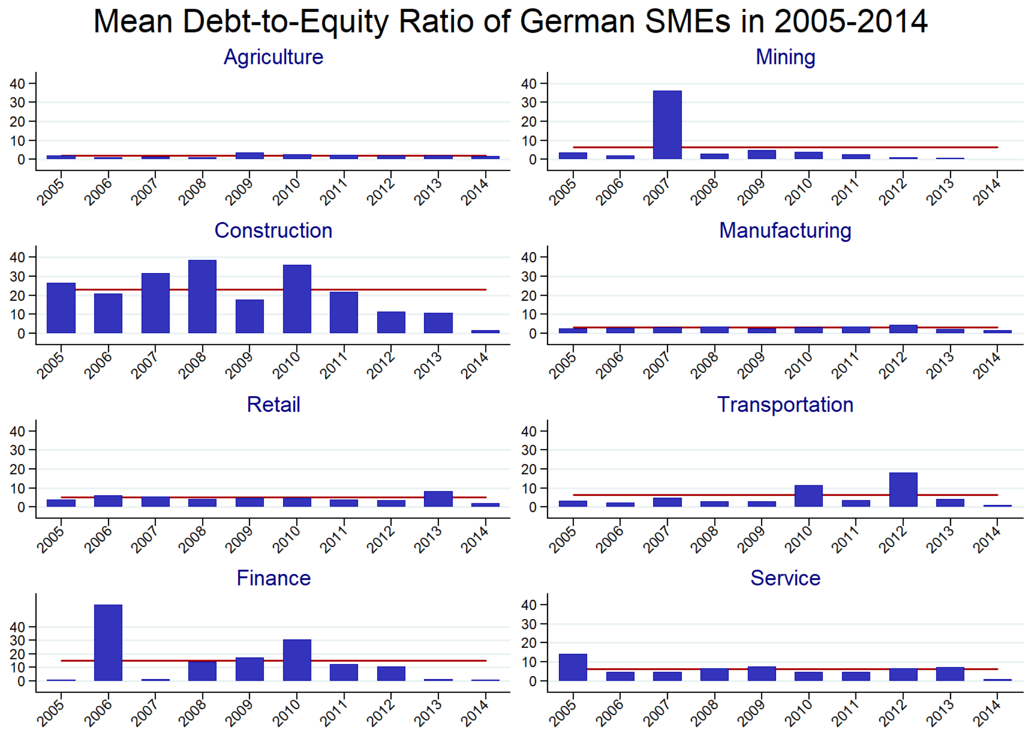


Figure 2.2:
Debt-to-equity ratio of German SMEs per industry from 2005 to 2014
The figure illustrates the overall yearly mean of the debt-to-equity ratio of SMEs in Germany, depicted before removing outliers. The horizontal axis represents the years under consideration, while the vertical axis denotes the yearly mean debt-to-equity ratio. The blue columns represent the yearly means of debt-to-equity ratios within each industry. The red lines represent the overall industry means of the debt-to-equity ratio. This visualization offers an overview of the trend in the debt-to-equity ratio of German SMEs over the specified time period, highlighting any notable fluctuations or patterns.

The same visualizations as in Figure 2.1 and Figure 2.2, but using the dataset after outlier removal, are shown in Figure B.1 and Figure B.2 respectively.

Table 2.3 presents the composition of the sample after outliers were excluded, detailing the percentages of SMEs from various industries classified according to the Standard Industrial Classification (SIC). Manufacturing represents the largest share of observations (30%), followed by wholesale and retail trade (22%), service and public administration (18%), among others.

Table 2.3: Sample composition by industry (by SIC classification)

Industry	Industry Abbreviation	Freq. (after trimming)	%
Agriculture, forestry, and fishing	Agriculture	731	1.03
Mining and quarrying	Mining	159	0.22
Construction	Construction	8,913	12.60
Manufacturing	Manufacturing	21,109	29.84
Wholesale and retail trade	Retail	15,418	21.79
Transportation and public utilities	Transportation	11,407	16.12
Finance, insurance and real estate	Finance	480	0.68
Service and public administration	Service	12,512	17.68
Total		**70,734**	**100.00**

2.4 Model and methodology

Our hypothesis for individual firms is that the debt-to-equity ratio is determined by the debt-to-equity ratio in the previous period, non-debt tax shield, and size. We choose these independent variables as they are recognized in the literature as determinants of capital structure, and they can be addressed by economic policy tools.

We build the firm-level model for all SMEs irrespective of their industry belongingness as follows:

$$DE_{i,t} = \alpha_0 + \alpha_1 DE_{i,t-1} + \alpha_2 NDS_{i,t} + \alpha_3 s_{i,t} + c_{i,t} + u_i, \tag{2.4}$$

where DE is the debt-to-equity ratio, i is the firm index, t stands for time, NDS is the non-debt tax shield, s is size, α_0, α_0, α_0 are the coefficients, and u_i is the innovation. The unobserved heterogeneity $c_{i,t}$ is used only by the DPF estimator, and:

$$c_{i,t} = \alpha_6 \overline{DE}_{\text{industry},i,t-1} + \alpha_7 \overline{NDS}_{\text{industry},i,t} + \alpha_8 \overline{s}_{\text{industry},i,t}, \tag{2.5}$$

where bars denote the overall time-series averages of the corresponding exogenous variables.

We propose that in each industry, a company's debt-to-equity ratio is determined by the microeconomic variables in Equation 2.4 and macroeconomic conditions. The DPF estimator also uses the averages of the microeconomic and macroeconomic conditions and the SME's first value of DE.

The formulated model for leverage ratios pertaining to firms within each industry is as follows:

$$\begin{aligned} DE_{\text{industry},i,t} = \alpha_0 + \alpha_1 DE_{\text{industry},i,t-1} + \alpha_2 NDS_{\text{industry},i,t} + \\ \alpha_3 s_{\text{industry},i,t} + \alpha_4 TS_{t-1} + \alpha_5 EUI_{t-1} + c_{i,t} + u_{it}, \end{aligned} \tag{2.6}$$

where TS_{t-1} is the term spread in the previous period. The economic uncertainty index (EUI_{t-1}) is the economic uncertainty index in the previous period. The unobserved heterogeneity $c_{i,t}$ is used only by the DPF estimator, and:

$$c_{i,t} = \alpha_6 \overline{DE}_{\text{industry},i,t-1} + \alpha_7 \overline{NDS}_{\text{industry},i,t} + \alpha_8 \overline{s}_{\text{industry},i,t} + \alpha_9 \overline{TS}_{t-1} + \alpha_{10} \overline{EUI}_{t-1}, \tag{2.7}$$

where bars denote overall time-series averages of the exogenous variables in each of the 8 SIC industries.

In this article, we utilize panel estimation methods with German SMEs data. We employ standard estimators like the Blundell-Bond estimator, along with a more precise and less biased approach: the Dynamic Panel Fractional (DPF) estimator.

2.5 Dynamic Panel Fractional (DPF) Estimator

The authors of the dynamic panel fractional estimator (DPF), Elsas and Florysiak (2015), based on the Monte Carlo study, demonstrate that the DPF has higher precision of estimation for the speed of capital structure adjustment than fixed effects models and the instrumental variables (IV)-based estimators: GMM Blundell-Bond estimator, long difference estimator, and Least-squares dummy variable estimator. Moreover, the study by Elsas and Florysiak (2015) theoretically proves that the commonly used estimators produce biased estimates of the speed of capital structure adjustment, while the DPF estimator does not. Thus, we apply a left-censored version of the dynamic panel fractional (DPF) estimator to the speed of capital structure adjustment of German SMEs and compare the results to those produced by other methods.

The special characteristic of the DPF estimator is that it is not limited to fractional dependent variables. The DPF estimator can also be applied to nonfractional data, as it can transform the debt-to-equity ratio to a latent variable with values between 0 and 1 (or by researcher-defined upper bound) and achieves higher precision of estimations (Elsas and Florysiak, 2015). Elsas and Florysiak (2015) apply the DPF estimator to a nonfractional dependent variable, and the DPF estimator remains the best-performing estimator between the Blundell-Bond, LSDVC, and long difference estimator. Besides, the estimates of the nonfractional dependent variable by the DPF estimator are not biased. Due to this, we apply the DPF estimator to the nonfractional debt-to-equity ratio. Additionally, we apply the right-censored DPF estimator to the debt-to-equity ratios of the equity-financed firms to ensure the correctness of the model for the subgroup of the equity-financed firms (for which $DE \leq 1$).

To address the fractional nature of the dependent variable, DPF utilizes a latent, i.e., unobserved variable approach. DPF employs a censored Tobit specification, which is double censored for fractional dependent variables, accommodating corner observations. In other words, the dependent variable remains upper bound (UB) for the cases when the latent variable is taking a value more than the upper bound and equals 0 when the latent variable is less than 0; in the $[0, \mathrm{UB}]$ interval, the dependent variable is equalized to the latent variable.

$$y_{it} = \begin{cases} UB & \text{for } y^*_{it} \geq UB \\ y^*_{it} & \text{for } y^*_{it} \in (0, UB) \\ 0 & \text{for } y^*_{it} \leq 0 \end{cases} \tag{2.8}$$

The unobserved variable y^*_{it} is implied by the lagged dependent variable $y_{i,t-1}$, a vector of exogenous regressors Z_{it}, and a normally distributed error term, along with unobserved heterogeneity c_i.

$$y^*_{it} = Z_{it}\phi + \rho y_{i,t-1} + c_i + u_{it}, \tag{2.9}$$

where the error term u_{it} is normally distributed $u_{it} \sim N(0, \sigma_u^2)$. In our study, Z_{it} matrix incorporates firm-specific variables, including size and the non-debt tax shield, lagged term spread and lagged economic policy uncertainty index.

We follow Elsas & Florysiak (2015) and assume that the fixed effects in the DPF model have the distribution:

$$c_i = a_0 + a_1 y_{i,0} + \bar{Z}_i a_2 + a_i \tag{2.10}$$

where $a_i \sim N(0, \sigma_a^2)$. In other words, fixed effects depend on the time series averages of exogenous regressors and the initial leverage. The initial leverage is:

$$y^*_{i,0} = \lambda(X'_{i,0}\gamma) + a_0 + \frac{1}{T}\sum_{t=0}^{T} X'_{i,t} a_2 + a_i + u_{i,0}, \tag{2.11}$$

where we again follow Elsas & Florysiak (2015) and assume that for the initial leverage (at the beginning of the data generating process), $a_0 = 0.1$, $a_1 = 0.1$, $a_2 = -0.25$, $a_i \sim N(0, 0.01)$, and $u_i \sim N(0, 0.01)$. $Z_{i0}\phi = \lambda(X'_{i,0}\gamma)$, where λ is the true leverage, $X'_{i,t}$ is a matrix of the exogenous regressors, and γ is the corresponding coefficient (For more details, see the Monte Carlo simulation in Elsas and Florysiak (2015)).

The DPF estimator is a Maximum Likelihood estimator. The resulting log likelihood function takes the following form:

$$L = \sum_{i=1}^{N} \log\left\{\int_{-\infty}^{\infty}\left[\prod_{t=\tau_i}^{T_i} f_t\left(y_{i,t}|Z_{i,t}, y_{i,t-1}, \bar{Z}_i, y_{i,0}, a_i; \theta\right)\right]\frac{1}{\sigma_a}\phi\left(\frac{a_i}{\sigma_a}\right) da_i\right\}, \tag{2.12}$$

where τ_i represents the initial period, and T_i the final observation period for firm i in the imbalanced data.

For the case when the dependent variable is not fractional and has only one defined boundary (like debt-to-equity ratio $\mathrm{DE}, 0 < \mathrm{DE} < \infty$), one can imply the lower boundary and leave the upper boundary as is or set it to the maximum value observed in the data. In this study, we set the upper boundary of the DPF estimator to the maximum value observed in our data.

2.6 Results

2.6.1 Firm-specific variables

Before applying our model, we start our analysis by checking the nature of the debt-to-equity data. The results of the Breusch and Pagan Lagrange multiplier test for random effects suggest that the random effects model outperforms pooled OLS Hausman tests. This indicates that there are significant differences between German SMEs, thus we have individual effects (random effects). However, both random effects and fixed effects models perform poorly in estimating the debt-to-equity ratio.

In Table 2.4, we document coefficient estimates of different methods for our firm-level model of the debt-to-equity ratio described in Equation 2.4. The Blundell-Bond GMM estimator, developed by Blundell & Bond (1998), overcomes the endogeneity problem and is less biased compared to fixed effects and random effects models. The model estimated using GMM shows statistically significant effects for non-debt tax shield and firm size, with a speed of capital structure adjustment of 90%. However, due to the potential for overfitting endogenous variables, the Blundell-Bond GMM estimator may introduce bias. To validate the results, we check the validity of the instruments for the Blundell-Bond model at the firm-level and find that the instruments are not valid in this context. To address this, we utilize the unbiased DPF estimator for more precise results. The coefficients of our firm-level model are significant when assessed by the DPF estimator, affirming the validity of our model.

Table 2.4: Firm-level model for debt-to-equity ratio

Model Variables	Random Effects Model	Blundell Bond	Censored Tobit	DPF
Lag DE	0.5620***	0.0159	0.6440***	0.0514***
	(0.0032)	(0.0225)	(0.0051)	(-0.0022)
NDS	0.8460***	-0.3400	0.8210***	0.0939
	(0.1460)	(0.3620)	(0.1310)	(-0.0688)
Size	-0.0219***	-0.0541*	-0.0115**	0.0011
	(0.0068)	(0.0277)	(0.0056)	(0.0047)
For each ID the first entry of DE	—	—	—	0.0942
				(0.0850)
Mean DE	—	—	—	-0.0004***
				(0.0001)
Mean NDS	—	—	—	-0.0248***
				(0.0033)
Mean s	—	—	—	0.2058***
				(0.0063)
Const	0.5750***	1.3850***	0.3720***	1.0617***
	(0.0689)	(0.2800)	(0.0579)	(0.1051)
Observations	49,974	49,974	49,974	49,974
Number of firms	13,051	13,051	13,051	13,051
R-squared within	0.0000	—	—	—
R-squared between	0.5210	—	—	—
R-squared overall	0.4778	—	—	—
σ_u	0.6850	—	—	0.2966***
σ_e	0.8200	—	—	0.1917***
Rho	0.4110	—	—	0.7054
Valid Moment Conditions	—	No	—	—

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ Standard errors are in parenthesis. The moment conditions for the Blundell Bond GMM estimator are not valid here.

As evident from Table 2.4, the results of the Blundell-Bond estimator should be disregarded due to invalid moment conditions. We now turn our attention to the results from the remaining models. In the firm-level model presented in Table 2.4, the coefficients of the non-debt tax shield (NDS) are statistically significant in random effects and censored Tobit estimations, and the means of NDSs are statistically significant in DPF estimations. Similarly, the size variable exhibits statistical significance across all models. Furthermore, the lagged debt-to-equity ratio is statistically significant in all models. Overall, the findings highlight that NDS, firm size, and the lagged debt-to-equity ratio significantly influence debt financing decisions.

The robustness tests outlined in the appendix subsubsection B.2 confirm that our model for German SMEs, which includes NDS and size, performs slightly better than models incorporating other firm-specific variables such as tangibility and profitability.

Table 2.5, Table 2.6 and Table 2.7 present the coefficient estimates from the industry-leve debt-to-equity ratio model for German SMEs, using various estimation techniques. Specifically, Table 2.5 displays the estimation results of a differenced

Table 2.5: Panel a: Industry-specific model – Blundell-Bond estimator

Model Variables	Agriculture	Mining	Construction	Manufacturing	Retail	Transportation	Finance	Services
Lag DE	0.7010***	0.6283***	-0.0403***	0.0160	0.0230	0.0088	0.4943***	0.0070
	(0.0021)	(0.0114)	(0.0103)	(0.0183)	(0.0242)	(0.0293)	(0.0004)	(0.0217)
NDS	-4.9742***	9.3988***	-0.1948	-1.0457*	-0.2142	-1.7345	13.4694***	-0.0064
	(0.3463)	(0.6577)	(1.9032)	(0.6285)	(0.3306)	(1.1149)	(0.1398)	(0.3871)
Size	-0.3294***	-0.1001	-0.0478	-0.1794***	0.0179	-0.0187	-0.0842***	-0.0678
	(0.0279)	(0.0794)	(0.0661)	(0.0464)	(0.0460)	(0.0353)	(0.0047)	(0.0444)
Lag Term Spread	1.9545***	14.1222***	0.0720	0.7487***	-0.1927	0.5425	-2.5909***	0.4600
	(0.2775)	(0.2479)	(0.4709)	(0.2870)	(0.3440)	(0.3481)	(0.0599)	(0.3234)
Lag Uncertainty Index	0.0008***	-0.0066***	-0.0015***	-0.0004*	-0.0001	0.0001	0.0010***	0.0001
	(0.0001)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0002)
Constant	3.3611***	1.6477**	2.0522***	2.7092***	0.5836	0.9866**	0.7824***	1.2146***
	(0.2530)	(0.7440)	(0.6437)	(0.4817)	(0.4814)	(0.3838)	(0.0430)	(0.4153)
Observations	494	118	6,414	14,407	11,035	8,481	333	8,690
Number of firms	152	28	1594	4049	2783	1912	96	2435
Valid moment conditions	No	No	Yes (lag2)	Yes (lag2)	Yes (lag1)	Yes (lag1)	No	Yes (lag1)

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.

Note: The moment condition here is "no serial correlation in idiosyncratic errors". The model is estimated with robust errors. Here we use robust errors and correspondingly estimate differenced equations, as the GMM two-step standard errors are biased in all industry models.

Table 2.6: Panel b: Industry-specific model – Censored Tobit estimator

Model Variables	Agriculture	Mining	Construction	Manufacturing	Retail	Transportation	Finance	Services
Lag DE	0.6901***	0.7216***	0.5853***	0.6422***	0.5408***	0.6082***	0.6135***	0.6071***
	(0.1529)	(0.2635)	(0.0775)	(0.0295)	(0.0530)	(0.0762)	(0.1728)	(0.0330)
NDS	-1.1159	2.9625	1.6303	1.7697***	1.8257***	2.5908***	7.4793**	1.1520***
	(1.9774)	(3.2751)	(1.1966)	(0.3693)	(0.6086)	(0.7699)	(3.2511)	(0.4208)
Size	-0.0522	-0.2824	0.0619**	-0.1387***	-0.0431*	-0.0481*	0.0933	-0.0312*
	(0.0975)	(0.3779)	(0.0258)	(0.0195)	(0.0249)	(0.0257)	(0.1059)	(0.0187)
Lag Term Spread	1.6494	13.4576*	1.3407	1.3425	1.6184	-0.3414	-12.3409***	0.3254
	(2.5156)	(7.1734)	(1.1031)	(0.9207)	(1.0935)	(1.0216)	(4.0611)	(1.1585)
Lag Uncertainty	-0.0005	-0.0033	-0.0011**	-0.0002	-0.0009*	-0.0001	0.0022	-0.0008
Index	(0.0016)	(0.0043)	(0.0006)	(0.0004)	(0.0006)	(0.0004)	(0.0024)	(0.0005)
Constant	0.7829	3.2964	-0.1513	1.3649***	0.4771*	0.3442	-1.6542	0.1542
	(0.9674)	(4.3589)	(0.2716)	(0.2004)	(0.2792)	(0.2696)	(1.1061)	(0.1910)
Σ_u	0.6976**	1.1038**	0.9531***	0.6709***	1.3194***	0.9573***	1.4225***	0.9566***
	(0.3465)	(0.4355)	(0.1956)	(0.0540)	(0.1588)	(0.1952)	(0.3799)	(0.0902)
Σ_e	0.5777***	0.8569***	1.0298***	1.0070***	1.0674***	0.9719***	1.2554***	1.0534***
	(0.1642)	(0.2546)	(0.0846)	(0.0440)	(0.0594)	(0.0549)	(0.2646)	(0.0716)
ρ	0.5470	0.1000	0.0000	0.0000	0.5528	0.4962	0.5312	0.0000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are in parenthesis.

Note: The Tobit model is a left censored Tobit model at minimum DE, i.e. at 0. For highest precision possible, the model is estimated with bootstrapping method.

Table 2.7: Panel c: Industry-specific model – DPF estimator

Model Variables	Agriculture	Mining	Construction	Manufacturing	Retail	Transportation	Finance	Services
Lag DE	0.2292***	0.6654***	0.1121***	0.1426***	0.0926***	0.1137***	0.1702***	0.1118***
	(0.0278)	(0.0828)	(0.0068)	(0.0052)	(0.0055)	(0.0058)	(0.0417)	(0.0063)
NDS	0.5363	0.9559	-0.0244	-0.4649**	0.4390**	-0.2562	-0.1004	-0.0799
	(0.7011)	(1.7720)	(0.3652)	(0.2069)	(0.2190)	(0.1742)	(1.8411)	(0.1982)
Size	-0.0004	-0.0421	0.0026	-0.0382**	0.07100***	0.0101	-0.0776	0.0077
	(0.0300)	(0.1839)	(0.0164)	(0.0149)	(0.0185)	(0.0141)	(0.0527)	(0.0134)
Lag Term Spread	-0.0674	0.0342	0.2452	0.2194	0.5431*	0.2581	0.4971	0.1837
	(0.5715)	(2.2599)	(0.3492)	(0.2329)	(0.3006)	(0.2409)	(1.9552)	(0.2886)
Lag Uncertainty Index	0.0001	0.0004	-0.0008***	-0.0010***	-0.0010***	-0.0001	0.0003	-0.0005***
	(0.0003)	(0.0010)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0001)
For each ID the first DE	-0.2178***	-0.1238***	-0.0009	-0.0610***	-0.0967***	-0.0683***	-0.0292	-0.0924***
	(0.0250)	(0.0392)	(0.0084)	(0.0061)	(0.0076)	(0.0116)	(0.0287)	(0.0081)
Mean Lag DE	0.5090***	0.2953***	0.3470***	0.4249***	0.5811***	0.5512***	0.4830***	0.4455***
	(0.0562)	(0.0797)	(0.0172)	(0.0122)	(0.0155)	(0.0240)	(0.0887)	(0.0160)
Mean NDS	0.4816	-0.9515	2.5714***	2.1273***	0.7877**	0.5520**	1.5178	0.8358***
	(0.7936)	(1.8827)	(0.5038)	(0.3015)	(0.3961)	(0.2250)	(2.2965)	(0.3202)
Mean Size	-0.0118	0.0311	0.0687**	-0.0187	-0.0829***	-0.0088	0.1470**	-0.0230
	(0.0328)	(0.1860)	(0.0312)	(0.0172)	(0.0201)	(0.0163)	(0.0639)	(0.0148)
Mean Lag Term Spread	-1.8878	-12.3582	-2.0002	2.0809**	-0.6725	4.1296***	-18.3979**	-0.0113
	(2.2899)	(7.6526)	(2.0249)	(1.0561)	(1.5531)	(1.5801)	(8.0860)	(1.4109)
Mean Lag Uncertainty Index	0.0005	0.0056**	-0.0007	0.0013***	0.0007	-0.0012**	0.0022	0.0006
	(0.0007)	(0.0027)	(0.0007)	(0.0004)	(0.0005)	(0.0005)	(0.0027)	(0.0004)
Constant	0.1866	-0.6232	-0.3179	0.4778***	0.0246	0.0583	-1.1261**	-0.0079
	(0.1465)	(0.4526)	(0.3185)	(0.1063)	(0.1100)	(0.1103)	(0.5358)	(0.0792)
Σ_u	0.2449***	0.0000	0.4753***	0.3826***	0.4775***	0.3697***	0.4409***	0.4553***
	(0.0199)	(0.0691)	(0.0122)	(0.0072)	(0.0117)	(0.010)	(0.0594)	(0.0119)
Σ_e	0.14806***	0.2726***	0.2885***	0.3115***	0.3279***	0.2622***	0.3615***	0.2942***
	(0.0065)	(0.0256)	(0.0048)	(0.0032)	(0.0042)	(0.0033)	(0.0273)	(0.0039)
ρ	0.6233	0.0000	0.6223	0.5512	0.5929	0.5850	0.5495	0.6075
Observations	494	118	6,414	14,407	11,035	8,481	333	8,690
Number of firms	152	28	1,594	4,049	2,783	1,912	96	2,435
Log Likelihood	12.40	-34.83	-2715	-7504	-5448	-3423	-182.0	-4362
RMSE	0.2615	0.3018	0.2914	0.0485	0.0067	0.3281	0.3608	0.2932

*** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parenthesis.

Note: by construction of DPF, the mean Lag Term Spread presented here is the mean of the observations of term spread known up to the point. This differs from the yearly mean of Lag Term Spread, which would coincide to the variable itself, as term spread is a common variable for every industry.

model with robust errors, where a considerable number of model coefficients exhibit statistical significance. It is important to note that, while we report Blundell-Bond estimation results, we omit two-step GMM estimates in favor of first-differenced GMM due to unmet moment conditions. Table 2.6 presents the censored Tobit estimation, and Table 2.7 displays the DPF estimation. To ensure reliable statistical inference with an insufficient sample size, we utilize bootstrap-based sample augmentation mechanisms for the panel-censored Tobit estimations.

The lagged debt-to-equity ratio exhibits statistically significant coefficients across all industries in all estimations on both, Table 2.6 and Table 2.7, suggesting a robust autocorrelation in the dependent variable over time. Furthermore, the industry means of the lagged debt-to-equity ratio, incorporated in the DPF estimator in Table 2.7, consistently demonstrate statistical significance.

In Table 2.6, which presents the censored Tobit estimations, the coefficients of the non-debt tax shield in Table 2.6 are statistically significant in five out of eight industries, namely Manufacturing, Retail, Transportation, Finance, and Service industries, and they are all positive. It's noteworthy that the censored Tobit model solely reveals direct NDS effects. Table 2.7 provides a more detailed perspective from the DPF estimation.

In Table 2.7, which presents the DPF estimation of the industry-specific model, NDS or time-series averages of NDS have statistically significant coefficients in 5 out of 8 industries: manufacturing, retail, construction, transportation, and service. In two of these five industries, manufacturing, and retail, the coefficients of NDS are statistically significant, suggesting that the previous period NDS is a significant predictor of DE in these industries.

The industry-specific panel mean of non-debt tax shield (NDS) influences financing decisions (debt-to-equity ratio) in 5 industries: construction, manufacturing, retail, transportation, and service industries. This indicates that the industry average debt tax shield plays a role in shaping financing decisions in these 5 industries, and NDS-related policies are effective for companies in these sectors. However, NDS-related policies are unlikely to influence the financing decisions of companies in the other 3 industries: agricultural, mining, and financial services industries. This lack of impact on financial services firms is expected, given their indifference to a non-debt tax shield. However, this finding carries significant implications for policymakers concerning agricultural and mining SMEs. Policymakers should consider exploring alternative avenues to influence the financing decisions of SMEs in these sectors, as policies related to non-debt tax shields are unlikely to be effective.

Tables Table 2.5, Table 2.6 and Table 2.7 reveal that capital structure is sensitive to the non-debt tax shield in certain industries, implying that tax policies related to the non-debt tax shield can influence debt financing decisions. It would be valuable to compare these findings with studies on SMEs, such as Daskalakis and Psillaki (2008) and Matias and Serrasqueiro (2017) which also found a statistically significant influence of the non-debt tax shield on leverage. Moreover, our analysis delves deeper by identifying the specific industries where this effect occurs. Without this industry-level examination, we might have overlooked the fact that policies related to the non-debt tax shield are unlikely to significantly impact the agriculture industry, highlighting the importance of considering industry variations. We corroborate these differences across industries through ANOVA hypothesis testing of the various means of debt-to-equity ratio in each industry.

The signs of the relationship and the expected reaction of the debt-to-equity ratio to changes in the non-debt tax shield vary across industries, as highlighted in our research. In Table 2.6, we observe that the coefficient of the non-debt tax shield is negative for the agriculture industry, while positive for all other industries. This implies that, in response to an increase in non-debt tax shields, leverage might increase in all industries except agriculture. We attribute this discrepancy to the industry effect, which provides different incentives for firms in various sectors, leading to divergent reactions to changes in tax policy.

Our result in Table 2.7, shows that a non-debt tax shield is statistically significantly and positively related to the corporate debt level in the retail industry (0.4390**), and the average of a non-debt tax shield is also statistically significant, positively related to the debt-to-equity ratio, in the construction, manufacturing, retail, transport, and service industries. These findings infer that debt financing of construction, retail, transport, and service industries will increase in response to tax policy that promotes incorporating a non-debt tax shield.

In the manufacturing industry (column 4), the positive coefficient of mean NDS has a larger magnitude (2.1273***) than the negative NDS coefficient (-0.4649**). Leading to the conclusion that debt financing can decrease or increase in response to tax policy that promotes incorporating a non-debt tax shield, the result depends on how much the change in NDS changes the industry panel mean of the NDS. Specifically, if the change of the company's NDS changes the industry mean of NDS by more than 0.2185 points (which is a fraction of NDS's coefficient and Mean NDS coefficient, 0.46485/2.12734), then the debt-to-equity ratio of the company will rise in response to increased NDS of the company; otherwise, DE will decrease in response to increased NDS. Hence, the impact of tax policies promoting the incorporation of non-debt tax shields in the manufacturing industry appears ambiguous. Our findings indicate a mixed effect, with the relationship being positive in some instances and negative in others. As the coefficients for the remaining industries—agriculture, mining, and finance—are statistically insignificant, we can assume that changes in the non-debt tax shield will not significantly influence the debt-to-equity ratio of companies in those industries.

Possible explanation of the relationship betweeen non-debt tax shield and debt-financing is industry-specific characteristics of each sector. Specifically:

➤ Retailers often utilize debt to acquire amortizable assets, which contributes to an increase in their debt levels when their non-debt tax shield rises.

➤ the agriculture sector often relies on distinct financing mechanisms, such as crop loans and government subsidies, which may overshadow the effects of non-debt tax shields.

➤ Mining companies typically engage in substantial capital investment and may prioritize asset-based financing, rendering non-debt tax shields less relevant in their capital structure.

- Financial firms operate within unique regulatory environments and utilize diverse funding sources, which can attenuate the impact of tax policy changes on their capital structures.

- Additionally, an increase in the overall non-debt tax shield within the industry—often driven by tax policies that encourage the use of such shields—does not prompt the industries with special alternative financing sources (agriculture, mining and finance industries) and higher capital intensity to enhance their debt financing. Manufacturing still gets prompted as it has a mix of asset-intensive and variable capital needs.

In general, the government should apply a tax policy that promotes SME investments without causing high indebtedness and inefficiency. This entails incentivizing reinvestment of earnings and encouraging debt only when it does not lead to excessive indebtedness. It is prudent to compare the debt-to-equity ratios (DE) of industries against acceptable, healthy levels specific to each industry and address them accordingly.

As a rule of thumb, a DE (Debt-to-Equity) of less than two is considered favorable. However, for industries requiring minimal capital, a DE of up to 1.5 is deemed appropriate. Conversely, industries needing substantial capital may have a healthy average ratio value of up to 2.5. A notable exception is the finance industry, where higher DE ratios are common due to extensive reliance on external financing.

Given our finding that the debt-to-equity ratio is responsive to non-debt tax shields, policymakers have a potential lever to increase the leverage of small firms. However, caution is warranted to prevent DE from exceeding healthy industry levels and to avoid unnecessary accumulation of risk. A non-debt tax shield-related tax policy can indeed impact the leverage of German SMEs. Therefore, our **first policy implication** is as follows:

- Incentives for non-debt tax shields can be implemented when higher debt financing of SMEs is necessary, and the current debt-to-equity ratio (DE) is below a "healthy level" of DE.

Tax policies aimed at increasing non-debt tax shields would directly increase the debt-to-equity ratio (DE) in the retail industry, while indirect effects would be observed in the construction, manufacturing, retail, transportation, and service industries. However, the impact of non-debt tax shield changes on DE in the manufacturing industry remains ambiguous.

By presenting equations for both firm and industry levels, this paper provides insights into how adjustments in tax policies across various industries can influence changes in SMEs' capital structure. It elucidates that a higher non-debt tax shield could yield diverse effects across different industries, thereby averting the fallacy of drawing conclusions that are applicable only to certain industries and not universally to all SMEs.

In the industry-level analysis presented in Table 2.6 we observe that size, similar to NDS (Non-Debt Tax Shields), exerts a statistically significant influence on leverage across all industries. The positive coefficients of size in Table 2.6 suggest that smaller SMEs tend to utilize more debt compared to their larger counterparts. Interestingly, the firm-level model excluding macro and news-based variables also indicates that smaller firms exhibit a tendency to take on more debt. This seemingly contradicts the trade-off theory, which suggests a negative relationship between size and DE. However, a deeper examination using the DPF estimator reveals nuanced insights. Table 2.6 demonstrates that size remains a statistically significant variable in financial decision-making for five out of eight industries.

In Table 2.7 we observe significant coefficients of size in two industries: manufacturing and retail, indicating that company size influences financial decisions. Specifically, larger firms in the retail industry opt for higher leverage levels, whereas in the manufacturing industry, smaller firms tend to choose higher leverage levels. The DPF estimation provides further insights, revealing that industry time-series means of company sizes also significantly impact financing decisions in manufacturing, retail, and financial service companies. Larger SMEs in construction and financial services tend to take on more debt, whereas the opposite holds true for manufacturing companies. Regarding retail companies, the response of DE to NDS is ambiguous, although it is likely negative, as indicated by the need for the mean of NDS to change by over 1.16 (0.0829/0.0710) points for the effect of changed NDS to become positive.

2.6.2 Macroeconomic effects

The industry-level model is documented in Table 2.5, Table 2.6 and Table 2.7. In Table 2.7, we observe that the coefficients of interest rate spread and economic policy uncertainty are statistically significant in several industries. These results suggest that the selected macro variables do influence industry leverages in some industries.

Macroeconomic effects on SMEs' leverage are visible at the industry level. In the firm-level model (Equation 2.4), adding macro variables to firm-specific variables does not significantly improve our model, most probably because we do not control for the industry effects, as shown in the industry effects subsection. In the industry-specific model given in Equation 2.6, we consider industry effects, and adding macro variables significantly improves the performance of the model.

This study highlights the significance of the term spread as a determinant of the capital structure of German SMEs. In Table 2.7, we observe that the lagged term spread or its industry mean holds significance in the retail, and transportation, manufacturing and industry sectors.

Comparing our findings with previous studies focusing on SMEs and the role of the term spread in determining leverage, our results align with existing literature. In Table 2.7, we observe a direct impact of the previous period's term spread on leverage in the retail sector. This suggests that retail SMEs tend to exhibit higher leverage following periods characterized by high term spreads. The influence of the average interest rate spread on DE is positive in manufacturing and transportation industries and negative in financial services industry. This negative relationship between term spread and leverage in the finance industry mirrors the findings ofKorajczyk and Levy (2003).

As a lower debt-to-equity ratio signifies higher reinvestment, we draw our **second policy implication**:

- A higher term spread is associated with increased leverage in the retail industry in the following period.
- Increases in the average term spread of government bonds can lower the debt-to-equity ratio, prompting increased reinvestments by SMEs in the financial industry.
- Decreases in the average term spread of government bonds lead to higher debt-to-equity ratios in manufacturing and transportation companies.

We observe a statistically significant negative relationship between economic policy uncertainty, as measured by the news-generated Economic Policy Uncertainty Index, and leverage in four industries. In Table 2.7, the coefficients of the Uncertainty Index show significant negative signs in Construction, Manufacturing, Retail, and Services indicating their predictive value in these sectors. Our findings regarding the correlation between leverage and economic uncertainty align with those reported by Graham et al. (2015) and Zhang et al. (2015). Additionally, the means of the Economic Uncertainty Index have a statistically significant influence on the mining, manufacturing, and transportation industries. Hereby we draw our **third policy implication**:

- In the period following high economic policy uncertainty, SMEs in the construction, transportation, retail, and service industries tend to decrease their leverage.
- When economic policy uncertainty increases, resulting in a higher average level of uncertainty, mining companies tend to raise their debt levels, while transportation companies are inclined to reduce theirs.
- While increased uncertainty in the previous period (lagged EPU) may lead manufacturing firms to reduce debt financing, a significant rise in uncertainty in that period can elevate the average level of uncertainty (mean lagged EPU), subsequently encouraging these firms to increase their debt levels.

From the above findings, it is evident that policymakers should consider the effects of term spread and economic policy uncertainty when manipulating SME debt levels.

A novel insight from the industry-level model is that different SMEs adjust their leverage so that debt-to-equity ratios of companies within the same industry move in response to factors such as firm size, non-debt tax shield, last period's maturity risk premium (interest rate spread), and macroeconomic conditions, including tax code changes, macro news in newspapers, and economic uncertainty reflected in the policy uncertainty index. This finding aligns with the market timing theory, which suggests that capital structure adjusts based on market conditions.

A single policy intervention will not have a lasting effect on capital structure; therefore, it is important to understand how long SMEs will deviate from their target capital structure to accommodate endogenous market and policy-induced shocks. The adjustment speed of capital structure indicates the flexibility of SMEs' capital structures and the time it takes for them to readjust to their target capital structures under new circumstances. The speed of capital structure adjustment for German SMEs is presented in Table 2.8.

Table 2.8: Speed of adjustment (SOA) of capital structure in German SMEs

Estimation Methodology	**SOA**	**Half-lives**
Firm-Level Model		
Fixed Effects Model	99.52%	0.12 Year (around 1.5 Months)
Blundell Bond (GMM-SYS)	89.9%***	0.3 Years (4 Months)
Censored Tobit	99.9%**	0.1 Year (around 1.2 Months)
DPF	87.9%	0.33 Year (around 4 Months)

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Half-life is time needed for the 50% adjustment to the target after the shock to the error term (all forces not in the model).

Half-lives are calculated by: $\log(0.5)/\log(1-\text{SOA})$.

The estimated adjustment speed by the Censored Tobit estimator is 99.9%, corresponding to a half-life of 1.2 months, meaning that it takes German SMEs 1.2 months to adjust 50% to the target capital structure. This suggests that German SMEs will require approximately 2.4 months for full adjustment to their optimal capital structure under new circumstances. Policymakers can benefit from this information, knowing that SMEs need 2.4 months to return to their target leverage ratios. With this insight, policymakers will understand that after any market or policy shock, SMEs will react chaotically for 2.4 months before stabilizing at their new optimal capital structure, all else being equal.

The estimated adjustment speed, calculated using the DPF estimator—an unbiased estimator— is 87.9%, corresponding to a half-life of 4 months, indicating that it takes German SMEs 4 months to adjust 50% to the target capital structure. This implies that German SMEs will require approximately eight months for full adjustment to their optimal capital structure under new circumstances. Policymakers can benefit from this information, understanding that SMEs need eight months to return to their target leverage ratios. With this insight, policymakers will realize that after any market or policy shock, SMEs will react chaotically for eight months before stabilizing at their new optimal capital structure, all else being equal. Hereby we draw our **fourth policy implication**:

- A single-period shock induces short-term adjustments in the capital structures of SMEs. The effects of such a shock dissipate after approximately eight months.

The speed of capital structure adjustment is essential information for investment decision-making at the right moment. Using the Censored Tobit estimator, we conclude that the capital structure of German SMEs adjusts by 99% per year. This high speed implies that SMEs adjust their capital structure very quickly, taking around 2.4 months to do so. This level of flexibility makes investment in German SMEs attractive. Additionally, the high speed of capital structure adjustment suggests that the developed banking sector supports SMEs in getting closer to their leverage target.

The DPF estimator provides us with additional insight. It reveals that the speed of capital adjustment in German SMEs is not as fast as indicated by the Censored Tobit estimator. This suggests that German SMEs are not as flexible as they could be. There is a need to improve financing opportunities for German SMEs, which would support them in overcoming challenging situations such as recessions or financial crises.

2.6.3 Industry Effects

We evaluate industry effects by analyzing the differences in mean debt-to-equity ratios across various industries using an ANOVA test. The detailed results of this analysis are presented in Table 2.9.

Table 2.9:
ANOVA hypothesis testing for different means of DE in different industries.

Source	**SS**	**df**	**MS**	**F**	**Prob > F**
Between groups	2827643.6	8	353455.45	10.49	0.0000
Within groups	2.4574e+09	72912	33702.9919		
Total	2.4602e+09	72912	33738.0717		

Bartlett's test for equal variances: $\chi^2(8) = 7.0e+04$, $Prob > \chi^2 = 0.000$

The ANOVA results indicate significant differences in the means of DE across various industries. Additionally, Bartlett's test for equal variances confirms that DE ratios' variances among these industries are not homogeneous.

As shown in Table 2.9, the F-test indicates that the means of leverage ratios (DE) differ significantly across industries.[1]This suggests that the leverage ratios of German SMEs are influenced by statistically significant industry-specific factors.

A preliminary visual analysis suggests that capital structures among SMEs vary significantly across industries. As illustrated in Figure 2.1, the real estate and financial industries exhibit considerably higher leverage compared to other industries, while the service industry, encompassing education, arts, entertainment, recreation, health care, and social work, shows a notably lower debt-to-equity ratio. This observation, coupled with the ANOVA results presented in Figure 2.1, strongly supports our

[1]According to the ANOVA hypothesis test, the means of debt-to-equity ratios over the years do not exhibit statistically significant differences, allowing us to reject the year effect. Additionally, the interaction between year and industry is statistically insignificant.

hypothesis that industry characteristics influence the leverage decisions of SMEs. The visual evidence aligns with prior findings Serrasqueiro et al. (2011) suggesting that SMEs in the service industry may favour a lower debt-to-equity ratio. Furthermore, an additional ANOVA test confirms that the mean debt-to-equity ratio in the service industry significantly differs from those in other industries, highlighting the distinct leverage patterns of German SMEs in the service industry.

These findings are valuable for taxation policymakers in designing tax incentives that encourage investment and development among SMEs. Additionally, they provide insights for banks looking to develop funding products tailored to SMEs in industries that rely on debt to finance their investments.

The novel policy implication emerging from the observed industry effects is that a one-size-fits-all approach is suboptimal. The non-debt tax shield's usage could incentivize equity investments in agriculture, mining, construction, and transportation while potentially producing opposite effects in manufacturing, retail, or finance industries. Accordingly, we propose our **fifth policy implication**:

- The same policy for all industries is not optimal, as industries react to conditions diversely.

2.7 Conclusion

In this paper, we investigate the capital structure decisions of German SMEs over a 10-year period, analyzing data from 13051 SMEs. We examine both firm and industry-level factors and provide practical policy recommendations for different industries and SME groups.

The findings indicate that the capital structure decisions of German SMEs are influenced by firm-specific variables such as size and the non-debt tax shield (NDS), as well as industry effects and macroeconomic factors. Our analysis reveals a significant effect of the NDS on the capital structures of German SMEs across various industries, with notable statistical significance in sectors such as manufacturing, retail, construction, transportation, and services. Specifically, the coefficients of NDS exhibit positive relationships with debt-to-equity ratios in these industries, suggesting that tax policies promoting NDS can effectively enhance leverage. However, the impact on the manufacturing sector remains ambiguous, contingent upon the extent to which changes in individual firms' NDS influence the industry panel mean.

Moreover, the variable size demonstrates a statistically significant influence on leverage across the construction, manufacturing, retail, and finance industries. The signs of relationships between size and debt financing vary by industry, highlighting the necessity for industry-specific analyses in understanding how size affects capital structure decisions.

Furthermore, macroeconomic factors, including interest rate spread and the news-derived economic policy uncertainty index (EPU), play a critical role in shaping SMEs' leverage. The significant positive correlation between average economic policy uncertainty and debt levels in the mining industry highlights a strategic shift where firms may view debt as a means to capitalize on potential investment opportunities amid heightened uncertainty. Conversely, transportation companies exhibit a tendency to decrease leverage during periods of increased past uncertainty, reflecting a more conservative approach to debt financing.

The results underscore the necessity for policymakers to consider industry-specific variations when designing tax and economic policies. The divergent reactions of SMEs to non-debt tax shields and macroeconomic indicators emphasize the importance of tailored approaches that account for the unique characteristics of each sector. Effective tax policies should aim to incentivize investment while maintaining prudent levels of indebtedness, ultimately fostering sustainable growth in the SME landscape.

This study draws several policy implications for German SMEs:

1. **Non-Debt Tax Shields**: Incentives for a non-debt tax shield can be applied if higher debt financing of SMEs is needed, provided the current debt-to-equity ratio (DE) is lower than the "healthy level of DE."

2. **Tax Policies for NDS**: Tax policies promoting higher non-debt tax shields (NDS) would increase the debt-to-equity ratio (DE) in the retail industry through a direct mechanism and in construction, manufacturing, transportation, and service industries through indirect mechanisms. The impact of changes in NDS on DE remains ambiguous in the manufacturing sector.

3. **Term Spread and Reinvestment**: A higher term spread on government bonds boosts reinvestment by financial SMEs. An increase in the lagged term spread directly raises debt financing in the retail industry, while a rise in the industry mean of the lagged term spread drives up debt financing in manufacturing and transportation.

4. **Economic Policy Uncertainty**: In the period following an increase in economic policy uncertainty, SMEs' leverage tends to be lower across industries.

5. **Short-term Effects of External Shocks**: A single external shock can induce short-term changes in the capital structures of SMEs. However, the impact of such shocks is likely to dissipate within approximately eight months.

6. **Industry-Specific Policies**: The same policy for all industries is not optimal, as industries react differently to conditions, and their reactions have varying durations.

7. **Encouraging Trade Credit**: Policymakers can implement tax policies to reduce borrowing costs and shorten the average maturity of SMEs' debt by encouraging the use of trade credit.

For future research, it would be desirable to conduct the same analysis for periods during and after crises, or following the 2015 Investment Tax Act reform, as was done up to 2016 in section B.3. Additionally, extending the model to include a business survey-based expectations variable, such as the KfW-ifo SME Barometer, could provide valuable insights, as it measures the mood in German SMEs and has been computed since 2004 from ifo business climate survey. Another intriguing research direction would involve analyzing panel data from multiple countries and incorporating institutional determinants into the model, as observed in Ozkan (2001).

3 News-Driven Model for Timely Nowcasting of GDP in Germany

Abstract

This study advances the field of nowcasting GDP by introducing an innovative approach that meticulously preprocesses news media data and integrates it with lagged traditional economic variables to form a factor for nowcasting GDP. The research involves processing 14 years of news articles related to German GDP using advanced text preprocessing techniques, including a specific Boolean filtering method to exclude past-related sentences. It employs Latent Dirichlet Allocation (LDA) with comprehensive fine-tuning to probabilistically assign topics to preprocessed news texts. These topic frequencies are converted into time series and adjusted by polarity measures. The tone-adjusted topic frequency time series are then utilized as dynamic factors to model GDP dynamics.

Our findings demonstrate that our monthly news-driven model outperforms the widely recognized Ifo Business Climate Index in GDP nowcasting, with a nowcasting RMSFE of 0.52 in the period from Q1 2010 and Q3 2023 and out-of-sample forecasting RMSFE of 0.04 percentage points. Our model, with nowcasting RMSFE of 0.23 and a forecasting RMSFE of 0.04 percentage points in the period from 2012Q1 and 2019Q3, demonstrates superior nowcasting and forecasting performance compared to prominent models of GDP nowcasting with prominent GDP nowcasting indicators documented in Lehmann and Reif (2021). Incorporating news data into our model in a refined manner, significantly improves the accuracy of GDP predictions, underscoring the value of unconventional data sources for economic forecasting.

Keywords: Business cycles, GDP, real-time indicators, Nowcasting, Text Analysis, forecasting, Dynamic factor model (DFM), NLP.
JEL classification: C53, E32, C88, C82, E01.

3.1 Introduction

Real-time monitoring of economic conditions, especially during rapid disruption, is essential for making accurate policy decisions. The German Gross Domestic Product (GDP), however, is measured at low frequency and estimates are released with considerable delay, 30 days after the end of the quarter (Ashwin et al., 2021). The same is true for many of the conventional economic indicators. This makes timely nowcasting [1] of GDP challenging. In recent years, high-frequency indicators, such as news and other nonconventional indicators, have attracted the interest of researchers and policymakers.

In their systematic review of nowcasting economic activity, Stundziene et al. (2023) concluded that "future research should use more real-time indicators, unconventional (alternative) data, online data, and big data and test their predictive abilities." News data belongs to such unconventional data.

This paper demonstrates that timely economic signals extracted from newspaper text can significantly enhance nowcasts and forecasts of German GDP.

[1] Definition of nowcasting: using diverse data sources to estimate current variables.

Inspired by Thorsrud (2020), who pioneered the creation of a daily business cycle index using quarterly GDP and newspaper textual information, our study contributes to the literature on GDP nowcasting and text analysis by applying and refining unconventional textual data modelling techniques. Like Thorsrud (2020) and unlike many existing studies, such as the recent research by Koçak (2020), which focuses on nowcasting German GDP using nonconventional textual data from ECB president speeches while excluding comprehensive media news coverage, we analyze entire news articles.

We enhance existing methodologies by implementing a novel approach of filtering out past-tense sentences for higher accuracy. Our motivation stems from the observation that while the dynamic factor model utilizing topic time series derived from news data yields intriguing results, it also exposes certain weaknesses, particularly notable during and after the crisis. These weaknesses, identified in our analysis, are primarily due to journalistic references in news texts that recall past events for comparison purposes. To mitigate this issue, we preprocess articles by removing past-related sentences, thereby reducing the influence of past references in the text.

We classify and decompose news text into topics with the help of the Latent Dirichlet Allocation (LDA) method and refined text analysis methodology. Topics of news represent the major concept of news that might attract the attention of the market participants. Topics are interpreted from the economic perspective, and we then use the extracted dynamics of topics as dynamic factors which together with the starting values of industrial production and exports condition the dynamics of GDP.

Our approach to nowcasting GDP is closest to the one proposed by Thorsrud (2020) who applies daily news data for forecasting and nowcasting GDP. Unlike our paper, Thorsrud (2020) does not clean texts from past tense sentences including information about the past, nor do they perform out-of-sample forecasting. our approach differs from the approach by Thorsrud (2020) in that we do aggregations of the daily time series to monthly and quarterly time series, and use monthly data for nowcasting, we do not compare our results to GDP-related indices but to the GDP growth itself. Besides, we include lagged industrial production index and exports data into the model as additional factors, this makes the model more comprehensive.

The contribution of this work is unique in several ways. **First**, this paper contributes to GDP literature, which nowcast GDP by unconventional data, such as text. In contrast to previous works, this work extends the model specification- it uses the framework of the machine learning method to incorporate the resulting topics as exogenous variables in the dynamic factor model together with the previous period's industrial production index and exports. Though, Thorsrud (2020) already used whole text bodies for GDP nowcasting, it did not add any previous period's macroeconomic variables to the model. In our analysis, we posit that economic growth is shaped by a dual increment mechanism, not solely by the news flow (as inferred from Thorsrud (2020)). We argue that while one increment shaping GDP growth originates from current information, another arises from the recollection of the previous month's values of macroeconomic variables closely associated with GDP. **Second**, the paper contributes to news-based nowcasting literature by enhancing the implemented methodology. This work builds a comprehensive approach through increasing the input corpuses quality by mixing the boolean method and extra cleaning step of the text.

The **third** contribution of this paper is utilizing big data. Unlike most other works, We do not avoid handling big data and employ text bodies instead of titles. This brings us more insights into GDP-related news. In doing so we follow Thorsrud (2020), and focus on news texts instead of one part of news - announcements or titles, because "(media) news can reach a broader audience of economic agents, including announcements and alleviate information frictions" (Thorsrud (2020)).

Our research, focused on timely GDP forecasting, holds promise for multiple stakeholders. Policymakers stand to gain critical insights for informed decision-making, facilitating the formulation of effective fiscal and monetary policies. Businesses can utilize our forecasts to optimize operational strategies and investment decisions, enhancing their adaptability to economic fluctuations. Investors benefit from our analyses by gaining valuable intelligence to refine portfolio management strategies. Financial institutions can leverage our forecasts to improve risk management practices, ensuring prudent allocation of resources. Moreover, our research contributes to the broader academic discourse, advancing economic theory and empirical analysis.

The paper is structured as follows: Section 2 reviews the relevant literature. In Section 3, we provide an in-depth overview of our methodology, including the construction of the news-driven factors. Section 4 outlines our data collection process. The results, main findings, and discussion of our application to German GDP are presented in Section 5. Finally, Section 6 provides the conclusion.

3.2 Literature Review

3.2.1 News impact on GDP

The speculative efficiency hypothesis and attention theory suggest that agents take the news available as information into consideration when making decisions. The Efficient Market Hypothesis infers that new information gives rise to a new equilibrium.

Numerous studies suggest that news is a significant influencing factor on the GDP.

With the increasing number of artificial intelligence applications, current works nowcast GDP by NLP and artificial intelligence.

Kalamara et al. (2022) forecast UK GDP using their feature engineering-based approach. Feature engineering- based approach mixes counts of terms (term frequency vectors) with supervised machine learning algorithm-based text metrics: Dictionary methods (associate specific terms with specific scores and count the net score per article), Boolean method (takes text if a specific logical condition is met), Computer science-based sentiment-metric method and creates sentiment time series. Kalamara et al. (2022) conclude, that exploiting newspaper text can improve economic forecasts in absolute and marginal terms. They compare macroeconomic fundamentals forecasts produced by their feature engineering-based approach to the ones from a broad range of linear and non-linear supervised machine learning algorithms and argue that the approach delivers better forecasts rather than other text-based methods.

Shapiro et al. (2022) build economic sentiment analysis models and create a dictionary-based sentiment scoring model. They demonstrate that the key macroeconomic variables respond to dictionary-based sentiment score shocks.

Gentzkow et al. (2017) underline the importance of text for nowcasting GDP. Bybee et al. (2021) augment the VAR model of macroeconomic dynamics by the attention to LDA topics inferred from the full-text bodies of 800,000 news from 1984 to 2017. They find, that attention to news closely tracks and has a large incremental role in modelling macroeconomic dynamics.

Longo et al. (2022) forecast GDP one quarter to one year forward along the business cycle by neural networks. A recurrent neural network, long short-term memory (LSTM) network describes GDP movements quite well, though they do not perform well during the COVID pandemic. The authors explain this by the rapid data generating process and offer to use LSTM combined with a dynamic factor model DFM-GAS to predict sudden mean-shifting in GDP.

Loermann and Maas (2019) feedforward artificial neural network forecasts of GDP growth.

Gonzalez et al. (2000) forecast Canadian GDP growth by a neural network with two hidden layers and a hyperbolic tangent activation function. They find that neural networks have higher forecasting accuracy compared to the corresponding linear model, still the improvement in forecasting accuracy is not statistically significant as detected by the Diebold and Mariano test, a non-parametric sign test, Wilcoxon's signed-rank test, and the Ashley, Granger and Schmalensee test. Gonzalez et al. (2000) argue that neural networks can only be used as a complement to econometric methods and not as a substitute.

Babii et al. (2022) apply a regularized machine learning method, using a sparse-group LASSO estimator and mixed frequency data for real-time forecasting and nowcasting of US GDP. Machine learning method produced nowcasts outperform NY Fed nowcasts (based on state-space dynamic factor model) at two-month horizons and competes with it at one and two-month and end-of-quarter horizons. A disadvantage of this approach is that it is not based on a theoretical model.

Barbaglia et al. (2023) investigate whether the sentiment of the news related to the state of the economy tracks business cycle fluctuations. The sentiment scores are calculated aspect-based, i.e. only from the parts of the article that are semantically dependent on the token expressing economic concept (related to economy, inflation rate, unemployment rate, banking and financial sector, manufacturing, and monetary policy). The authors calculate the sentiment scores using a dictionary created by themselves. When several measures of economic sentiment are used together with the macroeconomic factors (real GDP, Industrial Production Index, total Nonfarm Payroll Employment, Consumer Price Index, the Chicago Fed National Activity Index, and the National Financial Conditions Index) selected by data-driven double lasso, forecasting is significantly improved.

3.2.2 GDP Nowcasting

Recent literature on GDP nowcasting encompasses various methodologies, ranging from traditional economic data analysis to the incorporation of unconventional data sources.

One branch of GDP nowcasting literature models GDP using **conventional economic data**. Marcellino and Schumacher (2010) adopt the state-space factor model and mixed-frequency data sampling (MIDAS) to nowcast and forecast quarterly German GDP growth based on 111 monthly macroeconomic indicators (with a ragged edge). Similarly, Kuzin et al. (2011) utilize the MIDAS model with 20 monthly indicators for the euro area. They based on MSE select well-performing MIDAS models, which turn out to include the following eight indicators: surveys on production expectations, order books, consumer confidence, industrial production of capital goods producers, the 3-month EURIBOR money intermarket rate, yields on 10-year government bonds, HWWA industrial raw material price index and passenger car registrations.

The second branch of GDP nowcasting literature focuses on **survey-based indicators**, such as the Ifo Business Climate Index and Purchasing Managers' Index (PMI). Survey data offers advantages in terms of timeliness and minimal revision compared to quantitative indicators from official statistics. Official statistics indicators often have a publication lag of one month or more, while survey indicators offer immediate insights at the end of each month and undergo only minimal revisions (Lehmann, 2023). Kuzin et al. (2013) employ single-indicator MIDAS models and large factor MIDAS models and 15 years of monthly data including survey-based data (industrial production by sector, incoming orders, turnover, consumer sentiment survey, business climate survey, construction, financial time series, raw material price indices, car registrations) to nowcast and forecast quarterly German GDP growth. They build different MIDAS models with combinations of monthly variables, and large factor models with all variables but different large factor MIDAS specifications and do pooling. Kuzin et al. (2013) compare the model's relative MSEs (relative to the in-sample mean) and find that pooling models outperform the single model selection approach. Except this, Kuzin et al. (2013) point out that pooling of all MIDAS and large factor MIDAS models leaves pooing between large factor models and pooing between MIDAS models behind, and concludes that taking model uncertainty into account improves forecasting and nowcasting. Kuzin et al. (2013) also find that the performances of the single models vary considerably over time. In summary, Kuzin et al. (2013) advocate pooling from all MIDAS and large factor MIDAS models, which may inherently encompass survey-based variables. The literature review conducted by Lehmann (2023) underscores that the ifo Business Climate Index for Industry and Trade, in contrast to hard indicators by the Federal Statistical Office of Germany or a diffusion index derived from a factor model, consistently demonstrates minimal prediction errors for GDP forecasts when conducted at the beginning of a quarter (Lehmann and Reif (2021), Heinisch and Scheufele (2019), Bandholz and Funke (2003)).

In some cases, researchers utilize an indicator derived from another survey-based indicator. For instance, the ifo Institute's ifoCAST indicator uses the ifo Business Climate Index. ifoCAST is produced by the mixed frequency dynamic factor model and selected variables from the large dataset, that currently comprises around 300 variables, including local and international indicators. ifoCAST enhances the classical dynamic factor model with two components. Firstly, it accounts for the trend-like decline in short-term fluctuations, leading to more accurate point and density forecasts. Secondly, ifoCAST models variable-specific lead, lag, and contemporaneous relationships of the indicators, ensuring that variables do not only act contemporaneously on the identified factor. Lehmann et al. (2020) utilize a dynamic factor model with Bayesian estimation methods, employing ifoCAST to forecast German GDP. Lehmann et al. (2020)'s findings indicate that the forecasts align with GDP realization, exhibiting a mean forecast error of 0.03 percentage points and an accuracy of 0.32 percentage points from 2011 to 2018. Lehmann (2023) analyzed of the literature focusing on the forecasting power of the Business Climate Index (BCI) in relation to economic indicators, including Gross Domestic Product (GDP). Their findings indicate that the ifo Business Climate Index (BCI) serves as a potent tool for GDP forecasting purposes. Similarly, Nunes (2005) nowcast Portuguese real GDP by the coincident indicator model. They extend the Stock and Watson single-index model that allows mixed frequency and missing data and nowcast GDP by letting the model consider the last quarter's GDP as missing data. They construct a monthly coincident index of economic activity from the coincident indicators of business surveys whereby they estimate unobserved common coincident component, of the unobserved 13 monthly series underlying quarterly GDP. Most recently, Zheng et al. (2024) nowcasted GDP by incorporating topic entropies (attention measures) from news articles along macroeconomic variables. This approach utilized a combination of MIDAS weighting schemes, as outlined by Babii et al. (2022), and random forest regression.

Furthermore, some papers emphasize the importance of the **diffusion index** for nowcasting GDP, this variable is valuable as it becomes available earlier than other economic numeric variables. A diffusion index measures the proportion of the component indicators that are improving and is used to measure the degree of propagation of economic expansions. Diffusion indices are created based on the responses in a business survey, these survey responses react to the change in the current month over the previous one. In the case of the U.S. for 10 indicators which are new orders, production, employment, supplier deliveries, inventories, ustomersínventories, prices, backlog of orders, exports, and imports. Diffusion indexes measure the proportion of the components that contribute positively to the index. The first step in computing the diffusion indexes is to calculate if a component increased, decreased, or had no change. Components that rise more than 0.05 percent are given a value of 1, components that change less than 0.05 percent are given a value of 0.5, and components that fall more than 0.05 percent are given a value of 0. Next, sum the values of the components. Third, divide by the number of components. Finally, multiply by 100. A difusion index is also calculated for Germany based on the ifo business climate survey responses. Lahiri and Monokroussos (2013) nowcast the US current quarter GDP growth using the MIDAS approach and include the monthly diffusion index, which is based on the American ISM business survey similar to the CESifo business survey. They show that the diffusion indices (both manufacturing and non-manufacturing iSM indices) help improve GDP nowcasts. Higgins (2014) developed the GDPNow model which forecasts GDP growth by Combining "bridge equation" forecasts with BVAR forecasts of the 13 GDP subcomponents. However, the authors apply the model to US data and do not claim that the model outperforms other estimates.

