Beyond the Headlines: Measuring Monetary Policy Uncertainty from Bank Earnings Calls*

Pablo Pastor y Camarasa†

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Abstract

The role of financial institutions in the impact of monetary policy uncertainty on the economy is not fully understood. I construct an index of bank-level monetary policy uncertainty from U.S. bank earnings calls since 2002 and validate the measure with its correlation with past interest rate forecast errors and aggregate disagreement in the Survey of Professional Forecasters. SVAR evidence reveals that monetary policy uncertainty lowers real GDP and increases credit spreads. Looking at the cross-section, banks with high uncertainty charge higher interest rates in syndicated loans. The findings stress that banks beliefs impacts both lending conditions and business cycle fluctuations.

Keywords: Monetary Policy, Textual Analysis, Knightian Uncertainty, Heterogeneous Expectations

JEL Codes: G21; G30; G40; D83; M1.

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†Ghent University, Department of Economics, pablo.pastor@ugent.be. Corresponding author.

1 Introduction

Over the last few years, uncertainty has risen on tariffs, economic policy, and monetary policy. This trend challenges central banks. Their credibility hinges on the ability to shape economic expectations through predictable policy actions and communication (Blinder et al., 2024; Ehrmann et al., 2025). If uncertainty persists over the response of monetary authorities to macroeconomic fluctuations, market expectations may de-anchor and undermine the central bank's capacity to stabilize the economy. Moreover, the transmission channels of monetary policy uncertainty remain unclear. While Husted et al. (2020) emphasizes financial frictions, theoretical contributions highlight the role of firm entry and exit dynamics through perceived uncertainty (Fasani et al., 2023). Hence, the literature disagrees on the channels of transmission of monetary policy uncertainty to the economy.

The paper goes beyond simple news-based indices. These indices assume an equal readership across different sectors of the economy and fail to capture beliefs about monetary policy. Furthermore, these approaches ignore banks despite their crucial role in monetary policy transmission (Dell'ariccia et al., 2017; Paligorova and Santos, 2017). The paper thus studies the impact of monetary policy uncertainty in the banking sector on the economy. It then goes one step further to compare the effect of firms' perceived uncertainty and bank-level uncertainty on investment. Finally, I exploit the granularity of the monetary policy uncertainty index to quantify the effect of uncertainty on loan pricing.

This paper makes three key contributions. First, I construct a novel bank-level indicator of perceived monetary policy uncertainty. Its granularity enables a deeper conceptual understanding of uncertainty with bank-level regressions. At the loan level, the index helps quantify the financial friction channel. Second, I present a new high-frequency identification strategy for uncertainty shocks using earnings call dates. I develop an instrument for monetary policy uncertainty on FOMC days orthogonalized to monetary policy surprises. Therefore, this is the first strategy using text metadata to causally identify the impact of monetary policy uncertainty on economic fluctuations. Third, I develop a comparable firm-level index of perceived uncertainty. This index overcomes the assumptions about media attention inherent to news-based measures and captures uncertainty from managerial discourse in earnings calls.

The paper uses text-mining techniques to identify monetary policy uncertainty from bank earnings calls. Earnings calls are of particular interest because they reveal the unscripted conversations between managers and analysts in a natural setting. To identify expressions related to monetary policy, I build a dictionary of monetary policy words by isolating sections of the Tealbooks A (formerly known as Greenbooks) based on their titles. When a title refers to monetary policy, the text following the title is extracted to create a dictionary of monetary policy words. Following Hassan et al. (2024) algorithm, I capture uncertainty at the bank level by counting the occurrence of risk words within 10 words of a monetary policy bi-gram. This new index uses 10,957 conversations from Q1 2001 through Q4 2023 for a sample of US banks.

Regressions on fundamentals highlight that banks perceive more monetary policy uncertainty if they have fewer deposits to fund their loan portfolio. On top of this, banks with elevated absolute past forecast errors tend to perceive more monetary policy uncertainty. Uncertainty at the bank level is thus linked to the unpredictability of monetary policy decisions. Looking at the cross-sectional sum of uncertainty words for banks, I find that bank monetary policy uncertainty peaks around shifts in the monetary policy regime, at the end of the forward guidance period, for example. Bank uncertainty also aligns with the inter-quartile range of interest rate forecasts in the Survey of Professional Forecasters and correlates with the news-based measure of Husted et al. (2020). This serves as a sanity check of the bank index and illustrates how aggregate forecasts and uncertainty in the banking sector are aligned.

I first study the aggregate causal impact of monetary policy uncertainty in the banking sector. I run a VAR à la Gertler and Karadi (2015) at the quarterly frequency to understand the macroeconomic implications of bank monetary policy uncertainty. The main threat to identification is that monetary policy uncertainty is endogenous to economic announcements and monetary policy decisions during the quarter. Quarterly monetary policy uncertainty is thus instrumented with monetary policy uncertainty on FOMC days to disentangle innovations in uncertainty from economic announcements. The former is then orthogonalized with respect to interest rates and forward guidance surprises. The movements in bank monetary policy uncertainty are then exogenous variations and identify monetary policy uncertainty shocks. The impulse response functions document how monetary policy uncertainty in the banking sector leads to declines in real GDP. Moreover, monetary policy uncertainty shocks tend to increase the credit spreads in the first year, consistent with Husted et al. (2020). The results are robust to using daily variation of uncertainty around FOMC days and introducing news-based monetary policy uncertainty in the VAR.

I then dive deeper into the transmission channels of monetary policy uncertainty shocks. Analysis reveals that aggregate monetary policy uncertainty in the banking sector predicts declines in investment at the firm level. The within-firm effect is robust to controlling for business cycle variables and macroeconomic expectations impacting investment opportunities. The impact on investment is concentrated on highly leveraged firms as in Husted et al. (2020). On top of standard controls, I build a measure of monetary policy uncertainty at the firm level using more than 200,000 earnings calls. While the firm measure has a limited negative impact on investment, it is more pronounced for leverage firms. This suggests that firm-level beliefs matter for monetary policy uncertainty, but their role remains secondary to the financial frictions channel identified in this paper.

Finally, I explore the impact of monetary policy uncertainty at the bank level to describe the exact mechanism linking monetary policy uncertainty and interest rate costs. The earnings calls dataset is merged with bank fundamentals and Dealscan to understand how monetary policy uncertainty impacts lending conditions. The evidence shows that high monetary policy uncertainty at the bank level impacts the all-in-drawn-spread even when controlling for credit demand. The impact is concentrated on term loans which are more long-term in nature. Banks therefore choose to secure high interest income in term loans when faced with unpredictable monetary policy. The results are robust to various clustering of standard errors, weighting observations by lenders' share and controlling for credit demand with Industry-Size-Location-Time fixed effects à la Degryse et al. (2019).

Relation to the literature. Recent empirical evidence uses survey data or stock returns to capture perceptions of monetary policy. While Bauer et al. (2023) use the Blue Chip Financial Forecasts, Istrefi and Mouabbi (2018) build a measure of monetary policy uncertainty from SPF forecasts. Both papers focus on financial markets participants and fail to analyze the beliefs of commercial banks. Other studies capture perceptions through the stock market's reaction to monetary policy (Gati and Handlan, 2021; Hattori et al., 2016). Combining both, Elenev et al. (2024) links stock market sensitivities to professional forecasters' perceptions. Such approaches, however, ignore the perceptions of lenders in the economy, despite the impact of monetary policy uncertainty running through financial frictions (Husted et al., 2020). It is also unclear whether survey respondents are involved in decisions linked to monetary policy. The empirical approach developed in this paper considers instead the views of banks active in the economy with text-mining techniques.

A large literature measures monetary policy uncertainty using financial instruments. Market-based proxies compute the implied distribution of possible policy rates from interest rate derivatives (Bundick and Herriford, 2017; De Pooter et al., 2021). The range of rates in the implied distribution then captures monetary policy uncertainty. The objective in this literature is to understand how uncertainty affects the transmission of monetary policy shocks (Tillmann, 2020). A common result is that uncertainty reduces the impact of monetary policy shocks on asset prices. Little is said, nonetheless, about the causal impact of monetary policy uncertainty on the economy. This is because uncertainty is often an endogenous variable (Creal and Wu, 2017). More recently, Bauer et al. (2021) builds a market-based measure of monetary policy uncertainty with the implied volatility of swap-rate contracts. The proxy allows for high-frequency identification of the causal impact of monetary policy uncertainty surprises on asset prices. Yet, the study remains silent on its effects on the broader economy. My index, in contrast, enables both high-frequency identification and measurement of macroeconomic implications.

This study belongs to a literature looking at the role of uncertainty in the economy. Baker et al. (2016) build a measure of economic policy uncertainty using newspaper, whereas Caldara and Iacoviello (2022) capture geopolitical risk from news outlets. Similarly, Husted et al. (2020) counts the number of monetary policy expressions in US newspapers. These studies find that uncertainty lowers both GDP and investment. Their main weakness is that they assume equal readership. It is therefore difficult to establish *who* holds these beliefs and how the beliefs about uncertainty impact micro-economic decisions. Moreover, these studies make no attempt to study the aggregate causal impact of uncertainty on the economy. A recent exception is Aikman et al. (2024), who build exogenous shocks to trust in central banks using narrative evidence. They find that trust shocks lead to weaker business conditions and increases in the VIX. The main difference with this paper is that they focus on household perceptions whereas this paper looks at banks' and firms' beliefs. Overall, the paper is the first attempt at measuring perceived monetary policy uncertainty in the private sector.

Finally, this paper contributes to a literature using text-as-data to measure beliefs. Hassan et al. (2019) measure political risk from firms' earnings calls. Later studies use earnings calls and 10-K documents to capture country-risk (Hassan et al., 2024), cyber risk (Jamilov et al., 2023; Florackis et al., 2022) and climate change risk (Sautner et al., 2023). These studies have had success in measuring risks otherwise impossible to capture with traditional data. In this paper, I follow the literature and use an algorithm developed in Hassan et al. (2019). I differ in two aspects. First, I am interested in fundamental uncertainty instead of risk. Indeed, the correlation between aggregate monetary policy uncertainty and forecast disagreement supports the idea that I capture shocks to the range of policy actions of central banks. Second, I am interested in the macroeconomic implications of monetary policy uncertainty. Using the earnings call dates, I am able to look at a subset of earnings calls happening on days without major macroeconomic announcement. The contribution of this paper is thus also methodological. It offers a new identification strategy using the timing of text data instead of studying earnings calls at the quarterly frequency as it is commonly done in this literature.

