Mind Your Language:
Market Responses to Central Bank Speeches*

Maximilian Ahrens

Oxford-Man Institute of Quantitative Finance, Department of Economics, University of Oxford

Deniz Erdemlioglu

Department of Finance, IESEG School of Management and CNRS

Michael McMahon

Department of Economics, University of Oxford

Christopher J. Neely

Research Division, Federal Reserve Bank of St. Louis

Xiye Yang

Department of Economics, Rutgers University

May 31, 2023

Abstract

Researchers have carefully studied post-meeting central bank communication and have found that it often moves markets, but they have paid less attention to the more frequent central bankers' speeches. We create a novel dataset of US Federal Reserve speeches and use supervised multimodal natural language processing methods to identify how monetary policy news affect financial volatility and tail risk through implied changes in forecasts of GDP, inflation, and unemployment. We find that news in central bankers' speeches can help explain volatility and tail risk in both equity and bond markets. We also find that markets attend to these signals more closely during *abnormal* GDP and inflation regimes. Our results challenge the conventional view that central bank communication primarily resolves uncertainty.

Keywords: Central Bank Communication, Multimodal Machine Learning, Natural Language Processing, Speech Analysis, High-Frequency Data, Volatility, Tail Risk.

JEL: E52, C45, C53, G12, G14

1 Introduction

A large branch of monetary policy research seeks to explain how central bank communication (CBC) steers market dynamics and expectations (Blinder, 2018). Theory suggests that if central bank announcements and speeches convey information on economic and monetary conditions, market participants will update their beliefs as reflected in their portfolio choices. Central bank communication can thus contribute to revaluing assets and stabilizing market conditions by reducing uncertainty (Bernanke et al., 2005). Empirical research largely corroborates this theoretical prediction and establishes a consensus that central bank communication influences asset prices through its effects on market participants' expectations about economic outlook and policy decisions (Bernanke and Kuttner, 2005; Ramey, 2016). Monetary policy communication also appears to influence investors' risk aversion and hence the risk premium (Hanson and Stein, 2015; Cieslak and Schrimpf, 2019; Swanson, 2021).

Despite these findings, there are still at least two unresolved issues: (i) how to identify monetary policy news in central bank communication, and (ii) how to identify effects of such news on market uncertainty, i.e., volatility and tail risk. Official central bank announcement dates, such as those of FOMC announcements, occur rather infrequently (every 6-8 weeks). However, policy makers and researchers have suggested that markets continually revise their understanding of central bank information as policy makers give speeches (Neuhierl and Weber, 2019). Although recent developments in natural language processing (NLP) have allowed economists to analyse text with machine learning methods (see e.g., Bholat et al., 2015; Hansen et al., 2018; Ahrens and McMahon, 2021), researchers have paid only limited attention to speeches so far[1], partly because their content is difficult to quantify and the field still lacks easily accessible datasets of central bank speeches.

In this paper, we develop a novel multimodal NLP method to identify macroeconomic news in central bank speeches and we assess their impact on market volatility and tail risk. To the best of our knowledge, we are the first to do so. Some earlier research has focused on how central bank communication affects volatility in financial markets (see e.g., Bekaert et al., 2013; Cieslak and Schrimpf, 2019; Ehrmann and Talmi, 2020; Gómez-Cram and Grotteria, 2022), while only Hattori et al. (2016) has studied tail risk.[2] Moreover, there is an extensive literature that studies the effects of central bank communication about the economic outlook on asset price surprises. Signals about the economic situation can have a multitude of different effects. The classic channel as emphasised in, for example, Romer and Romer (2000) and Nakamura and Steinsson (2018), is an information effect. The central bank, either explicitly or implicitly through its policy decision, releases superior information about the economy and this information is then incorporated in updated private sector forecasts. An alternative channel is one in which the central bank's information is not considered superior; releasing an alternative assessment of the state of the economy,

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[1]Recently, Neuhierl and Weber (2019) have investigated the tone of speeches by central bank chairs and vice-chairs while Petropoulos and Siakoulis (2021) use a mixture of machine learning and dictionary methods to calculate sentiment indices from central bank speeches. The latter authors argue that this sentiment predicts financial turmoil. Swanson (2023) highlights the importance of Fed Chair speeches using an event-study surprise decomposition, and Cieslak and McMahon (2023) focus on the communication of Fed stance and its effects on the risk premium.

[2]We focus on measuring market uncertainty rather than uncertainty about monetary policy (see e.g., Bauer et al., 2022; Husted et al., 2020; Ozdagli and Velikov, 2020; Tillmann, 2020), or uncertainty of monetary policy makers Cieslak et al. (2023).

that the market do not believe, could heighten concerns about the possibility of a monetary policy mistake which would make the economy more volatile (Caballero and Simsek, 2022; Cieslak and McMahon, 2023). The central bank may communicate, as part of its outlook, their view of uncertainty which can influence private views about uncertainty (Hansen et al., 2019). Finally, a cacophony of economic assessments, even if just reflecting different views on the outlook for the economy, might itself signal greater uncertainty surrounding the outlook which can increase the uncertainty of market participants about the economic and the policy outlook (Ahrens and McMahon, 2021).

Our methodological framework has two parts. First, we use machine learning methods from the field of multimodal natural language processing to infer implied macroeconomic forecast revisions from Fed officials' public speeches. Our training dataset consists of Greenbook texts and their respective forecasts, which allows us to learn a mapping from central bank language to central bank forecasts (see Ahrens and McMahon, 2021). In our test dataset, we then apply the learned mapping to central bank speeches to infer how news signals in speeches can predict revisions of public macroeconomic forecasts. Second, we investigate the high-frequency (intradaily) responses of market volatility and tail risk to speech-implied revisions in CPI, GDP, and unemployment outlooks.[3]

Our paper contributes to the literature in several ways. Most importantly, we show that central bankers' speeches have a statistically significant impact on volatility and tail risk in financial markets. In order to show this, we develop a new, multimodal methodological framework for identifying monetary policy news about GDP growth, CPI, and unemployment outlooks. We compare and contrast the performance of an extensive array of modern machine learning methods for multimodal NLP on our empirical datasets of Greenbook texts and forecasts as well as on FOMC members' speeches. We show that our speech-implied forecast revisions predict future changes in Survey of Professional Forecasters (SPF) forecasts substantially better than models that use purely tabular data and ignore the textual content of the speeches. It is these speech-implied macroeconomic news signals that explain a sizeable part of realized volatility and tail risk in financial markets. Furthermore, our findings suggest that markets 'listen' or react more strongly to news in central bank speeches during *abnormal* GDP and inflation regimes. In order to contribute to future examinations of Federal Reserve speeches, we make our comprehensive dataset on Federal Reserve speeches accessible to other researchers.

The remainder of the paper is organized as follows. In the next section, we review the related literature. Section 3 describes the data and section 4 introduces our methodological framework. In section 5 and 6, we present the empirical results pertaining to our analyses of speech-implied news and high-frequency market responses. Section 7 concludes the paper.

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[3]High-frequency market analysis is common in monetary research; see, for example, Gurkaynak et al. (2005); Gertler and Karadi (2015); Nakamura and Steinsson (2018); Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021).

2 Related Literature

Central Bank Communication Effects on Market Volatility and Tail Risk

Our paper is most closely related to studies of the high-frequency effects of CBC on market uncertainty and volatility. Cieslak and Schrimpf (2019) study the high-frequency effects of the non-monetary news component of communication on volatility. Leombroni et al. (2021) explore how CBC influences credit risk premia through high-frequency changes in yield curve. Ehrmann and Talmi (2020) measure textual differences between central bank announcements and find that higher levels of textual similarity to the previous announcement statement are usually associated with lower market volatility after the announcement date. Relying on a one-day event window, Hansen et al. (2019) analyse the Bank of England's Inflation Reports via topic modelling and find that communication of uncertainty plays an important role in shaping long-run interest rates. Bekaert et al. (2013) find evidence that looser policy reduces risk aversion and uncertainty. Gómez-Cram and Grotteria (2022) explore the price discovery process for several asset classes on FOMC announcement days. Bauer et al. (2022) develop a policy uncertainty measure based on financial derivatives, and show that FOMC (uncertainty cycle) announcements reduce uncertainty. Finally, Hattori et al. (2016) study the impact of Unconventional Monetary Policy (UMP) on stock market and bond market tail risk. UMP increases (decreases) the realized volatility of stocks (bonds), but lowers the tail risk in both markets. Forward guidance (and hence communication) appears to have stronger "dampening effects", compared to other UMP events.

We extend this line of research in two ways. First, these aforementioned studies often overlook extreme market responses when assessing the effects of news. For example, the main result of Hattori et al. (2016) that UMP decreases the tail risk in stock and bond markets does not appear to hold when we move outside the cycles of FOMC press releases. Unlike Hattori et al. (2016), we focus on the intraday market responses to speeches, which can occur at any time, rather than only the times of FOMC announcements, and measure the *realized* tail risk instead of the *implied* tail risk from derivatives. In contrast with Hattori et al. (2016), we find that speeches *increase* realized tail risk. This type of CBC does not appear to reduce uncertainty and calm financial markets.

Second, prior research on monetary policy news has commonly employed jump-diffusion models with Poisson jumps to capture responses to news. The approach of Bauer et al. (2022) relies on such a representation for "FOMC jumps". Despite its simplicity, these jump models are not compatible with the stylized facts of jump occurrences, as news-induced tail responses are persistent in the presence of heterogeneous investors interpreting the content of speeches. Consequently, these studies underestimate the realized tail risk. Departing from this conventional approach, we consider a more flexible model that allows for *time-varying* tails. This allows us to separate extreme volatility responses from the tail responses and, more importantly, to identify the speeches that create *tail cascades*. Unlike the previous studies treating jumps as one-shot events, we accommodate the stochastic intensity of jumps that potentially occurs from heterogeneous interpretation of news by market participants. Our high-frequency event study approach is hence more flexible methodologically and better captures the dynamics of intradaily volatility and tail risk.

Regime Dependence of Monetary Policy Effects

Both theory and data suggest that monetary policy is regime dependent. Mandler (2012) uses a threshold vector autoregression (VAR) framework to analyse the effectiveness of classical monetary policy shocks, depending on the respective inflationary regime in the US economy between 1965-2007. He finds that monetary policy shocks have markedly different effects in low and high inflation regimes. Such inflation regime differences can be theoretically motivated. Sizeable deviations from inflation target levels might affect a central bank's credibility and its ability to credibly signal. Similarly, substantial off-target inflation levels might affect private sector inflation expectations, altering the Philips curve and inflation dynamics (Mandler, 2012).

Tenreyro and Thwaites (2016) examine GDP regime dependence of monetary policy shock effects, derived from the unexpected component of interest rate changes. The empirical results of Tenreyro and Thwaites suggest that medium- to long-run monetary policy shock effects on the real economy strongly depend on the state of the business cycle. GDP growth is the most consistent factor determining monetary policy effectiveness, and shocks seem to have a more pronounced effect during economic upswings than during downswings.[4] They also find that contractionary shocks have greater impact than expansionary ones, with both being equally represented during recessions and booms. Desired effects of policy rate changes might be subdued during recessions and central bankers might rely more strongly on unconventional monetary policy near the effective lower bound (ELB). To the best of our knowledge, we are the first to investigate regime dependence — with regards to both inflation and GDP growth — of the effectiveness of unconventional monetary policy and central bank communication.

Text Analysis for Monetary Policy

Lastly, we are part of a burgeoning literature that uses natural language processing to analyse monetary policy. Various text analysis methods have been tested in this field. For example, researchers have used topic models (Hansen et al., 2019), combined dictionary methods with classic machine learning models such as XGBoost (Petropoulos and Siakoulis, 2021), and have deployed deep neural network models such as transformers (Cai et al., 2021). In our work, instead of choosing a specific NLP algorithm a priori, we decide to take a more model-agnostic, data-driven approach to reduce modeler bias. That is, we train a variety of NLP models and choose the algorithm that works best in our validation set.

Similarly, researchers have employed various frameworks and datasets to identify monetary policy news. In particular, researchers have often studied the market effects of central bank policy announcements. For instance, Lucca and Trebbi (2009) and Hansen and McMahon (2016) both leverage approaches from computational linguistics within a VAR framework to asses the effect of the content in FOMC statements on macroeconomic variables. Lucca and Trebbi (2009) find CBC to be a more important factor than contemporaneous policy rate decisions. Hansen and McMahon (2016) conclude that shocks to forward guidance have a stronger effects on markets than communication of current economic conditions. Handlan (2020)

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[4]Tenreyro and Thwaites (2016) further emphasize the historical evidence that fiscal policy measures have been more important in times of recession, while fiscal and monetary policy have historically reinforced one another during booms.

uses a deep neural network architecture to identify text-based shocks in FOMC announcements, assessing their impact on Fed funds futures. She finds that shocks derived from forward guidance wording of FOMC statements account for four times more variation in Fed funds future prices than direct announcements of changes in the target federal funds rate. Gómez-Cram and Grotteria (2022) apply a video analysis on words mentioned during central bank press conference videos. Nesbit (2020) proposes a word count based instrumental variable framework to identify monetary policy shocks in FOMC transcripts. Aruoba and Drechsel (2022) use NLP techniques to analyse FOMC meetings in order to measure the information set of the FOMC at the time of policy decisions. They then use these measures to generate estimates of FOMC monetary policy shocks.