The third branch of literature makes use of **unconventional data**. Most of such papers apply textual data and a machine learning algorithms in combination with statistical models to nowcast GDP or detect turning points. Dauphin et al. (2022) in their IMF working paper combine a machine learning algorithm (regularized regression methods, support vector machine, random forest, neural network) and dynamic factor model to nowcast GDP in Europe (Austria, Hungery, Ireland, Malta, Poland and Portugal). They use nontraditional variables such as Google search and air quality. They find that their dynamic factor models are performing better than machine learning methods in normal times, while machine learning models outperform dynamic factor models at finding business cycle switching points. In their sample compared to the benchmark AR model, the average forecast errors were reduced by up to 75 percent when applying the ML methods and by 50 percent when applying the dynamic factor model across all countries. Ashwin et al. (2021) use multilingual news from fifteen popular European newspapers from France, Germany, Italy, and Spain. They avoid working with local languages, google translate news into English with a machine, and nowcast GDP growth by the daily text-based sentiment metrics of the news with linear regressions and Non-linear machine learning models. They find that the sentiment indicators are very beneficial at the beginning, in the first half of the quarter and their power to nowcast diminishes as time passes and more indicators becomes available. The sentiment-based nowcasts are more precise than the ECB's official macroeconomic projections. Ashwin et al. (2021) find that standard linear methods (OLS) also work well in normal times, though non-linear machine learning models (Ridge Regression, Random Forests, Neural Networks and the Boosting Algorithm) capture extreme economic shocks better. Between different dictionaries, they recommend using a general-purpose (AFINN sentiment lexicon) dictionary for detecting turning points due to its consistency and robustness across time.

A subbranch of papers create **sentiment-based indices** for nowcasting GDP. Aguilar et al. (2021) build a daily economic news sentiment indicator, a MFBiVAR model and nowcast Spanish GDP. They compare their indicator to the Economic Sentiment Indicator (ESI) and show that it outpeforms ESI. Bortoli et al. (2018) take their approach, they create their own French unigram and bigram dictionary from stems they get from French news in the journal Le Monde 1990-2017, by stemming with snowball algorithm. They apply their dictionary to calculate continuous sentiment scores and create a synthetic, sentiment-based indicator and nowcast french GDP by augmenting the AR model with the sentiment. In a related study, Del Castillo (2022) developed an economic sentiment index (NESI) by analyzing texts from Spain's most widely read economic newspapers and employing a customized lexicon. This index exhibits a strong correlation with quarterly GDP volume growth in Spain.

Some other nontextual nonconventional data has also been used to nowcast GDP. For instance, Lehmann and Möhrle (2024) and Azarova et al. (2022) use high-frequency electricity consumption data to nowcast the regional GDP in Bavaria.

There are cases when researchers **mix unconventional data with conventional one**. In their study, Eraslan and Reif (2023) developed an innovative Bayesian dynamic factor model to create a weekly GDP indicator (WGDP) for Germany. They combined both conventional and unconventional data sources closely related to or representing economic activity. These included variables such as consumer spending, pedestrian frequency, Google Trends data on unemployment and short-time work, daily truck toll mileage index, total number of worldwide flights, real output in manufacturing, construction, and service sectors, real exports, retail sales, real turnover in wholesales and food services, and real gross domestic product. Results of this study are quite impressive; Eraslan and Reif (2023) document a weekly GDP mean absolute forecast error (MAFE) of 0.5 percentage points for the period from Q4 2020 to Q1 2023.

A smaller branch of the literature takes a **statistical approach**, to evaluate GDP growth-related features. For instance, Mitchell et al. (2022) nowcast euro area GDP growth density by building Bayesian Quantile regression with HS prior and 124 mixed-frequency monthly indicators. They apply the MCMC method with Gibbs sampling and use the top 30 principal components to nowcast GDP. Mitchell et al. (2022) claim their density nowcasts are accurate even for times of rapid recessions. Leiva-Leon et al. (2020) to measure the world's business cycle, evaluate recessionary episodes of heterogeneous deepness by building a nonlinear factor model.

3.3 Methodology

This section outlines the study's methodology for both quantitative (hard) and qualitative (soft) data used in this research for nowcasting GDP.

3.3.1 Boolean Method

This research utilizes a Boolean method for selecting news texts, a logical filtering technique that ensures relevance and specificity. This approach involves executing operations on textual data, specifically including articles or parts of articles in our analysis, only when they conform to predefined conditions. The detailed criteria for article selection are outlined below.

Logical Preconditions for Article Selection

We select articles from the database based not only on search terms but also on additional criteria to ensure they specifically discuss Germany and German GDP.

The logical preconditions that texts must meet to be included in the analysis are:

Table 3.1: Keywords in English and German

English Keywords	**German Keywords**
Upswing in Germany, upswing of the economy in Germany	Aufschwung in Deutschland, Aufschwung der Wirtschaft in Deutschland
Economic crisis in Germany	Wirtschaftskrise in Deutschland
Recession in Germany	Rezession in Deutschland
German economy	Deutsche Konjunktur, Deutsche Wirtschaft
Economic growth in Germany, German economic growth	Wirtschaftswachstum in Deutschland, Deutsche Wirtschaftswachstum
Gross domestic product in Germany, German gross domestic product/ GDP in Germany, German GDP	Bruttoinlandsprodukt in Deutschland, Deutsche Bruttoinlandsprodukt, BIP in Deutschland/Deutsche BIP

Text Segment Selection from the Selected Articles for German GDP Nowcasting

Text segment selection is crucial in our context since texts often mention past developments for the sake of comparison, which is mostly irrelevant for nowcasting and can burden the results.

We build upon existing research in text selection methods. For instance, Kelly et al. (2021) developed the hurdle distributed multinomial regression (HDMR) methodology. In contrast to their approach, our method utilizes artificial intelligence for selecting text segments based on whether they discuss the present period.

Cleaning Texts from Past-Related Information Using POS Tagging

We exclude past-related information from the text bodies, as it may introduce confusion and hinder accurate nowcasting. Without removing such information, results could be obscured and the identification of strong causal relationships undermined (refer to the appendix section on nowcasting with text data including past-related texts for details). Identifying past tense sentences involves recognizing their tense, which requires first identifying the grammatical parts of speech and their respective forms.

To assign grammatical parts of speech to each token within the text, we employ a Part-of-Speech (POS) tagger. Before POS tagging, a preprocessing step is undertaken, which includes cleaning the text to eliminate any remaining apostrophes, ensuring that tokens exclusively consist of words, and meticulously inspecting the text to remove non-printable characters. Following preprocessing, the POS tagger categorizes each word to determine its grammatical classification, encompassing nouns, verbs, adjectives, and other linguistic categories.

Due to radical differences in language structures across languages, good POS taggers have to adapt to each language, effective Part-of-Speech (POS) taggers must adapt to each language. For tagging German texts, we employ two taggers: TreeTagger and RNN Tagger.

TreeTagger, developed by Helmut Schmid and detailed in his paper Schmid (1999), has been successfully utilized for tagging German texts. It operates as a Markov model tagger with a decision tree that selects tags based on a set of features.

In our study, we perform POS tagging on each sentence in our database of news related to German GDP. Subsequently, we exclude sentences containing verbs in the past form. This exclusion criterion includes sentences with verbs in past participle form with helper verbs or modal verbs (full verb tagged as 'VVPP' with helper verbs tagged as 'VAPP' or modal verb tagged as 'VMPP'), as well as sentences with finite full verbs and past participle helper verbs ('VVFIN' and helper verbs-'VAPP').

While this cleaning method is generally effective, it occasionally lacks precision in rare cases. During our use of TreeTagger, we encountered issues with undetailed tagging, leading to the inadvertent deletion of sentences that were referring to future events rather than past events.

For enhanced precision in morphological tagging, we utilize the RNN (Recurrent Neural Network) Tagger. RNN Tagger is recognized for its superior accuracy compared to TreeTagger and is considered the most precise tagger available for German texts, surpassing other tools such as SpaCy's part-of-speech tagger. Developed by Helmut Schmid, RNN Tagger is detailed in his paper Schmid (2019). It operates on a deep learning algorithm employing bidirectional Long Short-Term Memory Networks (Bi-LSTMs). In addition to tagging parts-of-speech, RNN Tagger analyzes the structure of character-based word representations. It directly identifies the form of verbs or modal verbs, including whether they are in the past tense (indicated by the tag).

Sentences identified as containing past tense verbs are excluded from further analysis. With the assistance of POS tagging, we generate a dataframe containing sentences from which all past tense sentences have been removed. Subsequently, we reassemble the sentences for each news text and develop models using these newly cleaned text bodies.

The POS tagging with the RNN Tagger is implemented in Python, supported by Perl, PyTorch torchvision, and CUDA packages. Initially, we organize the sentences of each news article into a dataframe where all sentences from a single text are placed on the same line. For each cell in our dataframe containing a sentence, we tag the words using the RNN Tagger. If any word in a sentence is tagged with a label indicating past tense (e.g., 'VVPP.Psp' or 'VAFIN.3.Sg.Pres.Ind'), we classify the entire sentence as non-present. Subsequently, we drop the sentence and replace the cell contents with 'None'. After completing the cleaning of all news articles, we consolidate each line of the dataframe into a coherent text. This compiled text excludes any sentences that were previously dropped. Subsequently, we proceed to the next step: performing natural language processing on these refined news texts to prepare them for our final model.

In total, for the German dataset, we processed 17,810 lines containing 484,964 sentences. To expedite nowcasting, we transitioned from Google Colab to a Ludwig-Maximilian University server. Using the GPU (CPU + Nvidia Tesla V100 16GB Tensor Cores) and 40GB of RAM provided by LMU, and employing PyTorch 2.3.0, the entire cleaning process for the 14-year German database, including complex dependent sentences, was completed just in 21.4 hours. Cleaning one year of news took approximately 1.5 hours, and **one month's news was processed in as little as 7.7 minutes**. In summary, our approach is computationally efficient, especially when leveraging previously tagged data from previous years.

3.3.2 Natural Language Processing

We apply an automated procedure to create textual variables from unstructured data, namely, the body text of news articles. This textual data is in an unstructured format, which is not understandable for a machine. Therefore, it needs to be transformed into a form, which can be readable for the machine.

Data Pre-processing

In the first step of data preparation tokenization was applied to extract terms - single words, or a group of words from the text.

For transforming textual data from an unstructured format into a uniform format, text must be processed. The first step is **tokenization**, where text is tokenized into smaller components - tokens. For tokenization, we used the Python package Natural Language Toolkit (NLTK)'s RegexpTokenizer and word tokenizer. These tokens can be individual words or multi-word expressions. The tokens are then represented as vectors in a numerical format for further analysis.

To further transform the tokenized text to the base form, lemmatization or stemming techniques must be employed. For the reason of comparison, we apply both methods and check which one is more appropriate. **Stemming** is a technique of removing all prefixes or suffixes of the word. For 'economics' and 'economy' the stem is 'econom'. One of the stemmers available in Python is PorterStemmer. As it is believed to overperform other stemmers, we apply the Porterstemmer. The stems produced by a stemmer might not always be morphologically valid, due to this the stem might need to get to a more morphologically valid form. **Trimming** is a technique to correct the stems. We also apply a trimming technique after stemming. **Lemmatization** is a more precise technique for transforming data into a base format, while lematizing we allow the pos tags: noun, adjective, verb, adverb. After tokenization and lemmatization, the data still includes unwanted information causing noise.

After lemmatization the text has been pre-processed by **normalization** - enforcing lower case (convert words written with upper case capital letters to lower case). After that the text was processed by removing punctuation, special tags ("b, 'b), and square brackets. Before removing stopwords we do an **extra step** and exclude all the sentences that are before the actual start of the news text. For this, we remove the part of the text before the name of the section which normally is "Reserved section" ("Vorbehaltensection"). After this, we proceed by removing **stopwords**- a non-informative regularly used, common words like conjunctions 'but', 'and', 'because'. There is no package with a complete list of German stopwords. Because of this, for German texts we create our list of stopwords, which includes the existing lists of stopwords, in particular the German stopwords available in the *nltk* package and *utf8* German stoplist, we merge and extend them by our list of stopwords which includes month names, words such as first, second, third, journal section names. In Appendix C.14, we present the full list of stopwords.

After applying these text pre-processing methods, we receive a corpus in a "bag-of-words" format, in the final stage of data preparation, we transform the corpus to a matrix space, into a **Document-Term Matrix** or DTM matrix, which is readable for the machine from the uniformed text in "bag-of-words" format. We construct a set of terms that consist of one-word, two-word, and three-word which frequently appear in our texts. In the DTM, data are in the morphological root form.

In this study, the input for the LDA model is vectorized using CountVectorizer to transform the raw text data into a document-term matrix (a sparse matrix), where each entry represents the frequency of a term in a document. This step captures the raw frequency of terms across documents.

For validation purposes, the input to the LDA model is also prepared using the Term Frequency-Inverse Document Frequency (TF-IDF) vectorizer. TF-IDF weighting adjusts the count of each term by its frequency in the entire corpus and its inverse document frequency, which reduces the impact of commonly occurring terms.

3.3.3 Organizing Data by Date

To organize the data by date, we follow these steps:

1. **Extract Publication Dates:** For each text, we search for date patterns and extract the publication date. The date pattern search is applied to the original texts, as unnecessary parts before the start of the article body have been removed during preprocessing.

2. **Assign DateTime Stamps:** After extracting the publication date, we convert it into a standardized datetime format and assign a datetime stamp to each original text and corresponding preprocessed text.

3. **Sort Chronologically:** Once all texts have been assigned datetime stamps, we sort the entire dataset chronologically, with older texts preceding newer ones.

3.3.4 Hyperparameter Tuning Methodology for Latent Dirichlet Allocation (LDA) Model

Parameter tuning is pivotal in optimizing the performance of Latent Dirichlet Allocation (LDA). The selection of appropriate hyperparameters significantly influences the quality and interpretability of topics generated by the LDA model. A meticulous parameter tuning ensures that the LDA model effectively captures the underlying structure of the text corpus, leading to the extraction of coherent and semantically meaningful topics.

Notably, the number of topics and the learning decay parameter exert a profound impact on the granularity and temporal dynamics of the resulting topic distributions. During the parameter tuning process of the LDA model, we systematically explored a range of topics from 2 to 50 to capture a comprehensive understanding of the resulting topic distributions. Besides, we examined various values of the learning decay parameter (0.5, 0.7, and 0.9) to regulate the temporal impact of early iterations during model training.

In our exploration, we systematically varied the alpha (α), beta (β), and eta (η) values, between 'auto', 0.01, 0.1, and 1.0, where the 'auto' setting automatically computes these parameter values based on the number of documents, specifically, it employs a symmetric distribution of 1/number of topics.

Alpha (α): Regulates how topics are distributed inside a document. While a high alpha value permits documents to contain more topics, a low alpha value promotes sparsity in the document-topic distributions.

Beta(β): Controls the distribution of words per topic. While a high beta value permits topics to include more words, a low beta value promotes sparsity in the topic-word distributions.

Learning method: Controls the method used by the model to update its parameters during training. Options include "batch" and "online" learning methods.

Learning decay: Adjusts the learning rate for online learning, often denoted by η in the context of online learning algorithms.

Number of iterations (passes): Specifies the number of iterations or passes over the dataset during training.

Table 3.2: Hyperparameters for LDA Model Tuning

N	Hyperparameter	Description	Tested Values
1	Number of Topics (K)	Determines the number of topics to be extracted from the corpus.	2–50
2	Alpha (α)	Controls the distribution of topics per document.	'auto', 0.01, 0.1, 1.0
3	Beta (β)	Controls the distribution of words per topic.	'auto', 0.01, 0.1, 1.0
4	Learning Decay	Controls the learning rate for online learning.	0.5, 0.7, 0.9
5	Eta (η)	controls the prior of the topic-word distribution. Learning rate in online learning.	'auto', 0.01, 0.1, 1.0
6	Number of Iterations	Specifies the number of iterations over the dataset during training.	5, 10, 20

Latent Dirichlet Allocation Model Training with different Hyperparameter Combinations:

Before model training, we transformed the text corpus into a document-term matrix using the CountVectorizer technique. Subsequently, we trained multiple LDA models, each corresponding to a unique combination of hyperparameters.

Subsequently, we computed coherence scores to assess the quality and interpretability of the generated topics under different hyperparameters. Higher coherence scores generally indicate better-defined and more interpretable topics. We evaluated three coherence measures: C_v coherence, U_{mass} coherence, and C_{NPMI} coherence.

Coherence Measures:

- $\mathbf{C_v}$ **Coherence**: Introduced by Röder et al. (2015), this measure evaluates semantic coherence based on a sliding window of top words, reflecting how well the top words within a topic fit together. C_v coherence scores evaluate a model's ability to capture cohesive semantic patterns in topics. Coherence scores offer insights into the textual organization, but their accuracy varies due to the inability of their direct estimation under the scikit-learn LDA maximum likelihood setting. Instead, Gensim's LDA framework, utilizing a sparse matrix representation from scikit-learn's CountVectorizer, is typically employed for coherence score calculations. Notably, Gensim's LDA performance may fluctuate, particularly with medium-sized databases, while the maximum likelihood method is generally considered more accurate. To avoid the impact of these fluctuations, we also adopt an alternative approach by computing k-fold cross-validation perplexity scores using maximum likelihood estimation within scikit-learn's framework. These perplexity scores serve as quantitative benchmarks for comparing models with different parameters. We consider perplexity scores with coherence scores for determining the optimal number of topics and learning decay selection.

- **$\mathbf{U_{mass}}$ Coherence**: Measures coherence using document co-occurrence statistics, assessing how well the top words within a topic (represented as probability distributions) fit together.

- **$\mathbf{C_{NPMI}}$ Coherence**: C_{NPMI} is a normalized variant of Pointwise Mutual Information (PMI). Pointwise Mutual Information (PMI) coherence scores measure the effectiveness of a model by comparing the observed co-occurrence of terms with their expected probability. Higher PMI values suggest stronger semantic relationships between terms within a topic, hence a coherent and interpretable topic. C_{NPMI} measures the normalized associativity between words, with values ranging from -1 to 1. C_{NPMI} considers the marginal probabilities of words, in this way it handles corpus-specific characteristics and is not biased towards pairs of words that co-occur by chance.

Optimizing LDA Model by Balancing Coherence Scores and Cross-Validation Perplexity:

We evaluated each LDA model using the coherence measures and regarded the hyperparameter combinations yielding the highest coherence score as candidate optimal configurations. Due to the criticism towards choosing hyperparameters by the coherence scores, we find the optimal mode by utilizing k-fold cross-validation perplexity scores with the coherence scores.

Perplexity Scores

As introduced in Seminal work by Blei et al. (2003), perplexity is algebraically equivalent to the inverse of the geometric mean likelihood, reflecting the model's word-level prediction accuracy on test data. Perplexity assesses the LDA model's ability to predict unseen data, like a held-out test set, based on learned topic distributions. Lower perplexity scores indicate better generalization and suggest effective capture of meaningful and transferable topics. Besides, if the plot of perplexity versus the number of topics shows an "elbow" point, this point is typically considered optimal. Identifying this "elbow" balances model complexity with predictive performance, ensuring that the topics are neither too broad nor too specific. The perplexity of a test set D_{test} is calculated as:

$$\text{perplexity}(D_{\text{test}}) = \exp\left(-\frac{1}{\sum_{d=1}^{M} N_d} \sum_{d=1}^{M} \log p(w_d)\right), \tag{3.1}$$

where D_{test} represents a held-out test set of Documents, M is the number of documents in the test set. N_d is the number of words in the d-th document w_d. $p(w_d)$ is the probability assigned to the d-th document by the LDA model.

By plotting perplexity scores against the number of topics, we can discern trends highlighting the point at which perplexity plateaus or demonstrates less pronounced declines. This inflection point often signifies an optimal number of topics for the dataset, where the balance between complexity and generalization is achieved (compare Blei et al. (2003)).

GridSearchCV

To determine the optimal number of topics for Latent Dirichlet Allocation (LDA), we conducted a grid search using grid search cross-validation (GridSearchCV) with 5-folds. The GridSearchCV technique assesses the LDA model's predictive capability by computing the average negative log-likelihood (of observing the given data) across cross-validation folds. Lower negative values are indicative of superior model performance. We GridSearched all three datasets: fully cleaned, raw, and sentiment-cleaned. Table C.1 presents the best three results for each dataset based on the log-likelihood scores. Using GridSearch, we tested learning decay rates of 0.5, 0.7, and 0.9, along with the number of topics up to 51. We chose this range due to the increasing trend of the cross-validation perplexity scores. To reach thoroughness, we also tested the number of topics 55, 65, 75, and 85. The results affirmed that our initial range was more appropriate.

Following an initial grid search on key parameters, we applied a sequential grid search approach to optimize the model by tuning additional parameters. Specifically, after optimizing the number of topics and learning decay, we conducted an additional grid search focusing on the document-topic prior (alpha) and topic-word prior (beta) parameters. Throughout this process, we evaluated candidate models with all fine-tuned hyperparameters using both, coherence and perplexity scores to ensure a comprehensive assessment.

Selection of Optimal Parameters: We determined the optimal hyperparameters by analyzing coherence scores and cross-validation perplexity. Additionally, we incorporated recommendations from GridSearchCV, which suggested hyperparameters including the document-topic prior (α) and topic-word prior (β) parameters. The selected hyperparameters facilitated the generation of coherent and interpretable topics from the text corpora and improved out-of-sample performance. We report the best coherence scores and perplexity scores, along with the corresponding optimal hyperparameters. This comprehensive approach ensures the selection of hyperparameters that effectively capture the underlying semantic structure of the text corpus, thereby enhancing the utility of LDA-based topic modelling approaches in natural language processing tasks.

3.3.5 Latent Dirichlet Allocation (LDA)

To quantify the textual data, we apply latent Dirichlet allocation (LDA) introduced by Blei et al. (2003) as a machine learning algorithm for topic modelling. One of the reasons why we chose LDA is that it is an unsupervised text approach. The LDA method fundamentally decomposes the content of the text into groups of terms referred to as topics and reduces the dimensionality of textual information. It presents the main statements of the text on a low-dimensional latent space. On a low-dimensional latent space, the documents belonging to similar topics are closer and more easily interpretable. The LDA method is categorized as an unsupervised learning algorithm to determine K, a given number of meaningful word groupings (topics) in the textual data, and to represent each text document about these groupings (topics). This method discloses the hidden subjects in unlabelled textual data deprived of connecting subjects to specific word lists before the estimation rather than imposing any rule on the data. The results of the LDA method determine which terms are essential for separating the contents of texts.

The following section outlines the fundamental concept of the LDA model. Consider a scenario where we have D documents, each including N terms, and the goal is to classify these terms into K topics. In Latent Dirichlet Allocation (LDA):

- **Documents** are modelled as probabilistic mixtures of latent topics. Each document is a combination of topics contributing to its content.

- **Topics** are defined by probability distributions over words, indicating the likelihood of each word associated with a given topic.

- **Terms** in documents are generated based on the topics present. Specifically, the topic distribution for that document influences the distribution of terms in each document (see Blei et al. (2003) for more details).

These components interact through a joint distribution function within a Bayesian statistical framework, which captures the relationships among documents, topics, and terms:

$$P(\varphi, \theta, z, w) = P(\theta)P(\varphi) \prod_{d=1}^{D} P(z|\theta) \prod_{n=1}^{N} P(w|\varphi, z), \tag{3.2}$$

where $\theta_{d(1:D)}$ is the topic distribution of document d, $\varphi_{k(1:K)}$ is the term distribution of topic k, $z_{dn(1:D,1:N)}$ is the topic distribution of the term n in document d, and $w_{dn(1:D,1:N)}$ is the distribution of term n in document d. The posterior probability of parameter θ is expressed as:

$$P(\theta|\alpha) = \frac{1}{B(\alpha)} \prod_{K} \theta_K^{\alpha_{K-1}}, \tag{3.3}$$

under the condition that $\sum_k \theta_{kD} = 1$.

The prior distribution for document-topic associations follows a Dirichlet distribution with parameter α, where $\alpha < 1$. The posterior probability for the parameter φ is expressed as:

$$P(\varphi|\beta) = \frac{1}{B(\beta)} \prod_{K} \theta_K^{\beta_{K-1}}, \tag{3.4}$$

under the condition that $\sum_n \varphi_{kn} = 1$.

The prior distribution for the topic-word associations follows a Dirichlet distribution with a positive parameter β.

3.3.6 LDA estimation

Figure 3.1 represents a graphic expression of the LDA model and shows how the topics derive from a given textual dataset. We follow the following procedure:

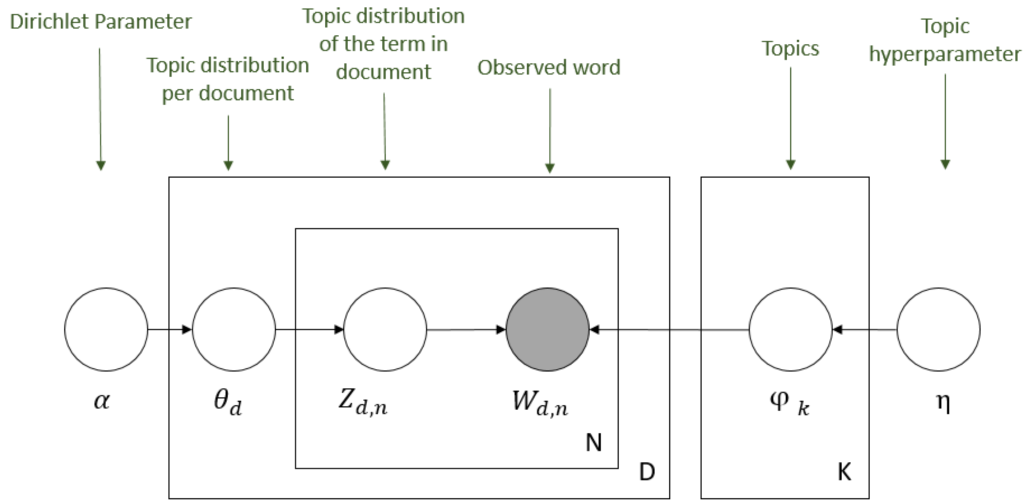


Figure 3.1: Estimation of LDA

This figure presents the procedure of estimating LDA.

There are two alternatives of Latent Dirichlet Allocation (LDA) model estimation in Python: the computationally demanding maximum likelihood method in scikit-learn and the Bayesian approach with Gibbs sampling provided by Gensim. The Appendix: Maximum Likelihood Estimation in Scikit-Learn's LDA describes how Latent Dirichlet Allocation (LDA) is estimated using the Maximum Likelihood Estimation technique implemented in Scikit-Learn. Meanwhile, theAppendix: Gibbs Sampler in Gensim's LDA explains how LDA is approached with a Bayesian framework and Gibbs Sampling, as implemented in the Gensim package.

3.3.7 Turning Text into Time Series

We turn text into time series as described in Thorsrud (2020), with the difference that in order to avoid data leakage, we exclude the step of standardization through the whole time spam on purpose.

We generate tone-adjusted time series of topic frequencies (represented as probabilities) for each topic. For chronological ordering, we utilize the timestamps attached to each news article.

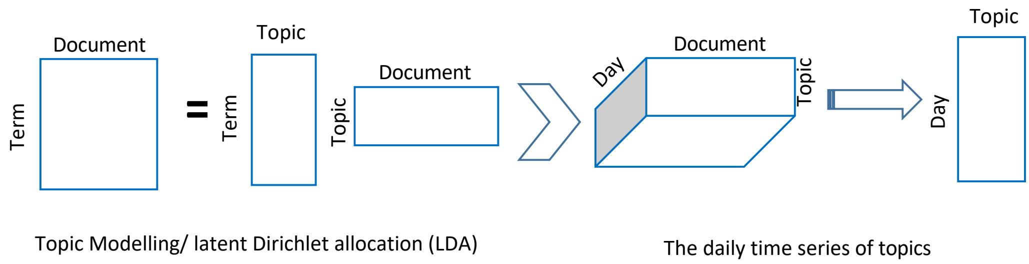
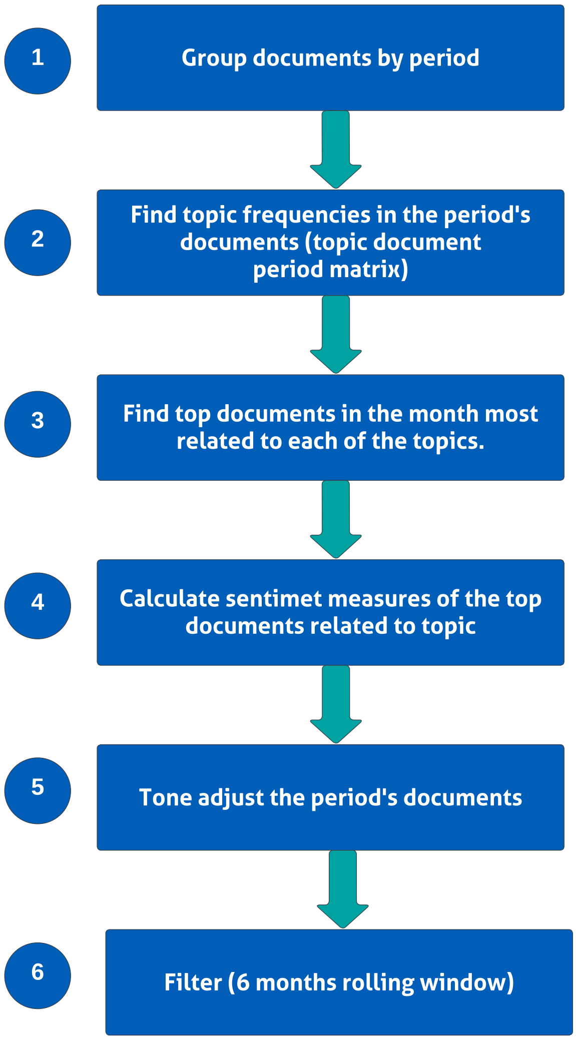


Figure 3.2: The Procedure of Creating Daily Time Series of Topics
This figure presents the procedure of creating a daily time series of topics. This figure is adapted from Sadoghi (2018). The LDA method uses the Term-Document matrix and extracts the given number of topics. The later step aggregates the information (Topic Probabilities) of topics on a daily base and creates a time series of topics.

First, we construct daily, monthly, and quarterly topic frequencies based on the news topics covered by the media. We aggregate the news by their publication dates into these time intervals to obtain the frequencies.

Then we find topic frequencies in the day's(month's and quarter's) document, a topic document day matrix(a topic document month matrix, a topic document quarter matrix). Find the top documents in the day (month, quarter) most related to each topics.

Figure 3.3: The Process of Converting Text Data into Time Series Representations



This procedure is conducted for all periods and creates a daily, monthly and quarterly time series.

3.3.8 Tone Adjustment

For each day and topic, we select the article most representative of that topic to determine the associated sentiment (positive or negative). We identify the top articles for each period by calculating topic probabilities for each document. We calculate topic probabilities using topic frequencies from our primary model and TF-IDF representation from the validating model (see the methodology in section C.18). Topic probabilities are computed using the scikit-learn LDA package by Pedregosa et al. (2011) as follows:

$$P(\text{topic } k \mid \text{document } d) = \theta_{dk} = \frac{n_{dk} + \alpha}{\sum_{k'} (n_{dk'} + \alpha)} \tag{3.5}$$

where:

- $P(\text{topic } k \mid \text{document } d)$ is the probability that topic k is assigned to document d.
- θ_{dk} is the probability that document d belongs to topic k.
- n_{dk} is the count of words assigned to topic k in document d.
- α is the Dirichlet parameter for document-topic distributions, controlling the prior distribution of document-topic probabilities.
- $\sum_{k'}(n_{dk'} + \alpha)$ sums over all topics k', ensuring that the denominator normalizes the probabilities across all topics for document d.

Sentiment Analysis for Tone Adjustment

To determine sentiment, we apply two measure: Tone Score and Polarity.

Tone Score: We calculate Tone Scores following the methodology outlined by Thorsrud (2020). This approach involves comparing the word usage in selected articles against a predefined list of positive and negative words from the *Harvard IV-4 Psychological Dictionary.* The resulting statistics, which reflect the balance between positive and negative words in the article, are used to adjust topic frequencies. The Tone Score for each article is computed as follows:

$$\text{Tone Score} = \frac{\text{Number of Positive Words} - \text{Number of Negative Words}}{\text{Total Number of Words}} \tag{3.6}$$

In Thorsrud (2020), tone adjustment is based on the tone of the article that best represents the topic within the given period.

Polarity Measure: Research suggests that polarity measures may provide superior performance compared to tone scores. To assess this, we compute the Polarity Measure in addition to Tone Scores and compare their effectiveness. The polarity of each article is calculated as follows:

$$\text{Polarity} = \frac{\sum(\text{Word Score in the Pre-defined Lexicon} \times \text{Frequency of the Word})}{\text{Total Number of Words}} \tag{3.7}$$

In our study, we employ the Polarity Measure, utilizing the Pattern Lexicon, where word scores range from -1 to 1. Our results demonstrate that the Polarity Measure provides superior performance compared to the Tone Score in the context of GDP nowcasting. Therefore, we use the Polarity Measure, calculated with the TextBlob Python library, as the primary metric for sentiment analysis.

3.3.9 Avoiding Data Leakages

To effectively avoid data leakage in our analysis, we implement the following strategies:

1. **Avoid Standardizing Text-Driven Variables**: Thorsrud (2020) utilizes a standardized time series of tone-adjusted topic frequencies. However, standardization across the entire sample can introduce data leakage, particularly due to the mean and standard deviation being influenced by future data points. This phenomenon, also known as look-ahead bias, distorts the model's ability to accurately reflect real-world predictive scenarios.

2. **Inclusion of Entire Text Domain for Frequency Filtering**: Following the guidelines from Kalamara et al. (2022), we refrain from excluding the top frequent and lowest frequent words based on the entire domain of texts. This approach ensures consistency in data preprocessing, as decisions regarding word frequencies are based solely on the corpus available at the time of nowcasting or forecasting. By avoiding premature exclusion of words, we prevent the introduction of biases that could affect the model's predictive accuracy.

3. **LDA Training using Count Vectorized instead of TF IDF Vectorized Data** To mitigate data leakage, we utilize Count Vectorized data instead of TF-IDF Vectorized for training and evaluating a Latent Dirichlet Allocation (LDA) model. This choice ensures that each document's word frequency representation is computed independently of the corpora, preventing inadvertent inclusion of information from validation or test data in the training process. This approach significantly enhances the robustness and integrity of both the model's training and evaluation phases.

4. **Calculate Topic Probabilities Using Topic Frequency Instead of TF-IDF Representation** Topic probabilities were calculated based on topic frequency rather than TF-IDF representation, providing a direct measure of each topic's prevalence in the dataset without considering inverse document frequency.

5. **Boolean Selection and POS Tagging for Relevant Texts**: By employing Boolean selection criteria and leveraging Part-of-Speech (POS) tagging, we identify and include only the segments of texts pertinent to our GDP modelling and forecasting objectives. This targeted approach isolates news narratives

that are highly relevant for business cycle analysis, ensuring that the model is trained and evaluated on data that reflects current economic conditions without incorporating irrelevant or future information.

Implementing these methodologies ensures our modelling approach maintains integrity and reliability in GDP nowcasting and forecasting. By addressing data leakage and employing best practices in data preprocessing and feature selection, we enhance model robustness and improve the accuracy of economic predictions based on real-time data insights.

3.3.10 Dynamic Factor model

The primary econometric model utilized in this study is the **Dynamic Factor Model** introduced by Geweke (1977). The DFM is widely regarded as the gold standard in academic nowcasting, as highlighted by Lehmann et al. (2020), which cites studies validating its effectiveness for GDP nowcasting. We construct dynamic factor model model with one unknown factor using the time series derived from news data and selected conventional variables. The goal is to capture the underlying economic dynamics with a single unknown factor, combining unconventional and traditional data sources. In selecting the model specifications, we utilized the Akaike Information Criterion (AIC) to determine optimal number of factors, factor autocorrelation order, and error autocorrelation order. The AIC criteria guided our choice by balancing model complexity and goodness-of-fit to favour a parsimonious yet effective specification. Based on the AIC comparison, we chose to model our data with one factor, factor order two, and error order two.[2]

We consider the following Dynamic Factor Model with 1 common factor f_t:
For each time period $t = 1, \ldots, T$, we have m-variate observation vector of $i = 1, \ldots, m$ with m input time series $\mathbf{Y}_t = (y_{1t}, \ldots, y_{mt})'$. Each element of $\mathbf{Y}_t$ can be written as follows:
Observation Equation

$$y_{i,t} = \alpha_i + \beta_i' f_t + \epsilon_{i,t} \tag{3.8}$$

State Equation

$$f_t = T_1 f_{t-1} + T_2 f_{t-2} + \eta_t, \tag{3.9}$$

where:

[2]We utilize the Akaike Information Criterion (AIC) instead of the Bayesian Information Criterion (BIC) because AIC tends to favour more complex models that provide a better fit to the data, which aligns with our focus on predictive accuracy. Furthermore, the model selected based on the AIC criterion is parsimonious, and cross-validation results support our model specification.

- i is the index of the input time series. $i = 1, \ldots, m$ where m is the number of input time series.

- $y_{i,t}$ is the observation at time t for the i^{th} input time series. The input time series are covariance-stationary.

- The α_i is the intercept of the i^{th} input time series. If the input time series is assumed to be zero mean, the α_i intercept becomes 0.

- β_i is factor loadings matrix for the i^{th} input time series, that is constant over time. It is a slope coefficient that quantifies how changes in f_t affect $y_{i,t}$.

- f_t is the (unobserved) state vector, vector of latent factors, at time t and represents the contributions of the variable i to the common factor. In case of one latent factor k=1, the latent factor is $\begin{bmatrix} f_{1,t} \end{bmatrix}$.

- $\epsilon_{i,t}$ is the idiosyncratic error term for the i^{th} input time series at time t. $\epsilon_t = (\epsilon_{1,t} \ldots \epsilon_{m,t})$ is a vector with dimensions $[1 \times m]$. $\epsilon_t \sim AR(2)$ and is modeled as white noise with independent innovations θ_t, where $\theta_t \sim N(0, \gamma^2)$. Therefore, $\epsilon_t \sim N(0, \gamma^2)$. The covariance matrix of ϵ_t is a diagonal matrix, as its covariances are set to be uncorrelated across different time cross-sections, $\text{Cov}(\epsilon_t, \epsilon_{t'}) = 0 \; \forall t \neq t'$.

- T_1 and T_2 are transition matrices.

- $\eta_t \sim N(0, \sigma_\eta^2)$ is the innovation term, irregular component. $E[\epsilon_t \eta'_{t-j}] = 0$ for all j. $\text{Cov}(\eta_t) = \sigma_\eta^2 I$, where σ_η^2 represents the variance of the innovations, reflecting uncorrelated innovations across time.

The observation equation for the dynamic factor model can be aggregated and written in matrix form as:

$$\mathbf{Y} = \mathbf{F}\mathbf{B}' + \epsilon, \tag{3.10}$$

where:

- The $\mathbf{Y}$ is the $[T \times m]$ matrix.

- The $\mathbf{B}$ is the $[m \times k]$ factor loadings matrix, the design matrix. In case of one latent factor k=1, $\mathbf{B}$ has dimensions $[m \times 1]$.

- The $\mathbf{F}$ is the $[T \times k]$ common factor matrix. In case of one latent factor k=1, $\mathbf{F}$ has dimensions $[T \times 1]$.

- ϵ is of dimentions $[T \times m]$.

In our model, we exclusively use lagged conventional variables to prevent information leakage and avoid look-ahead bias. This approach ensures that the model is estimated in pseudo-real-time, meaning that at each forecast horizon, we use only the data that was actually available up to that point in the past. Specifically, the model's input data consists of lagged values of the industrial production index and lagged values of exports, known at the nowcasting period, as well as news data up to the nowcasting period.

Given that the dynamic factor model assumes weak covariance stationary input time series (weak stationarity),i.e. that the expectation of y_t and its autocovariances do not vary with time and are finite, we ensure all inputs meet this criterion by differencing non-stationary time series. We stop here if the time series becomes stationary. If the time series exhibits exponential growth/decay and variance instability we log transform and differentiate the time series, if variance gets stable we use the first difference of the log-transformed data. If it is still nonstationary we continue to second differencing.

Including intercepts that have been calculated or derived from the same dataset used for model training can lead to data leakage. Therefore, we do not utilize the means of the input time series to consider intercepts in our dynamic factor model, especially given that the means of our text-driven time series are approximately 0. Instead, we set $\alpha_i = 0$ and ensure that the input time series have a mean close to zero.

We ensure that no significant mean differences exist between the input time series by keeping the means to 0. This approach prevents the use of the dataset-wide means as intercepts. To assess mean differences between pairs of input time series, we perform T-tests, with significance determined by a p-value threshold of 0.05.

For stationary time series, we first check for significant mean differences between them. If we find significant differences, we apply first differencing to the affected time series to achieve stationarity.

For open-end data, we ensure continuous data streaming using the dynamic factor model, which provides robust and accurate estimates (maximum likelihood estimation via Kalman filter), even with open-end data. This capability relies on the **Kalman filter's recursive updates** and iterative state variable fitting within the dynamic factor model, demonstrated in the appendix (see Appendix: Kalman Filter's Recursive Updates).

Coefficients of determination (R^2 values of the regression of each observed variable on the estimated factors) assess the explanatory power of each observed variable on the variance of the estimated factors. These R^2 values quantify the contribution of individual observed variables to the variability captured by the factors. Higher R^2 values indicate a stronger association between the observed variable and the latent factor, suggesting that the variable provides substantial information about the economic condition.

These R^2 values offer valuable insights into the relative importance of different input variables in explaining the variability of the unobserved factor. By analyzing these values, we can pinpoint which variables exert substantial influence on the underlying economic trends. This enables informed prioritization of variables for further analysis and decision-making.

When working with a model containing a combination of first-differenced and level variables, it's crucial to interpret the R^2 values accordingly. Direct comparisons of R^2 values may not be appropriate due to the differing transformations. Specifically, we should understand the R^2 for the first differenced variables as indicators of the explanatory power of the changes in input time series on the unobserved factor. Also, it's important to note that R^2 is sensitive to scales.

It's worth noting that a low ^{2} value does not necessarily mean that a variable lacks significance. It may still provide valuable complementary information, contribute to small movements that enhance the dynamic factor's forecasting ability, and ultimately lead to overall model improvement.

3.3.11 Selection of Benchmark Indicator - ifo Business Climate Index (BCI)

We choose the ifo Business Climate Index (BCI) as our benchmark indicator and compare it with our own index for model evaluation purposes. The rationale behind selecting the ifo BCI stems from its established status as a premier leading indicator for gross domestic product (GDP) in Germany.

- **Long-standing Establishment:** The ifo Institute, Germany's largest business survey provider, has been conducting the ifo Business Climate Germany index since 1949 (Lehmann, 2023).

- **Frequency and Coverage:** This index is formulated monthly, drawing insights from a diverse spectrum of German firms spanning manufacturing, service, trade, and construction sectors.

- **Robust Sampling:** With a substantial pool of responses from approximately 9,000 German companies, the index offers a comprehensive and reliable snapshot of business sentiment and economic outlook.

- **Superior Predictive Accuracy:** In recent literature, as highlighted by Lehmann (2023), the ifo Business Climate Index for Industry and Trade has consistently demonstrated superior predictive accuracy for GDP compared to alternative indicators, such as hard data published by the Federal Statistical Office of Germany or diffusion indexes based on factor models Lehmann and Reif (2021); Heinisch and Scheufele (2019); Bandholz and Funke (2003).

In summary, the ifo Business Climate Index emerges as an ideal benchmark due to its timeliness, broad sector coverage, and well-established track record in economic forecasting literature.

3.3.12 Identifying business cycle regimes by Markow Switching Model

To assess the accuracy of our estimates across different economic conditions, we employ a Markov switching model to delineate distinct business cycle regimes.

As regime-switching models, especially Markov-switching models of real GDP, are known to predict business cycle switching in a timely manner (Chauvet and Piger (2002)) we build a Markov switching model with 3 states to identify and forecast business cycle states. Then we use the results of Markov switching model to see how our model performs in each state. The three states correspond to expansions, normal recessions and crisis. Many works, including Carstensen et al. (2020) suggest that a three-state Markov switching identifies business cycle turning points more appropriately.

The Markov switching (MS) model (proposed by Hamilton and Susmel (1994)) enables generating time series of the recession probabilities derived from the historical data of the indicator. Our three-state MS model finds expansion, recession and crisis probabilities through assuming that transitions between states is controlled by a state variable that follows the n-order, in our case 4 order, Markov process, i.e. the probability distribution of state in time t given the previous states only depends on the most recent 4 states. We build the version of Markov switching regression model by Kim and Nelson (2017), with 4 order autoregressive lag polynomial. The MS model applied by us can be written as:

$$
\begin{aligned}
y_t = aS_t + x_t'\beta S_t + \Phi_{1,S_t}(y_{t-1} - aS_{t-1} - x_{t-1}'\beta S_{t-1}) \\
+ \ldots + \Phi_{4,S_t}(y_{t-4} - aS_{t-4} - x_{t-4}'\beta S_{t-4}) + \epsilon_t,
\end{aligned}
\tag{3.11}
$$

where $\epsilon_t \sim N(0, \sigma^2_{S_t})$. The autoregressive coefficients Φ_{k,S_t} for $k \in (1, 2, 3, 4)$, mean of the process and the variance of error term $\sigma^2_{S_t}$ can switch across regimes. The parameter vector inclusive regime probabilities are estimated by the maximum likelihood method.

3.4 Data

In this study, we use two types of information, namely, hard and soft information. The former type of information is about macroeconomic indicators of Germany on a low, monthly, frequency. The following type of information is textual data in a high frequency which are available on an intraday basis and in an unstructured format.

This paper utilizes textual data published in Germany over a 14-year period, from 2010 to 2023.

We construct our textual dataset from news items related to GDP using the Nexis-Uni database, which contains over 84 billion public records. Our focus is on news items from online publishers. We use the keywords listed in Table 3.1 to search for relevant news articles. This search yields over 9 million unique German-language articles and over 8 million English-language articles. To analyze the articles specifically discussing the German GDP, we apply the Boolean method described in the methodology section, specifically in the subsubsection 3.3.1.

The final filtered German data corpus, with no duplicates and our boolean method (after removing the texts that include "Deutsch/Deutsche/Deutschland" less than 3 times) includes 16,517 documents and 484,964 sentences. If we consider dependent complex sentences as separate sentences, the count increases to 1,208,962 sentences.

The final, filtered English data corpus, with no duplicates, includes 59,271 documents. After additional cleaning, which involved removing texts containing the words 'German' or 'Germany' less than three times, and excluding texts that do not mention one of the following phrases: 'German GDP', 'Germany's GDP', 'German real GDP', 'GDP in Germany', or 'German', we are left with 20,625 news articles.

The hard information, specifically the macroeconomic variables, includes lagged data of First Release GDP Growth calculated by the First Release GDP from the German Central Bank ("Deutsche Bundesbank"), with the code BBKRT.Q.DE.Y.A.AG1.CA010.A.I.

We also include the lagged industrial production index as an input in the dynamic factor model. We take the monthly, seasonally adjusted industrial production index from OECD and with OECD code PRINTO01.

In the final Dynamic Factor model, we add exports of Germany, which we take from Thomson Reuters Eikon - Data (BD EXPORTS OF GOODS (FOB) CURA).

Subsection C.2 in the appendix presents descriptive statistics of the model variables.

3.5 Results and Discussion

In this results section, we present the findings of our nowcasting study utilizing German news media texts. We first applied Latent Dirichlet Allocation (LDA) to identify topics related to German GDP. Subsequently, we processed the LDA output to derive time series data on the frequencies of these topics over time. Next, we analyzed sentiment and subjectivity trends within the news articles, adjusting the tone of the identified topics using a polarity sentiment measure.

We incorporated these tone-adjusted topic frequencies with lagged and first-differenced industrial production index and exports into a dynamic factor model. Additionally, to enhance the nowcasting accuracy we removed past-related content from the texts and repeated the process to build dynamic factor models. We present the nowcasts and the performance of our dynamic factor modelling for datasets with and without historical information.

3.5.1 News-Derived Topics Related to German GDP

In this subsection, we present the findings from our Latent Dirichlet Allocation (LDA) analysis conducted on extensive news articles related to the German GDP. Hereby we present the LDA results for the sentiment-cleaned dataset, that delivers the best performance at nowcasting GDP growth. The LDA results of the raw dataset and of the fully cleaned news dataset are illustrated in the appendix subsubsection C.6, titled: "LDA Analysis Results". For each dataset, we identified 5 topics using the Latent Dirichlet Allocation (LDA) model. The comprehensive parameter fine-tuning is detailed in the appendix , titled: "LDA Model Parameter Tuning Results". This fine-tuning process ensured that our LDA model was optimized to generate coherent and semantically meaningful topics.

LDA Results with Sentiment-Cleaned News Dataset

The Sentiment-cleaned news dataset excludes sentences pertaining to past events when calculating sentiments and removes sentences from articles written during crisis periods. Using this curated dataset, we employed the LDA algorithm from the scikit-learn library in Python to identify topics related to the German GDP. The five topics identified from the sentiment-cleaned dataset using the LDA scikit-learn library algorithm in Python are summarized below in the Topic Summary.[3]

[3]We chose the scikit-learn library because its algorithm achieves better convergence of perplexity, whereas gensim requires extensive optimization and regularization.

Topic Summary

Topic 1: Economic Performance Assessment and Market Dynamics[4]

Key Terms: Prozent (percentage), Wirtschaft (economy), Quartal (quarter), Wachstum (growth), Konjunktur (economic situation), Monat (month), Steigen (grow), Erwarten (expect), Unternehmen (Companies), Rezession (Recession), Rückgang (decline), Bund (federal government), Euro (Euro), Punkt (point), Rechnen (calculate), Wirtschaftsleistung (economic performance), Lage (state), Stimmung (sentiment), Prozent Prozent (percent percent)[5], Stehen (stand), Industrie (industry), Folge (consequence), Wirtschaftswachstum (economic growth), Milliarde (billion), Entwicklung (development), Ökonomen (economists), Anstieg (increase), Vergleich (comparison), Fallen (fall), Experte (expert), Zahl (number), Konsum (consumption), Sehen (see), Prognose (forecast), Ende (end), Einschätzung (assessment), Inflation (inflation), Sinken (sink), Erholung (recovery), Aufschwung (upswing), Liegen (lie), Volkswirtschaft (national economy), Bundesregierung (federal government), Bruttoinlandsprodukt (gross domestic product), Wachsen (grow), Geben (give), Milliarde Euro (billion euros), Verbraucher (consumer), Legen (lay), Institut (institute).

Topic 2: Macroeconomic Indicators and Business

Key Terms: Prozent (percentage), Wirtschaft (economy), Unternehmen (companies), Wachstum (growth), Milliarde (billion), Konjunktur (economic situation), Quartal (quarter), Bund (federal government), Stehen (stand), Rechnen (calculate), Euro (Euro), Rezession (recession), Wirtschaftsleistung (economic performance), Folge (consequence), Steigen (rise), Sehen (see), Monat (month), Bundesregierung (federal government), Zeit (time), Land (country), Rückgang (decline), Ökonomen (economists), Daten (data), Investition (investment), Legen (place), Geben (give), Wirtschaftswachstum (economic growth), Milliarde Euro (billion euros), Volkswirtschaft (national economy), Experte (experts), Vergleich (comparison), Einschätzung (assessment), Ende (end), Erwartung (expectation), Arbeitsmarkt (labour market), Mensch (person), Entwicklung (development), Staat (state), Woche (week), Aufschwung (upswing), Angabe

[4] These titles are provided for reference purposes and serve as notations within our analysis. ChatGPT has generated the following titles: 1. Economic Outlook and Growth Trends, 2. Business Performance and Economic Indicators, 3. Business and Economic Forecasting, 4. Global Economic Concerns and Market Dynamics, 5. Financial Markets and Government Policies.

[5] The bigram "percent percent" is produced when we delete numbers and connecting words from sentences discussing percentage change or approximate percentages. For instance, "has grown from 10 percent to 10.4 percent".

(indication), Lage (situation), Punkt (point), Industrie (industry), Konsum (consumption), Zahl (number), Wachsen (grow), Sinken (fall), Zeigen (show), Geld (money).

Topic 3: Economic Performance and Consequences

Key Terms: Prozent (percentage), Wirtschaft (economy), Unternehmen (companies), Quartal (quarter), Wachstum (growth), Monat (month), Konjunktur (economic situation), Euro (Euro), Rechnen (calculate), Lage (situation), Steigen (rise), Volkswirtschaft (national economy), Ende (end), Wirtschaftsleistung (economic performance), Folge (consequence), Bundesregierung (federal government), Bund (federal government), Vergleich (comparison), Sehen (see), Milliarde (billion), Industrie (industry), Stimmung (mood), Firma (company), Wirtschaftswachstum (economic growth), Stehen (stand), Investition (investment), Messe (fair), Erwarten (expect), Konsum (consumption), Entwicklung (development), Prozent Prozent (percentage points), Staat (state), Land (country), Auto (car), Zahl (number), Zeit (time), Ökonomen (economists), Arbeitsmarkt (labour market), Politik (politics), Aufschwung (upswing), Verbraucher (consumers), Bank (bank), Geben (give), Risiko (risk), Mensch (person), Sinken (fall), Experte (expert), Inflation (inflation), Rezession (recession), Rückgang (decline).

Topic 4: International Trade and Market Conditions

Key Terms: Prozent (percentage), Wirtschaft (economy), Unternehmen (companies), Land (country), Milliarde (billion), Stehen (stand), Staat (state), Sehen (see), Mensch (person), Wirtschaftsleistung (economic performance), Ende (end), Monat (month), Liegen (lie), Wachstum (growth), Volkswirtschaft (national economy), Geben (give), Bund (federal government), Firma (company), Steigen (rise), Industrie (industry), Wert (value), Quartal (quarter), Entwicklung (development), Handelsstreit (trade dispute), Präsident (president), Wirtschaftswachstum (economic growth), Rezession (recession), Drohen (threaten), Dollar (dollar), Lage (situation), Euro (Euro), Woche (week), Konjunktur (economic situation), Ökonomen (economists), Milliarde Dollar (billion dollars), Vergleich (comparison), Rechnen (calculate), Handelskonflikt (trade conflict), Bundesregierung (federal government), Zeit (time), Handelskrieg (trade war), Wachsen (grow), Brexit (Brexit), Treffen (meeting), Tag (day), Stimmung (mood), Verbraucher (consumers), Seite (side), Einschätzung (assessment), Folge (consequence).

Topic 5: Financial Markets and Economic Policies

Key Terms: Prozent (percentage), Unternehmen (companies), Wirtschaft (economy), Euro (Euro), Land (country), Milliarde (billion), Stehen (stand), Sehen (see), Bank (bank), Ende (end), Milliarde Euro (billion euros), Zeit (time), Entwicklung (development), Mensch (person), Monat (month), Firma (company), Zahl (number), Woche (week), Regierung (government), Geld (money), Geben (give), Staat (state), Markt (market), Steigen (rise), Bundesregierung (federal government), Liegen (lie), Politik (politics), Wachstum (growth), Teil (part), Folge (consequence), Aktie (share), Welt (world), Tag (day), Industrie (industry), Dollar (dollar), Stellen (positions), Zukunft (future), Risiko (risk), Problem (problem), Investition (investment), Krise (crisis), Thema (topic), Preis (price), Setzen (set), Vergleich (comparison), Wert (value), Geschäft (business), Kosten (costs), Konjunktur (economic situation), Treffen (meeting).

The first topic, "Economic Performance Assessment and Market Dynamics," entails a comprehensive evaluation of economic performance indicators. This topic includes the following aspects: growth, economic conditions, recession, economic performance, decline, recovery, upswing, GDP, sector-specific analyses (calculation, economists, Euro, Milliards, experts, assessment, sentiment), and inflation trends (inflation, consumer).

The second topic, "Macroeconomic Indicators and Business," revolves around the interplay between business performance and critical macroeconomic indicators. These include, on one side, business (company as a third term, industry), and on the other side, the federal government, macroeconomic indicators: growth, employment rates (labour market, person), consumer spending patterns (expectation, consumption), business cycle, and investment trends.

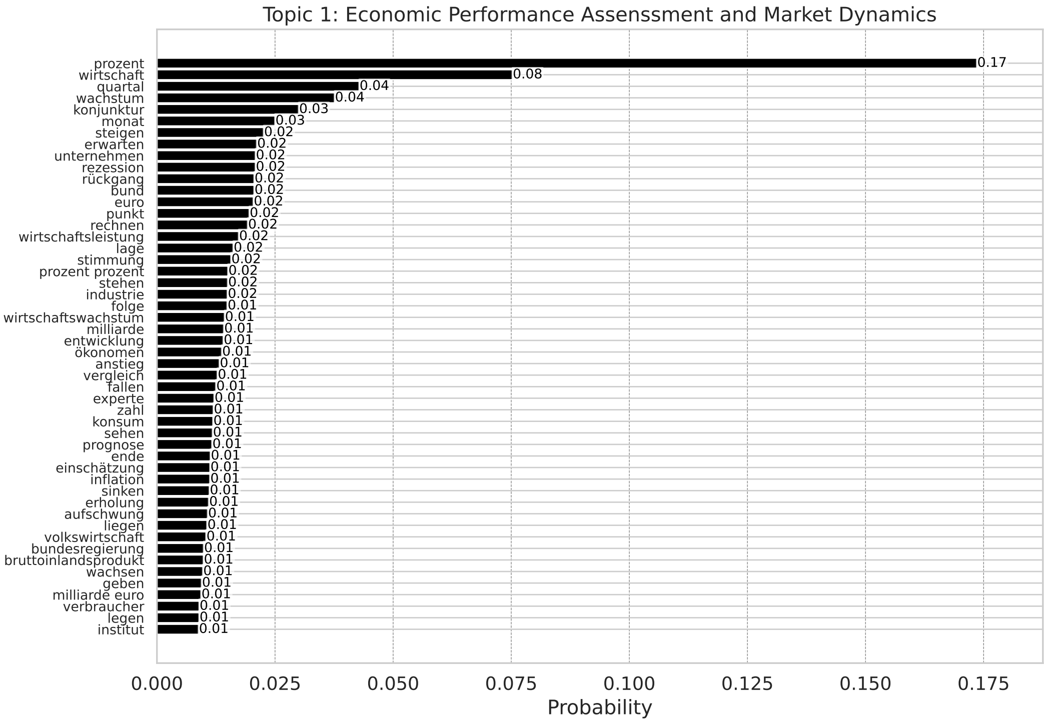
The third topic, "Economic Performance and Consequences," focuses on the consequences of the economic situation. It involves the impacts on mood, investment, the labour market, expectations, consumer behaviour, auto sales, inflation, and associated risks affecting economic stability and growth.

The fourth topic, "International Trade and Market Conditions," explores themes: global trade disputes, the effects of geopolitical events like Brexit and trade wars, currency (including the dollar), corporate responses, and their implications for economic performance.

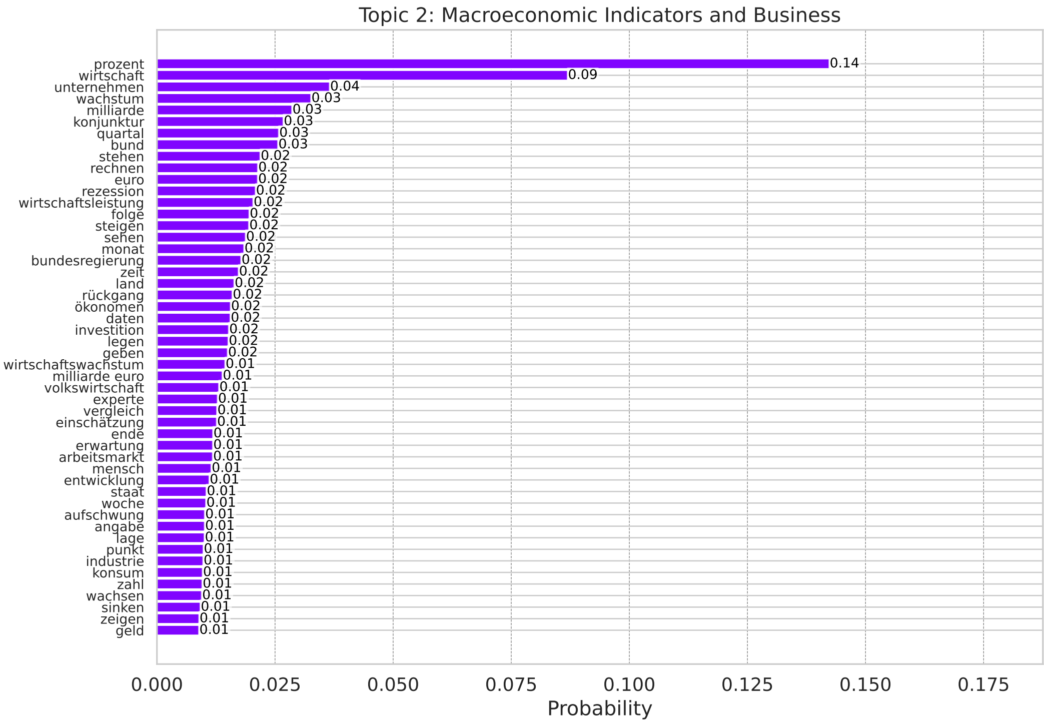
Finally, the fifth topic, "Financial Markets and Economic Policies," delves into the intersection of financial markets and governmental economic policies. The topic discusses dynamics in banking, monetary policies, government, stock market movements, investment strategies, associated risks, and costs.

