Fireflies in the Mist: Central Bank Communication and Uncertainty*

Dogukan Guney†

June 27, 2024

Abstract

Leveraging a novel dataset composed of FOMC members' speeches, this paper shows how a more transparent approach to monetary policy communication can lead to significant positive outcomes in the economy. By dissipating uncertainty surrounding monetary policy, transparency in Fed communication results in higher levels of industrial production and lower unemployment rates. It stimulates household consumption and has positive effects on consumer sentiment. Furthermore, it contributes to the stabilization of financial markets by reducing the volatility of asset prices and narrowing credit spreads, simultaneously leading to an increase in the value of stocks for both large and small U.S. companies.

Keywords: monetary policy communication, uncertainty, identification through heteroskedasticity, textual analysis.

JEL Codes: C32, D80, E52, E58

*I am deeply grateful to Tiziana Assenza and Patrick Fève for their invaluable guidance. For helpful suggestions and discussions, I thank Patrick Coen, Fabrice Collard, René Garcia, Laura Gáti, Christian Hellwig, Koen Jochmans, Òscar Jordà, Narayana Kocherlakota, Pascal Lavergne, Michael McMahon, Nour Meddahi, Elena Pastorino, Giovanni Ricco, Philipp Wangner, Johannes Wohlfart, and all TSE Macro Workshop participants.

†Toulouse School of Economics, dogukan.guney@tse-fr.eu

"*When I began my time as Chairman, one of my priorities was to make the Federal Reserve more transparent . . . I believed then, as I do today, that transparency in monetary policy enhances public understanding and confidence, promotes informed discussion of policy options, increases the accountability of monetary policymakers for reaching their mandated objectives, and ultimately makes policy more effective by tightening the linkage between monetary policy, financial conditions, and the real economy.*"

Ben Bernanke

Herbert Stein Memorial Lecture, 19 November 2013

1 Introduction

Fed's communication strategies have undergone significant changes over the last 25 years. Towards the end of Alan Greenspan's era, and especially following Ben Bernanke's appointment to the Federal Open Market Committee (FOMC), the Fed began prioritizing effective communication. This focus intensified when Bernanke became chairman in 2006, leading the Fed to adopt a more systematic and transparent communication strategy with both the general public and the markets. As indicated in the quote above, Bernanke believed that a transparent communication strategy can enhance public understanding of Fed policies. Therefore, one of the primary goals of this reform in Fed communication was to alleviate uncertainties surrounding policies and improve the ability of households and markets to form more accurate expectations about key macroeconomic variables. This would consequently lead to better-informed decisions by firms and households, resulting in positive outcomes in the markets and the broader economy.

Following Bernanke's intuition, this paper examines the effects of the Fed's more transparent communication strategy on monetary policy uncertainty and its macroeconomic consequences. Within the contemporary central banking framework, communication is recognized as an effective monetary policy tool. Especially when interest rates are constrained by the zero lower bound, central banks use communication policies to provide forward guidance and influence medium-to-long term asset yields. This, in turn, can positively impact economic activity and mitigate the severe effects of recessions. In this paper, I discuss a new channel activated by the Fed's communication policy: the uncertainty channel. This channel works primarily through the impact of Fed's monetary policy communication on reducing monetary policy uncertainty.

I employed a simple time series model featuring a regime switch to causally identify the impact of more transparent Fed communication on monetary policy uncertainty.[1] The findings show that more frequent and transparent MP communication significantly and immediately reduces MP uncertainty. This reduction in policy uncertainty subsequently increase industrial production, decrease unemployment, and improve labor market conditions. Both durable and non-durable goods consumption rises in the following months, while households experience a growth in their real disposable income only after two years. Although there is an observed increase in the producer price index, there is no evidence of a significant change in the consumer price index. Moreover, the reduction in uncertainty provides a clearer view in financial markets, as evidenced by a decrease in expected volatility in stock prices. Additionally, credit spreads narrow, and stock prices of both large and small firms rise. Eventually, the acceleration in economic and financial activity, as well as price increases in producer goods, prompts the Fed to respond with an increase in interest rates.

To measure the MP communication, I focus on FOMC members' speeches as my dataset for several reasons. First, these speeches are less examined in the literature compared to other Federal Reserve documents, such as FOMC policy statements or meeting minutes. Bianchi et al. (2023) find that much of the monetary policy surprises occur outside of the tight policy announcement windows. Swanson and Jayawickrema (2021) and Swanson (2023) claim that speeches by the Fed chairs are at least as important as other FOMC announcements. Therefore, this gap in the literature provides an opportunity to explore an under-researched but evidently significant aspect of Fed communication. Second, the higher frequency of speeches compared to other Fed documents ensures more variation over time, which is crucial for econometric identification, as will be discussed in Section 3. Third, FOMC members' speeches are inherently more discretionary. Despite the Fed's established communication guidelines, each member retains the autonomy to choose the topics and tone of their talks. Due to this discretionary nature of speeches, it is unclear whether the overall effect of these speeches is to reduce uncertainty or create confusion about monetary policy.

Literature Review. The existing literature extensively discusses the adverse effects of uncertainty on economic and financial markets. Studies by Bloom (2009), Jurado et al. (2015) and Baker et al. (2016) (hereafter, BBD) indicate that economic uncertainty leads to recessionary pressures and heightened volatility in financial markets. Similarly, Husted et al. (2020) (hereafter, HRS) demonstrate that monetary policy uncertainty results in contractionary effects on the economy. Research by Jorda and Salyer (2003) suggests that

[1]From here onwards, I will use 'MP communication' and 'MP uncertainty' interchangeably with 'monetary policy communication' and 'monetary policy uncertainty' for readability purposes.

increased uncertainty about monetary policy is followed by a decline in nominal interest rates. As potential sources of economic uncertainty, Baker et al. (2023) discuss the role of natural disasters, terrorist attacks, military coups, and revolutions. Ludvigson et al. (2021) find that macroeconomic uncertainty during recessions is often an endogenous response to output shocks. Recently, Assenza et al. (2024) have shown that technology-related fake news can elevate macroeconomic uncertainty and harm economic activity.

On the other hand, researchers have devoted less attention to exploring strategies for mitigating uncertainty. Swanson (2006) finds that steps taken by the Fed in the late 1990s and early 2000s to increase FOMC transparency improved private sector interest rate forecasts. Cieslak and McMahon (2023) argue that an increase in FOMC members' relative hawkishness predicts a reduction in risk premium. Ahrens et al. (2023) find no evidence that FOMC members' speeches resolve uncertainty, contradicting the main finding of this paper, while Cieslak et al. (2023) examine the impact of uncertainty on FOMC decision-making.[2]

Concerning the technical aspect of the paper, existing literature on Fed regime switches predominantly addresses shifts in conventional monetary policy. For instance, Garcia and Perron (1996) investigate regime switches in U.S. real interest rates, while Sims and Zha (2006) and Davig and Doh (2014) analyze changes in U.S. monetary policy rule coefficients and shock volatilities over time. This paper also diverges from the mentioned literature by being the first study, to my knowledge, to utilize regime switches in an unconventional monetary policy setup to examine its impacts on the macroeconomy.

The rest of the paper is organized as follows: Section 2 introduces the data on FOMC members' speeches and uncertainty. Section 3 discusses the econometric model and presents the identification results. Section 4 explains the effects of the identified shocks on the economy. The final section concludes.

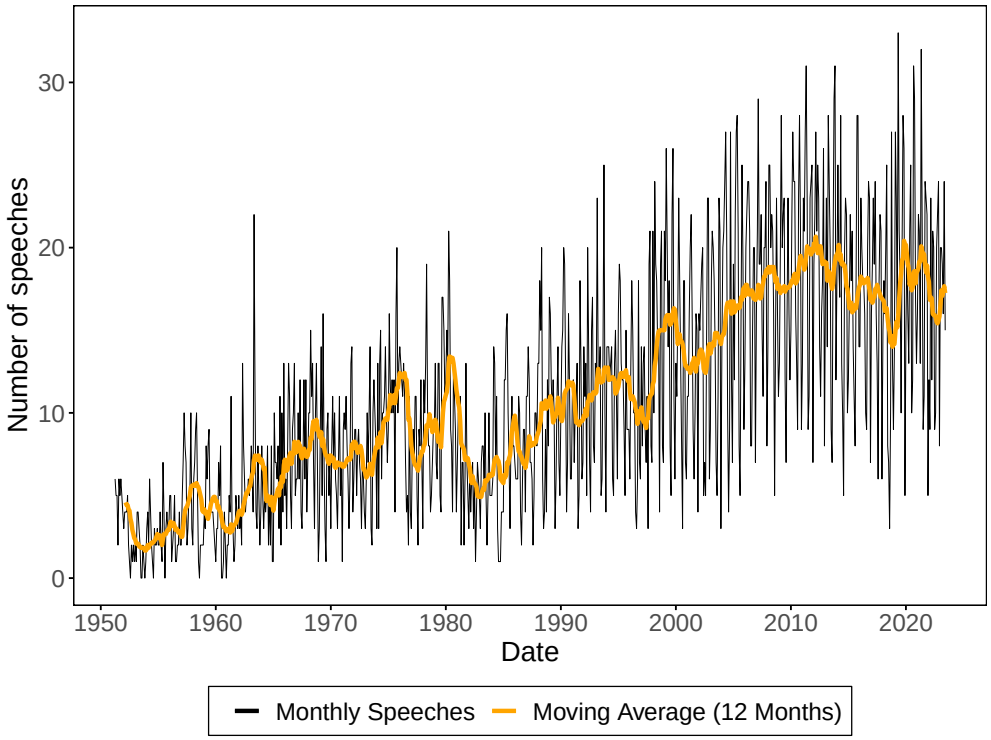
2 Data

2.1 FOMC Members' Speeches

In this section, I present the novel dataset I compiled, consisting of speeches delivered by members of the Federal Open Market Committee (FOMC), including chairs, vice chairs, governors, and presidents of the 12 Federal Reserve Banks. These speeches were collected from various sources, including the FRASER database and the websites of the Federal

[2]See Istrefi et al. (2023) and Alexopoulos et al. (2024) for other interesting research that uses speeches of Fed officials.

Figure 1: Number of Speeches Delivered by FOMC Members Over the Years



Notes. The figure illustrates the monthly frequency of speeches delivered by FOMC members, as depicted by the black line. The orange line represents a 12-month moving average of the black line, helps us see the overall trend over time. The moving average is calculated by shifting one month at a time.

