The Effects of Information Gaps in Central Bank Communications*

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Abstract

This paper shows that information gaps about the likely path of future interest rates between the Federal Open Market Committee (FOMC) meeting minutes and public speeches by the Chair and Vice Chair account for fluctuations in bond markets and the macroeconomy. I estimate a relationship between the text of public speeches and the high-frequency change in financial market expectations of future interest rates around these speeches. I measure information gaps as the differential information about the likely path of future interest rates between the public speeches and the private FOMC meeting minutes. In an event study, I show that these information gaps account for 11% of the variation in surprises in financial market expectations of future interest rates, which has a persistent effect along the yield curve. Using a structural vector autoregression identified with external instruments, I find that information gap surprises have persistent macroeconomic effects. I explain my results through a model in which central bank communications are inaccurate signals of their reaction function and the real rate of interest.

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1 Introduction

Since the early 1990s, central banks have increasingly used public communication to influence financial market expectations about future interest rates (Blinder, 2018). This communication channel is important for central banks, as these expectations permeate the broader economy, affecting household saving and firm investment decisions. However, conveying the complexities of likely future policy is challenging (Yellen, 2012), which can result in *information gaps* between public statements and the discussions held in private policy meetings. These gaps may distort market expectations, generating volatility in both financial markets and the macroeconomy.

In this paper, I examine information gaps regarding future interest rates using communications from the U.S. Federal Reserve (Fed). The Federal Open Market Committee (FOMC) meets eight times a year to discuss changes to current and likely future monetary policy, communicating the outcome through a speech called the FOMC announcement. Additionally, regularly held press conferences and speeches between policy meetings provide insights into the Fed's likely future actions. Several weeks after each policy meeting, a comprehensive summary called the FOMC minutes is released, which often contains information not communicated through previous channels (Swanson and Jayawickrema, 2023). I exploit this staggered release of detailed information to measure information gaps about future interest rates by comparing the textual information of public speeches to the FOMC minutes. I assume the FOMC minutes represent the central bank's knowledge about the likely path of future interest rates, and that speeches (FOMC announcements, press conferences, and intermeeting speeches) are a relatively less precise signal of this information.

I use two kinds of data to measure information gaps: the types and frequencies of language used in public speeches, and the high-frequency financial market reactions to these speeches. I measure how market expectations of future interest rates change in small time intervals around speech events, following the method of Swanson (2024). I estimate a relationship between these market reactions and the text of public speeches using a language model called Hurdle Distributed Multinomial Regression (Kelly, Manela, and Moreira, 2021). This approach allows me to quantify the information conveyed through language based on how financial markets respond to speeches. I then use this estimated relationship to construct textual information scores regarding the path of interest rates for both public speeches and the FOMC minutes. I define information gaps regarding future interest rates as the difference in textual information scores between a speech and the FOMC minutes. Importantly, these gaps are not observed by market participants in real time. If a speech signals a higher (lower) path for future interest rates compared to the minutes, the information gap for that speech is considered hawkish (dovish).

In an event study, I find that information gaps explain 11% of the variation in high-frequency changes to financial market expectations of future interest rates. Additionally, information gaps significantly impact the yield curve, with the strongest effect observed on 2-year Treasury bonds, which diminishes progressively up to 10-year bonds. I then use my information gap measure as a source of exogenous variation in the two-year Treasury yield within a structural vector autoregression. The results indicate that a surprise hawkish information gap leads to an increase in two-year Treasury yields, a decrease in inflation, and a rise in perceived financial market risk, along with a small but positive short-term increase in output. These effects persist for several months, suggesting that the influence of information gaps extends well beyond the immediate period surrounding communication events.

I explain my results with a model of imperfect information, in which the central bank imprecisely communicates details about its reaction function and the real interest rate. In this model, information gaps arise because increasing the precision of communication is assumed to be costly. With finite resources that can be allocated to communication—such as time or effort—communications will sometimes contain information gaps, even if they are accurate on average. The private sector consists of rational Bayesians who optimally update their beliefs in response to these signals using the Kalman filter. Since information gaps are not observed by the private sector in real time, they can influence rational expectations of future interest rates. My model predicts that information gaps in communications should have the same impact on market responses as changes in fundamental economic conditions, as markets are unable to distinguish between these two components, and that these effects persist along the yield curve. In my empirical work, I measure these information gaps as the textual information difference between public speeches and the detailed private FOMC minutes. I also confirm through event study regressions that information gaps, along with a residual "non-information gap" analogous to changes in fundamental economic conditions, have a statistically similar effect in financial markets, and these effects persist along the yield curve.

My research shows that information gaps in speeches account for variation in bond markets within small windows around speech events. If my information gap measure reflects the cost of producing and disseminating complex central bank communications, then technological innovations that enhance the ability to draft more precise and detailed communications could help mitigate the market volatility driven by these information gaps.

1.1 Related Literature

A large body of literature uses high-frequency market data to measure surprises to private sector expectations, serving as an empirical proxy for monetary policy shocks. Some studies focus on interest rate surprises at specific horizons (Kuttner, 2001; Kohn and Sack, 2003; Bernanke et al., 2004; Gertler and Karadi, 2015), while others summarise expectations across multiple horizons to study changes in the expected path of rates (Gürkaynak et al., 2005; Nakamura and Steinsson, 2018; Swanson and Jayawickrema, 2023; Swanson, 2024). I adopt the latter approach, as information gaps can influence both short-term and long-term policy, both of which are important for understanding the role of communications in shaping market expectations.

Some studies have estimated language models using central bank text to predict economic outcomes. Handlan (2022) develops a language model to predict market responses to FOMC announcement text and exploits the alternative phrasings of these announcements to identify forward guidance surprises. Ahrens et al. (2023) estimates a relationship between forecasts and the text in the Fed's Greenbook, then uses this relationship to predict information effects stemming from communications. They find that communications do not always reduce uncertainty. I reach a similar conclusion, but through the lens of how information gaps influence market expectations.

One approach to evaluating central bank communications is to examine their accessibility to a broader audience (McMahon and Naylor, 2023), the role of media pass-through in influencing market responses (Ehrmann and Talmi, 2020; Ter Ellen et al., 2022), or how professional forecasters interpret the central bank's communications (Gáti and Handlan, 2022). Another relevant strand of literature compares the textual information contained in public communications with that in private central bank documents. A common method for measuring monetary policy signals involves dictionary approaches, where researchers classify language as hawkish or dovish to construct a net hawkish-dovish sentiment score. Using this methodology, Cieslak and McMahon (2024) demonstrate that the sentiment of FOMC transcripts is reflected in a wide range of intermeeting speeches, which has implications for risk premia during the intermeeting period. Similarly, Tadle (2022) document that FOMC announcements and FOMC minutes have a similar textual sentiment. Acosta (2023) measures central bank transparency through a textual similarity metric between topics in FOMC minutes and transcripts, showing that increased transparency mitigates policy surprises related to FOMC announcements. I extend this line of research by investigating the properties of an information gap concerning future interest rates, using the delayed release of detailed meeting minutes compared to relatively less detailed speeches. Additionally, I adopt a data-driven approach to measure the information conveyed in text regarding interest rate expectations with financial market data.

More broadly, my paper fits into the literature studying how information, sentiment and beliefs can affect economic outcomes (Beaudry and Portier, 2006; Farmer, 1999, 2012, 2013). Several papers have examined the optimal disclosure and obfuscation of central bank information to influence economic outcomes (Morris and Shin, 2002; Amador and Weill, 2010; Eusepi and Preston, 2010; Iovino, La'O, and Mascarenhas, 2022). Yet, Reis (2013) argues that there is a lack of empirical evidence to support such strategic obfuscation, and it is the timing and form of central bank communications that matter. Bianchi and Melosi (2018) argue that welfare is higher when the central bank is transparent about its policy regime. Additionally, Ehrmann and Fratzscher (2005) found that increasing the scope of communications—when the Fed publicly released balance-of-risk assessments of FOMC members in 1999—lowered financial market volatility.

My paper touches on an ongoing debate in the literature regarding the empirical identification of monetary policy shocks. On the one hand, central bank communications and policy actions may reflect the central bank's internal forecasts about future economic conditions (Melosi, 2016; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021). On the other hand, Bauer and Swanson (2023a,b) argue that the information effects of such communications are likely small on average, suggesting that the private sector probably possesses imperfect information about how the central bank responds to economic conditions. My textual information gap measure is sufficiently broad to capture differential information about both expected future states and the central bank's responsiveness. I investigate a general failure of complete information between central banks and the private sector, focusing on how these information gaps in communications contribute to surprises in financial market interest rate expectations.

The remainder of my paper is structured as follows: Section 2 presents a model illustrating how information gaps can influence interest rate expectations and inflation. Section

3 describes the dataset I construct, which combines text and high-frequency financial market data. Section 4 outlines the textual analysis method used to measure information about future interest rates from the text data. Section 5 presents my main event study findings and macroeconomic results. Finally, Section 6 concludes the paper.

2 A Model of Central Bank Communication

In this section, I present a model to explain the financial market effects of information gaps in central bank communications. I start with a log-linearised neo-Fisherian model of price determination then introduce information asymmetries between the central bank and the private sector, giving a role for communicating.[1]

2.1 Log-Linearised Model

The log-linearised Fisher equation is the equilibrium relationship for the private sector. It models the nominal interest rate, i_t, in terms of the percentage deviation in the equilibrium real rate of return, r_t and the period t expectation of period $t+1$ log inflation, $\mathbb{E}_t\left[\pi_{t+1}\right]$, with

$$i_t = r_t + \mathbb{E}_t[\pi_{t+1}]. \tag{1}$$

The Fisher equation is a behavioural relationship, not simply an accounting identity. This is because it can be derived as an approximation to the optimality condition of households (Woodford, 2003). The real rate of return is modelled as a persistent exogenous process, independent of monetary policy, defined as

$$r_t = \rho r_{t-1} + \varepsilon_t^r, \tag{2}$$

where $\varepsilon_t^r \sim N(0, \sigma_r^2)$. The parameter $\rho \in (0, 1)$ determines the geometric slope of the yield curve in this model. The central bank sets nominal interest rates in response to inflation with the reaction function

$$i_t = \phi_t \pi_t, \tag{3}$$

[1]The non-linear setup is available in the appendix, A.1.

where ϕ_t is the central bank's time-varying responsiveness to inflation. Suppose this responsiveness is predetermined by one period following the process

$$\phi_{t+1} = \phi_t + \varepsilon_t^{\phi}, \tag{4}$$

where $\varepsilon_t^{\phi} \sim N(0, \sigma_{\phi}^2)$.[2] In practice, the central bank's responsiveness to the state of the economy may depend on the composition of central bank committees, changes in relative risk assessments, or, in the longer term, through economic research that influences the conduct of optimal monetary policy.[3]

Inflation is determined by the nominal interest rate, which must satisfy both the Fisher equation and the reaction function. Importantly for my application, the Fisher equation is forward-looking, which means the nominal interest rate depends not only on the current state of the economy, but also on the expected sequence of reaction functions and real interest rates. If the private sector perfectly observes the predetermined reaction function and the real interest rate, then equations (2) and (4) can be used to form full-information rational expectations about the sequence of future policy.

In practice, the importance of central bank communication arises because the private sector does not fully know how the central bank will set future policy. In my model, the two terms in the reaction function are the responsiveness coefficient and inflation. Therefore, information asymmetries about future policy could stem from one or both of these variables.

I introduce a role for central bank communication by assuming the following structure for the information sets of the central bank and the private sector. I assume the central bank is always perfectly informed about the reaction function and the real interest rate. At the end of period $t-1$, after markets have cleared, nature reveals ϕ_t and r_{t-1} to the private sector.[4] At the start of period t, both r_t and ϕ_{t+1} are determined but not observed by the private

[2] Bauer and Swanson (2023b) also assume a random walk process for a time-varying reaction function coefficient for simplicity. The Taylor principle, $\phi_t > 1$, can be imposed to ensure that monetary policy is always active with appropriate transformations. This complicates the algebra without adding to the intuition of the result, so I do not impose this here. In what follows, the model should be viewed as a local analysis for when $\phi_t > 1 \ \forall t$.

[3] Evidence of time-varying responsiveness has been shown in several studies. For example, Beyer and Farmer (2007) demonstrate a structural change from passive to active monetary policy pre- and post-Volcker at the end of the 1970s. Bauer and Swanson (2023b) argue that responsiveness has trended upward since the 1990s, and Cogley and Sargent (2005) show that responsiveness can display large fluctuations in short time periods.

[4] This could be thought of as the release of the FOMC minutes in terms of my empirical set-up.

sector, who instead forms rational prior beliefs about these unobserved state variables using the transition equation

$$\begin{bmatrix} r_t \\ \phi_{t+1} \end{bmatrix} = \begin{bmatrix} \rho & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} r_{t-1} \\ \phi_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^r \\ \varepsilon_t^\phi \end{bmatrix}. \tag{5}$$

Therefore, at the start of period t, the prior beliefs are ρr_{t-1} for the real interest rate and ϕ_t for the reaction function responsiveness. At this point, the central bank releases public communications in the form of noisy signals about ϕ_{t+1} and r_t, represented by the private sector's observation equation

$$\begin{bmatrix} s_t^r \\ s_t^\phi \end{bmatrix} = \begin{bmatrix} r_t \\ \phi_{t+1} \end{bmatrix} + \begin{bmatrix} z_t^r \\ z_t^\phi \end{bmatrix}, \tag{6}$$

where $z_t^r \sim N(0, \sigma_{zr}^2)$ and $z_t^\phi \sim N(0, \sigma_{z\phi}^2)$ are the information gaps about the real interest rate and reaction function responsiveness, respectively. Importantly, z_t^r and z_t^ϕ cannot be observed by the private sector in period t. I show in the appendix, A.3, that information gaps arise in an environment where the central bank communicates in such a way as to minimise the private sector's forecast errors, but it is costly to increase the precision of communications. The solution to this problem is independent of the rest of the model, so I proceed with $\sigma_{zr}^2, \sigma_{z\phi}^2 > 0$ taken as given.