Although each of these studies use different methods, they all utilise text to help us to identify effects of monetary policy. However, official central bank announcements, such as FOMC announcements, occur only infrequently (every 6-8 weeks). We therefore shift our focus on central bankers' speeches which happen in much higher frequency. Researchers have paid only limited attention to speeches, partly because their content is difficult to quantify. At the same time, central bank deliberation and communication is continuous (Neuhierl and Weber, 2019). Thus, it is important to frequently measure CBC effects.

A few notable papers move in this direction. Neuhierl and Weber (2019) find that the tone of US Fed chair and vice-chair speeches, measured via word count methods, can explain stock market price dynamics. Using a mixture of machine learning and dictionary methods, Petropoulos and Siakoulis (2021) derive sentiment indices from central bank speeches and find that the sentiment predicts financial turmoil. We use a two-step macroeconomic news identification framework, in which we first learn a mapping from central bank language to central bank forecasts with Greenbook data, and then infer how FOMC member speeches imply revisions to GDP, inflation, and unemployment forecasts — an approach which is motivated by Ahrens and McMahon (2021).

To identify the news content of a speech, we must control for market expectations. Ellen et al. (2022), for example, construct a monetary news series from the difference in narrative between central bank statements and news media coverage. The results of Ellen et al. (2022) highlight the pivotal role of news media as catalysts in the process of forming market expectations and confirm earlier findings in the literature that monetary policy shocks cause measurable macroeconomic responses. Similarly, Cai et al. (2021) analyse FOMC announcements using BERT (Devlin et al., 2019) and identify monetary policy and information shocks, controlling for market expectations by analysing relevant New York Times articles with NLP methods. Instead of inferring market expectations from noisy news media coverage, we take the latest forecast measures from the widely viewed Survey of Professional Forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia. SPF forecasts directly measure expected GDP growth, inflation, and unemployment. We then define a macroeconomic news shock as the difference between a speech-implied forecast revision and the most recent SPF forecast for that variable available at the time of the speech.

3 Federal Reserve and Markets Data

The data used in our paper consists of several types: FOMC member speeches, Greenbook text, Greenbook forecasts, SPF forecasts, and intraday volatility and tail risk measures of US stock and bond markets. We use Greenbook forecasts and the respective Greenbook text sections that describe them to map central bank language to central bank forecasts. We then apply our learned mapping to FOMC member speeches and assess how speech-implied forecast revisions affect volatility and tail risk in financial markets.

3.1 Federal Reserve Speech and Forecast Data

The central bank data is split into a training and a test set. We describe these datasets below.

Training set: In the training phase, we learn the mapping of the Fed's Greenbook texts associated with the descriptions of GDP growth, CPI, and unemployment outlooks to the change in the Greenbook forecasts of those variables from the previous forecast period. That is, we target the difference in a current period's one-quarter-ahead Greenbook forecast to the previous quarter's forecast, such that for any of our macroeconomic key figures of interest, y, we define $\Delta y_m = y_m - y_{m-1}$, where m indicates the date of the Greenbook forecast. We also tested a one-year-ahead horizon, although this was less informative as one-year forecasts tend to revert to long-run values. The training sample spans 145 Greenbook documents, from January 1, 1995 to December 31, 2013. We only consider the 8,155 Greenbook sections that directly relate to GDP growth, CPI, and unemployment (see Appendix A for a detailed list of section allocations). The average Greenbook section in our dataset has about $3,000$ words; the longest section consists of $31,000$ words and the shortest section contains around 140 words. At any date, we concatenate all Greenbook sections that relate to the same forecasting variable.

Test set: Training the NLP models consists of estimating complex mappings from Greenbook text on each date, for each variable, to the associated revisions to the one-quarter-ahead Greenbook forecasts on each date, for each variable. Once the models are trained, we apply the learned mappings to a test set consisting of FOMC members' speeches made from January 1, 2014 to December 31, 2021. The applied mappings imply one-quarter-ahead forecast revisions for GDP growth, CPI, and unemployment. We assume that central bankers' speeches convey news from the Fed's information set that can alter the economic outlook of private agents. The Fed's information set could contain private or superior information about economic conditions, superior or alternative analysis (as in Byrne et al., 2023), or new information about the Fed's own preferences for monetary policy.

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Figure 1: Comparison of Greenbook and SPF forecasts
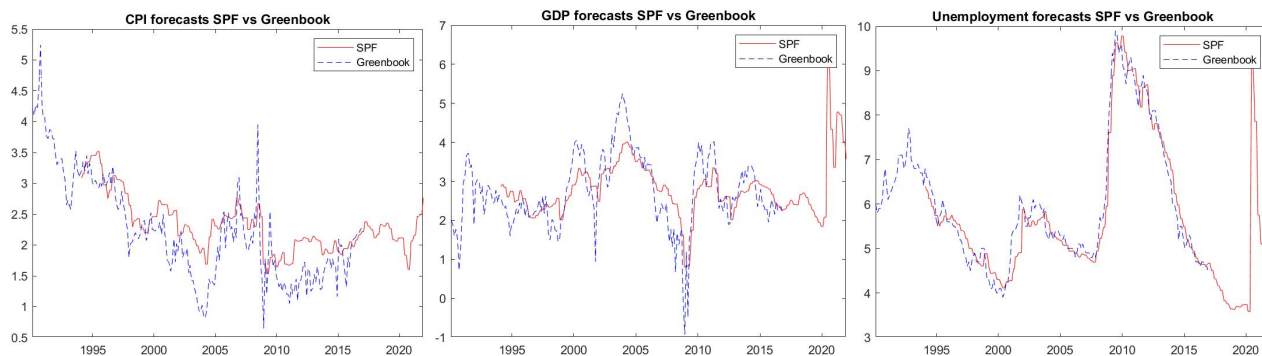
Notes: The figure displays the Greenbook and SPF forecasts over time for CPI (left panel), GDP (middle panel) and unemployment (right panel). The two forecasts match quite closely for the majority of the inspected time-series.

The target variables in the test set are the one-quarter-ahead respective changes in GDP growth, CPI, and unemployment in the SPF forecasts. The SPF is a publicly available and widely referenced source for economic forecasts. We use the SPF as our proxy for market expectations, rather than the next Greenbook forecasts, because Greenbook forecasts are released to the public with a 5-year delay. We expect that central bank speeches should have similar predictive power for Greenbook and SPF forecast revisions. Figure 1 corroborates the assumption that the SPF forecasts match the Greenbook forecasts quite well during 1993 to 2016. We assume that this pattern also holds post 2016, for which there was no public Greenbook data available when the data for this paper was collected. We release our dataset of central bank speeches, time-stamped on the minute of release, on our Github repository[5].

3.2 High-Frequency Market Data

We use high-frequency transaction prices for 22 Dow Jones Industrial Average (DJIA) stocks, together with 2-year, 5-year, and 10-year U.S. Treasury note and bond futures traded on the Chicago Board of Trade (CBOT). Appendix B lists the individual stocks and bonds. Wharton Research Data Services (WRDS) and Tick Data LLC provide data for individual stocks and bond futures, respectively. As is standard in the literature, we exclude U.S. holidays, Christmas periods, and weekends from our sample. We only consider trading hours from 9:30 EST−16:00 EST and 7:30 CT−14:00 CT, for stock and bond markets, respectively. To reduce the potential impact of market microstructure noise, we filter out *bouncebacks* and irregular quotes that typically occur in ultra high-frequency data. Using our adjusted data, we create equally-spaced 15-second observations, which is an appropriate frequency to implement our response measures. Our sample runs from January 1, 2014 through December 31, 2021.

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[5]github.com/MaximilianAhrens/data/tree/main/central_bank_speeches

4   Methodological Framework

Our methodological framework can be broken down into two parts. Section 4.1 explains our multimodal NLP framework used to estimate the mapping from central bank language to forecasts. We test and compare our estimation framework with a variety of machine learning algorithms. Section 4.2 then describes the measurements of the asset price dynamics and their relationship with the speech signals.

4.1   Multimodal NLP Framework

We seek to estimate how new information revealed in central bank speeches influences financial markets. To do so, we map central bank language to macroeconomic forecasts, controlling for the macroeconomic conditions at the time.

The macroeconomic conditionality is important because the effect of a given forecast revision on financial markets depends on initial economic conditions. This economic context requires the multimodal modelling approach. For example, a speech that raised forecast inflation would be a positive signal of improving conditions if inflation was below its desired level. However, the same speech would convey a negative signal if inflation was substantially above target. We employ multimodal machine learning approaches that allow us to use both text and tabular data when mapping central bank language to central bank forecasts and then predicting output, inflation, and unemployment outlook revisions.

4.1.1   Learning Mapping from Central Bank Language to Forecasts

We learn the mapping from the Fed's Greenbook text to the respective Greenbook forecasts. The Greenbooks contain dedicated sections on the Fed's forecasts of GDP growth, CPI, and unemployment, including the rationales for the forecasts. These sections allow us to map the Greenbook text - ergo central bank language - to central bank forecasts.

In the training phase, we estimate a separate mapping for each of the three variables, i.e., the one-quarter-ahead forecast change in CPI, GDP growth, or unemployment. We measure the change from the previous $(m-1)$ Greenbook to the current (m) in the one-quarter-ahead forecasts (q_1). CPI is denoted by π, GDP growth by g, and unemployment by u. Hence, our three target variables are: $\Delta\pi_{q_1,m}$, $\Delta g_{q_1,m}$, and $\Delta u_{q_1,m}$. For ease of notation in the following equations of our modelling framework, let y serve as a placeholder variable for any of the CPI, GDP growth, and unemployment variables. Hence, we denote our placeholder target variable as $\Delta y_{q_1,m}$.

To capture the economic context, we control for both change and level of the CPI, GDP, and unemployment of the previous Greenbook report, denoted as X_{m-1}. We fit a function, f, to learn how the respective Greenbook text maps into forecasts, controlling for macroeconomic conditions. The equations for CPI, GDP growth, and unemployment have the same explanatory variables, except for the text input, which is specific to the respective Greenbook forecast section. That is, θ_π represents the text features for the CPI corpus, while θ_g represents GDP-related text, and θ_u unemployment-related text. We use θ_y as a placeholder for any of the three text inputs. With this notation, $\theta_{y,k}$ represents the kth text feature for the respective target variable y. Let us define f as the function that takes text and tabular data as inputs

and maps them to the target output y, given parameters Ω, which are to be learned. We can now write out our regression equation as

$$\Delta y_{q_1,m} = f\left(X_{m-1}, \theta_{y_m}; \Omega\right). \tag{1}$$

If we assume linearity in function f, the regression equation can be written as follows:

$$\begin{aligned}
\Delta y_{q_1,m} = {}& \omega_\pi \pi_{q_1,m-1} + \omega_g g_{q_1,m-1} + \omega_u u_{q_1,m-1} \\
& + \omega_{\Delta u} \Delta u_{q_1,m-1} + \omega_{\Delta \pi} \Delta \pi_{q_1,m-1} + \omega_{\Delta g} \Delta g_{q_1,m-1} \\
& + \sum_{k=1}^{K} \omega_k \theta_{y,k,m} + \epsilon_m.
\end{aligned} \tag{2}$$

Here, the ωs represent the regression parameters and ϵ is the measurement error. We use the first 80% of the Greenbook dataset for training and the remaining 20% for validation. The data is furthermore de-meaned and standardized based on training set values. We did not randomly split the training and validation set to acknowledge the time-series characteristics (and therefore the potential for information leakage) in the data. We then train the machine learning models to map central bank texts and control variables to the respective target variables. We treat this as a regression problem and use a least squares error loss function, commonly used in economics and monetary policy econometrics.

4.1.2 Identifying Information Signals in Central Bank Speeches

In the test phase, we apply the trained models for each of the macroeconomic variables (CPI, GDP growth, unemployment) to the central bank speeches to infer macroeconomic forecast revisions. The text data is now the central bank speech content. The tabular data points on current economic conditions are the most recent SPF forecast levels and changes on GDP growth, CPI, and unemployment.[6] This procedure maps each central bank speech into an implied revision of the forecasts for CPI, GDP growth, and unemployment.

4.1.3 Calculating News Signals

Markets should only react to relevant news that have not yet been incorporated into asset prices. If a central bank speech does not change the expected macroeconomic path, then the speech has no news component. We proxy market expectations with the latest public SPF forecast for each target variable. We then calculate the difference between the most recent SPF forecast change $(\Delta y_{SPF,s})$ available at the time of each speech and the implied forecast change in each speech $(\Delta \hat{y}_{\text{speech},s})$. This difference is our forecast revision news, ν, for target variable, y, and speech event, s, such that

$$\nu_{y,s} = \Delta y_{\text{SPF},s} - \Delta \hat{y}_{\text{speech},s}. \tag{3}$$

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[6] As previously shown in Figure 1, the SPF forecasts track the Greenbook forecasts quite closely.