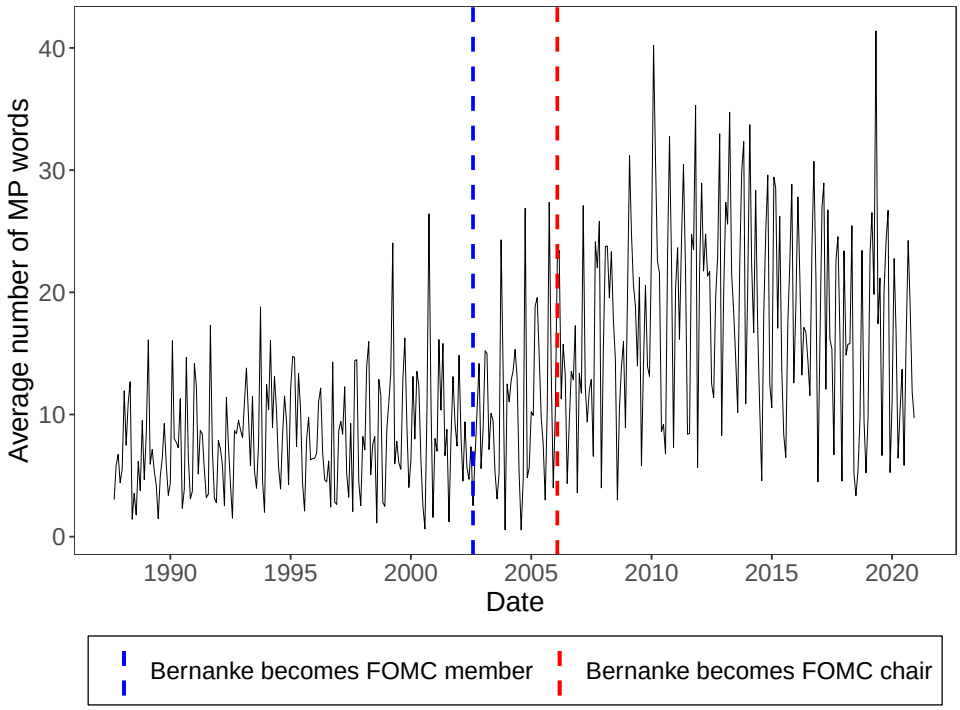
Reserve Board and the 12 Federal Reserve Banks.[3] In total, the dataset comprises 10,682 speeches spanning from March 1951 to December 2023. After a rigorous data cleaning procedure detailed in Appendix A.1, I retained 9,511 speeches.[4] Figure 1 depicts the trend in the number of speeches delivered over time. In the 1950s, the number of speeches given in a month was around 5, increasing to 20 speeches per month by around 2010. Occasionally, this number even reaches 30, indicating that either one of the FOMC members gives a speech every day.

To gauge the extent to which FOMC members discuss monetary policy during their speeches, I employed a dictionary-based text analysis method. This approach involves tallying the occurrences of specific words or phrases from a predefined dictionary within a given text. The dictionary I utilized is sourced from BBD and detailed in Table B.1. It comprises terms relevant to monetary policy such as "*federal funds rate*", "*money supply*",

[3]FRASER is an online data repository that offers historical data pertaining to the U.S. economy and the Federal Reserve.

[4]When I refer to speeches, it also includes documents publicly released by an FOMC member, but excludes social media posts.

Figure 2: Average Number of Monetary Policy Words Used by FOMC Members



Notes. The figure depicts the monthly frequency of monetary policy-related words used by FOMC members, normalized by the number of days in each month. These words are directly sourced from the dictionary outlined in Baker et al. (2016) and can be found in Appendix Table B.1. The vertical dashed blue line signifies the month when Ben Bernanke joined the FOMC. The second vertical dashed line, colored red, denotes the date when Bernanke took over the FOMC chair from Alan Greenspan.

"*open market operations*", "*quantitative easing*", "*discount window*", and so forth. Opting for this method offers several advantages. Firstly, from a methodological point of view, dictionary-based techniques are straightforward to implement and interpret. They require fewer computational resources and specialized expertise compared to more complex natural language processing methods, such as latent Dirichlet allocation or nonnegative matrix factorization. Secondly, these methods ensure transparency in the analysis process, enabling researchers to understand how text features are categorized based on predefined dictionaries, thereby enhancing the reproducibility and reliability of findings. Lastly, the MP uncertainty series, another key element in this paper, is directly taken from BBD. Employing their original dictionary and a similar methodology to quantify monetary policy communication also ensures compatibility between their uncertainty series and the MP communication series that I construct.

Figure 2 illustrates the series constructed using the described dictionary-based method. Specifically, it represents the number of words related to monetary policy used in speeches,

normalized by the number of days in each month. The vertical dashed blue line represents the month when Ben Bernanke joined the FOMC as a member. The left side of the red dashed line depicts the years of Alan Greenspan's chairmanship, while the right side reflects the tenure of subsequent Fed chairs, including Ben Bernanke (2006-2014), Janet Yellen (2014-2018), and Jerome Powell (2018-). The most striking observation in the figure is the significant increase in monetary policy communication following Bernanke's tenure on the FOMC. Both the average number of monetary policy words used and their volatility increase notably during the transition from Greenspan to Bernanke's leadership at the Fed.

2.2 Monetary Policy Uncertainty

The monetary policy uncertainty index used in this study is sourced from BBD, who employed a dictionary-based method on newspaper articles to quantify uncertainty. To build the index, they utilized the Access World News database, which encompasses over 2,000 U.S. newspapers. As the dictionary method, they applied what they call the E, P, U and M criteria. This involves flagging all newspaper articles in the database that includes at least one term from each of the following four dictionaries:

E: *economic, economy*

P: *congress, legislation, white house, regulation, federal reserve, deficit*

U: *uncertain, uncertainty*

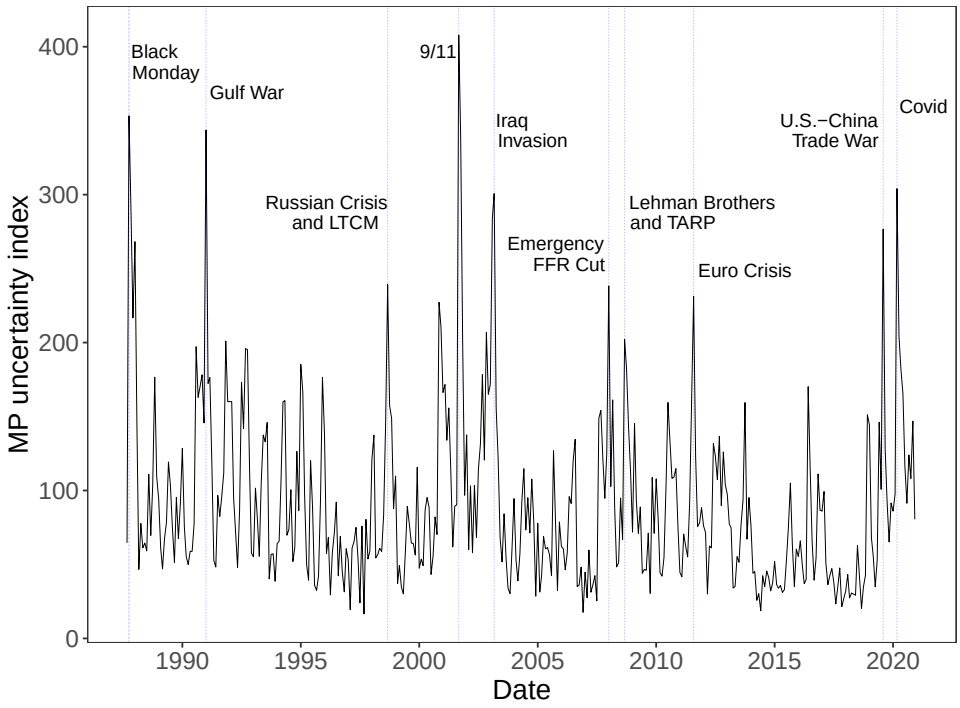
M: *federal reserve, the fed, money supply, open market operations, quantitative easing, monetary policy, fed funds rate, ...* (Please refer to Table B.1 for the full list of monetary policy terms.)

For each month, they summed the row counts of articles that met the defined criteria and divided this total by the number of articles published in the same newspapers. Finally, they normalized the index to have an average value of 100 from January 1985 to December 2010.

Figure 3 depicts the constructed monetary policy uncertainty series. The index exhibits several peaks during specific time intervals. It reaches its highest values during events such as Black Monday, the Gulf War, and the 9/11 attacks. Other notable peaks occur during the 2008 Financial Crisis and the European Debt Crisis. Additionally, the U.S.-China Trade War and the COVID-19 pandemic are the other developments that significantly increased monetary policy uncertainty in the U.S.

There are two other potential MP uncertainty series that could be used as alternatives to this one. The first alternative is also provided by BBD. Instead of focusing all U.S.

Figure 3: Monetary Policy Uncertainty Index



Notes. The index is borrowed from Baker et al. (2016) and can be found on the authors' website: https://www.policyuncertainty.com/monetary.html. It measures the uncertainty surrounding monetary policy and is calculated based on articles from U.S. newspapers covered by Access World News.

newspapers in the Access World News database, they applied the same dictionary method to 10 major national and regional U.S. newspapers.[5] The authors aim to capture trends in the mainstream media by considering only leading newspapers when constructing this alternative series. However, this index has its drawbacks, as focusing on a limited set of newspapers rather than all newspapers in Access World News introduces additional noise. Moreover, the 10 newspapers selected by BBD are not the top 10 most widely read newspapers in the U.S. anymore. For example, *Miami Herald*, *Boston Globe*, *San Francisco Chronicle*, and *Dallas Morning News* are not in the list of top 10 newspapers with the highest circulation in the U.S.[6]

Another candidate is the MP uncertainty index built by HRS, which focuses exclusively on the three largest newspapers in the U.S.: *the Washington Post*, *Wall Street Journal*, and *New York Times*. While they adopt a methodology similar to BBD, their dictionary is

[5]These 10 newspapers are: *USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times,* and *Wall Street Journal*.

