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“The Uncertainty Channel of Monetary Policy Communication”

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The Uncertainty Channel of Monetary Policy Communication*

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Abstract

This paper shows that central bank communication reduces monetary policy uncertainty, which in turn generates substantial effects on real economic activity. I construct a novel monthly measure of Federal Reserve communication from 9,298 speeches by FOMC members between 1951 and 2022 and relate it to a newspaper-based measure of U.S. monetary policy uncertainty. To address the simultaneity between communication and uncertainty, I exploit a shift in the volatility of communication associated with the Fed's transition toward greater transparency in the early 2000s and use the resulting heteroskedasticity to identify causal effects. An unexpected one-standard-deviation increase in communication lowers monetary policy uncertainty by about 0.25 standard deviations. Structural VAR estimates show sizable and persistent real effects: within two months, industrial production rises by about 0.3 percent, unemployment falls by 0.2 percentage points, and durable goods consumption increases by about 0.5 percent. These findings highlight an uncertainty channel of monetary policy communication and show that active communication can serve as an independent policy tool.

Keywords: Monetary Policy Communication, Uncertainty, Textual Analysis, Identification Through Heteroskedasticity.
JEL Codes: C32, D80, E52, E58.

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"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

Acts of communication can have three possible outcomes: clarification, confusion, or irrelevance, that is, a lack of relevant informational content. Central bank communication is no exception. When policymakers speak, economic agents may form a clearer view of the policy outlook, become more uncertain about future policy actions, or remain largely unaffected. This paper asks which of these outcomes characterizes U.S. Federal Reserve (Fed) communication on average. Does communication by Fed policymakers reduce monetary policy uncertainty, does it instead exacerbate it, or is it largely ineffective?

A large literature studies the macroeconomic effects of different forms of uncertainty. In the context of monetary policy, Husted et al. (2020) document the recessionary effects of monetary policy uncertainty. By contrast, considerably less is known about which policy tools are effective in reducing uncertainty once it arises. One natural candidate is monetary policy communication. Existing work on central bank communication primarily focuses on identifying monetary policy surprises using high-frequency movements around communication events (Gürkaynak et al. (2005), Swanson (2021), Altavilla et al. (2025)) and on characterizing the content of communication through topics, tone, or sentiment (Hansen and McMahon (2016), Istrefi et al. (2023)). Much less attention has been paid to whether central bank communication directly affects uncertainty itself. Recent contributions provide suggestive evidence: Ahrens et al. (2025) show that macroeconomic news embedded in Fed speeches influences market volatility and tail risk, while Cieslak and McMahon (2023) document that Fed communication shapes risk premia between Federal Open Market Committee (FOMC) meetings. This paper complements this literature by quantifying the direct causal effect of Federal Reserve communication on monetary policy uncertainty.

I study this question using speeches delivered by FOMC members. The novel dataset that

I compile covers the period from April 1951[1] to December 2022 and comprises a total of 9,298 speeches. Using a dictionary-based approach, I measure monetary policy communication by counting the monthly frequency of monetary-policy-related words in these speeches. This measure captures the intensity of communication about monetary policy, rather than its tone or hawkish-dovish content, consistent with the paper's focus on whether communicating more reduces uncertainty. As a measure of monetary policy uncertainty, I use the newspape-based index of Baker et al. (2016). Employing a linear specification identified through heteroskedasticity, I find that a one standard deviation increase in monetary policy communication—corresponding to approximately 240 additional monetary-policy-related words per month—causally reduces monetary policy uncertainty by about one quarter of a standard deviation.

A key challenge in assessing the effects of central bank communication is simultaneity: Fed communication may respond to the state of uncertainty, making simple correlations between communication and uncertainty difficult to interpret. I address this problem by exploiting a regime shift in the volatility of Fed communication associated with the institutional transition toward greater transparency. As emphasized by former Fed chair Ben Bernanke, beginning in the early 2000s, the Fed substantially expanded its public communication, leading to a marked increase in the intensity and variability of policymakers' speeches. I use this change in the volatility of communication to identify communication shocks through heteroskedasticity, following Rigobon (2003). The key insight is that, while the variance of communication shocks differs across transparency regimes, the structural relationship between communication and uncertainty remains unchanged. Differences in the covariance between communication and uncertainty across regimes therefore isolate exogenous variation in communication. This approach allows me to identify shocks to monetary policy communication that are distinct from policy rate changes and to trace their causal effects on uncertainty. I then estimate a larger structural vector autoregressive (VAR) model including monetary policy communication, monetary policy uncertainty, and macroeconomic and financial variables, and identify communication shocks using the same heteroskedasticity-based approach.

The results indicate that monetary policy communication shocks have expansionary effects on real economic activity. A one-standard-deviation communication shock increases industrial production by about 0.3 percent within two months and reduces the unemployment rate by about 0.2 percentage points, with effects that are highly persistent over the medium run. Labor market adjustments extend beyond headline unemployment: nonfarm payrolls and hours worked increase by 0.2 percent and 0.15 percent, respectively, while the help-wanted index rises to about 1 percent after six months, indicating stronger labor demand. Durable consumption increases by

[1] In March 1951, the Treasury-Federal Reserve Accord is signed, formally separating the Federal Reserve from U.S. Treasury debt management and marking the beginning of modern U.S. monetary policy.

about 0.5 percent, whereas non-durables and services show no statistically significant response. These patterns are consistent with an uncertainty channel: reductions in monetary policy uncertainty following increased communication bring forward firms' hiring and investment decisions. The stronger response of durables reinforces a similar mechanism on the household side. Because durable purchases are more postponable and involve greater irreversibility and financing exposure, lower uncertainty disproportionately releases wait-and-see behavior and stimulates big-ticket spending.

Price responses further suggest that monetary policy communication operates through real activity rather than immediate consumer price inflation. While consumer prices decline modestly, producer prices increase strongly following a communication-induced reduction in monetary policy uncertainty, rising by about 3 percent on impact. This pattern is consistent with firms expanding production and increasing demand for raw materials and intermediate inputs once uncertainty is resolved. Reduced uncertainty may also relax firms' incentives to postpone irreversible investment and production decisions. As emphasized by Bloom (2009), this puts upward pressure on producer prices before consumer prices adjust. Taken together, these responses suggest that the identified communication shock has expansionary but limited inflationary effects in the short run, with price pressures emerging upstream and passing through to households only gradually.

Financial market responses further support an uncertainty-based transmission of monetary policy communication. Following a communication-induced reduction in monetary policy uncertainty, measures of financial risk decline: credit spreads narrow and the VIX falls, indicating improved risk sentiment and lower perceived tail risk. Equity markets respond positively as well. Both the S&P 500 and the Russell 2000 increase by similar magnitudes, suggesting that the effects are broad-based and not concentrated among either large or small firms. Finally, policy rates respond only with a delay, indicating that the communication measure used here affects financial markets without immediate changes in the policy stance.

Taken together, the results are consistent with the presence of an *uncertainty channel* through which monetary policy communication can affect economic outcomes. This channel is distinct from more conventional monetary policy transmission mechanisms. In the standard interest rate channel, policy affects the economy by altering current or expected short-term rates, thereby influencing borrowing costs and intertemporal substitution. Similarly, hawkish or dovish communication typically operates by shifting expectations about the future path of policy rates. By contrast, the uncertainty channel emphasized here operates by shaping the clarity of the policy outlook, without requiring contemporaneous adjustments in the policy stance. The delayed response of policy rates observed in the data reinforces this distinction and suggests that communication can influence economic activity through a mechanism that is conceptually separate from rate-based signaling.

Related Literature. This paper relates to a broad literature studying the role of central bank communication in monetary policymaking. Its main contribution is to provide causal evidence on how the intensity of policy communication affects monetary policy uncertainty and how these effects propagate to real and financial outcomes. Accordingly, the paper contributes to three strands of the literature: monetary policy communication, uncertainty, and monetary policy transmission mechanisms.

A large literature studies central bank communication as an integral component of monetary policymaking. Early contributions document that policy statements and communication events move financial markets independently of policy actions (e.g., Bernanke and Kuttner (2005); Gürkaynak et al. (2005)). Subsequent work examines the institutional design of communication, the role of committees, and the evolution of transparency in monetary policy (e.g., Swanson (2006); Blinder (2007); Ehrmann and Fratzscher (2013); Spencer et al. (2013); Dincer and Eichengreen (2014); Naszodi et al. (2016); Acosta (2023b)). A growing strand of this literature uses text-based methods to quantify central bank communication and extract information from policy documents and speeches, including measures of tone, topics, and signaling content (e.g., Lucca and Trebbi (2009); Hansen and McMahon (2016); Hubert and Labondance (2021); Handlan (2022); Doh et al. (2026); Aruoba and Drechsel (2026)). Related work extends the analysis of communication beyond text, highlighting the role of vocal characteristics and nonverbal cues in shaping market responses (e.g., Gorodnichenko et al. (2023); Curti and Kazinnik (2023)). While this literature emphasizes the informational content, tone, or signaling role of communication, this paper instead asks whether communicating more intensively—independent of tone, sentiment, or delivery—reduces monetary policy uncertainty on average.

The paper also relates to a broad literature studying uncertainty and its macroeconomic consequences. A large body of work shows that increases in uncertainty are associated with declines in investment, employment, and economic activity (e.g., Bloom (2009); Jurado et al. (2015); Baker et al. (2016)). In the context of monetary policy, Husted et al. (2020) document that monetary policy uncertainty has recessionary effects, while a related strand of the literature emphasizes amplification mechanisms operating through financial markets, risk premia, and firm behavior (e.g., Jordà and Salyer (2003); Alfaro et al. (2024); Baker et al. (2024)). Despite this extensive evidence on the macroeconomic effects of uncertainty, comparatively less is known about which policy tools are effective in reducing uncertainty itself. This paper contributes to this literature by providing causal evidence that central bank communication can reduce monetary policy uncertainty and by quantifying the real and financial effects associated with this reduction.

Finally, the paper contributes to the literature on monetary policy transmission mechanisms. A large body of research identifies monetary policy shocks and studies their propagation to financial markets and the real economy (e.g., Romer and Romer (2004); Ramey (2016); Gertler and Karadi (2015); Nakamura and Steinsson (2018); Miranda-Agrippino and Ricco (2021)). More recent work highlights the importance of information effects and distinguishes between policy rate shocks and signals about the economic outlook (e.g., Jarociński and Karadi (2020); Bauer and Swanson (2023); Acosta (2023a)). This paper complements these contributions by identifying a communication-driven transmission mechanism that operates through changes in uncertainty rather than through contemporaneous adjustments in the policy stance.[2]

Roadmap. The remainder of the paper is organized as follows. Section 2 describes the data on FOMC members' speeches and introduces the monetary policy communication index. Section 3 presents the econometric framework, the identification strategy, and the baseline results from a bivariate system of monetary policy communication and uncertainty. Section 4 extends this framework by incorporating macroeconomic and financial variables and analyzes the effects of the identified communication shocks on real and financial outcomes. Section 5 concludes.

2 Data

2.1 FOMC Members' Speeches

This section introduces the dataset of speeches by FOMC members, including chairs, vice chairs, governors, and presidents of the regional Federal Reserve Banks. The speeches were collected from the FRASER database[3] and the official websites of the Federal Reserve Board and the regional Reserve Banks. In total, the raw dataset comprises more than 10,000 speeches spanning April 1951 to December 2022. After a rigorous cleaning procedure detailed in Data Appendix A.1, 9,298 speeches were retained for the same period.[4] Figure 1 illustrates the long-run trend in the number of speeches delivered by FOMC members. In the 1950s, the annual number of speeches was around 30. The series increases steadily over time and reaches roughly 200 speeches per year after 2010, implying that, on average, nearly one speech is delivered on each business day.

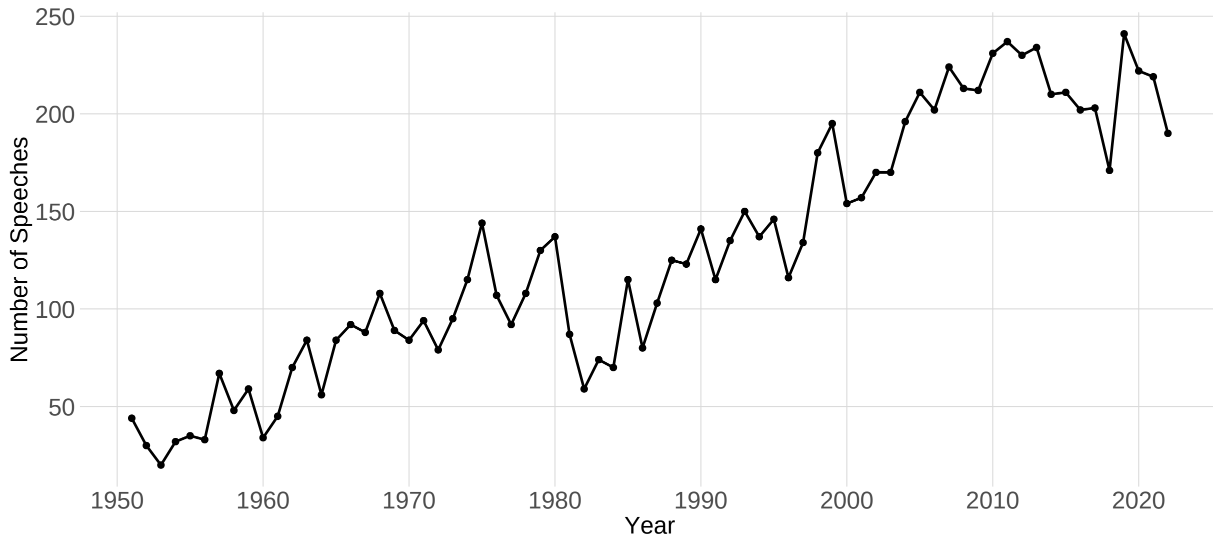
The speech texts are further preprocessed to ensure consistency and suitability for quantitative text analysis. The preprocessing procedure is detailed in Data Appendix A.2. Table 1 reports summary statistics for the resulting texts. The average speech contains 3,012 words, with a median of 2,836, and substantial dispersion across documents, as reflected in a standard deviation of 1,871 words. The distribution exhibits a long right tail, with speech lengths ranging from very

[2]Methodologically, the paper builds on a literature that exploits changes in volatility to achieve identification, including applications to monetary policy and financial markets (e.g., Rigobon and Sack (2003, 2004, 2005); Wright (2012); Lewbel (2012); Kilian and Lütkepohl (2018); Gürkaynak et al. (2020); Brunnermeier et al. (2021); Lewis (2021); Guay (2021); Carriero et al. (2021); Bertsche and Braun (2022)).

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

[4]References to speeches also include publicly released documents authored by an FOMC member.

Figure 1. Annual number of speeches by FOMC members.



Notes: The figure plots the annual number of speeches delivered by FOMC members. Points indicate yearly totals, and the solid line highlights the long-run trend in speech activity.

short documents to exceptionally long speeches exceeding 60,000 words. These patterns highlight considerable heterogeneity in communication intensity across FOMC members and over time.

2.2 Monetary Policy Communication

To measure the extent to which FOMC members discuss monetary policy in their speeches, I use a dictionary-based text analysis method. This approach counts the occurrences of specific words or phrases from a predefined dictionary within each text. The dictionary is sourced from Baker, Bloom and Davis (2016) (hereafter BBD) and detailed in Table A.1. It comprises terms relevant to monetary policy such as "*federal funds rate*", "*money supply*", "*open market operations*", "*quantitative easing*", "*discount window*", and so forth.

Dictionary-based techniques offer several advantages. First, they are straightforward to implement and interpret. They also require fewer computational resources and less specialized expertise compared to more complex natural language processing methods, such as latent Dirichlet allocation or nonnegative matrix factorization. Second, these methods offer transparency in the analysis, allowing researchers to see how text features are classified based on predefined dictionaries, which enhances the reproducibility and reliability of the results. Finally, the second key variable in this paper—monetary policy uncertainty, discussed in the next section—is taken from BBD. Using their original dictionary and a similar methodology to measure monetary policy communication ensures compatibility between their uncertainty series and the communication series constructed in this paper.

Words provide a natural measure of the content of monetary policy communication, but the

Table 1. Summary statistics of speech data.

Variable	Distribution				
	Mean	Median	Std. Dev.	Min	Max
Speech Length (words)	3,012	2,836	1,871	69	66,275

Notes: This table reports speech-level summary statistics. The sample comprises 9,298 speeches spanning the period from 1951:04 to 2022:12. A total of 77 documents contain zero or one word after preprocessing and are excluded from the summary statistics.

identity of the speaker may also matter, as audiences and markets may respond differently depending on who delivers a given message (D'Acunto et al. (2021); Wabitsch (2025)). To capture both dimensions, I construct a monthly monetary policy communication index that aggregates monetary policy-related words[5] across speeches while allowing for speaker-specific weights. Formally, the index is defined as

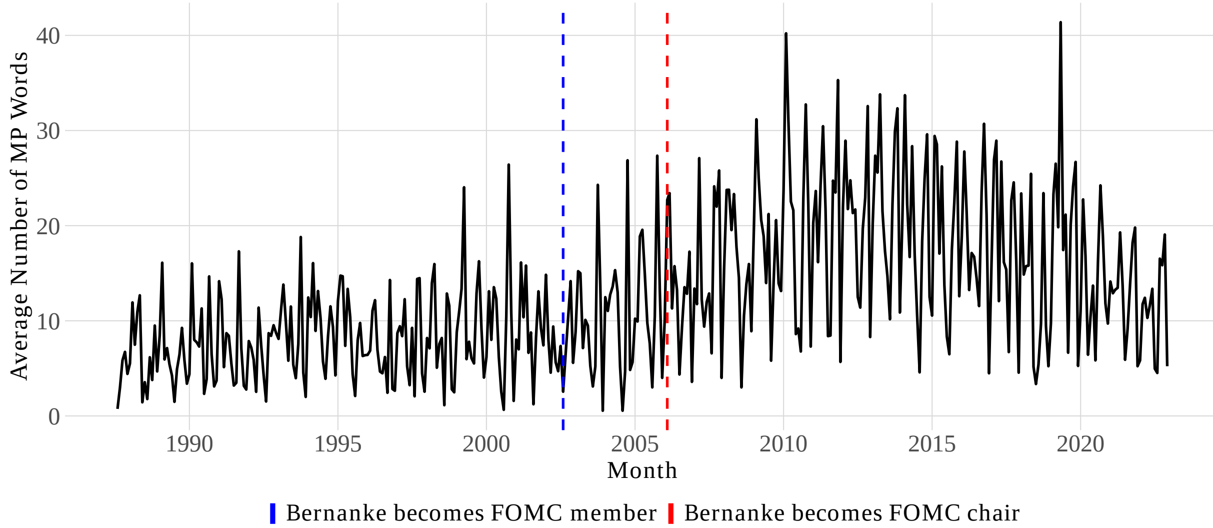
$$\text{MPComm}_t = \frac{1}{D_t} \sum_{i \in \mathcal{S}_t} w_{s(i)} \, \text{Words}_i, \tag{1}$$

where $\mathcal{S}_t$ denotes the set of FOMC speeches in month t, Words_i is the number of dictionary-based monetary policy terms in speech i, $w_{s(i)}$ is the weight assigned to the speaker delivering that speech, and D_t is the number of days in month t. The normalization by days ensures comparability across months with different numbers of calendar days. Weekends are included because FOMC members also deliver speeches on weekends, albeit less frequently. I do not normalize by total speech length, because the object of interest is the overall intensity of monetary policy communication directed to the public in a given month rather than the share of monetary policy content within individual speeches. In the baseline specification, all speakers receive equal weight ($w_s = 1$). Alternative speaker-weighting schemes are examined in the robustness analysis.