The list of top terms in the Topic Summary and the topic coherence network graph (Figure C.17) in the appendix demonstrate that several terms recur frequently across different topics. Given that LDA is a probabilistic topic model based on the concept that words are not exclusive to a single topic but rather have probabilities of occurring in multiple topics depending on the context, these recurrences are expected and reflect the underlying structure of the data. Besides, it is reasonable to have keyword overlaps, as it ensures that topics remain relevant to GDP while discussing other related areas. We explored the impact of removing these recurring terms, as detailed in the appendix subsubsection C.13, titled: 'Top Topic Terms Analysis with Recurrent Term Removal.' However, this intervention did not significantly enhance our results. Theoretical evidence supports the notion that creating a custom stoplist specifically tailored to the corpus provides minimal benefit for model training. Therefore, we adopted a more pragmatic approach, focusing on the removal of only the most common and universally identifiable stopwords. This method has proven more effective than recurrent word removal in prior studies Schofield et al. (2017), and as such, we refrained from further removal of top common words after eliminating standard stopwords.

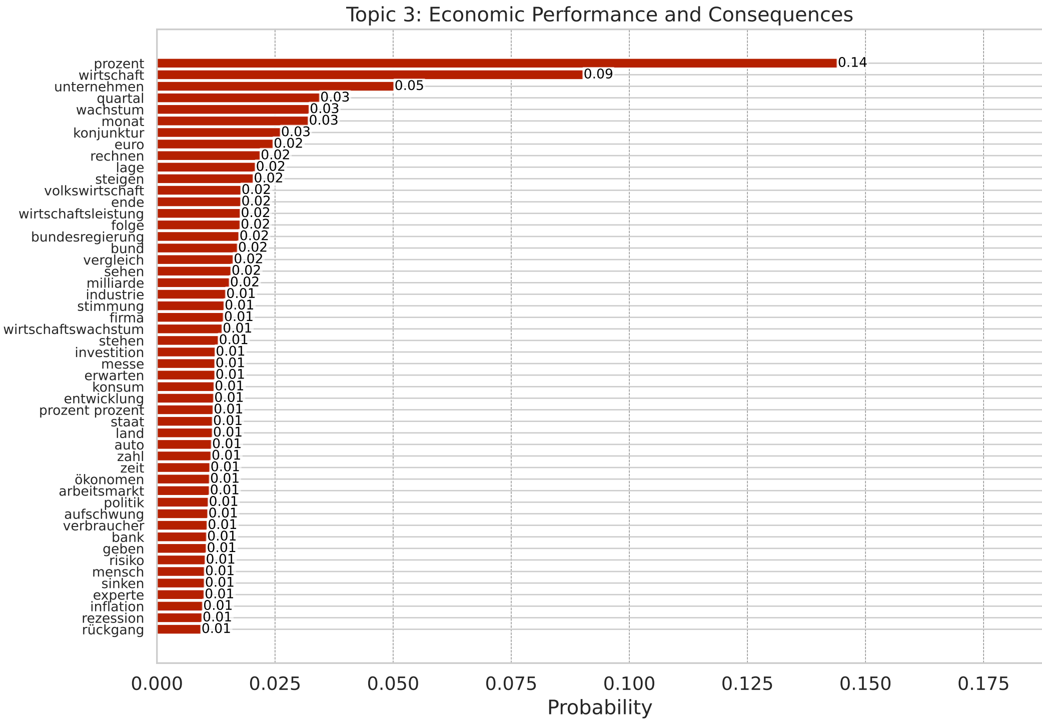
Figure 3.4 illustrates topic term probability distributions, which offer deeper insights into the significance and distinct characteristics that top terms contribute to each topic. The recurrence of certain terms across topics highlights their multifaceted roles within our dataset. Some terms show strong associations with specific topics while playing less prominent roles in others, emphasizing their importance in capturing the wide-ranging themes and nuances in the data.



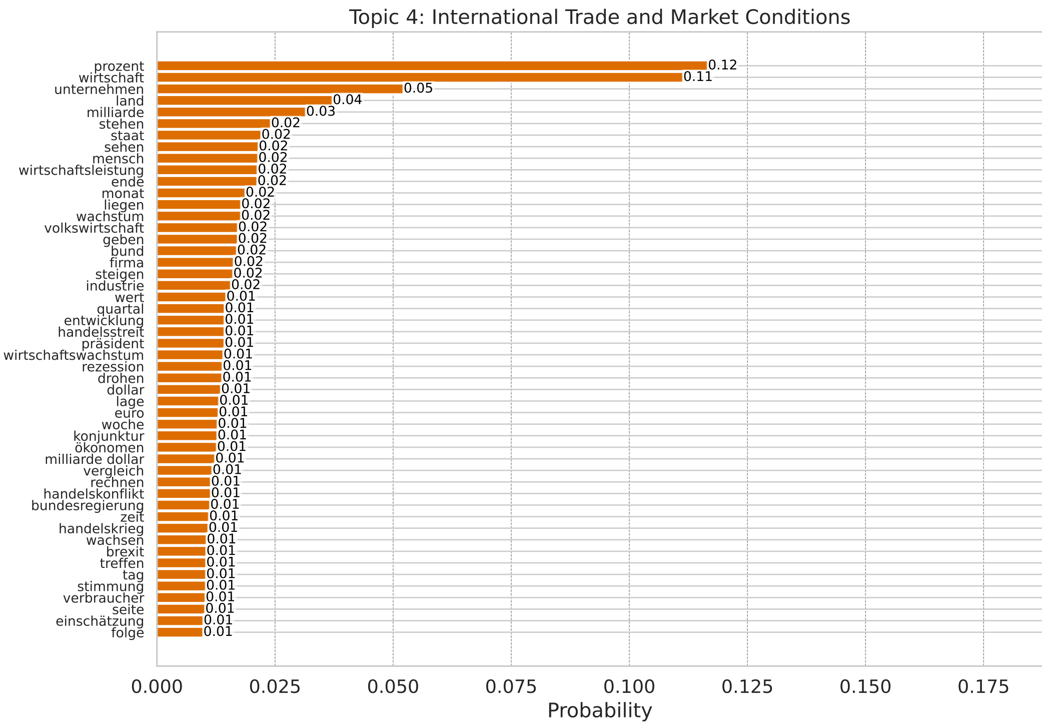
(a) Top Terms in Topic 1



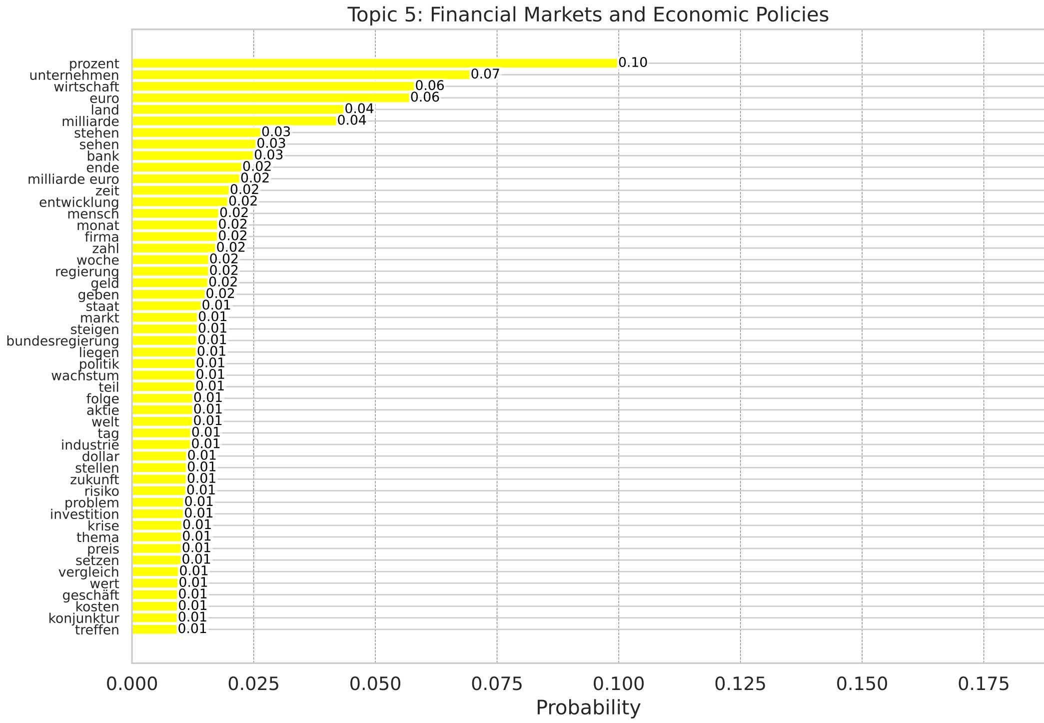
(b) Top Terms in Topic 2



(c) Top Terms in Topic 3



(d) Top Terms in Topic 4



(e) Top Terms in Topic 5

Figure 3.4: Probability Distributions of Top Terms in each Topic.
Note: The figure depicts the likelihood of the top terms appearing in each respective topic.

Overall, our analysis reveals coherent topics linking GDP with macroeconomic indicators, business dynamics, social implications of GDP growth, international trade, financial markets, and economic policies. This alignment underscores the interconnected nature of these factors in discussions surrounding GDP.

3.5.2 Sentiment Analysis in News

We start by analyzing the daily sentiment of GDP-related news articles over time. A high polarity score in these articles reflects positive sentiment, indicating that the articles generally convey optimistic or favourable opinions, attitudes, or emotions.

Figure 3.5 shows the overall daily polarity of the news in the initial raw dataset. This figure illustrates how the sentiment in GDP-related news has evolved. Notably, the sentiment of German GDP-related news exhibits increased variance over the past five years.

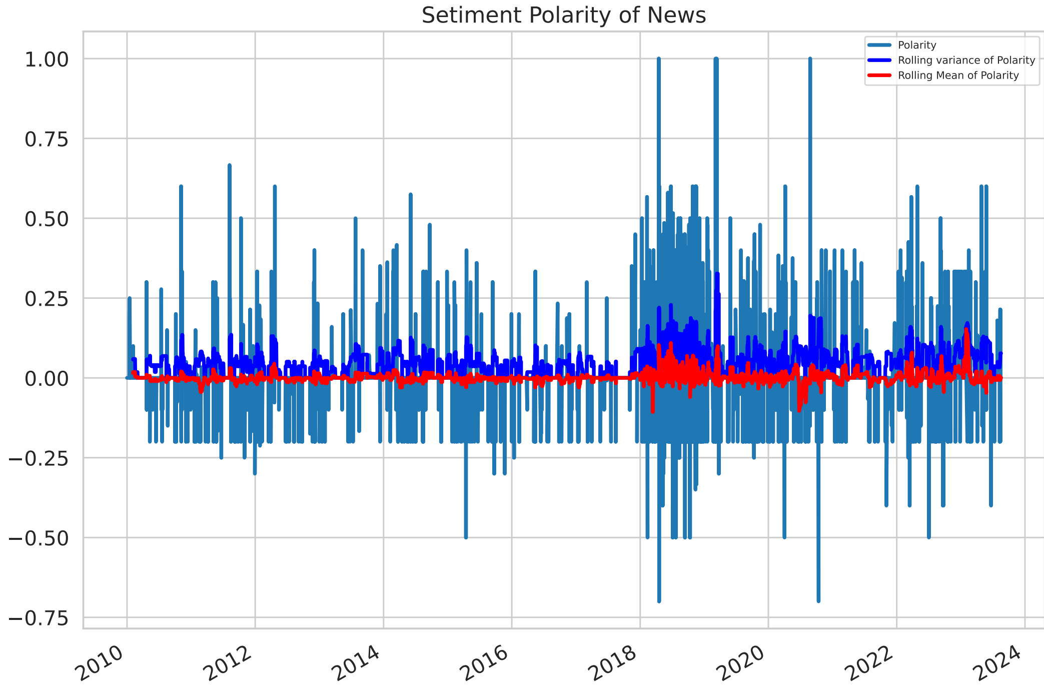


Figure 3.5: Polarity of News over Time in the Raw (Initial) Dataset
The figure illustrates the polarity of all GDP-related news over time, including its rolling variance and rolling mean. The red solid line represents the 30-day rolling mean of the polarity. The azure blue solid line represents the 30-day rolling variance of the polarity.

Figure 3.6 visualizes the overall daily polarity of the dataset, with past tense sentences removed from the sentiment. Comparing the overall polarities from this sentiment-cleaned dataset with those from the original dataset reveals significant shifts in polarity values, as well as changes in mean and variance. These differences highlight the impact of removing past-related textual content on sentiment analysis.

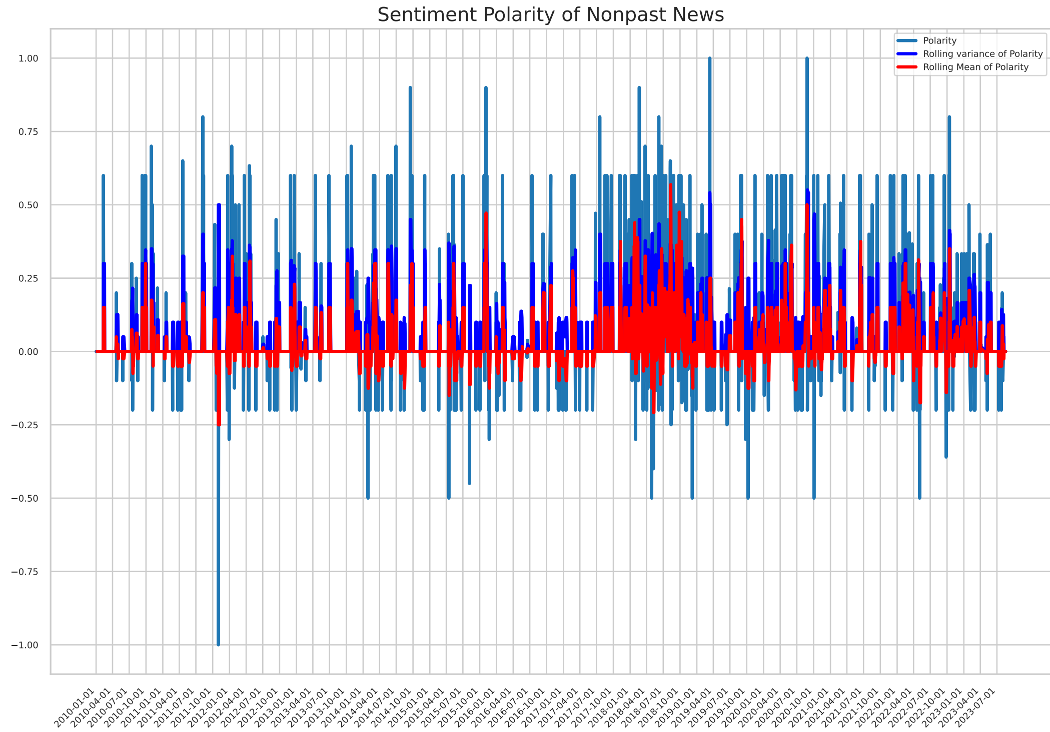


Figure 3.6: Polarity of News Over Time in Sentiment-Cleaned Dataset
The figure represents the polarity of all GDP-related news over time with its rolling variance and rolling mean. The red solid line is the 30-day rolling mean of the polarity. The azure blue solid line is the 30-day rolling variance of the polarity. Here, we employ a rolling window of 4 days.

The observed increase in daily sentiment and its rolling mean coincides with the period of the German government elections in September 2017 and the subsequent aftermath. This correlation suggests that the elections and their outcomes may have influenced public sentiment.

The overall monthly polarity of the sentiment-cleaned dataset is illustrated in Figure 3.7. The plot reveals that monthly sentiment was notably negative in August 2011, coinciding with the peak of the Eurozone balance-of-payments crisis. Additionally, the sentiment during the GDP decline in 2020 was the second most negative across the entire period.

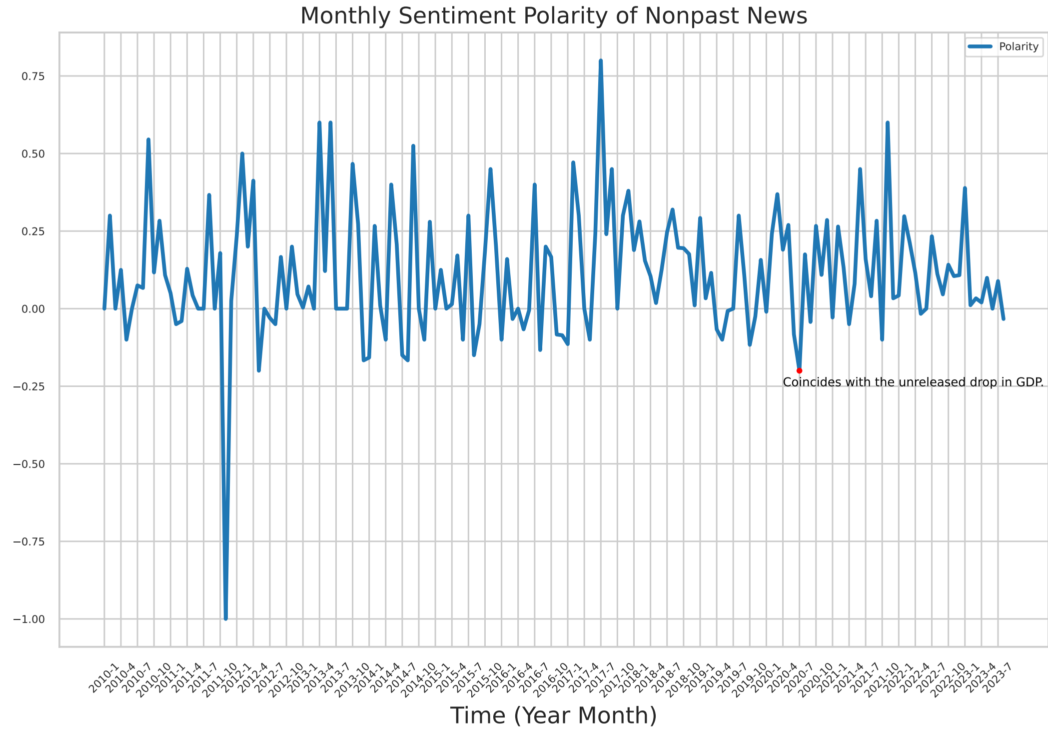


Figure 3.7: Polarity of News Over Time in Sentiment-Cleaned Nonpast Dataset
The figure represents the monthly polarity of all GDP-related news over time.

For comparison, the daily and monthly polarities of the fully cleaned non-past dataset—excluding past tense sentences from sentiment and incorporating topic frequency time series—are depicted in the appendix (Figure 3.6 and in Figure C.20).

Figure 3.8 illustrates the monthly polarity for each topic in the sentiment-cleaned dataset. For each period, the polarity of each topic is derived from the sentiment of the most relevant papers associated with that topic.

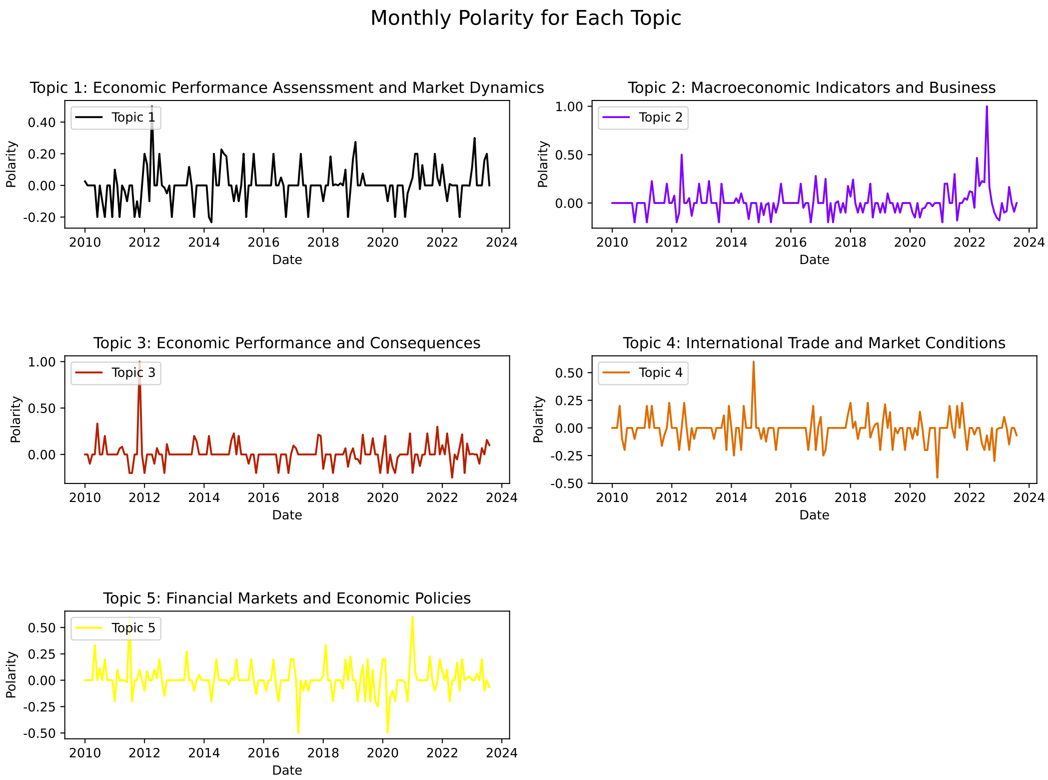


Figure 3.8:
Monthly Polarity for Each Topic Over Time in Sentiment-Cleaned Dataset
The figure represents the monthly polarity of GDP related Topics over time.

3.5.3 Dynamic Factor Prior to Eliminating Past Tense Sentences

Our monthly dynamic factor model incorporates tone-adjusted topic frequencies time series as input variables. In addition to this dataset, we incorporate the first difference of lagged industrial production index and export data into the model, acknowledging Germany's significant export orientation.[6] These additional time series data provide insights into the recent changes in the Industrial Production Index and exports based on the latest available economic data. This approach allows our model to integrate recent developments, contextualize news information, and offer an up-to-date understanding of the current state of the economy.

Figure 3.9 presents the monthly dynamic factor from our model, which was constructed using the initial raw data, augmented by first-differenced lagged industrial production index and first-differenced lagged export data. A visual inspection reveals that the monthly dynamic factor from the raw dataset exhibits substantial variation. Notably, it shows pronounced volatility from September 2014 to 2016, despite the actual GDP growth fluctuations being relatively modest. While the dynamic factor provides an early indication of increased volatility during the COVID-19 crisis, both during downturns and upswings, it does not correlate precisely with GDP growth

[6]We have taken into account the correlation between IPI and exports (0.4) and the Variance Inflation Factor values to ensure that collinearity does not significantly affect the model.

movements. Additionally, quarterly averages of the monthly dynamic factor fail to capture the large GDP growth downturn in the second quarter of 2020 and the subsequent large upswing in the third quarter of 2020.

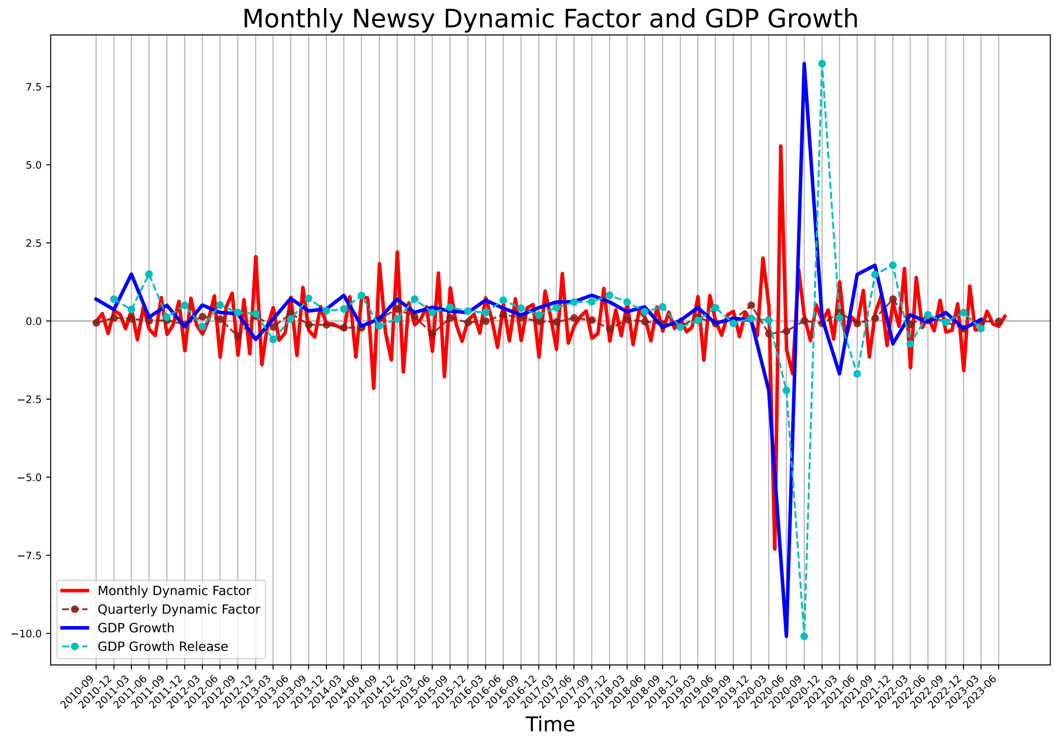


Figure 3.9: Dynamic
Factor Extracted from Raw News Dataset and First Release GDP Growth
The figure illustrates the dynamic factor derived from the raw news dataset and compares it with the initial release of GDP growth. The red line indicates GDP growth released with a one-month delay, while the blue line represents the dynamic factor.

In the following, we focus on quarterly level to capture a less volatile dynamic factor that accurately reflects the rapid downturn in GDP growth during the second quarter (Q2) of 2020 and the subsequent upswing in the third quarter (Q3) of 2020. We developed a quarterly dynamic factor model, which integrates quarterly raw news time series with first-differenced lagged values of the industrial production index and exports. Instead of averaging monthly dynamic factors, our approach uses quarterly raw news data directly, which includes quarterly topic frequencies and sentiments. We obtain these from an LDA model applied to news aggregated at a quarterly frequency and perform sentiment analysis on the most representative articles for each topic each quarter. Figure 3.10 illustrates the quarterly dynamic factor.

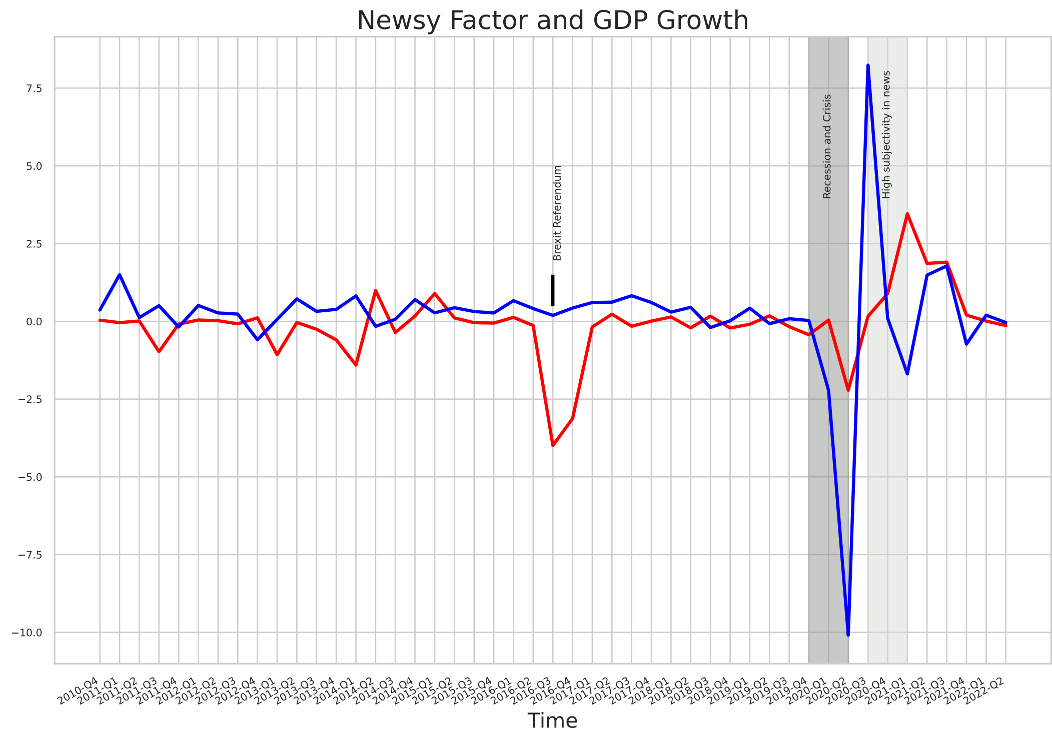


Figure 3.10: Quarterly
Dynamic Factor Based on Quarterly Raw News VS First Release GDP Growth
The figure presents the quarterly dynamic factor based on raw news data compared with the first release of GDP growth. The red line represents GDP growth, which is released with a one-month delay, while the blue line depicts the dynamic factor extracted from the raw dataset.

Although the quarterly dynamic factor model, constructed from raw news data, provides insightful results, it exhibits notable limitations in fitting the realized GDP, especially during and after Brexit and periods of economic crisis. Manual inspections reveal that these limitations arise from journalistic references in the news articles that either recall past events for comparison or draw parallels with historical situations. To address this issue, we preprocess the articles by removing past-tense sentences, thereby reducing the influence of historical references on the model's performance.

We hypothesize that journalistic references in news articles, which recall past events for comparison or draw parallels with historical situations, may contribute to the limitations of the dynamic factor model when using raw data to nowcast GDP growth. To test this hypothesis, the following subsection presents the reconstruction of the dynamic factor model, this time excluding past-related sentences from our dataset.

3.5.4 Dynamic Factor for Fully Cleaned Dataset

Figure C.23 illustrates the dynamic factor derived from a corpus thoroughly cleaned of past information. Compared to the monthly factor obtained from the model utilizing raw data, this cleaned factor shows reduced noise and better alignment with GDP growth, though it still struggles to detect the COVID-19 crisis. Moreover, Figure 3.12 presents the resulting dynamic factor captures GDP movements less than the very well acknowledged Business Climate Index. These deficiencies in the dynamic factor's ability to capture GDP growth may be attributed to excessive data cleaning.

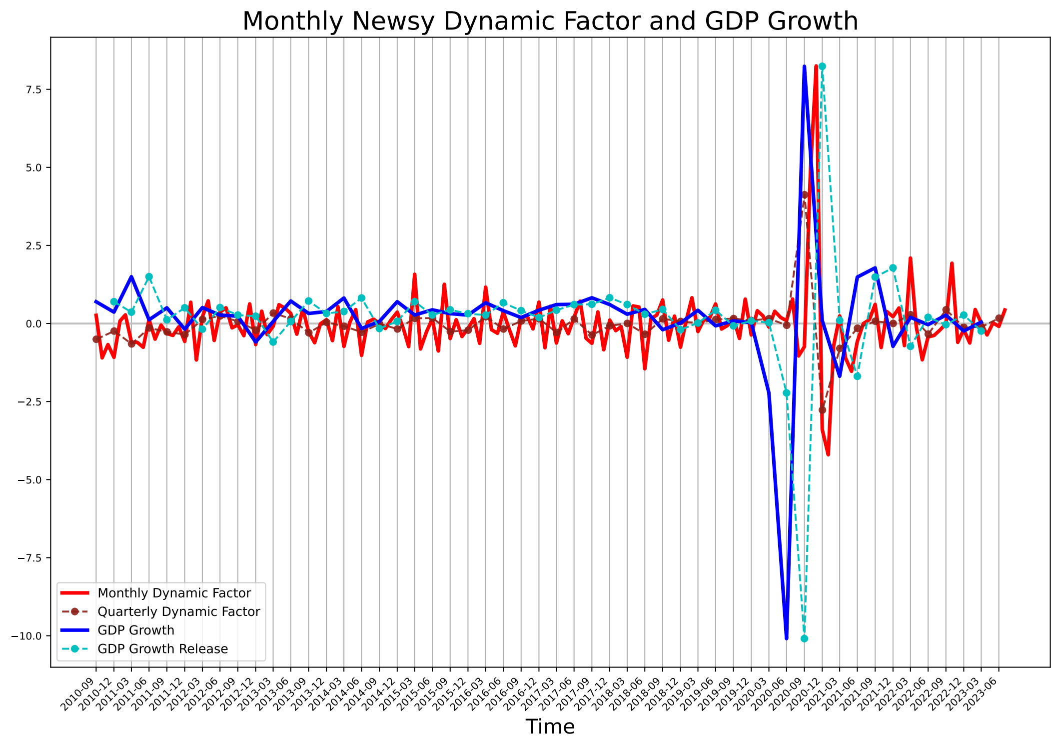


Figure 3.11: Dynamic Factor and First Release GDP Growth
The figure represents the dynamic factor produced from news fully cleaned from the past tense sentences. The dynamic factor is compared to the First Release GDP Growth.

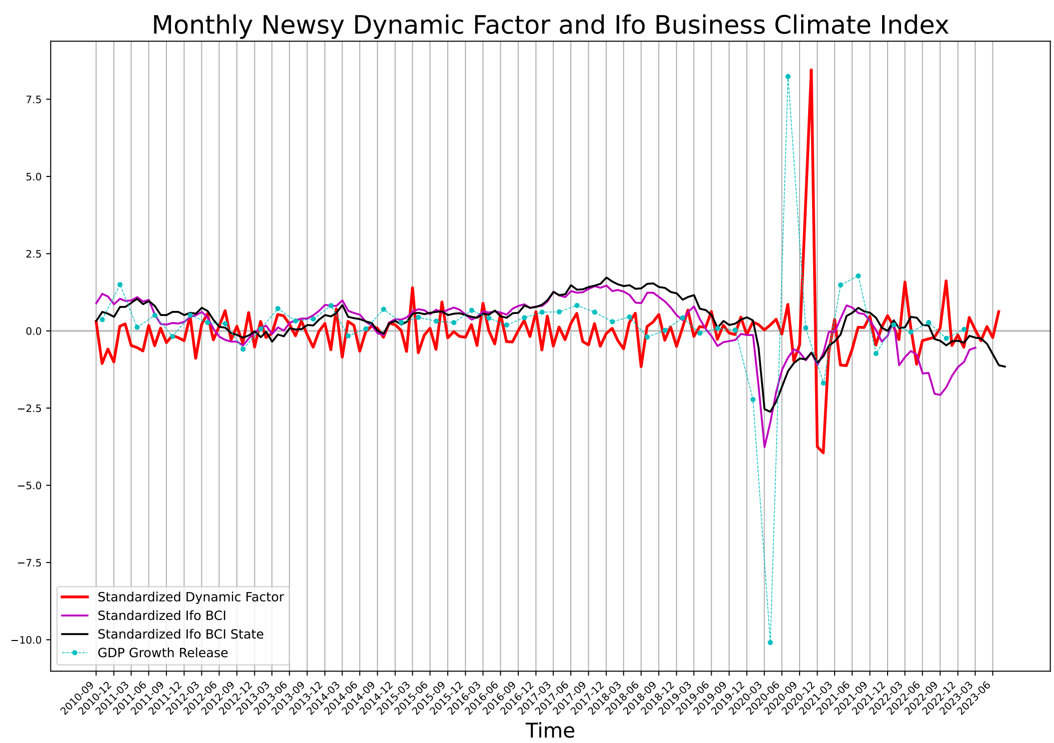


Figure 3.12: Comparision of the
Dynamic Factor from the Fully Cleaned Dataset to Ifo Business Climate Index
The figure represents the dynamic factor produced from fully cleaned news, previous period's industrial production index and previous period's exports. The performance of dynamic factor is compared to the performance of Buisness Climate Index of Germany developed by Ifo Institute - Leibniz Institute for Economic Research at the University of Munich.

Further analysis shows that cleaning both sentiment (tone) and topic frequencies, as done in the fully cleaned dataset, does not produce better results than cleaning only sentiment (tone) while leaving past-related text unaddressed in topic frequency calculations. Although adjusting the tone alone improves alignment with GDP growth data, incorporating topic frequencies calculated from cleaned textual data results in the loss of essential linguistic context and information.

In the perplexity score analysis, the LDA model achieves the best perplexity on the fully cleaned dataset. However, for nowcasting and forecasting purposes, the monthly news-based dynamic factor model demonstrated superior performance on the sentiment-cleaned dataset compared to both, the fully cleaned and raw datasets. These findings suggest that while comprehensive data cleaning enhances the effectiveness of the LDA model, the dynamic factor model benefits specifically from preprocessing that retains sentiment relevant to the present context without altering the topic frequencies. This approach preserves crucial contextual information in the texts, which is essential for understanding linguistic nuances and supporting accurate nowcasting and forecasting performance.

3.5.5 Main Result: Dynamic Factor for Sentiment-Cleaned Dataset

The sentiment-cleaned dataset refines sentiments by removing past tense sentences from each month's top topic-related articles, aiming to retain a present-related tone. We use this cleaned tone to adjust the original topic frequencies. Like other datasets, we augment news data by integrating lagged industrial production index and export data into the dynamic factor model, acknowledging the significant export orientation of the German economy. Consequently, the dynamic factor derived from the sentiment-cleaned dataset closely aligns with the first release of GDP growth, demonstrating robust performance even when confronted with an incomplete industrial production index and export data.

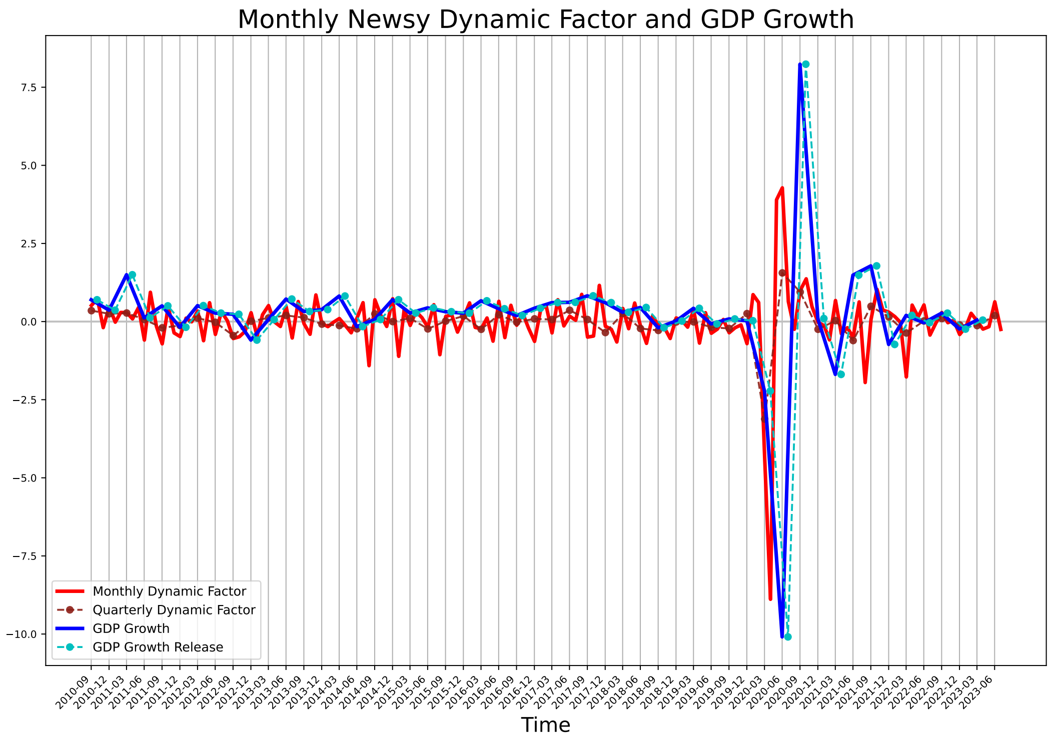


Figure 3.13: Dynamic Factor with Sentiment-Cleaned Dataset vs. First Release GDP Growth

This figure compares the dynamic factor derived from sentiment-cleaned news data, lagged industrial production index, and lagged exports with the First Release of GDP Growth. The red line represents the dynamic factor, the blue line depicts the GDP growth released one month later, and the green line shows the First Release GDP at the time of release.

We observe that the dynamic factor from the sentiment-cleaned dataset, as shown in Figure 3.13, closely aligns with the initial release GDP growth. This improved fit with GDP growth represents a significant advancement over the alignment of the dynamic factor derived from the raw dataset, illustrated in Figure 3.9 and Figure 3.10.

As shown in Figure 3.13 the dynamic factor captures GDP movements more effectively than the widely recognized GDP Nowcasting Indices, such as the Ifo Business Climate Index (BCI) and the Ifo BCI State.

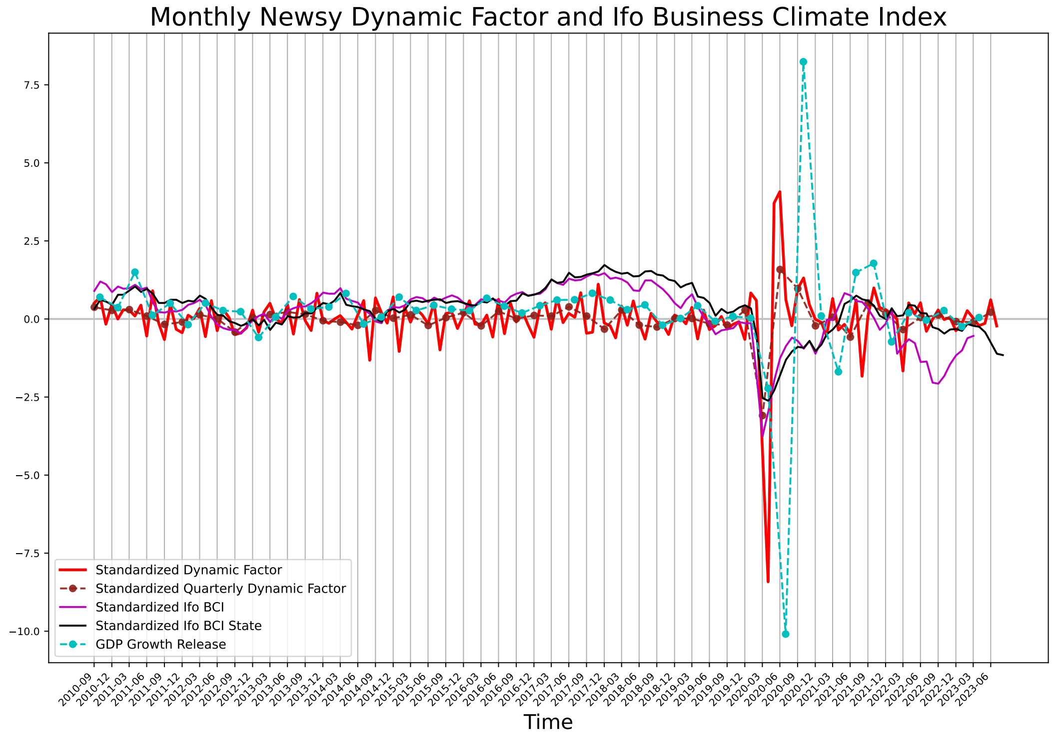


Figure 3.14: Dynamic Factor with Sentiment-Cleaned from Past Tense vs. ifo Business Climate Index and First Release GDP Growth
This graph compares how well the Dynamic Factor, derived from sentiment-cleaned dataset, and the Ifo Business Climate Index (BCI) align with the First Release Gross Domestic Product (GDP) Growth. The Dynamic Factor is derived from a model incorporating five GDP-related topic time series generated from sentiment-cleaned news articles. In contrast, the Ifo Business Climate Index (BCI) reflects the prevailing business sentiment in Germany. The graph demonstrates that the Dynamic Factor aligns more closely with GDP growth than the BCI, highlighting the superior ability of sentiment trends from news articles to track GDP growth compared to traditional business sentiment indices.

3.5.6 Evaluating the Accuracy of Monthly Dynamic Factor Model Nowcasts: An Analysis of Root Mean Squared Forecast Errors (RMSFEs)

Table 3.4 presents the RMSFE values for the dynamic factor model applied to the sentiment-cleaned dataset. This model incorporates the differenced lagged industrial production index and the differenced logarithm of lagged exports. Note that the dataset has an open end, missing the most recent values for the industrial production index and exports.

Table 3.3: RMSFE of Monthly News-Based and Ifo Business Climate State-Based Dynamic Factor Models, Presented in Percentage Points (p.p.).

Horizon	**Dataset**	**Newsy Model**		**ifo BCI State Model**		**Preferred Model**
		RMSFE	NTS	RMSFE	NTS	
Nowcast	Sentiment-Cleaned	0.52	0.27	0.56	0.29	Newsy Model
	Fully Cleaned	0.61	0.30	0.61	0.31	Newsy Model
Out-of-Sample Forecast	Sentiment-Cleaned	h=1: 0.04 h=2: 0.03	h=1: 0.02 h=2: 0.02	h=1: 4.87 h=2: 1.75	h=1: 2.55 h=2: 0.91	Newsy Model
	Fully Cleaned	h=1: 0.05 h=2: 0.06	h=1: 0.02 h=2: 0.03	h=1: 17.33 h=2: 0.18	h=1: 8.87 h=2: 0.09	Newsy Model

Note: For the ifo BCI State-based dynamic factor model with $H = 1$ out-of-sample forecasting, the initial parameters of the autoregressive components, specifically the forecasts of the input values, are non-stationary.

Following the approach described in the research paper by Lehmann et al. (2020), we calculated the Noise-to-Signal Ratio (NTS) by dividing the RMSE of our model by the standard deviation of GDP growth, which was 1.91% for the period from Q2 2010 to Q3 2023. The NTS serves as an indicator of the practical usefulness of our model, with a value below 1 indicating effective performance. It is noteworthy that the sentiment-cleaned dataset produced an NTS of 0.27, suggesting that our factor model produces accurate nowcasts and shows promise for future applications.

Figure 3.15 illustrates the quarterly root squared errors (RSEs) and the root mean squared forecast errors (RMSFE) to evaluate the nowcasting performance of our model over time. Despite including the COVID-19 crisis period in the dataset, our model achieved an RMSFE of 0.52 percentage points, demonstrating its strong performance.

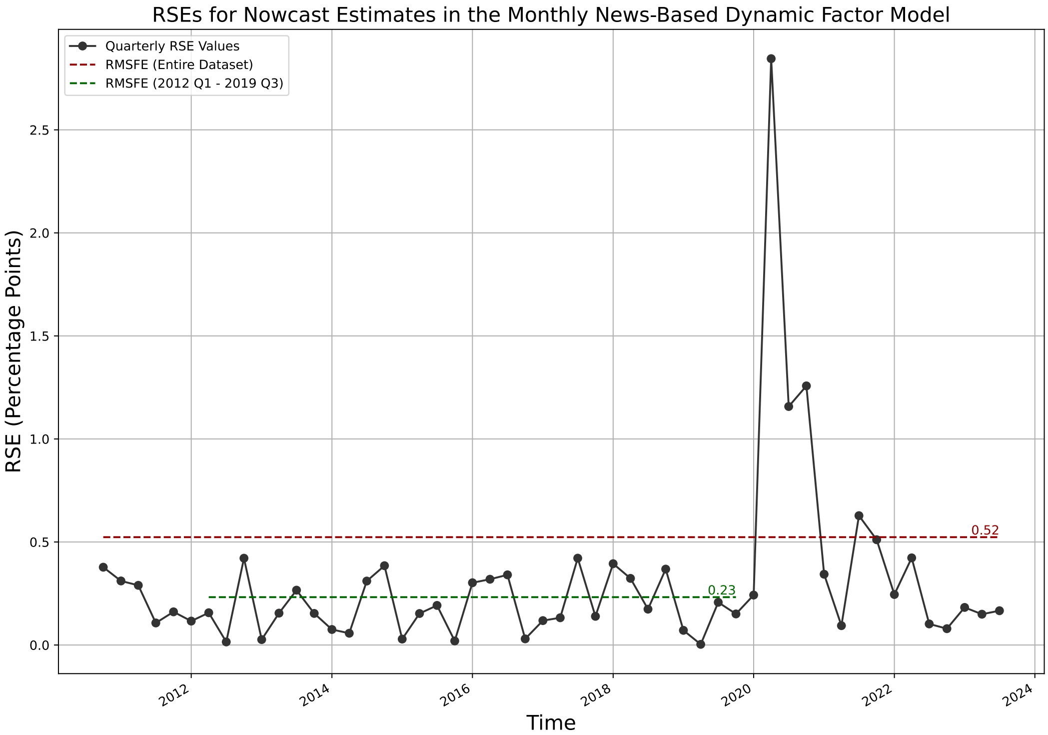


Figure 3.15: The figure presents the RSFEs of the Monthly News-Based Dynamic Factor Model Nowcasts with Sentiment-Cleaned Dataset, model with differenced known industrial production index and differenced log known export.

In the causality analysis detailed in section C.10, we found that the last two lags of the dynamic factor Granger-cause GDP growth. Building on this insight, we utilized a simple 3-period rolling average of the dynamic factor to forecast current GDP growth. The resulting nowcast RMSFE for the sentiment-cleaned dataset, covering the period from Q2 2010 to Q3 2023, is 0.22, demonstrating a significant improvement over the initial results.

$$\widehat{\mathrm{GDP}}_t = \frac{DF_t + DF_{t-1} + DF_{t-2}}{3}$$

$$\mathrm{RMSFE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\frac{DF_t + DF_{t-1} + DF_{t-2}}{3} - \mathrm{GDP}_t\right)^2}$$

Table 3.4: RMSFE of the Monthly News-Based and Ifo Business Climate Index-Based Dynamic Factor Models, Incorporating Two Lags of the Dynamic Factor, Expressed in Percentage Points (p.p.).

Horizon	**Dataset**	**Newsy Model**		**ifo BCI State Model**		**Preferred Model**
		RMSFE	NTS	RMSFE	NTS	
Nowcast	Sentiment-Cleaned	0.22	0.11	0.24	0.12	Newsy Model
	Fully Cleaned	0.25	0.13	0.25	0.13	Newsy Model

Employing the standardized first difference of the logarithm of lagged conventional variables, with standardization performed using an expanding window approach to mitigate data leakage, leads to a reduction of the nowcasting Root Mean Squared Forecast Error (RMSFE) to 0.17 percentage points (refer to section C.10).

3.5.7 Comparative Analysis of RMSFE: Monthly News-Based Dynamic Factor Model vs. Best Performing Models for German GDP in the Literature

We present the Root Mean Squared Forecast Error (RMSFE) of GDP nowcasting from Lehmann and Reif (2021) for the period Q1 2012 to Q3 2019 in Table 3.5 for comparative analysis. The time span analyzed in Lehmann and Reif (2021) excludes the COVID-19 crisis period.

For the same sample period the nowcast RMSFE of our model is 0.23, with corresponding noise-to-signal ratio of 0.73. The forecast RMSFE of our model is 0.04, with corresponding noise-to-signal ratio of 0.13. In Table 3.5 we present comparative RMSEs of our model comapred to the models built in Lehmann and Reif (2021) with different GDP nowcasting indices.

Table 3.5: RMSFE comparison of different indicators for AR-X(0,0) and AR-X(0,q) models for GDP nowcasting as presented in Lehmann and Reif (2021)

Horizon	Indicator	RMSFE (AR-X(0,0))	RMSFE (AR-X(0,q))	Relative RMSFE of (AR-X(0,0))	Relative RMSFE of (AR-X(0,q))
Nowcast	ifo Business Situation Germany	0.38	0.36	0.61	0.64
	ifo Business Climate Germany	0.37	0.37	0.62	0.62
	ifo Business Expectations Germany	0.34	0.40	0.68	0.58
	PMI Composite Output Index	0.36	0.36	0.64	0.64
	DG ECFIN Economic Sentiment Indicator	0.39	0.37	0.59	0.62
	ZEW Current Economic Situation	0.44	0.49	0.52	0.47
Forecast	ifo Business Situation Germany	0.39	0.39	0.10	0.10
	ifo Business Climate Germany	0.45	0.47	0.09	0.09
	ifo Business Expectations Germany	0.45	0.55	0.09	0.07
	PMI Composite Output Index	0.44	0.43	0.09	0.09
	DG ECFIN Economic Sentiment Indicator	0.40	0.46	0.01	0.09
	ZEW Current Economic Situation	0.52	0.51	0.08	0.08

Note: The nowcasts and forecasts in Lehmann and Reif (2021) are for the period from first quarter of 2012 to 3rd Quarter 2019. Excluding COVID-19 crisis period. All RMSFE values are measured in percentage points. Relative RMSFEs are expressed relative to the performance of the newsy dynamic factor model.

In line with Lehmann et al. (2020), we present the relative Root Mean Squared Forecast Errors (RMSFEs) of our model. This metric compares the RMSFE derived from our dynamic factor to that of the benchmark forecasts, as documented in the final columns of Table 3.5. The relative RMSFEs are consistently less than 1, indicating superior performance compared to the models developed for the same period as those in Lehmann and Reif (2021). Moreover, the RMSFE for the period analysied in Table 3.5 the RMSFE of our model is 0.23 percentage points. This demonstrates our model's enhanced accuracy in both nowcasting and forecasting.

According to Lehmann et al. (2020), the dynamic factor model developed using ifoCAST to nowcast German GDP reported a root mean square error (RMSE) of 0.32 percentage points for the period from 2011 to 2018. In contrast, our model achieves an RMSE of 0.23 percentage points for the same period. This comparison highlights the superior accuracy of our model.

When utilizing the average of the current dynamic factor and the last two lags of dynamic factors to nowcast GDP, the accuracy of the nowcasts surpasses even further the results presented in Lehmann and Reif (2021) and in Lehmann et al. (2020).

In exploring alternative unconventional estimates, we reference Lehmann and Möhrle (2024), who forecasted Bavarian industrial production using electricity data. Due to the distinct focuses and methodologies of the models, we cannot make a direct comparison to our model; however, we will present several relevant observations. They report a monthly 'average RMSFE' of 1.6 percentage points from 2012 to 2019, while our model's quarterly RMSFE in the same period is lower at 0.24 percentage points. In 2020, their RMSFE surged to 9.4 percentage points, whereas ours increased to 2.9 percentage points. Despite the differences between models, the low RMSFE of our model, particularly in 2020, suggests that sentiment trends from news articles may serve as a robust supplement to both traditional and unconventional economic indicators.

Eraslan and Reif (2023) forecast German GDP using a combination of conventional and unconventional text-generated data, achieving a weekly mean absolute forecast error (MAFE) of 0.5 percentage points for the period from Q4 2020 to Q1 2023. In comparison, our model attains a MAFE of 0.22 for the same period. For completeness, the MAFE across our entire dataset is 0.27.

3.5.8 Precision of the News-Based Dynamic Factor Model Across Business Cycle States

In the appendix section C.10 our Markov Switching model indicates recession from first quarter 2020 to the second quarter of 2020. We find that the precision of our model is particularly high during non-crisis periods (see Figure 3.13). This is also evident in the RSEs graph over time (refer to Figure 3.15). If we exclude Q1 and Q2 of 2020, we obtain an RMSFE of nowcast estimates equal to 0.31 percentage points, which is significantly lower than the RMSFE for the entire dataset. During the crisis period RMSFE is jumping up to 2 percentage points.

3.5.9 High-Frequency Nowcasting of GDP Using Daily and Weekly Data

Our methodology facilitates high-frequency nowcasting of GDP using daily and weekly data. By extracting sentiments from daily news, we construct dynamic news-based indicators on a daily basis. In spite of this, our study primarily focuses on monthly GDP forecasts due to the missing availability of daily or weekly GDP-related metrics. Notably, there has been an attempt to construct a weekly industrial production index based on electricity consumption data, which could serve as a proxy for GDP. However, this index is currently available only for Bavaria and has not yet been extended to other regions across Germany. Recently, Eraslan and Reif (2023) introduced a latent weekly GDP indicator for Germany, developed using a mixed-frequency Bayesian dynamic factor model that incorporates both conventional and unconventional data sources. However, the time series is not yet available for open access.

We recognize the potential of combining unconventional data sources, such as electricity consumption and the Newsy Dynamic Factor, for high-frequency GDP nowcasting on a weekly or daily basis. With this in mind, we present weekly tone-adjusted topic frequencies for nowcasting German GDP, providing the highest-frequency data available for GDP forecasting using dynamic factor models or other approaches. Weekly tone-adjusted topic frequencies are documented in Figure 3.18, with its building blocks—weekly topic frequencies and weekly polarities—illustrated in Figure 3.16 and Figure 3.17, respectively.

Enhancements, such as incorporating forecasts of economic indicators like the industrial production index and exports, could significantly bolster the model's performance.

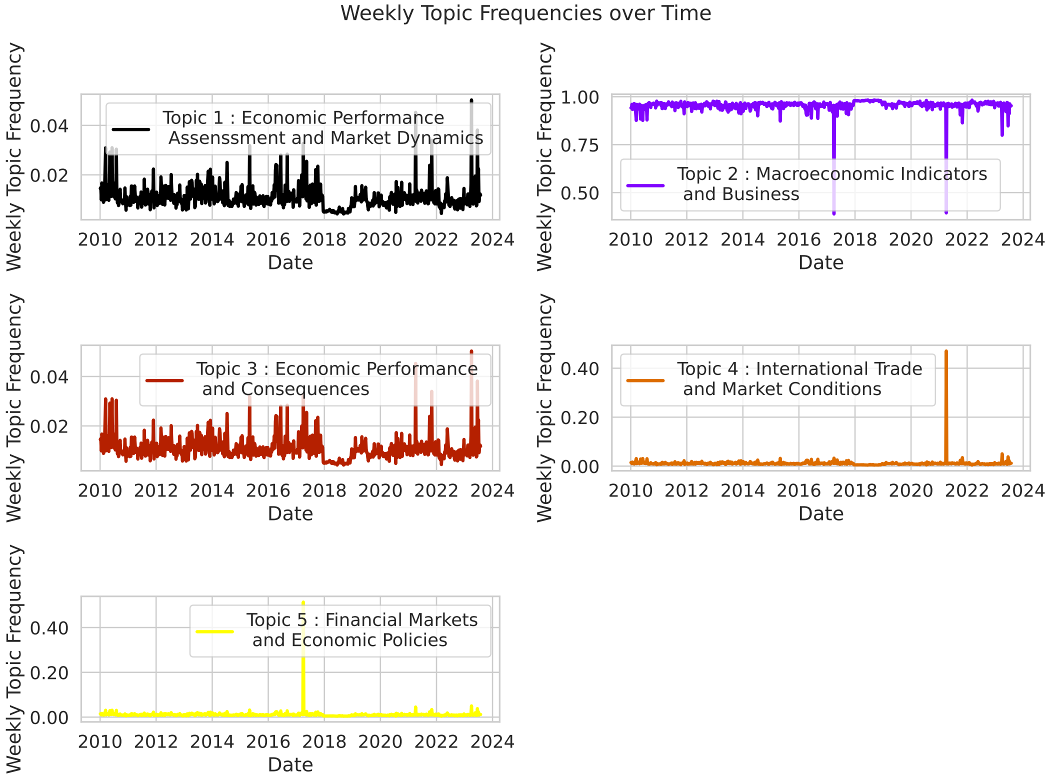


Figure 3.16: Weekly Topic Frequencies over Time from Sentiment-Cleaned Dataset. The figure illustrates weekly topic frequencies over time.