[6]For further details, please refer to https://www.statista.com/statistics/272790/circulation-of-the-biggest-daily-newspapers-in-the-us/.

noticeably smaller, as shown in Table B.2. Importantly, the index of HRS is constructed by dividing the number of articles mentioning monetary policy uncertainty by the total number of articles mentioning "Federal Reserve". This normalization is different from the approach taken by BBD, who divide directly by the total number of newspaper articles.

Comparing the two dictionaries in Table B.1 and B.2, along with the different normalization procedures, we observe a distinction between the purposes of the two indices. HRS aim to construct an index that captures uncertainty about U.S. monetary policy, whereas BBD aim to capture monetary policy uncertainty in the U.S. regardless of its origin. This paper is interested in overall monetary policy uncertainty prevailing in the United States and whether the Fed can mitigate it through communication. Therefore, the index by BBD is more preferable.[7]

Finally, there are other prominent series in the literature, such as those developed by Jurado et al. (2015). These series address different types of uncertainties, including what they refer to as macro uncertainty, real uncertainty, and financial uncertainty. However, the focus of this paper is specifically on a particular uncertainty relevant to monetary policy.

3 Econometric Model and Identification Results

The challenge in identifying the impact of MP communication on MP uncertainty stems from the classical simultaneity problem in econometrics. It is likely that there exists a bidirectional relationship between MP communication and uncertainty, making it impossible to determine the causal impact of one variable on the other without imposing additional structural assumptions.

3.1 A Regime Shift in Fed Communication

To address the mentioned econometric challenge and shed light on the causal relationship between the variables of interest, I propose employing the identification through heteroskedasticity method, as suggested by Rigobon (2003) and implemented by Rigobon and Sack (2003, 2004, 2005) in various contexts. This method is based on the heteroskedasticity of structural error terms and is applicable when the variables exhibit regime switches. As illustrated in Figure 2, there is a noticeable shift both in the frequency and volatility of monetary policy-related words in FOMC members' speeches. This shift is not arbitrary but reflects a change in the approach to monetary policy communication from

[7]The main results will also be presented using these alternative uncertainty measures in Section 4.

Greenspan's chair term to Bernanke's tenure. Alan Greenspan was not a strong advocate of transparent central bank communication, as evidenced by his later famous remarks:

"*Since I've become a central banker, I've learned to mumble with great incoherence. If I seem unduly clear to you, you must have misunderstood what I said.*" (Alan Greenspan, US Congress, 22 September 1987)

On the other hand, Ben Bernanke supported a more transparent and clear communication strategy, as discussed earlier.

To further explore the possibility of a regime shift in MP communication, I employ three statistical tests recommended by Andrews (1993): the Wald test, LM test, and LR test. These tests are proposed to evaluate parameter stability and structural change. I begin by fitting a bivariate VAR model to MP communication and MP uncertainty variables, with a lag number of 12 selected via Bayesian Information Criterion (BIC). Subsequently, I derive the reduced form residuals from this model. Next, I sequentially partition this reduced form error series into two segments by shifting in time, ensuring each segment comprises at least 15% of the data. Finally, I calculate the variance of each segment and iteratively compute the three test statistics for the variances. These statistics provide insights into whether there is a significant change in the volatility of MP communication.

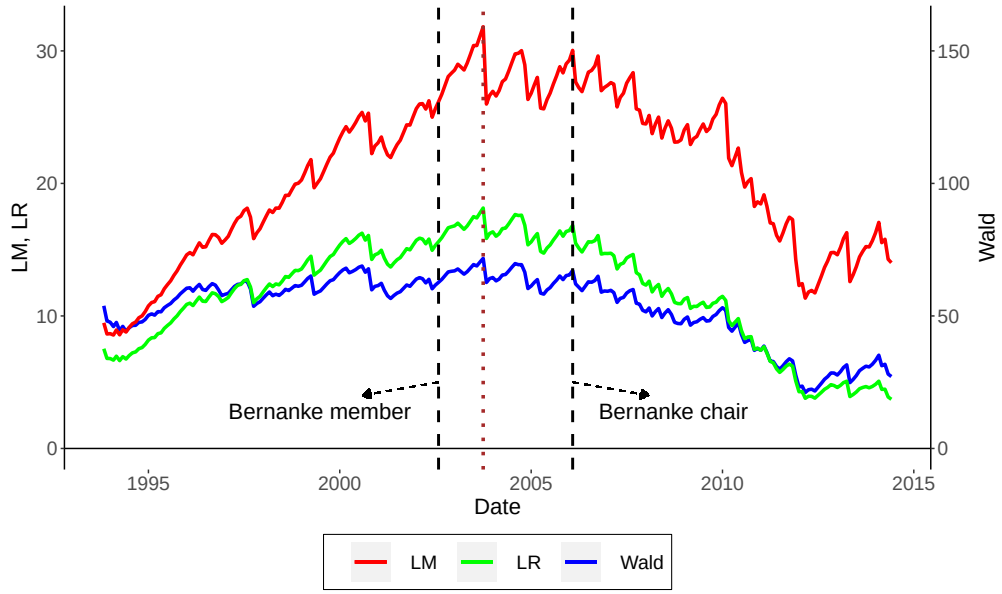
Figure 4 shows the results of the Wald, LM, and LR tests. All test statistics exhibit a peak in October 2003, marked by a vertical brown dotted line, where they are significantly different from zero. This period marks the time when Ben Bernanke joined the FOMC, initially as a member in August 2002, before eventually becoming the chair in February 2006. The shift in communication strategy towards a more transparent and refined communication appears to have begun to spread within the committee during this period.

Further evidence of this shift can be seen when counting the occurrences of the word "*communication*" in FOMC meeting transcripts.[8] Between 2000 and 2002, this word appeared an average of 3.6 times per transcript. In 2003, it spiked to 18 times per transcript, five times the average of the preceding three years. Notably, in the August 8, 2006 meeting—the fifth meeting with Bernanke as chair—the word appeared 70 times. This simple statistic shows that communication became an important agenda item of the FOMC meetings during this period of time.

The change in the Fed's communication strategy is further corroborated by statements from FOMC members and meeting participants. For instance, the following excerpts are drawn from three different FOMC meeting transcripts:

[8]Transcripts are the most detailed records of FOMC meetings. They are made available to the public five years after the meetings are held.

Figure 4: Structural Break Test



Notes. The three test statistics are constructed following the approach detailed in Andrews (1993). They are computed using the reduced form residuals of monetary policy communication, obtained after fitting a bivariate VAR model including monetary policy uncertainty. A lag number of 12 is selected based on the Bayesian Information Criterion. The vertical dashed black lines represent the dates when Bernanke joins the FOMC as a member and when he becomes the chair. All three test statistics display a peak in October 2003, marked by a vertical brown dotted line.

W. Poole: "... *I think that's probably true of communication strategy as well. We need to develop a standard strategy ...*" (28 October 2003)

D. Kos: "... *the market's reaction has progressively become more benign as the Committee has become more transparent and the communications policy has evolved ...*" (21 September 2004)

R. Kroszner: "... *Obviously the question that we are dealing with now is not just optimal monetary policy but also optimal information disclosure and optimal communication policy ...*" (28 March 2006)

These excerpts show the FOMC members' focus on the Fed's communication strategy during the 2003-2006 period. The alignment of statistical and anecdotal evidence underscores the robustness of the observed shift toward more transparent and improved MP communication.

On the other hand, we don't observe such a structural break in the MP uncertainty index, as shown in Figure 3. While turbulent periods are sometimes present in the index, they are conceptually distinct from a regime change such as the one observed in the MP communication series. A similar statistical analysis using Wald, LM, and LR tests also

rejected the existence of a regime switch in this series.

3.2 Partial Identification

Following similar notations in Rigobon and Sack (2004), the econometric model is specified by the following system of equations:

$$m_t = \beta u_t + \gamma z_t + \varepsilon_t, \tag{1}$$

$$u_t = \alpha m_t + z_t + \eta_t, \tag{2}$$

where m_t represents the variable for monetary policy communication, u_t denotes monetary policy uncertainty, z_t encompasses a vector of unobserved common shocks, while ε_t and η_t stand for monetary policy communication shock and monetary policy uncertainty shock, respectively. These equations suffer from the well-known simultaneity problem, and the parameters cannot be identified without additional restrictions. As discussed in Section 3.1, we can (partially) address the identification issue by assuming that there are two regimes in monetary policy communication. Without loss of generality and just for illustrative purpose, let's consider a case in which z_t is a single variable.[9] Denoting with σ_{x,R_i} the standard deviation of shock x in regime $i \in \{1, 2\}$ ($i = 1$ is Greenspan regime, $i = 2$ is Bernanke regime), I impose the following restrictions:

$$\sigma^2_{\varepsilon,R_1} \neq \sigma^2_{\varepsilon,R_2}, \tag{3}$$

$$\sigma^2_{\eta,R_1} = \sigma^2_{\eta,R_2}, \tag{4}$$

$$\sigma^2_{z,R_1} = \sigma^2_{z,R_2}, \tag{5}$$

and the parameters α, β, and γ remain stable over time.[10] In simpler terms, Equation (3) means that the variance of monetary policy shocks differs across the two regimes, while Equations (4) and (5) imply that other shocks maintain constant variances.[11] Under this structure, we can show that the parameter of interest α, representing the impact of MP communication on MP uncertainty, is identifiable, even though not all parameters are.

[9] The results can be easily generalized for a multivariate z_t.

[10] Sims and Zha (2006) test the stability of monetary policy reaction function using a similar regime-switching model. They find that stable monetary policy reaction function coefficients, combined with heteroskedastic surprises, best fit the historical data.

[11] Presumably, $\sigma_{\varepsilon,R_1} < \sigma_{\varepsilon,R_2}$, although this assumption is more restrictive and not necessary for identification. However, results in the next section indicate that this is indeed the case.