Figure 2 displays the monetary policy communication series constructed using the dictionary-based method described above. The vertical blue dashed line marks the month Ben Bernanke joined the FOMC as a member, while the red dashed line indicates the start of his tenure as Chair. The period to the left of the red line corresponds to Alan Greenspan's chairmanship, while the period to the right covers the tenures of Ben Bernanke (2006–2014), Janet Yellen (2014–2018), and Jerome Powell (2018–present). The most salient pattern in Figure 2 is the marked rise in monetary policy communication following Ben Bernanke's entry into the FOMC, and more prominently, during his tenure as Chair. Both the level and volatility of monetary policy communication increase substantially around the leadership transition from Greenspan to Bernanke: the mean rises

[5] Before matching, both the speech texts and the dictionary terms are reduced to their root forms (stemming). This means that different inflected versions of a word—such as plurals or verb forms—are treated as the same term, which helps avoid missing relevant matches due to suffixes or other morphological variations.

Figure 2. Monetary policy communication series.



Notes: The figure depicts the monetary policy communication index, defined as 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 A.1. The blue dashed line marks August 2002, when Ben Bernanke joined the FOMC as a governor. The red dashed line marks February 2006, when Bernanke became FOMC chair, succeeding Alan Greenspan.

from about 258 words per month under Greenspan to 523 in the post-Greenspan period, while the standard deviation increases from roughly 152 to 240. This shift points to a change in the Fed's communication strategy, reflecting a greater institutional emphasis on external engagement and more frequent use of public communication as a policy tool. The nature of this structural change—and its central role in causal identification in the empirical analysis—will be discussed in detail in Section 3.1.

2.3 Monetary Policy Uncertainty

Monetary policy uncertainty is the second key variable used to address the research question of this study. The index is sourced from BBD, who employed a dictionary-based method on newspaper articles to quantify uncertainty. To construct the index, they used the Access World News database, which contains over 2,000 U.S. newspapers. Their dictionary-based approach applies what they refer to as the E, P, U, and M criteria, which flag all articles that contain at least one term from each of the following four dictionaries:

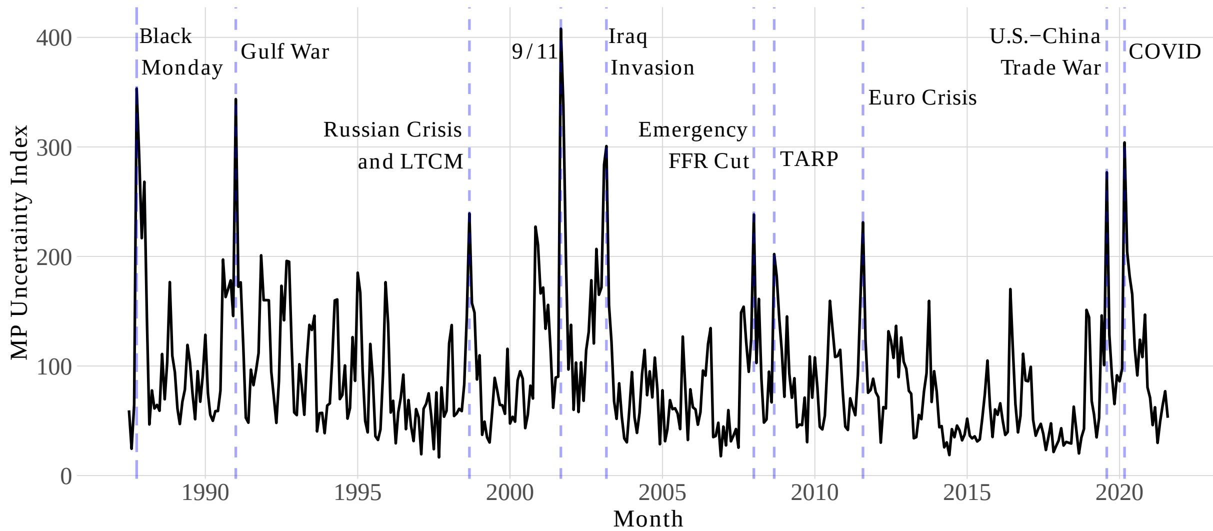
E: *economic, economy*

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

U: *uncertain, uncertainty*

M: *federal reserve, money supply, quantitative easing, monetary policy, fed funds rate, ...*

Figure 3. Monetary policy uncertainty series.



Notes: The index is borrowed from Baker et al. (2016) and is available on the authors' website: `https://www.policyuncertainty.com/monetary.html` . It measures uncertainty surrounding monetary policy and is constructed using articles from U.S. newspapers in the Access World News database. "LTCM" refers to the collapse of Long-Term Capital Management in 1998, a major hedge fund failure that raised systemic risk concerns. "TARP" denotes the Troubled Asset Relief Program, a large-scale government intervention launched in 2008 in response to the financial crisis.

(Please refer to Table A.1 for the full list of monetary policy terms.)

For each newspaper and month, BBD compute the share of articles that satisfy the E, P, U, and M criteria. These newspaper-level series are then standardized by their own time-series standard deviation, averaged across newspapers, and finally rescaled to have a mean of 100 over January 1985–December 2010.

Figure 3 presents the monetary policy uncertainty series, which displays distinct spikes corresponding to major economic and geopolitical events. These episodes elevated uncertainty by increasing the difficulty of forecasting the stance, timing, or effectiveness of monetary policy. For instance, Black Monday and the 9/11 attacks generated sudden financial instability, while the Gulf War introduced geopolitical tensions with potential macroeconomic repercussions. The Global Financial Crisis and the European Debt Crisis raised doubts about the responsiveness and capacity of monetary authorities amid systemic stress. More recently, the U.S.–China Trade War and the COVID–19 pandemic disrupted global economic conditions, complicating the Fed's policy decisions and amplifying uncertainty around the future path of monetary policy.

3 Econometric Model and Identification Results

The main identification challenge in estimating the effect of monetary policy communication on monetary policy uncertainty (hereafter MP communication and MP uncertainty) is simultaneity.

MP communication may respond to the level of uncertainty, while MP uncertainty may in turn be affected by communication, so that the two variables are probably jointly determined. As a result, simple correlations between MP communication and MP uncertainty do not admit a causal interpretation.

3.1 A Regime Shift in Fed Communication

To address the identification challenge, I employ identification through heteroskedasticity, following Rigobon (2003) and its applications in Rigobon and Sack (2003, 2004, 2005). The approach exploits regime-dependent variation in the volatility of structural shocks. As shown in Figure 2, MP communication displays a pronounced increase in both level and volatility around the transition from Alan Greenspan to Ben Bernanke. This change reflects a broader shift in the Federal Reserve's communication strategy toward greater transparency. Earlier Federal Reserve communication under Greenspan was generally more cautious and less expansive. Greenspan himself famously remarked:

"*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)

By contrast, Bernanke advocated a substantially more transparent and active communication strategy. During his tenure, the Federal Reserve expanded the frequency and scope of public communication, including more speeches, press conferences, and forward guidance initiatives, leading to a marked increase in policy-related communication.

Why Does Communication Volatility Also Increase? The increase in the volatility of MP communication is driven by the so-called blackout period (also known as the purdah period). This refers to a time interval during which members of a central bank's monetary policy committee are not allowed to publicly express their views on monetary policy or macroeconomic developments. In practice, this implies that policymakers refrain from giving public speeches on economic issues.

This practice is not unique to the Federal Reserve; it is also implemented by other central banks, including the European Central Bank, the Bank of England, and the Bank of Japan, although the exact duration of the blackout period varies across institutions. For FOMC participants, the blackout period became formally binding following the adoption of institutional policy guidelines on June 22, 2011. According to these guidelines, the blackout period begins on the Tuesday morning of the week preceding each scheduled FOMC meeting and ends at midnight on the Thursday following the meeting. This corresponds to approximately 10 days of restricted communication around each of the eight regularly scheduled FOMC meetings per year.

The policy was further tightened on January 31, 2017, when the start of the blackout period was moved to the second Saturday preceding the meeting, extending its average duration to about 13 days. Although the blackout period became formally codified in 2011, there is substantial evidence that similar restrictions were informally followed prior to this date, with the purdah concept being applied in practice at least since the 1980s (Ehrmann and Fratzscher (2007, 2009)).[6]

The blackout period plays a central role in explaining the volatility of monetary policy communication. While overall communication increased following Bernanke's leadership, the imposed communication restrictions around FOMC meetings generate periods of silence, contributing to higher volatility. Importantly, FOMC meeting dates are determined at least one year in advance and vary across calendar months. As a result, the number of blackout days in a given month changes exogenously over time, independently of contemporaneous economic conditions.[7]

On the other hand, testing directly for a structural change in the volatility of MP communication shocks is not feasible without first identifying the shocks themselves. To provide suggestive evidence for this assumption, I therefore apply the Wald structural break test of Andrews (1993) to the volatility of MP communication innovations. These innovations are obtained as residuals from a regression of MP communication on its own lags, as well as lagged MP uncertainty and a set of standard macroeconomic controls, including log industrial production, the unemployment rate, PCE inflation, PPI inflation, the 3-month Treasury bill yield, the shadow policy rate of Xia and Wu (2016), and the first business cycle factor of McCracken and Ng (2021). I then sequentially partition the residual series into two subsamples, each containing at least 10% of the observations, and compute the Wald statistic based on differences in the mean absolute value of the innovations across subsamples. Data descriptions and the detailed methodology are provided in Data Appendix A.4 and Technical Appendix B.1.

Figure 4 shows that the Wald structural break statistic begins to rise around 2002 and first exceeds the 1 percent critical value when Ben Bernanke joins the FOMC in August 2002 (first vertical dashed line). The statistic continues to increase and reaches a peak in July 2004. This pattern indicates a significant increase in the volatility of MP communication during the early phase of the Greenspan–Bernanke transition, consistent with the view that the shift toward more active and intensive communication began to diffuse within the Committee during this period.[8]

Further evidence of this shift can be seen when counting the occurrences of the word "*communication*" in FOMC meeting transcripts.[9] Between 2000 and 2002, this word appeared an average

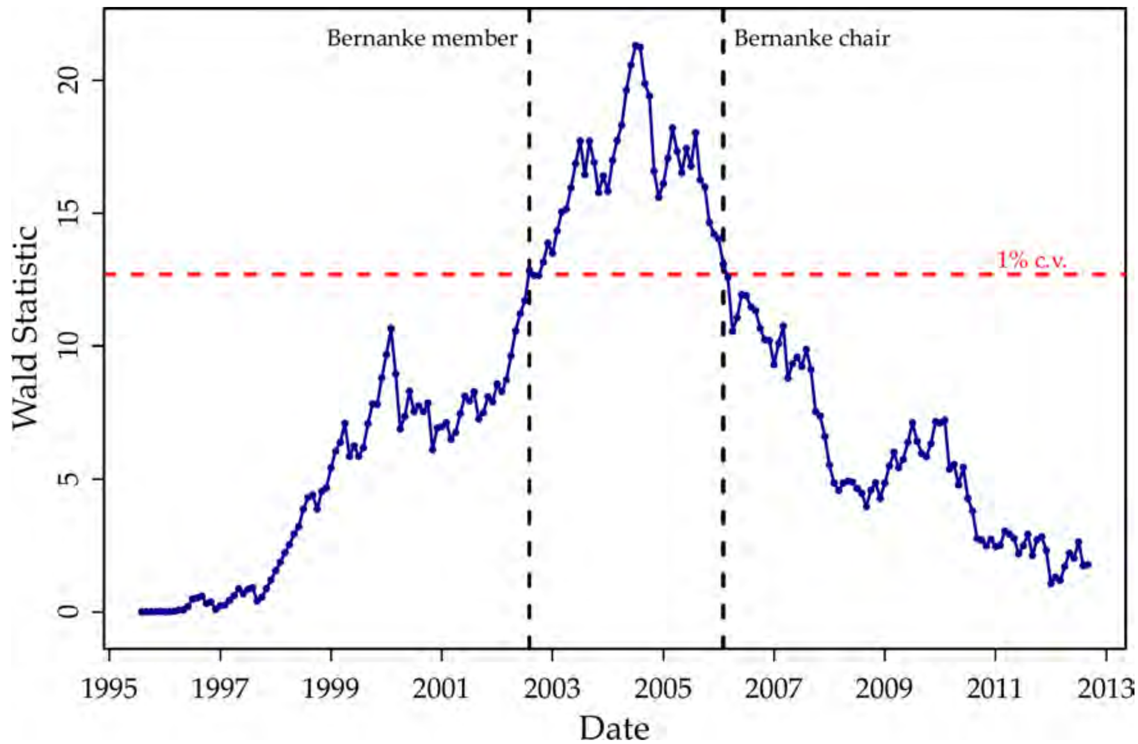
[6] For details, see FOMC Policy on External Communications of Committee Participants.

[7] This exogenous variation in blackout days also provides a suitable instrumental variable (IV) for the volume of FOMC members' public speeches and related measures constructed from the speech dataset.

[8] As a robustness check, I redo the test while controlling for potential mean shifts by including two binary indicators: the first takes the value one from August 2002 onward, when Bernanke joined the Board of Governors, and the second from February 2006 onward, when he became Chair. The results in Figure B.1 remain unchanged.

[9] 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 Wald statistic is computed following Andrews (1993), using monetary policy communication innovations obtained as residuals from a regression of communication on its own lags, as well as lagged monetary policy uncertainty and standard macroeconomic controls. These controls include log industrial production, the unemployment rate, PCE inflation, PPI inflation, the 3-month Treasury bill yield, the shadow policy rate of Xia and Wu (2016), and the first business cycle factor of McCracken and Ng (2021). Up to 10 lags are included. The main blue line shows the Wald test statistic for a structural break in the volatility of MP communication innovations, where volatility is measured by the absolute value of the innovations. The vertical dashed black lines mark August 2002, when Bernanke joined the FOMC, and February 2006, when he became Chair. The horizontal dashed red line denotes the 1% critical value.

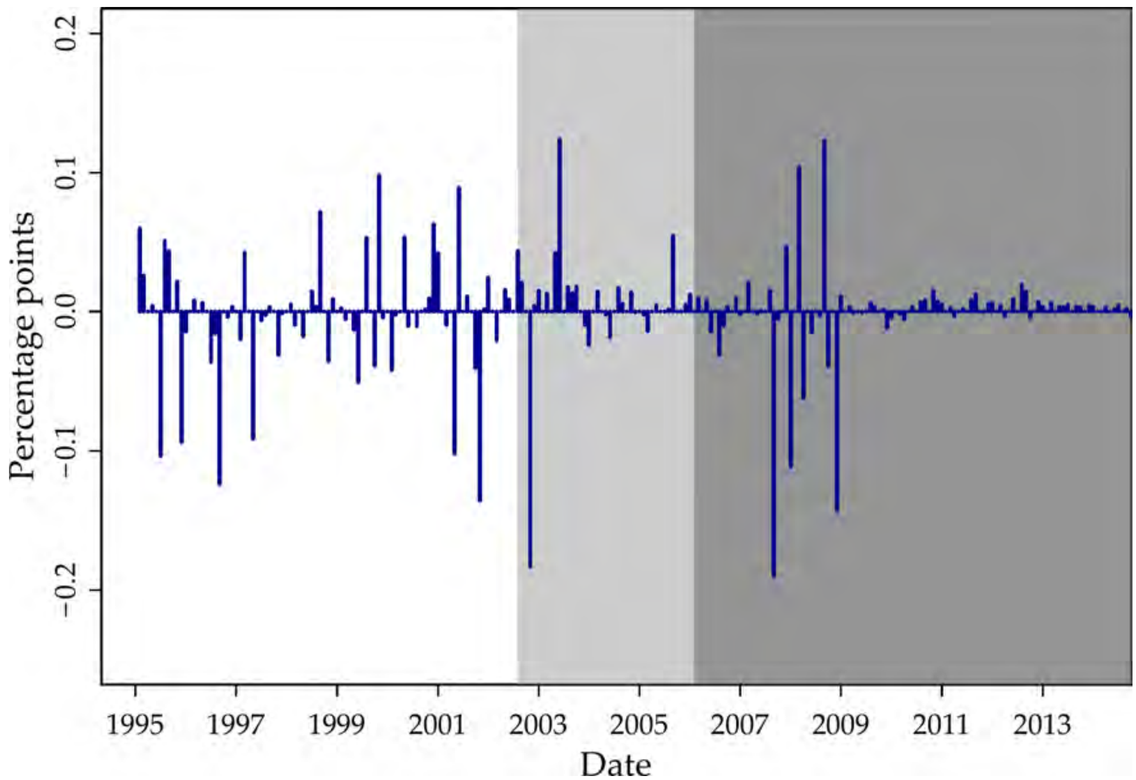
of 3.6 times per transcript. In 2003, it spiked to 18 times per transcript, five times the average of the preceding three years. Notably, in the August 8, 2006 meeting—the fifth meeting with Bernanke as chair—the word appeared 70 times. This simple statistic shows that communication became an important 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:

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)

Figure 5. Federal funds rate surprises at FOMC meetings.



Notes: The series shows federal funds rate surprises at FOMC meetings, measured using the target factor of Gürkaynak et al. (2005) and extended to the present by Acosta et al. (2024). The light shaded area marks the period after Bernanke joined the FOMC as a Governor (August 2002–January 2006). The darker shaded area denotes his tenure as Chair (February 2006–January 2014).

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 supports the interpretation of a shift toward more transparent and improved monetary policy communication.

Finally, Figure 5 plots federal funds rate surprises at FOMC meetings, extending the series in Lunsford (2020). The figure shows a clear decline in the magnitude of policy rate surprises following Bernanke's entry into the Committee and his subsequent chairmanship. The average absolute surprise falls from 3.2 basis points in February 1995–July 2002 to 2.4 basis points in August 2002–January 2006, and further to 1.9 basis points in February 2006–January 2014.