2 Measuring Monetary Policy Uncertainty

2.1 Data and Pre-processing

The dataset comprises 10,957 bank earnings calls spanning from Q1 2001 to Q4 2023. These transcripts are extracted from Refinitiv Event Search. Earnings calls are a conference calls in which analysts have the opportunity to ask questions to managers about earnings of the past quarter. During these conversations managers often talk about the macroeconomic environment such as political risk or country risk (Hassan et al., 2019, 2024).

After some initial cleaning that removes special characters from the .txt format, I segment the text into sections where managers speak and analysts ask questions. This is done with speaker names and punctuation cues: I separate questions in the Q&A section from answers of CEOs by identifying the name of the speaker. If the speaker is a "Corporate Participants" (CP) representing the bank, the text is an answer. When the "Conference Call Participants" (CCP) speaks, the text is a question.[1] The rest of the paper uses the concatenated text of the presentation and answers to conduct the analysis. I merge the bank earnings calls with fundamentals from SNL Financials for 323 US banks. Appendix B shows the descriptive statistics of banks in the sample. The bank fundamentals are in line with the literature. The equity-to-asset ratio is around 11% whereas loan-to-deposit ratio is around 92%. These banks are thus on average well capitalized and lend actively.

[1] If the name of the speaker is not provided in the transcript, a sentence is identified as a question if it finishes by '?'.

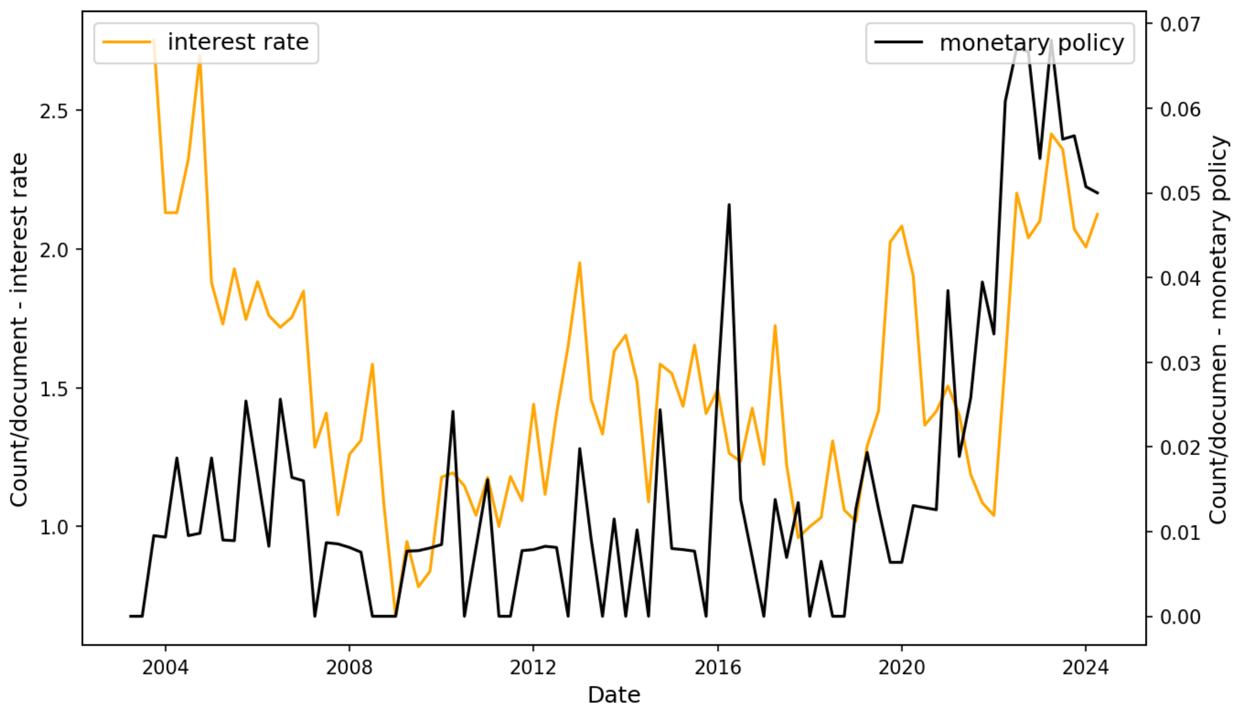
2.2 Attention to Monetary Policy in the banking sector

With the return of high inflation, monetary policy has been at the center of public attention in the last three years. Banks have always mentioned macroeconomic factors in their conversations with managers and analysts. This phenomenon is not novel; empirical evidence suggests that the mention of macroeconomic factors in firms' 10-K documents during times of crisis dates back to the 1990s (Flynn and Sastry, 2023). Figure 1 plots the count of mentions of the bi-grams "monetary policy" and "interest rate" per bank earnings call. The graph corroborates these results: banks have indeed paid attention to monetary policy over the last 20 years. What is striking from the graph is that both mentions of the bi-grams "interest rate" and "monetary policy" have reached a new peak over the last 3 years. The attention to "interest rate" is particularly elevated in 2012 with the intensification of forward guidance. The first lift-off since the GFC in 2016 then marks a surge in attention to monetary policy. The Great Financial Crisis stressed the role of monetary policy in stabilizing the economy. The next crisis, during the COVID-19 pandemic, thus naturally led to more attention to monetary authorities. Overall, the graph documents that attention to monetary policy in the banking sector is at an all-time high relative to the past two decades. This underscores the relevance of studying beliefs about monetary policy in the banking sector.

2.3 A dictionary of monetary policy words

This paper develops a new text-mining index which captures the level of uncertainty about monetary policy among US banks. The main difficulty lies in separating the text referring to monetary policy from parts of the text related to the situation of the bank. The first step consists in constructing a dictionary of terms related to monetary policy. To assemble this dictionary, I download Tealbooks A (formerly known as Greenbooks) from the Federal Reserve website from June 2010 until December 2017. These statements offer two advantages. First, they tend to focus on economic matters and employ a specialized vocabulary that

Figure 1: Mentions of Monetary Policy and Interest rate



Notes. The graph shows the average number of times banks mention the bi-gram "interest rate" and "monetary policy" per earnings calls.

reduces noise in the dictionary. Second, they facilitate the distinction of words related to the economy and monetary policy. Indeed, central banks often mention words related to the economy and monetary policy together. Hence, building a dictionary from FOMC statements or Beige books leads to words referring to both the economy and monetary policy. The Tealbooks A are unique in that they employ headers, with sections covering monetary policy, risks and uncertainties as well as the economy. I take advantage of this natural separation between topics. The algorithm isolates texts following a title referring to monetary policy and separates them from titles referring to economic growth and risks[2].

Using regular expressions, I extract the text following a monetary policy title and group it in a monetary policy text. The monetary policy text is then treated as a 'bag-of-words' for which the order of words does not matter. The text has many tables and numeric characters since Tealbooks A are used to communicate central bank forecasts. I therefore

[2]An example of the Teal book header structure is given in Appendix A.1 and the full list of titles is presented in Appendix A.2

start by removing numeric characters, date expressions and double white spaces in rows of tables. Finally, I run all the text through a cleaning algorithm that removes stop words and alphanumeric characters smaller than two characters.

The text is broken into bi-grams. Using a count-vectorizer yields 25391 bi-grams, which are ranked by absolute frequency. First, I remove bi-grams based on their frequency. A bi-gram is retained in the list if it appears in at least half of the Tealbooks. Since I have 61 Tealbooks, a bi-gram has to appear at least 31 times in the text to be in the list. Next, I select monetary policy bi-grams out of the remaining list. If the bi-gram has an ambiguous meaning and could be interpreted differently in another context such as "balance sheet" or "asset price", it does not appear in the list. I also remove bi-grams that appear less than 30 times in the economic words section (following the same algorithm). Noise remains in the list and I thus finish by removing bi-grams containing the nouns "inflation" and "price". As such, I obtain a list of 101 words referring to monetary policy. I add monetary policy words from Baker et al. (2016) to include synonyms identified in the literature. The whole list can be found in Appendix A.

2.4 Monetary policy uncertainty at the bank level

One contribution of the paper is to build an index of monetary policy uncertainty at the bank level based on bank earnings. The algorithm follows Hassan et al. (2024, 2019) to limit measurement errors arising from algorithmic choices. The index is built as follows:

$$MPUn_{i,t} = \frac{1}{B_{it}} \sum_{b}^{B_{it}} \Big([|b - r| < 10] \Big) \tag{1}$$

The algorithm isolates bi-grams b that refer to monetary policy from the dictionary described above. It then searches for synonyms of risk and uncertainty within 10 words of the monetary policy bi-grams. The risk words are synonyms obtained from the Oxford English Dictionary. The algorithm counts the occurrences of these risk words associated with monetary policy and normalizes by B_{it}, the total number of bi-grams in the earnings calls.

2.5 Index validation - Why pay attention to monetary policy?

To validate the index, this section regresses the bank-level monetary policy uncertainty and attention on their fundamentals. The main regression follows:

$$y_{i,t} = \delta_t + \beta X_{i,t} + \epsilon_{i,t} \tag{2}$$

This regression measures the correlation between bank fundamentals and bank-level attention and uncertainty. $y_{i,t}$ is the text-mining variable of interest either $MPAtt_{i,t}$, an indicator of bank attention counting the number of bi-grams related to monetary policy or $MPUn_{b,t}$, the bank-level monetary policy uncertainty index described in section 2. $X_{i,t}$ are bank controls. δ_t is a time fixed effects controlling for macroeconomic factors impacting aggregate uncertainty. Standard errors are clustered at the bank level. The regression is at the quarterly level and only includes time fixed effects. This means that the coefficient β in the regression can be interpreted as a between-effect comparing two banks. This modeling choice is deliberate to understand how bank beliefs correlate with their characteristics.

Table 1 presents a regression of bank attention and uncertainty about monetary policy against bank fundamentals. Column (1) highlights that attention and bank fundamentals are correlated. Bigger banks pay more attention to monetary policy than smaller banks. One explanation is that large banks tend to have economic analysis departments which provides a deeper analysis of monetary policy. Banks with a lower equity-to-asset ratio and less provisioning also pay more attention to monetary policy. This indicates that having more portfolio risk or less capital buffer makes banks more wary of the conduct of monetary policy. Moreover, less capitalized banks with high loan-to-deposit ratios are more concerned about monetary policy. They often have a large quantity of loans and a low amount of deposits to fund these assets. These banks would see a dramatic fall in asset value if interest rates were to rise. Banks with low levels of provisions are likely to be more risk-averse and talk more about monetary policy uncertainty. The results of Table 1 are thus consistent with the idea that monetary policy uncertainty is in line with bank fundamentals.