Solving the reduced form Equations (1) and (2) yields

$$m_t = \frac{1}{1-\alpha\beta}\big[(\beta+\gamma)z_t + \beta\eta_t + \varepsilon_t\big],$$
$$u_t = \frac{1}{1-\alpha\beta}\big[(1+\alpha\gamma)z_t + \eta_t + \alpha\varepsilon_t\big].$$

The covariance matrices of the variables under two regimes are $\Omega_{R_i} = E\big[[m_t u_t]' \cdot [m_t u_t] | t \in R_i\big]$ with $i \in \{1, 2\}$. In the assumed framework, these covariance matrices are dictated by:

$$\Omega_{R_i} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \sigma^2_{\varepsilon,R_i} + \beta^2\sigma^2_{\eta,R_i} + (\beta+\gamma)^2\sigma^2_{z,R_i} & \alpha\sigma^2_{\varepsilon,R_i} + \beta\sigma^2_{\eta,R_i} + (\beta+\gamma)(1+\alpha\gamma)\sigma^2_{z,R_i} \\ . & \alpha^2\sigma^2_{\varepsilon,R_i} + \sigma^2_{\eta,R_i} + (1+\alpha\gamma)^2\sigma^2_{z,R_i} \end{bmatrix}.$$

When we take the difference between the covariance matrices under the described assumptions, we get:

$$\Delta\Omega = \Omega_{R_1} - \Omega_{R_2} = \lambda\begin{bmatrix} 1 & \alpha \\ \alpha & \alpha^2 \end{bmatrix}, \tag{6}$$

where $\lambda = (\sigma^2_{\varepsilon,R_1} - \sigma^2_{\varepsilon,R_2})/(1-\alpha\beta)^2$. The system has two unknowns, α and λ, defined by three equations involving two variances and one covariance statistic. Hence, the system is overidentified. We can estimate α and λ using the generalized method of moments, as outlined by Rigobon and Sack (2004), Kilian and Lütkepohl (2017), and Lewbel (2012). Given its overidentification, we can examine the validity of the additional restrictions through the Sargan-Hansen test. A significant value of the test statistic implies the rejection of overidentifying restrictions. In this case, either the variance of at least one other shock also shifts, or the model parameters are not stable across the two assumed regimes.

As the benchmark case, I assumed regime 1 (Greenspan regime) to span from September 1987 to January 2006, corresponding to Greenspan's tenure as chair. Meanwhile, regime 2 (Bernanke regime) encompasses the period from February 2006 to December 2019. Although Bernanke's chairmanship ended in January 2014, subsequent Fed chairs continued adopting a transparent and careful communication strategy.[12] Hence, I denote the period following Bernanke's tenure as the Bernanke regime. Prior to estimating the model using GMM, the MP Communication and MP uncertainty series are normalized to have a mean of zero and a standard deviation of one over the period from September 1987 to December 2019.

[12]For example, Janet Yellen continued to hold press conferences after every two consecutive FOMC meetings and gave numerous public speeches. Jerome Powell further increased the frequency of press conferences, holding them after every FOMC meeting.

Table 1: Estimation Results

	Partial Identification		Full Identification	
	Point	Std Dev	Point	Std Dev
$\hat{\alpha}$	-0.24**	0.11	-0.26**	0.12
$\hat{\beta}$	-	-	0.16	0.10
$\hat{\sigma}^2_{\varepsilon,R_1}$	-	-	0.26***	0.03
$\hat{\sigma}^2_{\varepsilon,R_2}$	-	-	0.63***	0.07
$\hat{\sigma}^2_{\eta}$	-	-	0.45***	0.07
				p-value
O.I. test: $\hat{\zeta}_{partial\ identification}$				0.24
O.I. test: $\hat{\zeta}_{full\ identification}$				0.15

Notes. Iterative GMM estimation, as outlined in Hansen et al. (1996), is employed. The estimation data is monthly and spans from September 1987 (Greenspan's first month as FOMC chair) to December 2019. Regime 1 is defined as the period from September 1987 to January 2006, while regime 2 is defined as the period from February 2006 to December 2019. Standard errors of the estimated parameters are derived from 1,000 bootstrap replications, following the procedure outlined in Rigobon (2003). *, **, and *** means statistically different from zero at 10, 5, and 1% level of significance.

Subsequently, a bivariate VAR with a lag number of 12 (determined by BIC) is fitted to eliminate serial correlation. The first two columns of Table 1 display the results of the partial identification for the benchmark scenario. The analysis reveals a significant negative impact of MP communication on MP uncertainty. Specifically, a one standard deviation increase in MP communication causes an average reduction of 0.24 standard deviations in MP uncertainty.[13] Additionally, the p-value of the Sargan-Hansen test is reported as 0.24, indicating that the overidentifying restrictions of the model are not rejected.

As a robustness check, Appendix Table C.1 presents the results when the regime switch is assumed to occur in October 2003, the month in which the Wald, LM, and LR test statistics peak. As shown in the table, the α estimate is very close to the benchmark result and is statistically significant. Similarly, the overidentification test does not reject the model's restrictions.

[13]This causal statement is conditional on the informational content of the speeches being kept constant. One can, of course, discuss monetary policy without providing any substantive information, which would naturally have no impact on uncertainty.

3.3 Full Identification

If we exclude the common shocks z_t from the econometric specification, we can demonstrate that all parameters—α, β, $\sigma^2_{\varepsilon,R_1}$, $\sigma^2_{\varepsilon,R_2}$, and σ^2_{η}—are identifiable. Consider a simplified two-variable system of equations, which is a pared-down version of Equations (1) and (2):

$$m_t = \beta u_t + \varepsilon_t, \tag{7}$$

$$u_t = \alpha m_t + \eta_t. \tag{8}$$

With the constraints set forth in (3) and (4), and α and β remaining stable across two regimes, the covariance matrices become:

$$\Omega_{R_i} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \sigma^2_{\varepsilon,R_i} + \beta^2\sigma^2_{\eta,R_i} & \alpha\sigma^2_{\varepsilon,R_i} + \beta\sigma^2_{\eta,R_i} \\ \cdot & \alpha^2\sigma^2_{\varepsilon,R_i} + \sigma^2_{\eta,R_i} \end{bmatrix}.$$

In this specification, there are five parameters to identify, with six equations comprising four covariance and two variance statistics under two regimes. We can once again estimate the model parameters using GMM, starting with fitting a bivariate VAR. Given that the system is overidentified anew, we can conduct a Sargan-Hansen test to verify the validity of additional restrictions.

The results of full identification are presented in columns 3-4 of Table 1. We observe that a one standard deviation increase in MP communication leads to a decrease in MP uncertainty by 0.26 standard deviations. The result is statistically significant and mirrors the findings of the partial identification case. Conversely, the effect of MP uncertainty on communication, denoted as β, is estimated to be positive but not statistically significant. Furthermore, the variance of MP communication shocks during the Bernanke regime (0.63) is more than double that during the Greenspan regime (0.26). While the Sargan-Hansen test statistic is slightly lower compared to the partial identification case, remaining at 0.15, it still indicates that the overidentifying restrictions are not rejected. As a robustness check, Appendix Table C.1 displays the results when the regime switch is assumed to occur in October 2003. Remarkably, the estimated parameter values closely resemble those of the benchmark case.[14]

The results from both partial and full identification methods consistently highlight the negative impact of Fed communication on monetary policy uncertainty. This raises an

[14]The partial and full models are also estimated after demeaning the MP communication series separately under the two regimes. This conceptually resembles estimating a regime-switching model with two means and two variances. This approach yields very similar results to those in Table 1.

important question: which economic mechanisms drive this phenomenon? One possible explanation is that FOMC members and the chair possess superior information compared to other economic agents, enabling them to offer valuable insights during public engagements, thus reducing uncertainty.[15] Additionally, public speeches by Fed officials may enhance market participants' understanding of the Fed's monetary policy reaction function, leading to more accurate predictions of future policy decisions. Although there may be other mechanisms driving the observed results, a deeper analysis of these channels is beyond the scope of this paper.

4 Propagation of MP Communication Shocks

The full-identification scheme enables us to extract the structural shocks of monetary policy uncertainty and monetary policy communication. To examine how these shocks transmit through the economy, I adopt a two-step approach. First step is to extract the MP communication and MP uncertainty shocks, while the second step is to use these shocks in a structural vector autoregressive model (SVAR) to plot impulse response functions (IRF).[16] This approach is preferred over other IRF techniques, such as local projections, to demonstrate the importance of MP uncertainty through the propagation of MP communication shocks.

4.1 The Benchmark SVARs

As the benchmark, I conduct two SVAR experiments, ordering the structural shocks first in each case, and applying the Cholesky decomposition. The ordering of other variables is irrelevant since I am solely concerned with the impulse response functions of the variables to the identified structural shock. In other words, the only assumption imposed here is that the variables in the system have no immediate effect on the variable ordered first, which corresponds to the structural shock recovered from the heteroskedasticity-based identification.

I opt for a parsimonious framework by defining the following two sets of variables for the

[15]For a more detailed discussion of the Fed's information effect, see Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021), Acosta (2023), Bauer and Swanson (2023).

[16]The same VAR variables are used in both steps to eliminate temporal relationships, with the exception that the MP communication series is replaced with the structural shock series in the second step. The two-step approach is accounted for when plotting the confidence intervals via bootstrap.

two benchmark SVARs:

$$Y_{1,t} = [shock_{mpc,t}, mpu_t, ip_t, unemp_t], \tag{9}$$

$$Y_{2,t} = [shock_{mpu,t}, mpu_t, ip_t, unemp_t]. \tag{10}$$

Here, $shock_{mpc,t}$ represents the structural shock associated with monetary policy communication, while $shock_{mpu,t}$ denotes the structural shock pertaining to monetary policy uncertainty. Additionally, mpu_t refers to monetary policy uncertainty, ip_t represents the logarithm of industrial production, and $unemp_t$ indicates the unemployment rate.[17,18] The shocks are scaled such that the impact effect of the shocks on MP uncertainty is equivalent to a one-standard deviation change in this variable. Confidence intervals for the IRFs are obtained using the bootstrap-after-bootstrap method of Kilian (1998). For the sampling, I used the residual-based moving block bootstrap technique instead of sampling from distinct vectors of residuals (see Brüggemann et al. (2016)).[19]

I present the impulse response functions obtained from the two benchmark SVARs in Figure 5. In particular, Panel (a) depicts the IRFs for MP uncertainty, industrial production, and unemployment rate in response to a shock to MP communication, while Panel (b) shows the IRFs of the same variables in response to a shock to MP uncertainty. I find that a positive shock to MP communication reduces MP uncertainty on impact. However, the effect of the shock is short-lived and returns to zero after approximately six months. On the other hand, the effects of the shock on output and the labor market are more enduring. Industrial production increases by 0.4% after four months and remains close to this level for an extended period. Similarly, the unemployment rate drops by 0.1 percentage points (pp) and maintain this level over the long term. The IRFs in Figure 5, Panel (b), conversely, depict a pattern that is opposite to the results in Panel (a). A positive shock to MP uncertainty reduces industrial production by 0.4% and increases unemployment by 0.1 pp, mirroring the results of HRS. The main novelty in Figure 5 is that it illustrates the power of MP communication to reverse the recessionary effects of policy uncertainty. Moreover, the impact of communication on real economic variables is quite sizable and persistent.