Lunsford (2020) documents a similar decline and attributes it to stronger forward guidance in FOMC policy statements. Consistent with this interpretation, he identifies a structural break in federal funds rate surprises in August 2003, close to the peak of the Wald statistic reported in Figure 4. Taken together, this evidence suggests that enhanced FOMC communication—through both policy statements and increased public speeches—may have improved the predictability of monetary policy, contributing to the observed decline in absolute surprises.

3.2 Identifying the Causal Effect of Communication on Uncertainty

This section identifies the causal effect of monetary policy communication on monetary policy uncertainty within an empirical framework while relying on minimal assumptions. The objective is to recover the parameter governing the response of uncertainty to communication without fully identifying the structural system. I do so by assuming a change in the volatility of communication shocks, motivated by the statistical and anecdotal evidence presented in Section 3.1. This assumption allows communication shocks to be distinguished from uncertainty shocks and thereby identifies the parameter of interest while leaving the remaining parameters unrestricted.

Following Rigobon (2003) and Rigobon and Sack (2004), the empirical model is specified by the system:

$$m_t = \beta u_t + \gamma z_t + \varepsilon_t, \tag{2}$$

$$u_t = \alpha m_t + z_t + \eta_t, \tag{3}$$

where m_t and u_t denote the reduced-form innovations to MP communication and MP uncertainty, respectively, obtained from a bivariate VAR with 12 lags selected by the Bayesian Information Criterion (BIC). The vector z_t captures unobserved common shocks, while ε_t and η_t represent the structural communication and uncertainty shocks.[10] For expositional clarity, I treat z_t as a single common shock without loss of generality.[11]

The system is subject to simultaneity, so the structural parameters are not identified without additional restrictions. Identification can be achieved by allowing the volatility of communication shocks to differ across regimes, which generates the heteroskedastic variation needed to disentangle communication and uncertainty shocks. Let σ_{x,R_i} denote the standard deviation of shock x in regime $i \in \{1,2\}$, where $i = 1$ corresponds to the Greenspan regime and $i = 2$ to the Bernanke regime.[12] The identifying restrictions are:

$$\sigma^2_{\varepsilon,R_1} \neq \sigma^2_{\varepsilon,R_2},, \tag{4}$$

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

$$\sigma^2_{z,R_1} = \sigma^2_{z,R_2}, \tag{6}$$

[10] The loading of the common shock z_t is normalized to unity in the uncertainty equation and denoted by γ in the communication equation; this normalization is without loss of generality and immaterial for the analysis.

[11] The results generalize straightforwardly to a multivariate z_t.

[12] Although Bernanke's chairmanship ended in January 2014, subsequent Federal Reserve chairs continued to adopt a similarly transparent communication strategy. Accordingly, I treat the entire post-2014 period as part of the Bernanke regime.

and the parameters α, β, and γ are assumed constant across regimes.

Equations (4)–(6) impose that the variance of communication shocks differs across regimes, while the variances of uncertainty and common shocks remain constant.[13] Under this heteroskedastic structure, the parameter of interest α, capturing the causal effect of MP communication on MP uncertainty, is identified even though the remaining structural parameters are not. Although the regime-dependent variance structure cannot be tested directly, it implies cross-regime restrictions on the reduced-form covariance matrices that can be evaluated empirically. In particular, under the assumption that only the variance of communication shocks changes across regimes, the covariance matrices in the two regimes must satisfy a set of overidentifying restrictions. I assess these restrictions using a standard overidentification test. Failure to reject provides support for the maintained heteroskedastic identification structure and the resulting estimate of α.

Solving the system (2)–(3) yields:

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

Let the regime-specific covariance matrices be $\Omega_{R_i} = E\big([m_t\ u_t]'\,[m_t\ u_t] \mid t \in R_i\big)$ for $i \in \{1,2\}$. The implied covariance matrices are given by:

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

Taking the difference between the covariance matrices across regimes and imposing the variance restrictions yields:

$$\Delta\Omega = \Omega_{R_1} - \Omega_{R_2} = \lambda \begin{bmatrix} 1 & \alpha \\ \alpha & \alpha^2 \end{bmatrix}, \tag{7}$$

where $\lambda = (\sigma^2_{\varepsilon,R_1} - \sigma^2_{\varepsilon,R_2})/(1-\alpha\beta)^2$. This matrix equation delivers three moment conditions (two variances and one covariance) in the two unknowns α and λ, implying overidentification.

In the baseline specification, I set the regime shift to July 2004, when the Wald statistic reaches its peak. The Greenspan regime therefore spans August 1987–June 2004, while the Bernanke regime covers July 2004–December 2022. Prior to estimation, the MP communication and MP uncertainty series are normalized to have mean zero and unit standard deviation over the full sample to facilitate interpretation. I estimate the parameters α and λ by Generalized Method of

[13] One may expect $\sigma_{\varepsilon,R_1} < \sigma_{\varepsilon,R_2}$, although this ordering is not required for identification. The empirical estimates reported in the next section are consistent with this pattern.

Table 2. Baseline estimates.

Specification	Parameters					J-Test
	α	β	$\sigma^2_{\varepsilon,R_1}$	$\sigma^2_{\varepsilon,R_2}$	σ^2_{η}	p-value
With common shocks	-0.24^{**}	–	–	–	–	0.30
	(0.11)					
Without common shocks	-0.26^{**}	0.13	0.24^{***}	0.59^{***}	0.47^{***}	0.19
	(0.13)	(0.13)	(0.03)	(0.07)	(0.06)	

Notes: The parameters are estimated by GMM. Reported standard errors are based on the residual-based moving block bootstrap procedure of Jentsch and Lunsford (2019), adapted to account for heteroskedasticity in the residuals, and computed using 1,000 replications. The J-test reports the p-value of the Sargan–Hansen test of overidentifying restrictions.

Moments (GMM) following Rigobon and Sack (2004), Lewbel (2012), and Kilian and Lütkepohl (2018). Because the system is overidentified, I assess the validity of the additional moment restrictions using the Sargan–Hansen test. Rejection implies that at least one maintained restriction fails—either the variance of another structural shock also changes across regimes or the structural parameters are not stable.

The first row of Table 2 reports the baseline estimate of $\alpha = -0.24$, which is statistically significant at the five percent level. Inference is based on standard errors obtained from a residual-based moving block bootstrap following Jentsch and Lunsford (2019); see Technical Appendix B.2. The estimate implies that a one-standard deviation increase in MP communication—approximately 240 additional MP-related words per month—reduces MP uncertainty by about 0.24 standard deviations. The estimated variance-shift parameter λ (not reported in the table) equals 0.38 and is statistically different from zero (t-statistic $= 5.50$), indicating a change in the volatility of communication shocks across regimes as required for heteroskedastic identification. The Sargan-Hansen J-test does not reject the overidentifying restrictions ($p = 0.30$), supporting the maintained identification structure.

3.3 Full Identification of the Structural System

If the common shocks z_t are excluded from the specification, all structural parameters—α, β, $\sigma^2_{\varepsilon,R_1}$, $\sigma^2_{\varepsilon,R_2}$, and σ^2_{η}—are identified. Consider the two-variable system obtained by restricting equations (2)–(3):

$$m_t = \beta u_t + \varepsilon_t, \tag{8}$$

$$u_t = \alpha m_t + \eta_t. \tag{9}$$

Under the variance restrictions in (4)–(5) and assuming that α and β are constant across regimes, the regime-specific covariance matrices are given by

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

In this specification, five parameters are to be identified, while the two regimes provide six distinct second-moment conditions—four variances and two covariances. The parameters can therefore be estimated by GMM. Because the system is overidentified in this specification as well, the additional restrictions can be assessed using the Sargan–Hansen test.

The results of full identification are reported in the second row of Table 2. A one-standard deviation increase in MP communication reduces MP uncertainty by 0.26 standard deviations. The estimate is statistically significant and closely aligns with the corresponding estimate from the model featuring common shocks. The variance of communication shocks in the Bernanke regime (0.59) is more than twice that in the Greenspan regime (0.24). A back-of-the-envelope calculation based on $\lambda = (\sigma^2_{\varepsilon,R_1} - \sigma^2_{\varepsilon,R_2})/(1-\alpha\beta)^2$ yields $\lambda \approx 0.33$, close to the directly estimated value (0.38). Although the Sargan–Hansen statistic is slightly lower than in the specification with common shocks ($p = 0.19$), the overidentifying restrictions remain unrefuted. Finally, the effect of MP uncertainty on communication, denoted by β, is positive but statistically insignificant.

3.4 Robustness of the Estimates

A range of robustness checks is conducted to assess the sensitivity of the baseline results to alternative assumptions regarding regime timing, measurement choices, and the proxy for monetary policy uncertainty. The estimates from these alternative specifications are reported in Table 3, with Panel A including common shocks and Panel B excluding them.

I begin by examining the sensitivity of the results to the assumed timing of the regime change in the volatility of structural communication shocks. Because identification through heteroskedasticity treats structural communication shocks as latent and recovers them only through cross-regime variance differences, the timing of this volatility break cannot be tested directly. I therefore infer the break date from anecdotal and reduced-form evidence, using the Wald structural break test applied to communication innovations (Figure 4). The baseline specification assumes that the regime shift occurs in July 2004, when the Wald statistic exceeds the 1% critical value and reaches its peak. Nevertheless, the true change in communication-shock volatility may have occurred at a different date. To evaluate the role of this assumption, I consider three alternative specifications: a break at the start of Bernanke's chairmanship (February 2006), and breaks three months before and after the Wald peak (March 2004 and October 2004). In all three cases, the estimated response of uncertainty to communication remains negative and statistically significant, and the overidentifying restrictions are not rejected. These results indicate that the estimates are stable to reasonable variation in the assumed break date.

I next assess whether the findings depend on the specific composition of the monetary policy dictionary. Starting from the BBD dictionary, I construct two alternatives: a smaller dictionary that excludes selected terms and a larger dictionary that augments the baseline list with additional monetary policy expressions. The resulting dictionaries are reported in Tables A.2 and A.3. Reconstructing the communication series with each dictionary and re-estimating the model yields effects that remain negative, statistically significant, and close in magnitude to the baseline across both specifications. The overidentifying restrictions continue to hold. Hence, the estimated relationship does not appear to be driven by particular dictionary entries.

To assess the role of differences in communication formats, I exclude the Chair's press conferences from the construction of the communication measure. Press conferences represent a distinct form of policy communication, combining prepared statements with structured question-answer sessions, and may therefore convey information differently from other speeches. This format was introduced in April 2011 under Chair Bernanke, initially following every other scheduled FOMC meeting, a practice maintained under Chair Yellen; since 2019, under Chair Powell, press conferences have followed every meeting. Re-estimating the model with these press conferences removed leaves the estimated effect of communication on uncertainty largely unchanged in sign, magnitude, and statistical significance, and the overidentifying restrictions remain satisfied. I then conduct a stricter specification by excluding all speeches delivered by the Chair, in addition to press conferences. In this case, the estimated effect becomes smaller and is no longer statistically significant. This pattern suggests that the Chair's communication plays an important role in driving the baseline results and accounts for a substantial share of the information content in the speech dataset.

The role of speaker prominence is examined by altering the weighting scheme used to construct the communication index. In the baseline specification, all speakers receive equal weight in Equation (1). To allow for greater influence of the FOMC Chair, I assign a weight twice as large to Chair speeches (i.e., $w_{\text{Chair}} = 2$) while leaving the weights of other participants unchanged. The communication series is recomputed under this scheme and the model re-estimated. The resulting estimates remain negative, statistically significant, and very similar to the baseline, with the overidentifying restrictions again satisfied. This evidence suggests that the findings are not sensitive to plausible alternative speaker weights.

Finally, I replace the baseline monetary policy uncertainty measure with the alternative index constructed by BBD using a restricted sample of the 10 largest U.S. newspapers. This variant applies the same E-P-U-M dictionary methodology as the baseline series but limits the source material to a small set of prominent national and regional outlets. Re-estimating the model with

Table 3. Robustness of the estimates.

Panel A. With common shocks

SPECIFICATION	PARAMETERS					J-TEST
	α	β	$\sigma^2_{\varepsilon,R_1}$	$\sigma^2_{\varepsilon,R_2}$	σ^2_{η}	p-value
Structural Break Date						
Bernanke chair	-0.28^{**}	–	–	–	–	0.34
	(0.12)					
Wald peak -3m	-0.23^{**}	–	–	–	–	0.28
	(0.11)					
Wald peak +3m	-0.25^{**}	–	–	–	–	0.32
	(0.11)					
Monetary Policy Dictionary						
Smaller dictionary	-0.25^{**}	–	–	–	–	0.29
	(0.11)					
Larger dictionary	-0.23^{**}	–	–	–	–	0.30
	(0.10)					
Monetary Policy Speeches						
Excluding chair press conferences	-0.24^{**}	–	–	–	–	0.30
	(0.11)					
Excluding all chair speeches	-0.19	–	–	–	–	0.31
	(0.12)					
Speaker Weighting						
Chair-weighted ($\times$2)	-0.25^{**}	–	–	–	–	0.28
	(0.11)					
Monetary Policy Uncertainty						
BBD – 10 newspapers	-0.43	–	–	–	–	0.15
	(0.83)					

Panel B. Without common shocks

Specification	Parameters					J-Test
	α	β	$\sigma^2_{\varepsilon,R_1}$	$\sigma^2_{\varepsilon,R_2}$	σ^2_{η}	p-value
Structural Break Date						
Bernanke chair	-0.30^{**}	0.16	0.26^{***}	0.63^{***}	0.49^{***}	0.22
	(0.13)	(0.12)	(0.04)	(0.08)	(0.07)	
Wald peak -3m	-0.25^{**}	0.12	0.24^{***}	0.59^{***}	0.47^{***}	0.17
	(0.12)	(0.12)	(0.03)	(0.06)	(0.06)	
Wald peak +3m	-0.26^{**}	0.13	0.24^{***}	0.60^{***}	0.48^{***}	0.21
	(0.12)	(0.12)	(0.03)	(0.07)	(0.06)	
Monetary Policy Dictionary						
Smaller dictionary	-0.26^{**}	0.13	0.25^{***}	0.60^{***}	0.48^{***}	0.18
	(0.13)	(0.13)	(0.03)	(0.07)	(0.06)	
Larger dictionary	-0.24^{**}	0.10	0.21^{***}	0.58^{***}	0.47^{***}	0.19
	(0.11)	(0.10)	(0.03)	(0.07)	(0.06)	
Monetary Policy Speeches						
Excluding chair press conferences	-0.25^{**}	0.13	0.25^{***}	0.62^{***}	0.47^{***}	0.19
	(0.13)	(0.13)	(0.03)	(0.07)	(0.06)	
Excluding all chair speeches	-0.20	0.07	0.27^{***}	0.63^{***}	0.47^{***}	0.20
	(0.13)	(0.14)	(0.04)	(0.07)	(0.06)	
Speaker Weighting						
Chair-weighted ($\times 2$)	-0.27^{**}	0.17	0.25^{***}	0.62^{***}	0.48^{***}	0.17
	(0.12)	(0.12)	(0.03)	(0.07)	(0.07)	
Monetary Policy Uncertainty						
BBD – 10 newspapers	-0.34	0.21	0.24^{***}	0.58^{**}	0.44^{***}	0.07
	(0.23)	(0.20)	(0.09)	(0.27)	(0.16)	

Notes: The parameters are estimated by GMM. Reported standard errors are based on the residual-based moving block bootstrap procedure, adapted to account for heteroskedasticity in the residuals, and computed using 1,000 replications. The J-test reports the p-value of the Sargan–Hansen test of overidentifying restrictions.

this proxy still yields a negative effect of communication on uncertainty; however, the results are not statistically significant and are rejected by the Sargan–Hansen test when common shocks are removed from the specification.

The weaker precision in the latter case is consistent with the noisier construction of the 10-newspaper index. Restricting the sample to a narrow set of outlets excludes a large share of local reporting and reduces cross-sectional coverage of monetary policy discussions in the media. Moreover, not all newspapers in the restricted set remain among the highest-circulation U.S. outlets.[14] These considerations suggest that the 10-newspaper series provides a less comprehensive measure of aggregate monetary policy uncertainty than the baseline BBD index. Overall, the results remain consistent with the baseline interpretation while underscoring the advantages of the broader newspaper coverage.[15,16,17]

3.5 Identification Without Pre-Specified Regimes

In the baseline specification, identification relies on a discrete regime shift in the volatility of communication shocks, with a fixed break date separating the Greenspan and Bernanke regimes. While this approach follows the standard heteroskedasticity-based identification framework, it requires specifying the timing of the volatility change ex ante. To address this limitation, I complement the baseline analysis with the identification strategy of Lewis (2021), which exploits continuous time variation in the volatility of reduced-form innovations and therefore does not require pre-specified volatility regimes. Identification instead follows from the autocovariance of squared VAR residuals, which carries information about the structural parameters when shock variances are serially persistent.

As in the baseline specification, I estimate a bivariate VAR with 12 lags for monetary policy communication and uncertainty and obtain the reduced-form residuals m_t and u_t. The system is the same as in (2)–(3) and may still feature common shocks. Following Lewis (2021), I assess

[14] For current circulation rankings, see Statista.

[15] Another alternative monetary policy uncertainty measure is provided by Husted et al. (2020), who construct an index using a similar dictionary-based methodology to Baker et al. (2016) but with a smaller monetary policy dictionary (see Table A.4) and a newspaper sample restricted to three major U.S. outlets. The index is normalized by the number of articles mentioning the Federal Reserve rather than by total newspaper coverage. This difference has important implications for interpretation: the Husted et al. (2020) index captures the share of Federal Reserve-related coverage conveying uncertainty—essentially measuring how uncertain the tone is when monetary policy is discussed—whereas the BBD index measures the overall volume of monetary policy uncertainty in the media. Because this paper studies how overall monetary policy uncertainty responds to central bank communication, the broader BBD index is more directly aligned with the research question. Re-estimating the model with the Husted et al. (2020) measure yields negative but statistically insignificant effects of communication on uncertainty.

[16] As an additional robustness check, I include FOMC policy statements in the dataset. These statements, which are typically 1–2 pages long, have been released after FOMC meetings since 1994. Incorporating this additional source leaves the results unchanged. The findings are also robust to alternative weighting schemes applied to these documents.