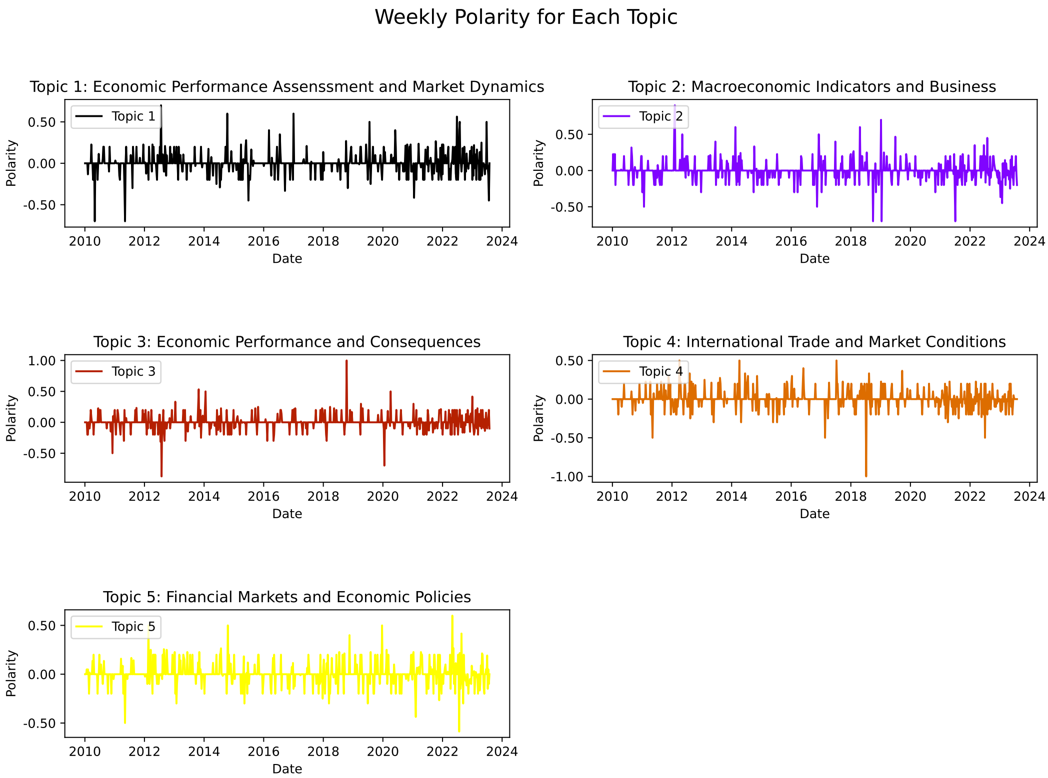


Figure 3.17: Weekly Polarities for Each Topic over Time from Sentiment-Cleaned Dataset. The figure illustrates weekly polarities over time.

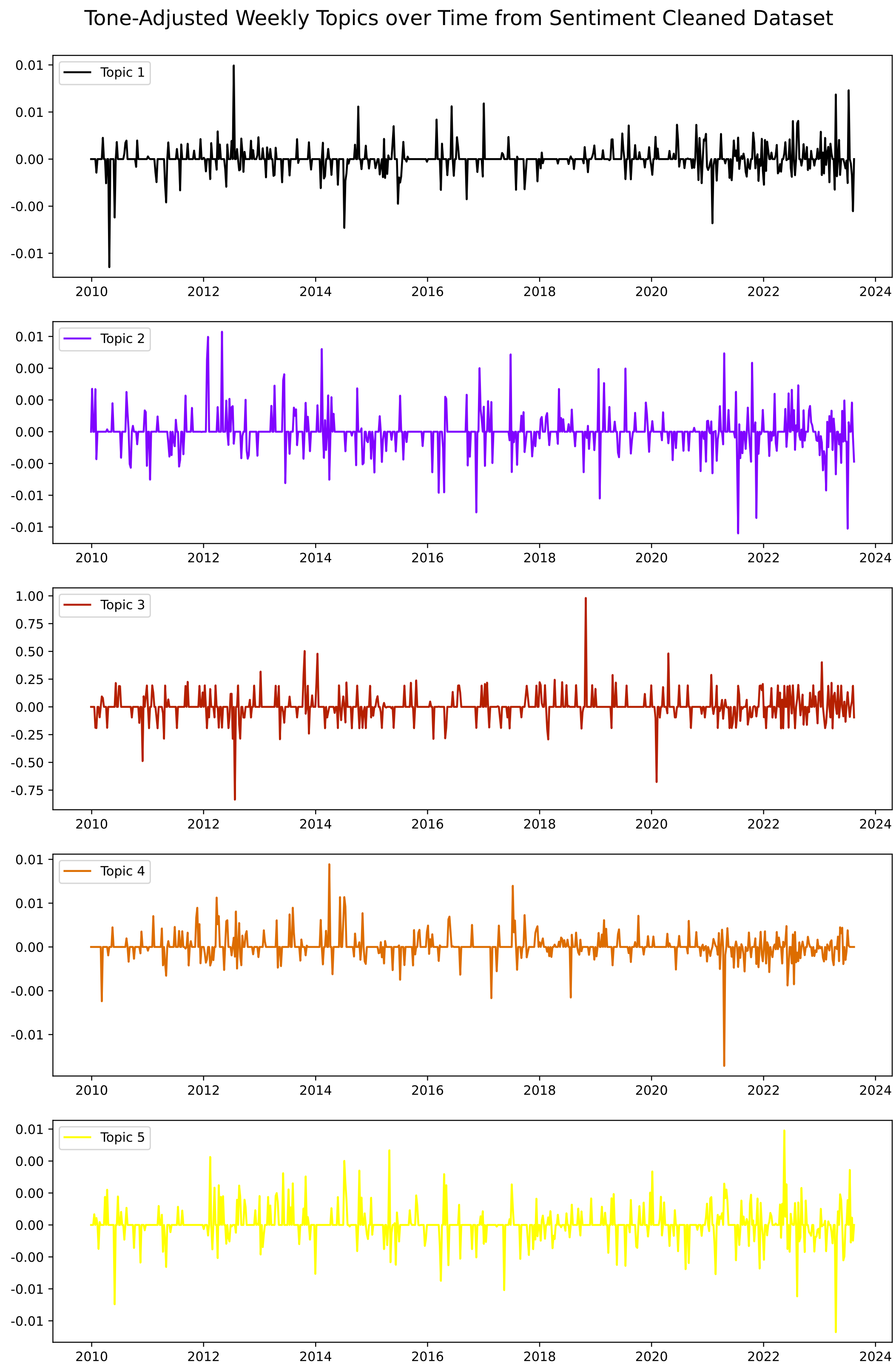


Figure 3.18: Weekly
Tone-Adjusted Topic Frequencies over Time from Sentiment-Cleaned Dataset.
The figure illustrates weekly tone-adjusted topic frequencies over time.

Constructing a dynamic factor model is feasible by incorporating weekly tone-adjusted topic frequencies, alone or with various high-frequency GDP indicators that may become available shortly. These indicators include country-level electricity consumption, freight transport, retail sales, google trends of unemployment, financial market data, employment statistics, steel production, and car registrations. This comprehensive approach could enhance the precision and timeliness of GDP nowcasts by leveraging the combined predictive power of these diverse data sources.

3.5.10 Discussion

Our overall findings from the dynamic factor model support the hypothesis that news influences GDP and can improve GDP forecasting. Our findings align with established theories such as attention theory and the efficient market hypothesis, all of which posit that news significantly influences economic agents' decisions and macroeconomic outcomes. Specifically, our study corroborates existing literature linking news content to GDP movements. In contrast to previous research, such as Thorsrud (2020), which demonstrates that news can nowcast GDP, our approach enhances GDP predictions by systematically removing past-related data from news and integrating unconventional news variables with lagged economic indicators. Besides, we apply a comprehensive parameter fine tuning, while Thorsrud (2020) is using only perplexity scores, which is indeed not the best practice and might lead to choosing higher than optimal number of topics.

While our methodology diverges from studies that solely analyze macroeconomic announcement titles, our results reaffirm the profound impact of news dynamics on GDP outcomes.

The research encounters inherent limitations with both the main model, the dynamic factor model, and the alternative neural network model used for validation. The dynamic factor model requires precise specification of latent factors and lag orders, assumes linearity in the relationship between latent factors and observed variables, independence of errors, and demands stationary data. The limitations of the neural network model lie in its reliance on abundant data for effective training and generalization, yet it is complex and lacks transparency in model interpretation. These challenges underscore the critical need for rigorous validation and thoughtful model selection to ensure robust and meaningful outcomes in scientific research.

We acknowledge that media news data is not the only unconventional data to be considered for high-frequency nowcasting GDP. Another promising unconventional data of such high frequency as ours is electricity data, though it has not yet been aggregated to country level. Lehmann and Möhrle (2024) nowcasts economic activity on weekly frequency using high-frequency, unconventional data. However, a key distinction is that while our research utilizes nationwide data, the German electricity data used in their study has not been aggregated to the country level and is specifically available for Bavaria.

In the future our weekly tone-adjusted topic frequencies time series data can be used to create indicators or it can be incorporated in a bigger model with other unconventional data to nowcast German GDP. For example, one could integrate our tone-adjusted topic frequency time series into a dynamic factor model, alongside high-frequency nowcasts of industrial production derived from electricity consumption data and export forecasts based on aggregated business balance panel data.

Future work involves transitioning from Latent Dirichlet Allocation (LDA) to more advanced text analysis models that account for the interconnections and relationships between parts of speech, capturing the nuances of how words are connected in sentences. One such model is BERTopic, which uses BERT embeddings to understand contextual relationships. This transition is crucial given the distinct linguistic complexities of German, which feature extensive nominalization, intricate dependent clauses, and nested subordinate clauses, unlike the generally simpler structures in English. Adopting models like BERTopic is expected to enhance our analysis by effectively managing these linguistic complexities.

Additionally, future improvements can involve incorporating a broader range of conventional macroeconomic variables into the final model. This integration might provide a more comprehensive analysis and allow for a deeper understanding of the interplay between text data and macroeconomic indicators. Aside from statistical data, experimenting with survey-based data, such as the Purchasing Managers' Index (PMI), could also be valuable. Although caution is needed due to the high correlation between the PMI and the Industrial Production Index, including the PMI may capture different aspects of the economy, even though it might introduce some potential duplication.

3.6 Conclusion

Recently, text-generated indicators have gained recognition as substitutes and complementaries to traditional data sources in economic nowcasting. This study advances the field by integrating meticulously preprocessed news media data with lagged traditional economic variables—specifically, the industrial production index (IPI) and exports—to enhance the accuracy of German GDP nowcasting. Our approach involved processing 14 years of news articles using advanced text preprocessing techniques, including Boolean filtering to exclude past-tense sentences, thereby refining sentiment accuracy and improving nowcasting precision.

Using Latent Dirichlet Allocation (LDA) with comprehensive fine-tuning, we probabilistically assigned topics to preprocessed news texts, converting topic frequencies into time series adjusted by polarity measures. These tone-adjusted topic frequency time series served as the observed variables for the dynamic factor model. The model demonstrated superior predictive capabilities compared to well-established indicators such as the ifo Business Climate Index (BCI) and ifoCAST.

Our findings demonstrate that our news-driven dynamic factor model consistently outperforms leading indices such as the Ifo BCI and the Ifo BCI State Index in both nowcasting and forecasting German GDP growth. The model's ability to accurately predict initial GDP releases highlights the effectiveness of integrating unconventional data sources for enhancing GDP nowcasting.

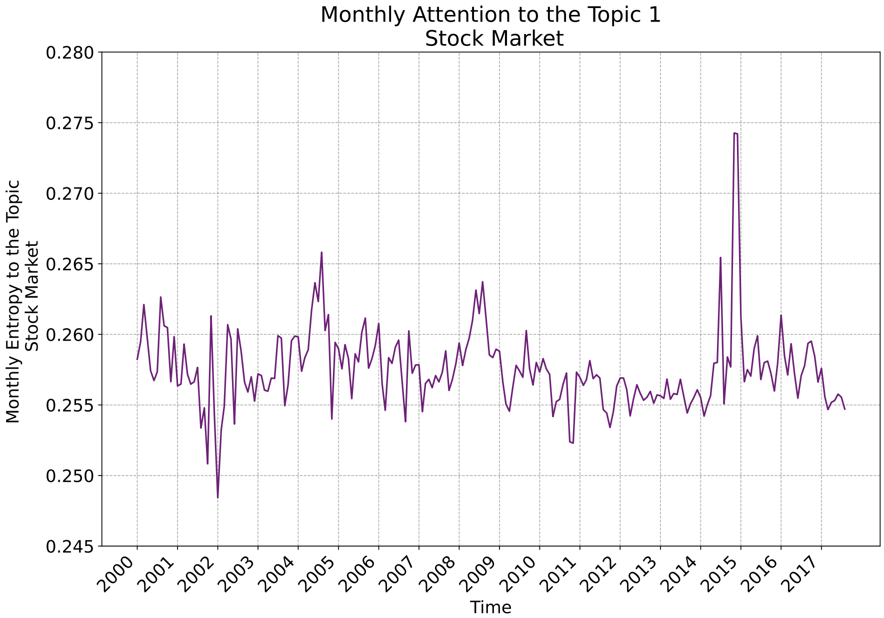
While this study showcases the strengths of integrating refined text-driven data sources for GDP nowcasting, it also acknowledges areas for future exploration. Future research could focus on further refining text preprocessing techniques and validating the robustness of this approach across different countries. Additionally, applying this methodology to other indicators beyond GDP could yield valuable insights into various aspects of economic performance.

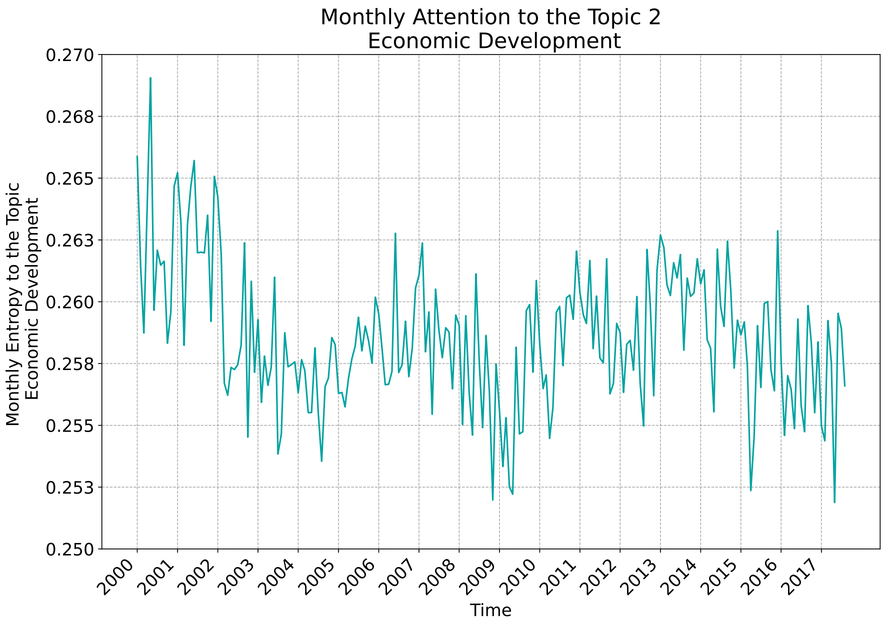
In conclusion, our study underscores the strategic advantage of leveraging unconventional data sources, particularly news data, for GDP forecasting in Germany. By advancing methodologies in text-driven economic analysis, we contribute to the ongoing evolution of economic forecasting practices, paving the way for more accurate and timely insights into economic trends and dynamics.

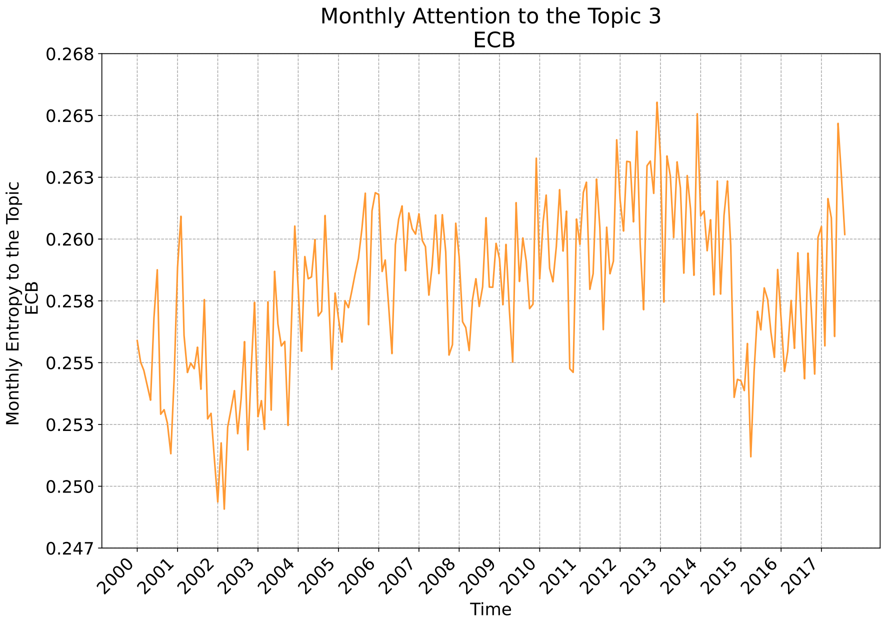
4 Appendices

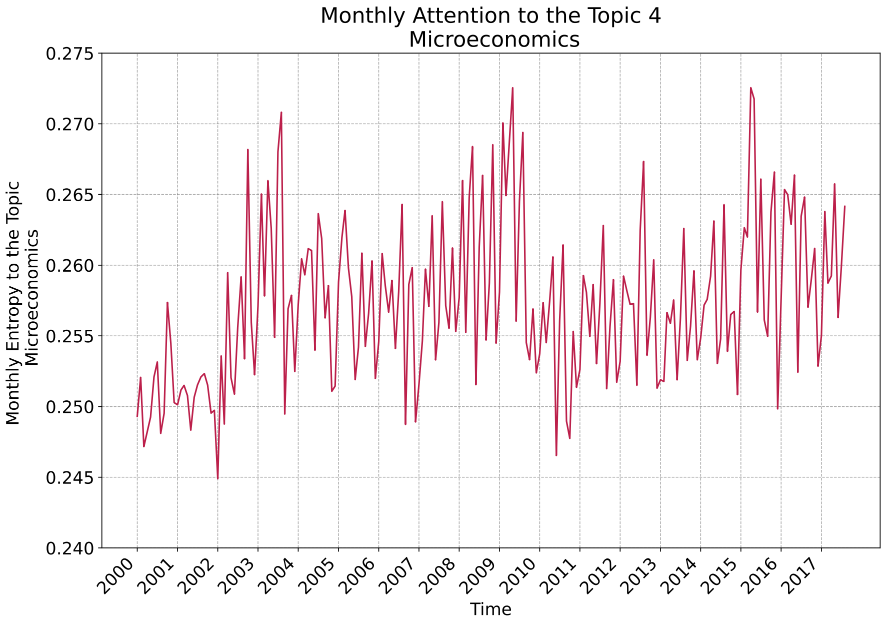
A Appendix to Chapter 1: Beyond Tradition: A Hybrid Model Unveiling News Impact on Exchange Rates

A.1 Attention to U.S. Dollar-Related Topics in News Articles









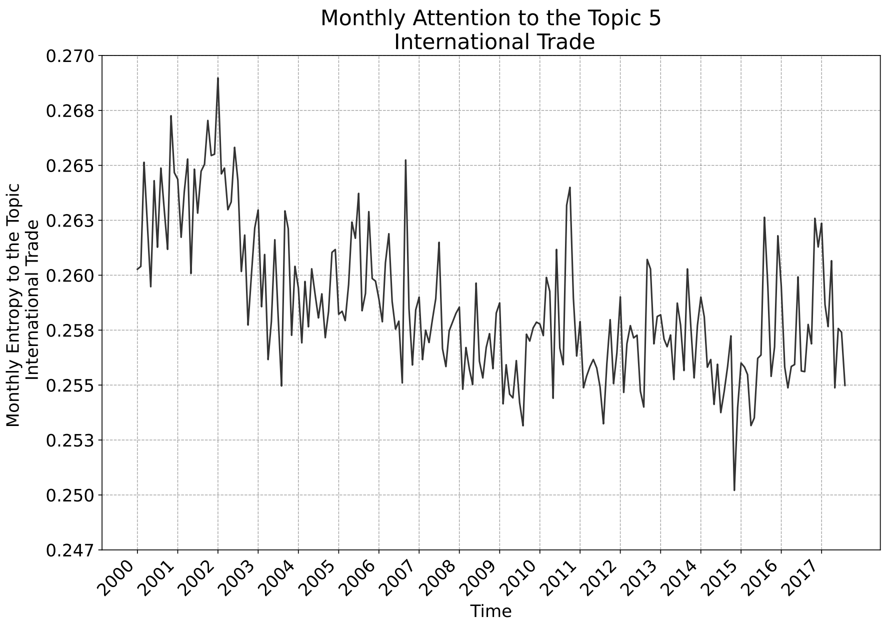


Figure A.1: Monthly attention to U.S. Dollar-related news topics over time, measured by the average news entropies.

The attention measures in Figure A.1 align with key economic events. For example, attention to stock market news spiked around the Lehman Brothers bankruptcy in September 2008 and during the 50% drop in global oil prices from June to December 2014, reflecting the public's sensitivity to major market disruptions.

A.2 Descriptive Statistics

Table A.1: Descriptive Statistics: Observations from 2000 to 2018

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
GBP/USD	0.0000	0.0180	-0.0473	0.0483
EUR/USD	-0.0014	0.0230	-0.0619	0.0597
Stock Market News	-0.0003	0.0064	-0.0186	0.0145
Economic Development News	-0.0002	0.0112	-0.0304	0.0276
FED News	-0.0001	0.0111	-0.0247	0.0250
Micro Finance News	0.0007	0.0253	-0.0649	0.0568
International Trade News	-0.0004	0.0104	-0.0277	0.0280
CPI_US	0.0020	0.0020	-0.0035	0.0071
Money Market Rate_US	0.0001	0.0005	-0.0012	0.0016
IPI_US	0.0011	0.0047	-0.0124	0.0124
M2_US	0.0048	0.0025	-0.0015	0.0114
EPU_US	0.0127	0.5501	-1.2536	1.5021
CPI_UK	0.0021	0.0028	-0.0054	0.0086
Money Market Rate_UK	0.0000	0.0004	-0.0011	0.0011
IPI_UK	-0.0002	0.0065	-0.0191	0.0179
M2_UK	0.0045	0.0209	-0.0770	0.0663
EPU_UK	0.0004	0.2899	-0.6566	0.7539
CPI_EU	0.0016	0.0031	-0.0071	0.0097
Money Market Rate_EU	0.0027	0.0557	-0.1600	0.1600
IPI_EU	0.0014	0.0075	-0.0170	0.0192
M2_EU	0.0315	0.3480	-0.9000	1.0000
EPU_EU	-0.0063	0.2034	-0.5429	0.5251

Note: The descriptive statistics are presented for the final variables, which have been transformed by taking their natural logarithms and subsequently first-differenced.

A.3 Data Preprocessing: Addressing Nonstationarity and Outliers

Our analysis commences with an examination of the time series attributes of each variable. The Augmented Dickey-Fuller (ADF) test identifies nonstationarity among all variables. To address this, we apply a logarithmic transformation followed by first-order differencing to the variables. This transformation maintains monotonicity, ensuring the preservation of analytical integrity and enhancing the interpretability of impulse response analyses. Additionally, we employ the 1.5 interquartile range (IQR) method for outlier removal. As a result of this data transformation and outlier handling, all variables, including the monthly U.S. Dollar exchange rates, exhibit stationarity.

A.4 Selection of the Estimation Method

We employ the Engel-Granger procedure to select the appropriate estimator for our extended Taylor model, given the I(1) characteristics of our initial time series. This involves several steps:

1. **Residual Stationarity Test:** We conduct a cointegration regression between the exchange rate and other variables.

2. **Model Selection:** Residuals from this regression are tested for stationarity using Augmented Dickey-Fuller (ADF) test. If the residuals of this regression are stationary, indicating a cointegrating relationship, we proceed to use models such as the Vector Error Correction (VEC) model or Structural Vector Autoregression (SVAR) model with cointegration restrictions. Conversely, if the residuals are nonstationary, we construct a Vector Autoregression (VAR) model, ensuring its stability through diagnostic tests.

3. **Cointegration Assessment:** We then estimate the cointegration regression between the exchange rate and other variables, employing eigenvectors calculated via the Johansen procedure as weights.

4. **ADF Test:** Subsequently, we assess the stationarity of the residuals using the Augmented Dickey-Fuller (ADF) test.

Based on the nonstationarity of the residuals, the Engel-Granger procedure concludes the absence of cointegration between exchange rates and other variables, making the application of the VAR model feasible.

After selecting the VAR model using the Engel-Granger procedure, we verify the stationarity of the first differences of all logarithmized variables. Since they all exhibit stationarity, we proceed to construct the VAR model in the first differences of logarithmed variables.

A.5 Forecast Error Decomposition and Impulse-Response Analysis

The impulse-responses and forecast error decomposition, as described by Pfaff (2008), are based upon the Wold moving average decomposition for stable VAR(p)-processes which is defined as:

$$y_t = \Phi_0 u_t + \Phi_1 u_{t-1} + \Phi_2 u_{t-2} + \dots \ , \tag{A.1}$$

where $\Phi_0 = I_K$ and Φ_s can be computed recursively according to:

$$\Phi_s = \sum_{j=1}^{s} \Phi_{s-j} A_j \text{ for } s = 1, 2, \dots, \tag{A.2}$$

where $A_j = 0$ for $j > p$.

Finally, forecasts for horizons $h \geq 1$ of an empirical VAR(p)-process can be generated recursively according to:

$$y_{T+h|T} = A_1 y_{T+h-1|T} + \dots + A_p y_{T+h-p|T} \ , \tag{A.3}$$

where $y_{T+j|T} = y_{T+j}$ for $j \leq 0$. The forecast error covariance matrix is given as:

$$Cov\left(\begin{bmatrix} y_{T+1} - y_{T+1|T} \\ \vdots \\ y_{T+h} - y_{T+h|T} \end{bmatrix}\right) = \begin{bmatrix} I & 0 & \cdots & 0 \\ \Phi_1 & I & & 0 \\ \vdots & & \ddots & 0 \\ \Phi_{h-1} & \Phi_{h-2} & \dots & I \end{bmatrix} (\Sigma_u \otimes I_h) \begin{bmatrix} I & 0 & \cdots & 0 \\ \Phi_1 & I & & 0 \\ \vdots & & \ddots & 0 \\ \Phi_{h-1} & \Phi_{h-2} & \dots & I \end{bmatrix}^{\top}$$

and the matrices Φ_i are the empirical coefficient matrices of the Wold moving average representation of a stable VAR(p)-process as shown above. The operator $\otimes$ is the Kronecker product. The impulse response analysis (see Equation A.1 and Equation A.2 above) is used to investigate the dynamic interactions between the endogenous variables. The $(i, j)th$ coefficients of the matrices Φ_s are thereby interpreted as the expected response of variable $y_{i,t+s}$ to a unit change in variable y_{jt}. These effects can be accumulated through time, $s = 1, 2, \dots$, and hence one would obtain the simulated impact of a unit change in variable j to the variable i at time s. Aside of these impulse response coefficients, it is often conceivable to use orthogonal impulse responses as an alternative. This is the case, if the underlying shocks are less likely to occur in isolation, but when contemporaneous correlations between the components of the error process u_t exist, i.e., the off-diagonal elements of Σ_u are non-zero. The orthogonal impulse responses are derived from a Choleski decomposition of the error variance-covariance matrix: $\Sigma_u = PP^{\top}$ with P being a lower triangular. The moving average representation can then be transformed to:

$$y_t = \Psi_0 \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \dots \ , \tag{A.4}$$

where $\varepsilon_t = P^{-1} u_t$ and $\Psi_i = \Phi_i P$ for $i = 0, 1, 2, \dots$ and $\Psi_0 = P$. Incidentally, because the matrix P is lower triangular, it follows that only a shock in the first variable of a VAR(p)-process does exert an influence on all the remaining ones and that the second and following variables cannot have a direct impact on y_{1t}. Please note, that a different ordering of the variables might produce different outcomes with respect to the impulse responses.

A.6 Forecast Error Variance Decomposition (FEVD) Results

Table A.2: FEVD for GBP/USD

Month	GBP /USD	CPI US	CPI UK	IR US	IR UK	IPI US	IPI UK	M2 US	M2 UK	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	EPU US	EPU UK
1	75,4	0,1	0,1	5,5	0,1	0,0	0,4	0,5	16,2	0,1	1,2	0,1	0,1	0,0	0,0	0,3
2	60,8	0,1	0,4	7,1	1,4	0,1	0,3	7,1	14,3	0,6	1,7	0,2	1,1	2,2	0,2	2,5
3	52,1	0,2	0,4	6,0	1,7	1,9	0,3	10,7	12,1	2,8	2,1	0,1	3,9	1,9	1,3	2,4
4	47,8	1,0	0,3	7,1	2,8	2,5	0,4	10,1	11,1	2,5	2,1	0,4	3,5	2,5	3,5	2,3
5	43,1	1,1	5,4	6,5	3,7	2,7	0,5	9,4	10,1	2,4	2,4	1,1	3,5	2,3	3,5	2,5
6	41,2	1,1	5,9	6,9	3,6	3,3	0,7	9,1	9,8	2,3	3,0	1,1	3,3	2,2	4,3	2,4
7	39,2	1,3	6,0	7,0	3,5	4,9	0,7	8,8	9,4	2,5	2,8	1,3	3,2	2,7	4,2	2,6
8	37,8	1,3	5,8	6,8	3,4	4,9	0,9	9,1	10,0	2,8	3,0	1,4	3,2	2,6	4,5	2,5
9	36,6	1,6	5,7	6,5	3,5	5,0	0,9	9,2	9,7	3,1	2,9	1,4	3,2	2,9	4,9	3,1
10	35,7	1,9	5,6	6,5	3,4	4,8	1,0	9,0	9,9	3,0	2,8	1,5	3,3	3,8	4,7	3,1
11	34,9	1,9	5,6	7,1	3,3	4,7	1,0	9,4	9,7	3,1	2,8	1,5	3,3	4,1	4,6	3,0
12	34,2	1,9	5,8	7,0	3,3	4,7	1,1	9,6	9,5	3,1	3,0	1,6	3,2	4,3	4,5	3,0
13	33,5	1,9	5,7	7,2	3,5	4,6	1,1	9,5	9,7	3,2	3,0	1,6	3,3	4,2	4,9	3,2
14	33,1	2,0	5,8	7,1	3,4	4,6	1,4	9,3	9,5	3,3	3,0	1,7	3,6	4,3	4,9	3,1
15	32,8	2,3	5,8	7,1	3,4	4,7	1,4	9,2	9,4	3,2	3,0	1,7	3,7	4,3	4,8	3,1
16	32,6	2,3	5,8	7,1	3,4	4,6	1,5	9,2	9,3	3,3	3,1	1,8	3,8	4,3	4,8	3,1
17	32,5	2,3	5,8	7,2	3,4	4,6	1,5	9,2	9,3	3,3	3,0	1,9	3,7	4,2	4,8	3,1
18	32,2	2,3	5,9	7,2	3,4	4,6	1,5	9,2	9,4	3,4	3,2	1,9	3,8	4,2	4,8	3,1
19	32,1	2,3	5,9	7,2	3,4	4,6	1,5	9,2	9,4	3,4	3,2	1,9	3,8	4,2	4,8	3,1
20	32,0	2,3	6,0	7,2	3,4	4,6	1,5	9,2	9,4	3,4	3,2	1,9	3,8	4,2	4,7	3,2
21	32,0	2,3	6,0	7,2	3,4	4,6	1,5	9,1	9,4	3,4	3,2	1,9	3,9	4,3	4,7	3,2
22	31,9	2,3	6,0	7,2	3,4	4,7	1,5	9,1	9,4	3,4	3,2	1,9	3,9	4,3	4,8	3,2
23	31,8	2,3	5,9	7,2	3,4	4,7	1,5	9,1	9,4	3,4	3,2	1,9	3,9	4,3	4,7	3,2
24	31,7	2,3	5,9	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,2	1,9	3,9	4,3	4,7	3,2
25	31,6	2,3	6,0	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,2	1,9	3,9	4,3	4,7	3,2
26	31,6	2,3	6,0	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,2	2,0	3,9	4,3	4,7	3,2
27	31,6	2,3	6,1	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,2	2,0	3,9	4,3	4,7	3,2
28	31,5	2,3	6,0	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,3	2,0	3,9	4,3	4,7	3,2
29	31,5	2,3	6,1	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,3	1,9	3,9	4,3	4,7	3,2
30	31,4	2,3	6,1	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,3	2,0	3,9	4,3	4,7	3,2
31	31,4	2,3	6,1	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,3	2,0	3,9	4,3	4,7	3,2
32	31,4	2,3	6,1	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,3	2,0	3,9	4,3	4,7	3,2
33	31,4	2,3	6,1	7,2	3,4	4,7	1,6	9,1	9,4	3,4	3,3	2,0	3,9	4,3	4,7	3,2
34	31,3	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,4	3,4	3,3	2,0	3,9	4,3	4,7	3,2
35	31,3	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,4	3,4	3,3	2,0	3,9	4,3	4,7	3,2
36	31,3	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,4	3,4	3,3	2,0	4,0	4,3	4,7	3,2
37	31,3	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,4	3,4	3,3	2,0	4,0	4,3	4,7	3,2
38	31,3	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,4	3,4	3,3	2,0	4,0	4,3	4,7	3,2
39	31,3	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,3	3,4	3,4	2,0	4,0	4,3	4,7	3,2
40	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,3	3,4	3,4	2,0	4,0	4,3	4,7	3,2
41	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,1	9,3	3,4	3,4	2,0	4,0	4,3	4,7	3,2
42	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,0	9,3	3,4	3,4	2,0	4,0	4,3	4,7	3,2
43	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,0	9,3	3,4	3,4	2,0	4,0	4,3	4,7	3,2
44	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,0	9,4	3,4	3,4	2,0	4,0	4,3	4,7	3,2
45	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,0	9,4	3,4	3,4	2,0	4,0	4,3	4,7	3,2
46	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,0	9,4	3,4	3,4	2,0	4,0	4,3	4,7	3,2
47	31,2	2,3	6,1	7,2	3,4	4,7	1,7	9,0	9,4	3,4	3,4	2,0	4,0	4,3	4,7	3,2

In Table A.2, topics are as follows: **Topic 1:** Stock Market News- *Commodities, Oil, Gas, Precious Metals, and Stock Exchange Markets.* **Topic 2:** Economic Development News- *Economic Growth, GDP, Inflation, Economic Policy, Monetary Policy, Consumption, Federal Reserves, and Unemployment.* **Topic 3:** FED News- *Central Banks, Interest Rates, Bonds, Currency Markets, Public Debt, and Government.* **Topic 4:** Microeconomics News- *Company's Profits, Sales, Financial Results, and Cash Flow.* **Topic 5:** International Trade News- *Imports, Foreign Investment, Trade in Goods and Services, and Globalization.* IR denotes interest rate.

Table A.3: FEVD for EUR/USD

Month	EUR /USD	CPI US	CPI EU	IR US	IR EU	IPI US	IPI EU	M2 US	M2 EU	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	EPU US	EPU EU
1	90,0	0,4	0,4	1,7	0,2	0,0	0,1	0,0	0,4	0,0	4,6	1,5	0,1	0,1	0,4	0,3
2	80,5	0,6	2,3	2,1	0,3	0,7	0,7	0,0	1,6	2,7	4,8	1,8	1,3	0,1	0,3	0,3
3	71,9	0,6	2,1	1,9	1,9	0,9	0,7	1,0	1,9	5,7	4,3	1,6	2,1	0,9	2,1	0,4
4	68,3	0,6	2,6	2,1	1,8	1,1	1,0	2,3	2,0	6,1	4,1	2,1	2,1	1,3	2,1	0,6
5	62,8	1,0	2,7	2,1	2,8	1,7	1,1	2,9	2,1	6,6	4,7	2,1	2,2	1,2	2,0	2,3
6	60,0	1,0	3,4	2,2	3,4	1,9	1,6	2,9	2,2	6,9	4,7	2,0	2,1	1,1	2,1	2,5
7	56,8	1,1	3,6	2,7	3,3	2,1	1,6	3,2	2,2	6,6	4,5	2,0	2,1	1,2	3,7	3,5
8	54,3	1,1	3,5	2,6	3,2	2,3	2,8	3,0	2,4	7,6	4,9	1,9	2,0	1,2	3,7	3,4
9	53,1	1,8	3,4	2,6	3,5	2,3	2,9	3,0	2,4	7,5	4,9	2,0	2,1	1,2	3,6	3,9
10	52,2	1,8	3,6	2,6	3,8	2,3	2,9	2,9	2,3	7,4	4,8	1,9	2,5	1,1	3,9	4,0
11	51,2	1,8	3,5	2,8	3,7	2,3	2,9	3,5	2,5	7,4	4,7	2,0	2,4	1,3	3,9	4,0
12	50,4	1,8	3,4	2,8	3,7	2,4	3,1	3,7	2,8	7,3	4,9	2,0	2,5	1,4	3,9	4,0
13	50,1	1,8	3,4	2,8	3,7	2,9	3,2	3,6	3,0	7,2	4,8	2,0	2,5	1,4	3,8	3,9
14	49,8	1,8	3,4	2,9	3,6	3,2	3,1	3,6	3,1	7,1	4,7	2,0	2,5	1,6	3,8	3,9
15	49,3	2,0	3,4	3,1	3,6	3,4	3,1	3,6	3,0	7,0	4,7	2,0	2,4	1,6	3,8	3,9
16	48,9	2,0	3,4	3,1	3,6	3,4	3,3	3,9	3,0	7,0	4,8	2,0	2,5	1,6	3,9	3,8
17	48,6	2,0	3,3	3,1	3,6	3,4	3,3	3,8	3,0	7,1	4,8	2,0	2,5	1,7	3,9	3,8
18	48,4	2,0	3,3	3,1	3,6	3,4	3,3	3,8	3,0	7,1	4,8	2,0	2,5	1,7	3,9	3,9
19	48,3	2,0	3,4	3,1	3,6	3,4	3,3	3,8	3,0	7,1	4,8	2,0	2,5	1,7	3,9	3,9
20	48,1	2,0	3,4	3,1	3,7	3,4	3,3	4,0	3,0	7,1	4,8	2,0	2,5	1,7	3,9	3,9
21	47,9	2,0	3,4	3,1	3,7	3,5	3,3	4,0	3,0	7,1	4,9	2,1	2,5	1,7	3,9	3,9
22	47,7	2,0	3,4	3,1	3,7	3,5	3,3	4,1	3,1	7,1	4,9	2,1	2,5	1,7	4,0	4,0
23	47,6	2,0	3,4	3,1	3,7	3,5	3,3	4,1	3,1	7,1	4,8	2,1	2,5	1,7	4,0	4,0
24	47,6	2,1	3,4	3,1	3,7	3,5	3,3	4,1	3,2	7,1	4,8	2,1	2,5	1,7	4,0	4,0
25	47,4	2,1	3,4	3,2	3,7	3,5	3,3	4,2	3,1	7,1	4,8	2,1	2,5	1,7	4,0	4,0
26	47,4	2,1	3,4	3,2	3,7	3,5	3,4	4,2	3,1	7,1	4,9	2,1	2,5	1,7	4,0	4,0
27	47,3	2,1	3,4	3,2	3,7	3,5	3,3	4,1	3,2	7,1	4,9	2,2	2,5	1,7	4,0	4,0
28	47,2	2,1	3,4	3,2	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,5	1,7	4,0	4,0
29	47,2	2,1	3,4	3,2	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,5	1,7	4,0	4,0
30	47,1	2,1	3,4	3,2	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,5	1,7	4,0	4,0
31	47,1	2,1	3,4	3,2	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,5	1,7	4,0	4,0
32	47,0	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,4	1,7	4,0	3,9
33	47,0	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,4	1,7	4,0	3,9
34	46,9	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,4	1,8	4,0	3,9
35	46,9	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,4	1,8	4,0	3,9
36	46,9	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,4	1,8	4,0	3,9
37	46,9	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,4	1,8	4,0	3,9
38	46,9	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,5	1,8	4,0	3,9
39	46,9	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,2	7,1	4,9	2,2	2,5	1,8	4,0	3,9
40	46,9	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9
41	46,8	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9
42	46,8	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9
43	46,8	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9
44	46,8	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9
45	46,8	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9
46	46,8	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9
47	46,8	2,1	3,4	3,3	3,7	3,5	3,4	4,2	3,3	7,1	4,9	2,2	2,5	1,8	4,0	3,9

In Table A.3, column titles use the following notation: **Topic 1:** Stock Market News. **Topic 2:** Economic Development News. **Topic 3:** FED News. **Topic 4:** Microeconomic News. **Topic 5:** International Trade News.

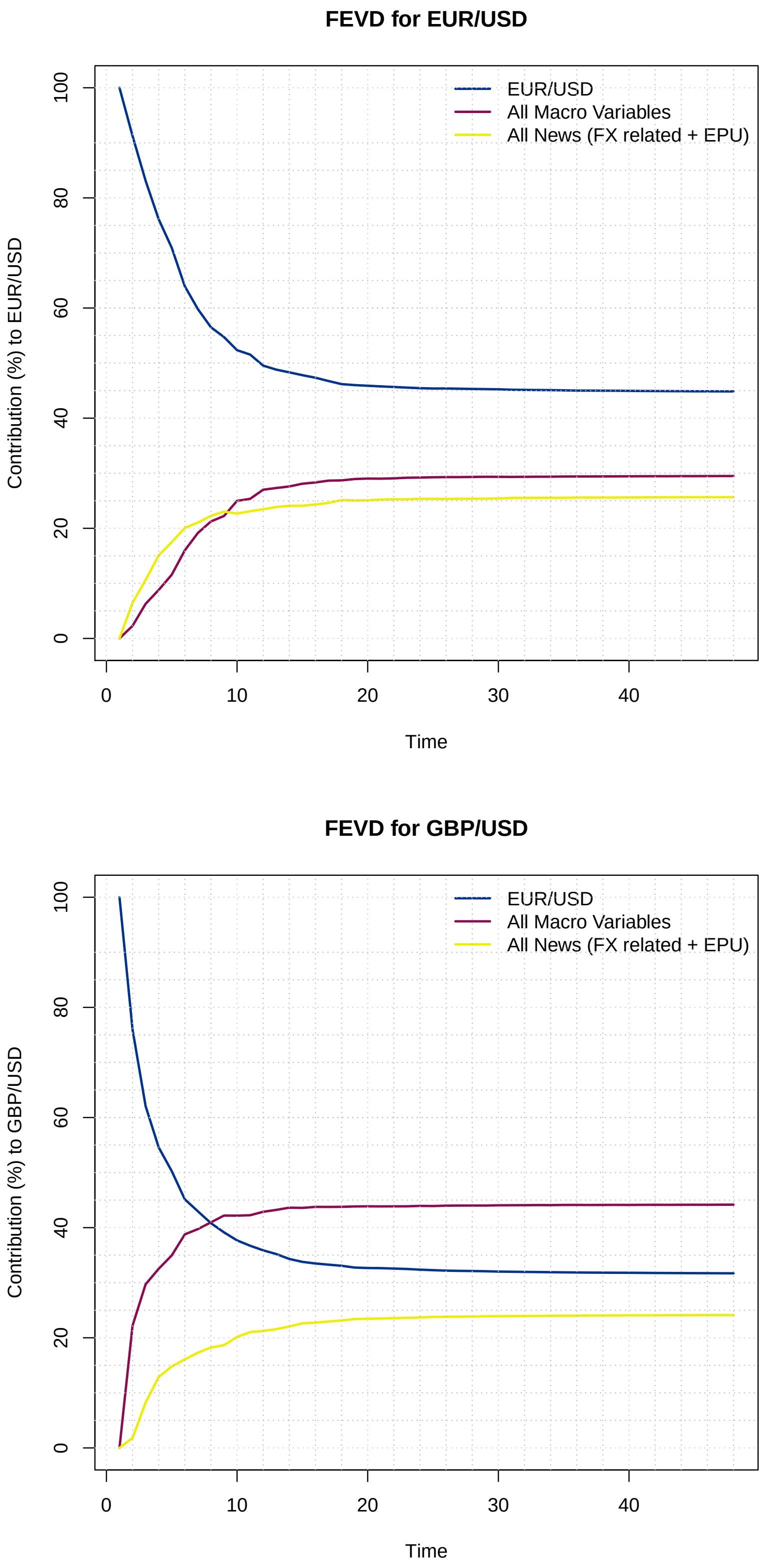


Figure A.2: FEVD
for Foreign Exchange (FX) Rates to Summed Up Macro and News Variables

A.7 Robustness

In this section, we discuss the results of extensive robustness checks for our specification.

Robustness Check of U.S. Dollar-Related News Variables

We evaluate the stability and reliability of the entropy variables derived from U.S. Dollar-related news topics through a robustness test, analyzing the variability of each entropy variable over time using rolling standard deviations computed over distinct intervals (12, 24, 30, 36, 48, 60 months window sizes). By setting a threshold at 0.1, deviations beyond this threshold indicate potential instability. Variables exceeding this threshold are deemed non-robust, while those remaining within acceptable bounds are considered robust. Here we present Rolling Standard Deviation for Entropy Variables of Topics Related to the U.S. Dollar. As we see they never cross the threshold, verifying the robuustness of our entropy variables.

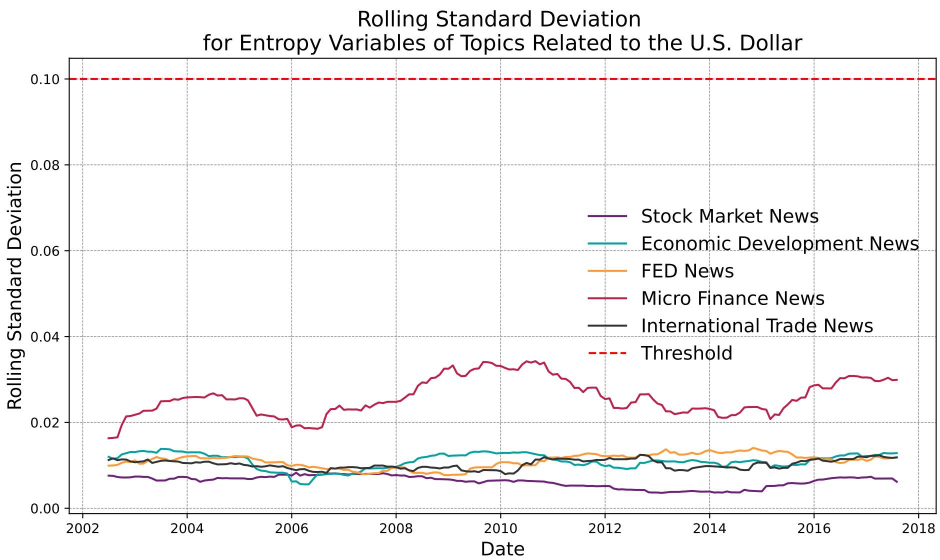


Figure A.3: Rolling
Standard Deviation for Entropy Variables of Topics Related to the U.S. Dollar

Model Specification Robustness

VAR models operate under the assumption that the residuals of the model follow a normal distribution. To assess the **normality of the residuals** in our VAR models, we employ the Jarque-Bera (JB) test of normality. From the JB test results presented in Table A.4, it is evident that the p-values of all news-extended models exceed 0.1. This indicates that we fail to reject the null hypothesis, suggesting that the residuals conform to a normal distribution.

Table A.4: Jarque-Bera Test Results for Residual Normality in VAR(7) Models

Currency	Test Statistics	Critical Value	P-value	Df	Result
With News					
GBP/USD	20.77	46.19	0.937***	32	Accept H_0
EUR/USD	21.35	46.19	0.924***	32	Accept H_0
Without News					
GBP/USD	34.00	28.87	0.013*	18	Accept H_0
EUR/USD	24.29	28.87	0.146***	18	Accept H_0

Note: The Jarque-Bera test assesses the normality of residuals in the VAR(7) model. H_0 represents the null hypothesis that model residuals are normally distributed.

Serial correlation of residuals presents a potential issue in VAR models. To evaluate its presence, we conduct the Durbin-Watson test and Portmanteau Test on the residuals. The Durbin-Watson statistics, all approximately 2.0, suggest no autocorrelation in the residuals. Furthermore, the p-values of the Portmanteau test for both models—those without news and those with news—are above 0.1. Therefore, we infer the absence of serial correlations between residuals.

The next issue that could arise in a VAR model is **heteroskedasticity**. To assess the presence of heteroskedasticity in our VAR model residuals, we conduct an Arch test. The p-values for both models are close to 0, indicating rejection of the null hypothesis regarding the presence of heteroskedasticity in the residuals.

Next, we assess the **stability** of our VAR models. A VAR(p)-process can be represented in a first-order vector autoregressive form, known as the companion form. Stability of the VAR(p)-process requires the absence of roots in or on the complex unit circle for its reverse characteristic polynomial. This condition is expressed as:

$$\det(I_K - A_1 z - \cdots - A_p z^p) \neq 0 \quad \text{for } z \leq 1 \tag{A.5}$$

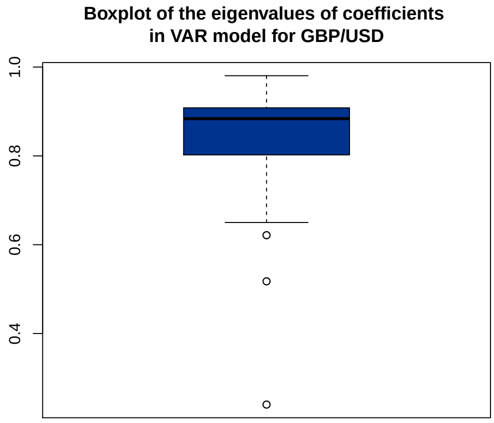
This condition is equivalent to ensuring that all eigenvalues of the companion matrix A have a modulus less than 1. To verify this, we compute the eigenvalues of the reverse characteristic polynomial.

Table A.5 presents the eigenvalues obtained from the reverse characteristic polynomial of a VAR(7) model for GBP/USD and EUR/USD and represent the solutions to the characteristic equation. Each row corresponds to a specific root number, providing both the real and imaginary components of the inverse roots.

Table A.5: Inverse Roots of a VAR(7) Model for GBP/USD and EUR/USD

Root Number	**GBP/USD Inverse Roots**	**EUR/USD Inverse Roots**
1	$0.76, 0.00i$	$0.67, 0.00i$
2	$-0.22, 0.74i$	$0.52, 0.48i$
3	$-0.22, -0.74i$	$0.52, -0.48i$
4	$0.23, 0.40i$	$-0.06, 0.59i$
5	$0.23, -0.40i$	$-0.06, -0.59i$
6	$-0.67, 0.00i$	$-0.58, 0.16i$
7	$-0.32, 0.00i$	$-0.58, -0.16i$

If the absolute values (moduli) of the eigenvalues of the coefficients (A matrix) in a VAR(p) process are less than one, the process is deemed stable or covariance stationary. The boxplots in Figure A.4, depicting the eigenvalues of our VAR(7) models, demonstrate that all eigenvalues reside within the [-1, 1] interval. This observation confirms that the moduli of the eigenvalues are less than one, validating the stability of the VAR models.



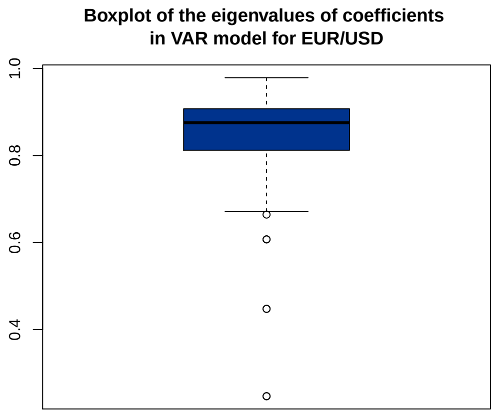


Figure A.4: Eigenvalues of VAR models

To validate our model's assumption about the **relationship between news variables and exchange rates**, we conduct multivariate F-type Granger-causality tests and Wald-type instantaneous causality tests.[7] Before conducting the tests, we ensure that all involved variables are stationary. Table A.6 presents the results of the multivariate Granger causality test. As shown, we cannot reject the null hypothesis of the Granger causality tests, indicating that GBP/USD and EUR/USD do not Granger-cause exogenous variables.

The p-values of the **instantaneous causality tests** are below the 0.01 level of significance, leading us to reject the null hypothesis. This suggests the presence of instantaneous causality between GBP/USD and macroeconomic variables, as well as news entropies, implying that future values of news entropies and macro variables can enhance exchange rate forecasts.

The presence of instantaneous causality between exchange rates and exogenous

[7]Instantaneous Causality: x is said to instantaneously Granger-cause y if a model that incorporates current, past, and future values of x along with current and past values of y has a smaller forecast error compared to a model that only uses current and past values of x and y.

variables, coupled with the absence of causal links from exchange rates to exogenous variables, aligns with the foundational assumptions of our VAR models for exchange rates and precludes the possibility of reverse causality. The identification of instantaneous causality between exchange rates and exogenous variables suggests the existence of contemporaneous relationships between these variables. This implies that fluctuations in exchange rates and exogenous variables may occur simultaneously, exerting mutual influence on each other.

Table A.6: Causality Tests for Model's Exogenous Variables and Exchange Rates

Null Hypothesis	**Statistics**	**P-Value**	**Result**
GBP/USD does not Granger Cause exogenous variables	F-Test =1.2126	0.0768	Accept H_0
EUR/USD does not Granger Cause exogenous variables	F-Test = 1.1739	0.1174	Accept H_0
No instantaneous causality between GBP/USD and exogenous variables	χ^2 = 35.582	0.002	Reject H_0
No instantaneous causality between EUR/USD and exogenous variables	χ^2 = 34.217	0.003	Reject H_0

To determine if **Granger causality tests** support the hypothesis that news causes fluctuations in exchange rates, we conduct bivariate Granger causality (F-type) tests. Granger causality in this context implies that past values of news significantly affect the current exchange rate when past news values are considered as regressors. The results of these tests are provided in Table A.7.

Table A.7: Bivariate Granger Causality Tests: Do News Granger Cause FX?

H_0 Hypothesis: News do not granger cause GBP/USD F-test Statistics of Bivariate Granger Causality Test							
Lag	**Topic 1**	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**	**EPU_US**	**EPU_UK**
1	6.24***	2.83*	0.00	1.58	0.09	1.21	18.58***
2	2.10	1.05	0.08	0.69	0.0	1.22	6.64***
3	2.58**	0.81	0.50	0.51	1.44	0.92	4.97***
4	1.63	0.79	0.48	2.72**	2.09*	1.41	3.92***
5	1.25	0.70	1.14	2.16*	1.57	2.73**	3.84***
6	1.11	0.66	0.94	1.77	1.31	2.483**	3.153*
7	1.16	0.80	0.92	1.61	1.23	2.16**	2.83***
H_0 Hypothesis: News do not granger cause EUR/USD F-test Statistics of Bivariate Granger Causality Test							
Lag	**Topic 1**	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**	**EPU_US**	**EPU_EU**
1	5.07**	5.37**	0.57	5.89**	0.37	0.23	0.19
2	3.25**	3.00**	0.87	4.63***	1.56	1.10	1.45
3	2.59**	1.88	0.66	2.95**	1.37	0.68	0.89
4	1.93	1.63	0.55	2.16*	1.91	0.53	0.86
5	1.36	1.16	0.48	1.55	1.38	0.72	1.00
6	1.33	1.68	0.99	1.84*	2.19	0.48	1.19
7	1.05	1.50	1.09	1.47	1.79*	0.61	1.37**

Note: This table presents the results of Granger causality tests with the null hypothesis H_0 of no Granger causality. The significance markers denote rejection of the null hypothesis at the following levels: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

The results in Table A.7 indicate that USD-related news topics and Economic Policy Uncertainty indices exhibit significant predictive power for GBP/USD and EUR/USD exchange rates. This highlights the importance of incorporating these variables as explanatory factors in exchange rate models. Despite the absence of Granger causality for certain variables, such as Topic 3 (for GBP/USD and EUR/USD) and EPU_{US} (for EUR/USD) across all lagged terms, as well as for some other variables in specific lagged terms, we include them in the model due to their theoretical relevance, observed correlations, and their contribution to enhancing the model's explanatory power. Excluding these variables decreases the model's explanatory power and increases the risk of omitted variable bias.

To assess whether incorporating news into our model enhances its explanatory power we **compare our model to a Taylor rule model without news**, we constructed a Taylor rule model without news and compared it with our news-augmented Taylor model for each exchange rate. Notably, the residuals of the model without news normalized after including 7 lags in the model. Residuals of the model without news had high variance, In contrast, the residuals of the models incorporating news exhibited significantly lower variances (0.0001% for GBP/USD and 0.004% for EUR/USD).

In the long term, for models excluding news variables, the forecast error decomposition showed that the exchange rate itself explained 52% and 77% of the variance for GBP/USD and EUR/USD, respectively. However, in models incorporating both, macroeconomic and news variables, these unexplained variances dropped to 32% and 48%. This indicates that including news variables reduces the unexplained variance in models that rely solely on macroeconomic variables.

In summary, despite the increased complexity of models incorporating news variables, they outperformed their counterparts without news. This suggests that the inclusion of news variables significantly improves the models' explanatory power, warranting the assessment of additional variable coefficients.

We also **compare our model to the model with only news variables** and no macroeconomic variables. The p-value of the residuals normality test for the model with only news variables is lower (0.82 for GBP/USD and 0.21 for EUR/USD) than the corresponding p-value of the model with news and macroeconomic variables. The residuals of the model with only news variables have higher variance (0.0002 for GBP/USD and 0.0003 for EUR/USD) than the model with news and macroeconomic variables.

In the long run, the forecast error decomposition percentage explained by the exchange rate itself is 66% for GBP/USD and 69% for EUR/USD, while corresponding values lie at 32% and 48% for the models with news and macroeconomic variables. This indicates that a larger portion of exchange rate movements is explained by the exogenous variables in the model with both macroeconomic and news variables, and that our model, which incorporates both, outperforms the model that relies solely on news variables.

What is the explanatory power of the model for interest rates? We constructed an **analogous model for the U.S. money market rate**. The R^2 value of the normality test for the VAR residuals is 0.89, indicating strong explanatory power and supporting the validity of our model. The residuals exhibit a mean of -3.3206e-18 and a variance of 9.0227e-08, with no detectable autocorrelation.

In summary, all of the robustness checks outlined in this section affirm the resilience of our news-enhanced exchange rate model, which integrates news into the well-established Taylor rule model. Furthermore, we demonstrate that our news-enhanced exchange rate model outperforms both the Taylor rule model without news and news-based models that do not incorporate macroeconomic variables.

A.8 Theoretical Foundations

Literature Review on Exchange Rate Determinants This section explores the literature on exchange rate determinants as outlined by economic theory. We then compare these theoretical factors with U.S. Dollar-related topics we have identified to assess their relevance for exchange rate identification according to theory.

Stock Exchange According to monetary models of exchange rate determination Gavin (1989), stock prices influence exchange rate movements through aggregate demand. Stock prices alter aggregate demand through wealth effects on consumption and the effects of capital valuation on investment decisions, and the altered aggregate demand in turn influences the floating exchange rates. Portfolio-balance models suggest an influence of the stock market on exchange rates through investors' portfolio decisions.

A number of existing studies examine the relationship of stock market and exchange rates. Some of them, Xie et al. (2020), Coronado et al. (2020), Walid et al. (2011), Tsai (2012) recognize that stock prices are helpful for predicting exchange rates.

International Trade According to economic theory and prior research, international trade influences exchange rates through three main channels:
1) **Current Account Imbalance:** International trade may affect exchange rates through the imbalance of the current account, either in deficit or surplus. The current account encompasses net trade in goods and services, net earnings on cross-border investments, and net transfer payments. When a country runs a current account deficit, it needs to purchase foreign currency with its local currency, increasing the demand for the foreign currency relative to the local currency, thus decreasing the price of the local currency, ceteris paribus. Fratzscher (2009) found that the sizes of current accounts and US foreign investments were significant determinants of exchange rates of the USD vis-à-vis 54 foreign currencies. Recently, Guo and Chen (2023) concluded that international trade news events significantly influenced the RMB exchange rate.
2) **Expectations about Trade Policy Changes:** International trade influences exchange rates through expectations about changes in trade policy (Hogan et al., 1991), including alterations in international taxation (fiscal policy), globalization strategy, and actions of local government trade departments (e.g., the agency treasury in the USA). If the USA has a trade deficit, the Federal Reserve is likely to increase protectionist policies. A clear example of this is the increase in import tariffs on steel and aluminum, impacting automobile imports in the U.S. Additionally, cutting

budget deficits often accompanies changes in trade policy. In 2019, reducing the budget deficit was part of the U.S. plan to address the current account deficit (130.4 Billion in the first quarter of 2019). After information about the expected drop in net trade is released, there may be less available foreign currency due to a decrease in its supply on the local market (due to the expectation that the supply of foreign currency from abroad will decrease in the future and will cost more), resulting in an increase in the price of the foreign currency relative to the local currency. This devaluation of the local currency and jump in the foreign exchange rate is known as an increase in **exchange rate exposure**, potentially causing losses or gains in the economy. 3) **Commodities Trading:** Commodities trading, as part of international trading, can influence exchange rates, especially for commodity-exporting countries. Oil, for instance, is primarily traded in U.S. dollars and influences the USD exchange rate due to this fact as well. Recent literature underscores the relationship between oil prices and the USD exchange rate (e.g., Fratzscher et al. (2014)). Similarly, there is a long-term relationship between precious metal prices, such as gold, and the USD exchange rate.