I am assuming that the central bank's signals are unbiased and, on average, the communications are correct. This 'truth plus white noise' representation of incomplete information is a commonly used approach (Lucas Jr., 1973; Pearlman et al., 1986; Blanchard et al., 2013; Haldane et al., 2020). After observing the communications, the private sector updates its prior beliefs with the Kalman filter to form the optimal posterior beliefs given by

$$r_{t|t} = (1 - k_r)\rho r_{t-1} + k_r s_t^r, \tag{7}$$

and

$$\phi_{t+1|t} = (1 - k_\phi)\phi_t + k_\phi s_t^\phi, \tag{8}$$

which are rational expectations for the private sector under imperfect information.[5] The notation $x_{n|t}$ denotes expectations for x_n formed in period t using the Kalman filter. The Kalman gains, k_r and k_ϕ, are real numbers in $(0, 1)$ given by

[5]Since I model r_t and ϕ_{t+1} as stochastic processes independent from each other and the rest of the model, the Kalman filter is appropriate to derive optimal beliefs.

$$k_r = \frac{\sigma_r^2}{\sigma_r^2 + \sigma_{zr}^2}, \quad k_\phi = \frac{\sigma_\phi^2}{\sigma_\phi^2 + \sigma_{z\phi}^2}. \tag{9}$$

Intuitively, the Kalman gains represent the fraction of the variation in the communication attributed to changes in the unobserved state variable, and they are the optimal weight to place on the communications in the belief update step.[6]

The forward solution for the nominal interest rate to a first-order approximation can be written as

$$i_t \approx \frac{\phi_{t+1|t}}{\phi_{t+1|t} - \rho} r_{t|t}. \tag{10}$$

Therefore, inflation consistent with this nominal interest rate, must be

$$\pi_t = \frac{1}{\phi_t} \frac{\phi_{t+1|t}}{\phi_{t+1|t} - \rho} r_{t|t}. \tag{11}$$

The solutions to my model are given by equations (10) and (11).[7] These equations show that the equilibrium under imperfect information depends on the beliefs formed about the reaction function and real interest rate from the communication signals released by the central bank.

From equation (10), the total change in the equilibrium nominal interest rate in response to the communications s_t^r and s_t^ϕ can be written as

$$di_t = \underbrace{\left(\omega_{1t}\, dz_t^\phi + \omega_{2t}\, dz_t^r\right)}_{\text{information gap}} + \underbrace{\left(\omega_{1t}\, d\phi_{t+1} + \omega_{2t}\, dz_t^r\right)}_{\text{non-information gap}}. \tag{12}$$

where the weights ω_{1t} and ω_{2t} are given by

$$\omega_{1t} = \frac{\phi_{t+1|t}}{\phi_{t+1|t} - \rho} k_r\,, \quad \omega_{2t} = -\frac{\rho r_{t|t}}{(\phi_{t+1|t} - \rho)^2} k_\phi. \tag{13}$$

Communications about future policy affect current interest rates through the Fisher equation being forward-looking and depending on the entire path of expected interest rates, called the yield curve. The effect of a communication on the yield curve can be seen from the j-step ahead interest rate expectation, up to a first order, with

[6]For more detail on the Kalman filter, see Hamilton (1994) or Baley and Veldkamp (2023).
[7]Derivations are in the Appendix.

$$\mathbb{E}_t\left[i_{t+j}\right] \approx \rho^j \frac{\phi_{t+1|t}}{\phi_{t+1|t} - \rho} r_{t|t}. \tag{14}$$

Then, the total change in interest rate expectations from the communications is

$$d\mathbb{E}_t\left[i_{t+j}\right] = \rho^j \left(\omega_{1t}(dr_t + dz_t^r) + \omega_{2t}(d\phi_{t+1} + dz_t^{\phi})\right) = \rho^j di_t. \tag{15}$$

This last equation shows that a communication in period t affects the path of expected interest rates by an amount the depends on the change in the period t equilibrium nominal rate.

My model predicts that the effect on interest rate expectations from an actual change in the reaction function responsiveness or real interest rates, is the same as the effect from the information gap. This is due to the private sector's inability to disentangle the information gap from the communication signals. As the nominal interest rate depends on the variables within the reaction function, information gaps regarding these variables can influence interest rate expectations. My empirical work does not separately identify information gaps related to responsiveness and the economic outlook. Instead, I compare the overall information content regarding future interest rates derived from communications with private central bank information, which implicitly encompasses both responsiveness and the economic outlook.

Specifically, in the context of the model, my empirical work decomposes the response to communications observed in financial markets—analogous to the left-hand side of (12), into an information gap component (analogous to dz_t^{ϕ} and dz_t^r) and a non-information gap component (analogous to $d\phi_{t+1}$ and dr_t). My model predicts that a hawkish information gap has a persistent and diminishing effect along the yield curve. Moreover, my model suggests that both the information gap and non-information gap components should have the same effect on interest rate expectations. I verify these predictions through an event study analysis.

3 Data

In this section, I describe how I construct my dataset, which uses text and high-frequency financial market data, to estimate a relationship between the textual information and market outcomes.

3.1 Text Data

The speech events I study are FOMC announcements, press conferences, and intermeeting speeches by the Chair and Vice Chair from February 1993 to December 2019. FOMC announcements are the first speeches following FOMC meetings; however, they are not particularly detailed, typically a few hundred words long. Since April 2011, press conferences are conducted after every other meeting, approximately an hour after the initial FOMC announcements. Intermeeting speeches cover a wide range of topics, including providing additional clarity on the conduct of monetary policy, testimony to Congress and the Senate, commentary on the state of the economy, and various administrative speeches that likely contain little to no news regarding monetary policy. Swanson and Jayawickrema (2023) show intermeeting speeches contain important information about the likely path of future interest rates, based off the financial market response to these speeches.

There are 218 FOMC meeting minutes from February 1993 to December 2019. From February 1993 to November 2004, the minutes were released shortly after the subsequent FOMC meeting. Since December 2004, the minutes have been made available three weeks after the FOMC meeting. Despite this delay, the release of the minutes often generates financial market responses. This suggests that there is information in the minutes that is not communicated through other channels beforehand, implying there are information gaps between the minutes and previous communications.

The FOMC minutes provide a detailed account of how specific dimensions of the economy influenced policy decisions and contain information regarding the reaction function and the economic outlook. I interpret the minutes as a precise signal of information that the central bank wishes the public to possess.[8] However, due to their complexity, they require additional time to prepare and are therefore released several weeks after the FOMC meeting. The purpose of the minutes, as stated on the Federal Reserve's website, is:

> *"The minutes of each regularly scheduled meeting of the Committee provide a timely summary of significant policy issues addressed by meeting participants. The minutes record all decisions taken by the Committee with respect to these policy issues and explain the reasoning behind these decisions."*

[8]This contrasts with the FOMC meeting transcripts, which are released with a long delay of five years to promote open discussion within the FOMC, and likely captures more debate and 'spitballing' of ideas that may ultimately have little bearing on the chosen policy stance. In contrast, the minutes are constructed to be an informative signal of the key points from the FOMC meeting.

Intermeeting speeches, press conferences, and FOMC announcements generally have a narrower scope compared to the FOMC minutes, both in terms of length and the range of topics discussed. Speeches may emphasise certain points more or less than the FOMC minutes or focus on entirely different subjects. The difference in meaning for future monetary policy between these two types of text is what I refer to as an information gap.

Text data is unstructured in its raw format, and preprocessing is a necessary step for use in an empirical analysis. In the appendix I describe the steps I take for cleaning the text data of speeches and minutes for use in the econometric analysis.

3.2 Financial Market Data

I use financial market data to measure changes in expectations in small time windows around a communication event, which relies on several key assumptions. First, it is assumed that financial markets react optimally to the information conveyed by the communication. For example, if a communication signals something to the markets that they already know, then market prices should not change. Second, there should be no other event within this small time window that could influence financial markets. Third, markets react quickly to this information so that changes in prices during the selected small time window accurately capture the effect of the communication.

The financial market contracts I use to measure market expectations are federal fund rate futures and Eurodollar futures.[9] Federal fund futures measure market beliefs about the target federal funds rate, while Eurodollar futures measure expected interest rates at longer horizons. Federal funds futures represent the expected average federal funds rate for the month in which the contract expires. I use only the current month's federal funds rate futures to measure surprises in the policy target.[10] Eurodollar futures expire on a predetermined date each quarter, with their price reflecting expected interest rates at that time.

For example, the first Eurodollar contract is the one that expires soonest and measures interest rate expectations for the current quarter. The second Eurodollar contract expires in the following quarter on a set date and measures expected interest rates for the next quarter,

[9] Eurodollar futures contracts are not related to the Euro or United States Dollar currencies, despite their naming. Data for surprises in federal fund futures around FOMC announcements are gratefully obtained from Marek Jarocinski's website.

[10] As described in past papers (Gürkaynak et al., 2005), the federal funds futures contract price reflects the average effective federal funds rate within the month, and the surprise must be adjusted based on the day of the month the announcement occurred.

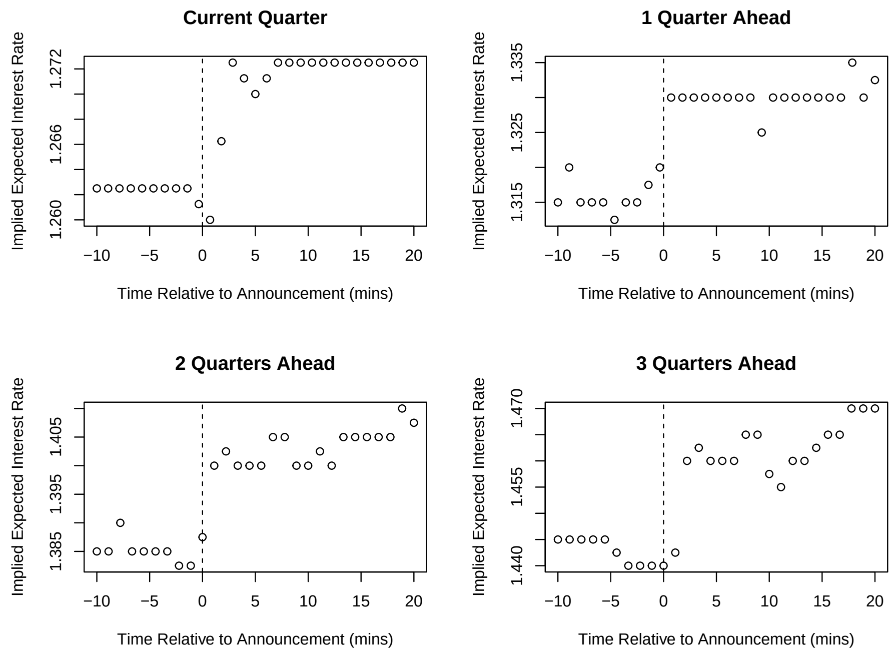


Figure 1: Market response to the FOMC announcement on 14th June, 2017 at 13:00 EST, where the target federal funds rate increased from 1 to 1.25 percentage points.

and so forth. I use the first four Eurodollar futures contracts to measure the path of expected interest rates up to one year ahead. Using notation commonly found in the literature, let $MP1$ denote the change in the current month's federal funds future, and $ED1$ to $ED4$ denote the changes in the first four Eurodollar futures contracts.

An example of this event study approach is shown in Figure 1 with the first four Eurodollar futures. The horizontal axis represents a 30-minute window around an FOMC announcement, while the vertical axis denotes the implied expected interest rate derived from the contract price. Markets reacted swiftly to this announcement, and overall, beliefs about the policy path increased: the communication resulted in a hawkish surprise. The equilibrium contract price reflects the mix of beliefs held by financial market participants. Prior to the announcement, some may have correctly forecast a 25 basis point increase in the target rate, while others did not. Upon impact, the announcement provided information about the change in the policy target and may also have signalled information about future rate changes.

I use three types of influential public speech events: FOMC announcements, press conferences, and intermeeting speeches by the Chair and Vice Chair of the Fed. FOMC announcements contain news about the target federal funds rate and news about future interest rates. Conversely, press conference and intermeeting speeches come with no change in the target federal funds rate, so these communications can only affect market expectations about future interest rates. I follow the methods of Gürkaynak et al. (2005) and Swanson (2024) to extract information about the likely path of future interest rates from FOMC announcements based on market responses, which I briefly explain here.[11]

For FOMC announcements, I construct a 188×5 matrix of futures contract changes, $\{MP1, ED1, ED2, ED3, ED4\}$.[12] I obtain the first two principle components, and rotate the second principle component to be orthogonal to news about the target federal funds rate, $MP1$. The first principle component is interpreted as surprises in the policy target, and the rotated second principle component reflects surprises in the policy path. This is because the rotated second principle component measures the surprise in expected interest rates for reasons other than the surprise in the current federal funds rate, which must be due to information about future interest rates. For press conferences and intermeeting speeches, I have a 460×4 matrix of Eurodollar futures contract surprises, $\{ED1, ED2, ED3, ED4\}$, as there can be no surprises to the current federal funds rate from such a speech. For these speeches, the first principle component only reflects changes in the policy path as the policy target never changes during these events.