[17] I also implement an IV specification using the number of blackout (purdah) days in each month as an instrument for monetary policy communication. The first-stage F-statistic is around 13, and the results are very similar to the baseline. They are also robust to controlling for additional macroeconomic and financial variables.

whether the time-varying volatility in the residuals generates sufficient autocovariance structure to identify α. The key object is the lag-1 autocovariance matrix of the vectorised outer product of residuals. Define $\xi_t = \text{vech}(\nu_t \nu_t')$ where $\nu_t = (m_t, u_t)'$, so that $\xi_t = (m_t^2, m_t u_t, u_t^2)'$ is a 3×1 vector. The identification matrix is then

$$\mathcal{M} = \frac{1}{T-1} \sum_{t=2}^{T} \xi_t \xi_{t-1}', \tag{10}$$

whose rank determines the number of structural shocks with time-varying volatility. I test this condition using the rank test of Cragg and Donald (1996). For a null hypothesis $\text{rank}(\mathcal{M}) = r$, the test statistic is

$$CD_r = T \cdot \hat{m}_r' \widehat{\text{Var}}(\hat{m}_r)^{-1} \hat{m} * r \xrightarrow{d} \chi^2 * (d-r)^2, \tag{11}$$

where $\hat{m}_r$ is the vector of singular values of $\mathcal{M}$ associated with the rank restriction, $\widehat{\text{Var}}(\hat{m}_r)$ is a HAC variance estimator based on a Bartlett kernel with bandwidth $b = \lfloor 4(T/100)^{2/9} \rfloor$ following Newey and West (1994), and $d = n(n+1)/2 = 3$ is the dimension of ξ_t. Rejection of $H_0 : \text{rank}(\mathcal{M}) = 0$ and failure to reject $H_0 : \text{rank}(\mathcal{M}) = 1$ indicate that exactly one structural shock exhibits time-varying volatility. Since the test does not determine which shock this is, identification of α requires the additional assumption that the time-varying volatility is associated with the monetary policy communication shock.

Given this identification condition, α can be recovered in closed form as

$$\alpha = \frac{\text{cov}(m_t u_t,\ m_{t-p}^2)}{\text{cov}(m_t^2,\ m_{t-p}^2)}. \tag{12}$$

Equation (12) corresponds to an IV estimator, where m_{t-p}^2 instruments the endogenous regressor m_t^2 and $m_t u_t$ is the dependent variable. The formal derivation is provided in Technical Appendix B.3.

Table 4 reports the results obtained from this identification strategy. The Cragg–Donald test strongly rejects the null of rank zero but fails to reject rank one ($p = 0.85$), indicating that exactly one shock exhibits time-varying volatility. Interpreting this shock as the monetary policy communication shock, consistent with the baseline identification, the evidence supports the validity of both the Rigobon (2003) and Lewis (2021) approaches.

The estimated coefficient α equals -0.19 and is statistically significant at the five percent level. The estimate has the same sign and significance as in the baseline specification, although its magnitude is slightly smaller. Overall, the negative effect of MP communication on MP uncertainty appears robust to alternative identification assumptions and does not rely on pre-specified regime switches.

Table 4. Identification through time-varying volatility.

	ESTIMATION		CRAGG–DONALD RANK TEST	
	α	Std. Error	$r = 0$	$r = 1$
TVV Identification (Lewis 2021)	-0.191^{**}	0.087	62.10	1.38
			$(p = 0.00)$	$(p = 0.85)$

Notes: The parameter α is estimated using the moment condition implied by time-varying volatility, following Lewis (2021). Standard errors are computed using a residual-based moving block bootstrap with 1,000 replications. The Cragg–Donald statistic tests the rank of the identification matrix $\mathcal{M}$. Rejecting $r = 0$ but not $r = 1$ implies that exactly one structural shock exhibits time-varying volatility, thereby satisfying the identification condition.

3.6 Time Invariance of the Structural Impact Matrix

Let B denote the structural impact matrix of the structural shocks on the reduced-form residuals. The identification strategy relies on time variation in the volatility of structural shocks while the structural impact matrix is assumed to remain constant over time. In the notation of the model, this implies that the contemporaneous transmission matrix $B(\alpha, \beta, \gamma)$ remains fixed across regimes. This assumption ensures that changes in the reduced-form covariance matrix can be attributed to shifts in shock variances rather than to changes in the underlying structural relationships.

Allowing the impact matrix B to vary over time would in principle represent a strong departure from the standard framework, as no existing identification scheme can flexibly accommodate a fully time-varying B without imposing strong functional-form restrictions. Even simple recursive short-run restrictions are generally insufficient to identify B when it varies over time. While some work allows for time-varying structural parameters—for example, time-varying parameter VAR models as in Cogley and Sargent (2005) and Primiceri (2005)—these approaches typically rely on Bayesian frameworks in which prior assumptions help separate variation in B from variation in shock variances. In contrast, most identification strategies in the structural VAR literature maintain a constant impact matrix.

Similarly, assuming stable structural coefficients across regimes is standard in heteroskedasticity-based identification approaches in macroeconometrics. For example, Rigobon and Sack (2003, 2004, 2005), Wright (2012), and Gürkaynak et al. (2020) identify structural relationships from regime-dependent changes in shock variances while maintaining constant structural coefficients. Moreover, Sims and Zha (2006) show that U.S. monetary policy data are better characterized by shifts in shock variances than by changes in structural parameters.

The overidentification tests provide an indirect check of the assumption that the structural impact matrix B remains constant over time. If B were changing across regimes, these changes would be reflected in the variance-covariance matrix of the reduced-form residuals. In the baseline specifications with and without common shocks, this would lead to substantial changes in the model moments and therefore to large overidentification test statistics. In none of the specifications does the overidentification test reject the model, providing support for the maintained assumption of parameter stability.

3.7 Discussion of the Result

The main empirical finding of this section is that increases in monetary policy communication reduce monetary policy uncertainty. This negative effect is estimated consistently across both identification strategies—whether common shocks are included or excluded—and remains economically similar in magnitude. Moreover, the result proves robust to a wide range of alternative specifications, including different regime break dates, communication dictionaries, speech samples, speaker-weighting schemes, uncertainty measures, and identification approaches that do not require pre-specified volatility regimes. Taken together, the evidence indicates a stable and systematic relationship between central bank communication and monetary policy uncertainty.

One plausible interpretation of this finding is that more intensive central bank communication improves the information environment faced by households, firms, and financial markets. By providing clearer guidance about the central bank's objectives, reaction function, and assessment of economic conditions, communication reduces uncertainty about the future path of monetary policy. This channel is particularly relevant in periods of heightened macroeconomic volatility, when agents face greater difficulty in forming expectations about policy actions. Increased communication may also coordinate beliefs by anchoring expectations around a shared policy narrative, thereby lowering dispersion in perceived policy risks. Under this interpretation, the observed decline in monetary policy uncertainty reflects improved transparency and predictability of central bank actions arising from more intensive communication and clearer guidance about future policy.

4 Propagation of Communication Shocks

This section extends the two-variable framework introduced in Section 3 to a multivariate setting in order to study the transmission of monetary policy communication shocks to the broader economy. While the baseline model isolates the causal effect of communication on monetary policy uncertainty, it does not capture how these shocks propagate to real activity and financial markets. To address this, I extend the two-variable system to a multivariate framework and maintain the heteroskedasticity-based identification strategy under the same two-regime structure.

The multivariate framework serves two main purposes. First, it allows me to trace the dynamic effects of communication-driven changes in uncertainty on output, labor market conditions, consumption, prices, and financial indicators. This provides direct evidence on the macroeconomic and financial transmission channels of monetary policy communication. Second, it offers a robustness check for the identification strategy developed in Section 3. Specifically, I examine whether the estimated effect of communication on uncertainty remains stable once additional variables are included in the system.

4.1 Multivariate Framework and Identification

Let x_t denote a $K \times 1$ vector of endogenous variables that includes monetary policy communication, monetary policy uncertainty, and additional macroeconomic and financial indicators. The dynamics of x_t are described by a VAR of order p:

$$x_t = c + A_1 x_{t-1} + \cdots + A_p x_{t-p} + v_t, \tag{13}$$

where v_t denotes the vector of reduced-form innovations.

Assuming that the implied vector moving average (VMA) representation of x_t is invertible, the reduced-form innovations can be written as

$$v_t = Be_t, \tag{14}$$

where e_t is a $K \times 1$ vector of structural shocks and B is a conformable loading matrix.[18]

Let b denote the column of B associated with the communication shock, and $\Omega_{R_i} = E(v_t v_t' \mid t \in R_i)$ the covariance matrix of reduced-form innovations in regime $i \in \{1, 2\}$. Under the assumption that only the communication shock exhibits a change in volatility and that the matrix B remains constant, the covariance matrices in the two regimes are given by

$$\Omega_{R_1} = bb'\sigma^2_{c,R_1} + \Sigma_0, \tag{15}$$

$$\Omega_{R_2} = bb'\sigma^2_{c,R_2} + \Sigma_0, \tag{16}$$

where σ^2_{c,R_i} denotes the variance of the communication shock in regime i, and Σ_0 collects the contribution of all other shocks.

[18] More generally, one may allow for unobserved common shocks and write

$$v_t = Be_t + Dz_t,$$

where z_t denotes unobserved common shocks and D is a conformable loading matrix. As in Section 3, the presence of common shocks does not affect identification, since the identifying variation relies on changes in the volatility of the communication shock across regimes.

Taking differences across regimes yields

$$\Delta\Omega = \Omega_{R_1} - \Omega_{R_2} = (\sigma^2_{c,R_1} - \sigma^2_{c,R_2}) \begin{bmatrix} b_1^2 & b_1 b_2 & \cdots & b_1 b_K \\ b_2 b_1 & b_2^2 & \cdots & b_2 b_K \\ \vdots & \vdots & \ddots & \vdots \\ b_K b_1 & b_K b_2 & \cdots & b_K^2 \end{bmatrix}. \tag{17}$$

The expression in (17) can be rewritten as

$$\Delta\Omega = \tilde{\lambda} \begin{bmatrix} 1 & \theta_2 & \cdots & \theta_K \\ \theta_2 & \theta_2^2 & \cdots & \theta_2 \theta_K \\ \vdots & \vdots & \ddots & \vdots \\ \theta_K & \theta_K \theta_2 & \cdots & \theta_K^2 \end{bmatrix}, \tag{18}$$

where $\tilde{\lambda} = (\sigma^2_{c,R_1} - \sigma^2_{c,R_2}) b_1^2$ and $\theta_j = b_j / b_1$ for $j = 2, \ldots, K$.

This representation implies that all columns (and rows) of $\Delta\Omega$ are proportional to each other. Therefore, under the maintained assumptions, $\Delta\Omega$ is a rank-one matrix. Since $\Delta\Omega$ is symmetric, it provides $K(K+1)/2$ moment conditions that can be used to estimate $(\theta_2, \ldots, \theta_K)$ using GMM. The impact effects of the communication shock are identified up to sign and an appropriate scale normalization, corresponding to the first column of the matrix in equation (18).

4.2 Baseline Multivariate Specification

The baseline specification includes seven variables: monetary policy communication, monetary policy uncertainty, the 3-month Treasury bill yield, log industrial production, the unemployment rate, inflation (PCE), and the first business cycle factor of McCracken and Ng (2021). The 3-month Treasury bill yield is used as a proxy for the stance of monetary policy, as it captures short-term rate movements while mitigating concerns related to the zero lower bound over the sample period. PCE inflation is preferred over other inflation measures, as it is the measure officially targeted by the Federal Reserve, although the results are robust to using CPI or the GDP deflator. The first business cycle factor is included to capture potentially missing dynamics in the VAR specification. The VAR is estimated with two lags, selected according to the BIC.

While the assumption that only communication shocks exhibit regime-dependent volatility is strong, the data provide substantial support for it. In particular, the leading eigenvalue of $\Delta\Omega$ is more than twelve times larger than the second, and accounts for over 80 percent of the total variation. This indicates that $\Delta\Omega$ is well-approximated by a rank-one matrix, consistent with the maintained identification assumption.

In the impulse response analysis, moment conditions based on the first column of equation (18) are used, as these directly identify the parameters of interest, namely the impact effects of a MP communication shock. Employing the full set of $K(K+1)/2$ moment conditions would impose additional cross-equation restrictions that are more sensitive to sampling variation. Nevertheless, estimates based on the full set are quantitatively similar and are discussed as a robustness check. Moreover, when the model is estimated using the complete set of moments, the Sargan–Hansen overidentification test yields a p-value of 0.25, failing to reject the null of valid identifying restrictions.

Figure 6 reports impulse responses to a one-standard-deviation monetary policy communication shock, corresponding to an increase of 240 monetary-policy-related words per month. Following the shock, monetary policy uncertainty responds by -0.22 standard deviations on impact. This provides an important robustness check for the estimates in Section 3, where the impact effect is approximately -0.25. The effect dissipates relatively quickly, returning to zero within six months.

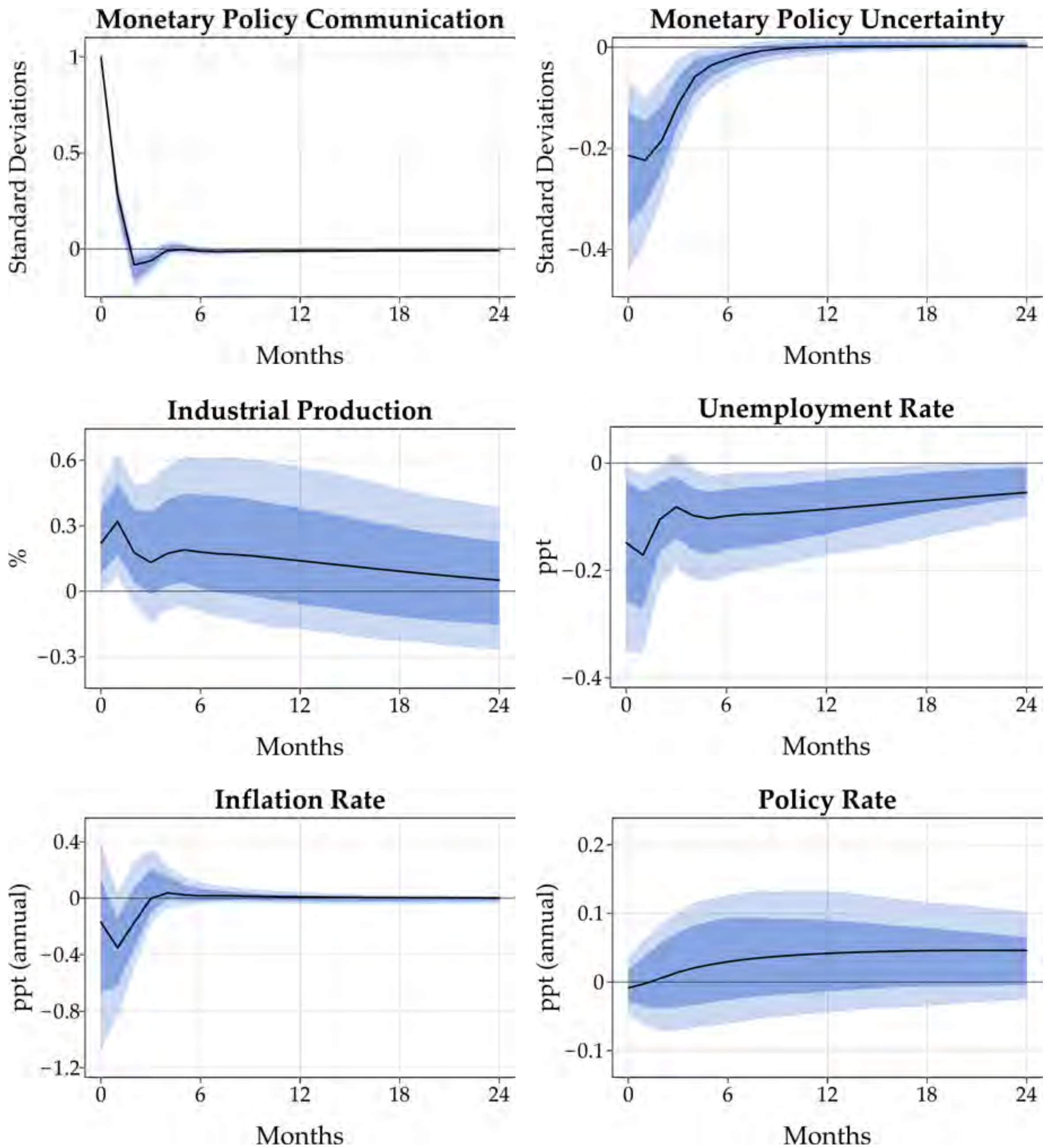
Turning to real activity, industrial production increases immediately, with a peak response of around 0.3 percent, before gradually declining toward zero. Consistent with this, the unemployment rate falls following the shock, reaching a maximum decline of almost 0.2 percentage points and remaining below its steady state for an extended period. Inflation declines on impact but quickly reverts to zero, indicating limited persistence in price dynamics; however, this response is not statistically significant at conventional confidence levels and should be interpreted with caution. Finally, the policy rate response is statistically insignificant on impact, before exhibiting a delayed and modest increase.

These results suggest that the identified communication shocks primarily operate through supply-side channels rather than demand-side forces. The combination of higher economic activity, lower unemployment, and declining inflation is difficult to reconcile with a standard demand-driven expansion. Instead, it is consistent with a reduction in uncertainty that supports supply-side adjustments.

The joint response of lower inflation and higher economic activity poses a trade-off for monetary policy. While the decline in inflation would call for a more accommodative stance, the increase in real activity would typically justify policy tightening. Consistent with these offsetting forces, the policy rate response is small and statistically insignificant, indicating that monetary policy does not adjust strongly following the communication shock.

Robustness. As a first robustness check, I exclude the COVID–19 period to assess whether the baseline results are driven by the extreme dynamics observed during the pandemic. To this end, the sample is truncated at December 2019, and the model is re-estimated over the pre-pandemic period. Figure C.1 reports the corresponding impulse responses. Overall, the results remain broadly consistent with the baseline specification. Monetary policy communication shocks con-

Figure 6. Baseline impulse responses.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the baseline VAR(2), estimated over 1987:08–2022:12. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

tinue to reduce uncertainty and generate expansionary effects on real activity. However, some differences in the dynamic responses emerge. In particular, industrial production and unemployment no longer exhibit an immediate jump on impact; instead, their responses build gradually over time, reaching peak effects after approximately one year. Inflation follows a slightly different pattern, with a modest increase after the initial decline. In addition, the policy rate responds more strongly than in the baseline, increasing gradually and reaching a peak effect of around 0.1 percentage points, indicating that the Federal Reserve responds to the improvement in economic activity once pandemic-related distortions are removed.

As an additional robustness check, I consider alternative measures of the stance of monetary policy. In particular, I replace the 3-month Treasury bill yield with the federal funds rate and, separately, with the shadow rate of Xia and Wu (2016). The impulse responses obtained under these alternative specifications are reported in Figures C.2 and C.3. The results remain very similar to those of the baseline specification, indicating that the findings are not sensitive to the choice of policy rate measure.

As a further robustness check, I vary the lag length of the VAR. In addition to the baseline specification with two lags, I estimate models with six and twelve lags, which are other common choices in monthly data applications. The corresponding impulse responses are reported in Figures C.4 and C.5. The results remain close to the baseline, with the main difference being that the inflation response becomes less precisely estimated.

When using twelve lags, the response of monetary policy communication exhibits a secondary peak around horizon $h = 12$, likely reflecting mild seasonality in the communication series. To assess whether this feature affects the results, I remove both trend and seasonal components using an STL decomposition and re-estimate the baseline specification. The results, reported in Figure C.6, are very similar to the baseline, indicating that mild seasonality in the communication measure does not drive the main findings.