Central Bank Central banks employ various tools to achieve specific economic policy goals and influence exchange rates through the financial markets channel. 1) A central bank's primary policy instrument that may affect the exchange rate is the **Monetary Policy Rate**, which is the interest rate at which commercial banks can borrow from the central bank. 2) Another tool used by central banks in the financial market is **FOREX Interventions**. The central bank buys or sells the local currency on the foreign exchange market to manipulate the exchange rate of the local currency by changing its demand. The effect of foreign market interventions, typically financed by foreign currency reserves, is significant. A notable example of currency manipulation is China's interventions on FOREX against the USD to devalue the renminbi. The only regulators of such actions are the IMF and WTO, although they have not historically been effective. 3) **Open Market Operations** is another tool employed by central banks in the financial market. When the central bank purchases or sells securities, primarily government bonds, from banks, it affects the money supply. Expansionary monetary policy involves the central bank purchasing bonds, increasing the money supply in banks, which may lead to currency devaluation in the long run, ceteris paribus.

Policy Rate The relationship between exchange rates and policy rates is formalized by Taylor rule models, which are more broadly discussed below. Rosa (2011) tested the impact of news about policy rate decisions and central bank communications on exchange rates using intraday data of the USD exchange rate versus the Euro, British pound, Canadian dollar, Swiss franc, and Japanese yen. They analyzed a one-hour window around the announcements and found highly significant and large effects of policy rate news on exchange rates for up to one hour after the announcement.

Clarida and Waldman (2008) build a robust monetary exchange rate model (with inflation targeting and interest rate rule, Calvo pricing, and PPP assumptions). By employing high-frequency data (inflation announcements) for ten countries, Clarida and Waldman (2008) show that "bad" news for inflation is "good news" for the nominal exchange rate. Moreover, Clarida and Waldman (2008) argue that the sign of covariance between an inflation shock and exchange rate can show how monetary policy is conducted. They state that under inflation-targeting monetary policy exchange rate after its initial jump in response to the breaking news, should depreciate in response to inflation shock in the long run, due to the PPP assumption.

Financial Performance and Tax Revenue In the case of a massive increase in local companies' financial performances due to a shift in productivity, the country's competitiveness might improve, and the local currency might strengthen, as the exchange rate reflects the country's export competitiveness. Furthermore, significant improvements in financial performance, expressed in the balance sheet, can bolster the government's tax revenue through increased taxable income. This strengthening, in turn, fosters greater stability within the country and serves as an indicator of its competitiveness. The financial performance of the business sector also influences exchange rates through the stock market. Positive news regarding company earnings can encourage investors to purchase stocks, leading to increased demand for the local currency and a stronger exchange rate.

Exchange Rate Reserves The size of foreign exchange (FX) reserves is identified as one of the top three determinants of post-2008 crises USD exchange rates vis-à-vis 54 countries, as noted in the ECB report Fratzscher (2009).

The effects outlined in this section are not accounted for in traditional macroeconomic fundamentals-based models, such as the Taylor rule model. Therefore, we anticipate capturing these effects on USD exchange rates by incorporating news into our model.

A.9 Impulse-Response Analysis

Impulse-response analysis serves as a vital tool for examining the dynamic reactions of variables to exogenous shocks. The impulse-response function (IRF) quantifies how a standard deviation shock to the i_{th} variable in y_t influences the y_{t+n} time period.

The IRF, denoted as $\phi_{ji}(n)$, is defined as:

$$\phi_{ji}(n) = e_j' A_n P e_i, \tag{A.6}$$

where $n = 0, 1, 2, ...,$ e_i represents a selection vector, A_n is the n_{th} coefficient matrix obtained from the infinite moving average representation of y_t, and P stems from the Cholesky decomposition of the covariance matrix of y_t ($PP' = \Sigma_\varepsilon$). One notable limitation of IRF is its lack of invariance to variable ordering.

In contrast, Koop et al. (1996) and Pesaran and Shin (1998) introduced the generalized impulse-response analysis (GIRF), which is invariant to variable ordering. The GIRF, denoted as $\phi_{ji}^g(n)$, is expressed as:

$$\phi_{ji}^g(n) = e_j' \sigma_{ii}^{-1/2} A_n \Sigma_\varepsilon e_i, \tag{A.7}$$

where σ_{ii} represents the ii_{th} element of the covariance matrix of residuals Σ_ε.

Dynamics of Exchange Rates in Response to U.S. Dollar-related News

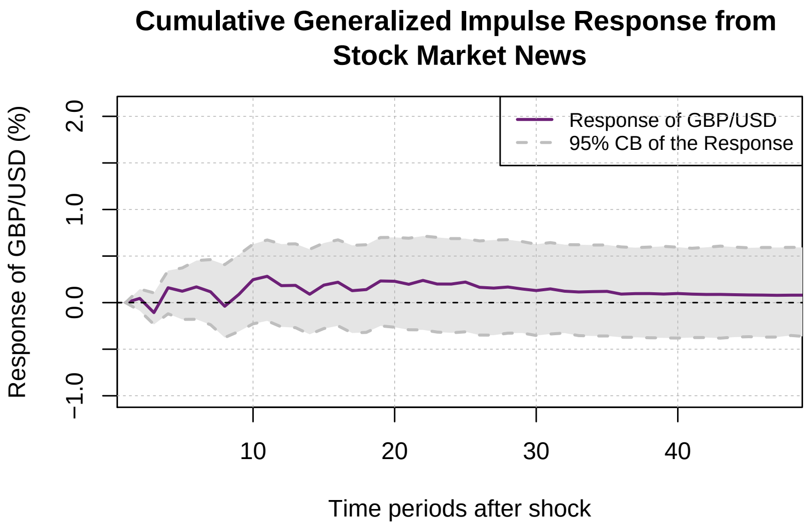
Figures A.5, A.6, A.7, A.8, and A.9 in this appendix illustrate the cumulative generalized impulse-response functions of exchange rates to various news topics. We utilize the cumulative impulse response function (CIRF) instead of the standard impulse response function (IRF), as it captures the total impact of shocks and mitigates the influence of specific historical points by aggregating responses over time. Notably, the exchange rate and news series in the model are presented as the first differences of natural logarithms, facilitating clear interpretations of resulting percentage impulse responses. The reported numbers on Figures A.5 to A.9 represent the percentage responses of exchange rates to a 1% shock in the respective news.

Figure A.5 illustrates the cumulative impulse-response function (CIRF) of exchange rates concerning the first news topic - Stock Market News. It depicts the percentage response of exchange rates to a 1% shock in stock market news.[8] In re-

[8] Our analysis measures the impulse-response of the monthly U.S. Dollar exchange rate's first difference to the attention given to the topic's first difference. This attention may result from positive or negative information, leading to a percentage change in the monthly U.S. Dollar exchange rate due to a one percent increase in attention to any news type. Even if the sign of this impulse-response function is not statistically significant, its fluctuations may correspond to a defined response to positive or negative news attention. We would like to highlight that the majority of the news in our dataset (69%) is neutral in tone, while positive and negative news account for 14% and 17%, respectively. This distribution of news sentiment supports our decision to analyze the data as a

sponse to a positive 1% stock market news shock, GBP/USD appreciates persistently over the full 48-month period depicted in Figure A.5. However, this appreciation effect is not statistically significant. This lack of significance may be attributed to the mixed nature of the news, which includes both positive and negative elements that could counterbalance each other. [9]

Similarly, the figure reveals that the appreciation of EUR relative to USD is persistent over the entire 48-month horizon, with statistically significant appreciation observed in some periods.



whole, rather than focusing separately on positive and negative subsamples, as the neutral news makes up a significant portion of the dataset.

[9]Our news dataset contains more positive news than negative news. The tests for asymmetric responses reveal no significant differences in reactions to positive versus negative news. Besides, Galati and Ho (2003) find that their formal testing does not provide evidence to reject the hypothesis of symmetric responses of exchange rates to positive and negative news.

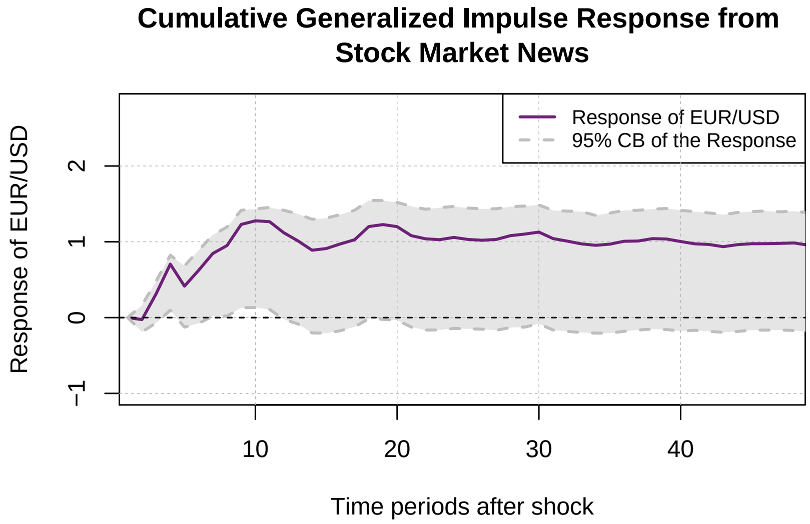


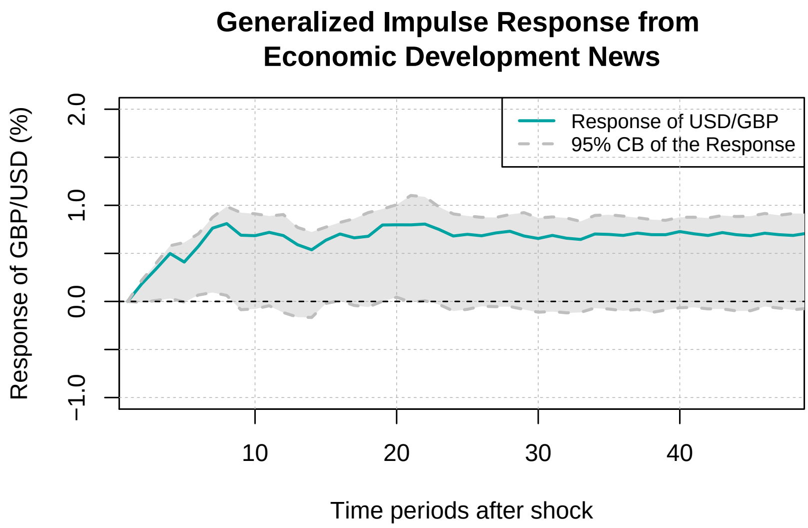
Figure A.5:
Cumulative GIRFs of exchange rates to Stock Market News 1% shock. The figure illustrates the cumulative generalized impulse response function (GIRF) of stock market (including oil commodities) news on exchange rates. The solid purple lines denote point estimates of exchange rate responses to the shock in stock market news, while the gray dotted lines represent 95% confidence bands (CB) derived from 1,000 bootstrap simulations. The gray shaded area indicates the 95% confidence interval (CI). The vertical axis displays the percentage response of exchange rates to a 1% shock in stock market news. The horizontal axis corresponds to the periods after the shock, with each period representing one month).

In summary, Figure A.5 demonstrates the influence of the U.S. Dollar-related topic "stock market" on exchange rates. A positive shock to the attention given to the "stock market" topic may lead to an appreciation of exchange rates vis-à-vis the USD in certain instances, resulting in a decrease in the price of the U.S. Dollar relative to foreign currencies.

The cumulative impulse response functions from our model exhibit large confidence intervals, reflecting the inherent complexity of exchange rates and the varying influence of news events. However, the model effectively demonstrates the existence of a historical impact from a 1% change in attention to FX-related news and is supported by strong Forecast Error Variance Decompositions (FEVDs), which reinforce its reliability in confirming this impact.

Figure A.6 illustrates the cumulative generalized impulse response functions of exchange rates to economic development news. It demonstrates that exchange rates do react to shocks in economic development news. From Figure A.6, we observe that a positive economic development news shock has a statistically significant impact on GBP/USD in the third month and from the fifth to the ninth month.

Regarding EUR/USD, the cumulative impulse response to economic development news is statistically significant and positive from the first to the fourth month and from the sixth to the ninth month.



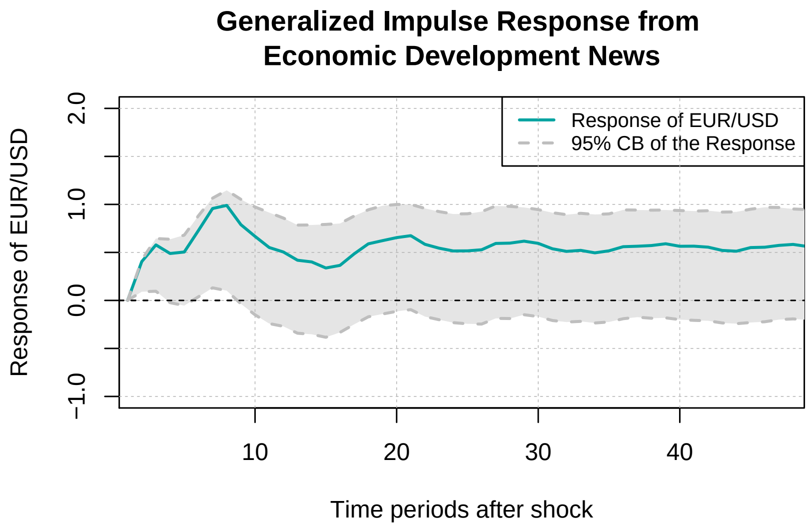
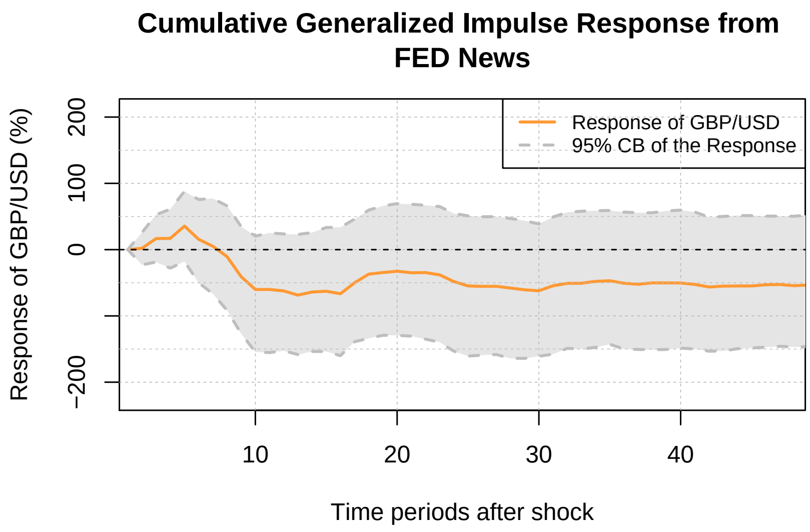


Figure A.6: Cumulative GIRFs of exchange rates to Economic Development News 1% shock. The figure illustrates the cumulative generalized impulse response functions (GIRFs) of exchange rates to Economic Development News. The green solid lines represent point estimates of exchange rate responses to shocks in economic development news entropy, while the gray dotted lines depict the 95% confidence bands (CB) from 1,000 bootstrap simulations. The gray shaded area indicates the 95% confidence interval (CI). The vertical axis displays the percentage response of exchange rates to a 1% shock in economic development news, and the horizontal axis denotes the time period after the shock (in months).



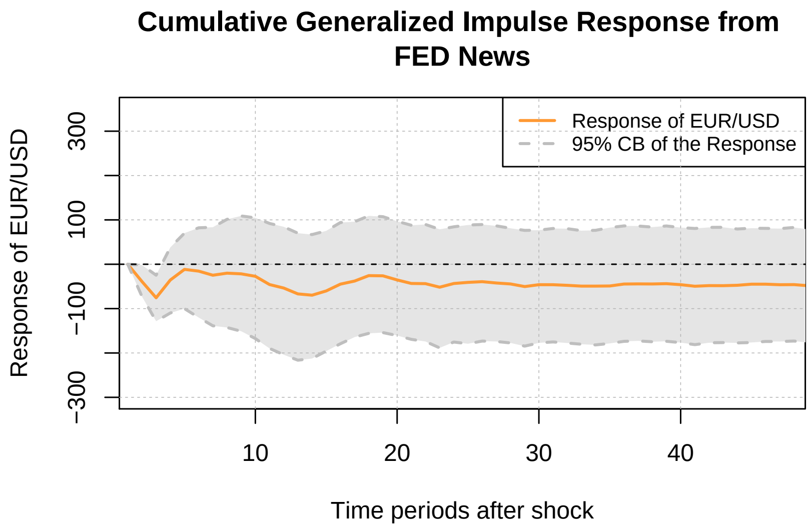


Figure A.7:
Cumulative GIRFs of exchange rates to FED News with a 1% shock. The figure illustrates the cumulative generalized impulse response functions (GIRFs) of exchange rates to FED news. The orange solid lines represent point estimates of exchange rate responses to a 1% shock in FED News, while the gray dotted lines depict the 95% confidence bands (CB) obtained from 1,000 bootstrap simulations. The gray shaded area indicates the 95% confidence interval (CI). The vertical axis displays the percentage response of exchange rates, while the horizontal axis shows the time periods after the shock (in months).

In summary, Figure A.6 supports our hypothesis that economic development news influences exchange rates. Moreover, it indicates that both GBP/USD and EUR/USD appreciate in response to positive economic development news shocks, with significant effects persisting for up to nine months.

On Figure A.7, we observe a consistent negative response of EUR/USD to FED news over the 48 months following the shock. The figure also indicates that the impact of FED news on EUR/USD is statistically significant from the first month to the fourth month after the shock. Specifically, this implies that the USD strengthens relative to the EUR in the initial quarter following increased attention to FED news in the U.S. media. Notably, the response peaks in the third month after the shock, with the EUR/USD exchange rate experiencing a 15% decline. Consequently, we infer that FED actions, as reflected in media coverage, result in a stronger U.S. Dollar compared to the Euro during the first quarter following the action, with the observed impact of a 1% increase in attention to FED news being particularly notable.

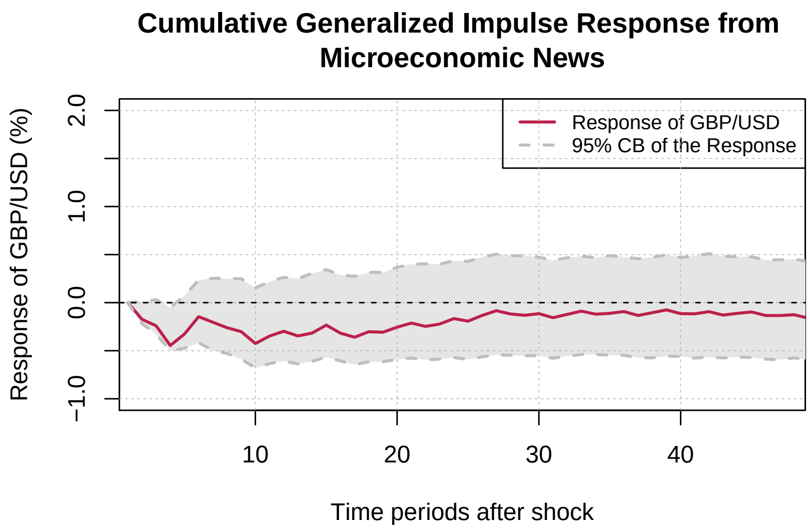
All in all, Figure A.7 also supports the hypothesis that the U.S. Dollar related topic "FED news" influences exchange rates, as increased attention to the FED news significantly depreciates EUR/USD in the first quarter after the shock.

Figure A.8 illustrates the response of EUR/USD to a 1% shock in microeconomic news from US sources. It shows a decreasing trend from the second to the eighth month, followed by an increase thereafter. However, the observed responses of EUR/USD are statistically insignificant across all months.

In conclusion, the impulse response depicted in Figure A.8 lends support to the notion that microeconomic news influences exchange rates. Specifically, GBP/USD depreciates during the initial quarter following a microeconomic news shock.

Figure A.9 illustrates the response of exchange rates to a shock in international trade news. Analysis of Figure A.9 reveals that GBP/USD appreciates in response to heightened attention to international trade news over the entire 48-month period following the shock. Furthermore, the observed appreciation is statistically significant in certain months.

To summarize, Figure A.9 confirms the hypothesis that international trade news impacts exchange rates. Specifically, GBP/USD appreciates in the second quarter following the shock in international trade news.



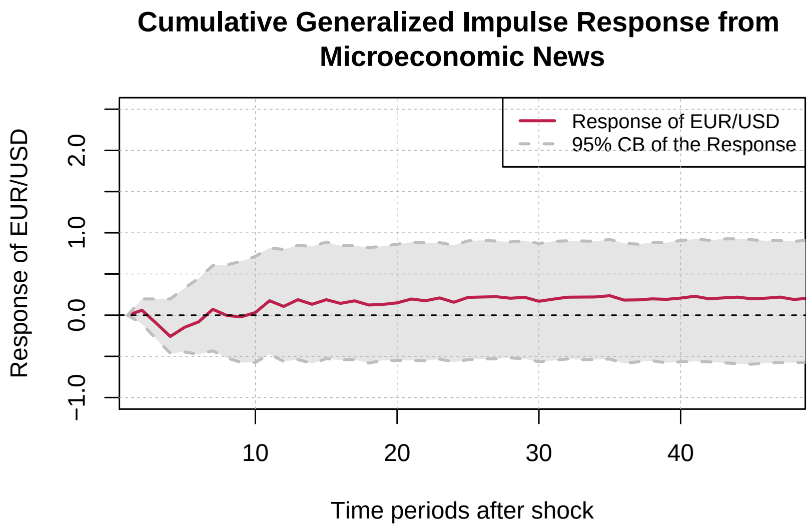
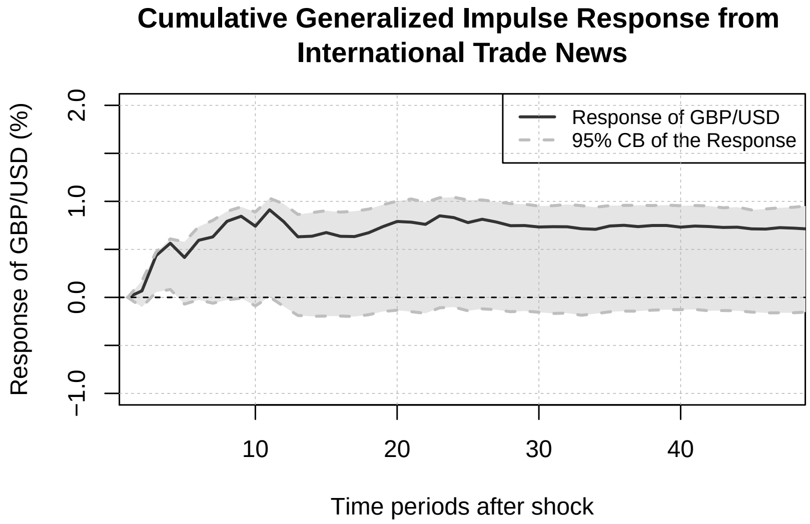


Figure A.8: Cumulative GIRFs of exchange rates in response to a 1% shock in Microeconomic News. This figure depicts the cumulative impulse response functions (GIRFs) of exchange rates to microeconomic news, including company earnings and related information. The solid red lines represent the point estimates of exchange rate responses to a 1% shock in microeconomic news entropy, while the gray dotted lines indicate the 95% confidence bands (CB) derived from 1,000 bootstrap simulations. The gray shaded area denotes the 95% confidence interval (CI). The vertical axis displays the exchange rate response in percentage terms, while the horizontal axis indicates the time period in months after the shock.



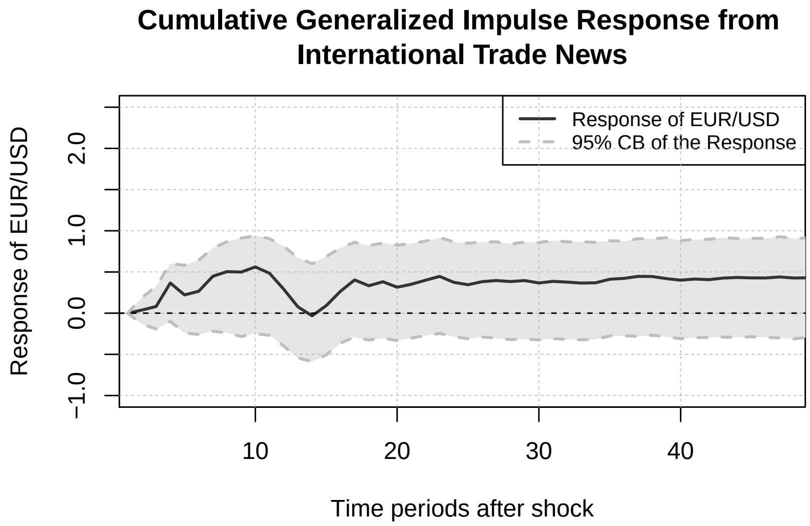


Figure A.9: Cumulative GIRFs of exchange rates in response to a 1% shock in International Trade News. This figure illustrates the cumulative generalized impulse response function (GIRF) of exchange rates to international trade news. The solid black lines represent the point estimates of exchange rate responses to a 1% shock in international trade news (entropy), while the gray dotted lines depict the 95% confidence bands (CB) derived from 1,000 bootstrap simulations. The gray shaded area indicates the 95% confidence interval (CI). The vertical axis displays the exchange rate response in percentage terms to a 1% change in the international trade news innovation, while the horizontal axis represents the time period in months after the shock.

Dynamics of Exchange Rates in Response to Selected Macroeconomic Variables

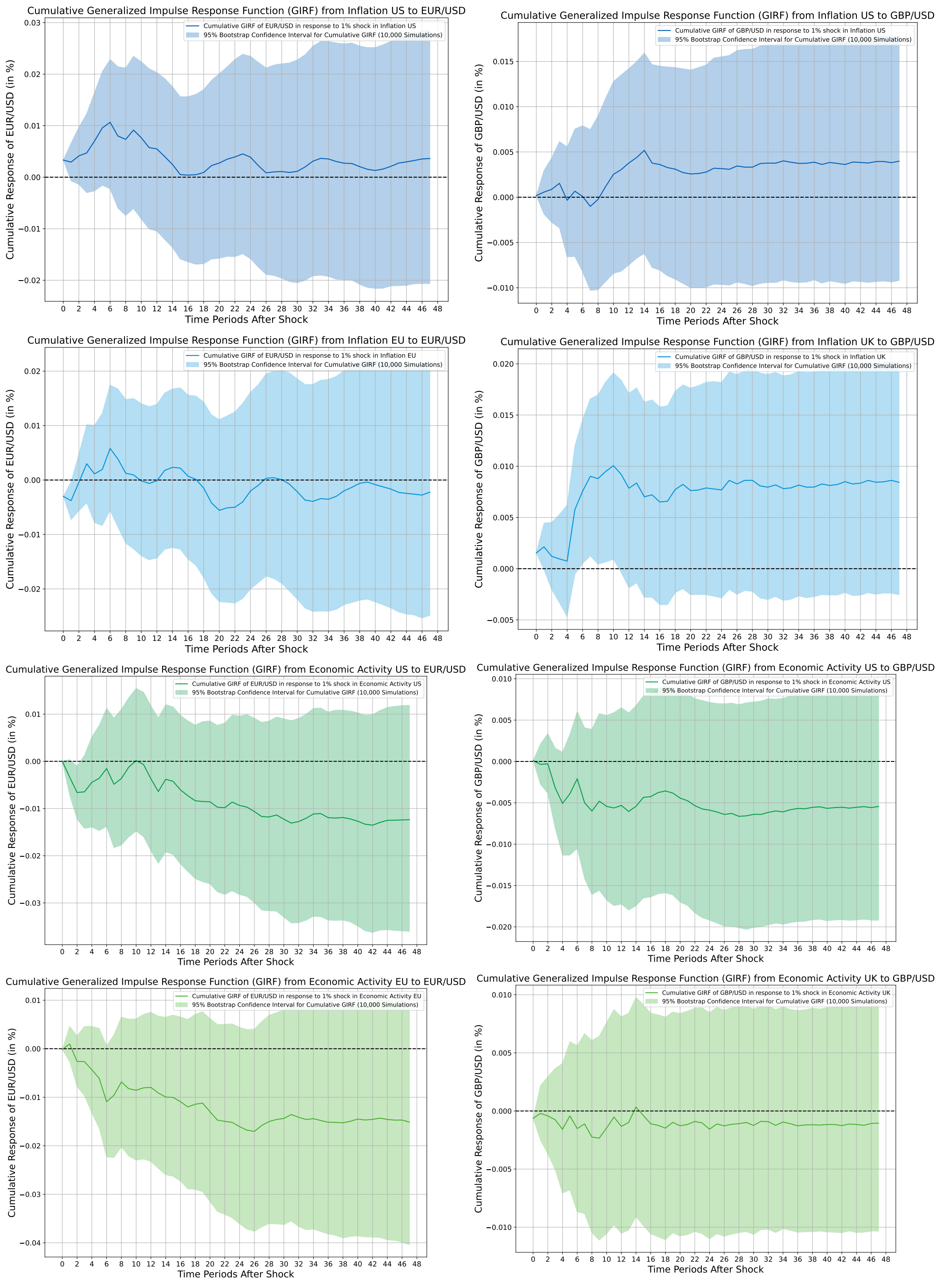


Figure A.9:
Cumulative GIRFs of Exchange Rates to Macroeconomic Variables (Part 1)

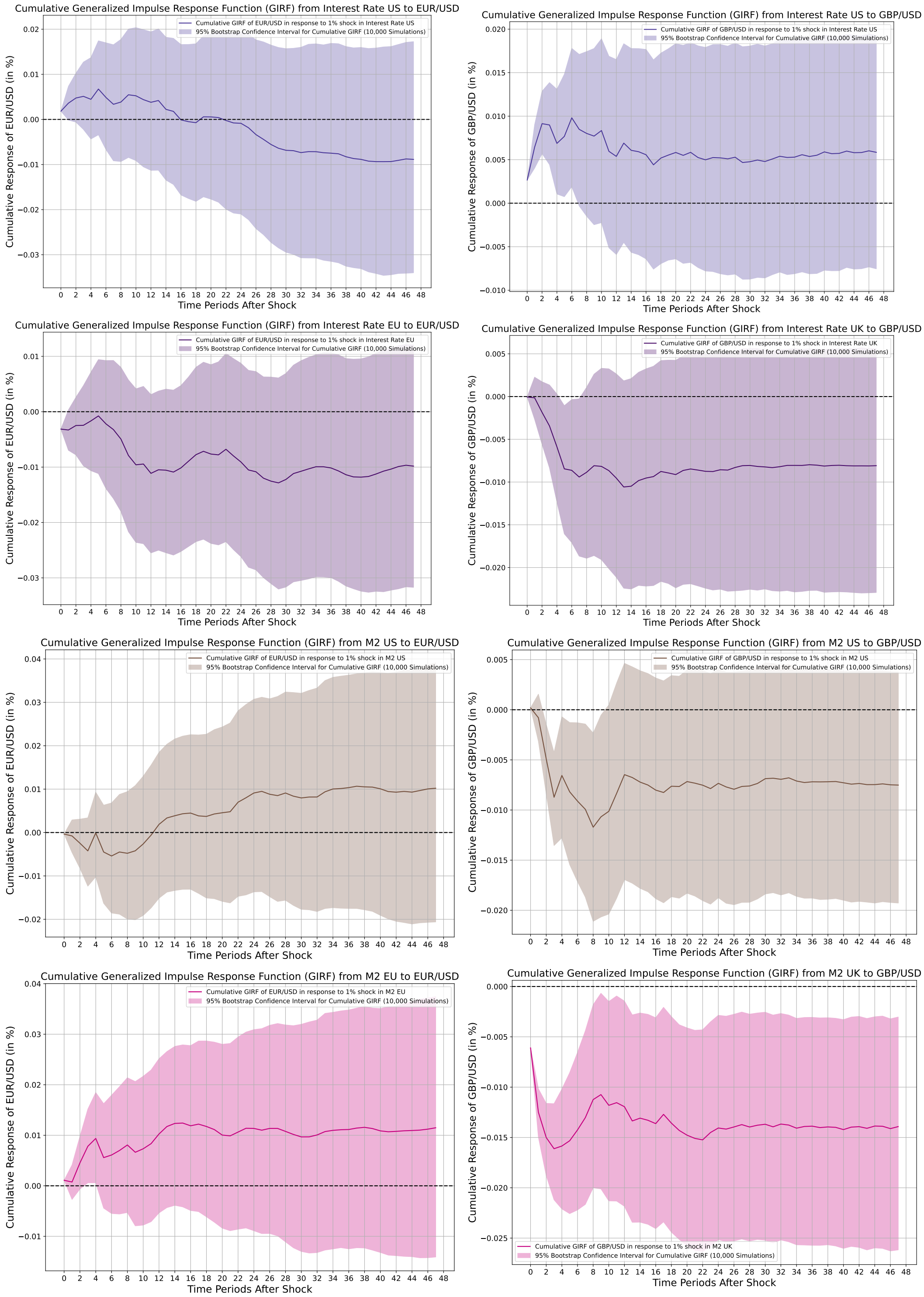


Figure A.9:
Cumulative GIRFs of Exchange Rates to Macroeconomic Variables (Part 2)

B Appendix to Chapter 2: Capital Structure Determinants in German SMEs: Panel Analysis and Policy Recommendations

B.1 Data Visualizations After Outlier Removal

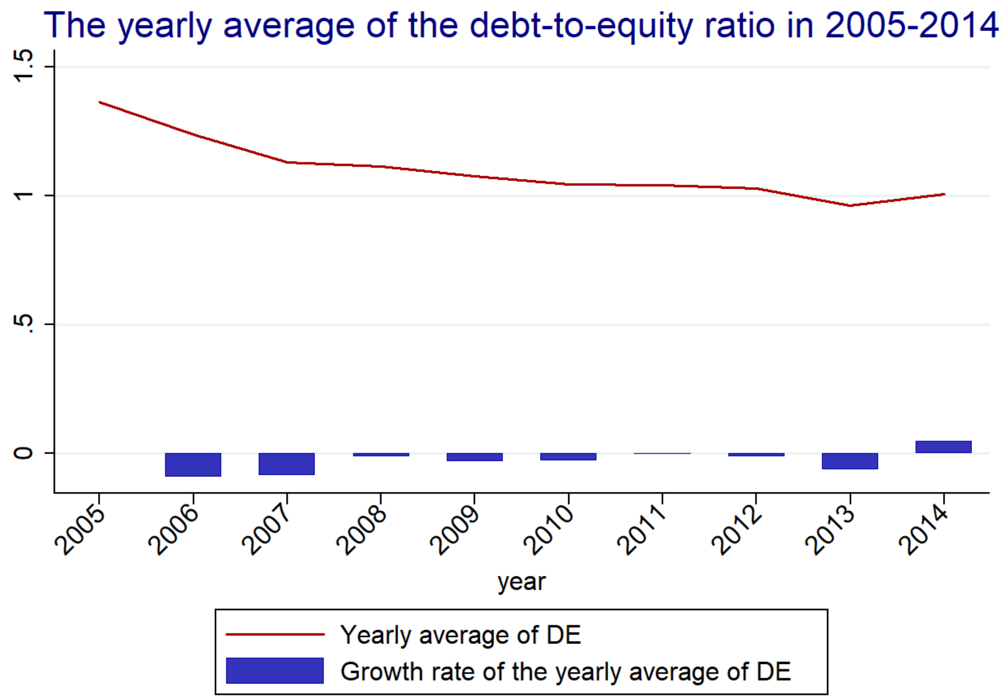


Figure B.1:
Overall yearly mean of the debt-to-equity ratio of SMEs in Germany
The figure illustrates the dynamics of overall yearly mean of the debt-to-equity ratio of SMEs in Germany after deleting outliers.

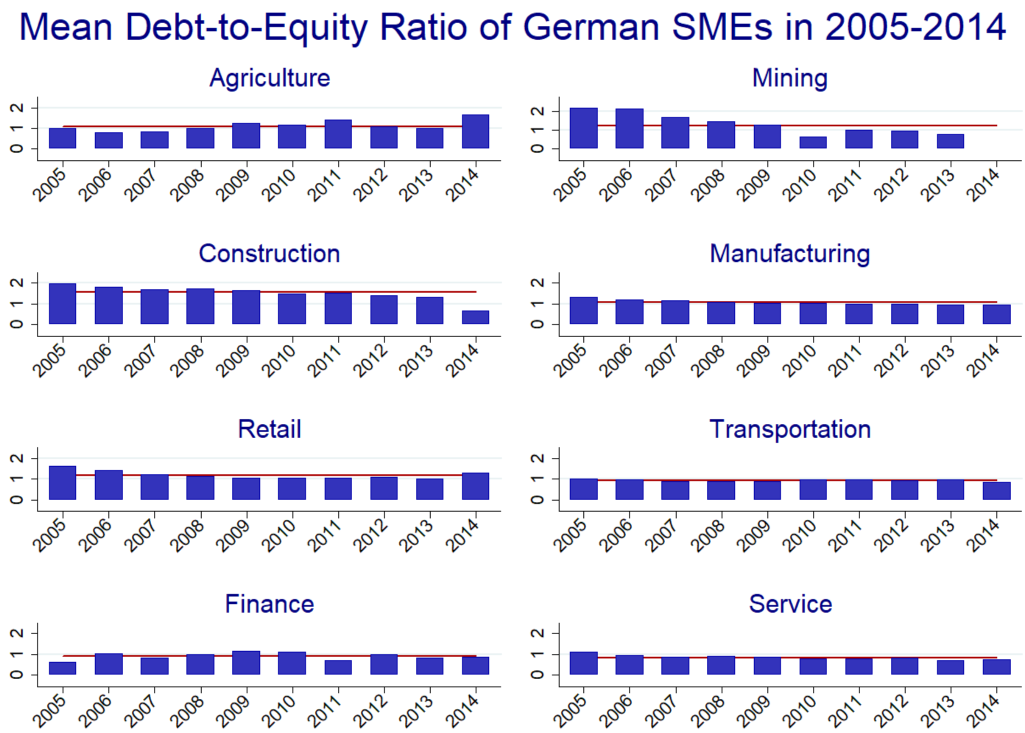


Figure B.2:
Debt-to-equity ratio of German SMEs per industry from 2005 to 2014
The figure illustrates the overall yearly mean of the debt-to-equity ratio of SMEs in Germany, depicted after removing outliers. The horizontal axis represents the years under consideration, while the vertical axis denotes the yearly mean debt-to-equity ratio. The blue columns represent the yearly means of debt-to-equity ratios within each industry. The red lines represent the overall industry means of the debt-to-equity ratio. This visualization offers an overview of the trend in the debt-to-equity ratio of German SMEs over the specified time period, highlighting any notable fluctuations or patterns.

B.2 Robustness Tests

If there is a significant omitted variable that influences the capital structure, it is likely to be suggested in the literature. To ensure the robustness of our model, we systematically add various variables proposed as determinants of leverage in the literature, both individually and in combination, and assess whether they improve the model's goodness-of-fit.

In our robustness check, we tested profitability (ROA), tangibility (long-term tangible assets / total assets), and net trade credit ((debtors/creditors)/sales) as alternative determinants of the debt-to-equity ratio. These alternative firm-specific variables were examined because there is some evidence in the literature suggesting that these variables can be important determinants of capital structure Seifert et al. (2013); García-Teruel and Martínez-Solano (2010); Antoniou et al. (2008); De Jong et al. (2008); Rubio and Sogorb (2011); Chang and Dasgupta (2009). From macroeconomic variables, we tested inflation (based on CPI), the indirect influence of which on leverage aligns with both the trade-off theory and pecking order theory.

However, models using inflation instead of term spread did not perform better. The model that showed the closest performance to our model included return on assets, net trade credit, tangibility, size, lagged inflation, and lagged uncertainty index. None of the simulations produced a significantly better model when compared using log-likelihoods, root mean square error (RMSE), and root mean square forecast error (RMSFE) using the 2 years of out-of-sample data till 2017.

There is no strong evidence suggesting that German SMEs with higher tangibility ratio, profitability, risk, or more trade credit use more debt than their counterparts. Compared to the variables in the robustness testing, non-debt tax shield and firm size have greater power as capital structure determinants. Additionally, dynamic panel data models have slightly higher rho coefficients in the case of our model. Table B.1 presents results of an alternative Industry-specific model with ROA, NTC, Tangibility, size, inflation and news-generated economic policy uncertainty index.

In Table B.2 we present the robustness test results for the single variable "tangibility".

Table B.2: Robustness Check of firm-level model: Size VS Tangibility for solvency group with debt-to-equity ratio less or equal to 1.

	(1)	(2)	(3)
Model Variables	DPF	DPF	DPF
Lag DE	0.1209***	0.1181***	0.1182***
NDS	-0.0294	0.0000	-0.4106***
Size	-0.0073	—	0.0056
Tangibility	—	0.5436***	0.5452***
Const	0.0018	-0.1702***	-0.1350***
Observations	49,974	49,974	49,974
Number of firms	13,051	13,051	13,051
For each ID the first entry of DE	-0.0659***	-0.0591***	-0.0590***
Mean DE	0.4814***	0.4333***	0.4329***
Mean NDS	1.2044***	-0.0293	-0.0404
Mean s	-0.0023	—	-0.0091
Mean Tang	—	0.0691**	0.0663**
Σ_u	0.4290***	0.3977	-0.0590***
Σ_e	0.3030***	0.2963	0.4329***
ρ	0.6671	0.6432	0.5733

*** p<0.01, ** p<0.05, * p<0.1

Table B.1: Industry-specific model with Alternative Variables– DPF Estimator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Agriculture	Mining	Construction	Manufacturing	Retail	Transportation	Finance	Services
Lag DE	0.2118***	0.6537***	0.1085***	0.1394***	0.0900***	0.1077***	0.1684***	0.1073***
	(0.0267)	(0.0868)	(0.0067)	(0.0051)	(0.0055)	(0.0055)	(0.0425)	(0.0061)
ROA	-0.6356	-1.1071*	0.2544**	-0.0558	0.1911*	0.1252*	-0.3896	-0.2107***
	(0.5779)	(0.6325)	(0.1059)	(0.0720)	(0.1102)	(0.0753)	(0.7032)	(0.0779)
NTC	0.1935**	1.3361	0.0913*	0.01717	0.2177***	0.029**	0.0109	0.1011***
	(0.0925)	(0.8822)	(0.0507)	(0.0143)	(0.0662)	(0.01469)	(0.1061)	(0.0182)
Tangibility	0.7054***	0.0422	0.4862***	0.5368***	0.6858***	0.6336***	0.0206	0.4551***
	(0.1776)	(0.4727)	(0.0889)	(0.0483)	(0.0718)	(0.04904)	(0.3542)	(0.0554)
Size	-0.1093*	-0.0382	0.0062	-0.0108	0.0936***	0.0384***	-0.0710	0.0061
	(0.0575)	(0.1680)	(0.0173)	(0.0148)	(0.0184)	(0.0141)	(0.0576)	(0.0135)
Inflation	0.6377	-4.6337	2.1576***	2.1410***	1.8776***	0.3110	6.07902	1.6116**
	(1.1814)	(4.3135)	(0.7903)	(0.5105)	(0.6511)	(0.5159)	(4.2792)	(0.6270)
Uncertainty Index	0.0001	0.0003	-0.0009***	-0.0011***	-0.0010***	-0.0002*	0.00007	-0.0006***
	(0.0003)	(0.0009)	(0.0002)	(0.0001)	(0.00013)	(0.0001)	(0.0009)	(0.0001)
For each ID the first DE	-0.2152***	-0.1358***	-0.0133*	-0.0607***	-0.0996***	-0.0556***	-0.0833*	-0.0734***
	(0.0294)	(0.0467)	(0.0074)	(0.0064)	(0.0072)	(0.0063)	(0.0492)	(0.0071)
Mean Lag DE	0.5158***	0.3176***	0.3513***	0.4180***	0.5553***	0.4507***	0.4882***	0.3863***
	(0.0574)	(0.0940)	(0.0168)	(0.0121)	(0.0154)	(0.0147)	(0.0771)	(0.0135)
Mean ROA	0.7017	-0.8593	-1.9244***	-0.4322**	-0.8064***	0.0074	-0.1817	0.0059
	(1.1468)	(1.4669)	(0.3560)	(0.1979)	(0.2850)	(0.2004)	(1.2288)	(0.1362)
Mean NTC	-0.1845	-2.1262*	-0.0101	0.0475	0.0006	-0.0614	-0.1832	-0.1255***
	(0.1377)	(1.1308)	(0.0117)	(0.0298)	(0.0065)	(0.0465)	(0.2562)	(0.0243)
Mean Tangibility	-0.3054	-0.0619	0.3434***	-0.0181	0.1290	-0.0446	0.7219*	0.2195***
	(0.2011)	(0.4813)	(0.1004)	(0.0600)	(0.1157)	(0.0572)	(0.3978)	(0.0627)
Mean Size	0.1262**	0.0335	0.0014	-0.0428**	-0.0909***	-0.0332**	0.2034**	-0.0046
	(0.0596)	(0.1733)	(0.0225)	(0.0169)	(0.0224)	(0.01579)	(0.08581)	(0.01545)
Mean Inflation	-0.5808	-21.6650	-2.1696	-4.7160**	-8.18676**	2.44515	-35.61998**	-3.29150
	(6.4632)	(18.1380)	(4.1926)	(2.3021)	(3.4202)	(3.5119)	(16.0178)	(3.0124)
Mean Uncertainty Index	0.0004	0.0017	0.0009*	0.0018***	0.0005	-0.0001	-0.0021	0.0011***
	(0.0007)	(0.0024)	(0.0005)	(0.0003)	(0.0005)	(0.0004)	(0.0022)	(0.0004)
Constant	-0.2553	0.3544	-0.1703	0.4012***	-0.0762	-0.3082***	-0.8611	-0.3310***
	(0.2377)	(0.5270)	(0.1627)	(0.1015)	(0.1471)	(0.1086)	(0.7528)	(0.1006)
Σ_u	0.2211***	0.0000	0.3990***	0.3726***	0.4312***	0.3250***	0.3938***	0.4022***
	(0.0223)	(0.1061)	(0.0118)	(0.0070)	(0.0097)	(0.0075)	(0.0901)	(0.0098)
Σ_e	0.1441***	0.2576***	0.2879***	0.3079***	0.3239***	0.2547***	0.3622***	0.2891***
	(0.0064)	(0.0242)	(0.0047)	(0.0032)	(0.0042)	(0.0031)	(0.0305)	(0.0038)
ρ	0.7019	0	0.6577	0.5943	0.6394	0.6194	0.5418	0.6594
	(0.2449***)	(0.0000)	(0.4753***)	(0.3826***)	(0.4775***)	(0.3697***)	(0.4409***)	(0.4553***)
Observations	494	118	6,414	14,407	11,035	8,481	333	8,690
Number of firms	152	28	1,594	4,049	2,783	1,912	96	2,435
Log Likelihood	27.79	-30.11	-2534	-7365	-5310	-3214	-175.6	-4164
RMSE	0.2615	0.3018	0.2913	0.3444	0.3859	0.3282	0.3608	0.2932

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parenthesis.

While the Dynamic Panel Fractional (DPF) estimator is theoretically consistent and empirically validated for unbiasedness, as demonstrated by studies like Elsas and Florysiak (2015), we conduct sensitivity checks to evaluate its robustness to sample changes. The results in Table B.2 indicate moderate to high sensitivity to specification changes in the firm-level model. We see that in case of many specification changes, which is removing Term Spread and and uncertainty index, the model results change. The model results do not change much if we only exclude/replace one variable. In the following section, we proceed with out-of-sample assessments in subsection "Out of Sample Assessments" to further evaluate the sensitivity to sample changes.

B.3 Endogeneity Assessment

The industry-specific residuals correlation heatmaps are depicted in Figure B.3. Our analysis indicates minimal evidence of endogeneity concerns, as the correlations between the model residuals and all except one explanatory variable remaining consistently low. However, one variable exhibits correlations ranging from 0.55 to 0.88 with the residuals, suggesting a potential endogeneity issue that may require further investigation. Given that our dynamic panel fractional estimator inherently addresses endogeneity, the observed correlations do not raise concerns regarding endogeneity in this analysis.

Please note that generally when the heatmap indicates a significantly high correlation between a model variable and the model residuals, a two-stage estimation is required to mitigate the endogeneity problem. In the first stage, the variable highly correlated with the residuals is regressed on its lag and other model variables. The predicted fitted values from this regression serve as an instrument in the second stage, where the dynamic panel fractional estimation of the dependent variable is conducted using the with the residuals highly correlated variable's instrument (predicted values from the first stage regression) alongside the other model variables. By applying this methodology—utilizing an instrument for a variable highly correlated with the residuals, specifically the lagged debt-to-equity ratio—instead of relying solely on the dynamic panel fractional estimator, the model strengthens as evidenced by the log-likelihoods comparison. When comparing the models with the instrument and the lagged debt-to-equity ratio (DPF framework), we observe that the significant coefficients consistently maintain their signs, with their magnitudes nearly equivalent. The logarithm of the debt-to-equity ratio also serves as a viable instrument, contributing to a more robust model characterized by improved log-likelihoods across all industries and a consistently reduced correlation (remaining below 0.57) between the model's residuals and the instrument. Although the use of this instrument impacts the significance of some coefficients, the uncertainty index continues to show significant effects for the Construction, Manufacturing, and Retail industries.

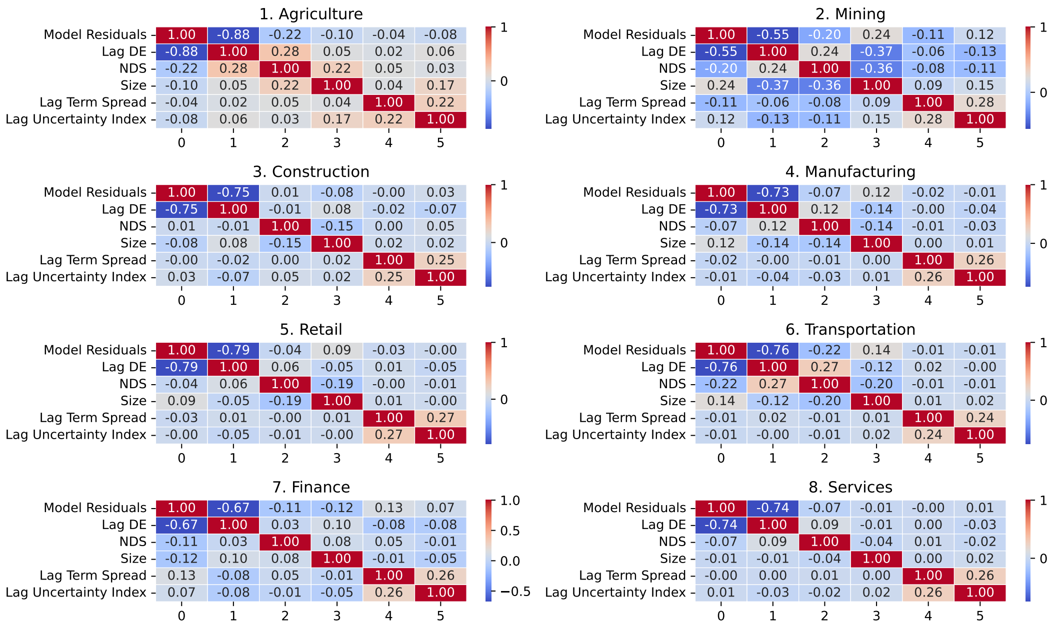


Figure B.3:
Correlation Heatmaps of Model Residuals and Model Variables
Correlation heatmaps of industry-specific residuals and model variables Lag DE, NDS, Size, Lag Term Spread, Lag Uncertainty Index.

Out of Sample Assessments

We perform out-of-sample assessments of our model utilizing data up to 2016. The comparative analysis between in-sample and out-of-sample firm-level alternative models is presented in Table B.3.

Overall, the results suggest that our model with the DPF estimator captures the relationships between the variables reasonably well, as indicated by the log likelihood values.

We evaluated sensitivity by comparing coefficients and standard errors between the in-sample and out-of-sample estimations. While the coefficients generally align in both cases, indicating consistency, there is sensitivity to changes in sample composition, as seen in the variations in coefficients between the two estimations. While most standard errors are manageable, some coefficients exhibit larger standard errors, indicating uncertainty in their estimates. This is expected, as the 2015 Investment Tax Act reform has been announced in 2015.

The significant difference in log likelihood values between the in-sample and out-of-sample estimations underscores potential limitations in the model's generalizability after the 2015 Investment Tax Act reform. With a change of approximately 9607, the model's performance varies significantly when applied to the sample after the 2015

Investment Tax Act. Interestingly, this phenomenon is not observed when altering the sample before the announcement of the 2015 Investment Tax Act.

While we acknowledge the observed variations in our model's performance in response to sample changes after the Investment Tax announcement, it's crucial to note that these fluctuations are even more pronounced in alternative models, as evidenced by Table B.1. Additionally, we evaluate the goodness of fit using the Root Mean Square Error (RMSE), where our model consistently demonstrates lower RMSE values (please compare RMSEs on Table 2.7 and Table B.1). This consistent outperformance in predictive accuracy underscores the robustness and superior performance of our model compared to alternatives, despite its sensitivity to significant changes, likely due to the substantial impact of the investment tax reform announcement on investment behavior.

Although our model is not without its limitations, it demonstrates a notable superiority compared to the alternatives proposed in the literature and those we have tested. Significantly, our model facilitates the derivation of meaningful policy implications. Nevertheless, it is essential to exercise caution and acknowledge the inherent limitations present in any modeling approach to capital structure.

Table B.3: Out of Sample Assessments

	DPF in sample	**DPF out of sample**
Lag DE	0.11250***	0.10258***
	(0.00251)	(0.00350)
ROA	0.00000	-0.01830
	(0.00000)	(0.03337)
NTC	-0.01196	0.02189**
	(0.02702)	(0.00957)
Tangibility	0.02604***	0.58829***
	(0.00642)	(0.04024)
Size	0.55558***	0.02155**
	(0.02598)	(0.00970)
Inflation	0.02412***	1.96347***
	(0.00668)	(0.42713)
Uncertainty Index	1.56415***	-0.00085***
	(0.26544)	(0.00009)
For each ID the first DE	-0.00077***	-0.04477***
	(0.00005)	(0.00524)
Mean Lag DE	-0.05887***	0.41629***
	(0.00333)	(0.00897)
Mean ROA	0.43593***	-0.12049
	(0.00614)	(0.07592)
Mean NTC	-0.24861***	-0.00170
	(0.07290)	(0.00627)
Mean Tangibility	-0.00510	0.05157
	(0.00536)	(0.04653)
Mean Size	0.04003	-0.02982***
	(0.02974)	(0.01143)
Mean Inflation	-0.02553***	-4.60634***
	(0.00770)	(1.76241)
Mean Uncertainty Index	-4.82687***	0.00115***
	(1.38113)	(0.00023)
Constant	0.00120***	-0.09570
	(0.00017)	(0.07317)
Σ_u	0.39714***	0.43549***
	(0.00378)	(0.00587)
Σ_e	0.29470***	0.32674***
	(0.00163)	(0.00267)
ρ	0.64489	0.63983
Observations	49,974	26,009
Number of firms	13,051	7,989
Log Likelihood	-23482	-13875

B.4 Other important nuances

Debt Maturity Structure Policymakers may seek insights into the types of debt SMEs would opt for amidst policy changes. Crafting a coherent policy that influences SMEs' capital structures requires not only understanding the circumstances under which SMEs choose debt financing but also explore how SMEs choose the maturity of their debt. Choosing long-term debt over short-term debt means certain debt financing in the longer term. To identify how SMEs choose between short-term and long-term debt we investigate the short-term and long-term debt-to-equity ratios of German SMEs. The model is the same as for debt-to-equity ratio, however it hypothesises that net trade credit may have influence when choosing between short-term and long-term debt. Our observations reveal that net trade credit does impact decisions between long-term and short-term debt. Specifically, net trade credit tends to encourage the preference for short-term debt over long-term debt.

Our findings suggest that if policymakers aim to reduce borrowing costs (interest paid) and the average maturity of SMEs' debt, implementing a tax policy that incentivizes the use of trade credit could be effective. For instance, a tax policy that induces different pre-tax returns compared to pre-tax returns abroad could be considered. Hereby we formulate our **sixth policy implication**:

- To reduce the borrowing costs and average maturity of SMEs' debt, policymakers can implement tax policies supportive of trade credit.

B.5 Discussion

The results presented in the Table 2.7 offer a nuanced understanding of how the Economic Policy Uncertainty (EPU) Index—a news-driven variable—alongside firm size and other factors, affects different industries in a sector-specific manner.

The negative and statistically significant coefficients of the lag economic policy uncertainty index in the construction, manufacturing, retail, and services industries, suggest that heightened economic policy uncertainty leads to reduced debt financing. This relationship aligns with the trade-off theory, which posits that firms balance the benefits of debt, such as tax shields, against the costs of financial distress. During periods of policy uncertainty, these industries may become more conservative in their debt usage due to the increased risk of financial distress (higher perceived cost of the debt financing), opting to reduce leverage. The negative sign of the economic policy uncertainty index also aligns with the Pecking Order Theory, which suggests that firms prefer internal financing over debt and equity, particularly during uncertain times.

The coefficients of the mean lagged Economic Policy Uncertainty (EPU) Index exhibit variation across sectors, underscoring the heterogeneous impacts of uncertainty on different industries. This variation suggests that industry-specific factors significantly influence debt financing decisions. Specifically, the mean of the lagged EPU Index the transportation sector shows a statistically significant negative coefficient, implying that heightened economic policy uncertainty may deter firms in this industry from utilizing debt as a financing option. Conversely, EPU Index demonstrates statistically significant positive coefficients in the mining and manufacturing sectors, indicating that increased uncertainty may encourage these industries to pursue debt financing. One plausible explanation for the observed positive relationship in the mining and manufacturing sectors is that firms may perceive debt financing as a strategic instrument to capitalize on investment opportunities amidst uncertainty. It is plausible that companies strategically opt for increased debt financing to position themselves advantageously for future growth and resilience. When the mean EPU increased in previous period, companies in these sectors may interpret this as a signal to secure debt financing to fuel necessary growth and expansion endeavors. By leveraging debt during heightened mean EPU, these firms can bolster their liquidity and invest in projects that reinforce their competitive position, effectively navigating the uncertainties of the economic landscape.

In summary, the divergent responses of sectors to the EPU index emphasize the need for tailored economic policies that consider sectoral vulnerabilities and strengths, especially in times of heightened economic policy uncertainty. The results demonstrate how news-driven variables like the EPU index can serve as valuable indicators for policymakers and economists, providing a comprehensive view of how uncertainty permeates different parts of the economy.

Moreover, the results for firm size, term spread, and other macroeconomic variables further support the idea that each sector responds differently to changes, underscoring the importance of sectoral analysis in economic modeling.

Future research could benefit from incorporating sector-specific variables, such as subsidies in the agriculture industry and commodity price volatility for mining industry, to improve the model's explanatory power for this sector and reduce the potential for omitted variable bias arising from unmodeled industry-specific factors.

C Appendix to Chapter 3: News-Driven Model for Timely Nowcasting of GDP in Germany

C.1 Latent Dirichlet Allocation (LDA) Model Parameter Tuning

The coherence scores provide insights into the quality of the topics generated by the LDA models. Figure C.1 displays the C_v coherence scores of LDA models trained on raw articles. A coherence score of 0.45 is consistent with similar contexts and datasets, suggesting the coherence score is reasonable and acceptable.