I combine the policy path surprises for FOMC announcements and intermeeting speeches to construct an overall measure of surprises to future interest rates. I scale this series such that a 0.01 change corresponds to a 1 basis point point change in the fourth Eurodollar futures contract, on average in sample, which I denote $\Delta\mathcal{P}_t$.[13] Next, I explain the estimation method used to measure information from text about future policy in public speeches.

[11] This approach has been widely used in the literature to measure surprises in beliefs about the expected path of future interest rates, often referred to as forward guidance surprises. For further details, see the appendix of Gürkaynak et al. (2005).

[12] For FOMC announcements, I use a 30-minute window (starting 10 minutes before and ending 20 minutes after the announcement start). For press conferences, I use a 60 minutes window. For intermeeting speeches, I calculate the approximate duration of the speech with an assumed 110 words per minute rate of speech, then place a 60 minute window around that to construct the price changes.

[13] As argued in Swanson (2024) and Swanson (2023), the effect of different communication events are similar, which motivates combining them to form a single policy path surprise series.

4 Text Analysis

In this section, I outline the methodology I use to estimate a relationship between speech text and market responses to measure the information conveyed through text regarding future interest rates.

4.1 Measuring Hawkish and Dovish Language

I model the information from text about future interest rates using the Hurdle Distributed Multinomial Regression (HDMR) text analysis method developed by Kelly et al. (2021). A key application of this method is its ability to construct sufficient statistics that extract relevant information from a piece of text to explain a variable of interest. In my case, this variable is the information from central bank text data that accounts for changes in expectations of future interest rates, denoted as $\Delta\mathcal{P}_t$.

HDMR employs a 'bag-of-words' approach, meaning that word tokens are modelled independently of each other. A word token refers to a specific word or phrase, such as `inflation` or `increased labour market tightness`. HDMR captures two dimensions of language: what was said (the extensive margin) and how much it was said (the intensive margin). The choice of vocabulary may signal different information compared to the frequency with which a word token is repeated. For instance, in the context of central bank communications, the inclusion of the token `inflation` in the vocabulary may not be surprising; however, the emphasis placed on inflation could carry significant information. Likewise, mentioning `financial crisis` might serve as an informative signal regardless of its emphasis.[14]

Let the count of word token j that appeared in speech event t be c_{tj}, for word tokens $j = 1, ..., J$ and speech events $t = 1, ..., T$. The length of a speech is defined as $l_t = \sum_{j=1}^{J} c_{tj}$, whether a word token was used is defined as $h_{tj} = \mathbb{1}[c_{tj} > 0]$, and the vocabulary size for each speech is defined as $v_t = \sum_{j=1}^{J} h_{tj}$. The policy path surprise generated by speech t is $\Delta\mathcal{P}_t$. The text data of speeches forms a $T \times J$ counts matrix with elements defined over the natural numbers. For each word token j, HDMR is used to estimate the two models:

$$\Pr(c_{tj} > 0 | \Delta\mathcal{P}_t) = \Lambda(\alpha_{tjs} + \gamma_j \Delta\mathcal{P}_t), \tag{16}$$

[14]Kelly et al. (2021) argue that with highly sparse count data, the large mass at zero counts is not well captured by the distributional assumptions of counts data models such as Poisson or negative binomial. By modelling the zero counts and repetitions separately, this issue is addressed.

and

$$\Pr(c_{tj}|c_{tj} > 0, \Delta\mathcal{P}_t) = \text{Pois}^{+}(\kappa_{tjs} + \varphi_j \Delta\mathcal{P}_t). \tag{17}$$

Equation (16) models the inclusion of word tokens using a logit function, while equation (17) represents repetitions of word tokens through a positive Poisson distribution.[15] Gáti and Handlan (2022) show Federal Reserve communications use consistent language over time when conveying the economic outlook, which supports my static coefficient estimation over a long period of time as markets are likely to learn the meanings of the language used over time.

The fixed effects α_{tjs} and κ_{tjs} are for event, t, word token, j, and speech-type, $s \in$ {FOMC announcement, press conference, Chair speech, Vice Chair speech}. The fixed effects scale the baseline intensities of word token use to reduce bias in estimating γ_j and φ_j. The word token, j, fixed effect controls for the baseline use of each word token. The event, t, fixed effect controls for period-specific language use. The speech-type, s, fixed effect controls for how language may differ between different types of communications. The event t fixed effects in both models are defined by plug-in estimators to approximate the distribution over all word tokens.[16] Importantly, there is an L1-norm (LASSO) penalisation over the estimated coefficients to reduce over-fitting.[17]

The estimated HDMR is a set of parameters, $\{\hat{\gamma}_j, \hat{\varphi} j\}_{j=1}^{J}$, that measure the hawkish or dovish news content derived from the vocabulary and emphasis in communications. If $\hat{\gamma}_j$ is positive (negative), word token j is more likely to be used in speeches that produce hawkish (dovish) surprises. Similarly, if $\hat{\varphi}_j$ is positive (negative), word token j tends to be repeated in speeches that result in hawkish (dovish) surprises. A word token used indiscriminately should be assigned a value of zero due to the L1-norm penalisation.[18]

[15]A positive Poisson distribution is a Poisson distribution conditioned on values greater than zero, with support on $\mathbb{N}_{\geq 1}$.

[16]This approximation of the maximum likelihood estimators hold asymptotically for a large vocabulary size, and is done for computational efficiency. In the estimation, the positive Poisson is scaled by the overall number of repetitions each period, and the logit is scaled by the vocabulary size. For details see Kelly et al. (2021).

[17]Whilst each individual model is 'small', penalisation helps the fit of the overall HDMR model, which is collection of $2J$ estimated logit and positive Poisson models. For the main results, I use the corrected Akaike information criterion (AIC) (Hurvich and Tsai, 1989) to select the optimal penalisation parameter for its applicability in high-dimensional settings.

[18]This data-driven approach to measuring information from text contrasts with dictionary methods, which classify language based on the researcher's domain-specific knowledge, as seen in Lucca and Trebbi (2009) or Cieslak and McMahon (2024).

In my application, there are $J = 4,280$ regularly used stemmed trigrams over the $T = 648$ speech events. I restrict attention of commonly used language so there is variation in the term frequencies for estimating parameters in the HDMR. Details of the cleaning the text data and construction of the counts matrix is explained in the appendix.

Figure 2 visualises the estimated inclusion model for some of the most frequently used word tokens with a word cloud. The larger the font of a word token, the more frequently it is used. The more red (blue) the colour, the more positive (negative) $\hat{\gamma}_j$ is and reflects a more hawkish (dovish) word token. For example, the trigram '`term inflat expect`' is a frequently used hawkish trigram.

Figure 2: Word cloud for phase inclusion sentiment and frequency.

Given an estimated HDMR, Kelly et al. (2021) prove two low-dimensional sufficient statistics can be constructed that extract the relevant information from the text data for predicting a variable of interest. In my application, this is the information from the communications text data that predict changes in the market response, and are given by

$$z_t^0 = \frac{1}{v_t} \sum_{j=1}^{J} \hat{\gamma}_j h_{tj}, \tag{18}$$

and

$$z_t^+ = \frac{1}{l_t - v_t} \sum_{j=1}^{J} \hat{\varphi}_j (c_{tj} - h_{tj}). \tag{19}$$

In equation (18), z_t^0 is called a 'sufficient reduction projection' for the extensive margin.

The indicator h_{tj} selects which word tokens were used in speech event t, and weights their importance by the estimated $\hat{\gamma}_j$ which measures how strong of a signal the inclusion of word token j is for $\Delta\mathcal{P}_t$. This is then normalised by the vocabulary size of the speech, v_t, to measure the intensity of each word token's use relative to all word tokens.

Similarly, in equation (19), z_t^+ is the sufficient reduction projection for the intensive margin. The difference $c_{tj} - h_{tj}$ is how many times word token j was repeated in speech event t. This is weighted by $\hat{\varphi}_j$, which measures how strong of a signal repetitions of word token j are for $\Delta\mathcal{P}_t$. This is then normalised by $l_t - v_t$ to measure the intensity of each word token's repetition. The sign and magnitude of these sufficient reduction projections reflect the overall hawkish or dovish textual information about the likely change in future interest rates.

I then use my estimated HDMR model, $\{\hat{\gamma}_j, \hat{\varphi}_j\}_{j=1}^J$, to measure information from the FOMC meeting minutes about the likely path of future interest rates. I add a tilde to denote variables derived from the FOMC minutes: let the counts matrix of word tokens in the FOMC minutes be represented as $\tilde{C}$, with elements $\tilde{c}_{tj}$. The columns correspond to the same word tokens used in the HDMR estimated from the communications.[19] I then construct the sufficient reduction projections for the minutes with

$$\tilde{z}_t^0 = \frac{1}{\tilde{v}_t}\sum_{j=1}^{J}\hat{\beta}_j\tilde{h}_{tj} \tag{20}$$

$$\tilde{z}_t^+ = \frac{1}{\tilde{l}_t - \tilde{v}_t}\sum_{j=1}^{J}\hat{\varphi}_j(\tilde{c}_{tj} - \tilde{h}_{tj}) \tag{21}$$

I standardise all four textual information (sentiment) series by subtracting their means and dividing by the sample standard deviation, for comparability between public speeches and FOMC minutes. The views of the FOMC potentially change over the intermeeting period, and the sentiment of the speeches is likely to reflect this change. Consequently, comparing intermeeting speeches with FOMC minutes from several weeks prior may exaggerate my information gap measure. However, FOMC meetings are not held continuously, so there is no daily sequence of FOMC minutes to which I can compare the intermeeting speeches. To approximate the time-varying sentiment of the FOMC, I use quadratic interpolation on

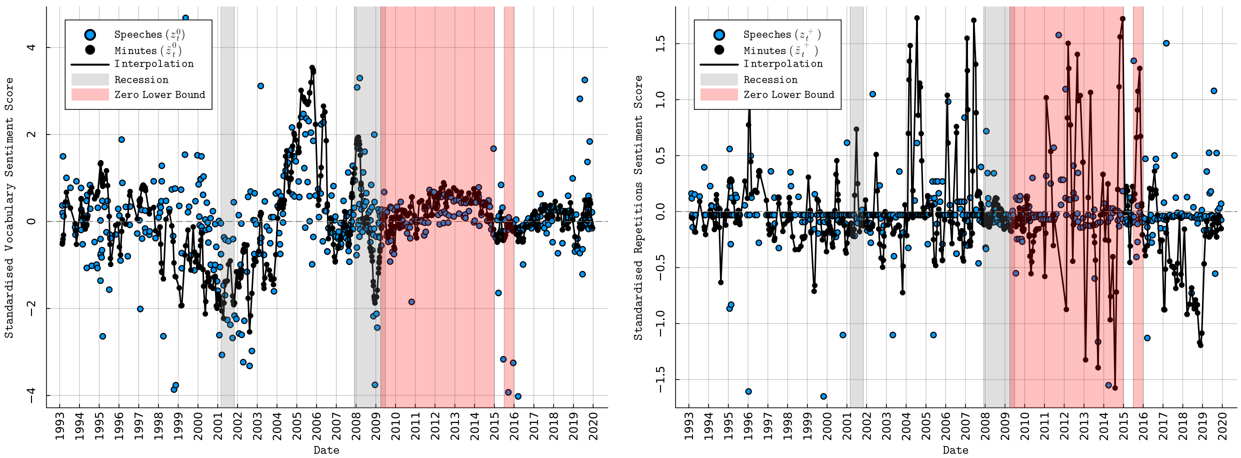
[19] I assume the information content of word token j is the same between speeches and the FOMC minutes after controlling for speech-type, phrase-type, and event-level fixed effects.

the $(\tilde{z}_t^0, \tilde{z}_t^+)$ series over the intermeeting period.[20] From now on, let $(\tilde{z}_t^0, \tilde{z}_t^+)$ represent the quadratic interpolated sentiment series from the minutes at each public speech event, t.

Figure 3: Sentiment Score Series for Vocabulary and Repetition.

(a) Vocabulary Sentiment.

(b) Repetition Sentiment.



Notes: Panel (a) shows the vocabulary sentiment series, and panel (b) shows the repetition sentiment series. The blue dots are from speeches and the solid black lines are the interpolated sufficient reduction projections from the FOMC minutes. NBER Recession and zero lower bound (ZLB) periods shaded. ZLB is defined as when the predicted interest rate from a Taylor rule is negative. Recession bands are NBER recession bands.

The standardised sentiment scores are shown in Figure 3, with a blue scatter plot for speeches and a connected black line for the interpolated sentiment from the FOMC minutes. Panel (a) indicates that both speeches and minutes convey a similar sentiment from the topics of discussion. In contrast, panel (b) reveals that the sentiment from the emphases in the FOMC minutes and speeches are unrelated. Together, panels (a) and (b) suggest that while speeches and FOMC minutes tend to convey similar information from the concepts discussed, they differ in the information conveyed through emphasis on these concepts.