I also estimate the model using the full set of moment conditions, with the corresponding impulse responses reported in Figure C.7. The results are quantitatively very similar to those of the baseline specification, although the confidence bands are somewhat wider, reflecting increased estimation uncertainty associated with the additional moment restrictions. Importantly, the Sargan–Hansen overidentification test yields a p-value of 0.25, failing to reject the identifying assumption that only monetary policy communication shocks exhibit changes in volatility across regimes while the coefficients of the matrix B remain stable.

Finally, I augment the VAR with high-frequency monetary policy surprises obtained from Acosta et al. (2024). These surprises are constructed around the release of FOMC policy statements and, when available, the subsequent press conferences by the Chair. The purpose of this exercise is to ensure that the identified communication shock is not capturing conventional monetary policy surprises. In particular, if monetary policy communication were correlated with these surprises, the estimated effects could partly reflect unexpected changes in policy rates.

The results, reported in Figure C.8, indicate that the monetary policy communication shock has no predictive power for high-frequency monetary policy surprises, as the response is negligible and statistically insignificant. This indicates that the identified communication shock is distinct from conventional monetary policy surprises. At the same time, controlling for these surprises leads to some quantitative changes in the estimated responses. In particular, the impact effect on uncertainty is estimated at approximately -0.25, which is even closer to the estimate obtained in Section 3. In addition, the responses of real activity become somewhat stronger, with industrial production reaching a peak increase of about 0.5 percent.

4.3 Transmission to the Broader Macroeconomy

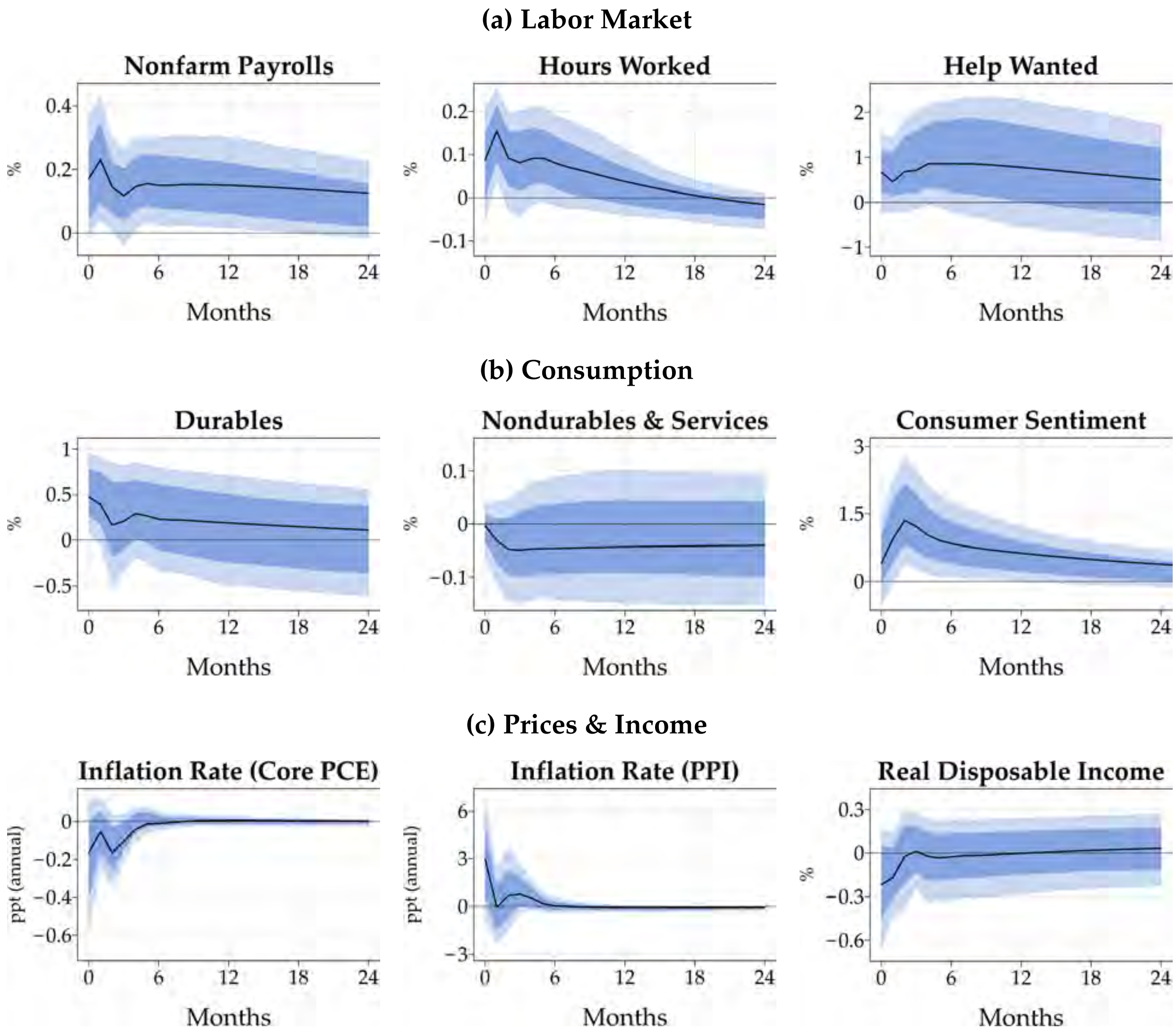
This subsection extends the baseline specification by augmenting the VAR with additional macroeconomic variables, introduced sequentially. The corresponding impulse responses are reported in Figure 7.

Panel (a) of Figure 7 reports the responses of labor market variables. Nonfarm payrolls increase on impact by about 0.2 percent and remain positive for an extended period, indicating a sustained improvement in employment. Hours worked also rise initially, by approximately 0.15 percent, but the effect is more short-lived and gradually declines toward zero. The help-wanted index, which captures firms' demand for labor through job advertisements, rises by roughly 1 percent about six months after the shock and remains elevated, pointing to a persistent strengthening in labor demand.

Panel (b) shows consumption responses. Durable consumption increases sharply by about 0.5 percent on impact and then gradually declines. In contrast, the response of nondurable and services consumption is close to zero and statistically insignificant. The stronger response of durable spending is consistent with households bringing forward purchases of high-commitment goods when uncertainty declines. Consumer sentiment also improves markedly, increasing by nearly 1.5 percent within three months, indicating that reduced uncertainty is associated with higher household confidence.

Panel (c) reports the responses of prices and income. Core PCE inflation declines in the first few months following the shock and gradually returns to zero, closely mirroring the response of aggregate inflation in the baseline specification. In contrast, proudcer price index (PPI) inflation increases strongly by about 3 percent on impact and then reverts to zero, consistent with increased demand for intermediate inputs as firms expand production following the communication shock. Real disposable income declines on impact and remains slightly negative in the short run, potentially reflecting higher household spending, particularly on durable goods. However, these responses should be interpreted with caution, given that the 90% confidence bands include zero.

Figure 7. Impulse responses of macro variables to communication shocks.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from a VAR(2) including baseline variables and, in turn, each additional macroeconomic variable, estimated over 1987:08–2022:12. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

4.4 Transmission to the Financial Markets

This subsection examines how monetary policy communication shocks transmit to financial markets, following an approach similar to Section 4.3. To this end, I augment the baseline specification with a set of financial variables, introduced sequentially. The corresponding impulse responses are reported in Figure 8.

Panel (a) of Figure 8 presents the responses of financial risk measures. The VIX declines following the shock, reaching a trough of about 1.5 points after two to three months before gradually returning to zero. This implies a decline of roughly 1.5 percentage points in expected stock market volatility over the next 30 days, expressed in annualized terms.

The credit spread, defined as the difference between the yields of AAA- and BAA-rated corporate bonds, also declines following the shock. The reduction is modest—around 3 basis points—but persistent, indicating a gradual easing of perceived credit risk and financial conditions. Taken together, these results point to a decline in financial risk premia following monetary policy communication shocks.

Panel (b) turns to stock market indices. The S&P 500, which tracks large-cap U.S. firms, and the Russell 2000, which captures small-cap firms, both increase following the shock. In both cases, the response builds over the first two to three months, reaching a peak of around 1 percent before gradually declining toward zero. The similar responses across the two indices suggest that MP communication shocks affect both large and small firms in a comparable manner. However, these responses should be interpreted with caution, as the 90% confidence bands include zero.

Panel (c) considers Treasury yield spreads. The responses of both the 2-year minus 3-month spread and the 10-year minus 3-month spread are very small and not statistically significant. Accordingly, there is little evidence that MP communication shocks that reduce MP uncertainty have a meaningful effect on the slope of the yield curve.

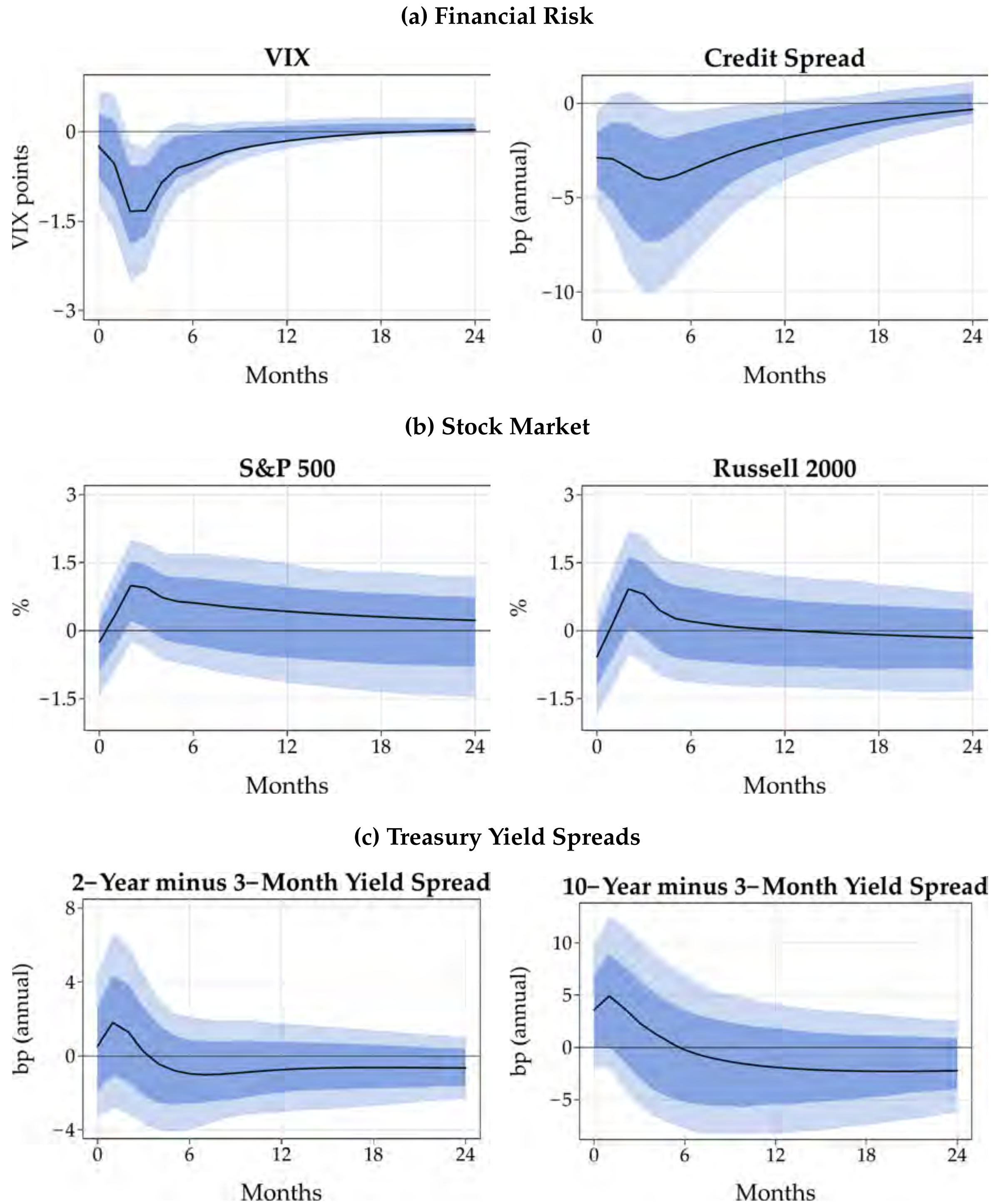
4.5 Distinguishing Monetary Policy Uncertainty from Alternative Channels

Are the macroeconomic and financial effects documented above driven by reductions in monetary policy uncertainty, or do other forces also play a role? While the baseline results point to an important role for the uncertainty channel, monetary policy communication may operate through additional mechanisms. In what follows, I examine some alternative explanations.

Importantly, the measure of monetary policy communication used in this paper captures the overall volume of communication, abstracting from its content, such as hawkish or dovish signals. While it is in principle possible that higher communication intensity is systematically associated with a particular policy stance, and thus affects interest rates through this channel, the results provide little support for such a mechanism. If monetary policy communication primarily affected expectations about the path of policy rates, one would expect to observe a significant response of short-term interest rates. However, as shown in the baseline impulse responses (Figure 6), the policy rate does not respond significantly following the communication shock.

Some robustness exercises reported in the Appendix do show a statistically significant increase in the policy rate. However, this response builds gradually over time and is more consistent with a reaction of monetary policy to improving economic conditions, rather than a direct effect of communication on policy expectations. If anything, a contractionary policy response as shown in IRFs would be expected to dampen economic activity, which is not observed in the data. In addition, when directly controlling for high-frequency monetary policy surprises (Figure C.8),

Figure 8. Impulse responses of financial variables to communication shocks.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from a VAR(2) including baseline variables and, in turn, each additional financial variable, estimated over 1987:08–2022:12 (1990:01–2022:12 for VIX specification). The credit spread is calculated as the difference between the yields of AAA-rated and BAA-rated corporate bonds. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

we find no correlation between these surprises and the identified communication shock, further indicating that it is distinct from conventional policy rate surprises.

Consistent with this interpretation, there is also little evidence of a meaningful effect on the yield curve. As shown in Panel (c) of Figure 8, the responses of Treasury yield spreads are small and not statistically significant. While the 10-year minus 3-month spread exhibits a slight positive response on impact, its magnitude is around 5 basis points, which is negligible relative to its sample mean of approximately 160 basis points and standard deviation of about 113 basis points. Moreover, the positive sign of the response would, if anything, be consistent with a contractionary interpretation. Taken together, these findings provide little support for the conventional interest rate channel as the primary mechanism behind the observed effects.

Another potential mechanism operates through household sentiment. As shown in Panel (b) of Figure 7, consumer sentiment does not respond significantly on impact; instead, the response builds gradually over the following two to three months. This delayed adjustment suggests that changes in sentiment are unlikely to account for the immediate increase in industrial production and the decline in unemployment. A more plausible interpretation is that improved production and labor market conditions, along with reduced uncertainty, drive subsequent increases in sentiment. Accordingly, the sentiment channel appears insufficient to explain the timing and magnitude of the baseline responses.

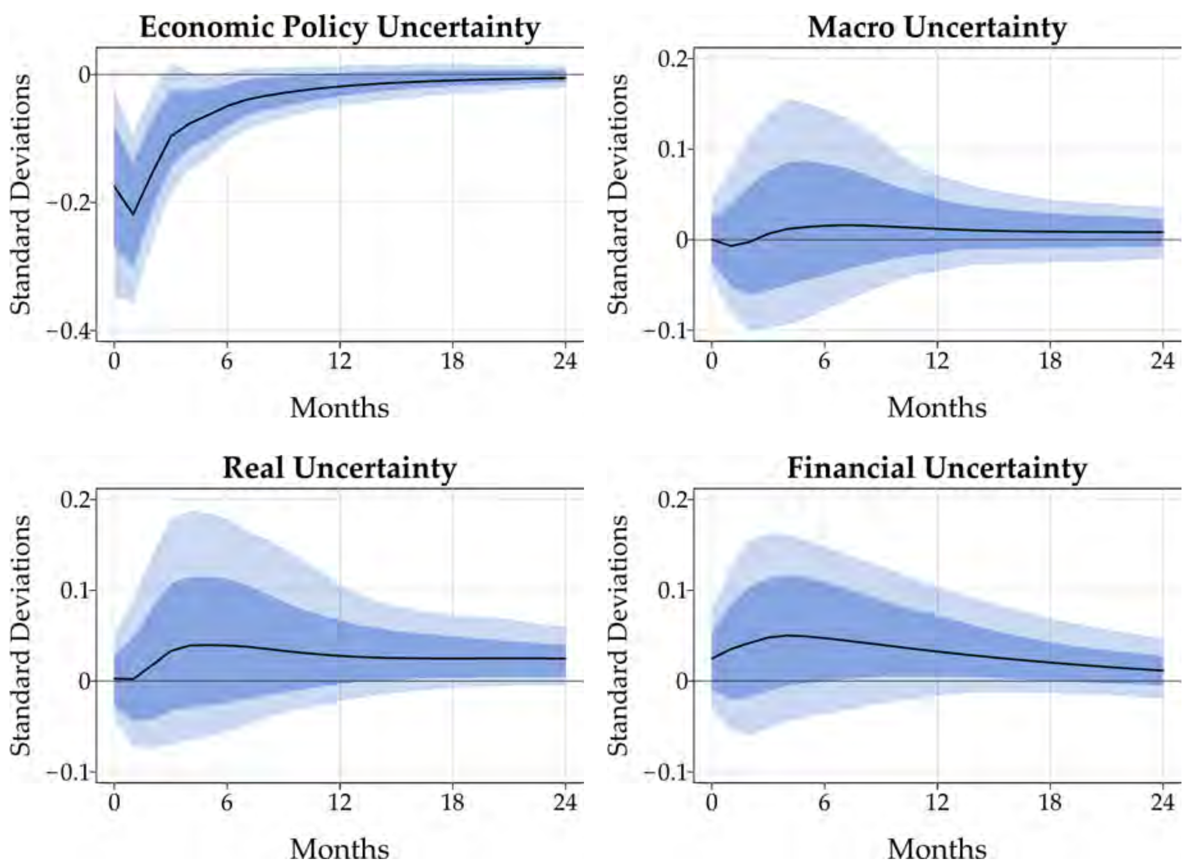
A final question is whether the relevant channel reflects other forms of uncertainty beyond monetary policy uncertainty. To assess this, I augment the baseline VAR with alternative uncertainty measures, following the same approach as in Sections 4.3 and 4.4. The responses of these variables to the communication shock are reported in Figure 9.

The first panel considers the economic policy uncertainty (EPU) index of Baker et al. (2016), which captures a broader notion of policy-related uncertainty. This measure exhibits a statistically significant decline following the shock, although the magnitude is somewhat smaller than that of monetary policy uncertainty. This pattern is consistent with the baseline results and provides additional support for the monetary policy uncertainty channel, as the EPU measure also incorporates monetary policy uncertainty.