For GDP, a positive difference, $\nu_{y,s}$, is bad news, because a positive value means that the central bank speech implies lower GDP growth than does the most recent SPF forecast. The opposite is true for unemployment. Here, a positive difference is good news, as the speech implies that the central bank expects unemployment rates to fall faster (or rise less quickly) than previously anticipated.

For CPI, the categorisation into good and bad news depends on the relation of the current inflation level to the target. The Fed aims for an inflation rate of around 2%, as do most central banks of advanced economies.[7] Therefore, a positive $\nu_{\pi,s}$ — i.e., an implied downward forecast revision — is good news when the forecast of inflation is above target. This means inflation will revert faster back to target than anticipated (or won't rise as fast as anticipated). Conversely, when forecast of inflation rate is below target, a negative $\nu_{\pi,s}$ is good news. A later analysis will assess how financial market volatility and tail risk react to these implied forecast-revisions.

4.1.4 Machine Learning Methods

We do not know, a priori, which statistical learning model would best approximates the function, f, in equation (1). We have relatively few data points compared to many machine learning projects (e.g. hundreds or thousands rather than millions or billions of data points). Each data point itself is rich in information, however, consisting of a high dimensional feature set. That is, each set of text can be several thousand words long, which presents a problem for many modern language models such as transformer family models (e.g. BERT-based models), which can usually only handle up to around 100-1,000 tokens per data point (Das et al., 2021). Some extensions based on sparse transformers have been proposed such as Child et al. (2019); Zaheer et al. (2020), which can handle sequences of a couple of thousand tokens. However, document lengths of $20,000+$ words would still pose a challenge. Lacking reason to favour a specific class of models, we deploy a range of models, to search broadly for the best model and reduce the a priori modeler bias of favouring one model over alternatives.

We therefore deploy an extensive array of multimodal machine learning algorithms to approximate function f and to learn parameters Ω. We use the multimodal machine learning benchmark suite, Auto-Gluon (AutoGL) (Erickson et al., 2020), and we add to it the class of multimodal supervised topic models (Card et al., 2018; Ahrens et al., 2021).

AutoGluon

AutoGL is an automated machine learning (AutoML) framework that has been developed to fuse multimodal features such as text, images, and tabular data. We chose this AutoML framework because it outperformed competing frameworks in multimodal benchmark tasks (see Erickson et al., 2020).

Base models: AutoGL fits machine learning *base models* and then combines them through ensembling and stacking to boost performance. AutoGL allows us to apply hyperparameter optimization over all models. The *base models* in AutoGL span the following broad machine learning algorithm classes:

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[7]The FOMC targets a 2% rate of change for the personal consumption expenditure price index (PCE), not the CPI. The two inflation rates are very highly correlated, however, which makes it reasonable to use information about implied CPI forecasts to proxy for PCE forecasts.

1. **K-nearest neighbours** (Dudani, 1976): AutoGL uses two variations of k-nearest neighbours (KNN) that differ in their weighting approaches. One allocates uniform weights to all points while the other weights points according to the inverse of their respective distances.

2. **Random forests** (Breiman, 2001): AutoGL again deploys two variations of this algorithm class. One option uses the information gain of nodes for the assessment of the split quality. The other option uses Gini impurity instead.

3. **Extremely randomized trees** (Geurts et al., 2006): For the random tree class, AutoGL deploys both an implementation resorting to information gain and another option that uses Gini impurity for the assessment of split quality.

4. **Boosted decision trees**: AutoGL runs (where applicable to the task) Extreme Gradient Boosting (Chen and Guestrin, 2016), Light Gradient Boosting (Ke et al., 2017), Categorical Boosting (Prokhorenkova et al., 2018).

5. **Neural networks**: Figure 2 schematically outlines AutoGL's neural network architecture, which Erickson et al. (2020) details. The architecture has been specifically designed for the multimodal use of categorical (text, images) and numerical data. It uses variable-specific embeddings for each of the categorical features. These are then concatenated with the numerical features into one overall input vector. This vector is in turn fed through a 3-layer feed-forward network as well as through a linear skip-connection (for details see Erickson et al., 2020). Model ensembling and stacking can be applied and are optimally chosen in the validation process.

Figure 2: AutoGL schematic neural network architecture
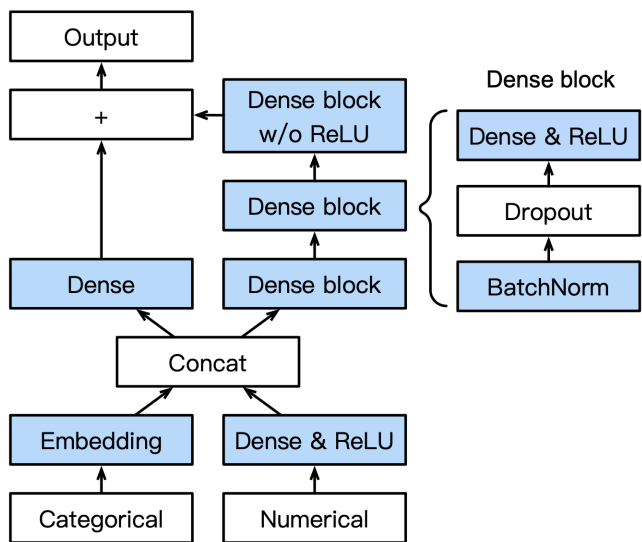
Notes: The figure displays the AutoGluon schematic neural network architecture, based on the design by Erickson et al. (2020), p. 3. Layers with learnable parameters coloured in blue.

Text representation options: We must also choose how to represent the text in machine-readable format. We define the following approaches:

1. **AutoTab**: Only tabular features are used. Text is excluded. AutoTab is our tabular data baseline next to an OLS regression that only uses tabular data.[8]

2. **AutoTab + tfidf**: Use tf-idf weighted word counts of the text as features. Standard text cleaning procedures of removing stopwords and punctuation have been applied.

3. **AutoTab + topics**: Use topic shares from supervised topic models as features (using rSCHOLAR without tabular data for the topic estimation).

4. **AutoMM transformer**: Use the AutoGL's multimodal modelling infrastructure that is based on a large language model (we use Roberta-base (Liu et al., 2019)) for multimodal fine-tuning. Tabular data can be fused into this process as well.[9]

5. **AutoTab + embed**: Use AutoMM transformer as well as AutoTab models that featurize text data as n-grams and ensemble over this zoo of models.[10]

4.2 Asset Price Dynamics

4.2.1 Underlying Continuous-Time Model

We model the intraday behaviour of asset prices with the following continuous-time model: The log-price X of each asset (stock or bond) follows an Itô semimartingale defined on a filtered space $(\Omega, \mathcal{F}_t, (\mathcal{F}_t)_{t \in [0,T]}, \mathbb{P})$ over an interval $[0, T]$. The Grigelionis decomposition (see e.g., Erdemlioglu and Yang, 2022; Boswijk et al., 2018; Dungey et al., 2018) implies that X_t has the following specification:

$$X_t = X_0 + \int_0^t b_s ds + \int_0^t \sigma_s dW_s + \delta * (\mu_t - \psi_t) + (\delta - h(\delta)) * \mu_t, \tag{4}$$

where b_s is the drift term, σ_s is the stochastic volatility component, W is a standard Brownian motion, δ is a predictable function, h is a truncation function (e.g., $h(x) = x1_{\{\|X\| \leq 1\}}$), μ is the jump measure of X, and ψ is its jump compensator, which adopts the decomposition

$$\psi_t(dt, dx) = [f_t(x)\lambda_t dx]dt$$

where the function, $f_t(x)$, controls the jump size distribution and λ_t denotes the jump intensity as in Erdemlioglu and Yang (2022) and Boswijk et al. (2018). We focus on the *tail* component of this jump

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[8] AutoGL's *TabularPredictor* approach.

[9] AutoGL's *MultimodalPredictor* approach.

[10] AutoGL's *TabularPredictor* approach with the *hyperparameter* option being set to *multimodal*.

compensator or λ_t, which captures the jump intensity dynamics.[11] We can specify λ_t as

$$\lambda_t = \lambda_0 + \int_0^t b_s' ds + \int_0^t \sigma_s' dW_s + \int_0^t \sigma_s'' dB_s + \delta' * \mu_t + \delta'' * \mu_t^\perp, \tag{5}$$

where B is a standard Brownian motion independent of W, $\mu_t^\perp$ is orthogonal to μ_t, and δ', δ'' are predictable. This model, given by equations (4) and (5), satisfies no-arbitrage conditions and leaves the volatility and jump components unrestricted. We now present our volatility and tail risk measures from this model.

4.2.2 High-Frequency Measurement of Volatility and Tail Risk

Given the price dynamics in equations (4) and (5), let us define the ith intradaily return on a trading day as $r_{i,t} = X_{i,t}$ - $X_{i-1,t}$. We can write the daily realized volatility (RV) as the square root of realized variance, which is the sum of the squared intraday returns $(1, \ldots, M)$. That is,

$$RV = \sqrt{\sum_{i=1}^{M} r_i^2}. \tag{6}$$

It is well-known that realized variance converges to quadratic variation (see e.g., Andersen et al., 2003, 2001 and Barndorff-Nielsen and Shephard, 2002 for in-depth discussion).

Turning to the estimation of $\lambda_{i,t}$ in equation (5), we define the post-signal realized intensity (RI) measure as

$$RI = \frac{\Delta_n^{\varpi \widehat{\beta}_i}}{k_n \Delta} \sum_{j=1}^{k_n} g\left(\frac{|r_i|}{\alpha \Delta^\varpi}\right) \frac{\alpha^{\widehat{\beta}}}{C_{\widehat{\beta}_i}(k_n)}, \tag{7}$$

where Δ is incremental change between observations, $\alpha \Delta^\varpi$ is threshold to retain only large jumps, $g(\cdot)$ admits a specific functional form, k_n is a constant which admits $(1/K \leq k_n \Delta^\rho \leq K)$ for $(0 < \rho < 1)$ and $(0 < K < \infty)$, and β_i is the estimator of jump activity index that controls the vibrancy of sharp fluctuations. In 7, $g(\cdot)$ as an auxiliary function that separates jump-type movements from the diffusive volatility, based on an α deviation (e.g., $\alpha = 2$, 3, 6) from the continuous component of the model.[12] We use RI as a proxy for time-varying (high-frequency) *tail risk* (TR), which is considerably accurate at high frequency, similar to the measures adapted in Bollerslev et al. (2015).[13]

In summary, we quantify two types of responses to CBC. First, communication likely creates sudden surges in market volatility. We assess these surges with realized volatility. Second, CBC can cause asset price jumps and persistently elevated jump intensity. Our approach allows us to first detect the speech-implied jumps, and then assess the 'intensity' of the jump responses. As Bollerslev et al. (2018) document,

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[11]See Andersen et al. (2020), who exploit jump intensity process to measure tail risk and assess its equity premium implications.

[12]See e.g., Erdemlioglu and Yang (2022), Boswijk et al. (2018) and Dungey et al. (2018) for implementation details, particularly on the selection of the functional form for $C_{\widehat{\beta}_i}(k_n)$ in (7).

[13]Our tail risk indicator RI is also quite similar to the estimator of Hill (1975). See also Aït-Sahalia and Jacod (2009) for a related discussion on the role of β_i in (7) when capturing tails of return distributions.

heterogeneous investors often release private information as they trade in the wake of such jumps, creating large price moves, which amplify high-frequency TR.

4.2.3   Identifying Association Between News and Market Reactions

The final step in our methodological framework is to measure how realized volatility and tail risk in both equity and bond markets react to central bankers' speeches. To this end, we regress the market reactions on the forecast revision implied by the corresponding speech. As the forecast revision itself is a linear combination of the central bank signal and the latest public forecast, we already control for the partial correlation between the SPF forecasts and the market reactions.[14] The same holds true for all control variables used in the creation of the speech signals. We don't add additional low-frequency macroeconomic control variables because market prices should already incorporate such publicly available information.

5   Results: Language Mapping and SPF Prediction

The first step of our method is to learn the mapping from central bank language to central bank forecasts. We train our model on the first 80% of the Greenbook sample, holding out the last 20% of observations for validation. In our validation set, we assess how well a model can map Greenbook language to Greenbook forecasts. For each machine-learning class, we select the best performing model from the validation set and then assess its performance on the test set. The test sample is the post-2013 sample of speeches in which we assess how well the speech signals predict subsequent changes in SPF forecasts. Given the results in the Tables 1, 2, and 3, we have reason to believe that the identified signals in the central bank speeches carry relevant information to change market expectations and hence public macroeconomic forecasts. The tables report the R^2 associated with predictions of SPF forecast revisions.