Figure C.1: C_v Coherence Scores of LDA Models Trained on Raw Articles

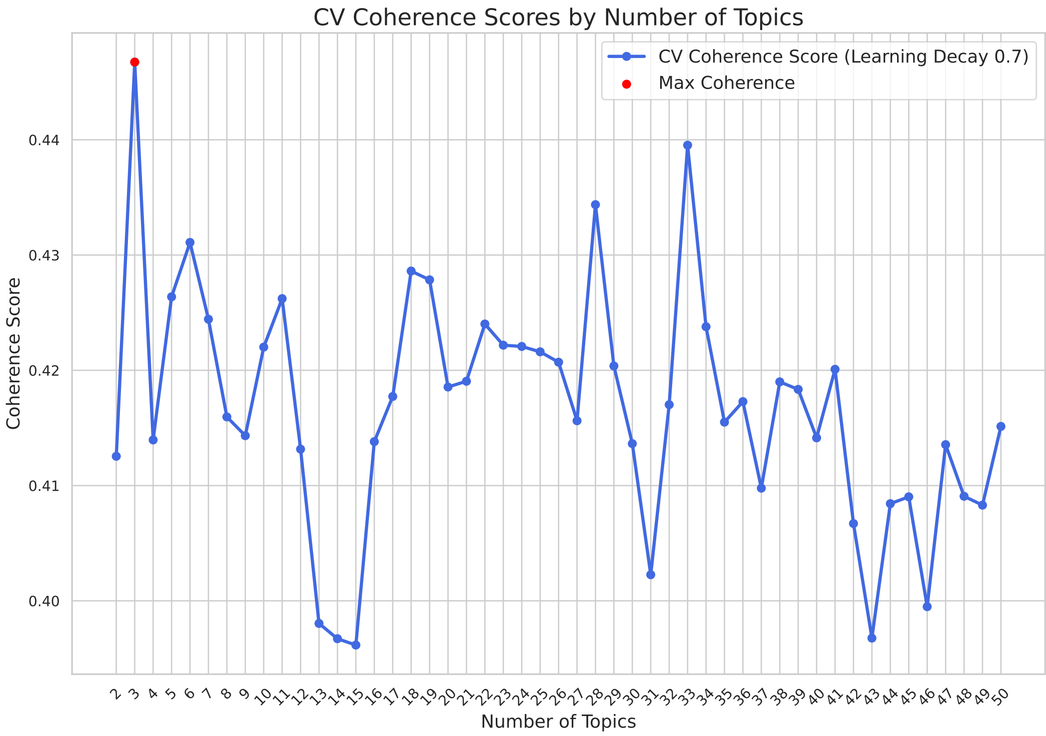
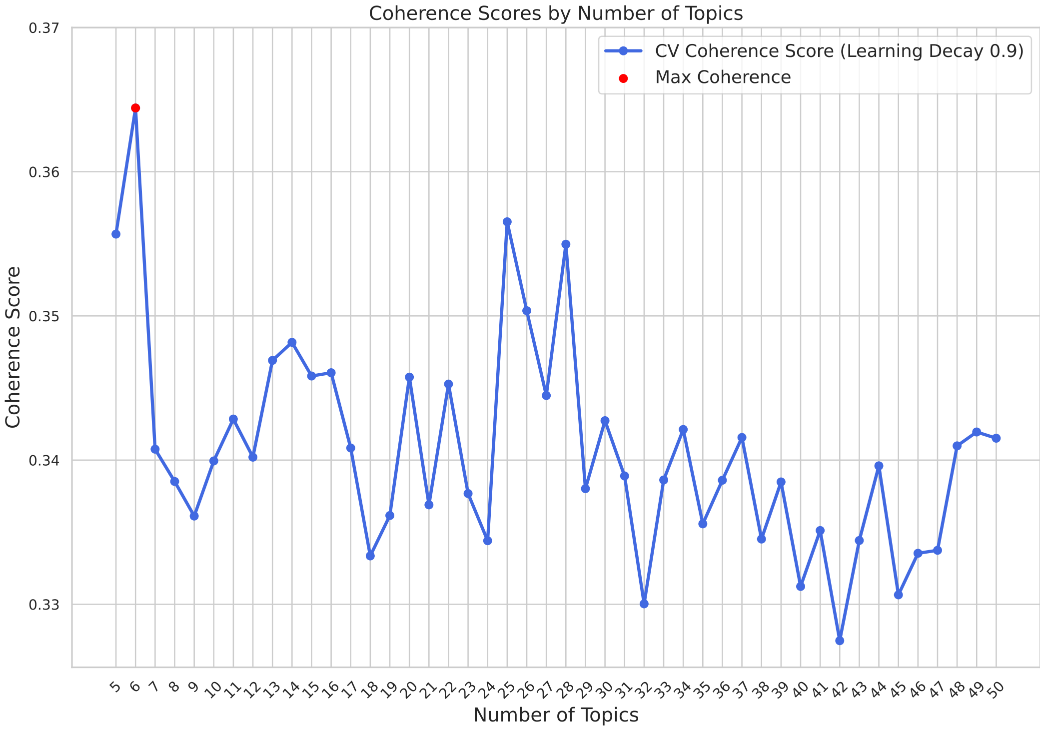


Figure C.2 shows the C_v coherence scores for LDA models trained on the sentiment-cleaned articles.

Figure C.2:
C_v Coherence Scores of LDA Model Trained on Sentiment-Cleaned Articles



The figure presents the coherence scores of the
LDA Model trained on articles with the Sentiment Cleaned from past tense.

Removing past tense sentences may result in more generic or less focused topics, leading to lower coherence scores. However, the C_v coherence score around 0.36 indicates moderate coherence in the generated topics, suggesting a level of interpretability and semantic alignment among the key terms.

The $Umass$ coherence scores provide another measure of topic coherence. Figure C.3 reports the U_{mass} coherence scores for LDA models trained on raw articles. An U_{mass} score of -1.1 indicates relatively low coherence among the top words within the topics. However, this is understandable given the diverse nature of GDP-related topics, which encompass a wide range of terms reflecting the complexity of the economic landscape.

Figure C.3: U_{mass} Coherence Scores of LDA Model Trained on Raw Articles

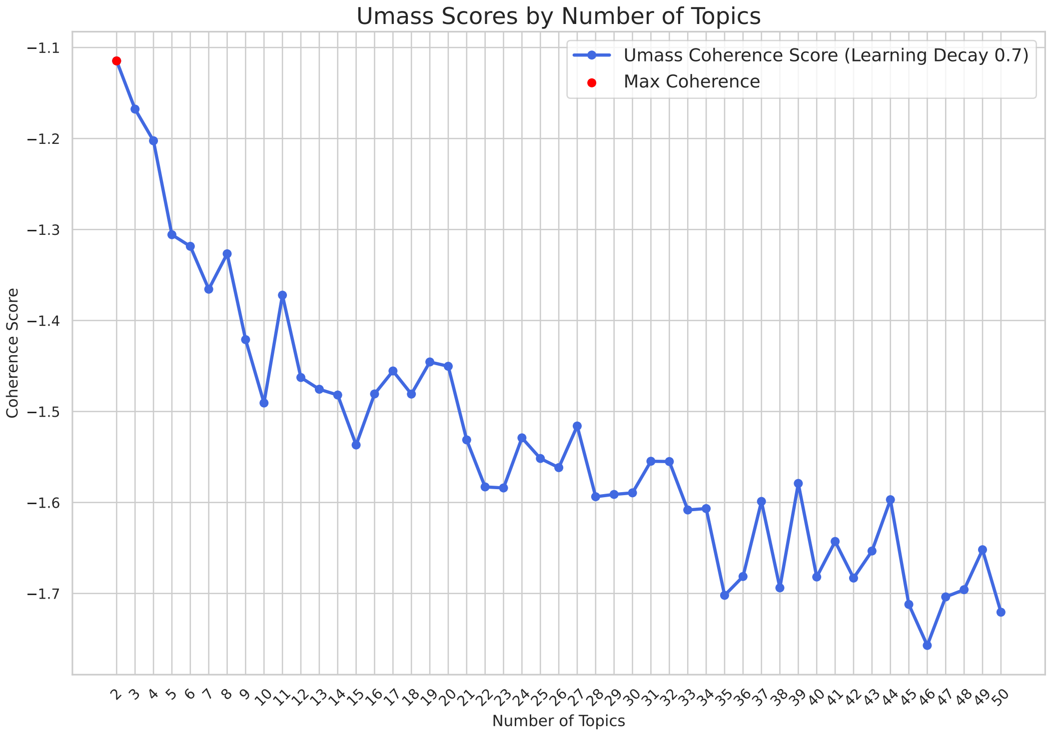
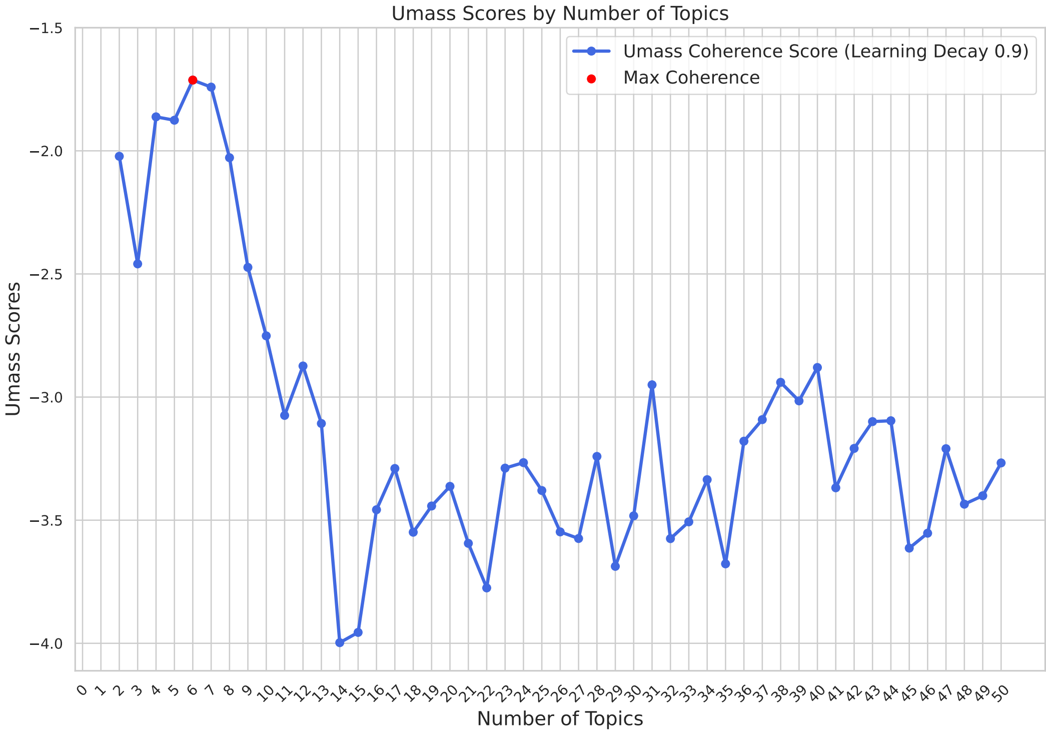


Figure C.4 shows the U_{mass} coherence scores for LDA models trained on sentiment-cleaned articles (where sentiment is calculated from articles cleaned of past tense sentences). With an U_{mass} score of -1.7, the coherence remains relatively low, suggesting that the top words within the topics are not highly coherent.

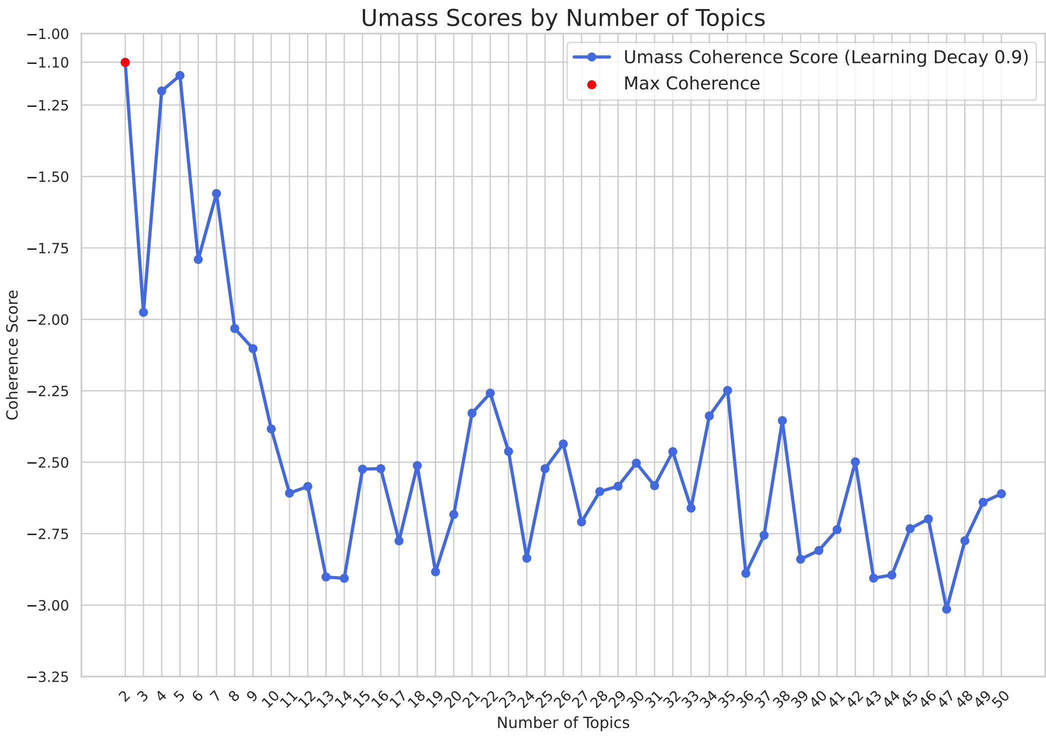
Figure C.4:
U_{mass} Coherence Scores of LDA Model Trained on Sentiment-Cleaned Articles



Note: Sentiment is calculated from cleaned, top topic-representative news.

Figure C.5 report the U_{mass} coherence scores of LDA models trained on a fully cleaned corpus.

Figure C.5:
U_{mass} Coherence Scores of LDA Model Trained on Fully Cleaned Articles



The highest U_{mass} score for the fully cleaned articles is -1.1, which is comparable to the score obtained from the raw data.

Figure C.6: C_{NPMI} Coherence Scores for Sentiment-Cleaned Articles

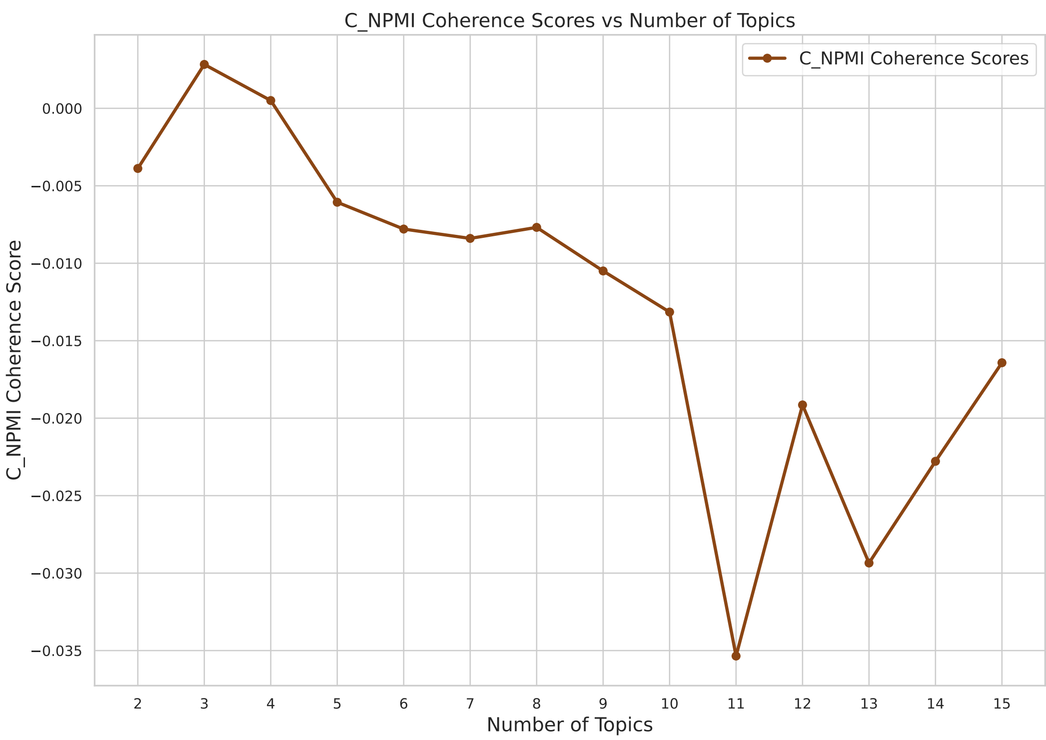


Figure C.6 indicates that the C_{NPMI} coherence scores for the 5-topic model are superior compared to those for the 6-topic model. This contrasts with the initial suggestion based on Umass and C_v coherence scores, which recommended a 6-topic model.

Table C.1: Grid Search Results for Optimal Number of LDA Topics

Dataset	**Grid Search**	**Best Parameters**	**Best Negative Log-Likelihood Score**
Raw	First	{learning_decay: 0.5, n_components: 2}	-9,589,182
	Second	{learning_decay: 0.5, n_components: 3}	-9,591,111
	Third	{learning_decay: 0.9, n_components: 5}	-10,281,506
Sentiment-Cleaned	First	{learning_decay: 0.9, n_components: 2}	-2,721,236
	Second	{learning_decay: 0.9, n_components: 3}	-2,809,413
	Third	{learning_decay: 0.9, n_components: 4}	-2,889,326
Fully Cleaned	First	{learning_decay: 0.5, n_components: 2}	-3,029,644
	Second	{learning_decay: 0.7, n_components: 5}	-10,535,676
	Third	{learning_decay: 0.5, n_components: 9}	-11,332,779

Figure C.7: Perplexity Scores of LDA Model Trained on Raw Articles

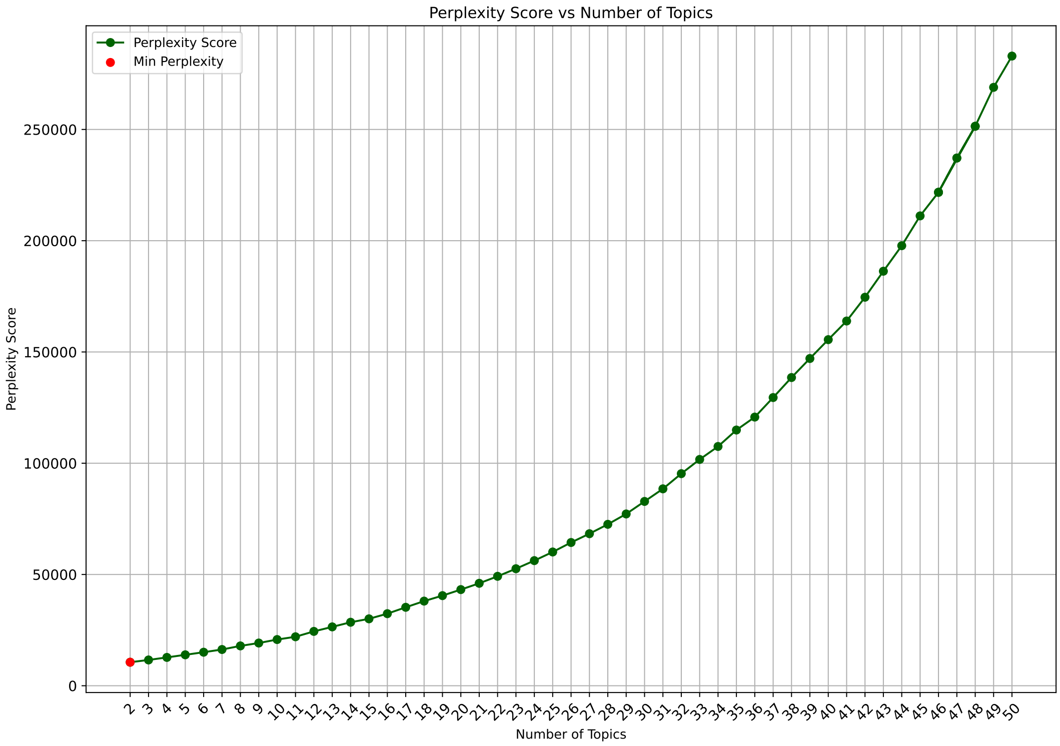


Figure C.8:
Perplexity Scores of LDA Model Trained on Sentiment-Cleaned Articles

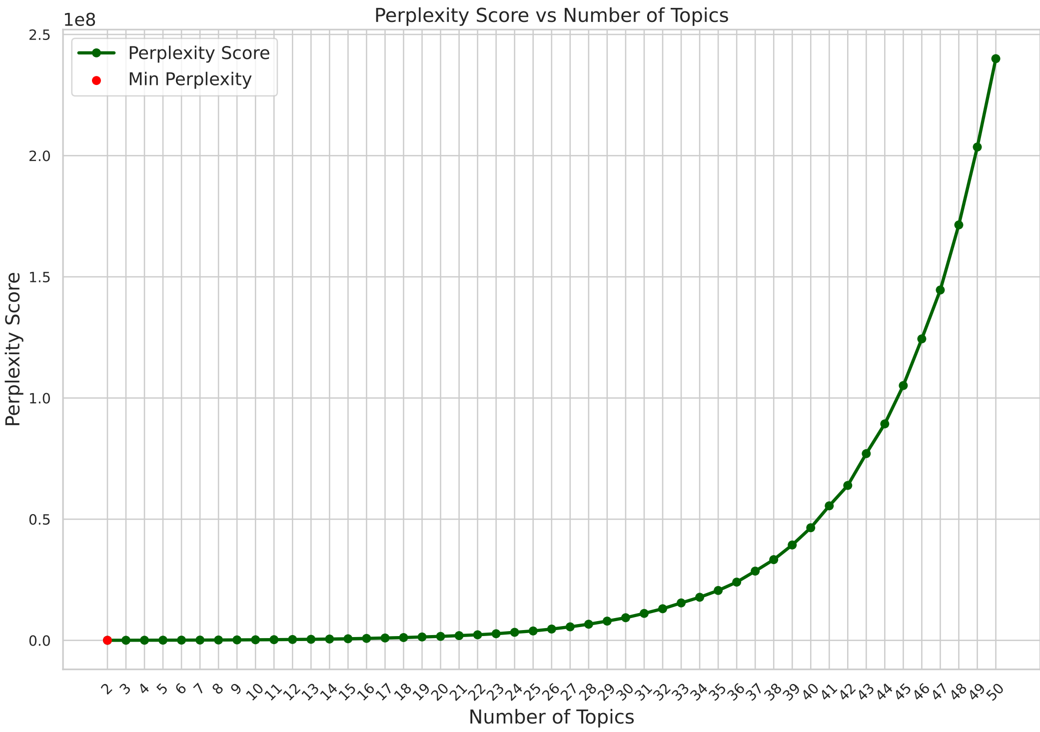
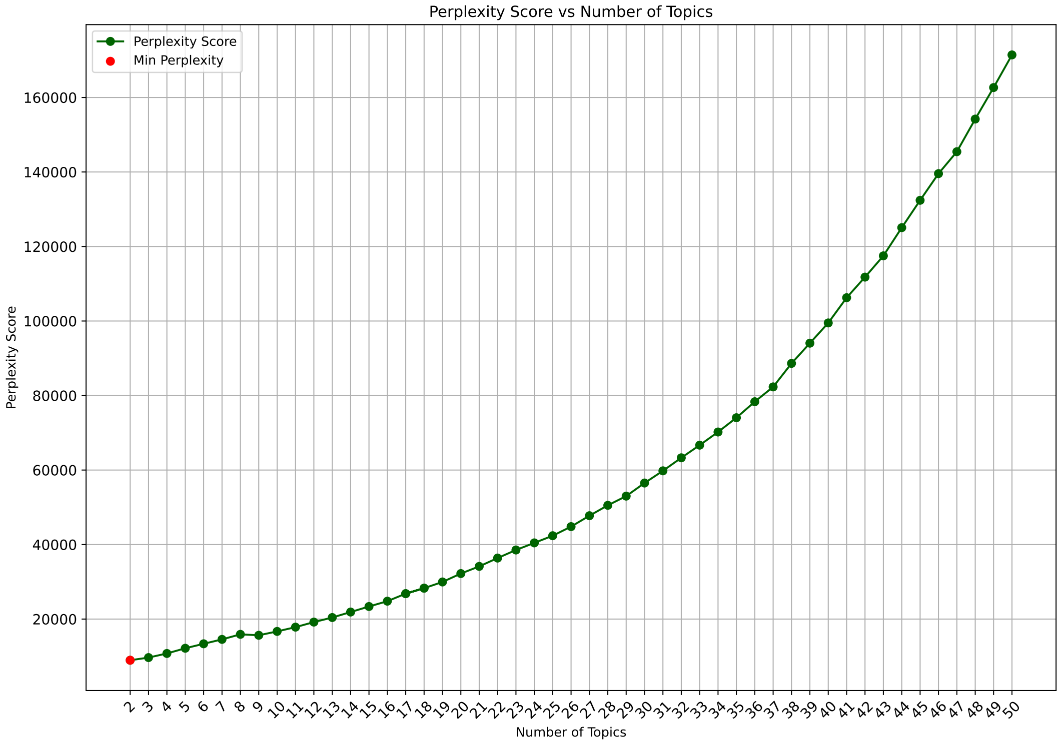


Figure C.9:
Perplexity Scores of LDA Model Trained on Articles Fully Cleaned Articles



For the raw dataset, the average perplexity scores from 5-fold cross-validation, as shown in Figure C.7, reveal a clear trend: average perplexity increases as the number of topics rises from 2 to 50. This finding aligns with theoretical expectations, suggesting that increased model complexity with more topics may adversely affect predictive accuracy. Concurrently, the U_{mass} scores in Figure C.3 also indicate that a lower number of topics is preferable. The C_v coherence scores in Figure C.1 further suggest optimal numbers of 3, 5, or 6 topics. Based on the grid search results (Table C.1), which identify 2, 3, and 5 topics as the best-performing configurations, we conclude that models with 3 or 5 topics are most suitable for the raw dataset.

For the sentiment-cleaned dataset, the average perplexity scores from 5-fold cross-validation, as shown in Figure C.8, increase consistently as the number of topics rises from 2 to 50. This suggests that a smaller number of topics is likely to result in a more accurate and coherent model. The Umass coherence scores in Figure C.4 indicate that the highest coherence is achieved with 6 topics, yielding a score of approximately -1.71. However, coherence scores diminish beyond 6 topics, suggesting reduced topic quality. Based on Umass, the optimal number of topics appears to be 4, 5, or 6. The C_v coherence scores shown in Figure C.2 suggest that 5, 6, 25, or 28 topics could be optimal. Notably, the C_{PMI} coherence scores favor 5 topics over 6.

In the gridsearch for the sentiment-cleaned dataset (Table C.1) topic numbers 4 and 5 are the fourth and fifth best, while number of topics 6 does not appear in the top five models. Consequently, we conclude that the model should use 4 or 5 topics for the sentiment-cleaned dataset.

Following these evaluations, we conducted a second round of fine-tuning. The grid search for the fully cleaned dataset indicated that the optimal model configuration includes 5 topics, with learning decay set to 0.9 and both alpha and beta parameters set to "auto," slightly outperforming the configuration with alpha = 0.01 and beta = 1.

For the fully cleaned dataset, the average perplexity scores from a 5-fold cross-validation decrease as the number of topics increases, suggesting choosing low number of topics. The top 3 best models suggested from the gridsearch (Table C.1) are models with 2, 5 and 9 topics. U_{mass} coherence scores (given on Figure C.5) are highest (least negative) for 2, 5 and 4 topics. Therefore, U_{mass} coherence scores, perplexity scores and gridsearch suggest choosing from topics with 2 or 5 topics for the fully cleaned dataset. After these evaluations, we do the second step of the sequential fine-tuning, the gridsearch of all parameters including the alpha and beta parameters for the fully cleaned dataset, indicates that we should build the model with 5 topics, learning decay 0.9, alpha 0.1 and beta 1.

Lastly, while quantitative metrics offer valuable insights, human evaluation remains crucial for assessing nuances such as relevance and clarity in the generated content (compare Hoyle et al. (2021). Therefore, integrating coherence metrics with human judgment is crucial for refining assessments and achieving a comprehensive evaluation of language model performance in academic contexts. Consequently, we have selected 5 topics as a balanced approach, capturing a diverse range of themes while maintaining a manageable analysis.

Our analysis provides important insights from the perplexity scores. For the sentiment-cleaned dataset, the average perplexity for a 5-topic model is 16,902 (with document topic prior=0.01 and topic word prior=1.0), compared to 12,164 for the fully cleaned dataset and 13,900 for the raw dataset. The fully cleaned dataset exhibits the lowest perplexity score, indicating that extensive data cleaning results in an LDA model with five topics that better predicts held-out data.

However, we should be cautious about drawing conclusions solely based on perplexity scores, as comparing perplexity across different datasets and vocabularies is not straightforward. As noted by Blei et al. (2003), models with richer and more diverse vocabularies generally exhibit higher perplexity. Consequently, a model with slightly higher perplexity might be more adept at capturing complex data patterns. Among the three datasets, the sentiment-cleaned dataset stands out for having the richest and most diverse overall set of vocabularies. This is attributed to the distinct vocabularies used for topic frequencies and sentiment analysis, which together encompass a broader range of words and contribute to a more nuanced representation. While the sentiment analysis vocabulary may be smaller and more focused due to the exclusion of past-related content, the inclusion of two distinct vocabularies results in a richer and more comprehensive linguistic representation. Given the variability in vocabularies across our datasets, we include all datasets—fully cleaned, sentiment-cleaned, and raw—in our analysis to ensure a thorough and balanced evaluation.

C.2 Descriptive Statistics of the Model Variables

Table C.2 presents the summary statistics of news topics before cleaning from past tense sentences.

Table C.2: Summary Statistics of News Topics in Raw German Dataset

	Topic 1	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**
Count	3237	3237	3237	3237	3237
Mean	-0.0038	0.0001	0.0007	0.0325	0.0207
Standard Deviation	1.0108	1.0184	1.0210	0.9867	1.0147
Minimum	-2.1621	-2.3886	-3.3571	-3.3405	-3.0798
25th Percentile	-0.6306	-0.7819	-0.5898	-0.5562	-0.5365
Median	-0.1005	0.0843	0.0056	-0.0720	-0.1151
75th Percentile	0.4476	0.6306	0.6798	0.5921	0.5437
Maximum	5.1326	3.5386	2.7565	4.2071	3.5908

Table C.3 presents the descriptive statistics of the sentiment-cleaned dataset.

Table C.3:
Summary Statistics of News Topics from Sentiment-Cleaned German Dataset

	Topic 1	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**
Count	3227	3227	3227	3227	3227
Mean	0.0005	0.0004	0.0127	0.0007	0.0006
Standard Deviation	0.0078	0.0101	0.1266	0.0109	0.0095
Minimum	-0.0877	-0.1319	-0.8389	-0.1665	-0.1442
25th Percentile	-0.0006	-0.0006	-0.0318	-0.0006	-0.0006
Median	0.0000	0.0000	0.0000	0.0000	0.0000
75th Percentile	0.0013	0.0012	0.0580	0.0012	0.0013
Maximum	0.1060	0.1571	0.8676	0.1836	0.1773

Table C.4 presents the summary statistics for the English dataset.

Table C.4: Summary Statistics of News Topics in the English Dataset

	Topic 1	**Topic 2**	**Topic 3**	**Topic 4**	**Topic 5**
Count	3982	3982	3982	3982	3982
Mean	0.0574	0.0007	0.0007	0.0007	0.0007
Standard Deviation	0.0425	0.0014	0.0006	0.0007	0.0009
Minimum	-0.2998	-0.0044	-0.0021	-0.0049	-0.0043
25th Percentile	0.0334	0.0003	0.0003	0.0003	0.0003
Median	0.0579	0.0006	0.0006	0.0006	0.0006
75th Percentile	0.0832	0.0009	0.0009	0.0009	0.0009
Maximum	0.2504	0.0561	0.0101	0.0126	0.0373

C.3 Topic Wordclouds

Topic 1: Economic Performance Assessment

Topic 2: Political and Economic Dynamics

Topic 3: Economic Indicators and Forecasts

Figure C.10:
Wordclouds of Topics with Top 50 Words for the Sentiment-Cleaned Dataset.

Figure C.10 presents the word clouds generated from LDA results without any preprocessing. Notably, these word clouds feature frequently occurring words such as "prozent" (percent), "wirtschaft" (economy), "unternehmen" (company), "euro" (euro), and "wachstum" (growth) across various clouds. These terms are intentionally retained to preserve the integrity of the probability distributions. Although these words are common, their inclusion is essential for accurate probability estimation and consistency in the distributions across topics.

C.4 News Time Series from Raw Dataset

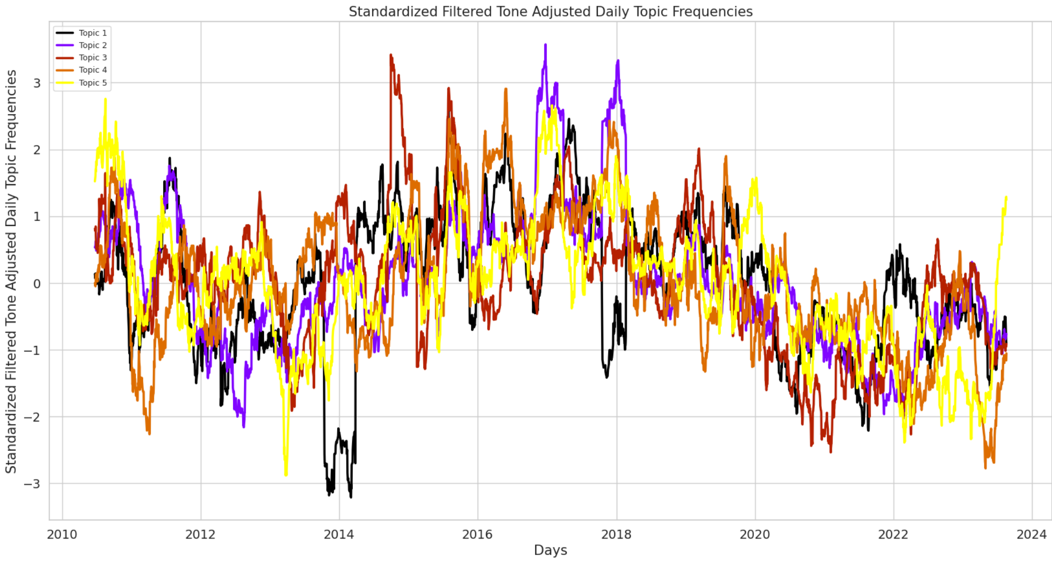


Figure C.11: Daily Standardized Filtered Tone Adjusted News Time Series from Raw Dataset: Derived from LDA with 5 Topics The figure represents the daily news time series before deleting past tense sentences.

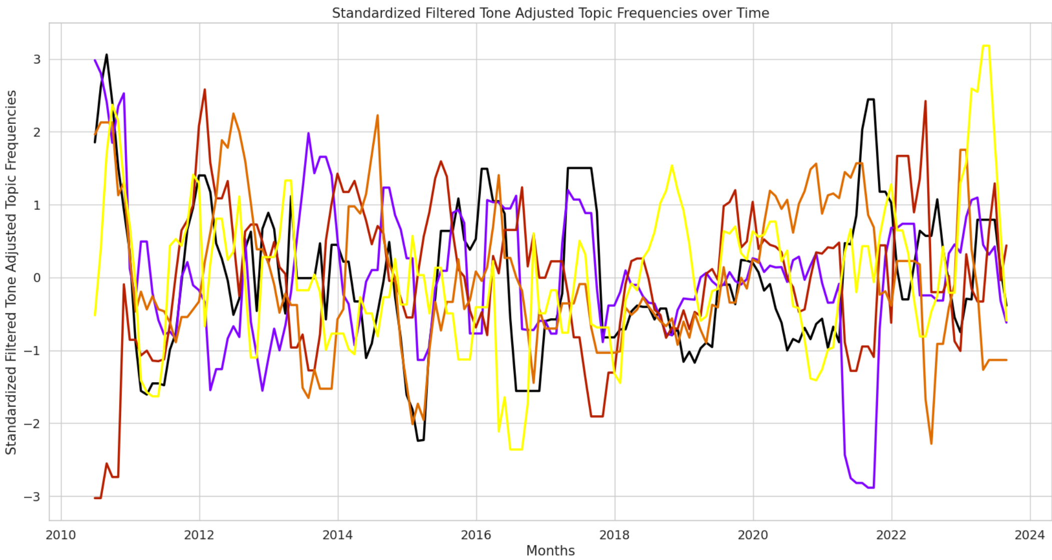


Figure C.12: Monthly Standardized Filtered Tone Adjusted News Time Series from Raw Dataset The figure represents the monthly news time series prior to the removal of past tense sentences.

As observed, the monthly time series from the raw dataset exhibits a noticeable divergence from GDP trends. This discrepancy may stem from several factors. One possible cause is the imprecision in the sentiment derived from the representative articles for each topic, particularly if sections related to past events distort the sentiment scores. Another factor could be inaccuracies in topic frequency calculations; however, this is unlikely given the rigorously fine-tuned LDA model employed for these calculations. Consequently, we proceed by removing past-related content from the texts and recalculating sentiment based on the revised dataset.

C.5 News Time Series from Sentiment-Cleaned Dataset

Figure C.14 presents the daily topic frequencies for the sentiment-cleaned dataset, where sentiment has been adjusted to exclude past-related content.

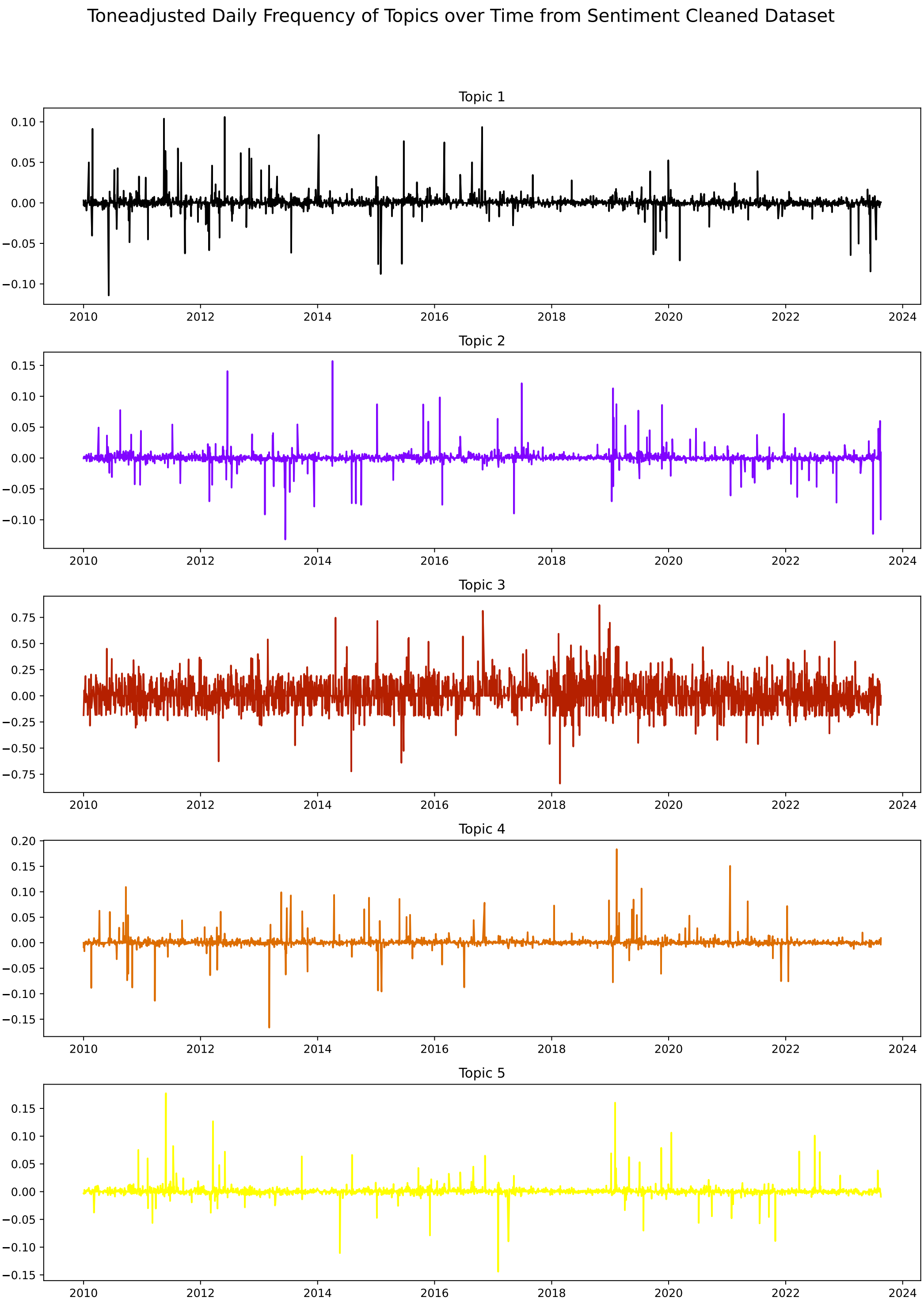


Figure C.13:
Daily Topic Frequencies, Original Values in the sentiment-cleaned Dataset
Daily topic frequencies in the sentiment-cleaned dataset.

Here we visualize the same dataset filtered and standardized.

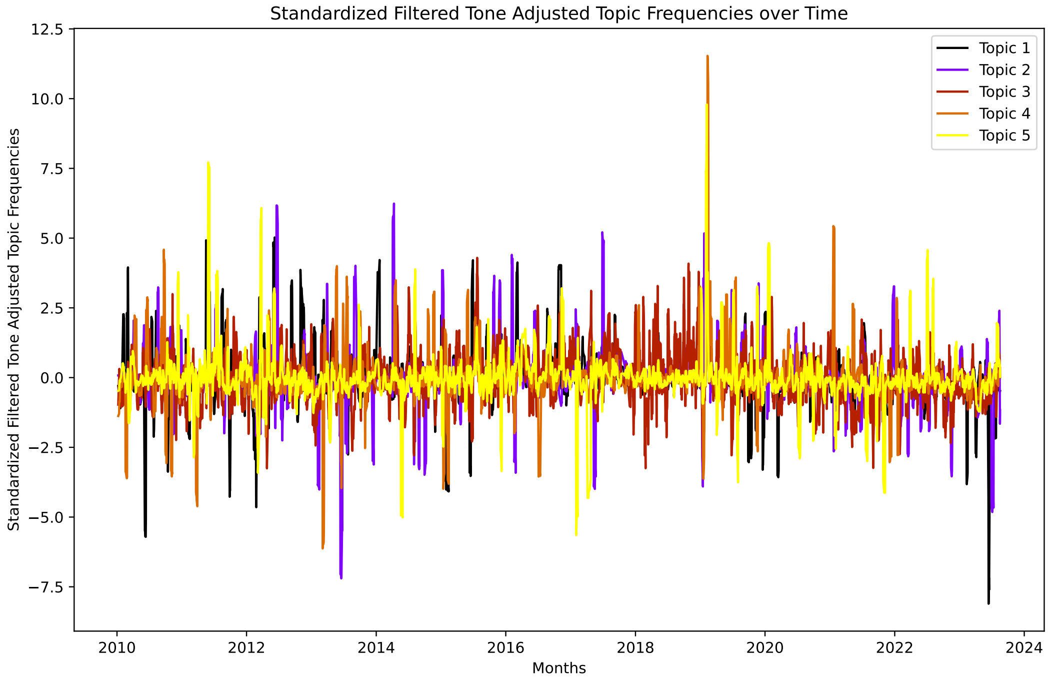


Figure C.14:
Daily Topic Frequencies, Standardized Filtered, the sentiment-cleaned Dataset
The figure illustrates standardized filtered daily topic frequencies in the sentiment-cleaned dataset.

Since all monthly time series from the sentiment-cleaned news dataset are stationary, no standardization is needed before integrating them into the dynamic factor model. Before this integration, we adjust the monthly topic frequencies by multiplying them with the corresponding monthly polarity values shown in Figure 3.8. These polarity values are also stationary, resulting in tone-adjusted topic frequencies for the model input.

C.6 LDA Analysis Results

LDA Results for the Fully Cleaned Dataset

Using the dataset fully cleaned of past tense sentences, where both sentiment and topic frequency time series are derived from the non-past sections of the documents, we identified five distinct topics through the Latent Dirichlet Allocation (LDA) model:

Topic 1: Economic Growth and Performance

Key Terms: Prozent (percent), Wirtschaft (economy), Quartal (quarter), Euro (euro), sagen (say), Wachstum (growth), Konjunktur (business cycle), steigen (rise), Unternehmen (companies), erwarten (expect), Monat (month), rechnen (calculate), Rezession (recession), Institut (institute), Industrie (industry), Bruttoinlandsprodukt (gross domestic product), Ökonomen (economists), Entwicklung (development), Punkt (point), Rückgang (decline), Experte (expert), Bund (the federal government), sinken (decrease), Folge (consequence), Wirtschaftsleistung (economic performance), stehen (stand), Lage (situation), Prozent (percent), wachsen (grow), Aufschwung (upturn).

Topic 2: Financial Markets and Banking

Key Terms: Bank (bank), Prozent (percent), zeigen (show), EUR (EUR), steigen (rise), liegen (lie), halten (hold), testen (test), Aktie (stock), Prozent (percent), Bank (bank), Prozent (percent), sagen (say), schneiden (cut), Aktienmarkt (stock market), Tools (tools), Aktienmarkt (stock market), Information (information), Finanznachrichten (financial news), Information (information), Finanznachrichten (financial news), Fonds (fund), Tools (tools), Aktienmarkt (stock market), Echtzeit (real-time), Fonds (fund), Analyse (analysis), Anzahl (number), Tools (tools), Echtzeit (real-time), Information (information), Aktienmarkt (stock market), Echtzeit (real-time), Information (information), Finanznachrichten (financial news), Fonds (fund), Analyse (analysis), Finanznachrichten (financial news), Anzahl (number), Tools (tools), Aktienmarkt (stock market), Aktienmarkt (stock market), Echtzeit (real-time), Finanznachrichten (financial news), Fonds (fund), Echtzeit (real-time), Information (information), Finanznachrichten (financial news), Tools (tools), Einbruch (crash).

Topic 3: Business and Economic Policies

Key Terms: sagen (say), Wirtschaft (economy), Unternehmen (companies), Chef (boss), Milliarde (billion), Euro (euro), EUR (EUR), Politik (policy), Entwicklung (development), Milliarde (billion), Euro (euro), Mensch (person), Vorjahr (previous year), Präsident (president), Steuer (tax), Branche (industry), Institut (institute), Wirtschaftswachstum (economic growth), Ergebnis (result), heißen (call), Bundesagentur (federal agency), Lage (situation), Partei (party), Industrie (industry), Investition (investment), Prozent (percent), Ergebnis (result), Steuer (tax), Studie (study), Gesellschaft (society), Einkauf (purchase), erwarten (expect).

Topic 4: Stock Market and Investments

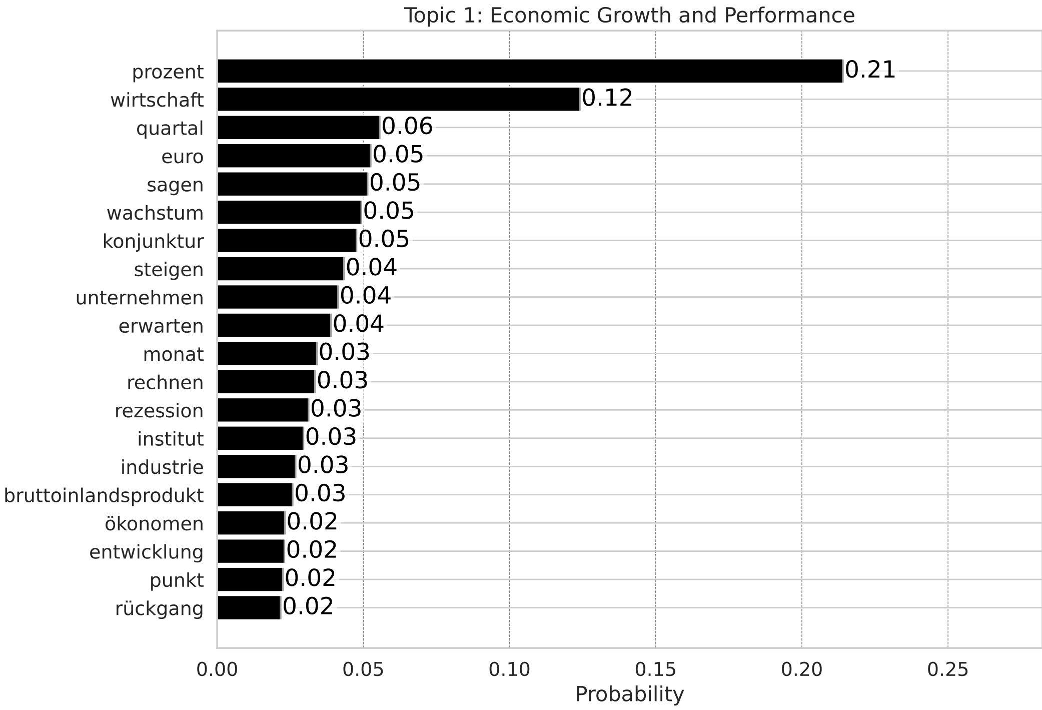
Key Terms: Prozent (percent), Euro (euro), Aktie (stock), Ziel (goal), Präsident (president), sagen (say), Dollar (dollar), Wirtschaft (economy), senken (lower), Milliarde (billion), Unternehmen (companies), heben (raise), Land (land), senken (lower), Ziel (goal), stehen (stand), heben (raise), Ziel (goal), Börse (stock exchange), Milliarde (billion), Euro

(euro), Analyst (analyst), Handel (trade), Bank (bank), geben (give), erwarten (expect), schreiben (write), Markt (market), AFX (afx), Anleger (investor), steigen (rise), Industrie (industry), Wirtschaftsnachrichten (financial news).

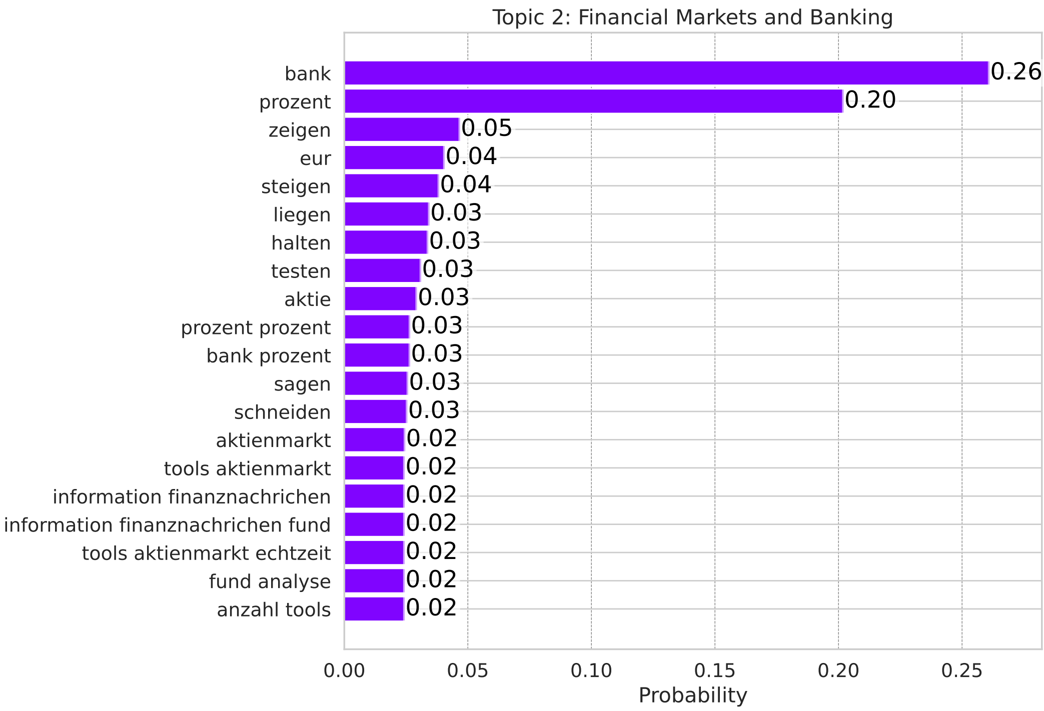
Topic 5: Government and Economic Regulation

Key Terms: sagen (say), Unternehmen (companies), Wirtschaft (economy), Prozent (percent), Euro (euro), Land (country), Milliarde (billion), stehen (stand), geben (give), Präsident (president), Mensch (person), Bank (bank), Ende (end), Million (million), Staat (state), Welt (world), Regierung (government), Politik (policy), Firma (company), Frage (question), sehen (see), Milliarde (billion), Euro (euro), Geld (money), zeigen (show), Industrie (industry), stellen (position), Woche (week), Bundesregierung (federal government), Tag (day), tun (do).

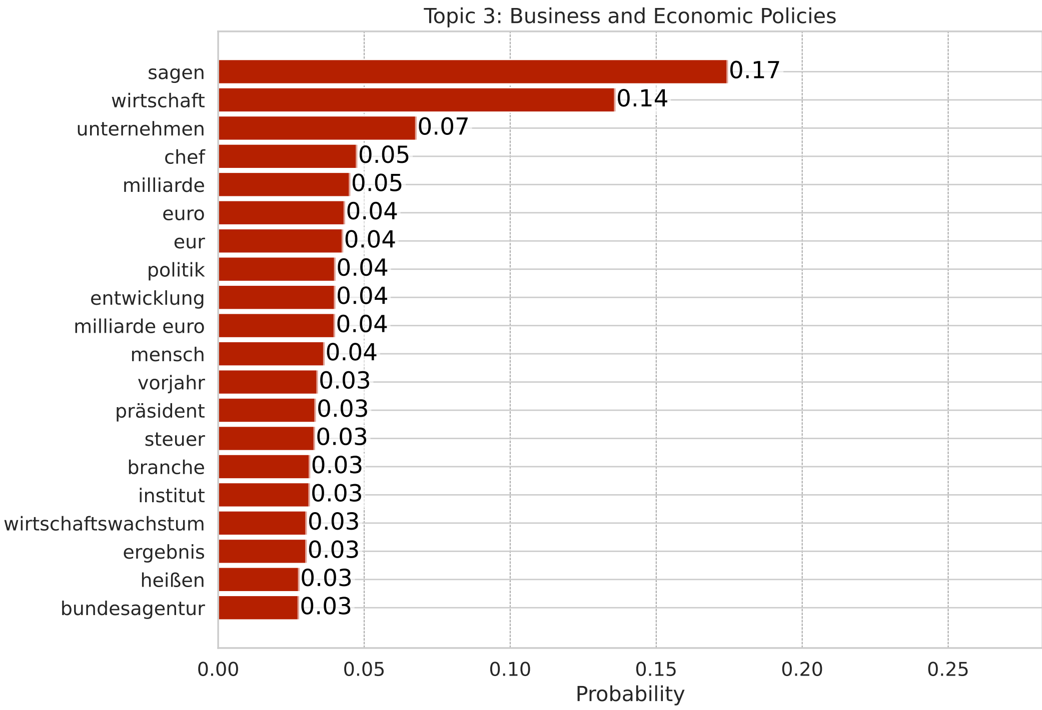
The topic-word probabilities of the five topics identified from the fully cleaned dataset, using the scikit-learn library algorithm in Python, are illustrated in Figure C.15.



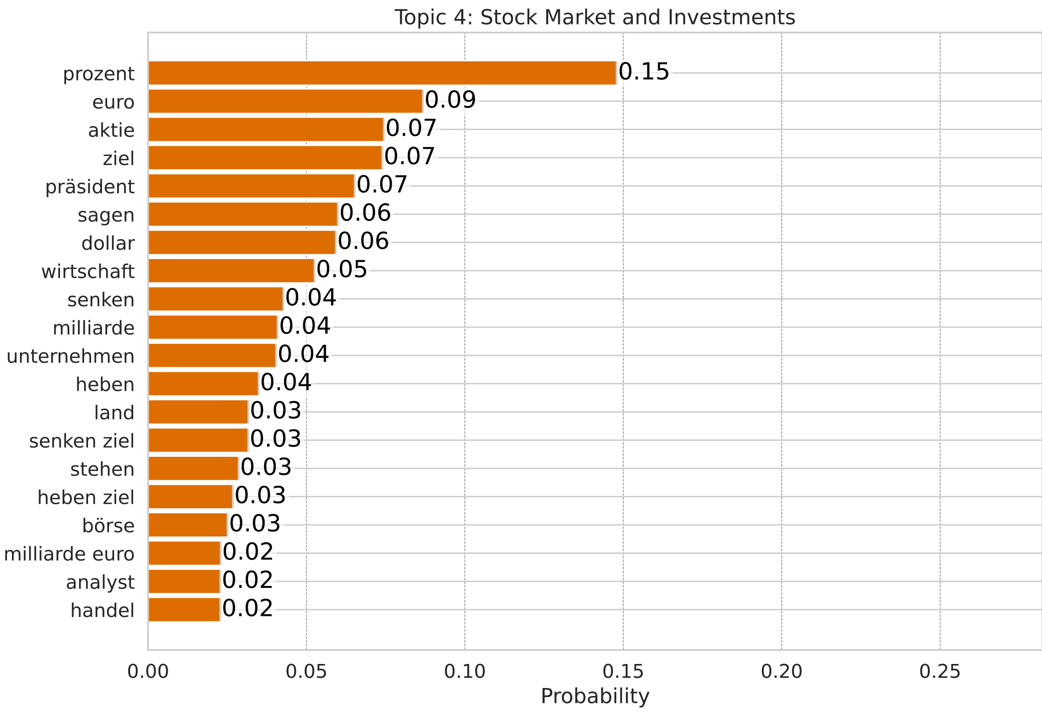
Top Terms in Topic 1



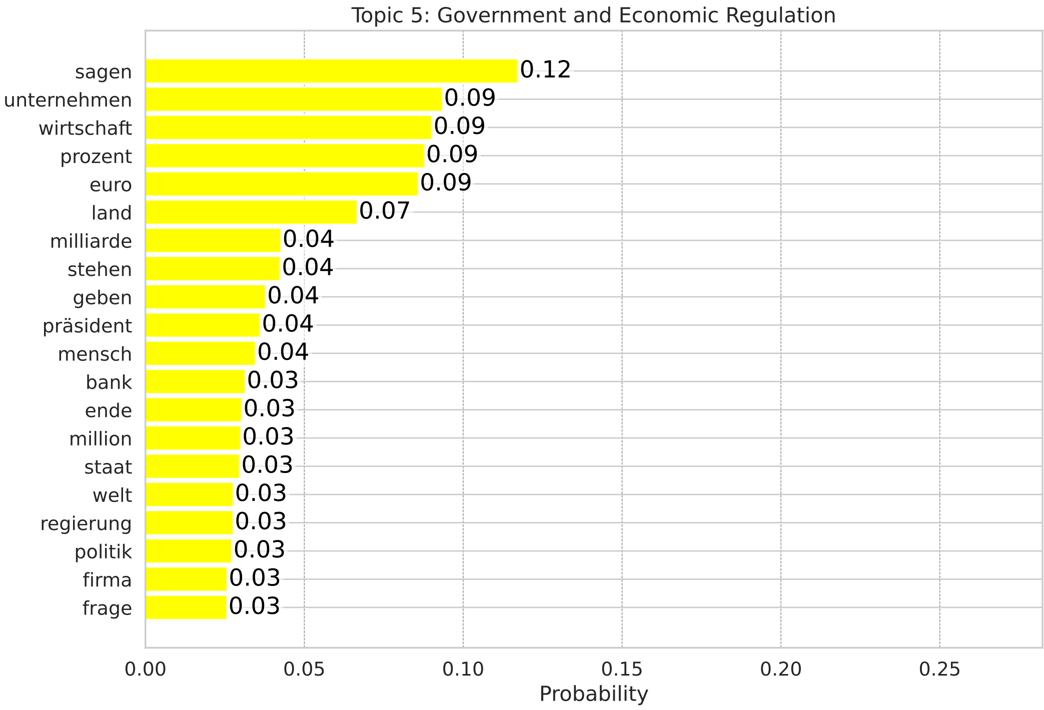
Top Terms in Topic 2



Top Terms in Topic 3



Top Terms in Topic 4



Top Terms in Topic 5

Figure C.15: Probability distributions of top terms in each topic. The figure represents the likelihood of the top terms appearing in each respective topic.

C.7 Interconnections Between Topics

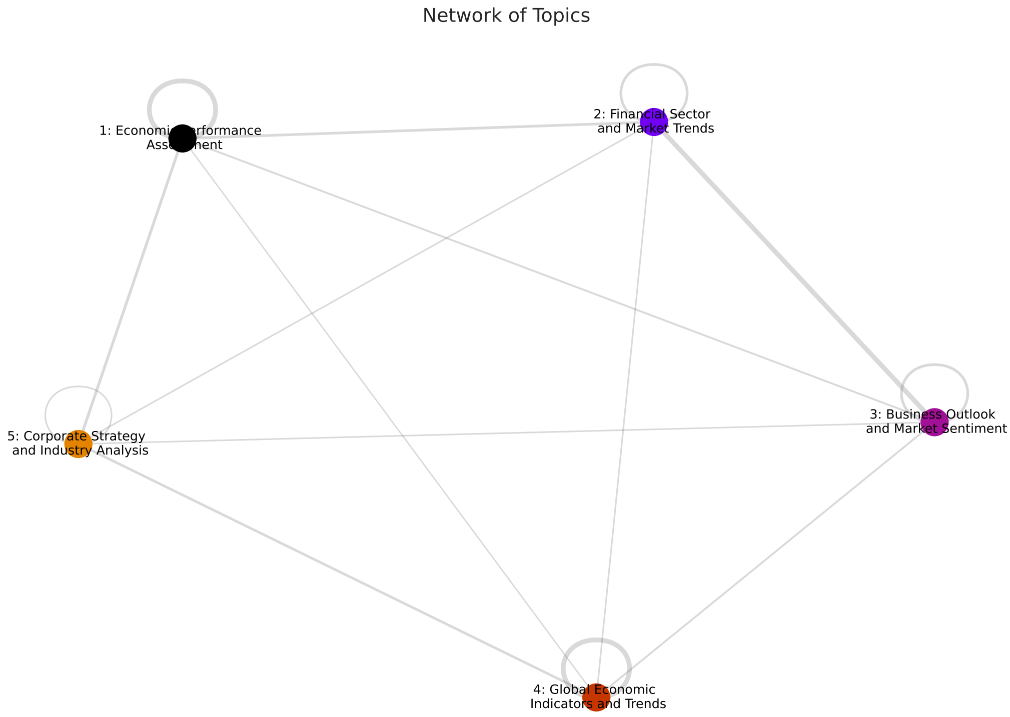


Figure C.16: Network of Topics from Raw Dataset
This network graph illustrates the thematic relationships among five topics identified through Latent Dirichlet Allocation (LDA) on the raw dataset. Nodes represent individual topics, while edges denote shared top words between topics. Thicker edges indicate stronger thematic connections. This visualization reveals clusters of related topics and common content themes across the dataset.