Table 1: Monetary Policy Beliefs and Bank Fundamentals

	(1) $\text{MPAtt}_{b,t}$	(2) $\text{MPUn}_{b,t}$
$\log(\text{Size})_{b,t}$	0.153***	-0.0194
	(0.0178)	(0.0121)
$\text{Eq/TA}_{b,t}$	-0.0250**	-0.0268***
	(0.00981)	(0.00644)
$\text{Cost/inc}_{b,t}$	-0.00412	-0.00387***
	(0.00254)	(0.00143)
$\text{Loans/dep}_{b,t}$	0.00320	0.00316**
	(0.00217)	(0.00146)
$\text{ROA}_{b,t}$	-0.0860***	-0.0369*
	(0.0312)	(0.0211)
$\text{LLP}_{b,t}$	-0.593***	-0.206***
	(0.0923)	(0.0773)
Time FEs	Yes	Yes
Bank FEs	No	No
N	9670	9670
R2	0.209	0.0490

This table shows regression of bank managers' attention and uncertainty index computed on their earning calls. Bank monetary policy attention is the count of monetary policy bigrams in earnings calls. Bank monetary policy uncertainty is computed looking at 10 words before and after the monetary policy words, and counting synonyms of risk words. All controls are winsorized at the first and 99th percentile. Attention and Uncertainty are winsorized at the 99th percentile only. Standard errors (in parentheses) are clustered at the bank-level and ***, ** and * refer to significance at the 1%, 5% and 10%.

2.6 Index validation - What is Monetary Policy Uncertainty ?

Uncertainty about monetary policy refers to both uncertainty about policy decisions and the transmission of monetary policy. This section relates bank-level monetary policy uncertainty to their interest rate forecasts. I download the forecast data from Reuters Economic Poll and merge them with banks' earnings calls. The merged dataset gives bank-level forecasts as well as consensus forecasts from Q1 2001 until Q4 2023 for 49 banks in the sample.

Table 2 uses bank forecast data to empirically test the relationship between bank-level uncertainty and interest rate predictability. I construct two measures of monetary policy unpredictability. First, the forecast error, $i - E_{t-1}[i_t]$, describes the difference between the actual interest rate and bank-level interest rate forecasts. The second measure, $|i - E_{t-1}[i_t]|$, is the absolute interest forecast error. Column (1) and (2) in Table **??** regress monetary policy uncertainty on forecasts errors. The correlation is weak without bank fixed effects and insignificant when looking at the within effect. In contrast, column (3) and (4) document a strong association between lagged absolute interest rate forecast errors and bank-level monetary policy uncertainty. As forecast errors increase by one standard deviation, monetary policy uncertainty surges by 0.171 (0.147) standard deviation between (within) banks. In column (6), I control for bank fundamentals in US banks and find that the effect is much stronger. The results suggest that interest rate predictability affects monetary policy uncertainty. It is thus uncertainty about what the committee decides, and not uncertainty about the transmission of monetary policy, that the text-based measure identifies.

Table 2: Relationship between Bank MP beliefs and interest rate forecasts

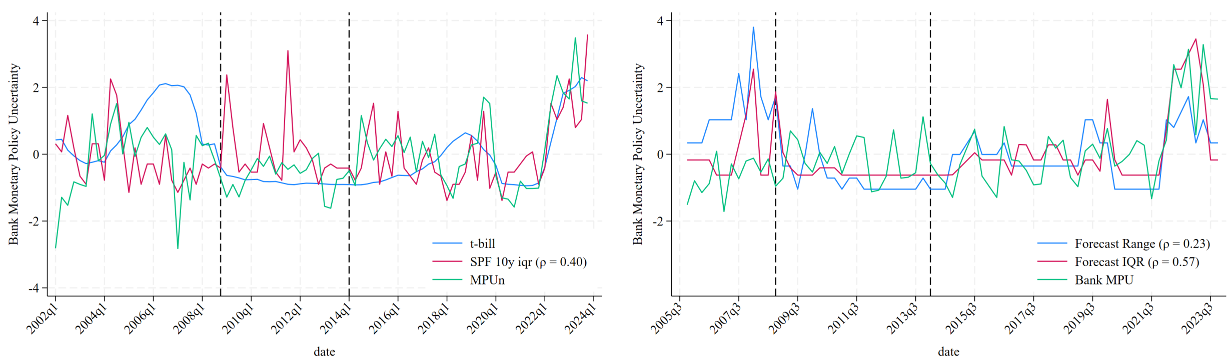
	(1) $\text{MPUn}_{b,t}$	(2) $\text{MPUn}_{b,t}$	(3) $\text{MPUn}_{b,t}$	(4) $\text{MPUn}_{b,t}$	(5) $\text{MPUn}_{b,t}$	(6) $\text{MPUn}_{b,t}$
$\text{i}_t - E_{t-1}[i_t]$	0.065	0.046			0.126	
	(0.072)	(0.069)			(0.093)	
$\lvert\text{i}_t - E_{t-1}[i_t]\rvert$			0.171^{**}	0.147^{**}		0.206^{**}
			(0.064)	(0.064)		(0.079)
$\log(\text{Size})_{b,t}$					0.419^{**}	0.288
					(0.138)	(0.150)
$\text{Eq/TA}_{b,t}$					0.080^{*}	0.055
					(0.035)	(0.044)
$\text{Cost/inc}_{b,t}$					-0.001	-0.002
					(0.008)	(0.007)
$\text{Loans/dep}_{b,t}$					0.009	0.009
					(0.006)	(0.006)
$\text{ROA}_{b,t}$					0.084	0.097
					(0.090)	(0.074)
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Bank FEs	No	Yes	No	Yes	Yes	Yes
Bank Controls	No	No	No	No	Yes	Yes
Sample					USA	USA
N	1,453	1,453	1,453	1,453	266	266
R2	0.078	0.171	0.086	0.177	0.363	0.367

This table shows regression of bank managers' uncertainty about monetary policy computed on their earning calls on the interest rate forecasts from Reuters Economic Polls. Bank monetary policy uncertainty is computed looking at 10 words before and after the monetary policy words, and counting synonyms of risk words. t-1[i_t] is the lagged three-months ahead interest rate forecast. t $\text{E}_{t-1}[i_t]$ is the interest rate forecast error computed as the difference between the Federal Fund Rate and the three-months ahead interest rate forecast. The bank controls are log(Size), Equity-to-assets ratio, Cost-to-Income ratio, Loans-to-deposit, and Return-on-assets (ROA). Standard errors (in parentheses) are clustered at the bank-level and ***, ** and * refer to significance at the 1%, 5% and 10%.

2.7 Index validation - Aggregate Uncertainty and Disagreement

Figure 2: Bank Monetary Policy Uncertainty and Forecast Disagreement

(a) SPF Forecasts **(b)** Bank Forecasts



Notes. Panel (a) documents the correlation between aggregate monetary policy Uncertainty in the banking sector and the inter-quartile range the ten-year rate from the Survey of Professional Forecasters from the Philadelphia Fed. Panel (b) illustrates the relationship between the banks' forecasts disagreements and aggregate monetary policy uncertainty for a sample of US and European Banks from Q1 2002 until Q4 2023. Banks' interest rate forecasts are taken from Reuters' Poll which are only available from Q3 2005. For each banks, I isolate the 3 months ahead forecasts of the Monetary Policy Reference rate. I compute the range (in blue) and the inter-quartile range (in red) of the forecasts. Bank MPU is computed as the sum of each bank's uncertainty for banks producing forecasts. The vertical dotted lines represent the period of Forward Guidance. All variables are standardized to facilitate comparison.

In this section, I study the relationship between forecast disagreement and aggregate monetary policy uncertainty. Figure 2 panel (a) plots the evolution of bank uncertainty against the inter-quartile range of forecasts from the Survey of Professional Forecasters. The graph suggests that there is no strong association between the two measures before the forward guidance period. However, over the last 10 years, bank monetary policy uncertainty and interest rate forecast disagreement are closely aligned with a correlation of 0.64. There is thus a emerging association between bank monetary policy uncertainty and the disagreement in forecasts.

Panel (b) in Figure 2 compares monetary policy uncertainty with interest rate forecast disagreement from the Reuters Economic Poll. The graph shows that monetary policy uncertainty in the banking sector is in line with the range of 3-month ahead forecasts. The correlation of 0.57 between the forecast inter-quartile range and bank monetary policy uncertainty (MPU) indicates that periods of disagreement are also associated with higher uncertainty. While panel (a) focuses on 10-year rate forecasts, panel (b) reflects short-term reference rates. Taken together, the evidence suggests that the index captures uncertainty about both short- and long-term rates.

The association between disagreement and uncertainty indicates that monetary policy uncertainty captured in earnings calls aligns with the concept of Knightian Uncertainty in (Ilut and Saijo, 2021; Bianchi et al., 2018; Ilut and Schneider, 2014). According to this literature, Knightian uncertainty gives rise to ambiguity. Ambiguity is the impossibility for agents to assign a single probability to future events. As such, agents are ambiguity-averse and behave as if they observed the worse probability distribution. In this context, macroeconomic models describe a situation in which the representative bank lends to the firm with the worst-case interest rate in mind. In other words, monetary policy uncertainty is fundamental because it refers to the unpredictability of monetary policy and the width of the possible interest rate decisions.

2.8 Business Cycle Behavior

Figure 3: Bank Monetary Policy Uncertainty and News-based measures

Notes. The graph documents the correlation between aggregate monetary policy uncertainty in the banking sector and news-based measured of uncertainty (Baker et al., 2016) (EPU) and monetary policy uncertainty (Husted et al., 2020) (News MPU). Aggregate monetary policy uncertainty is the cross-sectional sum of $MPUn_{b,t}$ from every bank in the US from 2002 Q1 until 2023 Q4. The vertical dotted lines represent the period of Forward Guidance. All variables are standardized to facilitate comparison.

This section explores how monetary policy uncertainty moves over the business cycle. Figure 3 illustrates that monetary policy uncertainty decreased when interest rates were high before the financial crisis. The forward guidance period in Q4 2008 marks the start of a period of historically low monetary policy uncertainty. The Fed's enhanced communication therefore managed to calm banks' perception of uncertainty. The end of forward guidance then sees a sudden surge of uncertainty when the interest rates start increasing. Around 2019, the change of dynamics in the Fed fund rate went hand in hand with a large increase in monetary policy uncertainty. Hence, over the last three years, monetary policy uncertainty has followed the reference rate. Regime shifts such as the end of forward guidance and before the Covid-19 mad policy less predictable. The graph thus illustrates that these shifts in policy are associated with monetary policy uncertainty.

Figure 3 contrasts bank policy uncertainty with other measures of uncertainty. Bank monetary policy uncertainty correlates with the established measure of economic policy uncertainty in Baker et al. (2016). The correlation increases from 0.15 to 0.57 when looking at a monetary policy news-based index from Husted et al. (2020). Uncertainty about monetary policy uncertainty revealed in the news therefore shapes managers' beliefs. However, the correlation is not perfect. One explanation is that subjective uncertainty at the bank level draws on different source of information. News is thus only a partial picture of the uncertainty perceived by agents.