For example, the second row of Table 1 indicates that the multimodal neural topic model (MM NTM non-linear) has an R^2 of 0.67 in predicting CPI forecast revisions in the Greenbook training set, 0.83 in the Greenbook validation set, and 0.735 in the test set (speeches). Appendix C shows all tested machine learning approaches.

For each of the three macroeconomic target variables, the best multimodal NLP models markedly outperform models that only use tabular data. Specifically, the multimodal neural topic model (MM NTM) class performs best both in the validation and in the test set. For CPI, Table 1 shows that the MM NTM (non-linear) model has an R^2 of 0.735 in the test set, which is 15% better than MM NTM (linear) and 44% better than the R^2 of the next best method. Likewise, Table 2 shows that MM NTM (non-linear) has an R^2 of 0.797 in the test set, which is right behind MM NTM (linear)'s R^2 of 0.825. Finally, Table 3 shows that MM NTM (non-linear) performs best again for unemployment, with an R^2 of 0.208, which is markedly better than the second best R^2 of 0.131, achieved by AutoTab.

Interestingly, AutoGL's models underperform an OLS regression for CPI inflation and GDP growth. There might be several explanations for this underperformance. The datasets at hand contain relatively few data points — a common challenge in macroeconomics and macro-finance, especially for 'data hungry'

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[14]See Frisch-Waugh-Lovel theorem such as Frisch and Waugh (1933) and Lovell (1963).

machine learning methods. AutoGL's machine learning models might therefore struggle to converge or might easily overfit on the limited training data. Second, macroeconomic forecasts (or the revisions to them) might be well approximated by a linear model, since such models are a very common design choice in monetary economics, macroeconomics, and macroeconometrics. Hence, perhaps the relatively strong performance of an OLS regression compared to the AutoGL models.

Table 1: Central Bank Language to Forecast Mapping - CPI Q1

Metric: R^2	train (GB)	val (GB)	test (speeches)
OLS	0.288		0.510
MM NTM (linear)	0.600	0.650	0.640
MM NTM (non-linear)	0.670	**0.830**	**0.735**
AutoTab	0.565	0.302	0.475
AutoTab + tfidf	0.953	0.305	0.299
AutoTab + topics	0.370	0.284	0.358
AutoTab + embed	0.573	0.139	0.132
AutoMM transformer	-0.155	-†	-0.292

Notes: The table reports R^2 for training, validation, and test sets for each of the models. Best performing model in validation and test set in bold. †: Model only reports MSE for validation set.

Table 2: Central Bank Language to Forecast Mapping - GDP Q1

Metric: R^2	train (GB)	val (GB)	test (speeches)
OLS	0.301		0.785
MM NTM (linear)	0.372	**0.426**	**0.825**
MM NTM (non-linear)	0.483	0.371	0.797
AutoTab	0.497	0.304	0.380
AutoTab + tfidf	0.752	0.240	0.268
AutoTab + topics	0.730	0.253	0.285
AutoTab + embed	0.587	0.220	0.142
AutoMM transformer	0.013	-†	-0.044

Notes: The table reports R^2 for training, validation, and test sets for each of the models. Best performing model in validation and test set in bold. †: Model only reports MSE for validation set.

Table 3: Central Bank Language to Forecast Mapping - Unemployment Q1

Metric: R^2	train (GB)	val (GB)	test (speeches)
OLS	0.231		-0.377
MM NTM (linear)	0.197	0.109	0.066
MM NTM (non-linear)	0.285	**0.457**	**0.208**
AutoTab	0.191	0.058	0.131
AutoTab + tfidf	0.577	0.113	-0.045
AutoTab + topics	0.278	0.053	-0.010
AutoTab + embed	0.415	0.145	-0.044
AutoMM transformer	-0.737	-†	-1.177

Notes: The table reports R^2 for training, validation, and test sets for each of the models. Best performing model in validation and test set in bold. †: Model only reports MSE for validation set.

6   Results: Intraday Market Effects

We use the model that performed best in the validation set (Greenbook data) to estimate the speech-implied information on GDP, CPI, and unemployment forecast revisions in the test set (speech data). The news on forecast revisions, as outlined in section 4.1.3, are defined as the difference between the speech-implied forecast for CPI, GDP, and unemployment outlook and the respective most recent SPF forecast. We then fit an OLS regression where we use the speech-implied news as independent variables. Market volatility and tail risk are the respective dependent variables. We first show our estimation results across regimes in section 6.1. In section 6.2, we then segment our speech dataset into low, normal, and high GDP and CPI regimes, respectively. Section 6.3 shows the news effect analysis by CPI regime. Section 6.4 covers the same analysis by GDP regime.

6.1   News Effects Across Regimes

We use the estimated realized volatility (RV) and tail risk (TR) in the 30-minute window after a speech as as our dependent variables. We regress both RV and TR on all absolute speech-implied news across all regimes. That is, we expect larger forecast revision news (in absolute value) to raise volatility and tail risk. The data is de-meaned and standardized. For each speech s, denote its CPI news component as $\nu_{\pi,s}$, GDP news as $\nu_{g,s}$, and unemployment news as $\nu_{u,s}$. The regression equations for realized volatility and tail risk are then

$$RV_s = \beta_0|\nu_{\pi,s}| + \beta_1|\nu_{g,s}| + \beta_2|\nu_{u,s}| + \epsilon_{RV} \tag{8}$$

$$TR_s = \rho_0|\nu_{\pi,s}| + \rho_1|\nu_{g,s}| + \rho_2|\nu_{u,s}| + \epsilon_{TR}. \tag{9}$$

We estimate both equations for both equity and bond markets.

Equity Markets

The positive and statistically significant coefficients in the top panel of Table 4 reveal that larger absolute forecast revision news, i.e., larger absolute differences between the implied forecast and the most recent SPF forecast, are associated with higher realized equity volatility. All three types of forecast revisions are highly statistically significant at the 10% level. The bottom panel of Table 4 indicates that the magnitude of speech-implied forecast revisions to CPI and unemployment has a statistically significant association with higher tail risk in equity markets. GDP news have no statistically significant effect.

Table 4: Association between absolute speech-implied forecast revision news and volatility (top panel) and tail risk (bottom panel) in equity markets across all regimes

Target variable: RV_e	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	0.1675	0.022	7.585	0.000	0.124	0.211
|GDP news|	0.0780	0.043	1.800	0.072	-0.007	0.163
|U news|	0.1967	0.024	8.078	0.000	0.149	0.244
R^2: 0.722	Adj. R^2: 0.718	n. obs.: 191	Heteroscedasticity robust standard errors			
Target variable: TR_e	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	2.2613	0.483	4.677	0.000	1.314	3.209
|GDP news|	1.1819	0.990	1.193	0.233	-0.759	3.123
|U news|	2.4452	0.484	5.056	0.000	1.497	3.393
R^2: 0.526	Adj. R^2: 0.519	n. obs.: 191	Heteroscedasticity robust standard errors			

Notes: The table shows the association between speech-implied forecast revision news in absolute value about CPI, GDP, and unemployment and realized volatility (top panel) and tail risk (bottom panel). The estimation results are reported for the U.S. equity market.

Bond Markets

Tables 5, 6, and 7 show the results for the 2-, 5-, and 10-year bond futures markets. The bond market results are similar to those of the equity market. Larger absolute speech-implied forecast revision news are strongly associated with higher realized bond price volatility and tail risk across maturities.

Table 5: Association between absolute speech-implied forecast revision news and volatility (top panel) and tail risk (bottom panel) in bond markets (2-year maturity) across all regimes

Target variable: $RV_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	0.0149	0.003	5.643	0.000	0.010	0.020
|GDP news|	0.0110	0.005	2.121	0.034	0.001	0.021
|U news|	0.0166	0.003	5.412	0.000	0.011	0.023
R^2: 0.672	Adj. R^2: 0.667	n. obs.: 175	Heteroscedasticity robust standard errors			
Target variable: $TR_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	3.7368	0.809	4.619	0.000	2.151	5.322
|GDP news|	5.4056	1.022	5.288	0.000	3.402	7.409
|U news|	3.3025	0.887	3.725	0.000	1.565	5.040
R^2: 0.508	Adj. R^2: 0.500	n. obs.: 175	Heteroscedasticity robust standard errors			

Notes: The table shows the association between speech-implied forecast revision news in absolute value about CPI, GDP, and unemployment and realized volatility (top panel) and tail risk (bottom panel). The estimation results are reported for 2-year maturity U.S. Treasury bond futures.

Table 6: Association between absolute speech-implied forecast revision news and volatility (top panel) and tail risk (bottom panel) in bond markets (5-year maturity) across all regimes

Target variable: $RV_{b,5y}$	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	0.0298	0.006	4.866	0.000	0.018	0.042
|GDP news|	0.0238	0.013	1.852	0.064	-0.001	0.049
|U news|	0.0354	0.006	5.900	0.000	0.024	0.047
R^2: 0.592	Adj. R^2: 0.588	n. obs.: 175	Heteroscedasticity robust standard errors			
Target variable: $TR_{b,5y}$	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	2.3726	0.744	3.189	0.001	0.914	3.831
|GDP news|	3.6080	1.500	2.405	0.016	0.667	6.549
|U news|	1.4576	0.684	2.132	0.033	0.118	2.797
R^2: 0.424	Adj. R^2: 0.413	n. obs.: 175	Heteroscedasticity robust standard errors			

Notes: The table shows the association between speech-implied forecast revision news in absolute value about CPI, GDP, and unemployment and realized volatility (top panel) and tail risk (bottom panel). The estimation results are reported for 5-year maturity U.S. Treasury bond futures.

Table 7: Association between absolute speech-implied forecast revision news and volatility (top panel) and tail risk (bottom panel) in bond markets (10-year maturity) across all regimes

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	0.0574	0.010	5.687	0.000	0.038	0.077
|GDP news|	0.0443	0.021	2.132	0.033	0.004	0.085
|U news|	0.0614	0.010	6.000	0.000	0.041	0.082

R^2: 0.650	Adj. R^2: 0.644	n. obs.: 175	Heteroscedasticity robust standard errors

Target variable: $TR_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
|CPI news|	1.8245	0.644	2.833	0.005	0.562	3.087
|GDP news|	3.0200	1.413	2.137	0.033	0.250	5.790
|U news|	1.3404	0.555	2.414	0.016	0.252	2.429

R^2: 0.434	Adj. R^2: 0.424	n. obs.: 175	Heteroscedasticity robust standard errors

Notes: The table shows the association between speech-implied forecast revision news in absolute value about CPI, GDP, and unemployment and realized volatility (top panel) and tail risk (bottom panel). The estimation results are reported for 10-year maturity U.S. Treasury bond futures.

6.2   Economic Regime Definitions

We also assess whether the effects of speech-implied forecast revisions depend on the GDP and inflation regimes. We do not separately analyse unemployment regimes. We divide our GDP and CPI datasets into a *high*, *normal*, and *low* regime (see Table 8). The categorisation is based on the Federal Reserve's inflation target and the historic distributions of the respective variables as depicted in Figure 3. Figure 4 shows the two time-series of the regime indicators.

Table 8: Categories of economic regimes

	CPI	**ΔGDP**
High	$\pi > 3\%$	$g > 3\%$
Normal	$1\% < \pi < 3\%$	$2\% < g < 3\%$
Low	$\pi < 1\%$	$g < 2\%$

Notes: The table presents the classification of different economic regimes (high, normal, low) for GDP and CPI.

Figure 3: Empirical distribution of CPI and GDP growth target variables
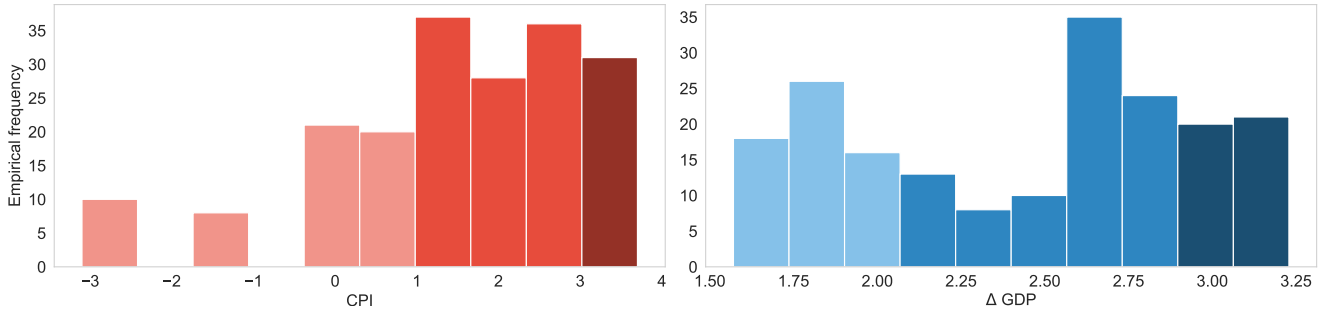
Notes: The figure shows the empirical distribution of CPI and GDP regimes. CPI: low regime (light red), normal regime (mid red), high regime (dark red). GDP: low regime (light blue), normal regime (mid blue), high regime (dark blue).