Table 1 shows that information from the vocabulary between speeches and the minutes is related, though not one-to-one. Additionally, the sentiment from the repetition of word tokens between speeches and the minutes is not related. These findings are conceptually aligned with Cieslak and McMahon (2024), who demonstrated that the hawkish-dovish tone of FOMC announcement texts is generally similar to that of FOMC meeting transcripts, yet

[20] The results are robust to alternative interpolation methods, such as linear, constant forward-looking, and constant backward-looking approaches. I focus on quadratic interpolation here, as it captures potential non-linear changes in sentiment over the intermeeting period. Furthermore, including the 420 intermeeting speeches does not impact the event study results, but these additional observations are crucial for identifying macroeconomic effects.

Table 1: Cross-Sentiment Score Correlations.

	(1) z_t^0	(2) z_t^+
$\tilde{z}_t^0$	0.336***	-0.015
	(7.355)	(0.581)
$\tilde{z}_t^+$	0.045	0.052
	(1.060)	(1.143)
Constant	0.003	0.000
Observations	648	648
R^2	0.125	0.002

Notes: These regressions show the correlations in the standardised sentiment scores between the public speeches and the FOMC meeting minutes; t-statistics in parentheses calculated with robust standard errors (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

they did not explicitly investigate the impact of information differentials on market outcomes, which is what I do next.

I define my textual information gap measure as the difference in the standardised sentiment scores between the public speeches and the minutes with:

$$dz_t^0 = z_t^0 - \tilde{z}_t^0, \tag{22}$$

and

$$dz_t^+ = z_t^+ - \tilde{z}_t^+. \tag{23}$$

For example, if dz_t^0 is positive (negative), speech event t used more hawkish (dovish) vocabulary about future interest rates compared to the FOMC minutes. Similarly, if dz_t^+ is positive (negative), speech event t emphasised more hawkish (dovish) concepts about future interest rates relative to the FOMC minutes. I test whether this information gap accounts for variations in the market response through the following regression:

$$\Delta\mathcal{P}_t = \theta_0 + \theta_1 dz_t^0 + \theta_2 dz_t^+ + \varepsilon_t. \tag{24}$$

Table 2 column (1) shows that textual information gaps from both the intensive and extensive margins account for changes in market beliefs about the likely path of interest rates. A one standard deviation increase in dz_t^0 is 1.16, which corresponds to a 1.6 basis point increase in the one-year ahead expected interest rate. Similarly, a one standard deviation

Table 2: Market Response Decomposition.

	(1) $\Delta\mathcal{P}_t$	(2) $\Delta\mathcal{P}_t$	(3) $\Delta\mathcal{P}_t$
dz_t^0	0.014***	0.025***	
	(6.472)	(8.647)	
dz_t^+	0.002***	0.004***	
	(2.997)	(3.091)	
$\tilde{z}_t^0$		0.021***	
		(7.526)	
$\tilde{z}_t^+$		0.004**	
		(2.184)	
z_t^0			0.024***
			(8.691)
z_t^+			0.004***
			(3.213)
Constant	-0.000	-0.000	-0.000
Observations	648	648	648
R^2	0.111	0.242	0.236
F	26.77	22.80	45.64

Notes: This table predicts the observed financial market response with the sufficient reduction projection textual sentiment series from the HDMR over the whole sample. The first column is the primary result of the paper showing the textual information gap measure predicts the market response and explains a meaningful proportion of its variation. The second through to third columns use a combination of the speech and minutes textual information to predict the market response. Robust t-statistics in parentheses, F statistic for overall significance reported (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

increase in dz_t^+ corresponds to a 0.26 basis point increase in the one-year ahead expected interest rate. Importantly, the textual information gap explains 11% of the variation in the market response, which is non-trivial if such information differentials are due to difficulties in conveying the detailed information content of the minutes.

Table 2, column (1), demonstrates that textual information gaps from both the intensive and extensive margins account for changes in market beliefs about the likely path of interest rates. A one standard deviation increase in dz_t^0 corresponds to an increase of 1.16, and to a 1.6 basis point rise in the one-year ahead expected interest rate. Similarly, a one standard deviation increase in dz_t^+ results in a 0.26 basis point increase in the one-year ahead expected interest rate. The textual information gap accounts for 11% of the variation in the market response, which is non-trivial, especially considering that such information differentials may arise from challenges in effectively conveying the detailed content of the minutes.

In the 'truth plus white noise' framework of communications in my model, the private sector responds equally to both the information gap and non-information gap terms. Table 2, column (2), regresses the market response against the textual information gap (the 'noise') and sentiment from the FOMC minutes (the 'truth'), revealing a statistically similar response.[21] This finding supports my interpretation that the information gap component remains unobserved by markets in real-time, yet still influences their decisions through its implicit presence in the communications. Table 2, column (3), indicates that both the inclusion and repetition dimensions of communications significantly predict the market response, accounting for 24% of its variation. This demonstrates that financial markets do indeed react to these dimensions of information from communications.

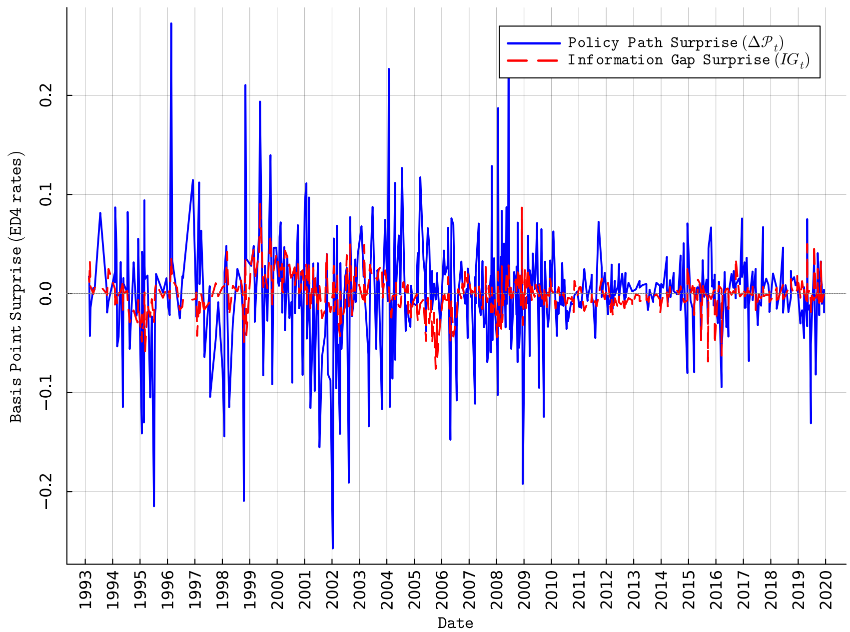
The textual information measures, as well as their differences, lack a straightforward interpretation. Therefore, I project the textual information gap series in the direction of the market response with (24), estimated in Table 2, column (1), to derive a scalar measure of the information gap in terms of one-year ahead rates. This approach allows me to decompose the market response into two components: an information gap and a non-information gap measure, both expressed in terms of one-year ahead expected interest rates. Let $\widehat{\Delta\mathcal{P}}_t = IG_t$ represent the information gap and $\hat{\varepsilon}_t = NIG_t$ denote the non-information gap, such that

$$\Delta\mathcal{P}_t \equiv IG_t + NIG_t. \tag{25}$$

Figure 4 plots $\Delta\mathcal{P}_t$ and IG_t across the entire sample. The plot illustrates that information gaps generally exhibit a smaller magnitude than the overall market response, with both displaying a decrease in variance over time. By definition, NIG_t is the difference between the blue line and the dashed red line. A positive value of IG_t indicates that a speech signalled more hawkish information about the policy path compared to the FOMC minutes. Since markets only observe the speech, the response tends to be more hawkish than it would have been had the speech conveyed the same sentiment as the FOMC minutes.

[21] At the 10% level, the joint null hypotheses of equivalence between the coefficients of the vocabulary sentiment variables (dz_t^0 and $\tilde{z}_t^0$) and the phrase repetition variables (dz_t^+ and $\tilde{z}_t^+$) cannot be rejected.

Figure 4: Policy Surprise Time Series.



Notes: The policy path surprise is calculated from financial market data to measure surprises to the likely path of future interest rates from public speeches of the Fed. The information gap surprise measure is the part of this response that can be predicted with a textual information difference between public speeches and the FOMC meeting minutes.

5 Financial Market and Macroeconomic Effects

I will now examine the implications of IG_t for financial markets and the macroeconomy, using methods from the high-frequency identification of monetary policy surprise literature (Kuttner, 2001; Gertler and Karadi, 2015; Bauer and Swanson, 2023b).

5.1 Financial Market Effects

I estimate the effect of information gaps about the likely path of future interest rates on asset markets in an event study. I obtain high-frequency changes in the 2, 5 and 10-year treasury bond prices and the value of the S&P500 stock index in the same small time intervals as the changes in interest rate expectations used to construct $\Delta\mathcal{P}_t$. I regress the percent change in the price of asset i at communication event t, denoted with $\%\Delta y_{it}$, on the information gap and non-information gap terms with

I estimate the effect of information gaps for the likely path of future interest rates on asset markets through an event study. I capture high-frequency changes in the prices of 2-, 5-, and 10-year treasury bonds, as well as the value of the S&P 500 stock index, within the

Table 3: Event Study Regressions: Bootstrap.

	2-year Treasuries	5-year Treasuries	10-year Treasuries	SP500 Stock Index
IG_t	-1.340***	-2.757***	-3.305***	-1.888
	(13.507)	(12.138)	(9.821)	(1.275)
NIG_t	-1.441***	-3.131***	-3.950***	-1.940***
	(26.687)	(21.416)	(16.929)	(3.047)
Constant	0.003**	0.005	0.004	0.057***
Observations	648	648	648	648
R^2	0.788	0.691	0.565	0.030
F	360.2	246.4	161.7	4.829

Notes: Estimations over all speech events in the sample from 1993 to 2019, including FOMC announcements, press conferences, Chair and Vice Chair speeches. Robust t-statistics in parentheses, F statistic for overall significance reported (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

same small time intervals as the changes in interest rate expectations used to construct $\Delta\mathcal{P}t$. I regress the percentage change in the price of asset i at communication event t, denoted as $\%\Delta y_{it}$, on the information gap and non-information gap terms with

$$\%\Delta y_{it} = \beta_0 + \beta_1 IG_t + \beta_2 NIG_t + e_t. \tag{26}$$

My model predicts that a hawkish (dovish) information gap should lead to an increase (decrease) in interest rate expectations, with a diminishing effect along the yield curve. Since I use bond prices as the dependent variable and a bond's price is inversely related to its yield, a decline in bond prices will result in an increase in yields. If treasury yields rise, investors are likely to rebalance their portfolios by shifting funds from stocks to bonds, which would cause stock prices to fall. Consequently, both stock and bond prices are expected to respond negatively to changes in IG_t and NIG_t. If IG_t accurately reflects an information gap that remains unobserved by the private sector in real-time, then, as my model predicts, the effects of IG_t and NIG_t along the yield curve should be similar.

Table 3 shows that treasury prices decline in response to both a hawkish information gap and a hawkish non-information gap, with a stronger price effect observed along the yield curve, as expected. For example, a hawkish information gap that raises one-year ahead rates by 1 basis point results in a 0.0134% reduction in the price of a two-year treasury bond. The magnitudes for each treasury type are statistically similar for both IG_t and NIG_t, consistent with my model's predictions. Information gaps do not predict the stock market response, but non-information gaps do. Perhaps this is due to information gaps sometimes signalling stronger than expected economic fundamentals through higher future interest rates, which dampens the expected negative stock price response.[22]

While information gaps do influence beliefs about interest rates along the yield curve, non-information gaps are more significant across the yield curve responses. In the Appendix, I replicate the same analysis for only FOMC announcements and for both FOMC announcements and press conferences, yielding similar results.[23] The key takeaway here is that the information differential about future monetary policy between speeches and the FOMC minutes is substantial enough to account for short-term financial market volatility.

An implication of the signal formulation of communications of the model in practice is that the weight assigned to speeches (the Kalman gains) may vary over time. If speeches become less precise on average, the private sector would gradually learn from this and subsequently place less weight on future speeches. Figure 5 displays recursive estimates of β_1 and β_2 from equation (5) over the period from 2000 to 2019, estimated using exponentially weighted least squares to account for sluggish belief updating.

The effects of both IG_t and NIG_t on treasury price responses have remained fairly stable over time, but not for the stock price responses. If speeches have a low signal-to-noise ratio, markets will learn to refrain from reacting to them, and implicitly, to the information gap. Conversely, if speeches are sufficiently informative, markets will adjust their reactions accordingly. Therefore, as shown in Figure 5, the signal-to-noise ratio appears to be relatively stable over time for treasuries, suggesting that speeches are perceived by financial market participants as containing sufficiently informative content, despite information gaps.