By contrast, the macro, real, and financial uncertainty measures of Jurado et al. (2015) do not display statistically significant responses. While financial uncertainty shows a slight positive movement on impact, the response is not statistically different from zero. These findings suggest that these alternative uncertainty measures are unlikely to be the primary mechanism behind the observed effects. Consistent with this interpretation, financial market-based indicators such as the VIX and credit spreads (Figure 8) respond only gradually and modestly, further indicating that financial uncertainty does not play a central role in the transmission of communication shocks.

On the other hand, this does not imply that the mechanisms just discussed are entirely absent

Figure 9. Impulse responses of uncertainty variables to communication shocks.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from a VAR(2) including baseline variables and, in turn, each additional uncertainty variable, estimated over 1987:08–2022:12. Economic policy uncertainty is taken from Baker et al. (2016), while the macro, real, and financial uncertainty measures are taken from Jurado et al. (2015). Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

from central bank communication. A large literature, as discussed in Section 1, shows that central bank communication operates through changes in expected policy rates and the yield curve. Alternative measures, constructed using different dictionaries, could assess whether Federal Reserve communication also affects other types of uncertainty or household sentiment.[19] Our contribution is to show that central bank communication operates not only through policy rate signaling but also through a second, accompanying mechanism—the *uncertainty channel of monetary policy communication*.

[19]Investigating these questions is left for future research.

4.6 The Uncertainty Channel of Monetary Policy Communication

The combination of a heating economy, rising PPI inflation, and a slight decline in consumer inflation points to a supply-side mechanism. These patterns cannot be explained by changes in policy rates or expectations of future policy rates, as evidenced by the muted response of the yield curve. Nor are they likely to be driven by shifts in sentiment or financial risk measures.

The evidence instead points to an immediate decline in monetary policy uncertainty and its expansionary effects on economic activity, accompanied by a modest decrease in inflation. This suggests that monetary policy communication operates not only through conventional mechanisms, such as forward guidance about policy rates, but also through a second, accompanying mechanism—the uncertainty channel. More broadly, the results highlight a distinct role for monetary policy communication in shaping macroeconomic and financial outcomes through changes in perceived policy uncertainty.

This naturally raises the question of why reductions in monetary policy uncertainty generate the observed macroeconomic responses. What mechanisms can rationalize the increase in economic activity, the decline in unemployment, and the compression of financial risk following a communication shock?

One possible explanation is provided by the real options framework, which emphasizes irreversible investment decisions. In this setting, firms delay investment when uncertainty is high, particularly when capital adjustment is costly or only partially reversible (e.g., Bernanke (1983); Abel and Eberly (1994, 1996); Bloom (2009)). When uncertainty declines, previously postponed investment and production decisions are implemented. This interpretation is closely aligned with the empirical findings, which show a rapid increase in industrial production and a decline in unemployment following the communication shock.

A second explanation operates through household behavior. Higher uncertainty induces precautionary saving and suppresses consumption, while its resolution leads to a recovery in spending (e.g., Leduc and Liu (2016); Basu and Bundick (2017)). The empirical evidence provides some support for this mechanism, although it appears limited. Durable consumption increases following the communication shock, consistent with households bringing forward high-commitment purchases. In contrast, nondurable and services consumption does not respond significantly, suggesting that the aggregate demand channel plays a more muted role.

Uncertainty may also influence firms' pricing decisions. When uncertainty is elevated, firms may raise markups to insure against potential future cost increases (e.g., Fernández-Villaverde et al. (2015)). A decline in uncertainty would then be expected to reduce markups and inflation. In line with this idea, the results show a decrease in consumption price inflation following the communication shock, although the effect is small and short-lived. At the same time, this pattern may also reflect an increase in effective supply, rather than changes in pricing behavior alone.

Taken together, the evidence points to real options theory as the primary explanation for the uncertainty channel. While precautionary demand and pricing theories also find some support in the data, their role appears comparatively limited.

5 Conclusion

This paper provides causal evidence that monetary policy communication reduces monetary policy uncertainty and that this reduction has meaningful macroeconomic and financial effects. Using a novel measure of Federal Reserve communication constructed from FOMC members' speeches, I show that an increase in communication leads to a significant decline in monetary policy uncertainty. The results further indicate that this reduction in uncertainty has expansionary effects on the real economy, increasing industrial production and lowering unemployment, while generating a modest and short-lived decline in consumer price inflation.

These findings highlight the presence of an uncertainty channel of monetary policy communication, distinct from conventional transmission mechanisms based on policy rate signaling or forward guidance. In addition to operating through changes in current or expected policy rates, communication affects economic outcomes by shaping the clarity of the policy environment and reducing uncertainty faced by firms and households.

The results also carry important implications for monetary policy design. While increased communication and transparency can enhance economic activity by reducing uncertainty, they may also contribute to an overheating of the economy and a widening of the output gap. In particular, by bringing forward investment, hiring, and durable consumption decisions, reductions in uncertainty can stimulate supply and demand in ways that may not always be consistent with the desired policy stance. Policymakers should therefore be mindful that more communication is not unambiguously beneficial and should carefully balance transparency with prevailing macroeconomic conditions.

More broadly, the findings suggest that theoretical models of monetary policy communication should explicitly incorporate the uncertainty channel alongside standard signaling mechanisms. Given its quantitatively important effects on both real and financial outcomes, treating communication solely as a tool for managing expectations about policy rates may overlook an important dimension of monetary transmission.

Several avenues for future research remain. First, alternative measures of central bank communication, constructed using different dictionaries or methods, could be used to assess whether communication also affects household sentiment and other types of uncertainty beyond monetary policy uncertainty. Second, incorporating the uncertainty channel of monetary policy communication into macroeconomic models, such as New Keynesian frameworks with information asymmetries between firms and the central bank, would provide a deeper understanding of its transmission mechanisms. Finally, extending the analysis to other central banks, countries, and policy domains would help evaluate the generality and broader relevance of the uncertainty channel.

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Appendix

The Uncertainty Channel of Monetary Policy Communication

A Data Appendix

A.1 Speech Data Cleaning

The data cleaning phase applies three criteria: the document must contain only the speech of the FOMC member, be self-explanatory, and be immediately publicly available. The first ensures that the views of others are not conflated with those of the member, maintaining the integrity of individual-level communication. The second requires that the speech be understandable without reliance on external context or accompanying materials. The third restricts the dataset to speeches that were made available to the public at the time of delivery, reflecting the information set accessible to market participants. Accordingly, documents meeting any of the following conditions were excluded:

- Documents consisting solely of slides,
- Transcripts of question-and-answer sessions,[20]
- 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,
- Documents without a specific date or listing only the year.

[20] 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 Speech Data Preprocessing

I preprocess the speech data to ensure suitability for quantitative text analysis and comparability across documents. This procedure standardizes the raw text and eliminates elements that do not carry semantic content. I follow the steps below to standardize the raw documents and remove noise.

- Punctuation is removed.
- All letters are converted to lowercase.
- Single-letter tokens are removed.
- Numerical expressions written in digit form are removed.
- Non-alphabetic characters are removed.

A.3 Dictionaries

Table A.1. Baker, Bloom and Davis (2016) dictionary of monetary policy words & phrases.

federal reserve	fed	money supply
open market operations	quantitative easing	monetary policy
fed funds rate	ffr	overnight lending rate
central bank	interest rates	fed chairman
fed chair	lender of last resort	discount window
Bernanke	Volcker	Greenspan
European Central Bank	ECB	Bank of England
Bank of Japan	BOJ	Bank of China
Bundesbank	Bank of France	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 A.2. Smaller dictionary of monetary policy words & phrases.

federal reserve	fed	money supply
open market operations	quantitative easing	monetary policy
fed funds rate	ffr	overnight lending rate
central bank	interest rates	fed chairman
fed chair	lender of last resort	discount window

Notes: The smaller dictionary is constructed from the Baker et al. (2016) monetary policy dictionary by removing the following terms: *"Bernanke," "Volcker," "Greenspan," "European Central Bank," "ECB," "Bank of England," "Bank of Japan," "BOJ," "Bank of China," "Bundesbank," "Bank of France,"* and *"Bank of Italy."*

Table A.3. Larger dictionary of monetary policy words & phrases.

federal reserve	fed	money supply
open market operations	quantitative easing	monetary policy
fed funds rate	ffr	overnight lending rate
central bank	interest rates	fed chairman
fed chair	lender of last resort	discount window
Bernanke	Volcker	Greenspan
European Central Bank	ECB	Bank of England
Bank of Japan	BOJ	Bank of China
Bundesbank	Bank of France	Bank of Italy
Yellen	Powell	balance sheet
large-scale asset purchases	LSAP	zero lower bound
ZLB	quantitative tightening	

Notes: The larger dictionary is constructed from the Baker et al. (2016) monetary policy dictionary by adding the following additional terms: *"Yellen," "Powell," "balance sheet," "large-scale asset purchases," "LSAP," "zero lower bound," "ZLB," "quantitative tightening."*

Table A.4. Husted, Rogers and Sun (2020) dictionary of monetary policy words & phrases.

monetary policy	interest rate
fed fund rate	federal fund rate
federal reserve	the fed
FOMC	federal open market committee

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

A.4 Data Sources

The data sources used in the empirical analysis are listed in Table A.5. Real durable goods consumption is constructed by dividing nominal durable consumption by the durable goods price index. The nondurable goods and services consumption series are combined using chain-type price indices following the method proposed by Whelan (2002). First, each series is converted to real terms in the same way as durable goods consumption. I then construct the combined consumption index using the following chaining formula:

$$Q(t) = Q(t-1)\sqrt{\frac{\sum_{i=1}^{n} P_i(t)Q_i(t)}{\sum_{i=1}^{n} P_i(t)Q_i(t-1)} \times \frac{\sum_{i=1}^{n} P_i(t-1)Q_i(t)}{\sum_{i=1}^{n} P_i(t-1)Q_i(t-1)}} \tag{19}$$

where $i \in 1, 2$ indexes nondurable goods and services. The credit spread is calculated as the difference between the yields of AAA-rated and BAA-rated corporate bonds. Treasury yield spreads are calculated with investment basis treasury yields.

Table A.5. Data sources.

Variable	Data Source
3-Month Treasury Yield (Discount Basis)	FRED, Code: TB3MS
3-Month Treasury Yield (Investment Basis)	FRED, Code: DGS3MO
2-Year Treasury Yield (Investment Basis)	FRED, Code: DGS2
10-Year Treasury Yield (Investment Basis)	FRED, Code: DGS10
Consumer Sentiment	FRED, Code: UMCSENT
Corporate Bond Yield AAA	FRED, Code: AAA
Corporate Bond Yield BAA	FRED, Code: DBAA
Durables Consumption (Nominal)	FRED, Code: PCEDG
Durables Price Index	FRED, Code: DDURRG3M086SBEA
Economic Policy Uncertainty	Baker et al. (2016)
Federal Funds Effective Rate	FRED, Code: DFF
Federal Funds Rate Surprises	Acosta et al. (2024)
Financial Uncertainty	Jurado et al. (2015)
First Business Cycle Factor	McCracken and Ng (2021)
Help Wanted Index	McCracken and Ng (2021)
Hours Worked	FRED, Code: AWHMAN
Industrial Production	FRED, Code: INDPRO
Macro Uncertainty	Jurado et al. (2015)
Monetary Policy Surprises	Acosta et al. (2024)
Monetary Policy Uncertainty	Baker et al. (2016)
Nondurables Consumption (Nominal)	FRED, Code: PCEND
Nondurables Price Index	FRED, Code: DNDGRG3M086SBEA
Nonfarm Payrolls	FRED, Code: PAYEMS
Personal Consumption Expenditures	FRED, Code: PCEPI
Personal Consumption Expenditures (Core)	FRED, Code: PCEPILFE
Producer Price Index	FRED, Code: PPIACO
Real Disposable Income	FRED, Code: DSPIC96
Real Uncertainty	Jurado et al. (2015)
Russell 2000	LSEG Data & Analytics
Services Consumption (Nominal)	FRED, Code: PCES
Services Price Index	FRED, Code: DSERRG3M086SBEA
Shadow Rate	Xia and Wu (2016)
S&P 500	Macrotrends
Unemployment Rate	FRED, Code: UNRATE
VIX	FRED, Code: VIXCLS

B Technical Appendix

B.1 Testing for Structural Breaks in Federal Reserve Communication Volatility

This appendix provides details for testing structural breaks in the volatility of Federal Reserve monetary policy communication. I first estimate an OLS regression to remove predictable variation in the MP communication series. The set of regressors consists of the monetary policy uncertainty index from Baker et al. (2016), log industrial production, the unemployment rate, PCE inflation, PPI inflation, the 3-month Treasury bill yield, the shadow policy rate of Xia and Wu (2016), and the first business cycle factor of McCracken and Ng (2021). The specification uses 10 lags of all variables, including the lagged dependent variable. The residuals from this regression capture reduced-form innovations in MP communication.

I then test for a structural break in the volatility of these residuals using the sup-Wald test. Following Andrews (1993), let $|\hat{\varepsilon}_t|$ denote the absolute residuals, which serve as a proxy for volatility. For each candidate break date τ, I split the sample into two regimes and compute the Wald statistic:

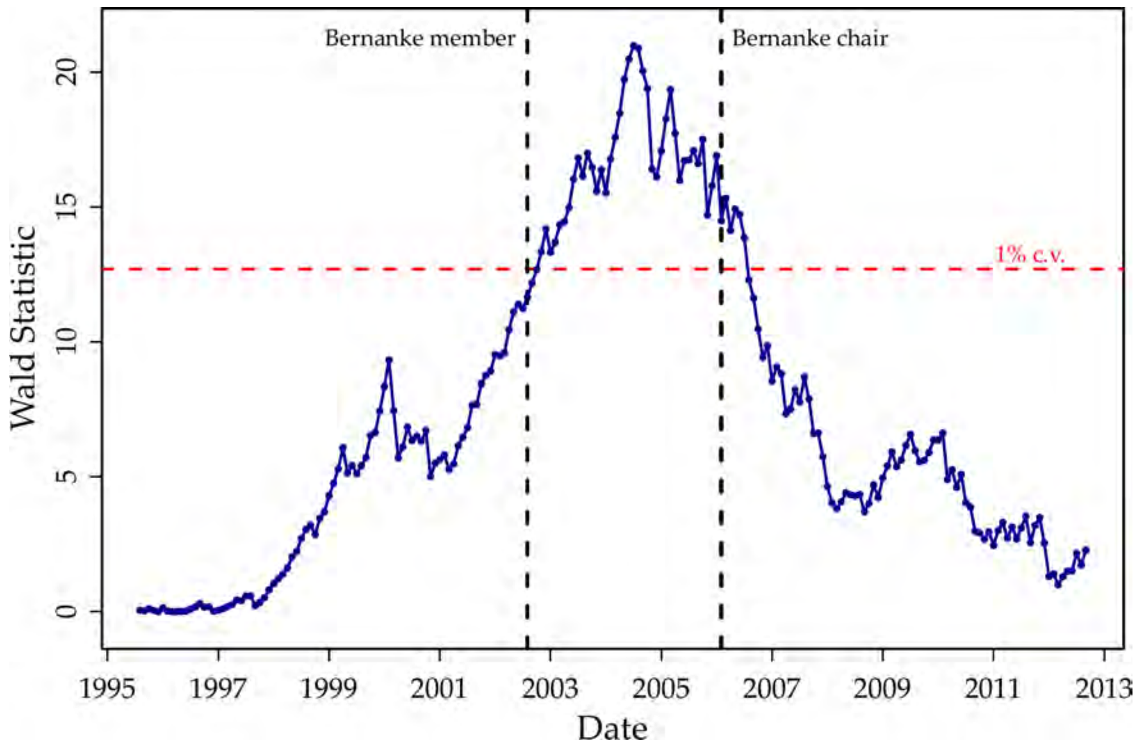
$$W(\tau) = T \cdot \frac{(\bar{U}_2(\tau) - \bar{U}_1(\tau))^2}{V(\tau)}, \tag{20}$$

where $\bar{U}_1(\tau) = \frac{1}{\tau}\sum_{t=1}^{\tau} |\hat{\varepsilon}_t|$ and $\bar{U}_2(\tau) = \frac{1}{T-\tau}\sum_{t=\tau+1}^{T} |\hat{\varepsilon}_t|$ are the mean absolute residuals before and after the break, $V(\tau) = \frac{T}{\tau}\mathrm{Var}(|\hat{\varepsilon}_t|_{t\leq\tau}) + \frac{T}{T-\tau}\mathrm{Var}(|\hat{\varepsilon}_t|_{t>\tau})$ is the variance adjustment term, and T is the sample size. The sup-Wald statistic is $W^* = \sup_\tau W(\tau)$.

Figure 4 plots the Wald statistics from 1995 to 2013. Following standard practice, I exclude at least the first and last 10 percent of observations from the search window to ensure sufficient data in each regime, yielding a trimming parameter $\lambda_0 \geq 0.10$. The sup-Wald statistic—the maximum value of $W(\tau)$ across all candidate break dates—equals 21.32, which exceeds Andrews (1993) 1% critical value of 12.69. I therefore reject the null hypothesis of constant volatility in $|\hat{\varepsilon}_t|$. The Wald statistic attains its maximum in July 2004, suggesting this date as the most likely timing of the structural break in communication volatility.

As a robustness check, I re-estimate the sup-Wald test while controlling for potential mean shifts associated with Ben Bernanke's appointment to the Federal Reserve Board of Governors. Specifically, I augment the baseline regression with two Bernanke indicators: a binary variable equal to one from August 2002 onward, when he joined the Board of Governors and the FOMC, and a binary variable equal to one from February 2006 onward, when he became Chair. This ensures that the detected volatility break is not confounded by changes in the average level of communication. Figure B.1 presents the results. The sup-Wald statistic remains above the 1% critical value, with the primary peak again occurring in July 2004, confirming that the structural break in communication volatility is robust to controlling for mean shifts.

Figure B.1. Structural break test: Robustness with Bernanke dummies.



Notes: The Wald statistic is computed following Andrews (1993), using monetary policy communication innovations obtained as residuals from a regression of communication on its own lags, as well as lagged monetary policy uncertainty and standard macroeconomic controls, and two Bernanke leadership indicators. The macroeconomic controls include log industrial production, the unemployment rate, PCE inflation, PPI inflation, the 3-month Treasury bill yield, the shadow policy rate of Xia and Wu (2016), and the first business cycle factor of McCracken and Ng (2021). Up to 10 lags are included. The Bernanke indicators consist of a binary variable equal to one from August 2002 onward, when he joined the Board of Governors and the FOMC, and a binary variable equal to one from February 2006 onward, when he became Chair. The main blue line shows the Wald test statistic for a structural break in the volatility of MP communication innovations, where volatility is measured by the absolute value of the innovations. The vertical dashed black lines mark August 2002, when Bernanke joined the FOMC, and February 2006, when he became Chair. The horizontal dashed red line denotes the 1% critical value.