Figure 4: Time-series of CPI and GDP growth regimes
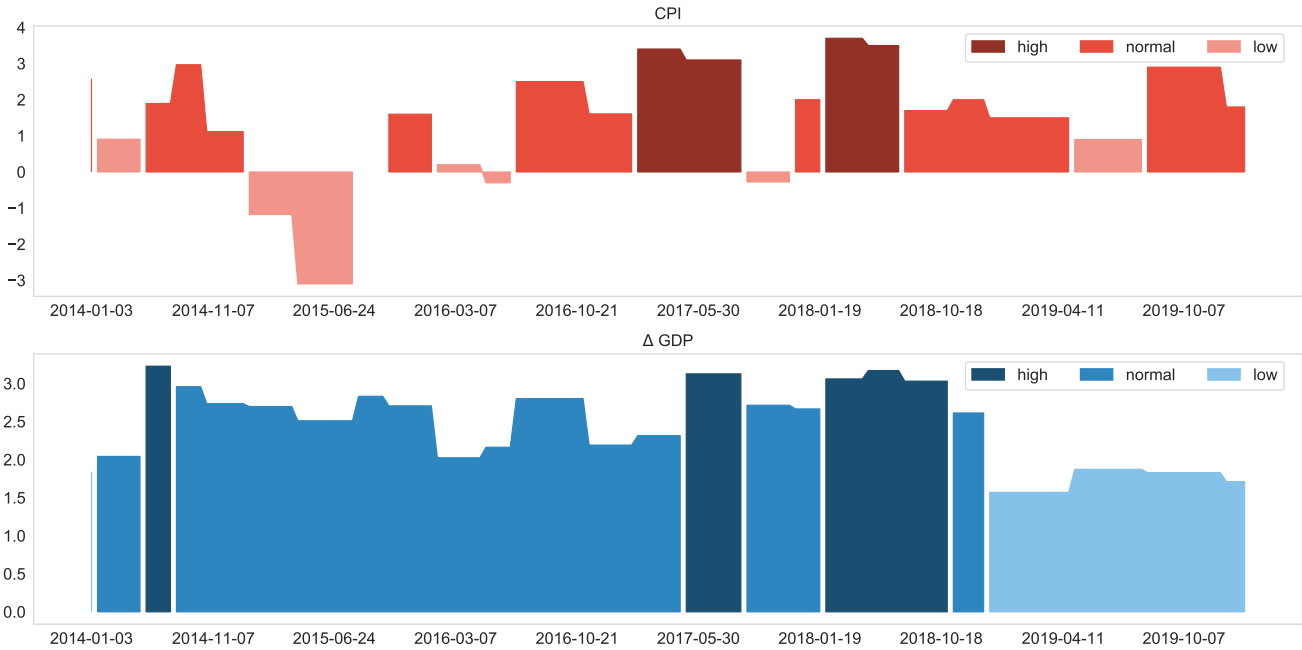
Notes: The figure displays the evolution of different economic regimes over time. CPI (upper panel): low regime (light red), normal regime (mid red), high regime (dark red). GDP (lower panel): low regime (light blue), normal regime (mid blue), high regime (dark blue).

Conditional on the regime classification, we categorise the speech-implied news into *good* and *bad* news for the market. The division in the GDP-regime is straightforward. In any GDP regime, speeches that imply higher (lower) GDP-growth than the most recent SPF forecast are good (bad) GDP news. Similarly, lower (higher) unemployment forecast revisions are good (bad) new. The story for the CPI regime is more complex: If a speech implies that inflation will move closer to the 2% target than the most recent SPF forecast, it is considered good news. If a speech implies that inflation will move further from the target,

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it is bad news. So, a speech that implies an increase in inflation would be good news if inflation is below target but bad news if inflation is above target. Table 9 outlines the news classifications.

Table 9: Central bank GDP news classification

	Good news	Bad news
High GDP	$g_{\mathrm{cb}} > g_{\mathrm{spf}}$	$g_{\mathrm{cb}} < g_{\mathrm{spf}}$
Normal GDP	$g_{\mathrm{cb}} > g_{\mathrm{spf}}$	$g_{\mathrm{cb}} < g_{\mathrm{spf}}$
Low GDP	$g_{\mathrm{cb}} > g_{\mathrm{spf}}$	$g_{\mathrm{cb}} < g_{\mathrm{spf}}$

Notes: The table presents the classification of *good* versus *bad* GDP news for different levels of GDP.

Table 10: Central bank CPI news classification

	Good news	Bad news
High CPI	$\pi_{\mathrm{cb}} < \pi_{\mathrm{spf}}$	$\pi_{\mathrm{cb}} > \pi_{\mathrm{spf}}$
Normal CPI (slightly above target)	$\pi_{\mathrm{cb}} < \pi_{\mathrm{spf}}|\pi_{\mathrm{spf}} > 2\%$	$\pi_{\mathrm{cb}} > \pi_{\mathrm{spf}}|\pi_{\mathrm{spf}} > 2\%$
Normal CPI (slightly below target)	$\pi_{\mathrm{cb}} > \pi_{\mathrm{spf}}|\pi_{\mathrm{spf}} < 2\%$	$\pi_{\mathrm{cb}} < \pi_{\mathrm{spf}}|\pi_{\mathrm{spf}} < 2\%$
Low CPI	$\pi_{\mathrm{cb}} > \pi_{\mathrm{spf}}$	$\pi_{\mathrm{cb}} < \pi_{\mathrm{spf}}$

Notes: The table presents the classification of *good* versus *bad* CPI news for different levels of CPI.

6.3 News Effects by CPI Regime

We now analyse the effects of speech-implied forecast revision news by CPI regime. We separate god news from bad news to assess whether asymmetric speech-implied news effects exist. The regression equations for realized volatility (RV) and tail risk (TR) in the 30 minutes after each speech are as follows:

$$RV_s = \beta_0|\nu_{\pi,s,good}| + \beta_1|\nu_{\pi,s,bad}| + \beta_2|\nu_{g,s,good}| + \beta_3|\nu_{g,s,bad}| + \beta_4|\nu_{u,s,good}| + \beta_5|\nu_{u,s,bad}| + \epsilon_{RV} \qquad (10)$$

$$TR_s = \rho_0|\nu_{\pi,s,good}| + \rho_1|\nu_{\pi,s,bad}| + \rho_2|\nu_{g,s,good}| + \rho_3|\nu_{g,s,bad}| + \rho_4|\nu_{u,s,good}| + \rho_5|\nu_{u,s,bad}| + \epsilon_{TR}. \qquad (11)$$

The variables have the same meaning as before. That is, for each speech s, denote its CPI news component as $\nu_{\pi,s}$, GDP news as $\nu_{g,s}$, and unemployment news as $\nu_{u,s}$. However, for each macroeconomic news component, we now have a *good news* variable and a *bad news* variable (both in absolute values), denoted by *good* and *bad* subscripts. We estimate the volatility regression for both the equity and the bond markets for each CPI regime: low, normal, and high. The tail risk equation is estimated by CPI regime for equity markets only, due to scope limitations of this paper.

Equity Markets

Table 11 reports the effects of speech-implied forecast revisions on realized volatility and tail risk in equity markets, broken down by CPI regime. Appendix D details these results for each CPI regime and target

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variable.

Table 11: Association between speech-implied forecast revisions and volatility in equity markets across CPI regimes

	High CPI regime		Low CPI regime		Normal CPI regime	
	RV	TR	RV	TR	RV	TR
|News CPI good|	+***	-	+***	-	-	+*
|News CPI bad|	+***	-	+**	-	-	-
|News GDP good|	-	-	+**	+***	-	-
|News GDP bad|	-	-	-	+*	-	-
|News U good|	+***	+***	-	-	-	-
|News U bad|	+**	-	+***	-	+***	+***
n. obs.	36		59		70	

Notes: $+$ = positive association. $*= p \leq 0.1$, $**= p \leq 0.05$, $***= p \leq 0.01$. $-$ = no statistically significant results.

High CPI regime: When CPI is high, speech-implied forecast revisions to CPI and unemployment forecasts have a statistically significant, positive association with realized volatility in equity markets in the 30 minutes after the speech (see the columns labeled RV). This holds true both for positive and negative news. Tail risk dynamics (see the columns labeled TR) are less strongly associated with central bank speech news signals in the high CPI regime.

Low CPI regime: A similar picture emerges in the low CPI regime. Speech-implied forecast revisions to CPI, good and bad, are strongly associated with increased equity market volatility. Low CPI regimes occur exclusively with normal or low GDP regimes (see Figure 4). Therefore, it is not surprising to see that speech-implied forecast revisions to GDP have a slightly stronger association with market volatility than during high CPI regimes, which almost exclusively co-occur with high GDP regimes. We interpret this as indicating that when the economy is in full swing, market sentiments tend to be optimistic and less 'attention' might be given to central bank announcements. Tail risk in the low CPI regime seems to be sensitive to both positive and negative speech-implied forecast revisions to GDP.

Normal CPI regime: Normal CPI times are defined as periods when the inflation rate is close to 2%. During these periods, there are no longer statistically significant associations between speech-implied forecast revisions of any kind and market volatility, except for negative unemployment news. Again, we would interpret these results as indicating that markets 'listen' less attentively to central bank communication when the economy is in normal or good times compared to periods of undesirably high or low inflation. Table 11 shows similar patterns for the prediction of equity volatility and tail risk in the normal CPI regime.

Bond Markets

Table 12 summarizes how speech-implied forecast revisions affect bond futures volatility across CPI regimes. Appendix F details the regression tables for each CPI regime and target variable combination. Bond markets produce patterns similar to those in equity markets: large speech-implied forecast revisions are more significantly associated with higher bond volatility when CPI is far from the target.

Table 12: Association between speech-implied forecast revisions and volatility in bond markets across CPI regimes

	High CPI regime			Low CPI regime			Normal CPI regime		
	2y	5y	10y	2y	5y	10y	2y	5y	10y
|News CPI good|	-	-	-	$+$***	$+$***	$+$***	-	-	-
|News CPI bad|	-	$+$*	-	-	$+$*	$+$*	-	-	-
|News GDP good|	$+$*	-	-	$+$***	-	-	-	-	-
|News GDP bad|	-	-	-	-	-	-	-	-	-
|News U good|	n/a	n/a	n/a	-	-	-	-	-	-
|News U bad|	$+$**	$+$**	$+$***	-	$+$*	$+$*	$+$***	$+$***	$+$***
n. obs.		33			42			52	

 Notes: $+$ = positive association. *= $p \leq 0.1$, **= $p \leq 0.05$, ***= $p \leq 0.01$. $-$ = no statistically significant results. 'n/a' = no observations available.

6.4   News Effects by GDP Regime

We now estimate equations (10) and (11) by different GDP regimes: low, normal, and high.

Equity Markets

Table 13 reports speech-implied forecast revision effects on realized volatility and tail risk in equity markets, broken down by GDP regime. Appendix E details these results for each CPI regime and target variable.

High and normal GDP regimes: In high GDP times, negative speech-implied-forecast revisions to unemployment raise equity RV and TR. Similarly, positive speech-implied revisions to CPI forecasts raise TR during normal GDP periods.

Low GDP regime: In low GDP times, all speech-implied forecast revisions influence equity RV and all GDP and unemployment revisions influence equity TR. That is, RV and TR are a substantially more sensitive to forecast revisions during periods of low economic activity.

Overall, markets 'listen' most carefully in times of economic distress. In normal or good times, news in central bank speeches have less impact on RV and TR in equity markets.

Table 13: Association between speech-implied forecast revisions and volatility in equity markets across GDP regimes

	High GDP regime		Low GDP regime		Normal GDP regime	
	RV	TR	RV	TR	RV	TR
|News CPI good|	-	-	$+^{***}$	-	-	$+^{**}$
|News CPI bad|	-	-	$+^{***}$	-	-	-
|News GDP good|	-	-	$+^{***}$	$+^{***}$	$+^{*}$	-
|News GDP bad|	-	-	$+^{***}$	$+^{*}$	-	-
|News U good|	-	n/a	$+^{**}$	$+^{**}$	-	-
|News U bad|	$+^{**}$	$+^{**}$	$+^{***}$	$+^{**}$	-	-
n. obs.	36		44		81	

Notes: + = positive association. *= $p \leq 0.1$, **= $p \leq 0.05$, ***= $p \leq 0.01$. − = no statistically significant results. 'n/a' = no observations available.

Bond Markets

Table 14 shows speech-implied forecast revision effects on realized volatility in bond futures markets, broken down by GDP regime. Appendix G details these results for each GDP regime. Bond markets are also most sensitive to central bank speeches in extreme GDP regimes. Low GDP regimes witness the most significant association between GDP and unemployment forecast revisions and bond volatility. But markets also appear to be more sensitive to central bank speeches in high GDP regimes than in periods of normal economic growth.