Monetary policy uncertainty in the banking sector is consistent with the historical conduct of monetary policy. A first increase in the interest rate after an accommodative period leads to surges in uncertainty. For example, uncertainty was particularly high at the end of the forward guidance period. Furthermore, the measure is in line with the news-based measure of monetary policy uncertainty, forecast disagreement and bank-level forecast errors. This suggests that monetary policy uncertainty corresponds to the difficulty in forecasting the future actions of monetary policy.

3 Aggregate impact of Monetary Policy Uncertainty

3.1 Empirical Specification

This section examines the impact of monetary policy uncertainty (MPU) shocks in the banking sector on macroeconomic outcomes. I use quarterly data spanning 2002 Q1 through 2023 Q4. The baseline specification includes: aggregate monetary policy uncertainty (constructed as the sum of bank-level uncertainty each quarter), the one-year government bond rate, the external bond premium from Gilchrist and Zakrajšek (2012), the economic policy uncertainty (EPU) index from Baker et al. (2016), the log consumer price index and the log real GDP. I adapt the VAR framework from Husted et al. (2020) by replacing their MPU index with the bank-based measure. The VAR includes a constant and four lags of each variable in the reduced-form specification.

3.2 Identification

I estimate the dynamic causal impact of monetary policy uncertainty shocks in the banking sector on economic activity using an external instrument approach a la Mertens and Ravn (2013), Stock and Watson (2018) and Rogers et al. (2018). The external instrument approach tackles two main endogeneity concerns: the presence of economic announcements and the impact of monetary policy decisions on uncertainty.

Monetary Policy Uncertainty on FOMC days. The first endogeneity concern is the presence of economic announcements impacting monetary policy uncertainty within the quarter. Table 13 in appendix H shows that monetary policy uncertainty correlates with macroeconomic variables with an R^2 of 0.199%. Macro-economic factors thus play a role in shaping uncertainty about monetary policy. To exclude the confounding impact of economic announcements, I build an indicator of monetary policy uncertainty surprises by looking at monetary policy uncertainty on FOMC days. This approach follows Husted et al. (2020) and (Fasani et al., 2023) who use the one-month ahead implied volatility of the one-year swap rate on FOMC days to identify monetary policy uncertainty shocks. One of the key methodological contributions of this paper is to use the fact that earnings calls are published at a daily frequency to identify monetary policy uncertainty surprises. Hence, I use the exact day of earnings calls and keep only those occurring on FOMC announcement days to build the instrument. This daily measure at the FOMC frequency is a cleaner proxy for monetary policy uncertainty innovations than the aggregate quarterly index[3].

[3] A potential issue with this strategy is that economic announcements are released on FOMC announcement days. However, Fasani et al. (2023) documents that only the FOMC announcement of 12th December 2012 was released on an FOMC announcement day. Since no earnings calls was conducted on the 12th December 2012, the impact of daily economic announcements on the daily bank MPU index is negligible.

An issue with measuring monetary policy uncertainty on FOMC days is that it may not represent beliefs in the banking sector. The subset of banks reporting earnings on FOMC days may systematically differ in balance sheet characteristics, which would affect their exposure to monetary policy decisions. For example, $BankMPUn_{FOMC,t}$ may appear elevated if banks with high loan-to-deposit ratios are over-represented in the sample on a given day. To address this concern, I estimate a first stage regression at the quarterly level for banks publishing earnings calls on FOMC days:

$$BankMPUn_{FOMC,b,t} = \delta_b + \beta X_{b,t} + AnalystMPU_{b,t} + \epsilon_{b,t} \tag{3}$$

In this regression, δ_b are bank fixed effects and $X_{b,t}$ are bank controls used in Table1: $log(size)_{b,t}$, $equity - to - asset_{b,t}$, $cost - to - income_{b,t}$, $loan - to - deposit_{b,t}$, $ROA_{b,t}$, $Loanlossprovisions_{b,t}$. The regression controls for analyst perceived monetary policy uncertainty revealed in the questions of the earnings calls. The residuals of this regression are then averaged for each FOMC days to have $\hat{\epsilon}_t$; an index of bank monetary policy uncertainty that is orthogonal to bank fundamentals. Figure 9 in Appendix E documents that monetary policy uncertainty on FOMC days correlates with market measured in the literature. The uncertainty measure has a coefficient of correlation of 0.46 with the daily variation in implied volatility of the one-year swap rate at an horizon of one month (used in Husted et al. (2020)). This suggests that uncertainty in the banking sector on FOMC days aligns with market measures.

Monetary Policy Uncertainty Surprises. A second endogeneity concern is the impact of monetary policy decisions on monetary policy uncertainty on FOMC days. For example, elevated uncertainty on FOMC days could signal positive surprises due to forward guidance. The identification thus follows Husted et al. (2020), Rogers et al. (2018) and Fasani et al. (2023) and identifies monetary policy uncertainty surprises as the component of monetary policy uncertainty orthogonal to interest rate surprises on FOMC days. A limitation of these studies is that they rely on data provided by Rogers et al. (2018), which ends in 2015 Q4. I therefore extend the sample with monetary policy surprises by Bauer and Swanson (2022). The authors compute three surprises as a change of rate over a 30-min window around a FOMC announcement. First, target surprises ($Target$) measures surprise changes in the current or next-month federal funds futures responses[4]. Second, the forward guidance surprises ($ED4s$) is the residuals of the fourth Eurodollar futures contract on the target surprises. Finally, asset purchase surprises ($TNOTE10s$) are the residuals of the change in ten-year yield over the target surprises and the forward guidance surprises.[5] The instrument is the residual $\hat{\eta_t}$ of the following regression:

$$\hat{\epsilon_t} = \beta_1 Target_t + \beta_2 ED4s + \beta_3 TNOTES10_t + \eta_t \tag{4}$$

Monetary policy uncertainty surprises are orthogonal to both changes in the present and future path of the interest rates. Table 3 shows the results of the regressions. Monetary policy uncertainty correlates to both present and future monetary policy surprises. A positive interest rate surprise lowers average monetary policy uncertainty on FOMC days whereas forward guidance surprises ($ED4s$) are positively associated with monetary policy uncertainty. Column (1) uses the Rogers et al. (2018) measures to compute the forward guidance and asset purchase surprises and draws the same conclusions as column (2). The R^2 stands between 0.315 and 0.333 which suggests that monetary policy uncertainty is related to decisions on FOMC days. Yet, around 70% over monetary policy uncertainty is unrelated to monetary policy decisions. It is this variation that I exploit as an instrument for aggregate monetary policy uncertainty in the banking sector.

[4]The Rogers et al. (2018) target surprises are used as baselines and I extend the sample with the FF1 and FF2 surprises from Bauer and Swanson (2022). The correlation over the common sample is 0.8153. The slightly different window does not seem to impact the computation of future surprises

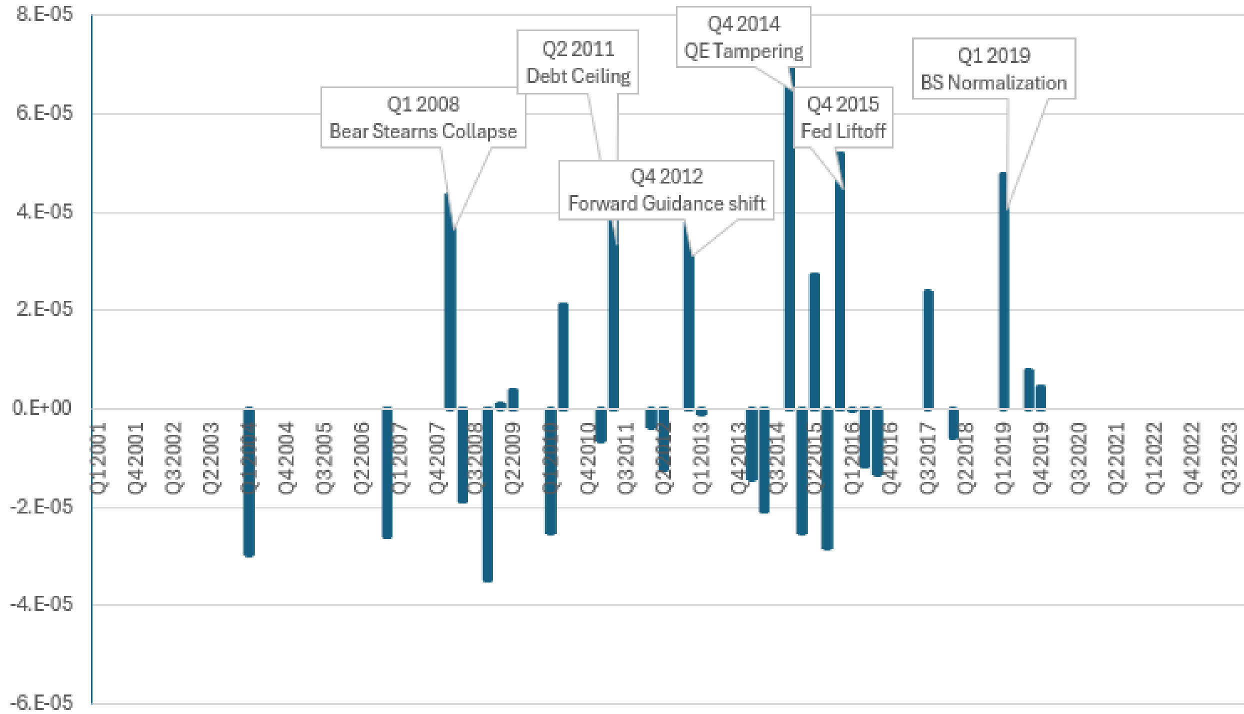
[5]See appendix E for summary statistics of the surprises.

Table 3: Monetary Policy Beliefs and Monetary Policy Surprises

	(1)	(2)
	$\hat{\epsilon}_t$	$\hat{\epsilon}_t$
Target	-0.000654**	-0.000723***
	(0.000258)	(0.000223)
ED4s RSW	0.000281***	
	(0.0000920)	
TNOTE10s RSW	0.0000448	
	(0.000186)	
ED4s		0.000338***
		(0.0000980)
TNOTE10s		-0.000213
		(0.000353)
Observations	37	49
R^2	0.333	0.315

Notes. This table shows regression of monetary policy uncertainty shocks on monetary policy surprises computed with Bauer and Swanson (2022) data. Target measures the surprise change in the current or next-month federal funds futures responses. The forward guidance surprises (ED4s) is computed as the residuals of the fourth Eurodollar futures contract on the target surprises. The asset purchase surprise (TNOTE10s) is residual of the change in ten-year yield over the target surprises and the forward guidance surprises. ED4s RSW is computed as the residuals of the fourth Eurodollar futures contract on the target surprises from Rogers et al. (2018). ONRUN101 is the residual of the change in ten-year yield over the target surprises and the forward guidance surprises from Rogers et al. (2018). Bauer and Swanson (2022) uses a 30-min window around FOMC annoucements while Rogers et al. (2018) computes the change from 15 min before FOMC annoucements to 1h 45 min afterwards. ***, ** and * refer to significance at the 1%, 5% and 10%.