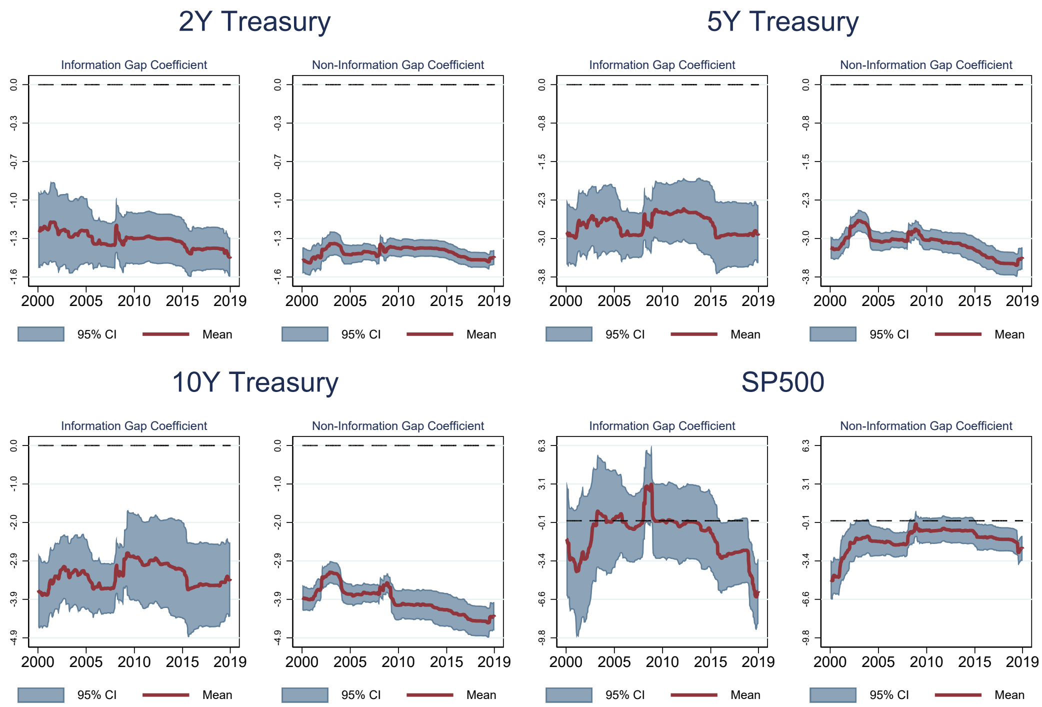
5.1.1 Bootstrap

A potential concern arises from the uncertainty surrounding the estimated HDMR model and the constructed regressors, dz_t^0 and dz_t^+. To address this sampling error, I resample 648 new observations, estimate the HDMR, and compute the asset responses from Table 3, done

[22]In the appendix I discuss whether the text of communications exhibits likely contains such signalling effects by analysing a type of data release from the Fed known as the summary of economic projections (SEP). I argue that the textual data primarily signals information other than the longer-term economic outlook of the SEP.

[23]This indicates that the interpolation of the FOMC minutes, which incorporates intermeeting speeches known in the literature to often contain crucial information about future policy, does not drive the results.

Figure 5: Recursive Event Study Estimates.



Notes: Recursive estimates using exponentially weighted least squares and robust standard errors, with a forgetting factor of 0.05, implying an effective sample of 200 speech events. The initial sample is the first 148 observations from 19 February 1993 to 21 December 1999. Each speech event is treated sequentially by the time they are delivered. Horizontal dashed line represents zero, and the vertical axes for each asset type are on the same scale.

5,000 times.[24] Table 4 presents the bootstrap estimates along with bootstrap standard errors in parentheses. The estimated coefficients are similar in magnitude to those in Table 3, and the qualitative interpretation remains unchanged. Therefore, there is no significant issue regarding estimation uncertainty from the language model and the constructed regressors.

5.2 Macroeconomic Effects

Next, I study the macroeconomic effects of my information gap surprise series. I estimate a monthly structural vector autoregression (SVAR) identified using external instruments, following methods commonly employed in the empirical macroeconomics literature (Mertens and Ravn, 2013; Gertler and Karadi, 2015; Bauer and Swanson, 2023b).

[24]Due to the computational demands of this resampling estimation, I limit the number of iterations to 5,000. Distributions of the coefficient estimates are provided in the Appendix.

Table 4: Asset Price Responses: Bootstrap Estimates

	2-year Treasuries	5-year Treasuries	10-year Treasuries	SP500 Stock Index
IG_t	-1.40	-2.99	-3.72	-2.11
	(0.14)	(0.31)	(0.46)	(1.79)
NIG_t	-1.44	-3.12	-3.93	-1.91
	(0.05)	(0.14)	(0.22)	(0.63)

Notes: Bootstrap estimates from 5,000 resample estimations for both the first-step language model, second-step decomposition and asset response regression. Bootstrap standard errors in parentheses.

I will briefly outline this method here, leaving details to the appendix. First, a reduced-form VAR is estimated, including an interest rate series to capture the stance of monetary policy. Then, an instrumental variable is use to predict exogenous variation in the fitted residuals of the interest rate series. Under instrumental relevance and exogeneity, the effect of a monetary policy shock on all variables in the VAR can be identified up to a scale. I use my information gap series as a source of exogenous variation for interest rates. Given that my information gap series is at an event-level frequency, I aggregate this series within each month to construct a total monthly information gap series, ensuring compatibility with the monthly frequency of the VAR.

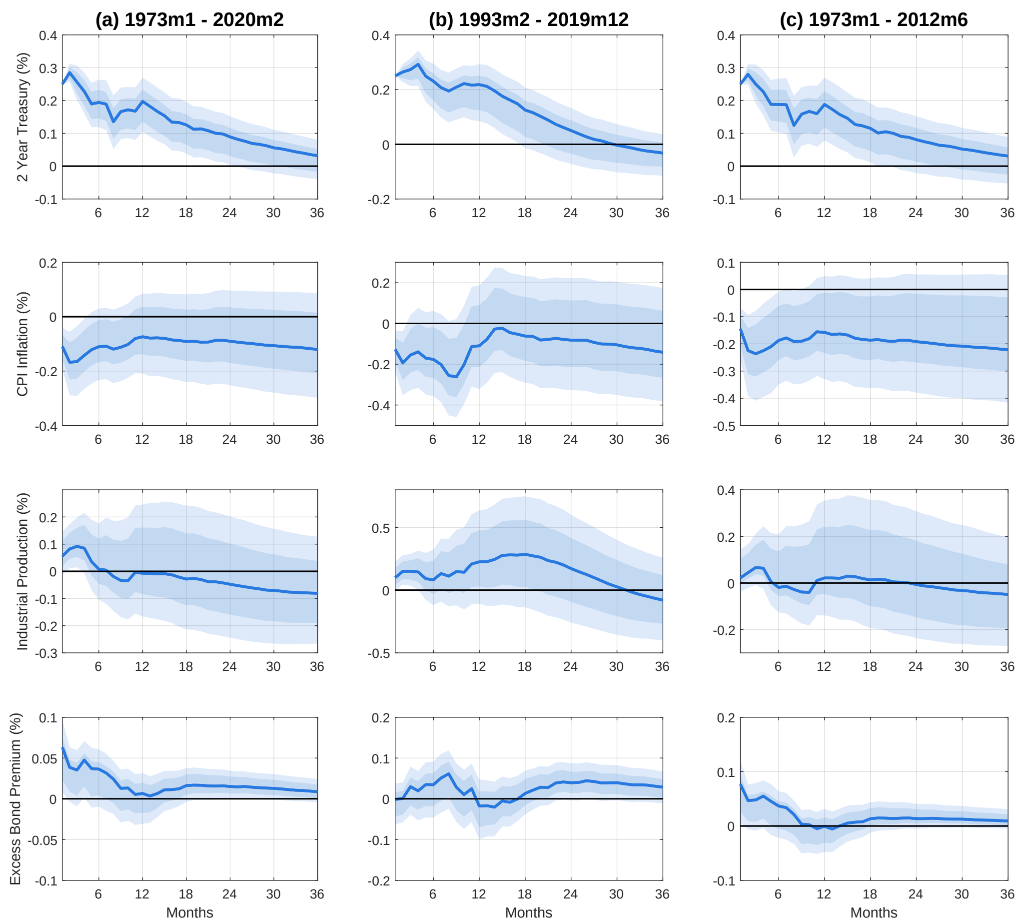
An advantage of this methodology is that the macroeconomic dynamics of the VAR can be estimated over a longer sample than the identification of the policy shocks. My information gap series is available from February 1993 to December 2019 for identifying the impact responses to a shock, but the VAR can be estimated over the same or an extended period. I include four variables in the VAR: the end-of-month two-year Treasury yield, CPI inflation, industrial production, and the 'GZ excess bond premium' (Gilchrist and Zakrajsek, 2012). This relatively small set of variables captures some of the key dimensions of monetary policy: interest rates, inflation, output, and credit market sentiment.[25]

Figure 6, column (a), shows the impulse responses to a hawkish information gap surprise, which, by construction, raises the two-year Treasury yield by 25 basis points on impact. The VAR dynamics are estimated over the full sample from January 1973 to February 2020,

[25]I use the end-of-month two-year Treasury yield to reflect the monetary policy stance for several reasons: it is not constrained by the zero lower bound during the period following the 2008 financial crisis; it reflects longer-term interest rates, unlike the shadow federal funds rate Wu and Xia (2016), which is more suited to my context of studying information gaps about future monetary policy; and by using the end-of-month value of the series, I can determine whether the effects of the information gap are lasting or dissipate quickly.

while the impact effects are identified over the sub-sample from February 1993 to December 2019.

Figure 6: Impulse responses to a hawkish information gap.



Notes: Responses to a hawkish information gap that raise the end-of-month two-year Treasury yield by 25 basis points. Shaded intervals represent 68 and 90% confidence intervals calculated with 10,000 wild bootstrap simulations which take into account the first-stage regression's coefficient uncertainty. Panel (a) shows results for the VAR estimated over 1973m1-2020m2, and impact effects identified over 1993m2-2019m12. Panel (b) estimates the VAR and identifies impact effects over the common sample 1993m2-2019m12. Panel (c) estimates the VAR over 1973m1-2012m6 and impact effects over 1993m2-2012m6, ending before the zero lower bound period.

The two-year Treasury yield remains elevated for several years after the initial impact, demonstrating the persistent effect of information gaps. Inflation decreases by approximately 0.1% on impact, rebounds after a few months, but maintains a persistently negative central forecast for several years. The excess bond premium increases by about 0.05% on impact, lasting several months, indicating a decline in financial market sentiment as the higher interest rates slow down economic activity and lower expected corporate bond yields.

Industrial production rises by around 0.05% on impact but quickly decays, showing no long-lasting effect on output. Over the longer term, the central forecast for output response turns negative, as would be expected from a surprise monetary tightening. The positive impact effect may suggest that hawkish information gaps are more likely to occur when the central bank expects economic activity to rise, with speeches using excessively hawkish language to signal efforts to dampen economic activity. However, this does not appear to hold for inflation, as the negative inflation response to a surprise interest rate tightening aligns with expectations.

Farmer, Nakamura, and Steinsson (2024) demonstrate that biases in initial beliefs can be highly persistent in contexts where agents gradually learn about the underlying model structure of the economy. In my context, information gaps regarding the future sequence of reaction functions could explain the persistent effect of biases in beliefs about future interest rates, even in light of subsequent communications, as learning is a gradual process. The first-stage F statistic for instrumental relevance is 12.01, and the robust F statistic is 9.52, which is near the weak instrument threshold of 10 suggested by Stock and Watson (2012).

Columns (b) and (c) of Figure 6 show impulse responses from a hawkish information gap surprises, estimated over different samples. Column (b) uses a common sample from February 1993 to February 2020 for both the VAR estimation and impact effect identification. The results are comparable, but the output response is more positive in the medium term, and the response of the excess bond premium is more gradual; the F and robust F statistics for instrumental relevance are 15.08 and 11.22, respectively. Bauer and Swanson (2023b) argue that using a longer VAR sample in monetary VARs, as in column (a), is good practice, as it helps to more accurately estimate the macroeconomic dynamics following a shock.

Column (c) estimates the VAR using data up to the zero lower bound and presents similar qualitative results to those observed previously. However, it exhibits an even weaker response in economic activity in both the short and medium terms. The first-stage F and robust F statistics are also weaker, at 8.30 and 7.39, respectively.

These VAR results rely on the inclusion of additional communication events such as Fed Chair speeches, Vice Chair speeches, and press conferences. When the identification is restricted to only FOMC announcements, it leads to very weak instruments for forecasting likely future interest rates, as demonstrated in previous studies (Miranda-Agrippino and Ricco, 2023; Swanson, 2024). Including intermeeting speeches enriches the information regarding monetary policy and enhances the relevance of the instruments for the end-of-month two-year Treasury yields. As noted by (Swanson and Jayawickrema, 2023; Swanson, 2023), Fed Chair speeches are highly informative about the likely path of future interest rates, and Bauer and Swanson (2023b) argue for including intermeeting communications to effectively identify the macroeconomic effects of central bank communications for these reasons.

Swanson (2024) use a range of Fed communications, including intermeeting speeches, to identify the macroeconomic effects of forward guidance surprises, orthogonalised with respect to surprise economic data releases. Similar to my findings, they observe an output puzzle with a comparable magnitude on impact and similar macroeconomic dynamics following the shock. In contrast, my IG_t series exhibits a negative impact effect on inflation, while the inflation impact effect in Swanson (2024) was zero. We both find a positive response to the excess bond premium.

My positive output response is similar to the signalling and information effects documented in Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021); although, I do not find a positive inflation response. These results suggest that the nature of my textual information gap surprise encompasses elements of both effects previously identified in the literature.

6 Conclusion

This paper compares the information about the likely path of future interest rates between the text of two types of Federal reserve communication: public speeches and the FOMC meeting minutes. The meeting minutes are a detailed account of FOMC policy meetings, but take several weeks to construct and disseminate. Public speeches, namely the FOMC announcements, press conferences and intermeeting speeches, are typically less detailed, but closely followed by financial market participants. I construct a textual measure of information about the likely path of future interest rates from public speeches and the high-frequency market response to those speeches. Information gaps are measured ex-post as the textual information difference between a speech and the meeting minutes. I show the information gap between these speeches and the meeting minutes accounts for 11% of the variation in changes in market beliefs about the likely path of future interest rates. Information gaps account for variation in longer-term interest rates along the yield curve, and generate medium-term macroeconomic effects.