Table 14: Association between speech-implied forecast revisions and volatility in bond markets across GDP regimes

	High GDP regime			Low GDP regime			Normal GDP regime		
	2y	5y	10y	2y	5y	10y	2y	5y	10y
|News CPI good|	$+^{***}$	-	-	n/a	n/a	n/a	$+^{***}$	-	-
|News CPI bad|	$+^{*}$	$+^{*}$	-	-	-	-	-	-	-
|News GDP good|	-	-	-	$+^{***}$	$+^{***}$	$+^{***}$	-	-	-
|News GDP bad|	-	-	-	-	-	-	-	-	-
|News U good|	n/a	n/a	n/a	-	$+^{**}$	$+^{**}$	-	-	-
|News U bad|	$+^{*}$	-	$+^{*}$	$+^{***}$	$+^{***}$	$+^{***}$	-	-	-
n. obs.	35			42			52		

Notes: + = positive association. *= $p \leq 0.1$, **= $p \leq 0.05$, ***= $p \leq 0.01$. − = no statistically significant results. 'n/a' = no observations available.

7 Conclusion

We use supervised multimodal natural language processing methods to map central bank language to forecasts of macroeconomic variables. We benchmark an extensive array of machine learning methods on this task. Finally, we apply this approach to a dataset of time-stamped speeches from Federal Reserve FOMC members in order to create an original monetary policy news series by taking the difference between central bank speech-implied forecast revisions and market expectations which we approximate with the latest available figures from the Survey of Professional Forecasters.

Our results indicate that news signals derived from central bank speeches can help explain volatility and tail risk in both equity and bond markets. Speech-implied news seem to carry information to which markets react - particularly in *abnormal* GDP and inflation regimes. We find no evidence that speeches resolve uncertainty. These findings underpin the importance of analysing the *continuous flow* of central bank communication with markets such as through FOMC member speeches.

Our analysis evaluates the market responses at the intradaily (high frequency) level. However, speech-implied macroeconomic news may affect volatility and tail risk (and other financial market variables) differently over longer-term horizons. We plan to analyse the impact across different time horizons in future work. Equally, we aim to extend our work in follow-up explorations by analysing speech differences in characteristics and market effects between central banks and between central bank board members.

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Appendix

A   List of Relevant Greenbook Sections

Table 15: Considered Greenbook sections per economic indicator

GDP	CPI	Unemployment
Ec.GDP	Ec.Prices	Ec.Labor
For.Ec.Overview	For.CostPrice	For.Labor
For.Ec.Summary	Ec.Wages	
For.Outlook		
For.HH		
For.G		
For.Inven		
For.BusInvest		
For.Trade		

Notes: In the table, EC = Economic Conditions Section, For = Forecasts Section.

B   Lists of Stocks and Bonds

Table 16: Stock tickers and names

AAPL	Apple	AXP	American	BA	Boeing	CAT	Caterpillar
CSCO	Cisco	CVX	Chevron	DIS	Disney	HD	Home
IBM	IBM	INTC	Intel	JNJ	Johnson	KO	Coca-Cola
MCD	McDonald's	MMM	3M	MRK	Merck	MSFT	MSFT
NKE	Nike	PFE	Pfizer	UNH	UnitedHealth	VZ	Verizon
WMT	Wal-Mart	XOM	Exxon				

Notes: The table lists the tickers and descriptions of the individual stocks used in our empirical analysis.

Table 17: Bond names and maturities

US Treasury Note Futures:	2-Year	5-Year	10-Year

Notes: The table lists the tickers and descriptions of the U.S. Treasury bond futures used in our empirical analysis.

C Additional Results: Language to Forecast Mapping

Table 18: CPI mapping and fit performance

Model \Predictive R^2	score test	score val	score train	data source
MM Neural Topic Model (non-lin)	**0.735**	**0.830**	0.670	joint MM tabular + topics
MM Neural Topic Model (linear)	**0.640**	**0.650**	0.600	joint MM tabular + topics
ExtraTreesMSE_BAG_L1	0.588	0.084	0.880	tabular
RandomForestMSE_BAG_L1	0.584	0.052	0.622	tabular + topics
ExtraTreesMSE_BAG_L1	0.584	0.089	0.595	tabular + topics
RandomForestMSE_BAG_L1	0.568	0.047	0.876	tabular
KNeighborsUnif_BAG_L1	0.559	0.141	0.460	tabular + topics
KNeighborsDist_BAG_L1	0.549	0.128	0.798	tabular + topics
KNeighborsUnif_BAG_L1	0.520	0.152	0.439	tabular + tfidf
KNeighborsDist_BAG_L1	0.519	0.146	1.000	tabular + tfidf
KNeighborsUnif_BAG_L1	0.516	0.142	0.442	tabular
NeuralNetFastAI_BAG_L1	0.515	0.233	0.251	tabular + topics
KNeighborsDist_BAG_L1	0.513	0.121	1.000	tabular
OLS	0.512		0.288	tabular
NeuralNetFastAI_BAG_L1	0.494	0.272	0.594	tabular
RandomForestMSE_BAG_L1	0.482	0.103	0.883	tabular + tfidf
WeightedEnsemble_L2	0.475	0.302	0.565	tabular
CatBoost_BAG_L1	0.386	0.200	0.698	tabular
CatBoost_BAG_L1	0.384	0.170	0.905	tabular + tfidf
XGBoost_BAG_L1	0.377	0.169	0.595	tabular + topics
XGBoost_BAG_L1	0.374	0.155	0.937	tabular + tfidf
LightGBMXT_BAG_L1	0.373	0.126	0.295	tabular
XGBoost_BAG_L1	0.368	0.152	0.770	tabular
WeightedEnsemble_L2	0.358	0.284	0.370	tabular + topics
LightGBMLarge_BAG_L1	0.357	0.080	0.646	tabular + tfidf
LightGBM_BAG_L1	0.327	0.136	0.294	tabular
WeightedEnsemble_L2	0.299	0.305	0.953	tabular + tfidf
LightGBM_BAG_L1	0.289	0.138	0.245	tabular + topics
NeuralNetTorch_BAG_L1	0.269	0.210	0.128	tabular + topics
NeuralNetTorch_BAG_L1	0.262	0.247	0.401	tabular
XGBoost_BAG_L1	0.260	0.056	0.783	tabular + embeddings
LightGBMXT_BAG_L1	0.252	0.092	0.348	tabular + tfidf
LightGBM_BAG_L1	0.252	0.131	0.368	tabular + tfidf
LightGBMLarge_BAG_L1	0.251	0.139	0.302	tabular
LightGBMLarge_BAG_L1	0.202	0.156	0.323	tabular + topics
ExtraTreesMSE_BAG_L1	0.193	0.143	0.889	tabular + tfidf
LightGBMLarge_BAG_L1	0.191	0.074	0.440	tabular + embeddings
CatBoost_BAG_L1	0.177	0.250	0.525	tabular + topics
LightGBMXT_BAG_L1	0.162	0.140	0.192	tabular + topics
NeuralNetFastAI_BAG_L1	0.148	0.280	0.912	tabular + tfidf
WeightedEnsemble_L2	0.132	0.139	0.573	tabular + embeddings
CatBoost_BAG_L1	0.126	0.116	0.633	tabular + embeddings
LightGBMXT_BAG_L1	0.116	0.001	0.520	tabular + embeddings
LightGBM_BAG_L1	0.112	-0.018	0.338	tabular + embeddings
NeuralNetTorch_BAG_L1	0.095	0.153	0.500	tabular + tfidf
NeuralNetTorch_BAG_L1	-0.030	0.076	0.161	tabular + embeddings
AutoGluon Multimodal Transformer	-0.292		-0.155	multimodal embeddings

Notes: The table reports the performance (predictive R^2) of different models for the language mapping analysis of the CPI.

Table 19: GDP mapping and fit performance

Model \Predictive R^2	score test	score val	score train	data source
MM Neural Topic Model (lin)	**0.825**	**0.426**	0.372	joint MM tabular + topics
MM Neural Topic Model (non-lin)	**0.797**	**0.371**	0.483	joint MM tabular + topics
WeightedEnsemble_L2	0.380	0.304	0.497	tabular
OLS	0.785	0.301		tabular
NeuralNetFastAI_BAG_L1	0.480	0.270	0.443	tabular
WeightedEnsemble_L2	0.285	0.253	0.730	tabular + topics
WeightedEnsemble_L2	0.268	0.240	0.752	tabular + tfidf
WeightedEnsemble_L2	0.142	0.220	0.587	tabular + embeddings
CatBoost_BAG_L1	0.249	0.211	0.552	tabular
RandomForestMSE_BAG_L1	0.302	0.204	0.892	tabular + tfidf
RandomForestMSE_BAG_L1	0.348	0.202	0.892	tabular + topics
ExtraTreesMSE_BAG_L1	0.408	0.193	0.891	tabular
ExtraTreesMSE_BAG_L1	0.381	0.192	0.890	tabular + topics
ExtraTreesMSE_BAG_L1	0.111	0.188	0.891	tabular + tfidf
CatBoost_BAG_L1	0.207	0.187	0.671	tabular + tfidf
LightGBMXT_BAG_L1	0.203	0.178	0.322	tabular
LightGBM_BAG_L1	0.154	0.172	0.367	tabular
XGBoost_BAG_L1	0.141	0.171	0.580	tabular + topics
CatBoost_BAG_L1	0.006	0.169	0.531	tabular + topics
CatBoost_BAG_L1	0.101	0.169	0.552	tabular + embeddings
LightGBM_BAG_L1	0.099	0.162	0.704	tabular + embeddings
NeuralNetTorch_BAG_L1	0.461	0.160	0.341	tabular
LightGBM_BAG_L1	0.101	0.159	0.734	tabular + tfidf
KNeighborsUnif_BAG_L1	0.253	0.158	0.402	tabular + tfidf
LightGBMLarge_BAG_L1	0.245	0.155	0.598	tabular
KNeighborsDist_BAG_L1	0.256	0.151	1.000	tabular + tfidf
NeuralNetTorch_BAG_L1	0.049	0.150	0.553	tabular + tfidf
LightGBMXT_BAG_L1	0.120	0.150	0.348	tabular + tfidf
RandomForestMSE_BAG_L1	0.394	0.150	0.885	tabular
LightGBMLarge_BAG_L1	0.111	0.149	0.536	tabular + topics
LightGBMLarge_BAG_L1	0.181	0.149	0.665	tabular + embeddings
XGBoost_BAG_L1	0.119	0.142	0.567	tabular
NeuralNetFastAI_BAG_L1	0.060	0.136	0.797	tabular + tfidf
KNeighborsDist_BAG_L1	0.255	0.132	1.000	tabular
KNeighborsUnif_BAG_L1	0.248	0.130	0.407	tabular
LightGBM_BAG_L1	0.111	0.126	0.496	tabular + topics
LightGBMXT_BAG_L1	0.105	0.125	0.505	tabular + embeddings
NeuralNetTorch_BAG_L1	-0.071	0.123	0.275	tabular + embeddings
NeuralNetTorch_BAG_L1	0.151	0.108	0.497	tabular + topics
XGBoost_BAG_L1	-0.015	0.107	0.663	tabular + embeddings
LightGBMLarge_BAG_L1	0.108	0.095	0.581	tabular + tfidf
XGBoost_BAG_L1	0.041	0.083	0.564	tabular + tfidf
KNeighborsUnif_BAG_L1	0.286	0.081	0.400	tabular + topics
KNeighborsDist_BAG_L1	0.274	0.074	1.000	tabular + topics
LightGBMXT_BAG_L1	0.097	0.049	0.318	tabular + topics
TextPredictor_BAG_L1	-0.077	-0.123	-0.103	tabular + embeddings
NeuralNetFastAI_BAG_L1	0.407	-0.126	0.438	tabular + topics
AutoGluon Multimodal Transformer	-0.044		0.013	multimodal transformer

Notes: The table reports the performance (predictive R^2) of different models for the language mapping analysis of the GDP.