Figure 4: Monetary Policy Uncertainty Surprises



Notes. The figure represents the bank monetary policy Uncertainty surprises constructed from the two-step identification strategy. The surprises are the residuals of a regression of monetary policy uncertainty on the target surprises, the Forward Guidance surprises and the Asset Purchases surprises computed from Bauer and Swanson (2022). The bars represent the FOMC meeting for which at least 5 banks present an earnings calls and fundamentals of the banks are known.

Narrative evidence. In this section, I provide narrative evidence on the nature of monetary policy uncertainty shocks. I look at the six largest monetary policy uncertainty surprise, listed in chronological order:

- Q1 2008: This quarter was marked by a high degree of uncertainty due to the aftermath of the Great Financial Crisis. Financial turmoil accelerated with the collapse of Bear Stearns in March 2008.
- Q2 2011: The Debt Ceiling debate was prominent in the economic discourse which added uncertainty about the reaction of monetary policy.
- Q4 2012: This quarter saw a shift in forward guidance policy, with an explicit mention of forward guidance numbers: "In particular, the Committee decided to keep the target

range for the federal funds rate at 0 to 1/4 percent and currently anticipates that this exceptionally low range for the federal funds rate will be appropriate at least as long as the unemployment rate remains above 6-1/2 percent, inflation between one and two years ahead is projected to be no more than a half percentage point above the Committee's 2 percent longer-run goal, and longer-term inflation expectations continue to be well anchored."

- Q4 2014: Quantitative Easing (QE) tampering was the main event of Q4 2014. The Fed tried to end the third program of QE. This led to substantial uncertainty in financial markets and the banking sector.

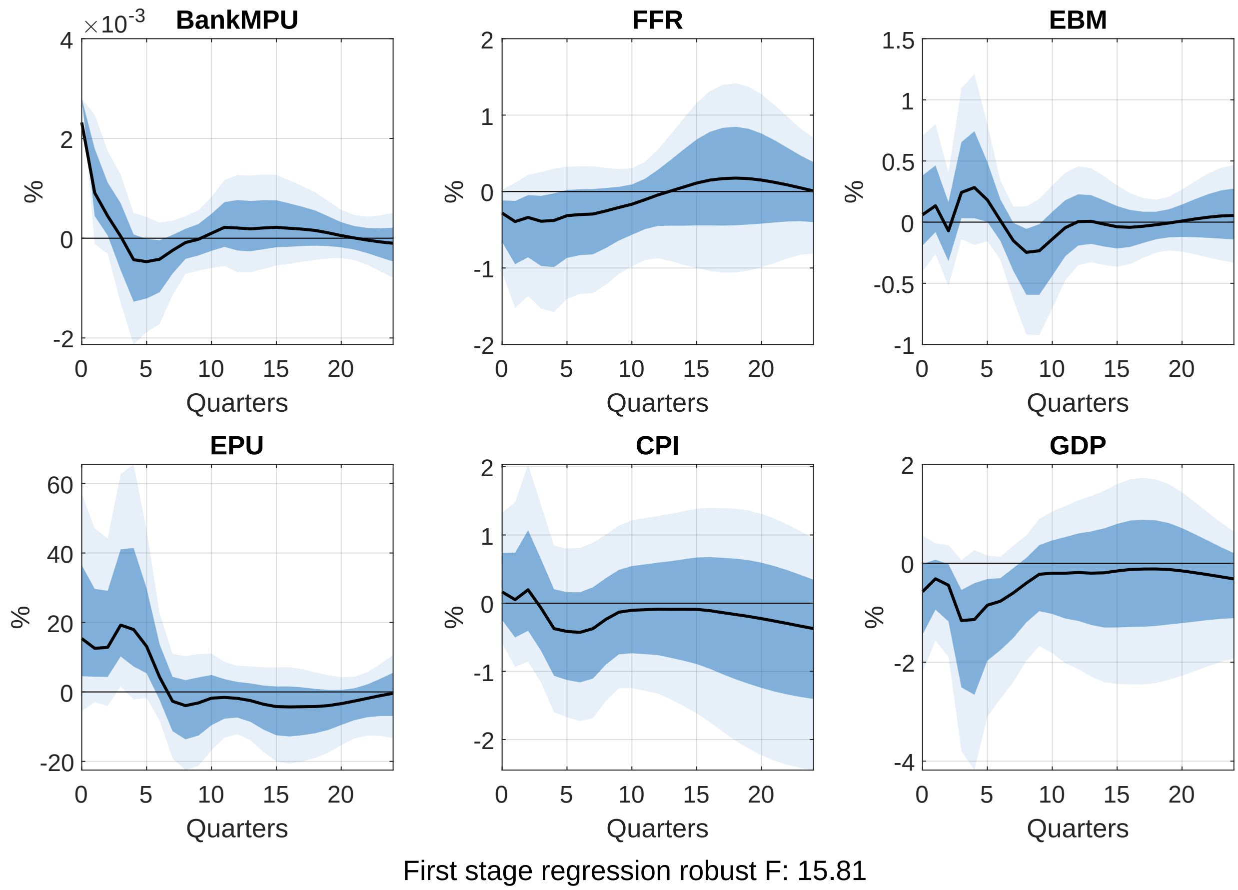
- Q4 2015: During the FOMC meeting in December 2015, the Fed increased rates for the first time since the financial crisis. This quarter marked the beginning of a period of rate increases, which led to heightened unpredictability and uncertainty about the future path of rates.

- Q1 2019: The quarter saw an increases supply of information on the ongoing balance sheet normalization program. The Fed provided more details on the size of its securities holdings and the new long-term operation practices.

Overall, monetary policy uncertainty surprises correspond to shift in the monetary policy regime. Instead of risk about the future path of rates, monetary policy uncertainty in the banking sector is Knightian uncertainty, as described by Kindleberger (1978) or Ilut and Schneider (2022). Once the language about forward guidance changes or a liquidity support program ends, the banking sector perceives higher uncertainty in the conduct of monetary policy. Hence, the index captures uncertainty about the different tools and policy actions of the Fed.

3.3 Macroeconomic impact of monetary policy uncertainty

Figure 5: Uncertainty and economic activity: Impulse Response Function



Notes. The figure displays the IRFs to a monetary policy uncertainty shock identified from an estimated quarterly SVAR using a US macroeconomic data. The identification strategy relies on high-frequency instrument using monetary policy uncertainty using earnings calls occurring on FOMC days only, where at least 5 banks conduct earnings calls. The daily uncertainty index is then orthogonalized with respect to bank fundamentals and monetary policy decisions. The scheme follows Husted et al. (2020) and Fasani et al. (2023). The response are shown in percentage and the unit of the shock is one standard deviation. The sample is from Q1 2002 until Q4 2023. 68% (dark blue) and 90% (light blue) errors bands are computed using bootstrap standard errors.

Figure 5 displays the impulse response functions of the SVAR with external instruments. The first stage regression shows that the instrument is strong with an F-statistic of 15.81, above the weak-instrument threshold of 10. The evidence suggests that the instrument is relevant for aggregate monetary policy uncertainty. On top of that, the instrument is orthogonal to monetary policy decisions and changes in bank fundamentals, which supports the exclusion restriction. The figure presents the impulse response function to a one standard deviation shock in bank policy uncertainty. Monetary policy uncertainty tend to be recessionary. Monetary policy uncertainty shocks in the banking sector precedes drops in economic activity measured by real GDP of 1.14%. The economy responds to a monetary policy uncertainty shock with higher borrowing costs in the first 5 quarters. The effect of bank MPU therefore seems to run through an increase in costs of financing. Policy uncertainty rises on impact. This suggests that monetary policy uncertainty surprises happen in an environment of elevated economic policy uncertainty. Finally, the figure highlights that the central bank reacts to the recession by lowering rates to stimulate the economy.

The results are robust to alternative specifications as shown in Appendix F. In the first robustness test, the specification completely ignores the impact of bank fundamentals. Since the choice of bank controls is somewhat arbitrary, Figure 10 runs the same specification as the baseline without orthogonalizing with respect to bank fundamentals. The results are not sensitive to the choice of bank fundamentals, as the IRFs are in line with the baseline. The next robustness exercise tests the stability of the results to the number of banks presenting earnings calls on a FOMC day. Only $\hat{\eta}$ for FOMC days with at least 5 banks conducting an earnings calls are retained in the baseline instrument. This is to make sure that the instrument is representative to the banking sector. Appendix F relaxes this restriction and documents that the results are robust to using all $\hat{\eta}$ as instruments. Figure 11 thus highlights that the number of banks presenting earnings calls on FOMC days is not factor impacting the results. Furthermore, I replace the EPU with Husted et al. (2020) MPU index in Figure 12. The results are unchanged: news MPU surges on impact and the IRFs illustrate a somewhat stronger negative effect on real GDP growth.[6] Finally, Appendix F discusses the robustness of the results to different monetary policy bi-grams.

[6]The robust F-stat drops to 7.86 in this robustness test. I thus use the Montiel Olea et al. (2021) weak-IV robust confidence interval to reduce concerns about weak instruments.