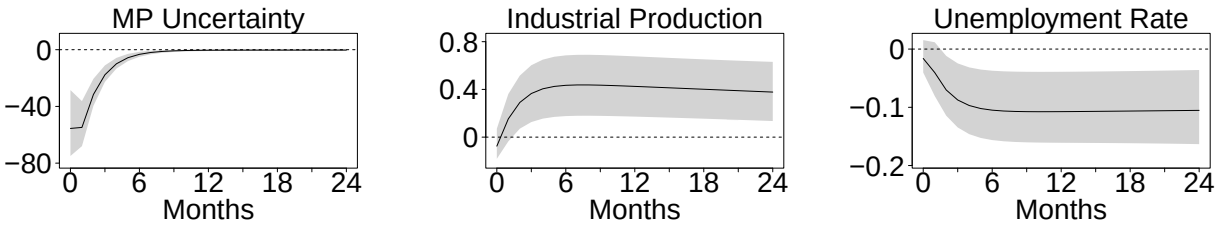
[17] Using the first difference after logarithm for ip_t also yields very similar results. However, I opt to maintain the logarithmic specification to ensure consistency with the frameworks used by Gertler and Karadi (2015), Baker et al. (2016), and Husted et al. (2020), facilitating ease of comparison.

[18] I also explored the external instrument (Proxy-VAR) approach by employing the structural shocks as external instruments (see Stock and Watson (2012, 2018), Kilian and Lütkepohl (2017), Mertens and Ravn (2013), Gertler and Karadi (2015), Baker et al. (2023)). Furthermore, I examined the impact of incorporating the monetary policy communication series into the second step VAR system. However, in none of these cases did the results fundamentally change.

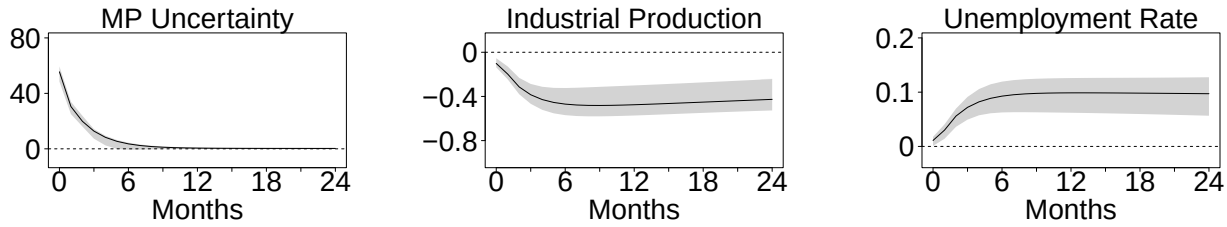
[19] Additionally, see Wright (2012), which employs a similar approach within a comparable framework as in this paper.

Figure 5: Impulse Response Functions

(a) Monetary Policy Communication Shock



(b) Monetary Policy Uncertainty Shock



Notes. Solid black lines show the IRFs, while the shaded gray areas indicate ±1 standard deviation confidence intervals around the mean response of 10,000 bootstrap replications. The response unit for industrial production is percent, while for unemployment, it is percentage points.

In order to verify the robustness of the results, I repeat the same experiment using alternative uncertainty measures discussed in Section 2. Specifically, I use the second MP uncertainty measure by BBD, which utilizes a smaller set of newspapers, their economic policy uncertainty measure, and the MP uncertainty measure constructed by HRS. The results are presented in Appendix Figure D.1. Using the alternative MP uncertainty measure by BBD yields similar results, with slight shrinkage in responses and wider confidence intervals. This is expected, as the number of newspapers used to create this uncertainty series is smaller. On the other hand, using the economic policy uncertainty measure results in more pronounced IRFs. An MP communication shock that reduces economic policy uncertainty by one standard deviation on impact doubles the responses of industrial production and unemployment, with narrower confidence intervals. This is logical because the same amount of reduction in overall economic policy uncertainty should have a more profound impact on the economy compared to a reduction in a single policy category, such as monetary policy uncertainty.[20] Lastly, using the MP uncertainty measure

[20]Even when unit shock normalization is applied, the IRFs of industrial production and unemployment from the SVAR using economic policy uncertainty are more than 1.5 times larger than those using the benchmark MP uncertainty. This indicates that the economic uncertainty channel has an additional amplification effect on the propagation of the MP communication shock compared to the monetary policy uncertainty channel.

from HRS produces IRFs that are not statistically significant. Although the responses have the expected signs, they are much smaller. As discussed in Section 2, the series created by HRS focuses on uncertainty emanating from U.S. monetary policy, whereas index of BBD encompasses monetary policy uncertainty in the U.S. regardless of the source. In this sense, the series by HRS addresses a narrower aspect of MP uncertainty. Consequently, using the HRS series results in attenuation in the propagation of the shock compared to using index of BBD.

Two points deserve further emphasis. Firstly, the incorporation of MP uncertainty into the VAR is crucial for capturing the effects of the communication shock on the real economy. The shock alone does not directly impact industrial production or unemployment. To illustrate this, I conducted a re-run of the identical SVAR model, omitting the MP uncertainty variable in the second step. As depicted in Appendix Figure E.1, Panel (a), the response of industrial production is now nearly zero and lacks statistical significance. Similarly, the response of the unemployment rate is not statistically significant, yet remains negative.

The second point meriting attention concerns the characteristics of the identified MP communication shock. Existing literature often focuses on the high-frequency identification of monetary policy surprises by analyzing asset price movements around declared Fed statements or speeches.[21] Financial assets such as federal funds futures or government bonds play a key role in the propagation of these surprises to the real economy. Another strand of the literature concentrates on the hawkish/dovish or positive/negative sentiments of Fed documents and speeches. The constructed communication series or identified shocks in this literature primarily work through the same asset pricing channel that was just described.[22] However, the MP communication shock examined in this paper operates through a different mechanism. It is not constructed to capture high-frequency asset price changes, the hawkish or dovish tendencies of FOMC members, or the positive or negative sentiments in their speeches.[23] The main feature of the MP communication shock is that it includes new information which reduces uncertainty. As discussed in Section 3, this new information can pertain to the economic environment, the monetary policy reaction function, the expectations of Fed members, the explanations of FOMC decisions, and so

[21] See, for example, Gürkaynak et al. (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Cieslak and Schrimpf (2019), Jarociński and Karadi (2020), Miranda-Agrippino and Ricco (2021), Swanson (2021, 2023), Swanson and Jayawickrema (2021), Bauer and Swanson (2023), Gorodnichenko et al. (2023), Curti and Kazinnik (2023), Jarociński (2024).

[22] See, among others, Lucca and Trebbi (2009), Apel and Grimaldi (2012), Hansen and McMahon (2016), Doh et al. (2022), Handlan (2022), Acosta (2023), Aruoba and Drechsel (2024).

[23] For example, regressing Gurkaynak, Sack and Swanson (2005) or Nakamura and Steinsson (2018) surprises on the MP communication shocks yields a relationship that is not statistically significant.

forth. Regardless of the nature of the information, the reduction in uncertainty positively impacts markets and stimulates economic activity.

One could also argue that MP communication shock brings to mind the "Fed information effect/shock" discussed by Romer and Romer (2000), Nakamura and Steinsson (2018), and Miranda-Agrippino and Ricco (2021). Although there are similarities, such as the source of the shocks being asymmetric information held by the Fed, there is also a distinct difference: In the "Fed information effect", interest rates and the stock market respond in the same direction immediately after the release of information, maintaining an active asset pricing channel in the propagation. For instance, an interest rate increase signals that the Fed anticipates stronger economic conditions ahead, which results in a positive effect of the shock on real economic activity, typically with a lag. In contrast, with the MP communication shock, the reduction in uncertainty is the main driver that boosts economic activity, which then leads to an increase in price indices, eventually prompting the Fed to respond by raising interest rates. In this context, the transmission of the shock differs, despite its origin in the Fed's asymmetric information. This propagation of the MP communication shock will be further elucidated in the analysis presented in Sections 4.2 and 4.3.

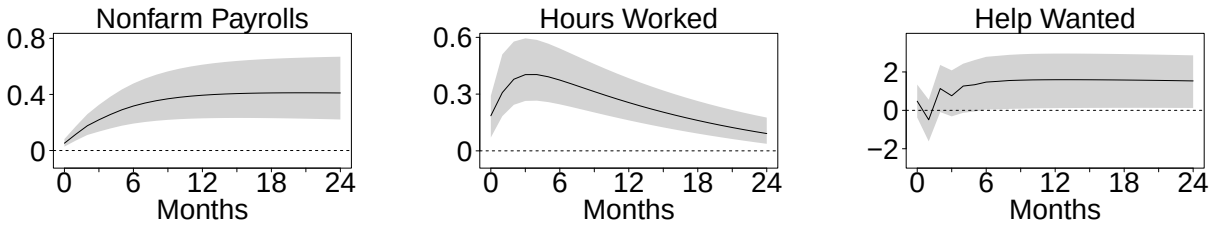
4.2 Transmission of the Shock to Broader Macroeconomy

To assess the influence of the structural MP communication shocks on other dimensions of the macroeconomy, I replicate a similar procedure as in the previous section. While maintaining all variables included in the SVAR specification in (9), I incrementally introduce additional economic variables, one at a time. Due to space constraints and the focus of the paper, I solely present the impulse response functions of these additional variables to MP communication shocks in Figure 6. All these additional variables are log-transformed, and the responses are expressed in percent terms.