B.2 Bootstrap Inference

Given the moderate sample size and the generated regressor problem arising from the preliminary VAR estimation, I implement a residual-based moving block bootstrap following Jentsch and Lunsford (2019). The bootstrap procedure proceeds as follows:

1. The VAR residuals are split into two regimes based on the predetermined cutoff date.

2. In each bootstrap replication, I resample residuals separately within each regime using overlapping blocks of length $L = 7$ months.[21] Blocks are drawn with replacement and concatenated until the resampled series matches the original regime-specific sample sizes. The resampled regimes are then combined to form a full residual series.

3. Using the bootstrapped residuals, I simulate a new dataset recursively from the estimated VAR and re-estimate the VAR on the simulated data.

4. I compute canonical residuals from the re-estimated VAR, split them again into regimes, and reconstruct the regime-difference moments.

5. I re-estimate the structural parameters by GMM using a fixed weighting matrix equal to the HAC matrix from the baseline GMM, constructed with a Bartlett kernel and bandwidth $b = \lfloor 4(T/100)^{2/9} \rfloor$ following Newey and West (1994).

6. For applications involving impulse response analysis, I recover the structural impact vector from the bootstrap GMM estimates and compute impulse response functions using the re-estimated VAR. The responses are normalized at horizon zero and stored for each replication.

7. Steps 2–6 are repeated $B = 1000$ times.

8. Bootstrap standard errors are computed as the sample standard deviations of the bootstrap parameter estimates. For impulse responses, confidence bands are constructed from the empirical distribution of the bootstrap IRFs. Inference is based on the resulting bootstrap t-statistics.

[21] The block length $L = 7$ is of order $T^{1/3}$, which corresponds to the MSE-optimal rate for variance estimation under the block bootstrap Hall et al. (1995). The results are robust to alternative choices of L (e.g., $L \in \{4, 6, 12\}$).

B.3 Derivation of the IV Estimator

Solving the system (2)–(3) yields:

$$m_t = \frac{1}{1-\alpha\beta}\left[(\beta+\gamma)z_t + \beta\eta_t + \varepsilon_t\right] \tag{21}$$

$$u_t = \frac{1}{1-\alpha\beta}\left[(1+\alpha\gamma)z_t + \eta_t + \alpha\varepsilon_t\right] \tag{22}$$

so that:

$$m_t u_t = \frac{1}{(1-\alpha\beta)^2}\left[(\beta+\gamma)(1+\alpha\gamma)z_t^2 + \beta\eta_t^2 + \alpha\varepsilon_t^2\right] \tag{23}$$

$$m_t^2 = \frac{1}{(1-\alpha\beta)^2}\left[(\beta+\gamma)^2 z_t^2 + \beta^2\eta_t^2 + \varepsilon_t^2\right] \tag{24}$$

where cross terms vanish by mutual orthogonality of ε_t, η_t, and z_t. Taking the covariance of (23) with m_{t-p}^2 and applying linearity of covariance:

$$\begin{aligned}
\operatorname{cov}(m_t u_t,\, m_{t-p}^2) = {} & \operatorname{cov}\left(\frac{\alpha\varepsilon_t^2}{(1-\alpha\beta)^2},\, \frac{\varepsilon_{t-p}^2}{(1-\alpha\beta)^2}\right) \\
& + \operatorname{cov}\left(\frac{\beta\eta_t^2}{(1-\alpha\beta)^2},\, \frac{\beta^2\eta_{t-p}^2}{(1-\alpha\beta)^2}\right) \\
& + \operatorname{cov}\left(\frac{(\beta+\gamma)(1+\alpha\gamma)z_t^2}{(1-\alpha\beta)^2},\, \frac{(\beta+\gamma)^2 z_{t-p}^2}{(1-\alpha\beta)^2}\right) \\
& + \text{cross-covariance terms}
\end{aligned} \tag{25}$$

The last two terms, together with the cross-covariance terms, are zero by the assumption of constant variance of η_t and z_t, so:

$$\operatorname{cov}(m_t u_t,\, m_{t-p}^2) = \frac{\alpha}{(1-\alpha\beta)^4}\operatorname{cov}(\varepsilon_t^2,\, \varepsilon_{t-p}^2) \tag{26}$$

Similarly, taking the covariance of (24) with m_{t-p}^2 gives:

$$\operatorname{cov}(m_t^2,\, m_{t-p}^2) = \frac{1}{(1-\alpha\beta)^4}\operatorname{cov}(\varepsilon_t^2,\, \varepsilon_{t-p}^2) \tag{27}$$

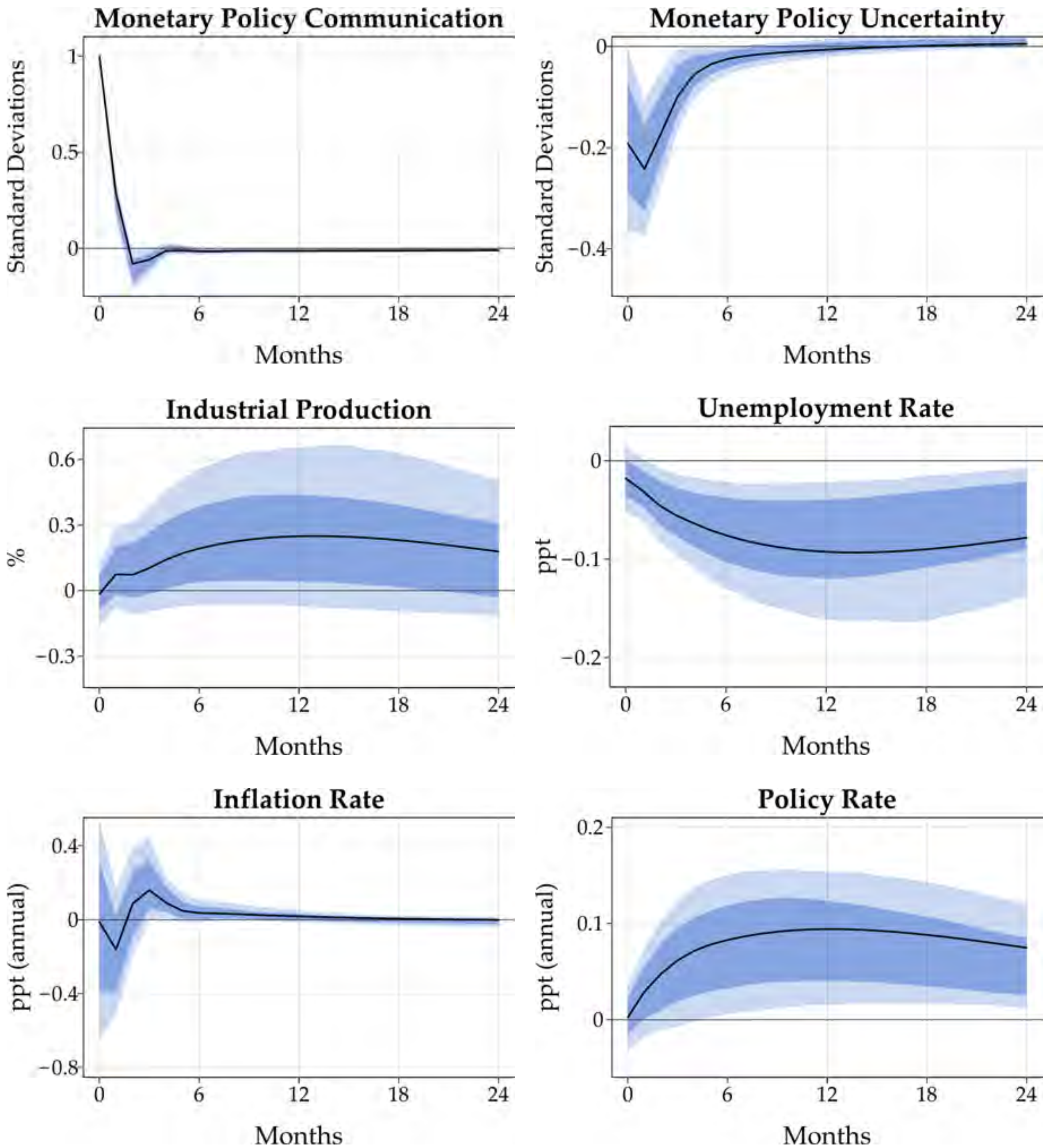
Dividing (26) by (27), the factor $\frac{1}{(1-\alpha\beta)^4}$ cancels, yielding:

$$\alpha = \frac{\operatorname{cov}(m_t u_t,\, m_{t-p}^2)}{\operatorname{cov}(m_t^2,\, m_{t-p}^2)} \tag{28}$$

C IRFs Across Alternative Specifications and Methods

C.1 Excluding the COVID–19 Period: 1987:08–2019:12

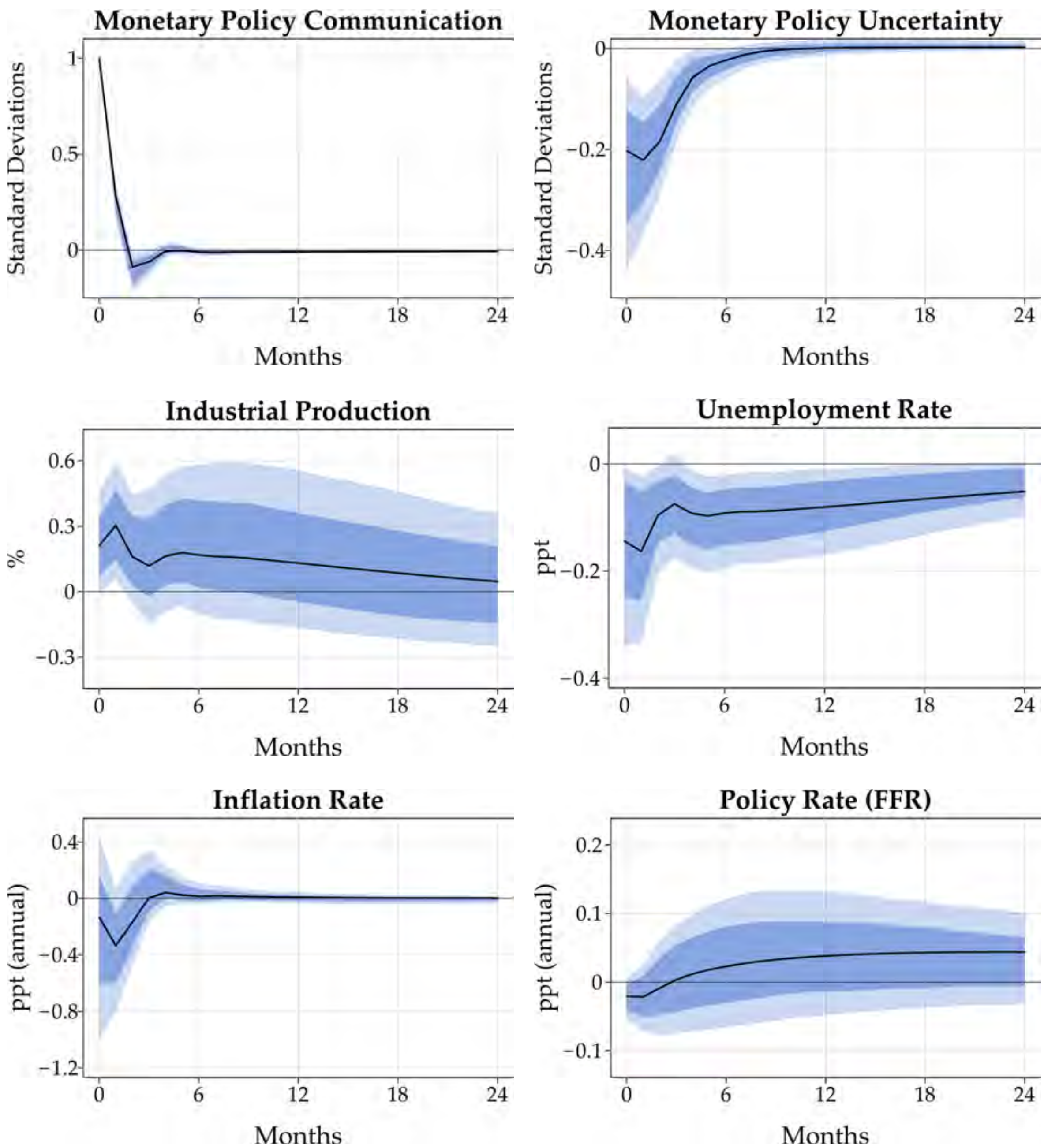
Figure C.1. Impulse responses estimated over the sample excluding the COVID–19 period.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the baseline VAR(2), estimated over the sample excluding the COVID–19 period (1987:08–2019:12). Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

C.2 Using the Federal Funds Rate as the Policy Rate

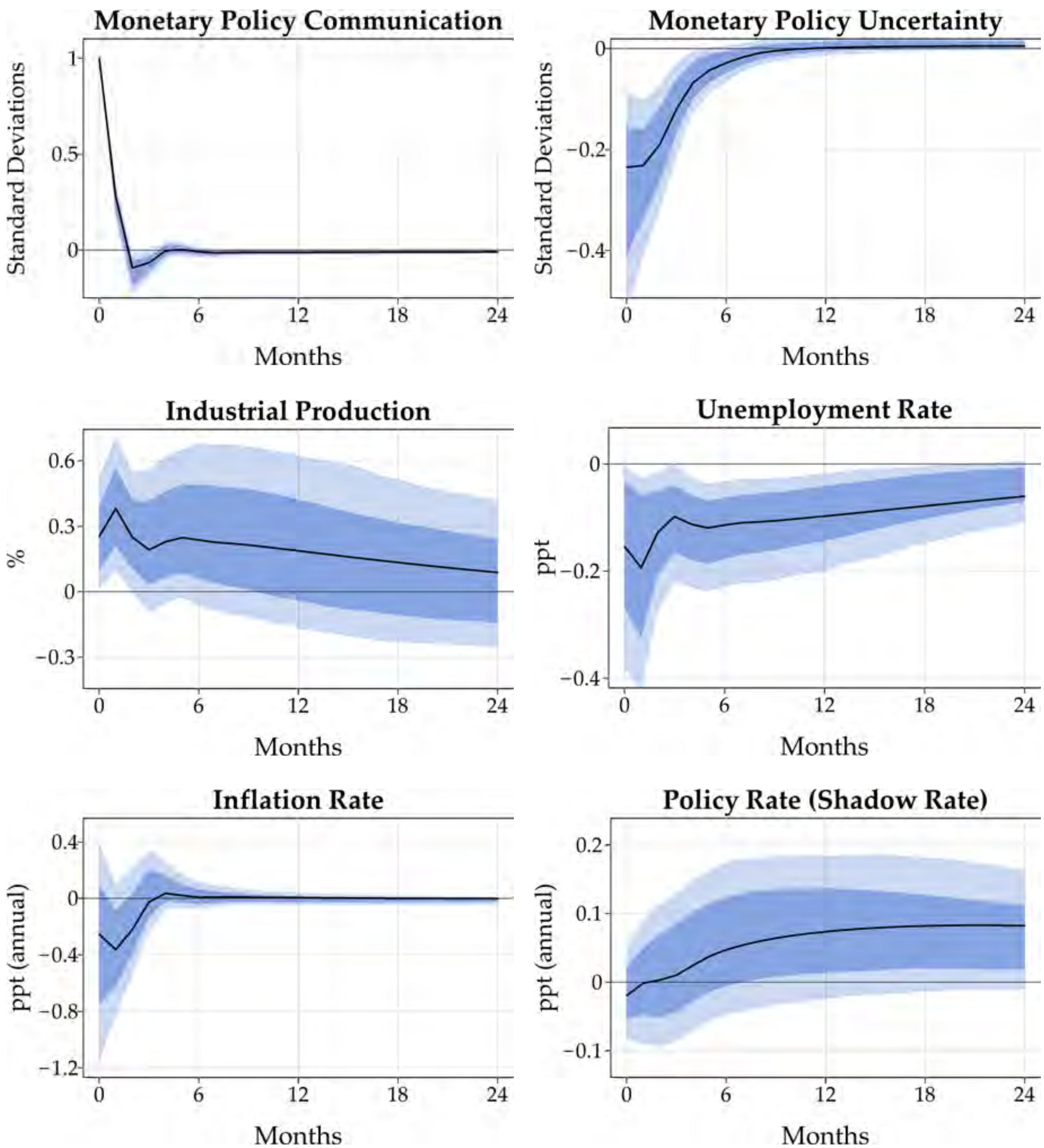
Figure C.2. Impulse responses: federal funds rate replacing the 3-month Treasury yield.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the baseline VAR(2), where the 3-month Treasury yield is replaced by the federal funds rate, estimated over 1987:08–2022:12. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