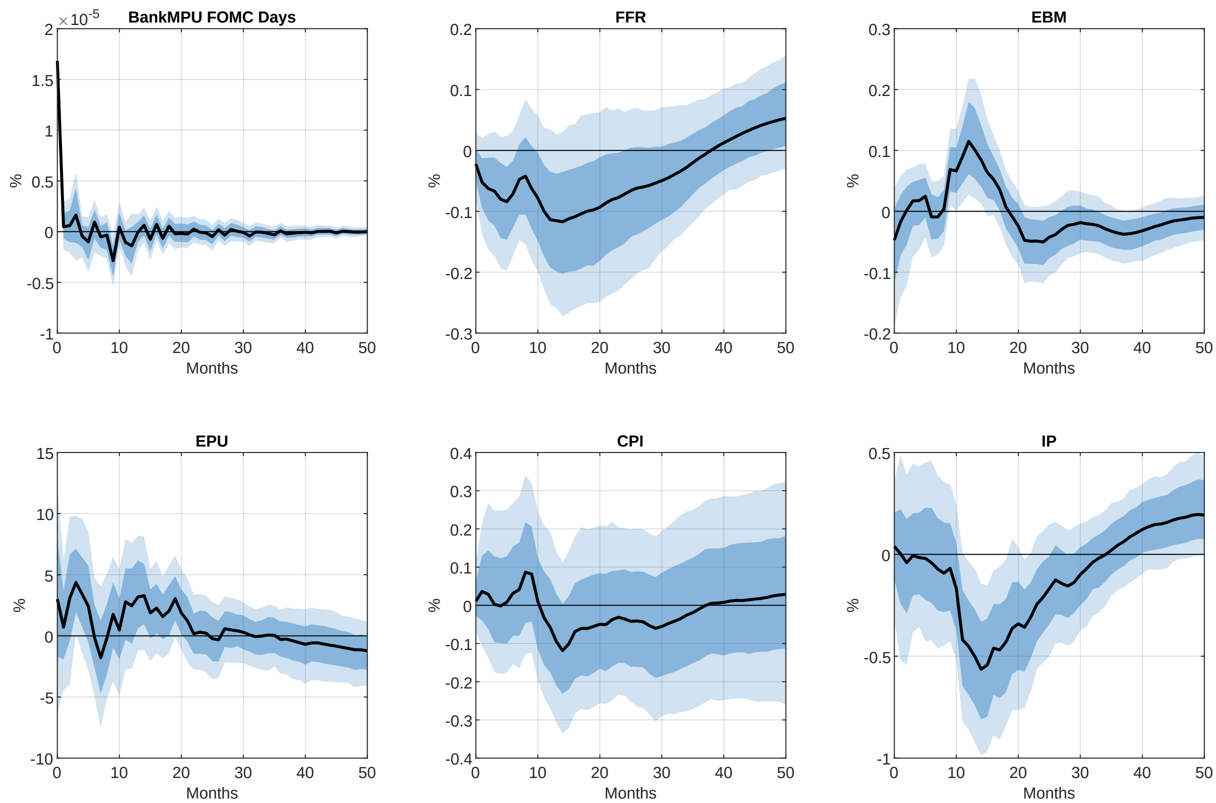
3.4 Additional SVAR results

Exploiting daily variations. Uncertainty on FOMC days is used as an instrument in Husted et al. (2020) and Fasani et al. (2023). They argue that the level of uncertainty on FOMC days is not polluted by the release of macro-economic data because only one FOMC meeting coincided with the release of unemployment report. Using the level of uncertainty as a source of variation can nonetheless be problematic. In their paper on market-based uncertainty, Bauer et al. (2021) use the daily changes of MPU around FOMC announcements instead of the level of the implied volatility. The argument is that using variations in MPU around FOMC announcements identifies changes to monetary policy uncertainty that are due to FOMC announcements. Indeed, the daily implied volatility might be high on an FOMC day but lower than to the day before so that uncertainty is decreasing on the FOMC day. In addition, lagged macro-economic announcement could influence bank managers and confound the results.

To address the potential identification concern, I identify monetary policy uncertainty surprises using the daily variation in bank MPU $\hat{\epsilon}_t$ on FOMC days: $\Delta\hat{\epsilon}_t$. The construction of the surprises follows the baseline with the exception that $\hat{\epsilon}_t$ is replaced with $\Delta\hat{\epsilon}_t$ in eq. (5). Appendix G, Table 3, presents the first-stage regression using this alternative specification. The results remain consistent: negative target rate surprises and forward guidance surprises are positively associated with daily variations in monetary policy uncertainty. The instrument for monetary policy uncertainty on FOMC days in the VAR is the residuals from this first-stage regression. The instrument exhibits a correlation of 0.63 with the daily surprises in the baseline. The stability of the results reduces endogeneity concerns in the baseline. This is because it highlights that most of the uncertainty on FOMC days stems from positive day-over-day changes.

Figure 6 presents the impulse function of an innovation in monetary policy uncertainty of one standard deviation. The VAR is run at the monthly level over the same sample as the quarterly VAR with a lag of 12 months and a constant. The following variables

Figure 6: Uncertainty and economic activity: Impulse Response Function



F-stat: 23.49, F-stat (robust): 5.29, R^2: 8.59

Notes. The figure displays the IRFs to a monetary policy uncertainty shock identified from an estimated monthly SVAR using a US macroeconomic data. The identification strategy relies on high-frequency instrument using earnings calls ocurring on FOMC days only. The scheme follows Husted et al. (2020) and Fasani et al. (2023). The response are shown in percentage and the unit of the shock is one standard deviation. The sample is from m1 2002 until m12 2003. 68% (dark blue) and 90%(light blue) errors bands are computed using bootstrap standard errors.

are introduced in the VAR: monetary policy uncertainty on FOMC days (constructed as the average residual of monetary policy uncertainty on bank fundamentals), the one-year government bond rate, the external bond premium from Gilchrist and Zakrajšek (2012), the economic policy uncertainty (EPU) index from Baker et al. (2016), the log consumer price index and the log industrial production.

Results in Figure 6 confirm that monetary policy uncertainty has a recessionary impact on economic activity. While the external bond premium is unaffected on impact, it increases steadily to reach its peak at 12 months. During this period, industrial production is not significantly affected by uncertainty surprises. However, in the medium run, the impact of monetary policy uncertainty on economic activity is negative. In line with Husted et al. (2020), the through of industrial production's response is at around 15 months. The magnitude of the effect is non-negligible. A one standard deviation shock in monetary policy uncertainty on FOMC announcement days leads to a fall in industrial production by 0.56% at the through. The effect is thus twice the impact of MPU in Husted et al. (2020). Overall, surprises in monetary policy uncertainty in the banking sector leads to a fall in economic in activity due to higher borrowing costs.

4 Transmission of Bank Monetary Policy Uncertainty

This section explores the transmission of monetary policy uncertainty shocks to the economy. Section 3 suggests that monetary policy uncertainty shocks in the banking sector impact the economy through a higher external bond premium. The analysis nonetheless fails to give conclusive evidence on the exact transmission channel. This section therefore differentiates between the indirect impact of monetary policy uncertainty running through financial frictions and the more direct impact of perceived monetary policy uncertainty at the firm-level argued in Fasani et al. (2023).

The literature disagrees on the mechanism behind the recessionary effect of monetary policy uncertainty. Financial friction theory argues that high uncertainty broadens the dispersion in future cash-flows and pushes the price of debt financing upwards (Gilchrist et al., 2014; Gilchrist and Zakrajšek, 2012). In contrast, uncertainty shocks force firms to suspend their investment decisions until uncertainty resolves according to wait-and-see explanations (Bloom, 2009; Fernández-Villaverde and Guerrón-Quintana, 2020). The role of firm-level monetary policy uncertainty in the recessionary impact of monetary policy uncertainty thus remains unclear.

To compare these predictions, the same algorithm as in section 2 is run with firm earnings calls. The firm dataset comprises 208,582 earnings calls from US firms[7] over the last 20 years. These transcripts are from Refinitiv Event Search, while the balance sheet information is from Compustat. By merging these two datasets at the gvkey-quarter level, I obtain the fundamental characteristics for 195,693 firm-quarter observations. I exclude the "Finance and Insurance" and "Utilities" firms from the sample to identify sectors that refer to the real economy. Finally, observations with negative assets, sales and book equity are excluded from the sample.

Using firm-level data from 2003 Q2 until 2024 Q1, I run the following regression:

$$\frac{\mathrm{CAPX}_{i,t+1}}{\mathrm{PPENT}_{i,t}} = \gamma_i + \beta_1 BankMPU_t + \beta_3 Q_{i,t} + \beta_4 \frac{\mathrm{CF}_{i,t}}{\mathrm{TA}_{i,t-1}} + \beta_5 \mathrm{SG}_{i,t} + \beta_6 \mathrm{Firm\ MPU}_{i,t} + \beta_7 M_t + \varepsilon_{i,t} \tag{5}$$

where the dependent variable $\frac{\mathrm{CAPX}_{i,t+1}}{\mathrm{PPENT}_{i,t}}$ measures the investment ratio of firm i at quarter t, following (Ottonello and Winberry, 2020) and Cloyne et al. (2023)). $BankMPU_t$ is the monetary policy uncertainty index, $Q_{i,t}$ is the Tobin's Q while $\frac{\mathrm{CF}_{i,t}}{\mathrm{TA}_{i,t-1}}$ and $\mathrm{SG}_{i,t}$ are the cash flows and sales growth following Husted et al. (2020). $M_{i,t}$ include GDP growth, the Economic Policy Uncertainty Index of Baker et al. (2016), the expected GDP growth over the next 6 months, Consumer Confidence and the Expected Business condition index from the University of Michigan. The macroeconomic variables control for macroeconomic conditions

[7] Excluding only the pharmaceutical sector and financial firms not classified as banks

and expectations about future investment profitability which impact investment decisions. Finally, this paper builds the uncertainty at the firm level. Following Husted et al. (2020), all variables are divided by their standard errors to facilitate the interpretation of coefficients.[8] The regression includes a firm (industry) γ_i fixed effect and standard errors are clustered at the firm (industry) and quarter level.

Table 4: Capital Investment and monetary policy uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inv_{t+1}	Inv_{t+1}	Inv_{t+1}	Inv_{t+1}	Inv_{t+1}	Inv_{t+1}	Inv_{t+1}
Bank MPU_t	-0.031**	-0.044***	-0.044***				
	(0.012)	(0.013)	(0.013)				
Low Lev × Bank MPU_t				0.000			
				(0.012)			
High Lev × Bank MPU_t				-0.052***	-0.052***		
				(0.011)	(0.006)		
Firm $\text{MPUn}_{i,t}$						-0.005*	
						(0.003)	
Low Lev × Firm $\text{MPUn}_{i,t}$							-0.002
							(0.006)
High Lev × Firm $\text{MPUn}_{i,t}$							-0.006***
							(0.002)
Ind FE	No	Sic 3 dig	Sic 2 dig	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	111,927	112,133	112,133	111,927	111,953	111,953	111,953
R2	0.053	0.063	0.071	0.058	0.058	0.052	0.052

This table shows regression of investment ($\text{CAPEX/PPENT}_{i,t}$) on Bank Monetary Policy Uncertainty surprises and Firm controls. Firm controls are Tobin's $Q_{i,t}$, $\frac{CashFlow_{i,t}}{TA_{i,t-1}}$ and real sales growth: $\frac{\Delta sales_{i,t}}{salesi_{,t-4}}$. Macroeconomic controls are GDP growth, the Economic Policy Uncertainty Index of Baker et al. (2016), the expected GDP growth over the next 6 months, Consumer Confidence and the Expected Business condition index from the University of Michigan. In all regressions, variables are normalized with their standard deviation to help the interpretation of the results. All balance sheet variables are winsorized at the 1 and 99th percentile. All the specifications contain a quarterly dummy to controly for seasonality in capital investment. Standard errors (in parentheses) are clustered at the firm-quarter level and ***, ** and * refer to significance at the 1%, 5% and 10%.