Table 20: Unemployment mapping and fit performance

Model \Predictive R^2	score_test	score_val	score_train	data source
MM Neural Topic Model (non-lin)	**0.208**	**0.457**	0.285	joint MM tabular + topics
WeightedEnsemble_L2	-0.044	0.145	0.415	tabular + embeddings
NeuralNetTorch_BAG_L1	-0.152	0.122	0.313	tabular + embeddings
WeightedEnsemble_L2	-0.045	0.113	0.577	tabular + tfidf
MM Neural Topic Model (linear)	0.066	0.109	0.197	joint MM tabular + topics
CatBoost_BAG_L1	-0.055	0.104	0.690	tabular + tfidf
LightGBMXT_BAG_L1	-0.068	0.074	0.336	tabular + tfidf
NeuralNetTorch_BAG_L1	-0.029	0.070	0.394	tabular + tfidf
WeightedEnsemble_L2	0.131	0.058	0.191	tabular
WeightedEnsemble_L2	-0.010	0.053	0.278	tabular + topics
NeuralNetFastAI_BAG_L1	0.124	0.047	0.237	tabular
CatBoost_BAG_L1	0.021	0.041	0.411	tabular + embeddings
NeuralNetTorch_BAG_L1	0.106	0.033	0.098	tabular
LightGBM_BAG_L1	0.006	0.027	0.349	tabular + embeddings
LightGBM_BAG_L1	-0.035	0.025	0.316	tabular + tfidf
CatBoost_BAG_L1	-0.003	0.021	0.260	tabular + topics
CatBoost_BAG_L1	0.019	0.010	0.095	tabular
RandomForestMSE_BAG_L1	-0.072	0.008	0.868	tabular + tfidf
NeuralNetTorch_BAG_L1	-0.004	0.006	0.022	tabular + topics
XGBoost_BAG_L1	-0.112	0.006	0.883	tabular + tfidf
LightGBMLarge_BAG_L1	-0.001	0.001	0.594	tabular + embeddings
LightGBMLarge_BAG_L1	0.002	-0.003	0.109	tabular + topics
ExtraTreesMSE_BAG_L1	-0.045	-0.003	0.868	tabular + tfidf
LightGBMXT_BAG_L1	-0.001	-0.005	0.084	tabular
LightGBMXT_BAG_L1	0.000	-0.006	0.009	tabular + topics
LightGBM_BAG_L1	0.000	-0.007	0.015	tabular + topics
LightGBMXT_BAG_L1	-0.005	-0.024	0.292	tabular + embeddings
XGBoost_BAG_L1	-0.043	-0.027	0.495	tabular + topics
LightGBM_BAG_L1	-0.002	-0.028	0.170	tabular
LightGBMLarge_BAG_L1	0.013	-0.034	0.094	tabular
NeuralNetFastAI_BAG_L1	0.002	-0.036	0.565	tabular + tfidf
XGBoost_BAG_L1	-0.061	-0.041	0.624	tabular + embeddings
LightGBMLarge_BAG_L1	-0.045	-0.044	0.519	tabular + tfidf
NeuralNetFastAI_BAG_L1	-0.016	-0.058	0.025	tabular + topics
RandomForestMSE_BAG_L1	-0.005	-0.101	0.855	tabular + topics
XGBoost_BAG_L1	-0.048	-0.126	0.277	tabular
ExtraTreesMSE_BAG_L1	0.008	-0.144	0.849	tabular
ExtraTreesMSE_BAG_L1	0.049	-0.163	0.848	tabular + topics
KNeighborsUnif_BAG_L1	-0.013	-0.185	0.188	tabular + tfidf
KNeighborsUnif_BAG_L1	-0.004	-0.187	0.186	tabular
KNeighborsUnif_BAG_L1	-0.048	-0.187	0.195	tabular + topics
TextPredictor_BAG_L1	-0.067	-0.190	-0.070	tabular + embeddings
KNeighborsDist_BAG_L1	-0.003	-0.191	1.000	tabular + tfidf
RandomForestMSE_BAG_L1	-0.034	-0.192	0.842	tabular
KNeighborsDist_BAG_L1	-0.030	-0.210	1.000	tabular + topics
KNeighborsDist_BAG_L1	0.003	-0.215	1.000	tabular
OLS	-0.377		0.231	tabular
AutoGluon Multimodal Transformer	-1.177		-0.737	multimodal transformer

Notes: The table reports the performance (predictive R^2) of different models for the language mapping analysis of the unemployment.

D   Additional Results: Equity Markets, CPI Regimes

D.1   High CPI Regime

Table 21: Association between news and market volatility, equity markets, high CPI regime

Target variable: RV_e	coef	std err	z	P> |z|	[0.025	0.975]
| CPI news pos. |	0.2740	0.070	3.936	0.000	0.138	0.410
| CPI news neg. |	0.1437	0.052	2.780	0.005	0.042	0.245
| GDP news pos. |	0.0820	0.164	0.499	0.618	-0.240	0.404
| GDP news neg. |	0.0118	0.087	0.136	0.892	-0.159	0.183
| U news pos. |	9.1621	2.098	4.368	0.000	5.051	13.273
| U news neg. |	0.1683	0.076	2.215	0.027	0.019	0.317
R^2: 0.917	Adj. R^2: 0.901	n. obs.: 36	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the equity market under the high CPI regime.

Table 22: Association between news and tail risk, equity markets, high CPI regime

Target variable: TR_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	3.1074	2.184	1.423	0.155	-1.173	7.388
| News CPI neg. |	2.7033	1.791	1.509	0.131	-0.808	6.215
| News GDP pos. |	-1.5404	4.349	-0.354	0.723	-10.064	6.983
| News GDP neg. |	0.8172	1.466	0.557	0.577	-2.056	3.690
| News U pos. |	187.3136	13.601	13.772	0.000	160.657	213.970
| News U neg. |	2.3664	2.479	0.955	0.340	-2.492	7.225
R^2: 0.683	Adj. R^2: 0.619	n. obs.: 36	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of tail risk regressions for the equity market under the high CPI regime.

D.2 Low CPI Regime

Table 23: Association between news and market volatility, equity markets, low CPI regime

Target variable: RV_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.1657	0.048	3.457	0.001	0.072	0.260
| News CPI neg. |	0.1305	0.064	2.046	0.041	0.005	0.256
| News GDP pos. |	0.4317	0.170	2.546	0.011	0.099	0.764
| News GDP neg. |	0.1279	0.158	0.812	0.417	-0.181	0.437
| News U pos. |	0.1730	0.160	1.084	0.278	-0.140	0.486
| News U neg. |	0.1008	0.029	3.459	0.001	0.044	0.158
R^2: 0.774	Adj. R^2: 0.748	n. obs.: 59	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the equity market under the low CPI regime.

Table 24: Association between news and tail risk, equity markets, low CPI regime

Target variable: TR_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	1.5924	1.068	1.491	0.136	-0.500	3.685
| News CPI neg. |	1.2883	1.368	0.942	0.346	-1.393	3.970
| News GDP pos. |	10.3541	3.365	3.077	0.002	3.759	16.949
| News GDP neg. |	4.6929	2.575	1.823	0.068	-0.354	9.740
| News U pos. |	3.5833	3.297	1.087	0.277	-2.880	10.046
| News U neg. |	-0.2576	0.663	-0.388	0.698	-1.557	1.042
R^2: 0.622	Adj. R^2: 0.580	n. obs.: 59	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of tail risk regressions for the equity market under the low CPI regime.

D.3 Normal CPI Regime

Table 25: Association between news and market volatility, equity markets, normal CPI regime

Target variable: RV_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.1013	0.070	1.447	0.148	-0.036	0.238
| News CPI neg. |	0.2412	0.161	1.494	0.135	-0.075	0.558
| News GDP pos. |	0.2766	0.199	1.392	0.164	-0.113	0.666
| News GDP neg. |	0.1507	0.243	0.620	0.536	-0.326	0.627
| News U pos. |	0.7982	0.909	0.878	0.380	-0.984	2.580
| News U neg. |	0.1983	0.059	3.369	0.001	0.083	0.314
R^2: 0.771	Adj. R^2: 0.749	n. obs.: 70	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the equity market under the normal CPI regime.

Table 26: Association between news and tail risk, equity markets, normal CPI regime

Target variable: TR_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	1.5422	0.892	1.729	0.084	-0.206	3.291
| News CPI neg. |	5.2256	3.888	1.344	0.179	-2.395	12.847
| News GDP pos. |	2.6501	2.156	1.229	0.219	-1.576	6.876
| News GDP neg. |	-0.1986	2.686	-0.074	0.941	-5.463	5.066
| News U pos. |	4.6007	14.375	0.320	0.749	-23.574	32.775
| News U neg. |	2.6626	0.624	4.264	0.000	1.439	3.886
R^2: 0.593	Adj. R^2: 0.555	n. obs.: 70	Heteroscedasticity robust standard errors			

*: $p \leq 0.1$,**: $p \leq 0.05$,***: $p \leq 0.01$

Notes: The table reports the estimation results of tail risk regressions for the equity market under the normal CPI regime.

E   Additional Results: Equity Markets, GDP Regimes

E.1   High GDP Regimes

Table 27: Association between news and market volatility, equity markets, high GDP regime

Target variable: RV_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.1078	0.068	1.586	0.113	-0.025	0.241
| News CPI neg. |	0.0011	0.089	0.012	0.990	-0.173	0.175
| News GDP pos. |	0.3347	0.292	1.148	0.251	-0.237	0.906
| News GDP neg. |	0.1446	0.106	1.358	0.174	-0.064	0.353
| News U pos. |	0.2226	0.216	1.032	0.302	-0.200	0.645
| News U neg. |	0.2192	0.100	2.200	0.028	0.024	0.414
R^2: 0.578	Adj. R^2: 0.545	n. obs.: 36	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the equity market under the high GDP regime.

Table 28: Association between news and tail risk, equity markets, high GDP regime

Target variable: TR_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.9807	1.686	0.582	0.561	-2.324	4.286
| News CPI neg. |	0.1379	1.242	0.111	0.912	-2.297	2.573
| News GDP pos. |	2.0496	3.835	0.534	0.593	-5.467	9.566
| News GDP neg. |	0.9372	2.394	0.391	0.695	-3.756	5.630
| News U neg. |	4.2181	1.666	2.531	0.011	0.952	7.484
R^2: 0.652	Adj. R^2: 0.596	n. obs.: 36	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of tail risk regressions for the equity market under the high GDP regime.

E.2 Low GDP Regime

Table 29: Association between news and market volatility, equity markets, low GDP regime

Target variable: RV_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.2141	0.049	4.330	0.000	0.117	0.311
| News CPI neg. |	0.1031	0.035	2.980	0.003	0.035	0.171
| News GDP pos. |	0.5916	0.060	9.840	0.000	0.474	0.709
| News GDP neg. |	0.1953	0.071	2.767	0.006	0.057	0.334
| News U pos. |	0.5219	0.272	1.918	0.055	-0.011	1.055
| News U neg. |	0.1513	0.026	5.795	0.000	0.100	0.202
R^2: 0.796	Adj. R^2: 0.778	n. obs.: 44	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the equity market under the low GDP regime.

Table 30: Association between news and tail risk, equity markets, low GDP regime

Target variable: TR_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	-0.4354	1.289	-0.338	0.735	-2.962	2.091
| News CPI neg. |	0.2284	1.619	0.141	0.888	-2.944	3.401
| News GDP pos. |	7.3587	1.744	4.219	0.000	3.940	10.777
| News GDP neg. |	5.0831	2.958	1.718	0.086	-0.715	10.881
| News U pos. |	8.7712	4.091	2.144	0.032	0.752	16.790
| News U neg. |	1.7789	0.894	1.991	0.047	0.028	3.530
R^2: 0.565	Adj. R^2: 0.517	n. obs.: 44	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of tail risk regressions for the equity market under the low GDP regime.

E.3 Normal GDP Regime

Table 31: Association between news and market volatility, equity markets, normal GDP regime

Target variable: RV_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.1482	0.095	1.560	0.119	-0.038	0.334
| News CPI neg. |	0.1780	0.183	0.974	0.330	-0.180	0.536
| News GDP pos. |	0.5693	0.335	1.700	0.089	-0.087	1.226
| News GDP neg. |	0.3184	1.055	0.302	0.763	-1.749	2.386
| News U pos. |	0.8327	0.593	1.405	0.160	-0.329	1.994
| News U neg. |	0.1523	0.179	0.853	0.394	-0.198	0.502
R^2: 0.858	Adj. R^2: 0.811	n. obs.: 81	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the equity market under the normal GDP regime.

Table 32: Association between news and tail risk, equity markets, normal GDP regime

Target variable: TR_e	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	2.4965	1.133	2.204	0.028	0.276	4.717
| News CPI neg. |	1.3217	2.863	0.462	0.644	-4.290	6.934
| News GDP pos. |	6.0009	5.160	1.163	0.245	-4.112	16.114
| News GDP neg. |	2.0084	5.287	0.380	0.704	-8.354	12.370
| News U pos. |	2.6617	3.787	0.703	0.482	-4.760	10.084
| News U neg. |	1.9410	2.169	0.895	0.371	-2.311	6.193
R^2: 0.546	Adj. R^2: 0.496	n. obs.: 81	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of tail risk regressions for the equity market under the normal GDP regime.

F   Additional Results: Bond Markets, CPI Regimes

F.1   High CPI Regime

Table 33: Association between news and market volatility, 2-year bonds, high CPI regime

Target variable: $RV_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0008	0.008	0.101	0.920	-0.015	0.017
| News CPI neg. |	-0.0069	0.008	-0.862	0.389	-0.023	0.009
| News GDP pos. |	0.0730	0.039	1.849	0.064	-0.004	0.150
| News GDP neg. |	0.0014	0.021	0.066	0.947	-0.039	0.042
| News U pos. |	0	0	nan	nan	0	0
| News U neg. |	0.0242	0.012	2.042	0.041	0.001	0.047
R^2: 0.830	Adj. R^2: 0.802	n. obs.: 33	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (2-year bonds) under the high CPI regime.