I explain my empirical findings with a macroeconomic model where information gaps affects rational expectations about the economic outlook and the sequence of future reaction functions of the central bank. Information gaps arise as it is costly to increase the precision of communications. In my empirical work, I treat the FOMC minutes as a precise signal of the information the central bank wishes the public to have, and information gaps between the minutes and relatively less-detailed speeches reflects the difficulty in immediately communicating complex information.

The trend observed among many central banks over the past thirty years has been a shift towards increased transparency and improved communication accuracy, with the Federal Reserve playing a leading role. If the information gaps I detect stem from challenges in the timely dissemination of complex information, advances in large language models could represent a technological innovation that reduces the cost of precise communication by enabling the faster distribution of detailed information. Exploring this potential is a goal for future research.

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A Appendix Additional Model Notes

A.1 Non-Linear Model Setup

The Fisher equation describes the relationship between the nominal interest rate, i_t to the real interest rate, r_t and this period's expectation of next period gross inflation, $\mathbb{E}_t\left[\Pi_{t+1}\right]$ with

$$(1+i_t) = (1+r_t)\mathbb{E}_t[\Pi_{t+1}]. \tag{27}$$

The gross real interest rate is assumed to follow the logarithmic random walk

$$(1+r_t) = (1+r_{t-1})^{\rho} e^{\varepsilon_t^r}, \tag{28}$$

where $\varepsilon_t^r \sim N(0, \sigma_r^2)$, and $\rho \in (0,1)$. The central bank sets the nominal interest rate in response to inflation with the reaction function

$$(1+i_t) = \Pi_t^{\phi_t} e^{\varepsilon_t^i}, \tag{29}$$

where the responsiveness coefficient is predetermined and follows the logarithmic random walk

$$(1+\phi_{t+1}) = (1+\phi_t) e^{\varepsilon_t^{\phi}}, \tag{30}$$

where $\varepsilon_t^{\phi} \sim N(0, \sigma_{\phi}^2)$. Log approximations for small r_t, i_t, and ϕ_t, and $\Pi_t = 1+\pi_t$ is presented in the main text.

A.2 Additional Model Derivations

Here I explain the steps for solving the model under imperfect information. Let $x_{t+n|t}$ denote the n-period ahead posterior belief of a variable, x, formed with the Kalman filter in period t. For completeness, the Fisher equation is

$$i_t = r_{t|t} + \mathbb{E}_t\left[\pi_{t+1}\right], \tag{31}$$

and the reaction function solved for inflation is

$$\pi_t = \frac{i_t}{\phi_t}. \tag{32}$$

Leading (32) by one period and taking expectations and substituting into the Fisher equation gives

$$i_t = r_{t|t} + \mathbb{E}_t\left[\frac{i_{t+1}}{\phi_{t+1}}\right]. \tag{33}$$

To simplify (33), I take a first-order approximation of i_{t+n}/ϕ_{t+n} $\forall n \geq 1$ about the zero inflationary steady state and period t beliefs of the period $t+1$ reaction function responsiveness, $i_{t+n} = 0, \phi_{t+n} = \phi_{t+n|t}$ with

$$\frac{i_{t+n}}{\phi_{t+n}} \approx (i_{t+n} - 0) \cdot \frac{1}{\phi_{t+n|t}} + (\phi_{t+n} - \phi_{t+n|t}) \cdot \left(-\frac{0}{\phi^2_{t+n|t}}\right) = \frac{i_{t+n}}{\phi_{t+n|t}}, \tag{34}$$

which eliminates the covariance terms and makes the expectation in (33) manageable with

$$i_t = r_{t|t} + \mathbb{E}_t\left[\frac{i_{t+1}}{\phi_{t+1|t}}\right], \tag{35}$$

and recursively substituting the Fisher equation led one-period ahead, using the law of iterated expectations, and the laws of motion for r_t and ϕ_{t+1} to obtain

$$i_t = r_{t|t} + \frac{\rho}{\phi_{t+1|t}} r_{t|t} + \frac{\rho^2}{\phi^2_{t+1|t}} r_{t|t} + \ldots \tag{36}$$

For $\left|\rho/\phi_{t+1|t}\right| < 1$ there exists a unique rational expectations equilibrium solution given by

$$i_t = \frac{\phi_{t+1|t}\, r_{t|t}}{\phi_{t+1|t} - \rho}. \tag{37}$$

Substituting (37) into the reaction function (32) solves for inflation in period t,

$$\pi_t = \frac{1}{\phi_t} \frac{\phi_{t+1|t}\, r_{t|t}}{\phi_{t+1|t} - \rho}. \tag{38}$$

This is a local result for an active policy rule. The model can be rewritten to impose that the Taylor principle holds, although this complicates the algebra without changing the implications of the model. From the expansion of (35), the n-step ahead interest rate expectation is

$$\mathbb{E}_t\left[i_{t+n}\right] \approx \rho^n \frac{\phi_{t+1|t}\, r_{t|t}}{\phi_{t+1|t} - \rho} = \rho^n i_t \tag{39}$$

This shows that the n-period ahead expected interest rate depends on the sequence of beliefs about the reaction function and the economic outlook due to the forward-looking nature of the Fisher equation.

A.3 Central Bank's Optimal Signal Precision Choice

Suppose the central bank faces a loss function that is increasing in the private sector's squared forecast errors of r_t and ϕ_{t+1}. This is shown in the loss function (40) where $r_{t|t}$ denotes the private sector's period t posterior belief of r_t after receiving a central bank communication. Similarly, $\phi_{t+1|t}$ denotes the period t posterior belief of the next period responsiveness coefficient after receiving a central bank communication. The parameter $\gamma \in [0, 1]$ reflects the central bank's aversion to private sector real interest rate forecast errors relative to reaction function forecast errors.

$$L_t = \mathbb{E}_t\left[\gamma(r_t - r_{t|t})^2 + (1-\gamma)(\phi_{t+1} - \phi_{t+1|t})^2\right]. \tag{40}$$

As explained in A.1, r_t and ϕ_{t+1} are independent processes, so there is no information from one that can be used to help forecast the other and the loss function cannot be simplified further. The central bank communicates the real interest rate and the next period reaction function with

$$s_t^r = r_t + \varepsilon_t^{sr}, \tag{41}$$

and

$$s_t^\phi = \phi_{t+1} + \varepsilon_t^{s\phi}, \tag{42}$$

where $\varepsilon_t^{sr} \sim N(0, \sigma_{sr}^2)$ and $\varepsilon_t^{s\phi} \sim N(0, \sigma_{s\phi}^2)$ are independent shocks. If the central bank could, they would set $\sigma_{sr} = \sigma_{s\phi} = 0$ and perfectly reveal the state of the economy to minimise their loss function. Suppose instead that the central bank must incur a cost to reduce the variance of the signal, modelled as power functions in (43) and (44), subject to the overall information constraint (45).

$$\sigma_{sr}^{-2} = c_r^{\beta_r} \tag{43}$$

$$\sigma_{s\phi}^{-2} = c_\phi^{\beta_\phi} \tag{44}$$

$$c_r + c_\phi \leq c \tag{45}$$

The constants β_r and β_ϕ are non-zero real numbers that capture the curvature of these communication technologies. The key feature of these functions is the precision is zero at the origin and tend to infinity as the communication cost tends to infinity. The constant c is the total cost that can be allocated to communicating.

For example, after an FOMC meeting, the time available for drafting the FOMC announcement is limited, and so is the number of words that can go in the announcement. These time, effort and length constraints on communicating motivate $0 < c < \infty$. The Nash equilibrium is solved for where the central bank knows the private sector uses the Kalman filter to update beliefs, and the private sector knows the functional form of the central bank's problem. Upon receiving a communication, the private sector using the Kalman filter to form beliefs with equations (46) and (47) which are known to the central bank.

$$r_{t|t} = r_{t-1} + k_r(r_t + \varepsilon_t^r - r_{t-1}) \tag{46}$$

$$\phi_{t+1|t} = \phi_t + k_\phi(\phi_{t+1} + \varepsilon_t^\phi - \phi_t) \tag{47}$$

Due to the assumptions on how information is received by the private sector, the Kalman gains are

$$k_r = \frac{\sigma_r^2}{\sigma_r^2 + \sigma_{sr}^2} = \frac{\sigma_{sr}^{-2}}{\sigma_r^{-2} + \sigma_{sr}^{-2}}, \tag{48}$$

and

$$k_\phi = \frac{\sigma_\phi^2}{\sigma_\phi^2 + \sigma_{s\phi}^2} = \frac{\sigma_{s\phi}^{-2}}{\sigma_\phi^{-2} + \sigma_{s\phi}^{-2}}. \tag{49}$$

The central bank chooses the cost to incur from communicating to minimise the expected loss

$$\begin{aligned}
L_t &= \mathbb{E}_t \left[\gamma (r_t - r_{t|t})^2 + (1-\gamma)(\phi_{t+1} - \phi_{t+1|t})^2 \right] \\
&= \mathbb{E}_t \left[\gamma \left\{ (1-k_r)\varepsilon_t^r - k_r \varepsilon_t^{sr}) \right\}^2 + (1-\gamma) \left\{ (1-k_\phi)\varepsilon_t^\phi + k_\phi \varepsilon_t^{s\phi} \right\}^2 \right] \\
&= \frac{\gamma}{\sigma_r^{-2} + \sigma_{sr}^{-2}} + \frac{1-\gamma}{\sigma_\phi^{-2} + \sigma_{s\phi}^{-2}}.
\end{aligned}$$

The central bank's problem is

$$\min_{\{c_r, c_\phi\}} \left[\frac{\gamma}{\sigma_r^{-2} + \sigma_{sr}^{-2}} + \frac{1-\gamma}{\sigma_\phi^{-2} + \sigma_{s\phi}^{-2}} \right] \quad \text{subject to} \quad \begin{aligned} & c_r + c_\phi \leq c, \quad c_\phi \geq 0, \quad c_r \geq 0, \\ & \sigma_{sr}^{-2} = c_r^{\beta_r}, \quad \sigma_{s\phi}^{-2} = c_\phi^{\beta_\phi}. \end{aligned}$$

The Lagrangian is

$$\mathcal{L}_t = L_t + \lambda [c - c_r - c_\phi],$$

with first-order conditions

$$\partial c_r: \ \frac{\gamma}{\left(\sigma_r^{-2} + c_r^{\beta_r}\right)^2} \beta_r c_r^{\beta_r - 1} \leq \lambda \ (= \text{ if } c_r^* > 0),$$

$$\partial c_\phi: \ \frac{1-\gamma}{\left(\sigma_\phi^{-2} + c_\phi^{\beta_\phi}\right)^2} \beta_\phi c_\phi^{\beta_\phi - 1} \leq \lambda \ (= \text{ if } c_\phi^* > 0),$$

and

$$\partial\lambda: \; c_r + c_\phi \leq c \; (= \text{ if } \lambda > 0).$$

Depending on β_r, β_ϕ the non-negativity constraints do not necessarily bind and corner solutions are possible where only one variable is communicated depending on the parameterisation. If an interior solution exists its general form, which can be solved with numerical methods for a given parameterisation is:

$$\frac{\gamma}{1-\gamma} = \frac{\beta_\phi c_\phi^{\beta_\phi - 1}}{\beta_r c_r^{\beta_r - 1}} \frac{\left(\sigma_r^{-2} + c_r^{\beta_r}\right)^2}{\left(\sigma_\phi^{\beta_\phi} + c_\phi^{\beta_\phi}\right)^2}.$$

Since the objective function is minimised when $c_r \to \infty$ and $c_\phi \to \infty$, the optimum will necessarily satisfy $\lambda > 0$. If the private sector does not have inferior knowledge of the real interest rate, r_t, that is, $r_t - r_{t|t} = 0 \; \forall t$, then the loss function is minimised for any $c_r \geq 0$, and only decreases in c_ϕ. In which case, the trade-off between communicating the state of the economy and the reaction function does not exist, and the central bank will allocate all effort to communicating the reaction function. A similar argument applies if the private sector knows the reaction function and not the real rate of interest.

A.3.1 Numerical Example

Here I give a numerical example of the problem for some intuition. For an interior solution where $\beta_r = \beta_\phi = 1$, the optimal signal precisions are

$$\sigma_{sr}^{-2} = c_r^* = \frac{c + \sigma_\phi^{-2} - \Gamma \sigma_r^{-2}}{1 + \Gamma},$$

and

$$\sigma_{s\phi}^{-2} = c_\phi^* = \frac{\Gamma\left(c + \sigma_r^{-2}\right) - \sigma_\phi^2}{1 + \Gamma},$$

where $\Gamma = \sqrt{(1-\gamma)/\gamma}$ measures the relative importance of communicating the reaction function versus communicating the state of the economy. Suppose $\sigma_r = \sigma_\phi = 0.1$, $c = 500$, $\gamma = 0.5$, then $(c_r^*, c_\phi^*) = (250, 250)$. If however, $\gamma = 0.75$ then $(c_r^*, c_\phi^*) = (343.8, 156.2)$. Higher γ increases σ_{sr}^{-2} and at the same time, reduces $\sigma_{s\phi}^{-2}$. Therefore, signalling effects about the real interest rate are stronger when γ is closer to unity: from the Fisher equation,

$$
\begin{aligned}
\mathbb{E}_t\left[\pi_{t+j}\right] &= \mathbb{E}_t\left[i_{t+j-1}\right] - r_{t|t} \\
&= \mathbb{E}_t\left[i_{t+j-1}\right] - ((1-k_r)r_{t-1} + k_r s_t^r)
\end{aligned}
$$

shows a larger value of γ means k_r is higher, and signals about r_t are stronger signals about expected inflation. Although, if r_t is known to the public and the central bank, then $r_t - r_{t|t} = 0$ would always hold and the central bank would only communicate about the reaction function. Which, as argued by Bauer and Swanson (2023a), the central bank and private sector on average do not have meaningfully different forecasts about the state of the economy. In terms of the model, on average, this may reflect γ being relatively small, as interest rate expectations depend on both the responsiveness and the economic outlook, and this is primarily what central banks focuses on communicating in practice.