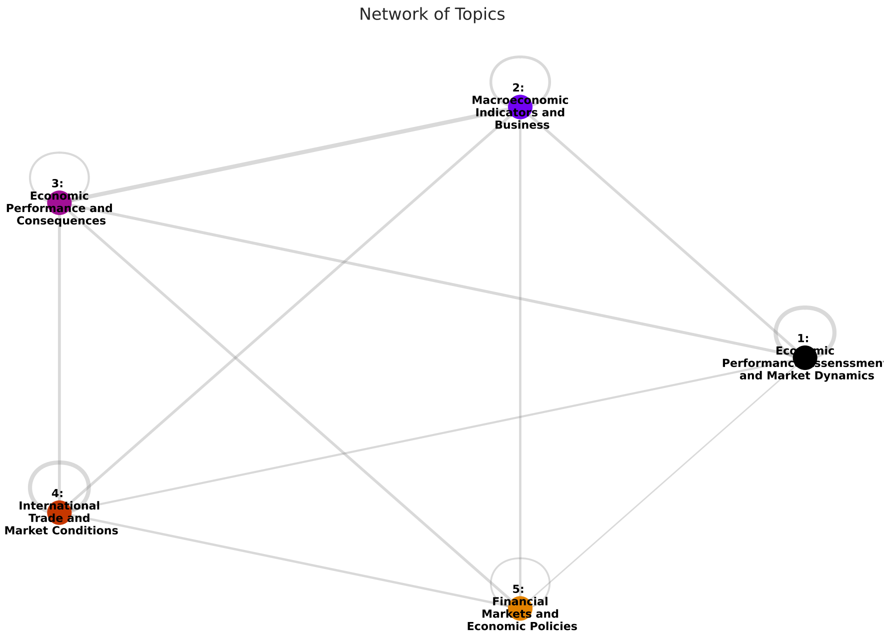


Figure C.17: Network of Topics from Sentiment-Cleaned Dataset
This network graph depicts the thematic associations among five topics identified through Latent Dirichlet Allocation (LDA) on a sentiment-cleaned dataset. Nodes represent individual topics, edges denote shared top words, and thicker edges signify stronger thematic connections. The visualization highlights clusters of related topics and common content themes across the dataset.

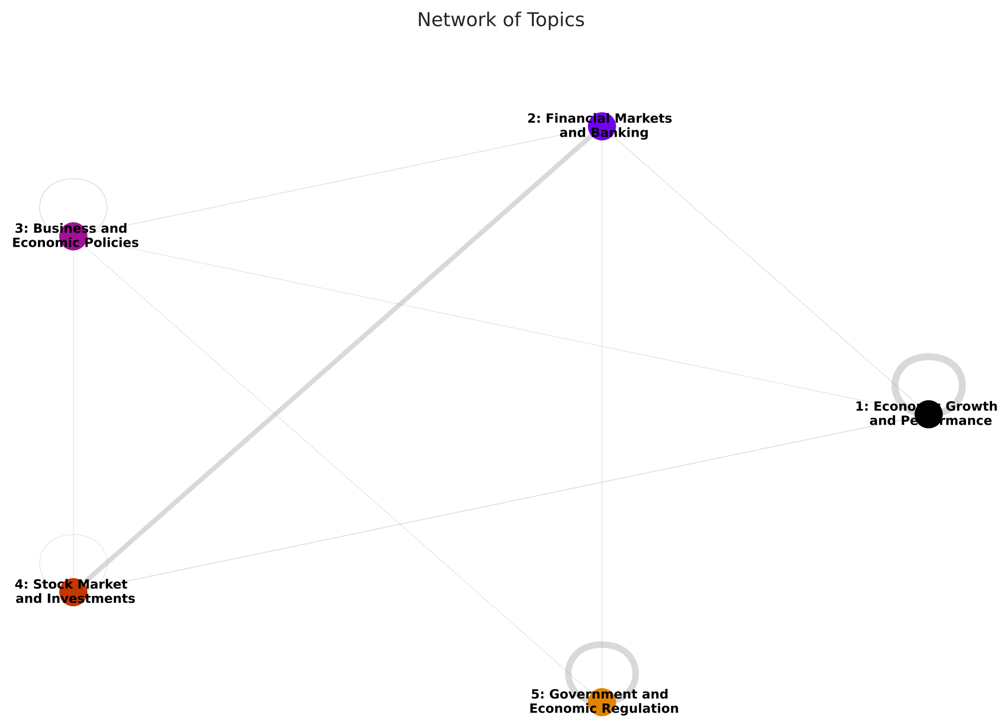


Figure C.18: Network of Topics from Fully Cleaned Dataset
This network graph illustrates the thematic relationships among five topics identified through Latent Dirichlet Allocation (LDA) on a fully cleaned dataset. Each node represents a distinct topic, and edges denote shared top words (from the top 50 words of each topic), with thicker edges indicating stronger thematic connections. This visualization highlights clusters of topics and reveals content overlaps across the dataset.

Figure C.16, Figure C.17, and Figure C.18 illustrate the network graphs depicting the relationships among five topics identified through Latent Dirichlet Allocation (LDA) on the raw, sentiment-cleaned, and fully cleaned datasets, respectively. In these visualizations, each node represents a distinct topic, while the edges denote shared top words and thematic connections between topics. The thickness of the edges reflects the strength of these associations, highlighting significant content overlaps and semantic themes across the datasets.

The topic diversity score for the sentiment-cleaned dataset, defined as the proportion of unique key terms relative to the total number of key terms, is 0.38, compared to 0.10 for the fully cleaned dataset. This indicates that approximately 38% of the key terms are unique across all topics in the sentiment-cleaned dataset. Such keyword overlaps are typical, as they ensure that topics remain relevant to GDP while covering related areas simultaneously. To further enhance topic diversity, one could consider using advanced models like BERTopic, which often yield more diverse topics, or expanding the dataset.

C.8 Polarity for Fully Cleaned Dataset

Figure 3.6 visualizes the overall daily polarity of the fully cleaned dataset, which has been processed to remove past-tense sentences from both, sentiment and topic frequency time series.

The comparison between this cleaned dataset and its original counterpart reveals significant shifts in polarity values. Notably, removing past-related content has led to observable changes in polarity trends. For instance, an increase in sentiment coincides with the period surrounding the German government elections in September 2017. This observation suggests that the elections and their aftermath may have influenced public sentiment, as reflected in the dataset.

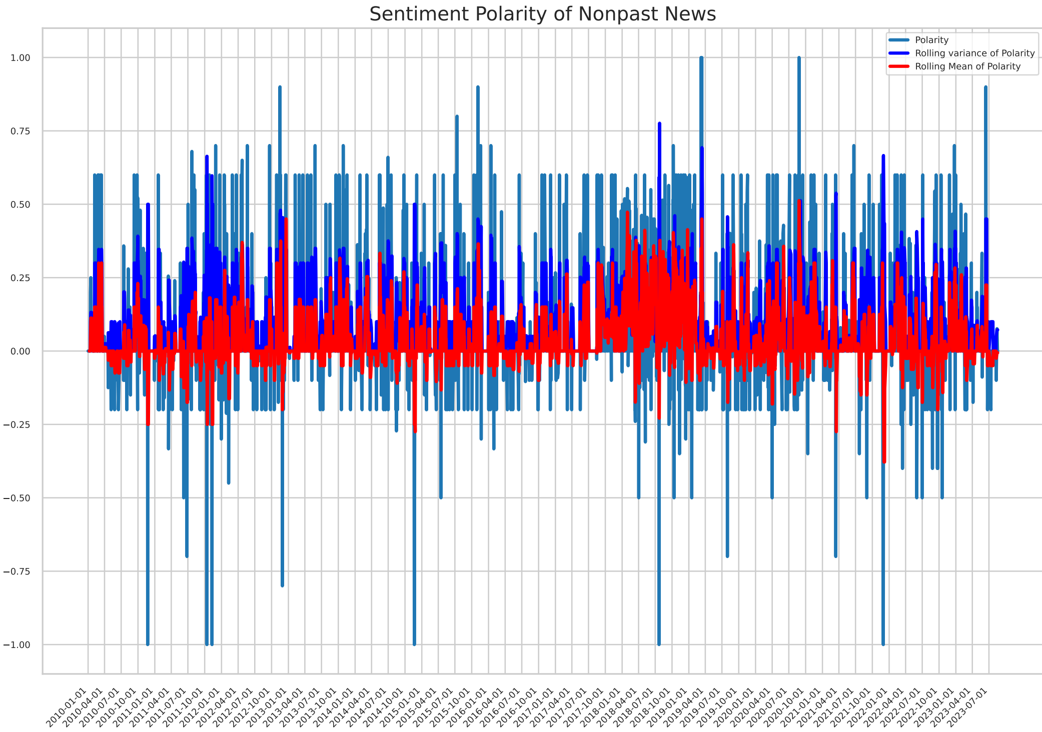


Figure C.19: Polarity of News Over Time in Fully Cleaned Dataset
The figure represents the polarity of all GDP-related news over time with its rolling variance and rolling mean. The red solid line is the 30-day rolling mean of the polarity. The azure blue solid line is the 30-day rolling variance of the polarity. Here, we employ a rolling window of 4 days.

Figure C.20 visualizes the overall monthly polarity of the fully cleaned dataset.

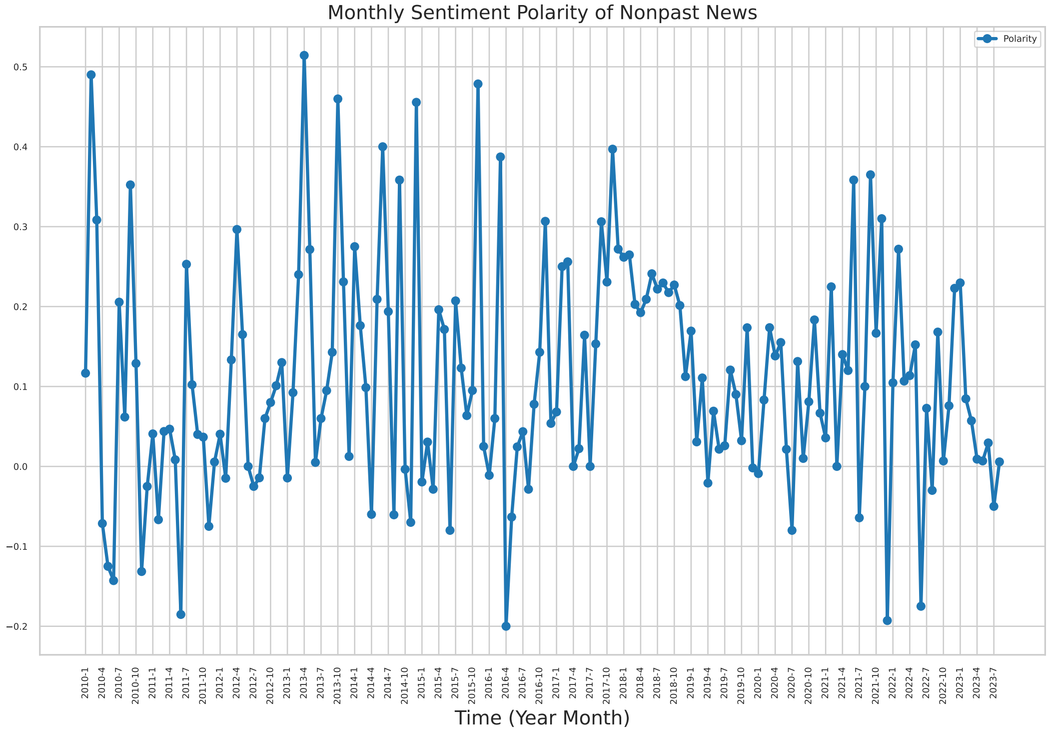


Figure C.20: Polarity of News Over Time in Fully Cleaned Dataset
The figure represents the monthly polarity of all GDP-related news over time.

C.9 RMSE Comparative Analysis between Quarterly Dynamic Factor Models Derived from Raw Dataset News and the Ifo Business Climate Index

In this subsection, we conduct a comparative analysis of the Root Mean Square Error (RMSE) between quarterly dynamic factor models derived from the news data before removing past tense sentences and the Ifo Business Climate Index.

Table C.5: RMSE Comparative Analysis between
Quarterly Models Using Raw Dataset News with Respect to Ifo Climate Index

Model	RMSE of News	RMSE of ifo BCI State	Preferred Model
Dynamic Factor Model	0.91	1.12	News Model
Coincident Index	9.18	19354.62	News Model
Basic OLS with Factors	2.02	2.02	Business Cycle State Model ($R^2 = 0.014$)
Basic OLS with raw values	1.66	1.84	News Model ($R^2 = 0.33$)
Rolling OLS with Factors (min n.obs 1)	2.00	0.46	Business Cycle Index State Model
Rolling OLS with raw values (min n.obs=5)	1.35	1.62	News Model
Rolling OLS with Factor in normal regime (till 2020Q1)	0.46	0.38	Business Cycle State Model
Rolling OLS with raw values in normal regime (till 2020Q1)	0.33	0.30	Business Cycle State Model
Recursive OLS with Factors	2.04	2.05	News Model
Recursive OLS with raw values	2.07	2.02	Business Cycle State Model
Recursive OLS with Factors in normal regime (till 2020Q1)	0.87	0.56	Business Cycle State Model
Recursive OLS with raw values in normal regime (till 2020Q1)	0.73	0.49	Business Cycle State Model
Error of predictions with recursive OLS with factors	mean 0.24 var 4.14	mean 0.16 var 6.41	Undecided
Error of predictions with recursive OLS with raw (till 2022Q2)	mean 0.70 var 2.07	mean 0.31 var 9.94	Undecided
Error of predictions with recursive OLS with raw (all)	mean 0.24 var 7.04	mean 0.70 var 16.57	News Model

C.10 Validation and Robustness Analysis

Our nowcasting model, which relies on text data, shows competitive performance compared to models based on expert judgment and survey data.

To validate the robustness of our models, we conduct several checks on both the Latent Dirichlet Allocation (LDA) and the dynamic factor model:

1. **LDA Model Validation**: We assess the robustness of the LDA model through multiple methods:

    - **Perplexity and Coherence Scores**: These metrics evaluate the quality and interpretability of the topics generated by the model.
    - **Topic Stability**: We test topic stability by running the LDA model with different random seeds, excluding the fixed seed equal to 42 used in our primary analysis. We ensure consistency, by comparing topics across these

different runs, indicating robustness and reliability.

- **Model Alternatives**: We employed LDA with TF-IDF processed news variables and carried out a parallel analysis using Latent Semantic Analysis (LSA), which substantiated the resilience of the LDA model.

2. **Dynamic Factor Model Validation**: We ensure the dynamic factor model's robustness through similar validation techniques, comparing its performance against established benchmarks and checking for consistency across different runs, alternatively processed variables, and parameter settings.

The results of these validation steps confirm that our models are robust and reliable, providing confidence in the accuracy of our nowcasting results.

Dynamic Factor Model Stability

We assess our dynamic factor models' stability utilizing news-driven and conventional variables. We assume that the common factor exhibits weak stationarity (variance-covariance stationary). To validate this, we conduct the Augmented Dickey-Fuller (ADF) test on the time series of factors derived from the monthly dynamic models.

Both sentiment-cleaned and fully cleaned datasets exhibit stationary dynamics over time in open-ended and close-end datasets. In the open-ended dataset, where we exclude the latest values of conventional variables to evaluate model robustness, the dynamic factors remain stationary. This stability is similarly observed in the close-end datasets, reaffirming the reliability of our model across different data configurations. Additionally, the common factors exhibit weak autocorrelation.

Table C.6 presents several evaluation metrics for the dynamic factor model constructed using the sentiment-cleaned dataset:

Table C.6: Model Evaluation Metrics

Metric	Value	Interpretation
Log Likelihood	3220,807	High value indicates good model fit.
AIC	-6381,613	Lower values indicate a better fit.
BIC	-6290,310	Lower values indicate a better fit.
HQIC	-6344,528	Lower values indicate a better fit.
Ljung-Box Q-test (Prob(Q))	0.96, 0.78, 0.83, 0.93, 0.93, 0.86, 0.96.	Values > 0.05 indicate no significant autocorrelation, supporting model robustness.

Dynamic Factor Model with News Variables and Expanding Window Standardized Conventional Variables

In the analysis, we employed an expanding window approach to standardize the first difference of the logarithm of lagged values for the Industrial Production Index (IPI) and exports. To prevent data leakage, we computed means and variances for standardization using only the data available up to each point. This approach ensures that we standardize each data point based solely on past information, avoiding contamination from future data during the standardization process. The resulting variables compare recent percentage growth rates with historical data, that assess whether current growth patterns are typical or anomalous. Rather than using first-differenced lagged values directly, we incorporated these standardized variables into the dynamic factor model.

The resulting nowcasting root mean squared forecast errors (RMSFEs) for the Monthly News-Based Dynamic Factor Model with standardized first-difference of the logarithm of lagged conventional variables (IPI and export) are presented in Table C.7. The improved accuracy of this model's fit to GDP surpasses the existing nowcasts of German GDP and our previous model using first-differenced lagged conventional variables.

Table C.7: RMSFE of Monthly News-Based Dynamic Factor Model with Standardized Conventional Variables, Presented in Percentage Points (p.p.).

Horizon	**Dataset**	**Newsy Model**	
		RMSFE	NTS
Nowcast	Sentiment-Cleaned	0.17	0.09
Out-of-Sample Forecast	Sentiment-Cleaned	h=1: 0.12 h=2: 0.16	h=1: 0.06 h=2: 0.08

Cross-Validation of the Dynamic Factor Model

We evaluated the performance of our monthly news-based dynamic factor model, applied to a sentiment-cleaned dataset with expanding window standardized conventional data, by predicting quarterly GDP growth through cross-validation. We trained the model on historical data and evaluated it on subsequent periods. Table C.8 presents the cross-validation results.

Table C.8: Cross-Validation
Results for Predicting Quarterly GDP Growth Using the Dynamic Factor Model

Fold	**Train RMSE**	**Test RMSE**
1	0.25	0.29
2	0.27	0.25
3	0.26	0.34
4	0.28	0.31
5	0.29	0.28
Average	**0.27**	**0.29**

Table C.8 summarizes the train RMSE and test RMSE values for each fold, along with their averages. The average Train RMSE across folds is 0.27 percentage points, while the average test RMSE is 0.29 percentage points. These results suggest that the dynamic factor model generalizes quite well to unseen data, as the test RMSE is not significantly higher than the train RMSE, indicating no overfitting, but slight underfitting. This validation approach provides confidence in the reliability of our predictions for quarterly GDP growth.

Cross-Dataset Validation: Newsy Dynamic Factor Model with English News Dataset

In this section, we explore the application of the Newsy Dynamic Factor Model to an English news dataset consisting of 20,625 news articles, covering the time span from Q1 2010 to Q2 2023. Similarly to the approach taken with the German news dataset, we filter out past tense sentences to focus on sentiment relevant to current economic conditions. Specifically for the English dataset, we employ a POS tagger to identify and exclude past tense sentences.

While the findings from the English news dataset may not exhibit the same level of robustness as those from the German news dataset, they still offer valuable insights. Below, we present the key findings and engage in a discussion of their implications.

Topic 1: Global Economic Performance and Policy Dynamics[10]

Key Terms: growth, country, market, policy, investment, export, government, bank, increase, sector, risk, level, demand, trade, crisis, expect, debt, forecast, price, inflation, capital, business, decline, area, grow, interest, measure, recovery, deficit, account, impact, unemployment, term, support, effect, cost, need, surplus, result, provide, reduce, change, consumption, asset, state, improve, income, point, balance, fund

Topic 2: Market Dynamics and Business Trends

Key Terms: market, business, company, sale, growth, people, product, lot, talk, question, want, mean, industry, number, increase, thank, work, share, let, revenue, cost, term, expect, grow, point, way, start, need, bit, world, health, investment, price, course, production, customer, country, change, lead, provide, use, happen, part, value, result, research, service, impact, call, level

Topic 3: Government Actions and Security Measures

Key Terms: people, country, government, state, world, work, want, use, security, tell, president, force, call, need, issue, part, attack, number, member, case, way, support, war, question, power, law, leader, change, talk, place, policy, try, trump, police, trade, plan, accord, leave, mean, week, man, gas, hold, fact, system, election, deal, meet, bring, help

Topic 4: Financial Markets and Investment Expectations

Key Terms: market, growth, expect, price, index, week, point, stock, bank, trade, investor, share, sale, inflation, dollar, gain, business, oil, drop, yield, follow, sector, level, hit, cut, forecast, consumer, figure, trading, bond, add, decline, start, risk, yesterday, service, expectation, move, eurozone, news, policy, interest, release, currency, pound, number, profit, confidence, deal, record

Topic 5: Debt Management and Economic Policies

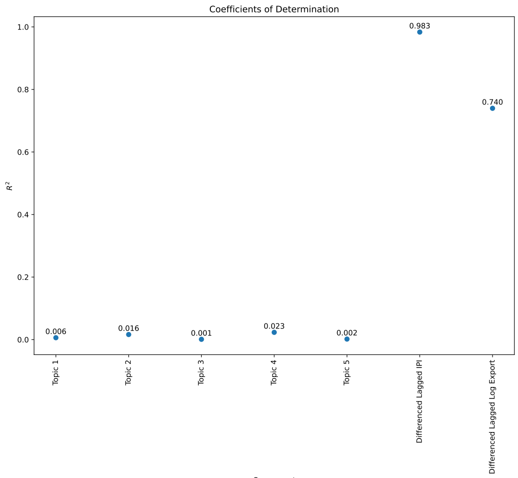
[10] These titles are provided for reference purposes and serve as notations within our analysis.

Key Terms: debt, country, government, bank, crisis, fund, need, bailout, bond, eurozone, leader, euro, deficit, market, budget, austerity, cut, problem, merkel, deal, money, state, finance, plan, member, reform, greek, currency, leave, measure, minister, policy, want, way, vote, agree, election, party, pay, tax, issue, week, rule, ecb, default, call, credit, union, rescue, zone

The identified topics span economic, political, and financial discourse issues. Topic 1, 'Global Economic Performance and Policy Dynamics,' explores factors influencing economic growth, market conditions, and government policies crucial for economic stability and development. Topic 2, 'Market Dynamics and Business Trends,' examines business operations, revenue generation strategies, and market dynamics impacting corporate performance. Topic 3, 'Government Actions and Security Measures,' focuses on governmental decisions, security policies, and their implications for national and international affairs. Topic 4, 'Financial Markets and Investment Expectations,' analyzes trends in financial markets, investment opportunities, and economic forecasts amid fluctuating market conditions. Lastly, Topic 5, 'Debt Management and Economic Policies,' delves into strategies for managing national debts, economic policies affecting debt dynamics, and their implications on fiscal health and stability.

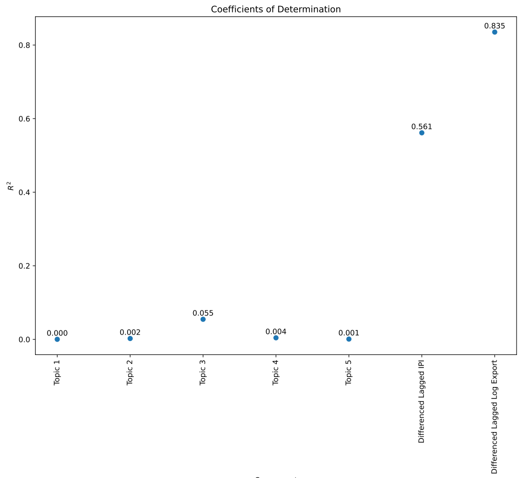
Despite originating from different datasets and focusing on an international perspective, the topics in English news exhibit some alignment with those in our German news data.

R-squared (R2) Coefficients of Determination for the Observed Variables



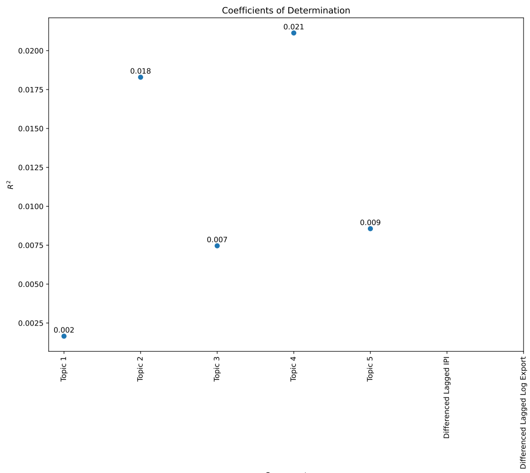
(a)

Fully Cleaned Dataset, Close Ended



(b)

Sentiment-Cleaned Dataset, Close-Ended



(c)

Sentiment-Cleaned Dataset, Open-Ended

Figure C.21: R-squared (R^2) coefficients of determination for the observed variables in the dynamic factor model. The coefficients on this figure measure the extent to which the dynamic factors explain the variation in each input time series. Interpretation of these coefficients should consider the model specification.

Correlation and Granger Causality Analysis

In this subsection, we first examine the correlation between GDP growth and the factor derived from the monthly dynamic factor model, utilizing a sentiment-cleaned dataset. Subsequently, we conduct a Granger causality test to investigate the predictive relationship between GDP growth and the factor time series.

The Pearson correlation coefficient ($r = 0.77$) demonstrates a strong and consistent relationship between GDP growth and the sentiment-derived factor.

To investigate this relationship further, we performed a Granger causality test to determine if the factor from the monthly dynamic factor model can predict GDP growth. We conducted the test for lags 1 through 4. Strong evidence of Granger causality was observed at lags 1 and 2, with all p-values below 0.05, suggesting that the factor significantly predicts GDP growth at these lags. Evidence at lags 3 and 4 was weaker, with significance detected only through the Chi-squared and Likelihood ratio tests.

Evaluating Model Accuracy During Crisis

Figure C.22 presents the results of the Markov switching model applied to German GDP growth data, identifying three distinct economic regimes.

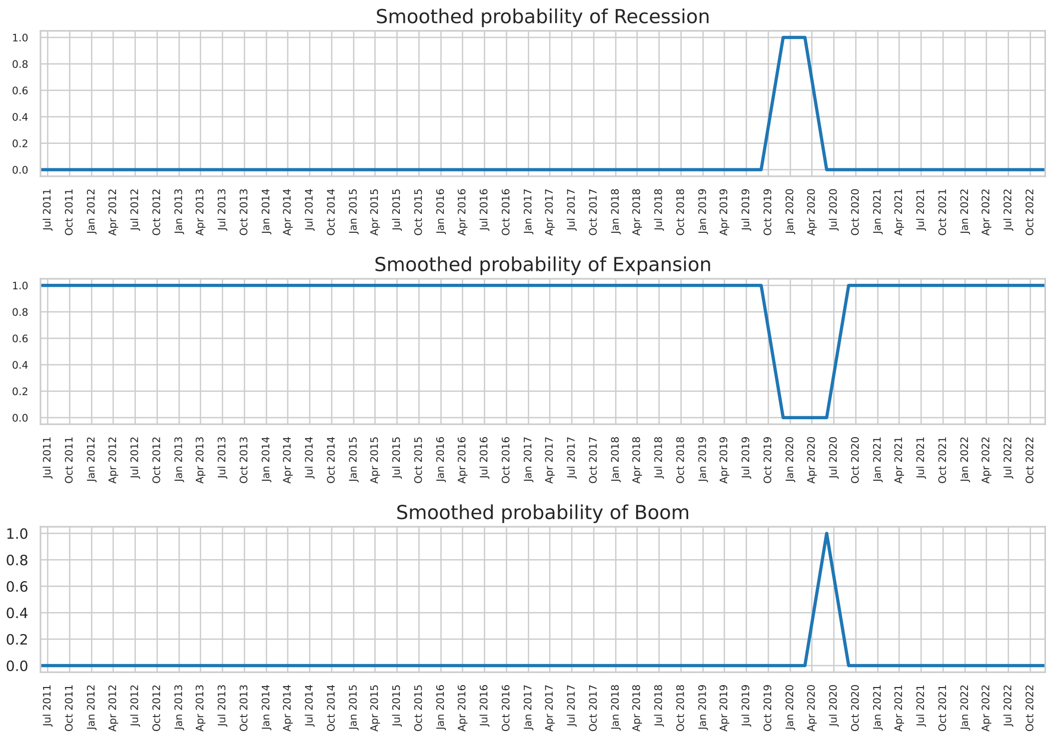


Figure C.22: Markov Switching Model with Three States
The figure illustrates the Markov switching model with three states applied to GDP growth data. The model captures transitions between different economic regimes, offering insights into dynamic changes in the underlying data-generating process.

We also review the business cycle dates provided by the German Council of Economic Experts on https://www.sachverstaendigenrat-wirtschaft.de/en/index.html, an academic body that advises German policymakers on economic policy and assesses macroeconomic developments in Germany. The German Council of Economic Experts identifies a business cycle peak in the fourth quarter of 2019 and a downturn from

February 2020 to the second quarter of 2020. These downturn periods partially overlap with the recession phases identified by our three-regime Markov Switching model. Consequently, we define the period from October 2019 to May 2020, characterized by a high smoothed probability of recession, as a recession phase. This recession is followed by a high probability of an economic boom, starting in June 2020 and continuing until September 2020, according to our model.

As observed, the goodness of fit of our model is somewhat lower during the crisis and boom periods identified by the Markov Switching model compared to expansion periods. Although modelling economic crises and boom presents inherent challenges, our model demonstrates a reasonably satisfactory performance during these phases.

C.11 Evaluation of Alternative Models and Methodologies

GDP-related Topics Identified by LDA with TF-IDF Vectorizer

To assess the impact of the vectorizer choice on the model, we applied a TF-IDF vectorizer instead of a Count Vectorizer. Unlike the Count Vectorizer, which counts word occurrences, the TF-IDF Vectorizer uses the whole corpus to weight a word's importance in a document by considering the inverse frequency of the word across the corpus. This method highlights more significant terms within the context of the corpus. The resulting topics for the sentiment-cleaned dataset are as follows:

Topic 1: Business Sentiment Assessment

Key Terms: prozent (percentage), erwartung (expectation), halb (half), ifochef, rendite (yield), zehnjährig (ten-year), geschäftslage (business situation), beurteilen (assess), monat (month), unternehmen (companies), wirtschaft (economy), stimmung (mood/sentiment), auto (car), bundesanleihe (federal bond), punkt (point), index, befragen (ask), rückgang (decline), bewerten (evaluate).

Topic 2: Market Dynamics and Reporting

Key Terms: prozent (percentage), exklusivinformation (exclusive information), wirtschaft (economy), magazinen (magazines), logistik (logistics), konjunktur (economic situation), unternehmen (companies), wirtschaftsleistung (economic performance), bund (federation), ökonomen (economists), volkswirtschaft (national economy), tjahr, rezession (recession), steigen (rise), vorabend (eve), quartal (quarter), publizieren (publish), service, wiederholen (repeat), volkswirt (economist), wachstum (growth), milliarde (billion), stagnation, stehen (stand), wirtschaftswachstum (economic growth), folge (consequence).

Topic 3: Trade Policy and Relations

Key Terms: wirtschaft (economy), strasse (street), prozent (percentage), industrie (industry), presse (press), oeffentlichkeitsarbeit (public relations), unternehmen (companies), milliarde (billion), verbraucher (consumer), land (country), abkommen (agreement), befragung (survey), euro (Euro), experte (expert), handel (trade), ausbreitung (spread), dihkchef, anstieg (increase), rückgäng (decline), volkswirtschaft (national economy), bundesregierung (federal government), folge (consequence), konjunktur (economic situation), lage (situation).

Topic 4: Government Policy and Economic Strategy

Key Terms: wirtschaft (economy), land (country), unternehmen (companies), kanzlerin (chancellor), prozent (percentage), milliarde (billion), firma (firm/company), mensch (person), bundesregierung (federal government), geben (give), ausbildung (education/training), euro (Euro), politik (politics), präsident (president), sehen (see), partei (party), digitalisierung (digitalization), abkommen (agreement), regierung (government), zukunft (future), treffen (meeting), gesellschaft (society), gespräch (conversation), zeit (time), fordern (demand), frage (question), fachkräftemangel (skills shortage), leben (life), intelligenz (intelligence).

Topic 5: Financial Markets and Economic Growth

Key Terms: prozent (percentage), wirtschaft (economy), unternehmen (companies), euro (Euro), wachstum (growth), quartal (quarter), milliarde (billion), monat (month), konjunktur (economic situation), land (country), stehen (stand), entwicklung (development), sehen (see), steigen (rise), rezession (recession), erwarten (expect), ende (end), rechnen (calculate), bank (bank), industrie (industry), zahl (number), folge (consequence), punkt (point), bund (federation), lage (situation), rückgang (decline), vergleich (comparison), wirtschaftswachstum (economic growth), aufschwung (upswing).

The topics identified through LDA analysis encompass various economic and policy-related themes. Topic 1, "Business Sentiment Assessment," delves into evaluating sentiment and expectations within the business community, focusing on factors like economic indicators and market reactions. Topic 2, "Market Dynamics and Reporting," focuses on the dynamics of economic reporting, examining trends, economic performance, and the impact on various sectors. Topic 3, "Trade Policy and Relations," explores international economic relations, trade agreements, and their implications on national economies. Topic 4, "Government Policy and Economic Strategy," encompasses discussions on governmental economic policies, strategies, and their socio-economic impacts. Lastly, Topic 5, "Financial Markets and Economic Growth," analyzes financial market trends, economic growth indicators, and their influence on overall economic stability. To sum up, these topics provide a comprehensive view of economic landscapes, policies, and their interconnectedness in shaping contemporary economic narratives.

As observed, applying different vectorizers does not significantly reduce the recurrence of the domain-specific terms. While it does improve coherence, it does not lead to a substantial decrease in the loss function or cross-validated perplexity scores, nor does it enhance GDP nowcasting performance.

Model Justification by Using LSA Instead of LDA

To justify the robustness of our model, we implemented Latent Semantic Analysis (LSA) as an alternative to Latent Dirichlet Allocation (LDA). LSA uses Singular Value Decomposition (SVD) to reduce the dimensionality of the word-document matrix, obtaining a k-dimensional approximation that retains the most significant features of the original data while discarding less important information. For five topics, the LSA model achieved a higher C_v score of 0.56. However, its U_{mass} score was -15.36, significantly lower than that of the LDA model. Since LSA is a linear matrix factorization technique and not a probabilistic model, it does not generate a probability distribution over words and topics. Therefore, traditional probabilistic metrics such as perplexity are unsuitable for evaluating LSA's performance. Although LSA has a higher C_v score, its substantially lower U_{mass} score indicates that LDA outperforms LSA in terms of topic coherence and model robustness for our analysis.

Dynamic Factor Model with Number of Topics Based on Non-Cross-Validation Perplexity Scores

Some studies, such as Thorsrud (2020), determine the number of topics based on perplexity scores rather than cross-validation scores, even though the literature suggests that this approach can lead to an excessive number of topics and potential overfitting. This method is used here for comparative purposes. Consequently, we constructed an LDA model with 22 topics for the fully cleaned dataset. Our dynamic factor model thus comprises 22 time series, each corresponding to one of these topics. Below, we present the results of the dynamic factor model utilizing 22 topics.

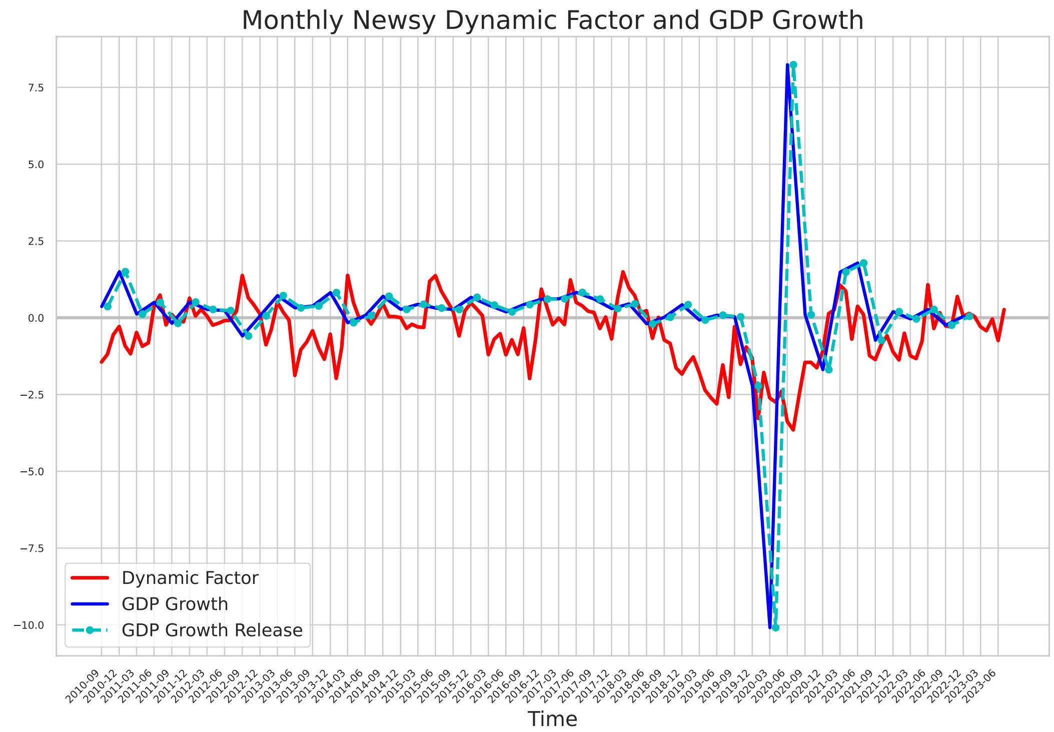


Figure C.23: Dynamic Factor and First Release GDP Growth
The figure illustrates the dynamic factor derived from the fully cleaned dataset, incorporating 22 tone-adjusted topic frequency time series. The dynamic factor is compared to the First Release of GDP Growth.

Moreover, Figure C.24 the resulting dynamic factor captures GDP movements less than the very well-acknowledged Business Climate Index.

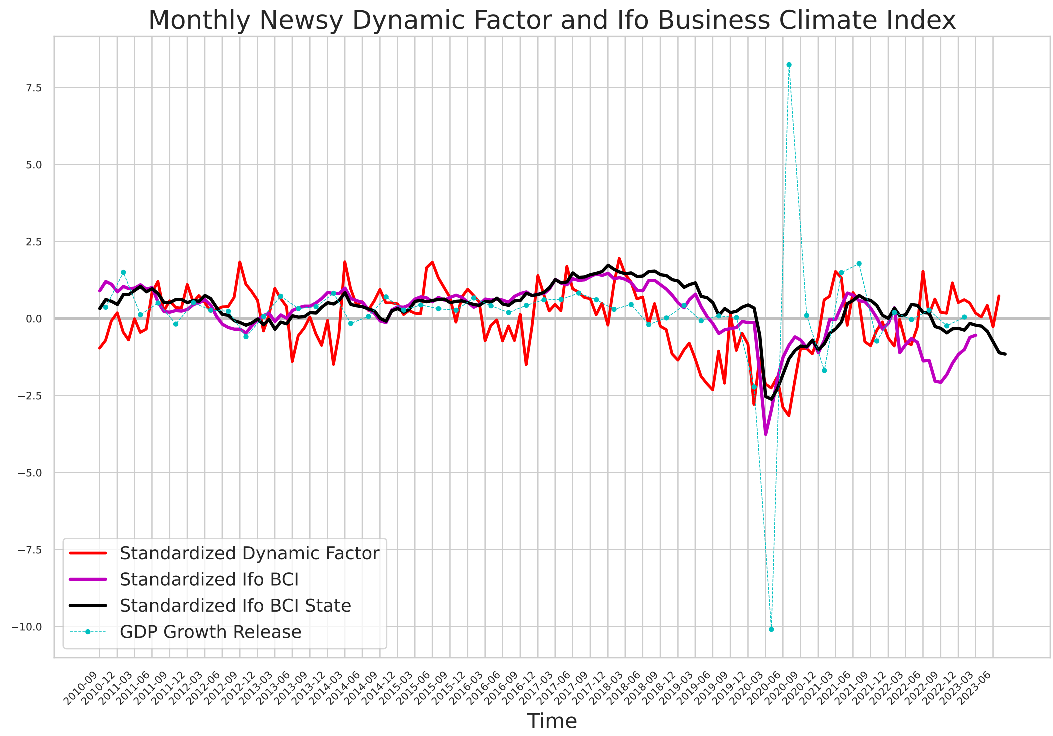


Figure C.24:
Comparision of the Newsy Dynamic Factor to Ifo Business Climate Index
This figure illustrates the dynamic factor derived in the same manner as our main model but with 22 Topics. It compares the performance of this dynamic factor to the Ifo Business Climate Index.

Results of the Dynamic Factor Models without News

We integrate the Industrial Production Index (IPI) and export data into our Dynamic Factor Model while considering the delays in the publication of these variables. As the current IPI and export figures for the ongoing period are not yet available, we have utilized lagged values of these variables. This method ensures that the data reflects only historical information, thus mitigating the risk of potential information leakage from future periods in line with best practices in time series analysis.

We apply first differencing to the lagged values of IPI and export before incorporating them into the model for several reasons. Firstly, it ensures the stationarity of the time series. Secondly, this process allows the time series to accurately capture the most recent rate of change in the Industrial Production Index (IPI) and exports based on the latest published data available to economic agents. This approach ensures that the model incorporates recent developments and contextualizes news information, thereby establishing an up-to-date understanding of the current state of the economy.

The model that uses only the first-differenced lagged Industrial Production Index (IPI) and lagged export without incorporating news data shows a poor fit. By replacing variables with the standardized lagged industrial index and standardized lagged export data, the model's accuracy improves compared to the model reliant solely on the first-differenced lagged Industrial Production Index (IPI) and lagged export.

The monthly dynamic factor derived from the model excluding news data, specifically utilizing the standardized lagged industrial index and standardized lagged export data, demonstrates inferior performance compared to our news-inclusive model utilizing the sentiment-cleaned dataset.

Figure C.25 illustrates the dynamic factor from the model without news data for the sentiment cleaned dataset.[11]

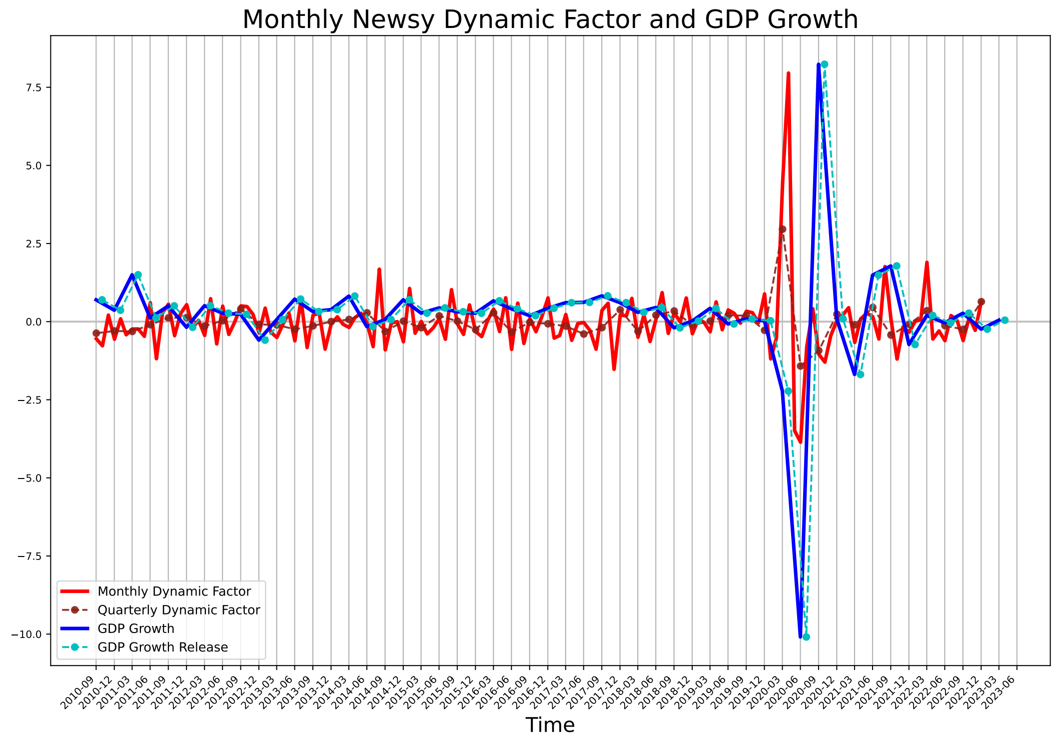


Figure C.25: Monthly Dynamic Factor generated without News VS GDP
The figure illustrates the dynamic factor received from the dynamic factor model without news.

We performed a comparative analysis of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) between models that incorporate news and those that do not. For both the sentiment-cleaned and fully cleaned datasets, the AIC and BIC values consistently favoured the models that included news. These results highlight the significant advantage of incorporating news variables in improving model performance.

[11]Note that the graphical representation for the sentiment-cleaned dataset is not included here, as it closely resembles the graph for the dynamic factor model without news data but with the Ifo Business Climate Index.

Table C.9: Comparison of AIC and BIC values for
Dynamic Factor Model with News and Dynamic Factor Model without News.

Dataset	Model with News	Model without News
Sentiment-cleaned	AIC: -5,513.09 BIC: -5,421.79	AIC: -755.62 BIC: -725.19
Fully cleaned	AIC: -6,847.76 BIC: -6,756.46	AIC: -1,425.87 BIC: -1,395.43

Note: The AIC and BIC values for models without news from the sentiment-cleaned dataset coincide with those from the fully cleaned dataset when all variables are considered in the same form and both datasets are kept closed-ended.

Results of the Dynamic Factor Models without News and with Ifo Business Climate Index Figure C.26 presents the dynamic factor from the models that exclude news and include the Ifo Business Climate Index..

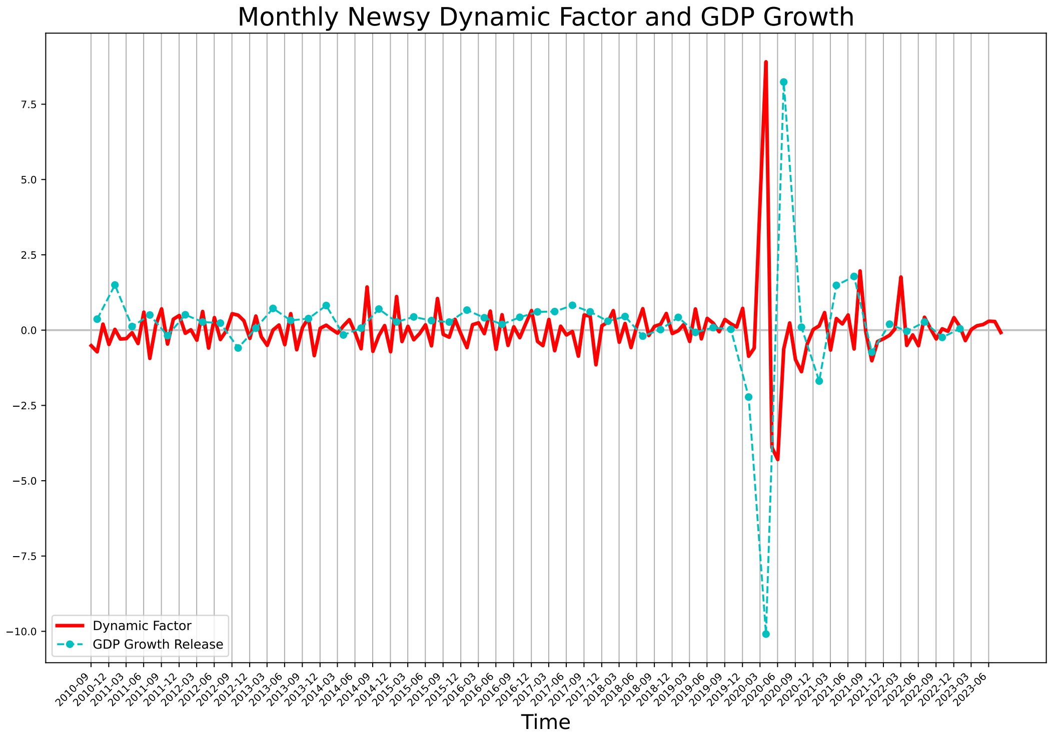


Figure C.26: Monthly Dynamic Factor without News
and with Ifo Business Climate Index (Sentiment-Cleaned Dataset) VS GDP
This figure shows the dynamic factor obtained from the model using the Ifo Business Climate Index (BCI) in place of news data. The comparison highlights how the model performs when excluding news data but including the BCI.

Results of the Dynamic Factor Model Based on News Data Only

We integrate the Industrial Production Index (IPI) and export data into our Dynamic Factor Model while considering the delays in the publication of these variables. As the current IPI and export figures for the ongoing period are not yet available, we have utilized lagged values of these variables. This method ensures that the data reflects only historical information, thus mitigating the risk of potential information leakage from future periods in line with best practices in time series analysis.

We apply first differencing to the lagged values of IPI and export before incorporating them into the model for several reasons. Firstly, it ensures the stationarity of the time series. Secondly, this process allows the time series to accurately capture the most recent rate of change in the Industrial Production Index (IPI) and exports based on the latest published data available to economic agents. This approach ensures that the model incorporates recent developments and contextualizes news information, thereby establishing an up-to-date understanding of the current state of the economy.

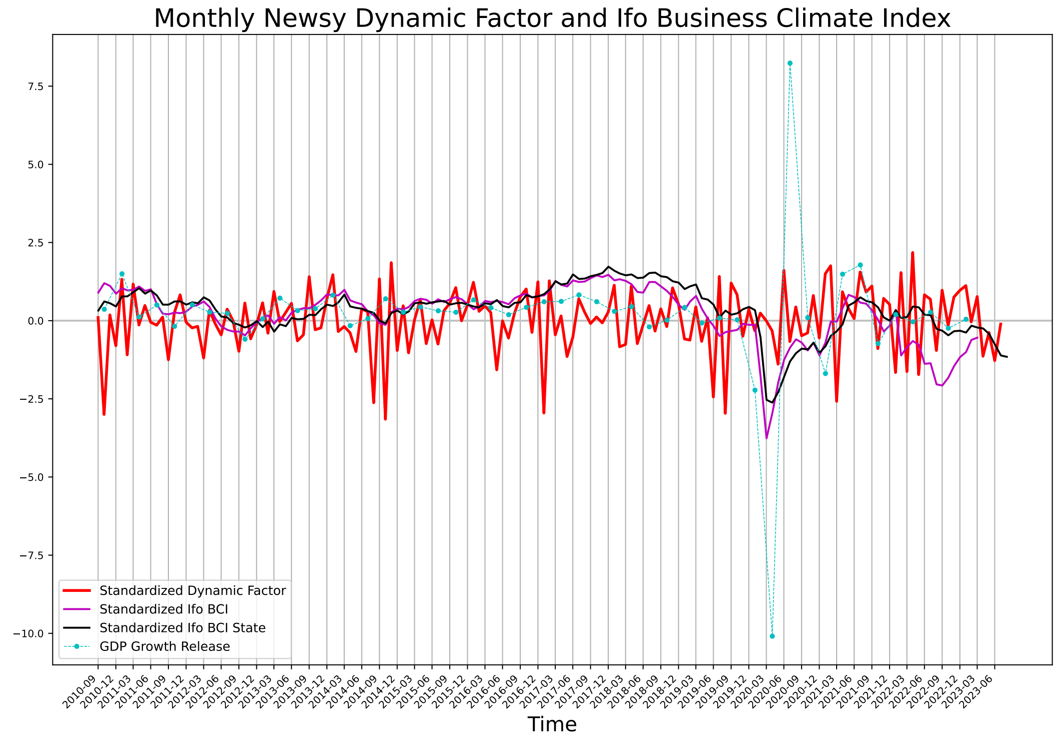


Figure C.27:
Monthly Dynamic Factor with only News (Sentiment-Cleaned Dataset) VS GDP
The figure illustrates the dynamic factor received from the dynamic factor model with only news.

Results with Cleaning the Texts from the Past Using RoBERTa

The Robustly Optimized BERT Pretraining Approach (RoBERTa) is a transformer-based AI model designed to enhance the pretraining of BERT (Bidirectional Encoder Representations from Transformers). In the context of past tense recognition, RoBERTa excels due to its robust architecture and extensive pre-training on diverse and large text corpora. This model utilizes self-attention mechanisms to capture long-range dependencies and nuanced linguistic features, making it highly effective for syntactic and semantic understanding.

RoBERTa exhibits high accuracy in tagging past tense sentences, though it necessitates substantial computational resources and fine-tuning. Moreover, its maximum input length is limited to 512 tokens, potentially leading to the truncation of long sentences and the loss of crucial contextual information required for accurate tense classification. Our testing revealed that while RoBERTa generally achieves high accuracy in our task, it does not consistently outperform simpler models like RNN taggers by a significant margin. The obtained sentences cleaned from past tense align closely with those produced by our RNN tagger.

Neural Network with and without News for Cross-Validation

We employ a feedforward neural network (NN), specifically a multi-layer perceptron (MLP) implemented using PyTorch, to forecast quarterly GDP growth rates. This model incorporates monthly news data along with lagged Industrial Production Index and lagged Exports. To match the quarterly frequency of the GDP growth data, we consolidated the monthly data into a quarterly frequency. The neural network, comprising one hidden layer, was trained on this aggregated dataset. Model performance was evaluated by comparing the predicted GDP growth rates to actual values, highlighting the network's effectiveness in capturing and forecasting economic trends.

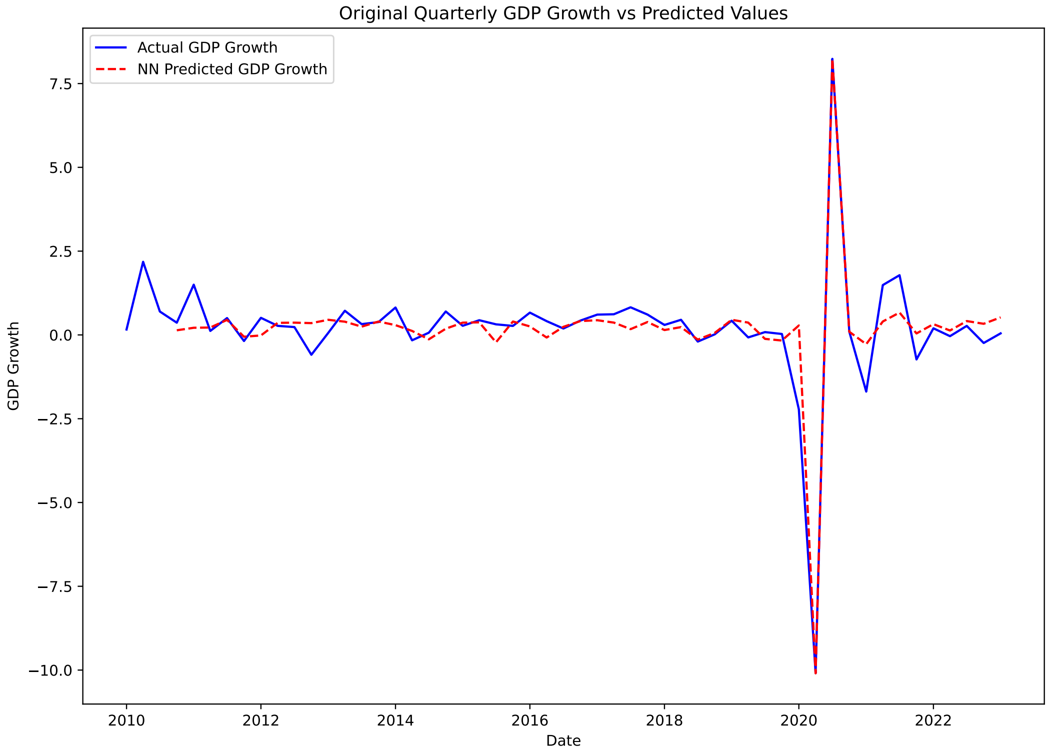


Figure C.28: Neural Network Predicted Values without News VS GDP Growth
This graph depicts neural network predicted values VS GDP growth.

Incorporating news topics into the neural network inputs enhances the model's fit and provides more accurate nowcasts (compare Figure C.28 to Figure C.29). Note that we use news data and lagged indices (differenced to ensure stationarity), with the dataset starting from October 1, 2010, aligning with the time span of the main, newsy model.