Table 4 confirms the results found in the quarterly VAR. Monetary policy uncertainty has

[8]All balance sheet variables are winzorised at the 1% and 99% as is common in this literature

a negative impact on economic activity. The coefficient in column (1) is half than the effect in Husted et al. (2020): a one standard deviation increase in monetary policy uncertainty leads to a fall in investment of 0.031 standard deviation vs 0.063 in Husted et al. (2020). A potential explanation for the negative impact of monetary policy uncertainty on economic activity is that uncertainty affects GDP by reducing investment decisions on impact. Column (2) and (3) present the results at the industry level with industry fixed effect at the two and three SIC digit levels. The results not only hold but become stronger at the industry level. Next, column (4) and (5) explore heterogeneity in the effect across different levels of leverage. The negative impact of monetary policy uncertainty on investment is concentrated among high leverage firms. The effect of bank MPU in this group is approximately 40% larger than in the baseline specification. Column (5) corroborates that the difference in the coefficient of high and low-leverage firms is statistically significant. Being financially constrained thus plays a central role in transmitting the impact of monetary policy uncertainty to investment decisions and the economy.

The last two columns introduce firm-level beliefs. While $FirmMPU_{i,t}$ is negatively correlated with investment, the effect is only significant at the 10% level. When looking at financially constrained leveraged firms, the significance improves to 1%. The last two columns of Table 4 provide some evidence of a direct impact of monetary policy uncertainty at the firm level on top of the indirect impact running through banks. Nonetheless, the magnitude is roughly one tenth smaller than that of bank MPU for highly leveraged firms. This highlights the dominant role of financial frictions in the transmission channel of monetary policy uncertainty. Appendix I discusses the dynamics of the effect of monetary policy uncertainty on firm investment.

To sum up, monetary policy uncertainty has a negative impact on economic activity through financial frictions. The elevated external bond premium in the quarterly VAR translates into more frictions for high leverage firms. These firms, in turn, lower investment. Another finding is that firm-level monetary policy uncertainty has a direct impact on investment but at a lower magnitude than bank monetary policy uncertainty. Across the specifications, the impact of bank MPU runs through financial frictions. More evidence is nonetheless needed to establish the relationship between bank monetary policy uncertainty and financial frictions. The next section therefore looks at bank pricing behavior in the syndicate loan market to understand the mechanism linking monetary policy uncertainty and interest rate costs.

5 Monetary Policy uncertainty and Loan Pricing

5.1 Empirical analysis: Syndicated loan evidence

This section examines how bank-level monetary policy uncertainty impacts the actions of banks in the syndicated loan data. To do so, I merge the bank uncertainty datasets with Dealscan at the bank-name quarter level. The datasets are first matched on the Lender Name and then on the Lender Parent Name. Firm data is then merged with quarterly firm fundamentals from Compustat. Standard cleaning is applied to the syndicated loan market. I remove transactions where the lender share is greater than 100% or smaller the 1%, tranche amounts are smaller than 100 USD and the maturity of the loans is smaller than 3 months. I drop transactions where the receiving firms is a financial firms (sic code 6000-6999). Following Lim et al. (2014), I exclude tranche types that are not common such as Lease or Letter of Credit[9]. Finally, I drop non-Lead banks defined as in Heider et al. (2019) and only retain transactions from US banks to US firms to prevent the effect of cultural distance found in Giannetti and Yafeh (2012).

To understand the impact of bank-level monetary policy uncertainty on lending conditions in the syndicated loan level, I estimate the following regression for firm f borrowing from bank b in the tranche i:

$$y_{f,b,i,t} = \alpha + FE_{f,b,i,t} + \beta_1 T_{i,t} + \beta_2 X_{f,t} + \beta_3 Z_{b,t} + \gamma MPU_{b,t} + \epsilon_{f,b,i,t} \tag{6}$$

[9]The full list is: Bankers Acceptance, Lease, Synthetic Lease, Standby Letter of Credit, Performance Standby Letter of Credit, Trade Letter of Credit, Multi-Option Facility and Undisclosed.

The dependent variable $y_{b,f,t}$ is the All-in-drawn spread, a common measure of loan pricing offered to firm f by bank b in the tranche i. The variable of interest is MPU which measures bank monetary policy uncertainty, described in 2. $T_{i,t}$ are tranche controls including $log(tranchamount)$, $LoanMaturity(month)$, $Secured - dummy$, $Covenant - Dummy$, $Performance - pricing - dummy$, Number of Lead Lenders and a dummy whether the firm f has borrowed from the bank b in the last five years. $X_{f,t}$ are firm characteristics. The controls include standard size and profitability measures such as $log(TotalAssets)$, the ratio of property plant and equipment over total asset $FixedAssetRatio$, and ROA as bigger and more profitable firm pay a lower costs on their debt. On top of this, the regression controls for credit worthiness with the book leverage ratio, the interest coverage ratio and a listed dummy, as in Degryse et al. (2019) and Lim et al. (2014). Bank-level characteristics are included as they influence loan pricing. These are $log(size)_{b,t}$, $equity - to - asset_{b,t}$, $loan - to - deposit_{b,t}$,$ROA_{b,t}$, $Loanlossprovisions_{b,t}$. The equity-to-asset ratio for example has been found to impact loan pricing in Schwert (2018).

Following Hassan et al. (2019), I control for bank sentiment with respect to the interest rates $MPSent$. Instead of conducting simple sentence identification, the algorithm looks at the sentiment of words within a 10 words window around monetary policy concepts. The sentiment scores are obtained from Shapiro et al. (2022). The sum of the sentiment scores is then divided by the number of bi-grams in the text. The final monetary policy sentiment is thus the average of these sentiment scores. The latter controls for beliefs about the first moment of the distribution of monetary policy shocks. Rates increase could be a positive news for some banks. This could impact their beliefs about the range of possible monetary policy actions. General sentiment or perceived uncertainty are also a confounding factors. I thus control for bank sentiment $Sent_{b,t}$ and uncertainty $Un_{b,t}$, where $Sent_{b,t}$ is computed with Shapiro et al. (2022) algorithms and $Un_{b,t}$ follows Hassan et al. (2019).

The high-dimensional structure of the dataset allows for a variety of fixed effect $FE_{f,b,t,i}$. Following Degryse et al. (2023), I introduce year fixed effects to remove the impact of macroeconomic factors. The regressions also includes a deal purpose fixed effect as in Lim et al. (2014) and a loan-type fixed effect (Berg et al., 2017). Finally, I control for industry-specific factors impacting loan pricing with a two-digit Standard Industrial Classification (SIC) fixed effect. Some specifications also control for credit demand with a firm*year fixed effect or an industry-size-location-year fixed effect a la Degryse et al. (2019). Standard errors are clustered at the bank level, which is the level of treatment.

5.2 Baseline results

Table 5 reports the results of the specification in eq.(6), over the entire sample of tranches in Dealscan. The findings highlight the role of bank-level perceived monetary policy uncertainty in loan pricing. After controlling for borrowers, lenders and tranche characteristics, column (1) documents that monetary policy uncertainty is positively associated with the All-in-drawn spread (AISD). A one standard deviation increase in monetary policy uncertainty leads to an increase in the AISD of 0.018 standard deviation. The economic magnitude is not negligible and is of similar magnitude as the impact of Loan-Loss Provisions (0.039) or ROA (-0.031). Column (2) adds a bank fixed effects to the specification and shows that the impact falls by 22%. This suggests that differences between banks in monetary policy uncertainty are a more important driver of loan pricing than within bank variations.

In column (3) and (4), the sample is broken down in credit lines and term loans. Banks usually use these two types of tranches differently across the business cycle. For example, credit lines tend to be more pro-cyclical in the United States than in Europe (Berg et al., 2017). The evidence illustrates that there is a significant impact on term loans and not on revolver loans (credit lines). Term loans are more long-term in nature. The results thus indicate that banks increase spreads on longer-term loans because they fear being locked-in with loans with lower-than-optimal interest rate. Finally, the last column introduces firm-year fixed effects to fully control for credit demand. The identification strategy is in the same vein as Khwaja and Mian (2008). In particular, I focus on tranches where at least two banks

Table 5: Relationship between Lending Conditions and bank monetary policy uncertainty

	(1) AISD	(2) AISD	(3) AISD	(4) AISD	(5) AISD
ROA	-0.031**	-0.015	-0.015	-0.015	-0.003
	(-2.43)	(-1.13)	(-0.73)	(-1.50)	(-0.99)
LLP	0.039**	0.045***	0.050***	0.040*	0.028**
	(2.26)	(7.00)	(3.80)	(1.91)	(2.72)
MPU	0.018***	0.014***	0.010	0.013**	0.008***
	(3.75)	(5.60)	(1.16)	(2.81)	(5.60)
Bank Controls	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
Tranche Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No
Tranche Type FE	Yes	Yes	Yes	Yes	Yes
Deal Purpose FE	Yes	Yes	Yes	No	Yes
Ind FE	Yes	Yes	Yes	Yes	No
Bank FE	No	Yes	Yes	Yes	No
Firm x Year FE	No	No	No	No	Yes
Loan Type			Credit Line	Term Loan	
N	20,006	20,003	12,792	6,826	17,174
R2	0.458	0.464	0.493	0.401	0.855

Notes. The table shows the OLS estimates from regressions of the All-In-Spread-Drawn (AISD) on bank monetary policy uncertainty, tranche, firm, and bank controls. Bank monetary policy uncertainty is computed looking at 10 words before and after the monetary policy words, and counting synonyms of risk words. The sample runs from Q1 2002 until Q4 2023 for US banks lending to US firms. The data is obtained merging our sentiment dataset and the syndicate loan market, and Compustat. We only retain observations where the bank is always the lead bank. The bank controls are log(Size), Equity-to-assets ratio, Return-on-assets (ROA), Loans-to-deposit and loan-loss-provisions. Tranche controls are log(Tranche Amount in USD), a secured and covenants dummy, a dummy for the presence of performance pricing, the number of lenders and a dummy equal to 1 if the bank has lent to the firm in the last three years. Firm Controls include log(Total Assets), fixed asset ratio, leverage, ROA, interest coverage ratio and a listed dummy. All variables are winzorized at the 1% level. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

are lending to the *same* firm in the *same* year. The identification rules out any demand side channels that could affect the lending conditions given to firms. As such, I am capturing how monetary policy uncertainty at the bank level impacts the lending conditions of two different banks lending to the same firm in the same year. Monetary policy uncertainty at the bank level is positively related to loan pricing after controlling for credit demand. However, the magnitude of the effect falls with respect to the baseline results whereas the significance increases. Appendix D shows that the results are robust to controlling for analysts beliefs, weighting tranches differently and introducing variations in our clustering strategy.