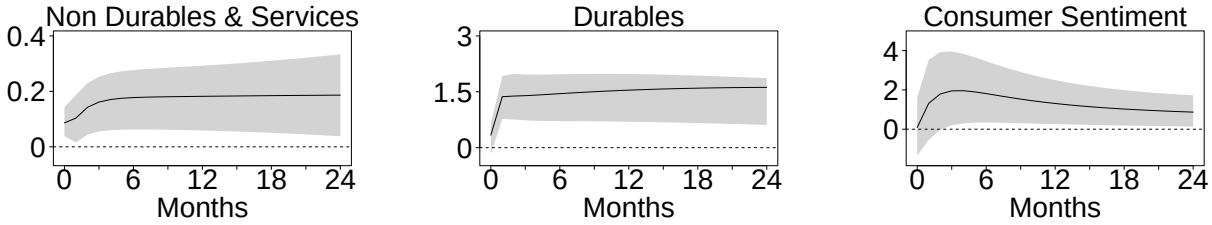
Figure 6, Panel (a), illustrates the reactions of labor market variables to the MP communication shock. Nonfarm payrolls exhibit a gradual increase, reaching the highest level after approximately one year. The response is quite persistent as in industrial production and unemployment rate. In contrast, the response of the number of hours worked is more immediate, with a 0.4% increase observed after four months. However, this impact is more temporary, tapering off towards zero after two years. The last plot in Panel (a) depicts the response of the number of advertisements for available job openings, known as the help-wanted index. This index primarily reflects the demand for labor in the market. We observe a 1.5% increase in help-wanted index seven months after the shock arrives, with the effect showing durability.

Figure 6: IRFs of Economic Variables

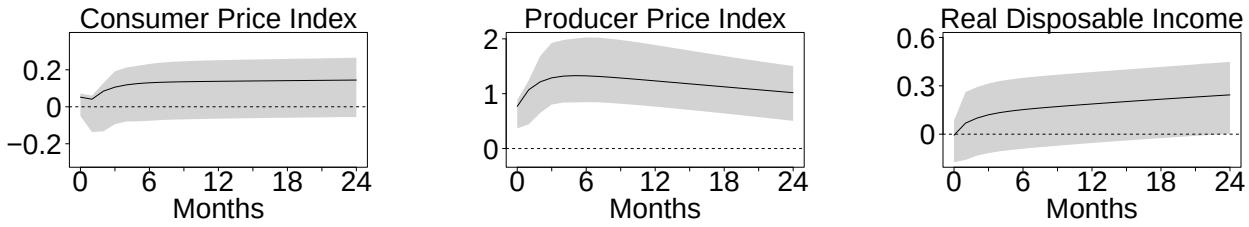
(a) Labor Market



(b) Consumption



(c) Prices & Income



Notes. Solid black lines show the IRFs, while the shaded gray areas indicate ±1 standard deviation confidence intervals around the mean response of 10,000 bootstrap replications. The IRF for each variable is obtained by adding the variable to the baseline VAR specification one at a time and then re-estimating the model. All response units are expressed in percent terms.

Figure 6, Panel (b), shows the IRFs of consumption-related variables.[24] Both non-durable goods & services and durable goods consumption increase following a monetary policy communication shock. The responses are statistically significant and highly persistent. Durable goods consumption rises by 1.5%, while non-durable goods & services consumption increases by 0.2%. The greater response in durable goods indicates that households are demanding bigger items after the resolution of uncertainty. Additionally, Panel (c) shows an improvement in consumer sentiment, which increases by almost 2% three months after the shock. This suggests that a communication shock that

[24]Given that the consumption data series begins only from January 2007 and the regime switch occurring in 2006 is essential for identification, the first step VAR excludes the consumption variable when deriving the shock series.

reduces uncertainty enhances consumer confidence.

Finally, Figure 6, Panel (c), presents the responses of price indices and real income to MP communication shock. Although there appears to be an increase in the consumer price index (CPI), it is not statistically significant. This can be attributed to two opposing forces canceling each other. In uncertain environments, individuals and businesses often demand a risk premium to compensate for the uncertainty they face, which is added to production costs or the prices of goods and services. Therefore, a decrease in uncertainty following an MP communication shock exerts downward pressure on prices. Conversely, the increase in demand for consumption goods, as evident from Panel (b), exerts upward pressure on prices. Consequently, the CPI response is not statistically significant, despite being positive. On the other hand, we observe a significant increase in the producer price index (PPI), which rises by 1.3% one quarter after the shock. This is mainly because firms, aiming to increase their production capacity after the resolution of uncertainty, demand more raw materials and intermediate goods, pushing the PPI up. Lastly, we see a slow increase in households' real disposable income, which becomes significant after two years. The overall increase in economic output eventually reflects in the real income levels of households, albeit with a delay.

4.3 Response of Financial Markets

In this section, I investigate the transmission of the MP communication shock to financial markets. Following the same procedure as in Section 4.2, I maintain the VAR structure in (9) and sequentially introduce financial variables. The impulse response functions are presented in Figure 7.

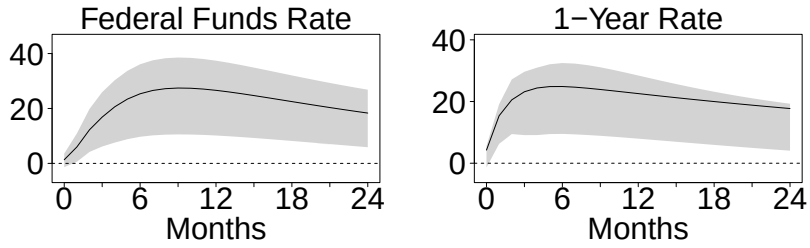
Panel (a) shows an increase in the effective federal funds rate and U.S. government bond yield with one-year maturity. Importantly, this increase occurs with a lag, contrasting with the "Fed information effect" channel discussed in Section 4.1. In fact, the findings in Panel (a) align more closely with the Taylor rule, which suggests that the Federal Reserve raises interest rates in response to increasing economic activity and prices.

On the other hand, we observe a decrease in credit spreads and the VIX index, both of which reflect financial market risk. This decrease is consistent with reduced monetary policy uncertainty, facilitating better borrowing conditions for firms and households, and providing clearer stock market outlooks.

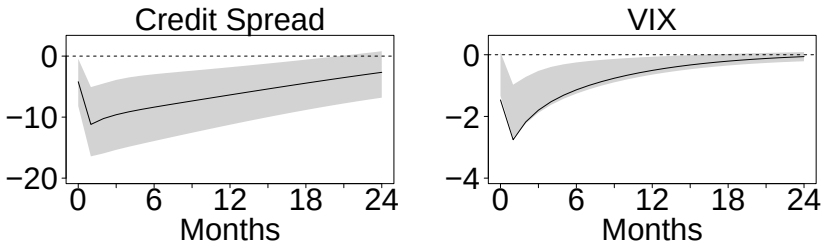
Lastly, both the S&P 500 and Russell 2000 indices rise following an MP communication shock. The S&P 500 tracks the largest U.S. companies, while the Russell 2000 comprises 2,000 small-cap firms. The stocks of both large and small firms perform better after the

Figure 7: IRFs of Financial Variables

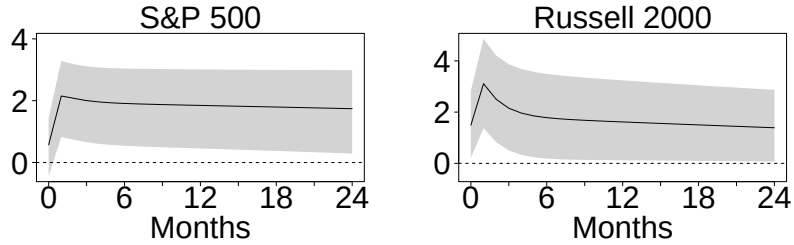
(a) Interest Rates



(b) Financial Risk



(c) Stock Market



Notes. Solid black lines show the IRFs, while the shaded gray areas indicate ±1 standard deviation confidence intervals around the mean response of 10,000 bootstrap replications. The IRF for each variable is obtained by adding the variable to the baseline VAR specification one at a time and then re-estimating the model. The response unit for S&P 500 and Russell 2000 is percent, while for the VIX it is expressed in "VIX points". 1 VIX point represents a 1% per annum change in the implied volatility of the S&P 500 index. All other responses are indicated in basis points.

shock, with a slightly more durable response observed for larger companies, as shown in Panel (c).

5 Conclusion

In this paper, I explored the impacts of a more frequent and transparent communication strategy by the Fed using a novel dataset composed of FOMC members' speeches. The

analysis yields several key findings. Firstly, positive shocks to monetary policy communication result in an immediate reduction in monetary policy uncertainty. While this reduction in uncertainty may be temporary, its effects on the economy are long-lasting. The two-step SVAR analysis, coupled with heteroskedastic shock terms, reveals that positive shocks to MP communication stimulate economic activity by increasing industrial production, decreasing unemployment, and improving labor market conditions. Additionally, it bolsters consumer confidence and prompts an increase in consumption of both non-durable goods & services and durables, with the latter exhibiting a more pronounced response. Financial markets also react positively, with interest rates and stock market indices witnessing increases, while measures of financial risk decrease. The robustness of the results is validated through various sensitivity analyses, including alternative uncertainty measures and different assumptions on the regime switch date, highlighting the consistency and reliability of the main findings across different specifications.

The uncertainty channel of monetary policy communication introduces a new perspective in the literature. It demonstrates that Fed communication goes beyond influencing medium-to-long term asset yields via forward guidance and its subsequent economic impacts. Fed communication also plays a crucial role in reducing uncertainty, enabling households and firms to better understand both current conditions and future prospects, thereby enhancing their consumption and investment decisions. Moreover, it alleviates pressures in credit markets, as seen in the narrowing of credit spreads. The positive effects on financial markets create an additional, indirect pathway to support the real economy by easing financial constraints.

Finally, the evidence of this new monetary policy channel underscores significant implications for policy authorities, highlighting the potential economic benefits derived from adopting a transparent policy-making strategy. An economy with institutions that prioritize transparent management ensures informed citizens and firms, promoting confidence, resilience, and sustainable growth. Therefore, policymakers should prioritize transparency as a cornerstone of effective policy frameworks.

References

Acosta, M. (2023) The perceived causes of monetary policy surprises. Working Paper, Federal Reserve Board.

Ahrens, M., Erdemlioğlu, D., McMahon, M., Neely, C. J., and Yang, X. (2023). Mind Your Language: Market Responses to Central Bank Speeches. CEPR Discussion Paper No. 18191.