B Preprocessing Text Data

Text data is unstructured in its raw format, and preprocessing is a necessary step for use in an empirical analysis. Here I describe my approach for cleaning the text data of speeches and minutes for later use in an econometric analysis by removing noise and retaining potentially important information in the text.

- I remove non-Latin characters such as numerals and punctuation. Punctuation typically does not contain important information. And numerals are unlikely to introduce useful information to each word token, but rather increase noise in the data. This is because introducing numerals as additional word tokens splits the set of word tokens up and reduces the frequency of each word token. This reduces the degrees of freedom available for each phrase in the econometric analysis. The context of, say, expected inflation being 2% versus 2.5% is not easily captured in the methods used, but 'increased expected inflation' would be.
- I use entity recognition to remove mentions of people. This helps clean parts of some text that lists attendees or acknowledgements. These word tokens are a more noisy version of the period and speech-type fixed effects are included in the econometric analysis.
- I remove stop words such as '`and`' or '`to`' which are uninformative in general.
- I remove words that are shorter than 3 characters and longer than 15. Most commonly used words with meaning, or acronyms, would fall into this category, and to remove non-word strings.
- Every word is Porter stemmed to strip away any suffix, e.g. the words `inflation` and `inflationary` are both converted to `inflat`. This groups words on the same concept but with slight variation in phrasing.

After this, each document is a list of stemmed words that capture the main information expressed in the document. I then vectorise each document by counting the frequency of trigrams that appear in each document. Each trigram is referred to as a word token. Trigrams are used in the main analysis to capture more context and improve interpretability. There is a trade-off with longer n-grams, as this can considerably reduce the total number of word tokens and frequencies of each word token, which would reduce the reliability of the econometric results.

Once I have a vector representation of each document by counts of all the trigrams that appear over all communications, I select the top 10% most commonly used word tokens from FOMC announcements, press conferences, and intermeeting speeches separately. Restricting attention to frequently used phrases improves the estimation of the language model because phrases with a low variation in their counts will reduce the accuracy of the estimated relationship between the use of that phrase and market outcomes.

C SVAR Notes

Assume the structural representation of the economy is given by the following monthly SVAR(12),

$$AY_t = \sum_{j=1}^{12} C_j Y_{t-j} + \varepsilon_t, \tag{50}$$

where C_j are matrices of coefficients and ε_t are fundamental shocks. A lag length of 12 is used for all series in the VAR to account for annual cycles as the data are on a monthly frequency. Premultiplying by A^{-1}, the VAR estimated by the econometrician is

$$Y_t = \sum_{j=1}^{12} B_j Y_{t-j} + u_t, \tag{51}$$

where u_t is a vector of residuals and B_j are matrices of coefficients. The goal of structural identification is to find a matrix S such that $\hat{u}_t = S\varepsilon_t$ which maps the known residuals to the unknown fundamental shocks. In this application, I am only looking at the effect of monetary policy shocks to the system, i.e. ε_t^p, and not shocks to all the variables used. This simplifies the problem to only studying how the variables in Y_t respond to one shock, and hence one column of S, corresponding to the policy variable, s_p. In my case, I use the surprise in future monetary policy due to information gaps in communications as an instrument. I sum this event level series to a monthly frequency to measure the total information gap that month, m_t, which is used to identify shocks to the end-of-month two-year Treasury yield.

For m_t to be a valid instrument, instrumental relevance, $\mathbb{E}[m_t \cdot \varepsilon_t^p] \neq 0$, and exogeneity, $\mathbb{E}[m_t \cdot \varepsilon_t^{-p}] = 0$, must be satisfied. Market-based monetary policy surprises around communication events should meet these criterion. It likely meets the exogeneity criterion because they are measured in small intervals around the communication events, and are likely uncorrelated with other shocks or variables. The part of the market response coming from information gaps is also likely exogenous because I am using variation in the informativeness of speeches versus the FOMC minutes, meaning the information gap is something the central bank intends to eventually close with the release of the minutes, but exists in the short-term due to the cost involved with constructing the minutes. The relevance criterion is likely met because communication events reveal important news about the conduct of monetary policy from either the component due to unanticipated policy rate changes, or information about how the central bank is setting policy. Similarly, the part of the market response coming from communication noise is likely relevant as shown in the event study regressions. I include intermeeting speeches as Bauer and Swanson (2023b) showed Chair and Vice Chair speeches considerably increase the instrumental relevance for the identification of monetary VARs.

The impact effect of a monetary policy shock can be identified up to a scale using a source of exogenous variation in the policy indicator. The first step regression is using least-squares to estimate

$$\hat{u}_t^p = \phi_0 + \phi_1 m_t + e_t, \tag{52}$$

which if m_t is a valid instrument, the fitted values from (52) are an exogenous source of variation of $\hat{u}_t^p$. Regressing the vector of reduced form residuals for the non-policy variables, $\hat{u}_t^{-p}$ on the fitted values from (52) is a source of exogenous variation for each variable of $\hat{u}_t^{-p}$. The reduced-form variance-covariance matrix can then be used to identify up to a scale how all variables in the VAR respond to a shock to the policy indicator variable, that is,

$$u_t^{-p} = \frac{s^{-p}}{s^p}\hat{u}_t^p + e_t^{-p}, \tag{53}$$

This defines the impact effects on all variables in the VAR from an information gap that shocks the policy variable.[26] The VAR dynamics estimated in (51) then trace out the path the economy follows after a shock. Importantly, the sample size for the identification of the impact of a monetary policy shock can be a subset of the sample used to estimate the reduced form VAR. It may be desirable to use as long a sample as possible for estimating the VAR coefficients to more accurately capture macroeconomic dynamics, rather than restrict the analysis to a period where only the monetary policy shocks are identified (Gertler and Karadi, 2015).

[26]See Gertler and Karadi (2015) for more detail and a proof of this result.

D Additional Results

Appendix Table A1: Market Response Decomposition: FOMC Announcements

	(1) 2Y Treas	(2) 5Y Treas	(3) 10Y Treas	(4) SP500
IG_t	-0.926***	-1.965***	-2.603***	-1.088
	(3.519)	(3.431)	(2.824)	(0.253)
NIG_t	-1.528***	-3.485***	-4.396***	-2.999**
	(14.648)	(13.357)	(10.567)	(2.336)
Constant	0.015***	0.024**	0.027	0.072
Observations	188	188	188	188
R^2	0.761	0.704	0.557	0.055
F	108.5	98.12	89.24	2.843

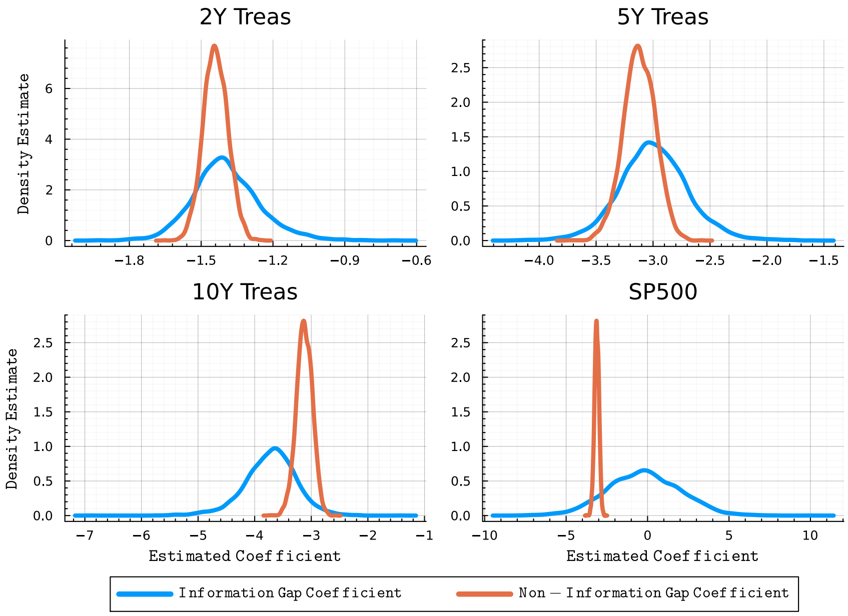
Notes: Event study regressions only for the 188 FOMC announcements in the sample that came with a speech explaining the policy stance. Robust t-statistics in parentheses, F statistic for overall significance reported (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix Table A2: Market Response Decomposition: FOMC Announcements and Press Conferences

	(1) 2Y Treas	(2) 5Y Treas	(3) 10Y Treas	(4) SP500
IG_t	-1.172***	-2.514***	-3.154***	-4.330
	(6.311)	(6.346)	(5.077)	(1.532)
NIG_t	-1.515***	-3.456***	-4.367***	-2.818**
	(14.600)	(13.554)	(11.017)	(2.269)
Constant	0.012***	0.020**	0.024	0.068
Observations	228	228	228	228
R^2	0.757	0.684	0.542	0.060
F	111.4	107.2	100.4	3.799

Notes: Event study regressions only for the 188 FOMC announcements and 40 press conferences in the sample. Robust t-statistics in parentheses, F statistic for overall significance reported (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix Figure A1: Asset Price Responses: Density Estimates for Bootstrap Coefficients.



Notes: I resample 648 speech-level events with replacement then estimate the HDMR, construct the dz_t^0 and dz_t^+ series, decompose $\Delta\mathcal{P}_t$ into an information gap and a non-information gap component which are then used to compute the asset prices responses. I do this 5,000 times. The kernel density estimates for the slope coefficients from these regressions are shown above.

D.1 What do Speeches Signal?

One debate in the literature studying the identification of monetary policy shocks is whether communications signal the Fed's internal macroeconomic forecasts and affect the market response. These signalling effects have been argued to be a confounding variable in measures of exogenous variation in the stance of policy and are responsible for 'price puzzles' in the empirical study of the macroeconomic propagation of monetary policy shocks (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020; Miranda-Agrippino and Ricco, 2021). For example, an increase in the interest rate today because inflation is expected to rise might bias the identification of the effect of interest rates on inflation in the 'wrong' direction, as short-term inflation was going to increase anyway. In contrast, another argument is that imperfect information about the central bank's time-varying reaction function can also be a source of policy surprises and generate the same type of bias (Bauer and Swanson, 2023a,b).

My information gap series potentially measures both economic forecast and reaction function information gaps. However, here I argue here that the information from speeches tends to be about factors other than economic forecasts on average. I exploit a type of

Appendix Table A3: Market Response by SEP Round

	$\Delta\mathcal{P}_t$
SEP_t	0.01*
	(1.70)
$dz_t^0 \times SEP_t$	-0.48
	(1.16)
$dz_t^+ \times SEP_t$	-0.00
	(0.39)
dz_t^0	1.27***
	(3.58)
dz_t^+	0.02**
	(2.31)
Constant	-0.01**
Observations	293

Notes: Robust t-statistics in parentheses.

data release by the FOMC called the summary of economic projections (SEP) that has been released after every other FOMC meeting since October 31 2007. The release of the SEP now coincides with FOMC press conferences, which are held every other FOMC meeting. Importantly, this means whether the SEP is released or not is independent of economic conditions or monetary policy. The SEP is a survey of the FOMC members about their personal macroeconomic forecasts, often referred to as the 'dot plots.' The exact format of this document has changed over time but focuses on forecasts of key economic variables: the federal funds rate, inflation, GDP and unemployment. The forecast horizon for these variables are for the end of the current calendar year, end of the next two calendar years, and a long-run forecast.[27]

To test whether the SEP crowds out some of the information released through the language in speeches, I estimate

$$\Delta\mathcal{P}_t = \beta_0 + \beta_1 SEP_t + \beta_2 z_t^0 \times SEP_t + \beta_3 z_t^+ \times SEP_t + \beta_4 z_t^0 + \beta_5 z_t^+ + e_t, \tag{54}$$

from October 31 2007 to December 2019. The variable SEP_t is an indicator variable that takes on value 1 if speech event t took place during an SEP round, and 0 otherwise.[28] The

[27] An SEP in November would contain a forecast that is approximately one-month ahead for December 31, as well as a 13-month ahead forecast, 25-month ahead forecast and a forecast for the long-run.

[28] There are 293 speeches from October 31 2007, including FOMC announcements and press conferences, and 54% of speeches took place during an SEP round.

interaction terms reflect whether the information from text about the path of policy differs between SEP rounds or not. If speeches primarily signal the economic outlook then post-SEP round speeches should have a reduced effect on the market response on average, with $\beta_1 < 0$ and $\beta_2 < 0$. However, if speeches signal information other than the economic outlook then $\beta_1 = \beta_2 = \beta_3 = 0$ would be expected. Table A3 provides evidence supporting the second claim, that there is no difference in how speech language affects belief updates about the policy path between SEP rounds or not. Therefore, speech text tends to signal information other than the long-term economic outlook, on average.