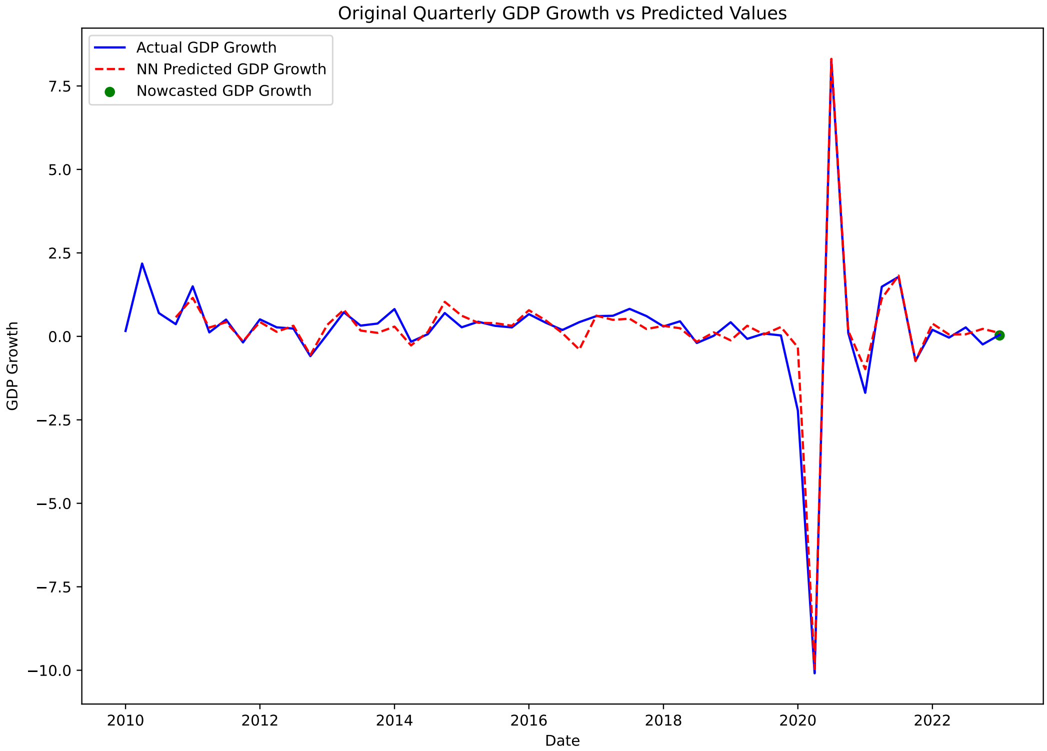
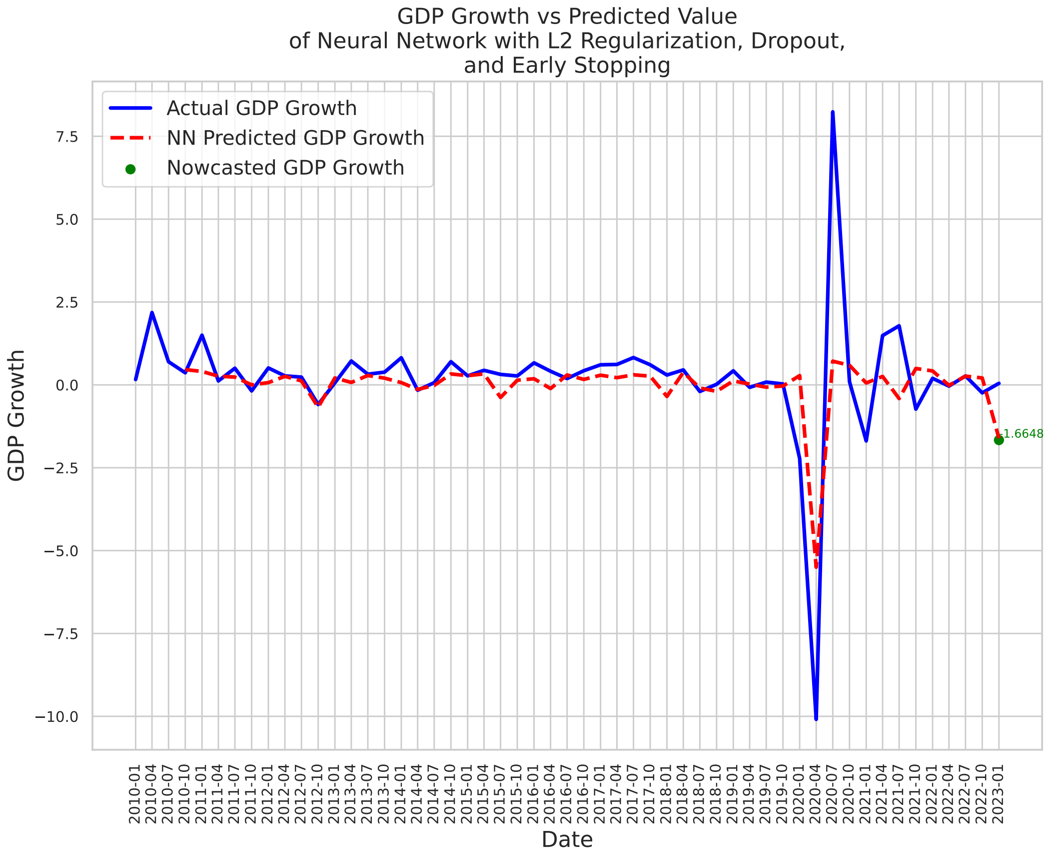
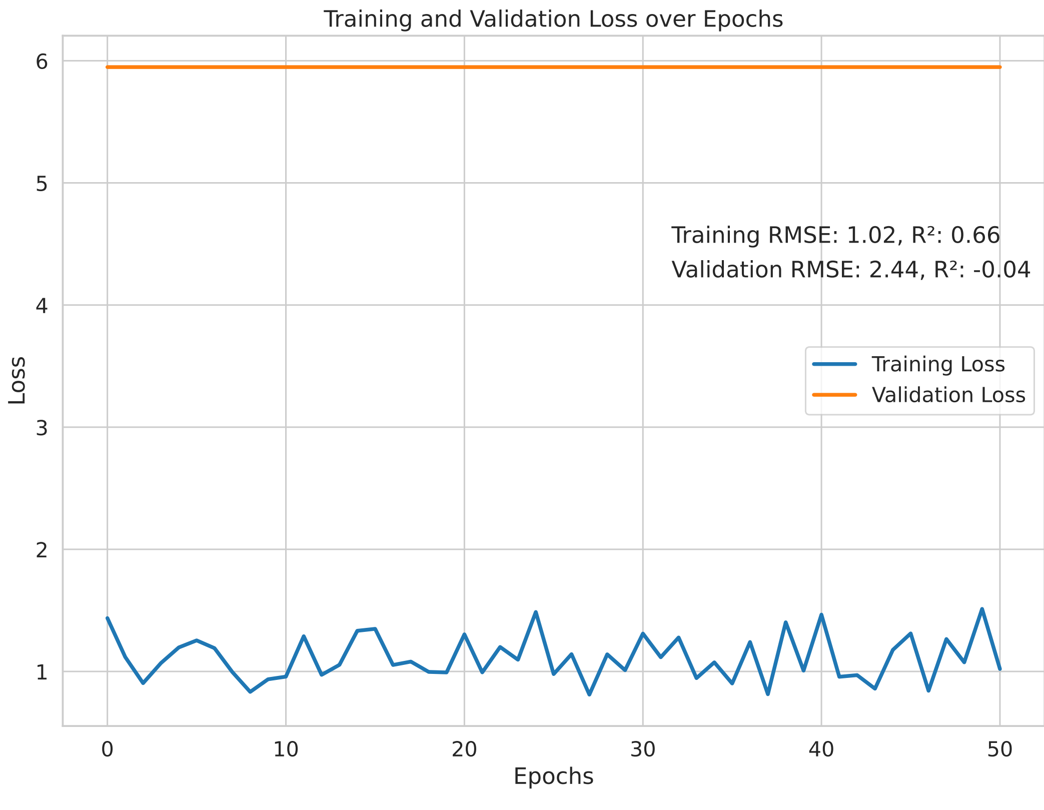


Figure C.29: Neural Network Predicted Values VS GDP Growth
This graph depicts Neural Network predicted values with sentiment-cleaned dataset (including News) VS GDP growth.

The neural networks shown in Figure C.28 and Figure C.29 are overfitting, as evidenced by the validation losses. To address overfitting in the neural networks, we introduced several regularization techniques. Specifically, we added a dropout layer with a probability of 0.5 after the first hidden layer. Additionally, we applied a learning rate decay of 0.001 and incorporated L2 regularization by setting the weight decay to 0.001 in the Adam optimizer. These measures help prevent overfitting by regularizing the network's parameters during optimization.



(a) Neural Network with LR Regularization, Dropout and Early Stopping



(b) Tranining and Validation Loss

**Fig-
ure C.30:** Neural Network with LR Regulation, Dropout and Early Stopping

The neural network with L2 regularization, dropout, and early stopping mitigates overfitting (compare Figure C.30), however, the nowcasts produced by the model remain unstable. To address this, we incorporated early stopping, which significantly enhanced model stability but resulted in a less impressive fit (see Figure C.30), with an RMSE of 1.4361. The model incorporating news data outperforms the one without, as evidenced by the steady validation loss in the former compared to the latter.

Comparison of MIDAS and Dynamic Factor Models for Nowcasting GDP Growth

For comparative purposes, we also construct a Mixed Data Sampling (MIDAS) model using our data. Figure C.31 presents the MIDAS model's GDP growth nowcasts compared to actual GDP growth. As observed, the nowcasts fail to capture the significant downturn in GDP growth in the first quarter of 2020 and do not perform as well as our newsy dynamic factor model.

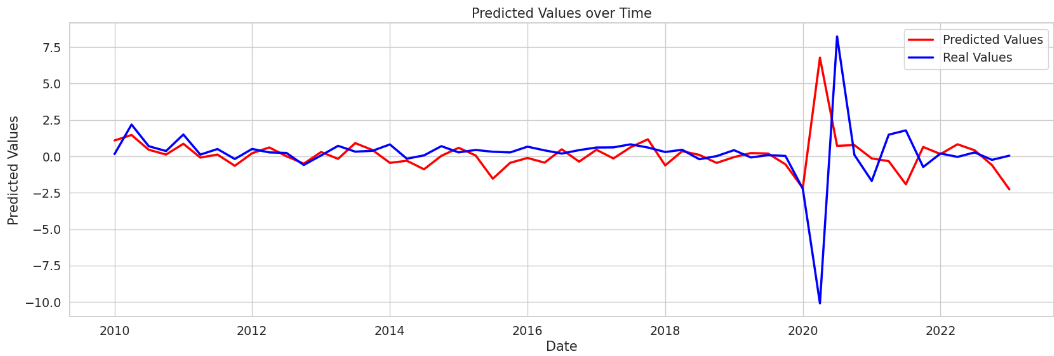


Figure C.31: MIDAS Model Predicted Values VS GDP Growth
This graph depicts the predicted values of the MIDAS model, using a sentiment-cleaned dataset, against GDP growth.

C.12 Subjectivity

Enhancing Objectivity through Removal of Subjective Articles

Subjectivity Measure: Enhancing Objectivity

To ensure the objectivity of the news, we integrate subjectivity measures to mitigate biases and enhance the reliability of our analysis. This approach aims to foster a more impartial assessment, thereby strengthening the validity and credibility of our conclusions.

We calculate the subjectivity measure (S) to quantify the subjectivity of a text and the extent to which a text expresses personal opinions or feelings rather than factual information. We achieve this by categorizing expressions within the text as either subjective or objective based on their semantic content and computing the ratio of subjective expressions to the total number of expressions:

$$S = \frac{\text{Number of subjective expressions}}{\text{Total number of expressions}} \tag{C.8}$$

Applying the subjectivity measure instead of polarity did not improve the performance of tone adjustment. Similarly, a combination of both, polarity and subjectivity measures did not yield better results.

In our experiment, we removed papers with a subjectivity measure exceeding 0.8, excluding 574 documents from the dataset. We then applied Latent Dirichlet Allocation (LDA) to the remaining objective papers.

Our analysis revealed that using the subjectivity measure alone, combining it with polarity measures, or excluding the most subjective papers did not surpass the performance achieved with tone adjustment using polarity. Consequently, we have decided to exclude subjectivity-related adjustments from the primary analysis.

Overall Subjectivity

The overall monthly subjectivity of the fully cleaned dataset is visualized in Figure C.32. This figure illustrates the subjectivity of news articles related to GDP over time.

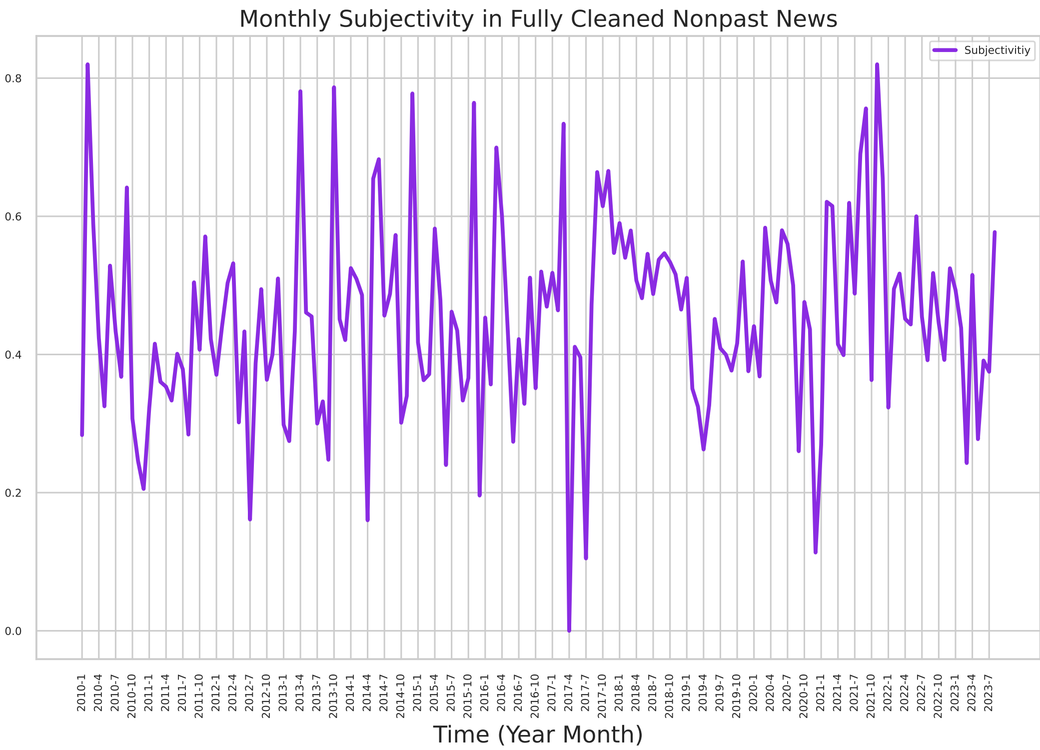
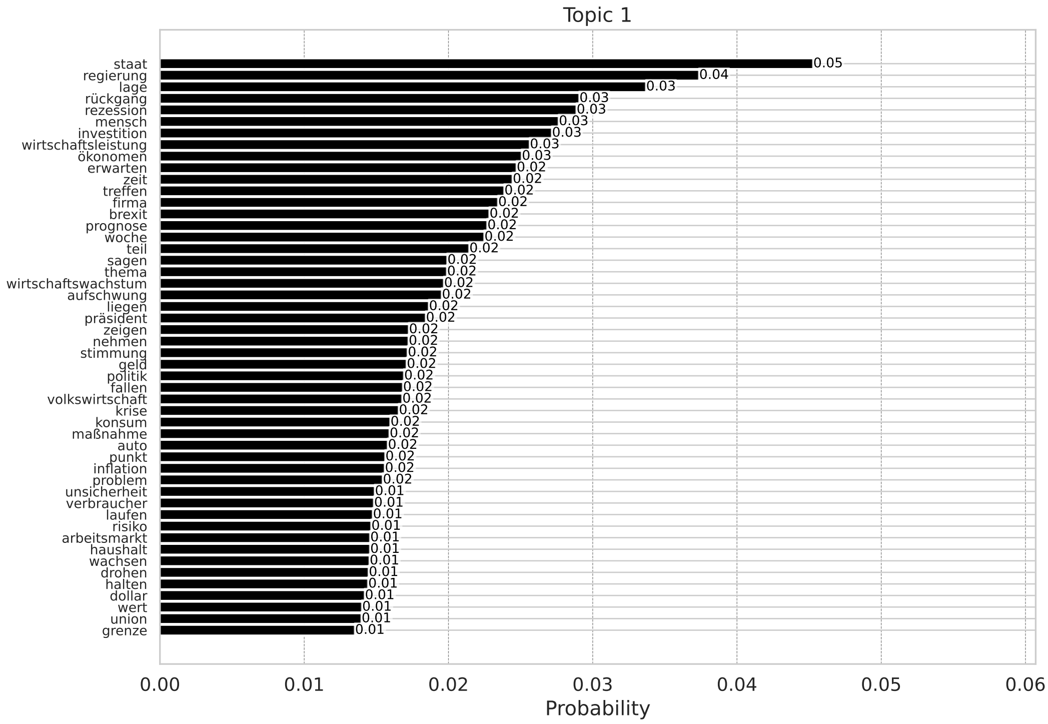


Figure C.32:
Overall Subjectivity of News Over Time in Fully Cleaned Nonpast Dataset
The figure depicts the subjectivity of all GDP-related news over time.

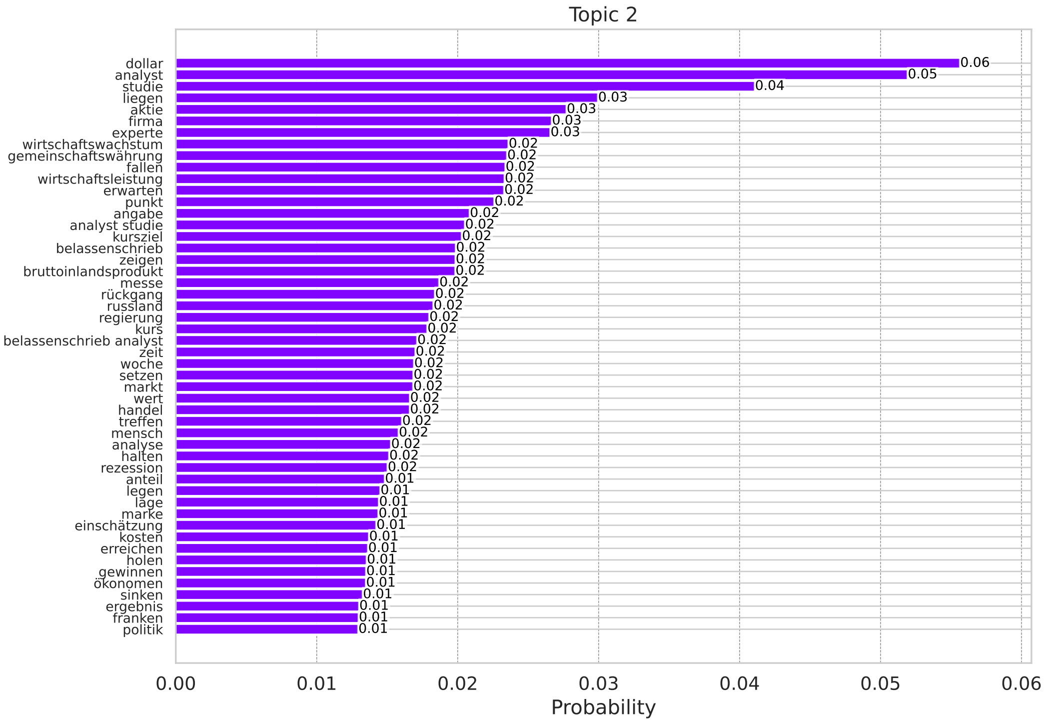
C.13 Top Topic Terms Analysis with Recurrent Term Removal

We have experimeted to remove the most recurrent terms in our corpus (top 10) and in the topic terms. These terms are: "wirtschaft", "unternehmen", "euro", "milliarde", "wachstum", "konjuktur", "monat", "steigen", "stehen", "industrie", "folge", "entwicklung", "vergleich", "sehen", "ende", "bundesregierung", "geben", "prozent", "land", "quartal", "konjunktur", "entwicklung", "milliarde euro", "rechnen", "bund", "zahl"

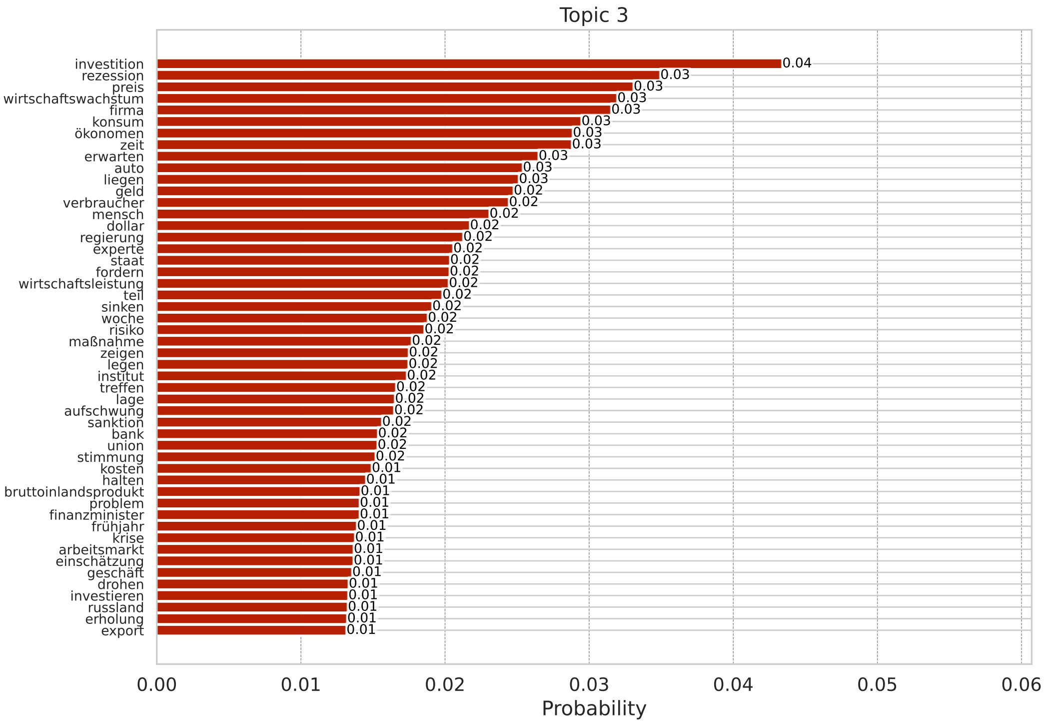
?? illustrates the resulting probability distributions of the top terms in each topic.



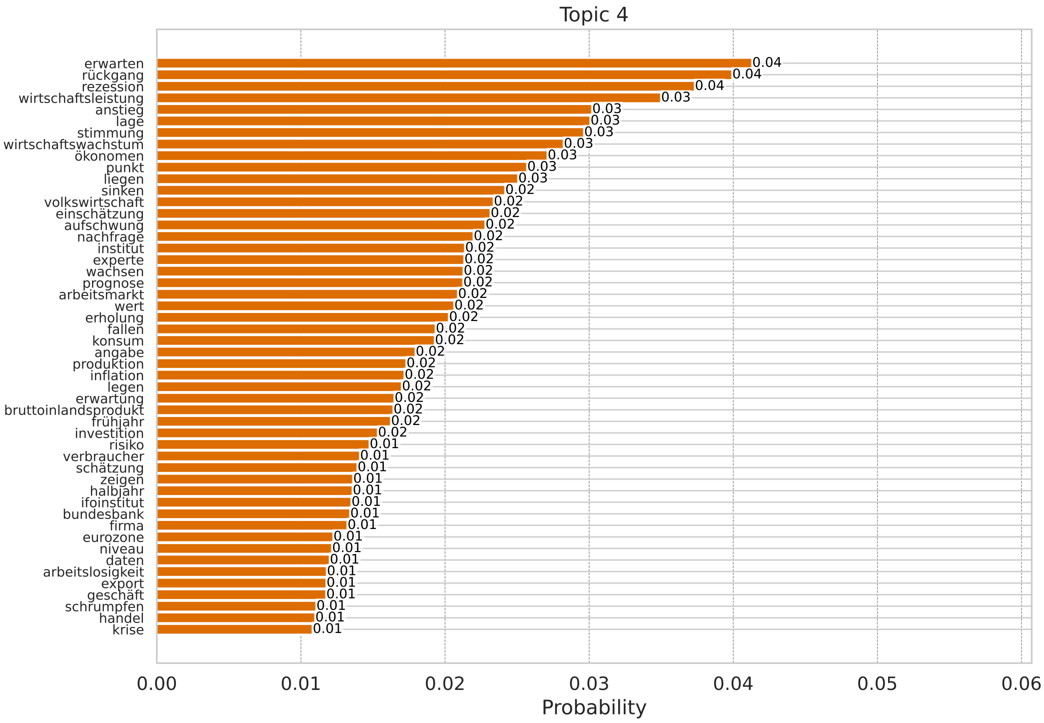
(a) Top Terms in Topic 1



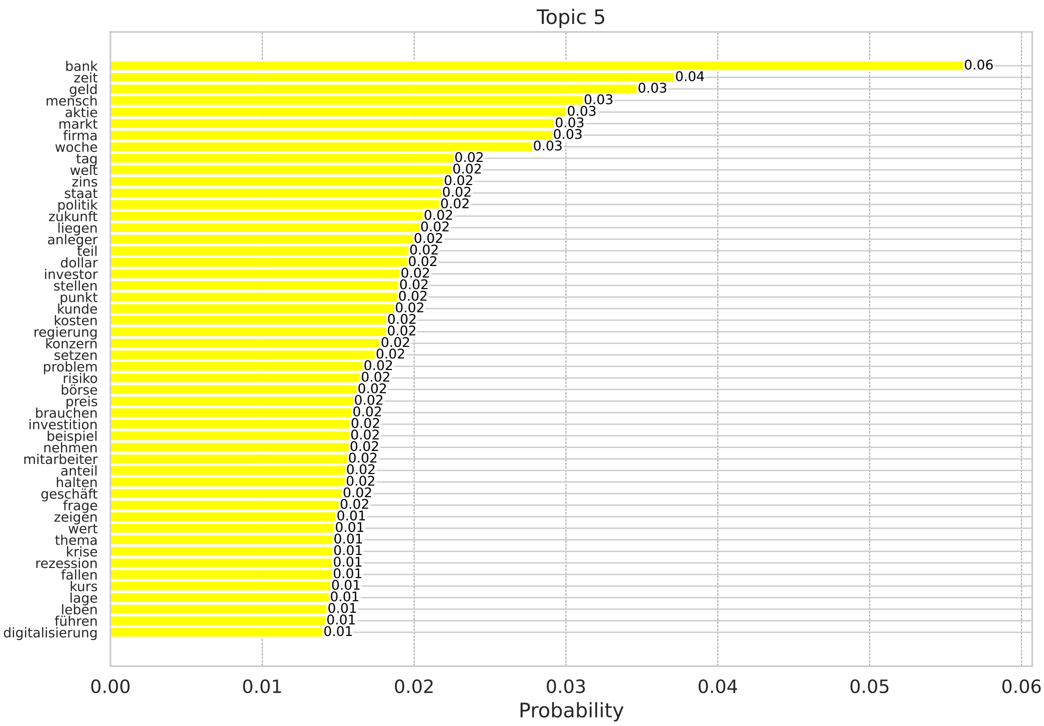
(b) Top Terms in Topic 2



(c) Top Terms in Topic 3



(d) Top Terms in Topic 4



(e) Top Terms in Topic 5

Figure C.33: Probability Distributions of Top Terms in Each Topic.
The figure depicts the likelihood of the top terms appearing in each respective topic, after removing common terms from our corpus. These terms were previously among the top terms in each topic.

The monthly dynamic factor model, incorporating data from LDA with recurrent terms removed, does not demonstrate superior performance. Comparisons of Root Mean Squared Forecast Errors (RMSFEs) and average perplexities reveal that the model without recurrent term removal performs better. Notably, removing the recurrent terms seems to reduce the model's effectiveness in identifying periods of economic crisis.

C.14 List of Stopwords

German stopwords:

The nltk stopwords were obtained from https://github.com/stopwords-iso/stopwords-de. The utf8 German stopwords were obtained from https://github.com/collective/collective.solr/blob/main/etc/german-stopwords.txt and was extended by the author.

nltk stopwords: "a", "ab", "aber", "ach", "acht", "achte", "achten", "achter", "achtes", "ag", "alle", "allein", "allem", "allen", "aller", "allerdings", "alles", "allgemeinen", "als", "also", "am", "an", "ander", "andere", "anderem", "anderen", "anderer", "anderes", "anderm", "andern", "anderr", "anders", "au", "auch", "auf", "aus", "ausser", "ausserdem", "außer", "außerdem", "b", "bald", "bei", "beide", "beiden", "beim", "beispiel", "bekannt", "bereits", "besonders", "besser", "besten", "bin", "bis", "bisher", "bist", "c", "d", "d.h", "da", "dabei", "dadurch", "dafür", "dagegen", "daher", "dahin", "dahinter", "damals", "damit", "danach", "daneben", "dank", "dann", "daran", "darauf", "daraus", "darf", "darfst", "darin", "darum", "darunter", "darüber", "das", "dasein", "daselbst", "dass", "dasselbe", "davon", "davor", "dazu", "dazwischen", "daß", "dein", "deine", "deinem", "deinen", "deiner", "deines", "dem", "dementsprechend", "demgegenüber", "demgemäss", "demgemäß", "demselben", "demzufolge", "den", "denen", "denn", "denselben", "der", "deren", "derer", "derjenige", "derjenigen", "dermassen", "dermaßen", "derselbe", "derselben", "des", "deshalb", "desselben", "dessen", "deswegen", "dich", "die", "diejenige", "diejenigen", "dies", "diese", "dieselbe", "dieselben", "diesem", "diesen", "dieser", "dieses", "dir", "doch", "dort", "drei", "drin", "dritte", "dritten", "dritter", "drittes", "du", "durch", "durchaus", "durfte", "durften", "dürfen", "dürft", "e", "eben", "ebenso", "ehrlich", "ei", "ei,", "eigen", "eigene", "eigenen", "eigener", "eigenes", "ein", "einander", "eine", "einem", "einen", "einer", "eines", "einig", "einige", "einigem", "einigen", "einiger", "einiges", "einmal", "eins", "elf", "en", "ende", "endlich", "entweder", "er", "ernst", "erst", "erste", "ersten", "erster", "erstes", "es", "etwa", "etwas", "euch", "euer", "eure", "eurem", "euren", "eurer", "eures", "f", "folgende", "früher", "fünf", "fünfte", "fünften", "fünfter", "fünftes", "für", "g", "gab", "ganz", "ganze", "ganzen", "ganzer", "ganzes", "gar", "gedurft", "gegen", "gegenüber", "gehabt", "gehen", "geht", "gekannt", "gekonnt", "gemacht", "gemocht", "gemusst", "genug", "gerade", "gern", "gesagt", "geschweige", "gewesen", "gewollt", "geworden", "gibt", "ging", "gleich", "gott", "gross", "grosse", "grossen", "grosser", "grosses", "groß", "große", "großen", "großer", "großes", "gut", "gute", "guter", "gutes", "h", "hab", "habe", "haben", "habt", "hast", "hat", "hatte", "hatten", "hattest", "hattet", "heisst", "her", "heute", "hier", "hin", "hinter", "hoch", "hätte", "hätten", "ich", "ihm", "ihn", "ihnen", "ihr", "ihre", "ihrem", "ihren", "ihrer", "ihres", "im", "immer", "in", "indem", "infolgedessen", "ins", "irgend", "ist", "j", "ja", "jahr", "jahre", "jahren", "je", "jede", "jedem", "jeden", "jeder", "jedermann", "jedermanns", "jedes", "jedoch", "jemand", "jemandem", "jemanden", "jene", "jenem", "jenen", "jener", "jenes", "jetzt", "k", "kam", "kann", "kannst", "kaum", 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"rund", "s", "sa", "sache", "sagt", "sagte", "sah", "satt", "schlecht", "schluss", "schon", "sechs", "sechste", "sechsten", "sechster", "sechstes", "sehr", "sei", "seid", "seien", "sein", "seine", "seinem", "seinen", "seiner", "seines", "seit", "seitdem", "selbst", "sich", "sie", "sieben", "siebente", "siebenten", "siebenter", "siebentes", "sind", "so", "solang", "solche", "solchem", "solchen", "solcher", "solches", "soll", "sollen", "sollst", "sollt", "sollte", "sollten", "sondern", "sonst", "soweit", "sowie", "später", "startseite", "statt", "steht", "suche", "t", "tag", "tage", "tagen", "tat", "teil", "tel", "tritt", "trotzdem", "tun", "u", "uhr", "um", "und", "uns", "unse", "unsem", "unsen", "unser", "unsere", "unserer", "unses", "unter", "v", "vergangenen", "viel", "viele", "vielem", "vielen", "vielleicht", "vier", "vierte", "vierten", "vierter", "viertes", "vom", "von", "vor", "w", "wahr", "wann", "war", "waren", "warst", "wart", "warum", "was", "weg", "wegen", "weil", "weit", "weiter", "weitere", "weiteren", "weiteres", "welche", "welchem", "welchen", "welcher", "welches", "wem", "wen", "wenig", "wenige", "weniger", "weniges", "wenigstens", "wenn", "wer", "werde", "werden", "werdet", "weshalb", "wessen", "wie", "wieder", "wieso", "will", "willst", "wir", "wird", "wirklich", "wirst", "wissen", "wo", "woher", "wohin", "wohl", "wollen", "wollt", "wollte", "wollten", "worden", "wurde", "wurden", "während", "währenddem", "währenddessen", "wäre", "würde", "würden", "x", "y", "z", "z.b", "zehn", "zehnte", "zehnten", "zehnter", "zehntes", "zeit", "zu", "zuerst", "zugleich", "zum", "zunächst", "zur", "zurück", "zusammen", "zwanzig", "zwar", "zwei", "zweite", "zweiten", "zweiter", "zweites", "zwischen", "zwölf", "über", "überhaupt", "übrigens".

utf8 German stoplist: "ab", "aber", "abk.", "alle", "allem", "allen", "aller", "alles", "allerdings", "allg.", "als", "also", "am", "an", "ander", "andere", "anderem", "anderen", "anderer", "anderes", "andern", "anders", "andernfalls", "andersherum", "anfangs", "auch", "anhand", "anschließend", "ansonsten", "anstatt", "auch", "auf", "aufgrund", "aus", "bei", "bes.", "bez.", "bin", "anders", "andersherum", "anfangs", "anhand", "anschließend", "ansonsten", "anstatt", "auch", "auf", "aufgrund", "aus", "außerdem", "befindet", "bei", "beide", "beim", "beispielsweise", "bereits", "besonders", "besteht", "bestimmte", "bestimmten", "bestimmter", "bevor", "bietet", "bis", "bleiben", "bringen", "bringt", "bsp", "bzw", "d.h", "da", "dabei", "dafür", "daher", "damit", "danach", "dann", "dar", "daran", "darauf", "daraus", "darf", "darstellt", "darüber", "das", "dass", "davon", "dazu", "dem", "demzufolge", "den", "denen", "denn", "der", "deren", "des", "dessen", "desto", "die", "dies", "diese", "diesem", "diesen", "dieser", "dieses", "doch", "dort", "durch", "ebenfalls", "eher", "eigenen", "eigentlich", "ein", "eine", "einem", "einen", "einer", "eines", "einigen", "einiges", "einmal", "einzelnen", "entscheidend", "entweder", "er", "erstmals", "es", "etc", "etwas", "euch", "folgende", "folgendem", "folgenden", "folgender", "folgendes", "folgt", "für", "ganz", "gegen", "gehen", "gemacht", "genannte", "genannten", "gerade", "gerne", "gibt", "gilt", "gleich", "gleichen", "gleichzeitig", "habe", "haben", "hält", "hat", "hatte", "hätte", "hauptsächlich", "her", "heutigen", "hier", "hierbei", "hierfür", "hin", "hingegen", "hinzu", "hoch", "ihn", "ihr", "ihre", "ihren", "ihrer", "im", "immer", "immerhin", "in", "indem", "insgesamt", "ist", "ja", "je", "jede", "jedem", "jeder", "jedes", "jedoch", "jetzt", "jeweilige", "jeweiligen", "jeweils", "kam", "kann", "keine", "kommen", "kommt", "können", "konnte", "könnte", "konnten", "lassen", "lässt", "lautet", "lediglich", "leider", "letztendlich", "letztere", "letzteres", "liegt", "machen", "macht", "mal", "man", "mehr", "mehrere", "meine", "meinem", "meisten", "mich", "mit", "mithilfe", "mittels", "möchte", "möglich", "möglichst", "momentan", "muss", "müssen", "musste", "nach", "nachdem", "nächsten", "nahezu", "nämlich", "natürlich", "neue", "neuen", "nicht", "nichts", "noch", "nun", "nur", "ob", "obwohl", "oder", "oftmals", "ohne", "per", "sämtliche", "scheint", "schon", "sehr", "sein", "seine", "seinem", "seinen", "sich", "sicherlich", "sie", "siehe", "sind", "so", "sobald", "sofern", "solche", "solchen", "soll", "sollen", "sollte", "sollten", "somit", "sondern", "sorgt", "sowie", "sowohl", "später", "sprich", "statt", "trotz", "über", "überhaupt", "um", "und", "uns", "unter", "usw", "viel", "viele", "vielen", "völlig", "vom", "von", "vor", "vorerst", "vorher", "während", "war", "wäre", "waren", "warum", "was", "weil", "weitere", "weiteren", "weiterer", "weiteres", "weiterhin", "welche", "welchen", "welcher", "welches", "wenn", "wer", "werden", "wesentlich", "wichtige", "wichtigsten", "wie", "wieder", "wiederum", "will", "wir", "wird", "wirklich", "wo", "wobei", "worden", "wurde", "wurden", "z.b", "ziemlich", "zu", "zuerst", "zum", "zur", "zusätzlich", "zuvor", "zwar", "zwecks", "bis", "bist", "bspw.", "deutlich", "da", "daß", "dass", "etwa", "für", "gibt", "insgesamt", "jahre", "jahr", "weitere", "können", "könnte", "mehr", "o.ä.", "ob", "oder", "o.g.", "ohne", "rund", "sein", "seine", "seinem", "seinen", "seiner", "seines", "selbst", "sich", "sicher", "sie", "sind", "so", "solche", "solchem", "solchen", "solcher", "solches", "sollte", "sondern", "sowie", "u.a.", "u.ä.", "u.g.", "ugs.", "um", "und", "uns", "unser", "unter", "uvm.", "über", "vgl.", "viel", "vielleicht", "vom", "von", "vor", "während", "wann", "warum", "was", "weg", "weil", "weiter", "welche", "welchem", "welchen", "welcher", "welches", "wenn", "wer", "wie", "wieder", "wir", "wo", "z.b.", "zu", "zum", "zur", "zwar"

Other stop words in the texts: "Morgen", "Datum", "Täglich", "us", "noticia", "", "gmt", "destati", "lesen", "re cord", "machen", "sehen" ,"gesehen", "einschließlich", "Bericht", "Financiera", "Denken", "Mln", "Deutschland", "Bln", "Könnten", "Cent", "Million", "Milliarde", " Netto", "Prozent", "Ent", "Deutschland", "Neu", "Euro", "BIP", "erhöht", "Well", "Eins", "Gruppe", "Jahre", "Daten" , "würde", "fällig", "Unternehmen", "https", "co", "RT", "Prozent", "Monat", "Deutsch", "Deutschland", "Quartal", "Ding", "Wirtschaft", "Zweite", "Erste", "Dritte", "Vierte", "Monate", "JJ", "pro", "Umdrehung", "Umdrehungen"

Stopextend by us: "Januar", "Februar", "März", "April", "Mai", "Juni", "Juli", "August", "September", "Oktober", "November", "Dezember", "Januar", "Februar", "März", "April", "Mai", "Juni", "Juli", "August", "September", "Oktober", "November", "Dezember", "Jahr", "Jahr", "Montag", "Dienstag", "Mittwoch", "Donnerstag", "Freitag", "Samstag", "Sonntag", "said", "end", "document", "’", "est", "copyright", "wordsbyline", "blogs", "u", "say", "percent", "also", " https", "co", "RT", "Prozent", "Monat", "Deutsch", "Deutschland", "Quartal", "Ding", "Wirtschaft", "Zweite", "Erste", "Dritte","vierter", "Monate", "JJ", "pro", "rev", "revs", "qq", "iq-Konsens", "deutsch", "Deutschland", "zeit", "Zeit", "Zeitverlag", "Vorbehaltensection".

C.15 Shannon's Entropy over Time

As depicted in Figure C.34, which illustrates topic entropies derived from the raw dataset, Topic 2, "Political and Economic Dynamics," shows a notable increase in new information and attention during significant events, such as the formation of a new government around the September 2017 federal elections and the COVID-19 pandemic crisis.

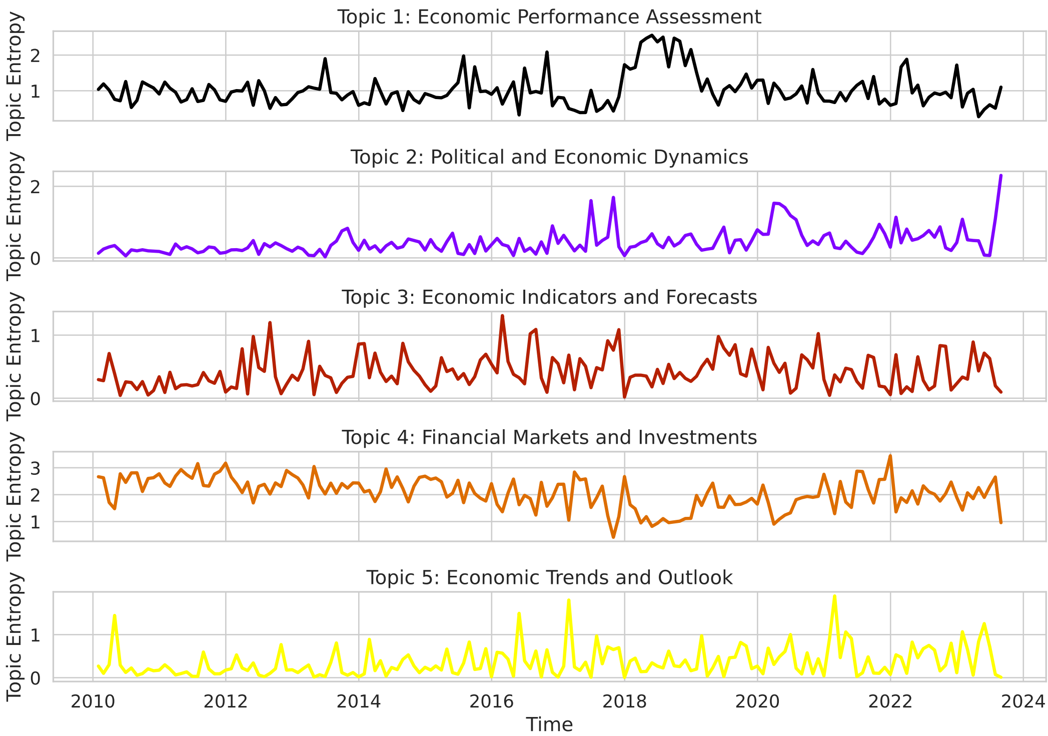

Figure C.34: Monthly attention to news topics in the sentiment-cleaned dataset The figure displays the monthly averages of news entropy for each topic, illustrating variations in attention over time.

C.16 Maximum Likelihood Estimation Technique Used in Scikit-Learn's LDA

The LDA implementation in scikit-learn utilizes the maximum likelihood estimation (MLE) method through variational inference. This involves iteratively estimating model parameters, such as topic distributions for documents and word distributions for topics, to maximize the likelihood of observing the provided data within the LDA framework. the Variational Bayes (VB) approach (using all training data in each update) is utilized for this task, iteratively updating parameters until convergence is reached. This method serves as the foundation of scikit-learn's LDA implementation, offering a robust tool for conducting topic modelling tasks.

In Scikit-Learn's implementation of Latent Dirichlet Allocation (LDA), the model parameters $\{\phi_k, \theta_d\}$ are estimated using Maximum Likelihood Estimation (MLE). The goal is to find the parameter values that maximize the likelihood function.

The likelihood function for LDA is represented as:

$$\mathcal{L}(\{\phi_k, \theta_d\}; \{w_{dn}\}) = \prod_{d=1}^{D} \int \left(\prod_{n=1}^{N_d} p(w_{dn} \mid \phi_{z_{dn}}) p(z_{dn} \mid \theta_d) \right) p(\theta_d \mid \alpha) \, d\theta_d, \qquad \text{(C.9)}$$

where:

- ϕ_k are the topic-word distributions, drawn from $\mathrm{Dir}(\eta)$.
- θ_d are the document-topic distributions, drawn from $\mathrm{Dir}(\alpha)$.
- w_{dn} represents the n-th word in document d.
- z_{dn} represents the topic assignment of w_{dn}.
- α is the Dirichlet prior parameter for θ_d.

Utilization of **Variational Bayes (VB)**:

- Initializing the variational parameters γ and ϕ
- Introduction of the Variational Distribution $q(\theta_d, Z \mid \gamma, \phi)$ to approximate $p(\theta_d, Z \mid W, \alpha, \eta)$.
- Steps in VB Algorithm to approximate the posterior distribution $p(\theta_d, Z \mid W, \alpha, \eta)$ using a variational distribution $q(\theta_d, Z \mid \gamma, \phi)$ that minimizes the Kullback-Leibler (KL) divergence between $q(\theta_d, Z \mid \gamma, \phi)$ and $p(\theta_d, Z \mid W, \alpha, \eta)$:
  - Initialization: Start with γ and ϕ.
  - E-step: Update γ and ϕ to maximize ELBO.
  - M-step: Update $\{\phi_k, \gamma_d\}$ using E-step results.
  - Iteration: Repeat until convergence.

For more details, please refer to Airoldi et al. (2015).

C.17 Gibbs Sampler Technique Used in Gensim's LDA

Gibbs sampler first formally introduced by Geman and Geman (1984) is a special case of the single-component Metropolis-Hastings algorithm developed by Hastings (1970). It is obtained from the Metropolis-Hasting (M-H) algorithm by choosing an appropriate proposal density and correspondingly, it is an M-H algorithm with an acceptance probability equal to 1. Gibbs sampler in difference from the M-H algorithm demands full conditional for each parameter to be known but does not demand calculation of acceptance probability of the drawn candidates. Because Gibbs sampler considers moves to very close points, it enables seeing the acceptance of drawn candidates equal to 1. Gibbs sampler solves the sampling problem caused by the high dimensionality of the joint distribution function by implying the Bayesian theorem and breaking the joint posterior $p(\theta, h|r)$ into its complete set of conditional distributions:

$$p(\theta, h|r) \propto p(r|\theta, h)p(h|\theta)p(\theta), \tag{C.10}$$

where ϕ_k represents the topic, θ_d represents the topic distribution across documents, z_{dn} represents the topic assignment of the term, and w_{dn} represents the specific term in document d.

Gibbs sampler instead of updating the whole set of the model parameters and missing data (θ and h) divides it into a vector of components $\theta_1, \theta_2 \ldots \theta_n$ and updates them one by one. It simplifies a complex high-dimensional problem by breaking it into simple low-dimensional problems. For instance, it leaves all the rest unchanged and updates θ_1 and replaces it with a draw from the full conditional distribution on all the other components. After this division, the set of conditional distributions consists of the following full conditional distributions:

$$\begin{aligned} p(h_t|y, h_{-t}, \theta_1 \ldots \theta_n) \\ p(\theta_1|y, h, \theta_-) \\ p(\theta_2|y, h, \theta_-) \\ \vdots \quad\quad \\ p(\theta_n|y, h, \theta_-), \end{aligned} \tag{C.11}$$

where:

- h_{-t} denotes the elements of $h = (h_1 \ldots h_T)$ excluding h_t.
- $\theta p(\theta_1|y, h, \theta_-) = (p(\theta))/(\int p(\theta)d\theta_1)$.
- A-posterior distribution function $p(.)$ is uniquely determined by a set of its conditional distributions.

Gibbs sampler can be used only when these full sets of conditional distributions is available for sampling. Given the full conditional densities the transition kernel (q) describes the density of going from one point X to another Y: Gibbs sampler chooses arbitrary starting points for each of the parameters and then generates samples from these full conditional distributions. This way, it enables indirect sampling from the joint distribution that (in accordance with the Clifford-Hammersley theorem) is known if full conditional posteriors are known. Gibbs sampler in case of given information r runs as described below in "Steps of Gibbs Sampling Algorithm". Starting states are chosen arbitrarily as the distribution of θ^i does not depend on θ^0, because the transition kernel gradually converges to the stationary distribution (having T dimension). $i+1^{th}$ iteration of each component of parameter θ_j is drawn from values of all other components of parameter vector from the previous iteration and given data r_i of this period. One run from Step 1 to Step 3, or in other words through the cycle that is called a complete sweep or a scan produces one draw and is repeated many thousand times.

Steps of Gibbs Sampling Algorithm

Step 1: Initialize $\theta^0 = (\theta_1^0, \theta_2^0, \ldots, \theta_n^0)$

Step 2: Generate θ^{i+1}:

$$\theta_1^{i+1} \sim f(\theta_1|\theta_2^i, \ldots, \theta_n^{i,r})$$

$$\theta_2^{i+1} \sim f(\theta_2|\theta_1^i, \theta_3^{i.} \cdots, \theta_n^i, r)$$

$$\cdots$$

$$\theta_n^{i+1} \sim f(\theta_n|\theta_1^{i+1}, \theta_2^{i+1} \ldots, \theta_{n-1}^{i+1}, r)$$

Step 3: Set $i = i + 1$ and repeat generating of θ^{i+1}

Source: Chen et al. (2000).

When estimating Latent Dirichlet Allocation (LDA) with Gibbs sampling, the parameter set θ includes the following components:

$$\theta = \{\phi_k, \theta_d, z_{dn}, w_{dn}\} \tag{C.12}$$

where ϕ_k represents the topic-word distributions, θ_d represents the topic distribution across documents, z_{dn} represents the topic assignment of the term, and w_{dn} represents the specific term in document d.

The Gibbs sampling is done as follows:

– Draw each topic ϕ_k from Dir(η) for $i \in (1, ..., K)$

– For each document:

  – draw $\theta_d \sim Dir(\alpha)$ - Topic distribution through document.

– for each word:

  – draw $z_{dn} \sim Mult(\theta_d)$ - Topic distribution of the term.

  – draw $w_{dn} \sim Mult(\phi_{z_{d,n}})$ - Term in document d.

– Use posterior expectations for information retrival

Here, $Dir(\eta)$ is a Dirichlet distribution with η hyperparameter and $Dir(\alpha)$ is a Dirichlet distribution with α hyperparameter.

C.18 Kalman Filter's Recursive Updates

The Kalman filter implements recursive updates and iterative state variable fitting within the dynamic factor model as follows:

1. **Initialization:**

   - Initialize the model parameter values $\theta = \{\alpha_i, \beta_i, T_1, T_2, \mathrm{Cov}(\epsilon_{i,t}), \mathrm{Cov}(\eta_t)\}$. *For parameter initialization, we employ the modified Powell's optimization method. It begins with random parameter values and predefined direction (unit vectors), performs a line search to find the optimal step size that minimizes the negative log-likelihood function of the state space model along each direction, updates parameters accordingly, and adjusts its direction set based on the parameter displacement vector. This iterative process continues until satisfactory minimization of the likelihood function is achieved (a small change in parameter values, or in the negative log-likelihood function).*
   - Initialize estimates of f_0 and corresponding covariance matrix P_0.

2. **Prediction Step:**

   - Predict the current state $\hat{f}_{t|t-1}$ based on the previous state estimate $\hat{f}_{t-1}$:

   $$\hat{f}_{t|t-1} = T_1 \hat{f}_{t-1} + T_2 \hat{f}_{t-2}$$

   - Estimate a joint probability distribution and Predict the covariance matrix $P_{t|t-1}$ of the state estimate:

   $$P_{t|t-1} = T_1 P_{t-1|t-1} T_1^{'} + T_2 P_{t-2} T_2^{'} + \mathrm{Cov}(\eta_t)$$

3. **Update Step:**

   - Incorporate the new observation $y_{i,t}$ to update the state estimate f_t and its covariance matrix P_t using the Kalman gain K_t:

   $$K_t = P_{t|t-1} \beta_i^{'} (\beta_i P_{t|t-1} \beta_i^{'} + \mathrm{Cov}(\epsilon_t))^{-1}$$

$$\hat{f}_t = \hat{f}_{t|t-1} + K_t(y_{i,t} - \beta_i' \hat{f}_{t|t-1})$$

$$P_{t|t} = (I - K_t \beta_i) P_{t|t-1}$$

4. **Iteration:** Repeat steps 2 and 3 for each new observation $y_{i,t}$ as it becomes available.

Calculating Topic Probabilities using TF-IDF Representation

For calculating topic probabilities using TF-IDF Representation, we transform the news-driven data into Term Frequency-Inverse Document Frequency (TF-IDF) representation, which is subsequently utilized to derive topic probabilities for each document. TF-IDF representation has an advantage over simple term frequency representation representation due to its ability to provide a more balanced representation and to diminish the impact of frequently occurring terms.

The Document-Term Matrix (DTM) can be transformed into a Term Frequency-Inverse Document Frequency (TF-IDF) features matrix. TF-IDF quantifies the importance of each term within a document by weighting it based on its significance. It is a form of term frequency that considers the importance of each term to a document. TF-IDF represents each document d as a vector in a vector space, ensuring that documents with similar content are mapped to similar vectors.

TF-IDF is calculated by multiplying two statistics: term frequency ($TF_{t,d}$) and inverse document frequency ($IDF_{t,d}$). Term frequency measures how often term t appears in document d, while inverse document frequency assesses the informativeness of the term to a document, calculated as the logarithm of the total number of documents (N) in the corpus divided by the document frequency (DF_t) - the number of documents containing term t at least once (compare Grootendorst (2022)).

$$TF\text{-}IDF_{t,d} = TF_{t,d} \cdot IDF_{t,d} = TF_{t,d} \cdot \log\left(\frac{N}{DF_t}\right) \tag{C.13}$$

where:

- DF_t is the document frequency of term t (the number of documents in which the term t occurs at least once).

Using the TF-IDF representation, we construct the document-topic probability matrix for each document with the formula:

$$P(\text{topic } j \mid \text{document } i) = \sum_{j=1}^{V} \theta_{i,j} \cdot \sum_{k=1}^{K} \phi_{k,j} \cdot y_{i,k}, \tag{C.14}$$

where:

- $\theta_{i,j}$ is the probability that document i belongs to topic j,
- $\phi_{k,j}$ is the probability that term k is generated by topic j,
- $y_{i,k}$ is the TF-IDF weight of term k in document i,
- V is the size of the term vocabulary,
- K is the number of topics.

The document-topic probability matrix is structured so that each row represents a document and each column corresponds to a topic. Within the matrix, each element indicates the likelihood of a document being associated with a specific topic. This computation is based on the TF-IDF weights of terms within each document, allowing us to measure the prominence of each topic's representation within the document.

To identify the representative document for a given topic within a specific period, we select the document with the highest probability for that topic (which corresponds to the maximum probability value of the topic's column within the document-topic probability matrix for the given period).

Code Implementation for Part III

C.19 For German Texts: Create Dataframe of Sentences from News Corpus

```
import pandas as pd
papers = pd.read_pickle('/content/drive/MyDrive/pkls/papers_NLP0.pkl')

for i in range(0, len(papers['Text'])):
  papers['Text'].iloc[i] = papers['Text'].iloc[i].replace(",",".")
  papers['Text'].iloc[i] = papers['Text'].iloc[i].replace("?",".")
  papers['Text'].iloc[i] = papers['Text'].iloc[i].replace("!",".")
  papers["Text"].iloc[i] = papers["Text"].iloc[i].replace(";",".")
  papers["Text"].iloc[i] = papers["Text"].iloc[i].replace("-"," ")
  papers["Text"].iloc[i] = papers["Text"].iloc[i].replace(":"," ")
  papers['Text'].iloc[i] = papers['Text'].iloc[i].replace("..",".")
  papers['Text'].iloc[i] = papers['Text'].iloc[i].replace(" .",".")
papers.head()
import re
Listofsentences = []
sentlist =[]
for i in range (0, len(papers['Text'])):
  sentlist=papers['Text'].iloc[i].split(".")
  Listofsentences.append(sentlist)
print (Listofsentences)

Listofsentences_pd=pd.DataFrame(Listofsentences)
#Save to Pickle
```

```
Listofsentences_pd.to_pickle(('/content/drive/MyDrive/pkls/df_all.pkl'))
#Save to CSV
Listofsentences_pd.to_csv('/content/drive/MyDrive/pkls/df_all.csv')
```

C.20 For German Texts: Clean German Texts from Past-Tense Sentences by RNN Tagger (Jupyter Compatible)

Before Cleaning from the Past: delete " and ' from dataframe

```
Listofsentences_pd= Listofsentences_pd.apply(lambda s:s.str.replace(r"[\"\',]", ''))
#Save to Pickle
Listofsentences_pd.to_pickle(('/content/drive/MyDrive/pkls/df_all.pkl'))
```

Package Installations for RNNTagger

```
!pip install perl

!pip3 install torch torchvision torchaudio

!pip install cuda-python==11.8.0
```

Import the Dataframe

```
import os
%cd

import pandas as pd
import pickle

df = pd.read_csv('df_all_witlostpartsbeforecomma.csv')

!pip install pickleshare

import pandas as pd
import numpy as np
```

Implementation of RNN Tagger for Our Dataset

```
!cd $HOME

import pandas as pd
import subprocess

def DeletePast_NNRTagger(df):
    for i in range(0,len(df)):
        for j in range(0,len(df.columns)):
            if not pd.isnull(df.iloc[i, j]):
                sent = df.iloc[i, j]
                echosent = f'"{sent}"'
                print(echosent)
                # Write sentence to file
                with open('ijtext.txt', 'w') as f:
                    f.write(echosent)
                # Run the shell command
                L = subprocess.run(["sh", "/dss/dsshome1/00/x/RNNTagger-1.4.4/RNNTagger
                /cmd/rnn-tagger-swiss-german.sh", "ijtext.txt"], capture_output=True,
```

```
                text=True)

                # Print the output
                #print(L.stdout.split('\n'))

                if ("Past" in L.stdout or ("VVPP.Psp" in L.stdout
                    and "VAFIN.3.Sg.Pres.Ind" in L.stdout)):
                    print("yes")
                    df.loc[i, j] = None
                else:
                    pass
            else:
                pass
    return df

df_RNN = DeletePast_NNRTagger(df)
```

C.21 For English Texts - Tag Parts of Speech in English Texts and Remove Past Sentences

This code block implements the part-of-speech tagging for English texts. For more information on the methods used, refer to Bird et al. (2009).

```
# This code utilizes the NLTK library for part-of-speech tagging and tense detection.
# For more information on NLTK, refer to:
#Bird, S., Klein, E., & Loper, E. (2009). Natural Language Processing with Python.
# Available online: https://www.nltk.org/
!pip install svgling
import nltk
from nltk import word_tokenize, pos_tag

def tense_detect(tagged_sentence):
  verb_tags = ['MD','MDF', 'BE','BEG','BEN','BED','BEDZ','BEZ','BEM','BER','DO','DOD',
  'DOZ', 'HV','HVG','HVN','HVD','HVZ', 'VB','VBG','VBN','VBD','VBZ','SH','TO']

  verb_phrase = []
  for item in tagged_sentence:
      if item[1] in verb_tags:
          verb_phrase.append(item)
  grammar = r'''
        future perfect continuous passive:     {<MDF><HV><BEN><BEG><VBN|VBD>+}
        conditional perfect continuous passive:{<MD><HV><BEN><BEG><VBN|VBD>+}
        future continuous passive:             {<MDF><BE><BEG><VBN|VBD>+}
        conditional continuous passive:        {<MD><BE><BEG><VBN|VBD>+}
        future perfect continuous:             {<MDF><HV><BEN><VBG|HVG|BEG>+}
        conditional perfect continuous:        {<MD><HV><BEN><VBG|HVG|BEG>+}
        past perfect continuous passive:       {<HVD><BEN><BEG><VBN|VBD>+}
        present perfect continuous passive:    {<HV|HVZ><BEN><BEG><VBN|VBD>+}
        future perfect passive:                {<MDF><HV><BEN><VBN|VBD>+}
        conditional perfect passive:           {<MD><HV><BEN><VBN|VBD>+}
        future continuous:                     {<MDF><BE><VBG|HVG|BEG>+ }
        conditional continuous:                {<MD><BE><VBG|HVG|BEG>+  }
        future indefinite passive:             {<MDF><BE><VBN|VBD>+ }
```

```
        conditional indefinite passive:       {<MD><BE><VBN|VBD>+  }
        future perfect:                       {<MDF><HV><HVN|BEN|VBN|VBD>+ }
        conditional perfect:                  {<MD><HV><HVN|BEN|VBN|VBD>+  }
        past continuous passive:              {<BED|BEDZ><BEG><VBN|VBD>+}
        past perfect continuous:              {<HVD><BEN><HVG|BEG|VBG>+}
        past perfect passive:                 {<HVD><BEN><VBN|VBD>+}
        present continuous passive:           {<BEM|BER|BEZ><BEG><VBN|VBD>+}
        present perfect continuous:           {<HV|HVZ><BEN><VBG|BEG|HVG>+}
        present perfect passive:              {<HV|HVZ><BEN><VBN|VBD>+}
        future indefinite:                    {<MDF><BE|DO|VB|HV>+ }
        conditional indefinite:               {<MD><BE|DO|VB|HV>+  }
        past continuous:                      {<BED|BEDZ><VBG|HVG|BEG>+}
        past perfect:                         {<HVD><BEN|VBN|HVD|HVN>+}
        past indefinite passive:              {<BED|BEDZ><VBN|VBD>+}
        present indefinite passive:           {<BEM|BER|BEZ><VBN|VBD>+}
        present continuous:                   {<BEM|BER|BEZ><BEG|VBG|HVG>+}
        present perfect:                      {<HV|HVZ><BEN|HVD|VBN|VBD>+  }
        past indefinite:                      {<DOD><VB|HV|DO>|<BEDZ|BED|HVD|VBN|VBD>+}
        infinitive:                           {<TO><BE|HV|VB>+}
        present indefinite:                   {<DO|DOZ><DO|HV|VB>+|<DO|HV|VB|BEZ|DOZ|
                                              BER|HVZ|BEM|VBZ>+}

        '''

  cp = nltk.RegexpParser(grammar)
  result = cp.parse(verb_phrase)
  display(result)

  tenses_set = set()
  for node in result:
      if type(node) is nltk.tree.Tree:
          tenses_set.add(node.label())
  return tenses_set

#Function for deleting past sentences from a list of ENGLISH TEXTS
# please, first run tense_detect
def nested_remove(L, x):
    if x in L:
        L.remove(x)
    else:
        for element in L:
            if type(element) is list:
                nested_remove(element, x)

import nltk
from nltk import word_tokenize, pos_tag, pos_tag_sents
nltk.download('averaged_perceptron_tagger')
nltk.download('punkt')
def DeletePast(Listofsentences_ENG):
  pasttenses = ["past indefinite", "past perfect continuous passive",
  "past continuous passive", "past perfect continuous", "past perfect passive",
  "past continuous", "past perfect", "past indefinite passive", "past indefinite",
  "present perfect", "present perfect continuous", "present perfect passive"]
  for x in Listofsentences_ENG:
```

```
    for y in x:
      print(y)
      try:
        tokenized = word_tokenize(y,language='english')
        tagged = pos_tag(tokenized, lang='eng')
        print(tagged)
        tense_detect(tagged)
        if any(ext in pasttenses for ext in list(tense_detect(tagged))) == True:
          #print(Listofsentences_ENG)
          #print("deletion")
          nested_remove(Listofsentences_ENG, y)
          #print("deletion done")
        else:
          #print("not past")
          pass
      except:
        pass
      return  Listofsentences_ENG


##test the code
text = [['I felt well', 'I feel well'], ['I like you'], ['It was planned']]

DeletePast(text)

DeletePast(Listofsentences_ENG)

Listofsentences_ENG

#save list of nonpast sentences to pickle
import pickle
with open('Listofsentences_ENG_notpast.pickle', 'wb') as b:
    pickle.dump(Listofsentences_ENG,b)
import os
os.listdir('.')
from google.colab import files
files.download('Listofsentences_ENG_notpast.pickle') # download the dumped file.
```

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