C.3 Using the Shadow Rate as the Policy Rate

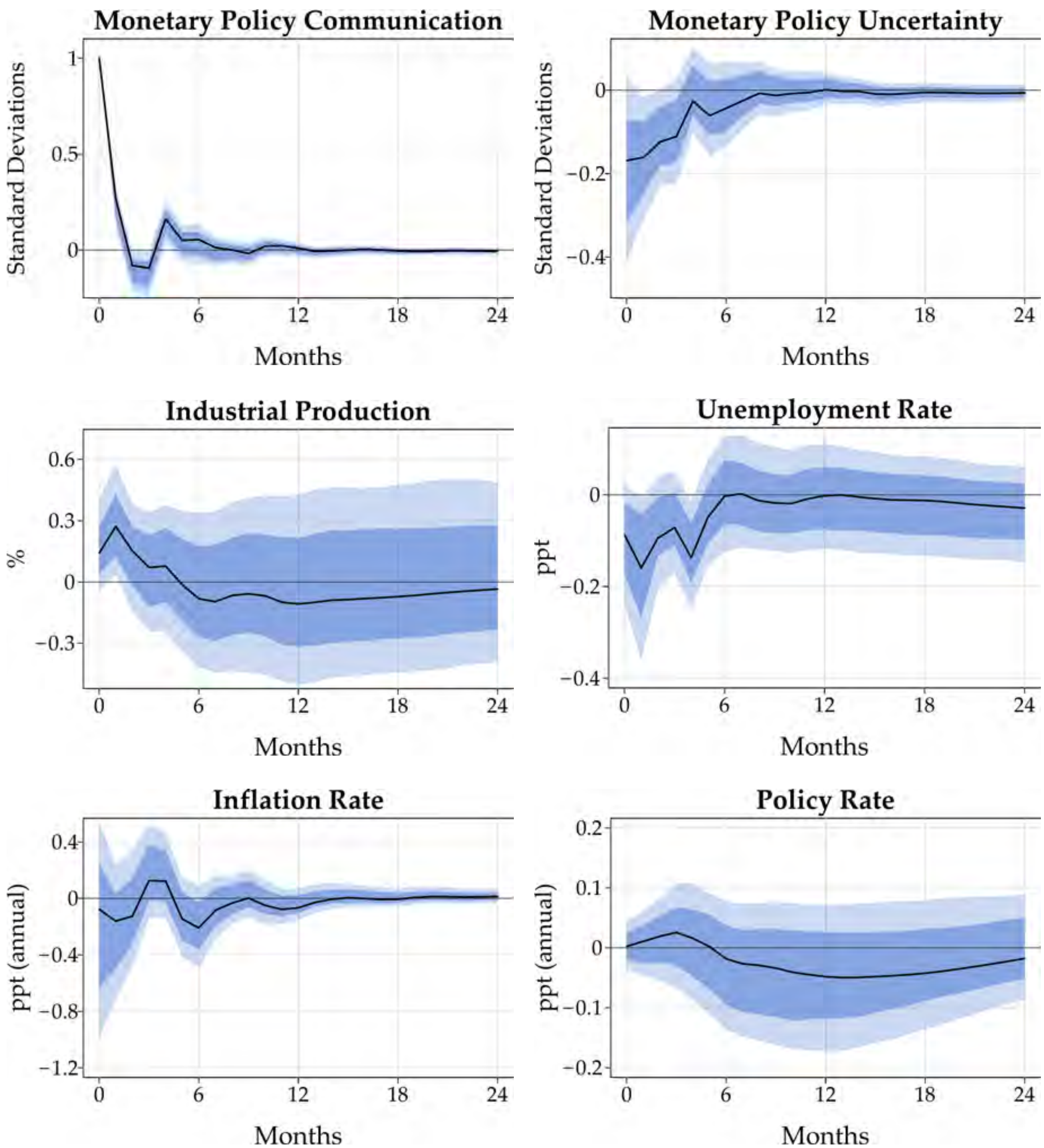
Figure C.3. Impulse responses: shadow rate of Xia and Wu (2016) replacing the 3-month Treasury yield.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the baseline VAR(2), where the 3-month Treasury yield is replaced by the shadow rate of Xia and Wu (2016). The estimation period is 1990:01–2022:12, limited by the availability of the shadow rate. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

C.4 VAR(6) Specification

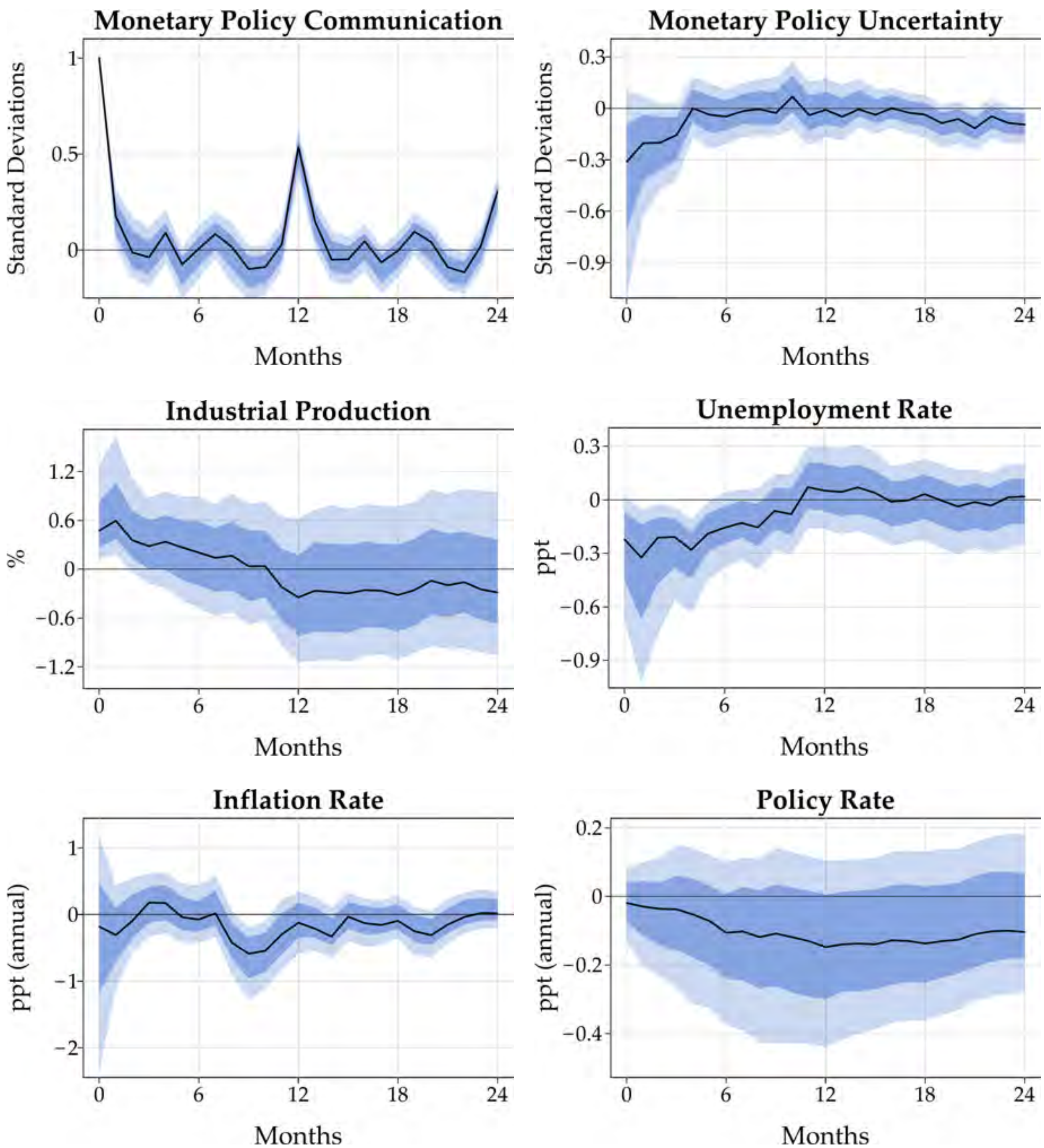
Figure C.4. Impulse responses: VAR(6) specification.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the VAR(6) specification, estimated over 1987:08–2022:12. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

C.5 VAR(12) Specification

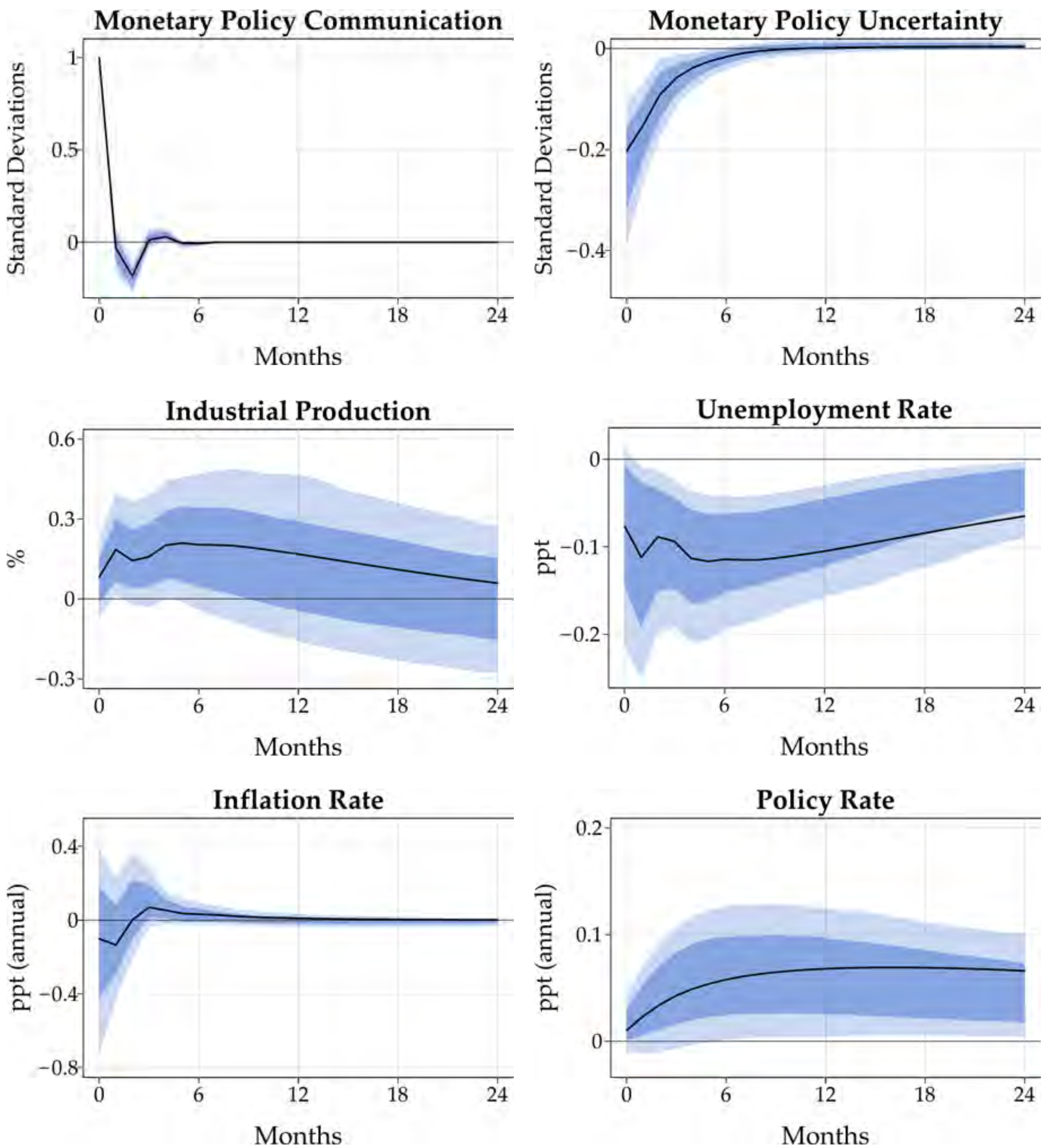
Figure C.5. Impulse responses: VAR(12) specification.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the VAR(12) specification, estimated over 1987:08–2022:12. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

C.6 Monetary Policy Communication Adjusted for Trend and Seasonality

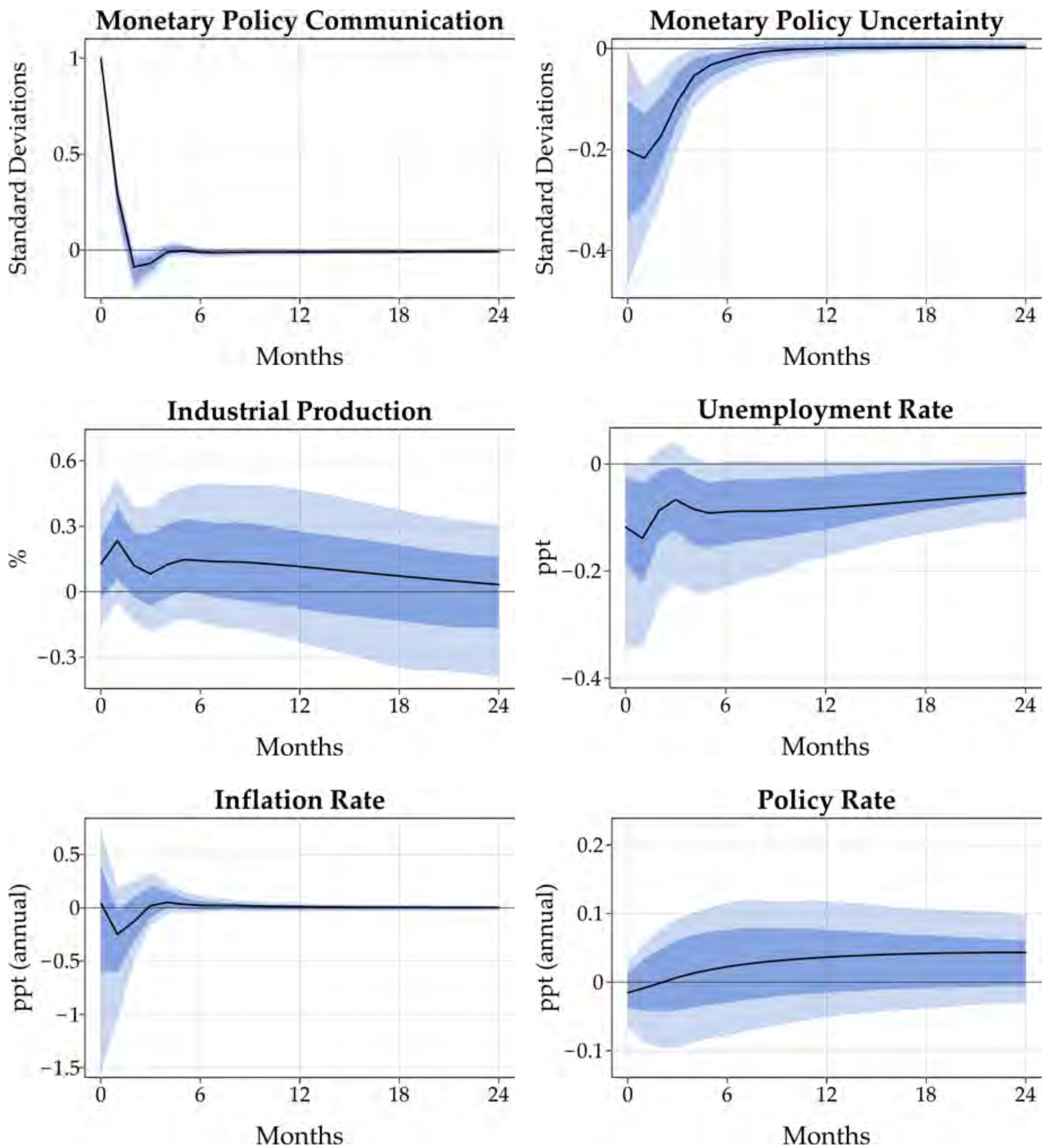
Figure C.6. Impulse responses: monetary policy communication adjusted for trend and seasonality.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the baseline VAR(2), estimated over 1987:08–2022:12, where monetary policy communication is constructed using the remainder component after removing trend and seasonality via the STL method. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications.

C.7 Using the Full Set of Moment Conditions

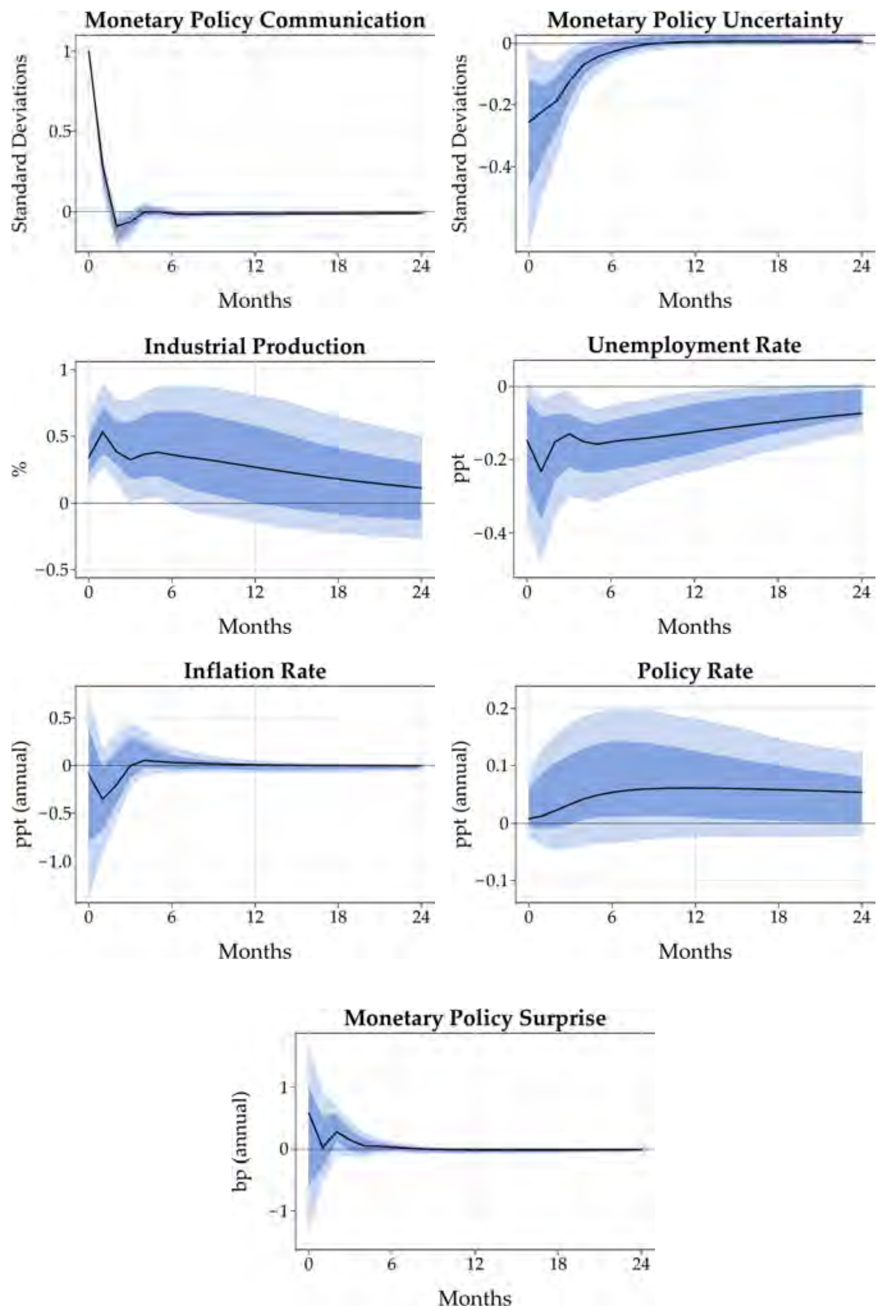
Figure C.7. Impulse responses: using the full set of moment conditions.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the baseline VAR(2), estimated over 1987:08–2022:12, using the full set of moments. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap, adapted for heteroskedasticity and computed using 1,000 replications. Given the large number of moment conditions, the GMM weighting matrix is re-estimated in each bootstrap draw.

C.8 Controlling for Monetary Policy Surprises

Figure C.8. Impulse responses: adding monetary policy surprises as a control.



Notes: The figure reports impulse responses to a one-standard-deviation monetary policy communication shock from the baseline VAR(2), controlling for monetary policy surprises from Acosta et al. (2024), which are constructed over a window encompassing the FOMC policy statement release and, when applicable, the Chair's press conference following the meeting. The sample is 1994:02–2022:12, limited by the availability of monetary policy surprises data. Shaded areas indicate 68% and 90% pointwise confidence intervals based on a residual-based moving block bootstrap adapted for heteroskedasticity, computed using 1,000 replications.