Alexopoulos, M., Han, X., Kryvtsov, O., and Zhang, X. (2024). More than words: Fed chairs' communication during congressional testimonies. *Journal of Monetary Economics*, 142, 103515.

Andrews, D. W. (1993). Tests for parameter instability and structural change with Unknown Change Point. *Econometrica*, 61(4), 821.

Apel, M. and Grimaldi, M. B. (2012). The information content of central bank minutes. Working Paper Series 261, Sveriges Riksbank (Central Bank of Sweden).

Aruoba, S. B., and Drechsel, T. (2024). Identifying Monetary Policy Shocks: A Natural Language Approach. Working Paper 32417, National Bureau of Economic Research.

Assenza, T., Collard, F., Fève, P., and Huber, S. (2024). From Buzz to Bust: How Fake News Shapes the Business Cycle. CEPR Discussion Paper No. 18912.

Auerbach, A. J., and Gorodnichenko, Y. (2012). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 4(2), 1–27.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593–1636.

Baker, S. R., Bloom, N., and Terry, S. J. (2023). Using disasters to estimate the impact of uncertainty. *Review of Economic Studies*, 91(2), 720–747.

Bauer, M. D., and Swanson, E. T. (2023). An alternative explanation for the "Fed information effect." *American Economic Review*, 113(3), 664–700.

Bernanke, B. S. (2020). The new tools of monetary policy. *American Economic Review*, 110(4), 943–983.

Bernanke, B. S. and Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve Policy? *The Journal of Finance*, 60(3), 1221–1257.

Bianchi, F., Ludvigson, S. C., and Ma, S. (2023). Monetary-Based Asset Pricing: A Mixed-Frequency Structural Approach. Working Paper 30072, National Bureau of Economic Research.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3), 623–685.

Brüggemann, R., Jentsch, C., and Trenkler, C. (2016). Inference in Vars with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 191(1), 69–85.

Campbell, J. R., Evans, C. L., Fisher, J. D., and Justiniano, A. (2012). Macroeconomic Effects of Federal Reserve Forward Guidance. *Brookings Papers on Economic Activity*, 43(1), 1–80.

Campbell, J. R., Ferroni, F., Fisher, J. D., and Melosi, L. (2019). The limits of forward guidance. *Journal of Monetary Economics*, 108, 118–134.

Campbell, J. R., Fisher, J. D., Justiniano, A., and Melosi, L. (2017). Forward guidance and macroeconomic outcomes since the financial crisis. *NBER Macroeconomics Annual*, 31(1), 283–357.

Cieslak, A., Hansen, S., McMahon, M., and Xiao, S. (2023). Policymakers' Uncertainty. Working Paper 31849, National Bureau of Economic Research.

Cieslak, A., and McMahon, M. (2023). Tough talk: The fed and the risk premium. Working Paper, Duke University.

Cieslak, A., and Schrimpf, A. (2019). Non-monetary news in Central Bank Communication. *Journal of International Economics*, 118, 293–315.

Collard, F., Fève, P., and Langot, F. (2002). Structural inference and the lucas critique. *Annales d'Économie et de Statistique*, (67/68), 183.

Curti, F., and Kazinnik, S. (2023). Let's face it: Quantifying the impact of nonverbal communication in FOMC Press Conferences. *Journal of Monetary Economics*, 139, 110–126.

Davig, T., and Doh, T. (2014). Monetary policy regime shifts and inflation persistence. *Review of Economics and Statistics*, 96(5), 862–875.

Del Negro, M., Giannoni, M. P., and Patterson, C. (2023). The forward guidance puzzle. *Journal of Political Economy Macroeconomics*, 1(1), 43–79.

Doh, T., Song, D., and Yang, S.K. (2022). Deciphering Federal Reserve communication via text analysis of alternative FOMC statements. Working Paper, Federal Reserve Bank of Kansas City.

Garcia, R., and Perron, P. (1996).An analysis of the real interest rate under regime shifts. *The Review of Economics and Statistics*, 78(1), 111.

Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as Data. *Journal of Economic Literature*, 57(3), 535–574.

Gertler, M., and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1), 44–76.

Gorodnichenko, Y., Pham, T., and Talavera, O. (2023). The Voice of Monetary Policy. *American Economic Review*, 113(2), 548–584.

Gürkaynak, R. S., Kısacıkoğlu, B., and Wright, J. H. (2020). Missing events in event studies: Identifying the effects of partially measured news surprises. *American Economic Review*, 110(12), 3871–3912.

Gürkaynak, R. S., Sack, B., and Swanson, E. (2005). Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking*, 1(1): 55–93.

Hamilton, J. D. (1994). *Time Series analysis*. Princeton University Press.

Handlan, A. (2022). Text Shocks and Monetary Surprises: Text Analysis of FOMC Statements with Machine Learning. Working Paper.

Hansen, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, 50(4), 1029-1054.

Hansen, L. P., Heaton, J., and Yaron, A. (1996). Finite-sample properties of some alternative GMM Estimators. *Journal of Business & Economic Statistics*, 14(3), 262.

Hansen, S., and McMahon, M. (2016). Shocking language: Understanding the macroeconomic effects of Central Bank Communication. *Journal of International Economics*, 99.

Hansen, S., McMahon, M., and Prat, A. (2017). Transparency and deliberation within the FOMC: A computational linguistics approach *The Quarterly Journal of Economics*, 133(2), 801–870.

Herwartz, H., and Lütkepohl, H. (2014). Structural vector autoregressions with Markov switching: Combining conventional with statistical identification of shocks. *Journal of Econometrics*, 183(1), 104–116.

Hoesch, L., Rossi, B., and Sekhposyan, T. (2023). Has the information channel of monetary policy disappeared? Revisiting the empirical evidence. *American Economic Journal: Macroeconomics*, 15(3), 355–387.

Hubert, P., and Labondance, F. (2021). The signaling effects of Central Bank tone. *European Economic Review*, 133, 103684.

Husted, L., Rogers, J., and Sun, B. (2020). Monetary policy uncertainty. *Journal of Monetary Economics*, 115, 20–36.

Istrefi, K., Odendahl, F., and Sestieri, G. (2023). Fed communication on financial stability concerns and monetary policy decisions: Revelations from speeches. *Journal of Banking and Finance*, 151, 106820.

Jarociński, M. (2024). Estimating the Fed's unconventional policy shocks. *Journal of Monetary Economics*, 103548.

Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises— the role of information shocks. *American Economic Journal: Macroeconomic*, 12(2), 1–43.

Jia, C. (2023). The informational effect of monetary policy and the case for policy commitment. *European Economic Review*, 156, 104468.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1), 161–182.

Jordà, Ò. and Salyer, K. D. (2003). The response of term rates to monetary policy uncertainty. *Review of Economic Dynamics*, 6(4), 941–962.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3), 1177–1216.

Kilian, L. (1998). Small-Sample Confidence Intervals For Impulse Response Functions. *Review of Economics and Statistics*, 80(2):218–230.

Kilian, L., and Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis.* Cambridge University Press.

Lanne, M., Lütkepohl, H., Maciejowska, K. (2010). Structural vector autoregressions with Markov switching. *Journal of Economic Dynamics and Control*, 34(2), 121–131.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, 30(1), 67–80.

Loughran, T., and McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-KS. *The Journal of Finance*, 66(1), 35–65.

Lucca, D. O., and Trebbi, F. (2009). Measuring central bank communication: An automated approach with application to FOMC statements. Working Paper 15367, National Bureau of Economic Research.

Ludvigson, S. C., Ma, S., and Ng, S. (2021). Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response. *American Economic Journal: Macroeconomics*, 13(4), 369-410.

Lunsford, K. G. (2020). Policy language and information effects in the early days of Federal Reserve Forward guidance. *American Economic Review*, 110(9), 2899–2934.

Malmendier, U., Nagel, S., and Yan, Z. (2021). The making of hawks and doves. *Journal of Monetary Economics*, 117, 19–42.

McCracken, M. W., and Ng, S. (2021). FRED-QD: A Quarterly Database for Macroeconomic Research. *Review*, 103(1), 1–44.

Mertens, K., and Ravn, M.O. (2013). The dynamic effects of personal and corporate income tax changes in the United States. *American Economic Review*, 103(4), pp. 1212–1247.

Melosi, L. (2016). Signalling effects of monetary policy. *The Review of Economic Studies*, 84(2), 853-884.

Miranda-Agrippino, S., and Ricco, G. (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, 13(3), 74–107.

Nakamura, E., and Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, 133(3), 1283–1330.

Newey, W. K., and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3), 703.

Piazzesi, M., and Swanson, E. T. (2008). Futures prices as risk-adjusted forecasts of monetary policy. *Journal of Monetary Economics*, 55(4), 677–691.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. *Handbook of Macroeconomics*, 71–162.

Rigobon, R. (2003). Identification through heteroskedasticity. *Review of Economics and Statistics*, 85(4), 777–792.

Rigobon, R., and Sack, B. (2003). Measuring the reaction of monetary policy to the stock market. *The Quarterly Journal of Economics*, 118(2), 639–669.

Rigobon, R., and Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51(8), 1553–1575.

Rigobon, R., and Sack, B. (2005). The effects of war risk on US financial markets. *Journal of Banking and Finance*, 29(7), 1769–1789.

Romer, C. D., and Romer, D. H. (2000). Federal Reserve Information and the behavior of interest rates. *American Economic Review*, 90(3), 429–457.

Romer, C. D., and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4), 1055–1084.

Sargan, J. D. (1958). The Estimation of Economic Relationships Using Instrumental Variables. *Econometrica*, 26(3), 393–415.

Sims, C. A., and Zha, T. (2006). Were there regime switches in U.S. monetary policy? *American Economic Review*, 96(1), 54–81.

Stock, J. H., and Watson, M. W. (2012). Disentangling the channels of the 2007–09 recession. *Brookings Papers on Economic Activity*, 42(1), 81–156.

Stock, J. H., and Watson, M. W. (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal*, 128(610), 917–948.

Swanson, E. T. (2006). Have increases in Federal Reserve transparency improved private sector interest rate forecasts? *Journal of Money, Credit, and Banking*, 38(3), 791-819.

Swanson, E. T. (2021). Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118, 32–53.

Swanson, E. T. (2023). The importance of fed chair speeches as a monetary policy tool. *AEA Papers and Proceedings*, 113, 394–400.