D.2 Robustness

D.2.1 Interpolation Methods

To include intermeeting speeches, I compare their sentiment with interpolated FOMC minutes sentiment. I show these findings are robust to a variety of interpolation methods.

Appendix Table A4: Sentiment Score Regressions

	Linear		Constant Left		Constant Right	
	z_t^0	z_t^+	z_t^0	z_t^+	z_t^0	z_t^+
$\tilde{z}_t^0$	0.351***	-0.015	0.346***	-0.035	0.318***	-0.014
	(7.478)	(0.584)	(6.685)	(0.910)	(7.319)	(0.579)
$\tilde{z}_t^+$	0.043	0.060	0.005	-0.001	0.034	0.036
	(0.993)	(1.235)	(0.332)	(0.202)	(0.981)	(1.116)
Constant	0.002	0.000	0.039	-0.004	0.002	0.000
Observations	648	648	532	532	648	648
R^2	0.129	0.002	0.118	0.001	0.119	0.001

Notes: Linear interpolation of the FOMC minute sentiment scores, $\tilde{z}_t^0$ and $\tilde{z}_t^+$ over time is a straight line connecting each point. Constant right interpolation compares the text sentiment of each communication event with the sentiment of the following FOMC meeting minutes. Constant left compares the sentiment scores of the FOMC minutes with each communication until the FOMC minutes are released, then since the minutes are public, there is no private information to compare the sentiment of later speeches. Robust t-statistics in parentheses (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix Table A5: Market Response Decomposition: Alternative Interpolation Methods

	Linear			Constant Left			Constant Right		
	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$	$\Delta\mathcal{P}_t$
dz_t^0	0.015***	0.025***		0.015***	0.025***		0.013***	0.025***	
	(6.518)	(8.627)		(6.064)	(7.823)		(6.583)	(8.724)	
dz_t^+	0.003***	0.004***		0.001	0.001*		0.002***	0.004***	
	(3.021)	(3.086)		(1.413)	(1.728)		(2.955)	(3.118)	
$\tilde{z}_t^0$		0.021***			0.022***			0.021***	
		(7.480)			(6.935)			(7.526)	
$\tilde{z}_t^+$		0.004**			0.001			0.004**	
		(2.109)			(1.557)			(2.355)	
z_t^0			0.024***			0.024***			0.024***
			(8.691)			(7.998)			(8.691)
z_t^+			0.004***			0.001**			0.004***
			(3.213)			(2.021)			(3.213)
Constant	-0.000	-0.000	-0.000	-0.002	-0.001	-0.000	-0.000	-0.000	-0.000
Observations	648	648	648	532	532	532	648	648	648
R^2	0.115	0.242	0.236	0.110	0.227	0.222	0.106	0.241	0.236
F	28.08	22.78	45.64	19.04	16.86	33.89	26.58	23.06	45.64

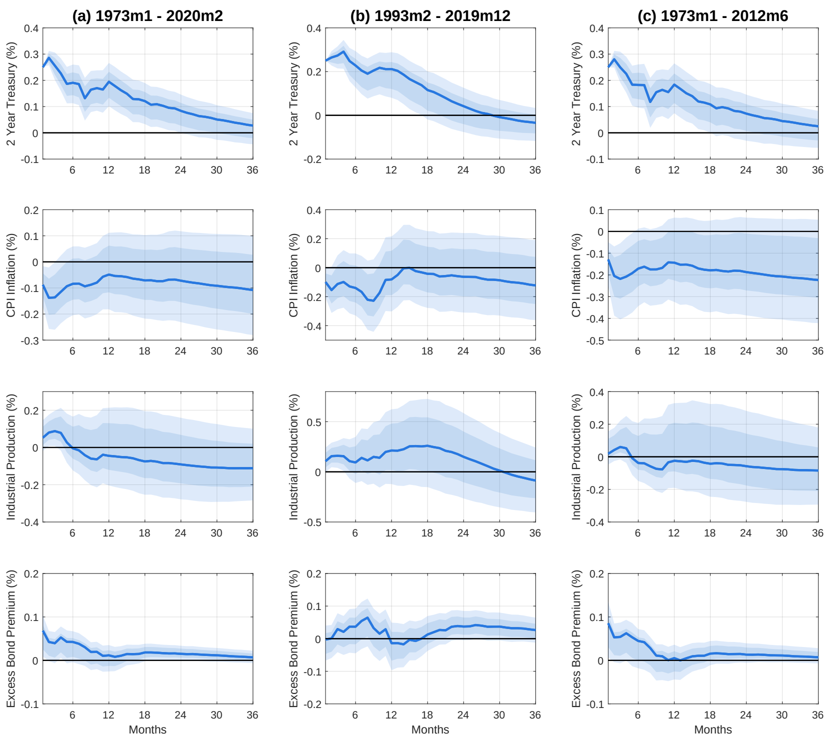
Notes: Linear interpolation of the FOMC minute sentiment scores, $\tilde{z}_t^0$ and $\tilde{z}_t^+$ over time is a straight line connecting each point. Constant right interpolation compares the text sentiment of each communication event with the sentiment of the following FOMC meeting minutes. Constant left compares the sentiment scores of the FOMC minutes with each communication until the FOMC minutes are released, then since the minutes are public, there is no private information to compare the sentiment of later speeches. Robust t-statistics in parentheses (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix Table A6: Event Study Regressions: Different Interpolations

	Linear				Constant Left				Constant Right			
	2Y Treas	5Y Treas	10Y Treas	SP500	2Y Treas	5Y Treas	10Y Treas	SP500	2Y Treas	5Y Treas	10Y Treas	SP500
IG_t	-1.342***	-2.781***	-3.331***	-1.829	-1.386***	-3.195***	-3.977***	-3.044**	-1.344***	-2.756***	-3.362***	-1.706
	(13.617)	(12.328)	(9.998)	(1.233)	(14.351)	(14.883)	(11.845)	(2.224)	(13.404)	(11.926)	(9.803)	(1.134)
NIG_t	-1.441***	-3.130***	-3.950***	-1.948***	-1.480***	-3.211***	-4.026***	-2.838***	-1.440***	-3.129***	-3.940***	-1.962***
	(26.749)	(21.395)	(16.906)	(3.058)	(29.973)	(21.377)	(16.077)	(4.067)	(26.587)	(21.415)	(16.877)	(3.072)
Constant	0.003**	0.005	0.004	0.057***	0.003*	0.004	0.004	0.068***	0.003**	0.005	0.004	0.057***
Observations	648	648	648	648	532	532	532	532	648	648	648	648
R^2	0.788	0.690	0.565	0.030	0.804	0.727	0.598	0.063	0.788	0.691	0.565	0.030
F	361.2	246.2	161.8	4.842	469.3	283.5	163.2	9.529	359	246.6	162.5	4.844

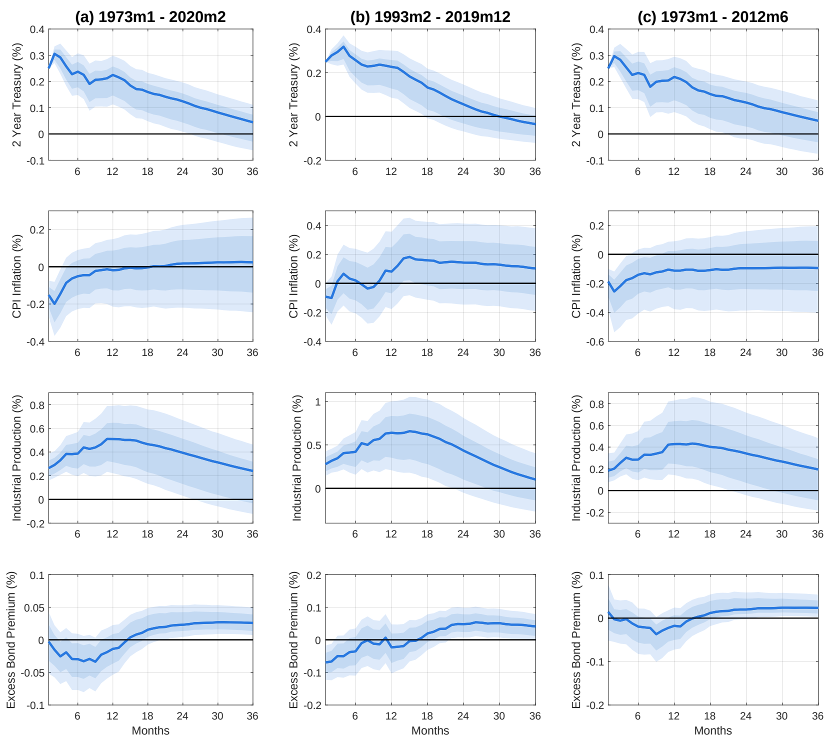
Notes: Linear interpolation of the FOMC minute sentiment scores, $\tilde{z}_t^0$ and $\tilde{z}_t^+$ over time is a straight line connecting each point. Constant right interpolation compares the text sentiment of each communication event with the sentiment of the following FOMC meeting minutes. Constant left compares the sentiment scores of the FOMC minutes with each communication until the FOMC minutes are released, then since the minutes are public, there is no private information to compare the sentiment of later speeches. Robust t-statistics in parentheses (*** = $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Appendix Figure A2: Impulse Responses to a Hawkish Information Gap: Linear Interpolation



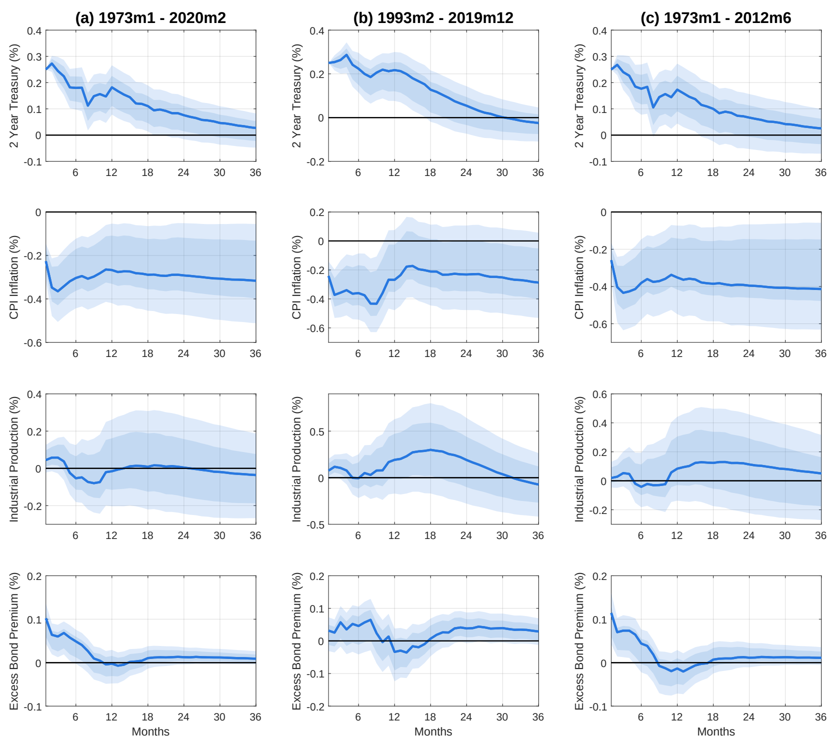
Notes: Responses to a hawkish information gap that raise the end-of-month two-year Treasury yield by 25 basis points using linear interpolation for the FOMC minutes. Shaded intervals represent 68 and 90% confidence intervals calculated with 10,000 wild bootstrap simulations which take into account the first-stage regression's coefficient uncertainty. Panel (a) shows results for the VAR estimated over 1973m1-2020m2, and impact effects identified over 1993m2-2019m12. Panel (b) estimates the VAR and identifies impact effects over the common sample 1993m2-2019m12. Panel (c) estimates the VAR over 1973m1-2012m6 and impact effects over 1993m2-2012m6, ending before the zero lower bound period.

Appendix Figure A3: Impulse Responses to a Hawkish Information Gap: Constant Left Interpolation



Notes: Responses to a hawkish information gap that raise the end-of-month two-year Treasury yield by 25 basis points using constant-left interpolation for the FOMC minutes, removing all speeches that came after the minutes release. Shaded intervals represent 68 and 90% confidence intervals calculated with 10,000 wild bootstrap simulations which take into account the first-stage regression's coefficient uncertainty. Panel (a) shows results for the VAR estimated over 1973m1-2020m2, and impact effects identified over 1993m2-2019m12. Panel (b) estimates the VAR and identifies impact effects over the common sample 1993m2-2019m12. Panel (c) estimates the VAR over 1973m1-2012m6 and impact effects over 1993m2-2012m6, ending before the zero lower bound period.

Appendix Figure A4: Impulse Responses to a Hawkish Information Gap: Constant Right Interpolation



Notes: Responses to a hawkish information gap that raise the end-of-month two-year Treasury yield by 25 basis points using constant-right interpolation for the FOMC minutes. Shaded intervals represent 68 and 90% confidence intervals calculated with 10,000 wild bootstrap simulations which take into account the first-stage regression's coefficient uncertainty. Panel (a) shows results for the VAR estimated over 1973m1-2020m2, and impact effects identified over 1993m2-2019m12. Panel (b) estimates the VAR and identifies impact effects over the common sample 1993m2-2019m12. Panel (c) estimates the VAR over 1973m1-2012m6 and impact effects over 1993m2-2012m6, ending before the zero lower bound period.