Table 34: Association between news and market volatility, 5-year bonds, high CPI regime

Target variable: $RV_{b,5y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	-0.0378	0.027	-1.418	0.156	-0.090	0.014
| News CPI neg. |	-0.0383	0.023	-1.668	0.095	-0.083	0.007
| News GDP pos. |	0.1472	0.118	1.245	0.213	-0.085	0.379
| News GDP neg. |	-0.0155	0.052	-0.299	0.765	-0.117	0.086
| News U pos. |	0	0	nan	nan	0	0
| News U neg. |	0.0876	0.039	2.248	0.025	0.011	0.164
R^2: 0.715	Adj. R^2: 0.655	n. obs.: 33	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (5-year bonds) under the high CPI regime.

Table 35: Association between news and market volatility, 10-year bonds, high CPI regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	-0.0410	0.036	-1.126	0.260	-0.112	0.030
| News CPI neg. |	-0.0499	0.037	-1.335	0.182	-0.123	0.023
| News GDP pos. |	0.2627	0.179	1.465	0.143	-0.089	0.614
| News GDP neg. |	-0.0118	0.087	-0.136	0.892	-0.182	0.158
| News U pos. |	0	0	nan	nan	0	0
| News U neg. |	0.1311	0.057	2.309	0.021	0.020	0.242
R^2: 0.799	Adj. R^2: 0.733	n. obs.: 33	Heteroscedasticity robust standard errors			

 Notes: The table reports the estimation results of volatility regressions for the bond market (10-year bonds) under the high CPI regime.

F.2   Low CPI Regime

Table 36: Association between news and market volatility, 2-year bonds, low CPI regime

Target variable: $RV_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI neg. |	-0.0161	0.015	-1.075	0.283	-0.045	0.013
| News GDP pos. |	0.0334	0.007	4.882	0.000	0.020	0.047
| News GDP neg. |	0.0115	0.014	0.850	0.395	-0.015	0.038
| News U pos. |	0.0468	0.031	1.508	0.131	-0.014	0.108
| News U neg. |	0.0250	0.006	4.519	0.000	0.014	0.036
R^2: 0.70	Adj. R^2: 0.660	n. obs.: 42	Heteroscedasticity robust standard errors			

 Notes: The table reports the estimation results of volatility regressions for the bond market (2-year bonds) under the low CPI regime.

Table 37: Association between news and market volatility, 5-year bonds, low CPI regime

Target variable: $RV_{b,5y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI neg. |	-0.0360	0.030	-1.186	0.236	-0.095	0.023
| News GDP pos. |	0.0789	0.015	5.352	0.000	0.050	0.108
| News GDP neg. |	0.0342	0.031	1.106	0.269	-0.026	0.095
| News U pos. |	0.1268	0.063	2.005	0.045	0.003	0.251
| News U neg. |	0.0521	0.012	4.296	0.000	0.028	0.076
R^2: 0.691	Adj. R^2: 0.649	n. obs.: 42	Heteroscedasticity robust standard errors			

 Notes: The table reports the estimation results of volatility regressions for the bond market (5-year bonds) under the low CPI regime.

Table 38: Association between news and market volatility, 10-year bonds, low CPI regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI neg. |	-0.0657	0.043	-1.511	0.131	-0.151	0.020
| News GDP pos. |	0.1629	0.026	6.207	0.000	0.111	0.214
| News GDP neg. |	0.0695	0.048	1.448	0.148	-0.025	0.164
| News U pos. |	0.2607	0.102	2.550	0.011	0.060	0.461
| News U neg. |	0.0835	0.018	4.598	0.000	0.048	0.119
R^2: 0.767	Adj. R^2: 0.735	n. obs.: 42	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (10-year bonds) under the low CPI regime.

F.3 Normal CPI Regime

Table 39: Association between news and market volatility, 2-year bonds, normal CPI regime

Target variable: $RV_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0069	0.006	1.165	0.244	-0.005	0.019
| News CPI neg. |	0.0112	0.018	0.624	0.533	-0.024	0.046
| News GDP pos. |	0.0102	0.013	0.785	0.433	-0.015	0.036
| News GDP neg. |	0.0088	0.028	0.319	0.750	-0.045	0.063
| News U pos. |	0.0719	0.063	1.140	0.254	-0.052	0.196
| News U neg. |	0.0221	0.006	3.702	0.000	0.010	0.034
R^2: 0.811	Adj. R^2: 0.716	n. obs.: 52	Heteroscedasticity robust standard errors			

20 basis point buffer to each extreme regime

Notes: The table reports the estimation results of volatility regressions for the bond market (2-year bonds) under the normal CPI regime.

Table 40: Association between news and market volatility, 5-year bonds, normal CPI regime

Target variable: $RV_{b,5y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0155	0.017	0.910	0.363	-0.018	0.049
| News CPI neg. |	0.0356	0.041	0.878	0.380	-0.044	0.115
| News GDP pos. |	0.0160	0.035	0.457	0.648	-0.053	0.085
| News GDP neg. |	0.0248	0.081	0.305	0.760	-0.134	0.184
| News U pos. |	0.1808	0.204	0.887	0.375	-0.219	0.580
| News U neg. |	0.0409	0.011	3.712	0.000	0.019	0.062

R^2: 0.737	Adj. R^2: 0.703	n. obs.: 52	Heteroscedasticity robust standard errors

20 basis point buffer to each extreme regime

Notes: The table reports the estimation results of volatility regressions for the bond market (5-year bonds) under the normal CPI regime.

Table 41: Association between news and market volatility, 10-year bonds, normal CPI regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0324	0.025	1.276	0.202	-0.017	0.082
| News CPI neg. |	0.0752	0.059	1.276	0.202	-0.040	0.191
| News GDP pos. |	0.0473	0.052	0.908	0.364	-0.055	0.150
| News GDP neg. |	0.0316	0.124	0.255	0.799	-0.211	0.274
| News U pos. |	0.2868	0.349	0.822	0.411	-0.397	0.970
| News U neg. |	0.0705	0.019	3.744	0.000	0.034	0.107

R^2: 0.767	Adj. R^2: 0.735	n. obs.: 52	Heteroscedasticity robust standard errors

20 basis point buffer to each extreme regime

Notes: The table reports the estimation results of volatility regressions for the bond market (10-year bonds) under the normal CPI regime.

G   Additional Results: Bond Markets, GDP Regimes

G.1   High GDP Regime

Table 42: Association between news and market volatility, 2-year bonds, high GDP regime

Target variable: $RV_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0130	0.005	2.653	0.008	0.003	0.023
| News CPI neg. |	0.0142	0.008	1.865	0.062	-0.001	0.029
| News GDP pos. |	0.0250	0.028	0.890	0.373	-0.030	0.080
| News GDP neg. |	0.0034	0.024	0.145	0.885	-0.043	0.050
| News U neg. |	0.0156	0.009	1.734	0.083	-0.002	0.033
R^2: 0.783	Adj. R^2: 0.747	n. obs.: 35	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (2-year bonds) under the high GDP regime.

Table 43: Association between news and market volatility, 5-year bonds, high GDP regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0162	0.014	1.135	0.257	-0.012	0.044
| News CPI neg. |	0.0358	0.020	1.825	0.068	-0.003	0.074
| News GDP pos. |	0.0327	0.060	0.546	0.585	-0.085	0.150
| News GDP neg. |	0.0015	0.052	0.028	0.977	-0.099	0.102
| News U neg. |	0.0335	0.024	1.394	0.163	-0.014	0.081
R^2: 0.641	Adj. R^2: 0.581	n. obs.: 35	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (5-year bonds) under the high GDP regime.

Table 44: Association between news and market volatility, 10-year bonds, high GDP regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0242	0.021	1.161	0.246	-0.017	0.065
| News CPI neg. |	0.0486	0.032	1.505	0.132	-0.015	0.112
| News GDP pos. |	0.0834	0.111	0.753	0.452	-0.134	0.301
| News GDP neg. |	0.0079	0.096	0.082	0.934	-0.181	0.197
| News U neg. |	0.0710	0.039	1.797	0.072	-0.006	0.148
R^2: 0.731	Adj. R^2: 0.687	n. obs.: 35	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (10-year bonds) under the high GDP regime.

G.2 Low GDP Regime

Table 45: Association between news and market volatility, 2-year bonds, low GDP regime

Target variable: $RV_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
	News CPI neg.		-0.0161	0.015	-1.075	0.283	-0.045	0.013
	News GDP pos.		0.0334	0.007	4.882	0.000	0.020	0.047
	News GDP neg.		0.0115	0.014	0.850	0.395	-0.015	0.038
	News U pos.		0.0468	0.031	1.508	0.131	-0.014	0.108
	News U neg.		0.0250	0.006	4.519	0.000	0.014	0.036
R^2: 0.700	Adj. R^2: 0.660	n. obs.: 42	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (2-year bonds) under the low GDP regime.

Table 46: Association between news and market volatility, 5-year bonds, low GDP regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
	News CPI neg.		-0.0360	0.030	-1.186	0.236	-0.095	0.023
	News GDP pos.		0.0789	0.015	5.352	0.000	0.050	0.108
	News GDP neg.		0.0342	0.031	1.106	0.269	-0.026	0.095
	News U pos.		0.1268	0.063	2.005	0.045	0.003	0.251
	News U neg.		0.0521	0.012	4.296	0.000	0.028	0.076
R^2: 0.691	Adj. R^2: 0.649	n. obs.: 42	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (5-year bonds) under the low GDP regime.

Table 47: Association between news and market volatility, 10-year bonds, low GDP regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
	News CPI neg.		-0.0657	0.043	-1.511	0.131	-0.151	0.020
	News GDP pos.		0.1629	0.026	6.207	0.000	0.111	0.214
	News GDP neg.		0.0695	0.048	1.448	0.148	-0.025	0.164
	News U pos.		0.2607	0.102	2.550	0.011	0.060	0.461
	News U neg.		0.0835	0.018	4.598	0.000	0.048	0.119
R^2: 0.767	Adj. R^2: 0.735	n. obs.: 42	Heteroscedasticity robust standard errors			

Notes: The table reports the estimation results of volatility regressions for the bond market (10-year bonds) under the low GDP regime.

G.3 Normal GDP Regime

Table 48: Association between news and market volatility, 2-year bonds, normal GDP regime

Target variable: $RV_{b,2y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0212	0.006	3.432	0.001	0.009	0.033
| News CPI neg. |	0.0032	0.014	0.220	0.826	-0.025	0.031
| News GDP pos. |	0.0406	0.035	1.154	0.248	-0.028	0.110
| News GDP neg. |	0.0215	0.037	0.579	0.563	-0.051	0.094
| News U pos. |	0.0051	0.017	0.301	0.763	-0.028	0.038
| News U neg. |	0.0162	0.015	1.058	0.290	-0.014	0.046
R^2: 0.658	Adj. R^2: 0.613	n. obs.: 52	Heteroscedasticity robust standard errors			

20 basis point buffer to each extreme regime

Notes: The table reports the estimation results of volatility regressions for the bond market (2-year bonds) under the normal GDP regime.

Table 49: Association between news and market volatility, 5-year bonds, normal GDP regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0163	0.013	1.245	0.213	-0.009	0.042
| News CPI neg. |	0.0010	0.034	0.030	0.976	-0.065	0.067
| News GDP pos. |	0.0247	0.094	0.264	0.792	-0.159	0.208
| News GDP neg. |	0.0459	0.081	0.567	0.571	-0.113	0.205
| News U pos. |	0.0345	0.039	0.874	0.382	-0.043	0.112
| News U neg. |	0.0486	0.041	1.180	0.238	-0.032	0.129
R^2: 0.516	Adj. R^2: 0.453	n. obs.: 52	Heteroscedasticity robust standard errors			

20 basis point buffer to each extreme regime

Notes: The table reports the estimation results of volatility regressions for the bond market (5-year bonds) under the normal GDP regime.

Table 50: Association between news and market volatility, 10-year bonds, normal GDP regime

Target variable: $RV_{b,10y}$	coef	std err	z	P> |z|	[0.025	0.975]
| News CPI pos. |	0.0415	0.026	1.607	0.108	-0.009	0.092
| News CPI neg. |	0.0005	0.056	0.009	0.993	-0.110	0.111
| News GDP pos. |	0.0595	0.153	0.390	0.696	-0.239	0.358
| News GDP neg. |	0.0811	0.143	0.566	0.572	-0.200	0.362
| News U pos. |	0.0600	0.073	0.821	0.412	-0.083	0.203
| News U neg. |	0.0808	0.067	1.205	0.228	-0.051	0.212

R^2: 0.543	Adj. R^2: 0.483	n. obs.: 52	Heteroscedasticity robust standard errors

20 basis point buffer to each extreme regime

Notes: The table reports the estimation results of volatility regressions for the bond market (10-year bonds) under the normal GDP regime.