Swanson, E. T., and Jayawickrema, V. (2021). Speeches by the Fed Chair Are More Important than FOMC Announcements: An Improved High-Frequency Measure of U.S. Monetary Policy Shocks. Working Paper, UC Irvine.

Todd, T. (2016). A Corollary of Accountability: A History of FOMC Policy Communication. Federal Reserve Bank of Kansas City.

Whelan, K. (2000). A guide to the use of chain aggregated nipa data. Federal Reserve Board.

Wright, J. H. (2012). What does monetary policy do to long-term interest rates at the zero lower bound? *The Economic Journal*, 122(564).

Appendix

A Data

A.1 Speech Data Cleaning

The criteria considered during the data cleaning phase are that the documents should contain only the speech of the FOMC member, be self-explanatory, and be immediately publicly available. The first criterion ensures that the views of other people are not confused with those of the members. The second criterion guarantees that economic agents and markets have instant access to these speech materials, aligning with the research question posed in this paper. Accordingly, documents falling under any of the following categories were eliminated from the dataset:

- Documents consisting solely of slides.
- Transcripts of question-and-answer sessions.[25]
- Forum discussions involving multiple speakers.
- Documents containing only links to speech videos.
- Documents that present the framework of a speech without the speech itself.
- Private letters between central bankers.
- Speeches given in languages other than English.
- Hand-written documents that are not legible.

[25] An exception to this is the Q&A part of the FOMC press conferences. Since this component is highly important in Fed communication, it is included in the dataset as it is.

A.2 Data Sources for IRFs

The data used to plot the IRFs in Section 4 are taken from various sources, as reported in Table A.1 below. Chain-type price indices are used to combine non-durable goods and services consumption series, following the procedure outlined in Whelan (2000).

Table A.1: IRF Data

Variable	Data Source
Industrial Production	FRED, Code: INDPRO
Unemployment Rate	FRED, Code: UNRATE
Nonfarm Payrolls	FRED, Code: PAYEMS
Hours Worked	FRED, Code: AWHMAN
Help Wanted Index	McCracken and Ng (2021)
Non Durables	FRED, Code: PCENDC96
Chain-Type Price Index Non Durables	FRED, Code: DNDGRG3M086SBEA
Services	FRED, Code: PCESC96
Chain-Type Price Index Services	FRED, Code: DSERRG3M086SBEA
Durables	FRED, Code: PCEDGC96
Consumer Sentiment	FRED, Code: UMCSENT
Consumer Price Index	FRED, Code: CPIAUCSL
Producer Price Index	FRED, Code: PPIACO
Real Disposable Income	FRED, Code: DSPIC96
Federal Funds Effective Rate	FRED, Code: FEDFUNDS
1-Year Rate	FRED, Code: DGS1
Credit Spread	Board of Governors of the Fed
VIX	FRED, Code: VIXCLS
S&P 500	Yahoo Finance
Russell 2000	Yahoo Finance

B Dictionaries

Table B.1: Baker, Bloom and Davis (2016) Dictionary of Monetary Policy Words & Phrases

Federal Reserve	Bernanke	European Central Bank
Fed	Volcker	ECB
Money Supply	Greenspan	Bank of England
Open Market Operations	Central Bank	Bank of Japan
Quantitative Easing	Interest Rates	BOJ
Monetary Policy	Fed Chairman	Bank of China
Fed Funds Rate	Fed Chair	Bundesbank
FFR	Lender of Last Resort	Bank of France
Overnight Lending Rate	Discount Window	Bank of Italy

Notes. The list of words is sourced from the authors' website: https://www.policyuncertainty.com/bbd_monetary.html. The only modification made was the addition of the word *FFR*, which stands for *Federal Funds Rate* that is already included in the list. Since these two words refer to the same concept, its inclusion does not alter the structure of the dictionary but enhances its comprehensiveness.

Table B.2: Husted, Rogers and Sun (2020) Dictionary of Monetary Policy Words & Phrases

Monetary Policy	Interest Rate	Federal Fund Rate
Fed Fund Rate	Federal Reserve	The Fed
FOMC	Federal Open Market Committee	

Notes. The list of words is directly sourced from section 2.1 of Husted et al. (2020).

C Robustness of Estimation Results

Table C.1: Estimation Results

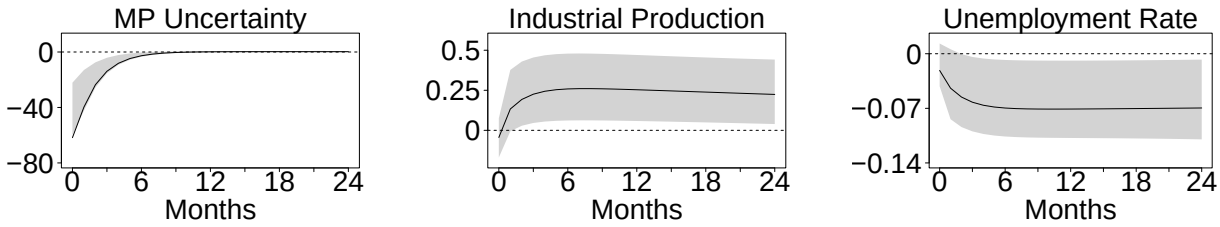
	Partial Identification		Full Identification	
	Point	Std Dev	Point	Std Dev
$\hat{\alpha}$	-0.21**	0.10	-0.22**	0.10
$\hat{\beta}$	-	-	0.13	0.09
$\hat{\sigma}^2_{\varepsilon,R_1}$	-	-	0.22***	0.03
$\hat{\sigma}^2_{\varepsilon,R_2}$	-	-	0.60***	0.06
$\hat{\sigma}^2_{\eta}$	-	-	0.45***	0.06
				p-value
O.I. test: $\hat{\zeta}_{partial\ identification}$				0.17
O.I. test: $\hat{\zeta}_{full\ identification}$				0.10

Notes. Iterative GMM estimation, as outlined in Hansen et al. (1996), is employed. The estimation data is monthly and spans from September 1987 (Greenspan's first month as FOMC chair) to December 2019. Regime 1 is defined as the period from September 1987 to September 2003, while regime 2 is defined as the period from October 2003 to December 2019. Standard errors of the estimated parameters are derived from 1,000 bootstrap replications, following the procedure outlined in Rigobon (2003). *, **, and *** means statistically different from zero at 10, 5, and 1% level of significance.

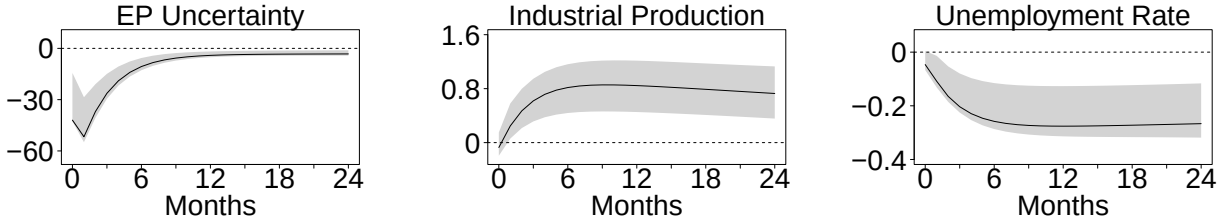
D Alternative Uncertainty Measures

Figure D.1: Alternative Uncertainty Variables in SVAR

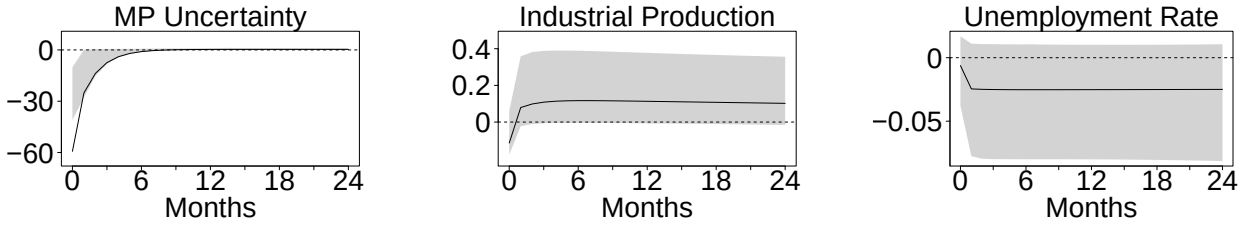
(a) Monetary Policy Uncertainty (10 newspapers) of Baker et al. (2016)



(b) Economic Policy Uncertainty of Baker et al. (2016)



(c) Monetary Policy Uncertainty of Husted et al. (2020)

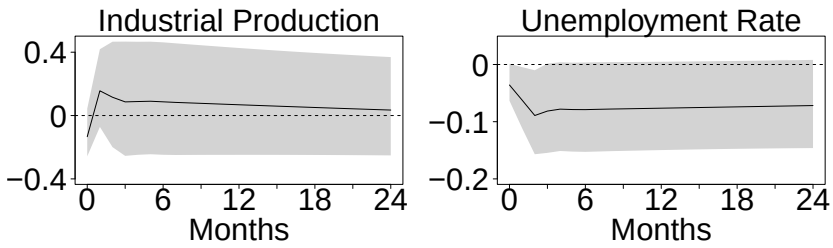


Notes. Solid black lines show the IRFs, while the shaded gray areas indicate ±1 standard deviation confidence intervals around the mean response of 10,000 bootstrap replications.

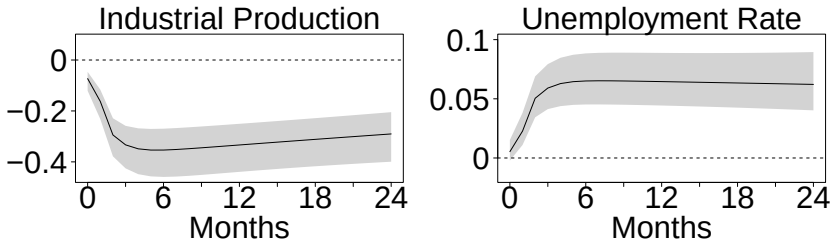
E SVARs Excluding MP Uncertainty

Figure E.1: Impulse Response Functions

(a) Monetary Policy Communication Shock



(b) Monetary Policy Uncertainty Shock



Notes. Solid black lines show the IRFs, while the shaded gray areas indicate ±1 standard deviation confidence intervals around the mean response of 10,000 bootstrap replications.