I find a robust association between bank-level monetary policy uncertainty and interest rates. The link between aggregate monetary policy uncertainty and external bond premium is thus confirmed with tranche-level regressions controlling for credit demand and macroeconomic shocks. The impact of monetary policy uncertainty thus runs through banks beliefs impacting lending conditions in credit markets. This result lends support to the financial friction channel argued in Husted et al. (2020). Elevated monetary policy uncertainty in the banking sector leads to surges in credit spreads. These elevated spreads then raise financial frictions for financial constrained firms.

6 Conclusion

In conclusion, the analysis sheds light on the impact of bank monetary policy uncertainty on economic activity. The study first reveals that monetary policy attention is at an all-time high: banks mention interest rates now more than ever. Using transcripts of banks' earnings calls, I build a measure of monetary policy uncertainty at the bank level by combining the unique vocabulary of Tealbooks A and algorithms from Hassan et al. (2019). The regression of monetary policy on bank fundamentals documents that bank-level monetary policy uncertainty is increasing in their loan-deposit ratio and decreasing in their equity position. Banks sensitive to interest rates changes thus perceive more uncertainty. Moreover, the paper establishes that monetary policy uncertainty is associated with lagged absolute forecast errors. Monetary policy uncertainty can thus be better understood as the unpredictability of FOMC board decisions rather than uncertainty about the transmission of monetary policy.

The index is then aggregated at the quarterly frequency and correlates with disagreement in the Survey of Professional Forecaster and the Reuters Economic poll, and news-based monetary policy uncertainty. Introducing aggregate bank monetary policy uncertainty in a SVAR at the quarterly frequency, the paper studies the macro-economic implications of monetary policy uncertainty. To alleviate endogeneity concerns, I build an instrument orthogonal to economic announcements, monetary policy decisions and bank fundamentals. The instrument is constructed by isolating monetary policy uncertainty on FOMC days and orthogonalizing daily monetary policy uncertainty with respect to interest rate surprises. The dynamic causal impact underscores the impact of monetary policy uncertainty on economic activity. The GDP falls in the first two years by more than 1% following the monetary policy uncertainty shock and the external bond premium surges. To fully identify the channel of transmission, the dataset is then merged with syndicated loan market data. Results at the bank level suggest that monetary policy uncertainty is linked to loan pricing. Comparing two banks lending to the same firm in the same year, banks perceiving more monetary policy uncertainty charge a higher All-in-Drawn-Spread. This indicates that uncertainty about monetary policy leads to greater financial frictions at the firm level. In addition, the findings rule out the possibility that monetary policy uncertainty is contaminated with global uncertainty in the economy.

While the literature argues that monetary policy uncertainty impacts firm investment directly (Husted et al., 2020; Fasani et al., 2023), I find that the effect running through firm-level beliefs is much weaker than the indirect effect through bank lending decisions. The indirect impact of monetary policy uncertainty through the banking sector therefore has important implications for the communication of monetary policy decisions. An unpredictable policy leading to errors in bank interest rate forecasts increases monetary policy uncertainty at the bank level. Consequently, inconsistent policy leads to surges in borrowing costs in the economy. Central bank communication should thus extensively communicate after large monetary policy surprises to reestablish the predictability of monetary policy. Finally, the paper calls for a closer monitoring of the banking sector perception of monetary policy decisions as these beliefs have real macroeconomic consequences.

7 Appendix

7.1 Appendix A.1: Example of Tealbooks

Figure 7: Example Tealbooks

(a) Economic growth Sections

Oil and Commodity Prices

- The spot price of Brent crude oil has increased about $1 per barrel since the time of the January Tealbook and is now trading at $56 per barrel, in line witl our January forecast. Spot prices have been supported by reports that OPEC countries implemented 90 percent of their agreed-upon production cuts in January. In contrast, the December 2019 futures price has dipped about $1.50 per barrel and is currently at $55 per barrel, reflecting an upward revision to the forecast for U.S. oil production over the medium term. In line with these futures quotes, we forecast that oil prices will decline very gradually over the projection period.

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- Prices for industrial metals have risen nearly 5 percent since the January Tealbook, driven mostly by recent supply shortages for copper, nickel, zinc, and aluminum but also supported by a pickup in demand from China. Lumbe prices are up nearly 11 percent so far in 2017 because of concerns that the U.S.–Canada trade dispute over softwood lumber will restrict Canadian exports to the United States later this year.

THE OUTLOOK FOR REAL GDP

After rising at an annual rate of about 2 percent in the fourth quarter of last year,

(b) Monetary Policy Sections

Monetary Policy

- The intercept-adjusted inertial Taylor (1999) rule that is used in our projection calls for the federal funds rate to increase a little less than 1 percentage point per year, on average, over the projection period and to be 3.4 percent in the fourth quarter of 2019.[3] The path for the federal funds rate is little changed from the January projection.
- We continue to assume that the SOMA portfolio will remain at its current level until the third quarter of 2017 and then begin to contract, as the proceeds from maturing assets are no longer reinvested.

Other Interest Rates

- The 10-year Treasury yield for the current quarter is essentially in line with our January projection. Over the medium term, the 10-year Treasury yield is still projected to rise significantly, from an average of 2.5 percent in the current quarter to 3.9 percent by the end of 2019.
- Triple-B corporate bond spreads are about 20 basis points narrower than we projected in the January Tealbook, and we carried forward part of the narrower spread in the forecast. The path of 30-year fixed mortgage rates was revised up slightly, but only because of a methodological change in the calculation of these rates.[4]

Equity Prices and Home Prices

- Equity prices have risen around 5½ percent since the January Tealbook, more than we had anticipated. We view this increase as having raised valuation pressures, which reduces slightly the scope for further stock price appreciation

Notes. The figure shows the Tealbooks A ("Report to the FOMC on Economic Conditions and Monetary Policy") published by the Federal Reserves. Before June 2010, this publication was known as the Greenbook. Panel (a) illustrates an example of the sections of titles classified as economic growth. Panel (b) is an example of Monetary Policy sections used to build the monetary policy dictionary.

7.2 Appendix A.2: Monetary policy dictionary

Table 6: List of monetary policy titles in Tealbooks A

Title
monetary policy
key background factors monetary policy
policy expectations and treasury yields
securities financing
special questions on the financing of cmbs and clos
special questions on long term changes in standards
treasury yields and policy expectations
special questions on the funding of high yield corporate bonds
special questions on the total return swaps referencing
financial institutions and short term funding markets
short term funding markets
special questions on market funding and liquidity
short term dollar funding markets and financial institutions
treasury and agency mbs market functioning
short term funding markets and financial institutions
treasury yields
treasury and agency finance and market functioning
treasury and other benchmark yields and policy expectations
policy expectations and treasury and agency mbs yields
policy expectations and asset prices
treasury and agency finance and short term funding markets
short term funding markets and year end dynamics
federal reserve operations and market functioning
short term funding markets and federal reserve operations
federal reserve operations and short term funding markets
federal reserve operations and short term funding marketsf
policy expectations and asset market developments
and federal reserve operations

Notes. The table depicts the list of monetary policy titles in the Tealbooks A. The titles are retrieved from the Tealbooks with regular expressions. The economic titles are the titles classified as having to do with domestic economic development and GDP outlook. The monetary policy titles are related to financial development related to monetary policy and the key background factors related to monetary policy. The texts following the titles are then cleaned removing newline characters, numeric characters, non-alphanumeric characters and big white space. Finally, stop-words are removed from the monetary policy and economic text.

Table 7: List of monetary policy words

money market	employment report	overnight index	issuance purchase
term premium	yield right	spread year	corporate bond
fund future	survey respondent	primary dealer	tips measure
security semiannual	premium basis	respondent percent	par security
bond spread	swap rate	maturity security	smoothed yield
financing rate	debt ceiling	policy expectation	swap quote
investment grade	target federal	market measure	yield notional
security yield	reverse repurchase	demand funding	term funding
valuation window	dollar funding	movement year	bond yield
repo rate	federal fund	source staff	straight read
source percent	path year	market participant	market stable
effective federal	distribution federal	repurchase agreement	curve smoothed
minute interval	curve indexation	financial market	fund rate
comparable maturity	agreement source	yield curve	market rate
future contract	curve run	nominal yield	policy rule
dollar percent	coupon security	run coupon	survey primary
future rate	dealer survey	policy path	interest rate
policy rate	yield source	market quote	intraday standard
commercial paper	data release	market expectation	notional par
window period	dealer market	yield basis	term rate
staff estimate	financial institution	market fund	funding market
yield period	note overnight	term yield	term security
path federal	yield investment	coupon source	downward revision
semiannual coupon	index percent	index swap	target range
monetary policy	forward rate	speculative grade	grade corporate
smoothed nominal	nominal security	deviation basis	liquidity functioning
debt limit	purchase program	risk premium	security basis
intermeeting period	term interest	dollar roll	central bank
general collateral			
Federal Reserve	Open Market	Alan Greenspan	Central Bank
The Fed	Quantitative Easing	Janet Yellen	Interest Rates
Money Supply	Monetary Policy	Jerome Powell	Fed Chairman
Fed Funds	Overnight Lending	Jay Powell	Fed Chair
Ben Bernanke	Central Bank	Last Resort	Discount Window
European Central	The ECB	Bank England	Bank Japan
The BOJ	Bank China	The Bundesbank	Bank France
Bank Italy			

Notes. The table shows the list of monetary policy bi-grams from the text following the monetary policy titles of Tealbooks A. The monetary policy bi-grams are obtained by looking at their frequency. A bigram has to appear in at least 30 Tealbooks A, has no ambiguous meaning, appears more than 30 economic sections of the Tealbooks A. Finally, I remove bigrams containing the unigram "inflation and price. Monetary policy words from Baker et al. (2016) are then added to the list.

7.3 Appendix B: Bank Fundamentals

Table 8: Summary Statistics for Banks

	N	Mean	SD	p25	p50	p75
$\text{MPAtt}_{b,t}$	10945	5.737	4.993	2.000	5.000	8.000
$\text{MPUn}_{b,t}$	10945	0.000	0.000	0.000	0.000	0.000
$\log(\text{Size})_{b,t}$	10320	15.899	1.648	14.769	15.649	16.688
$\text{Eq/TA}_{b,t}$	10319	10.923	3.592	8.976	10.542	12.344
$\text{Cost/inc}_{b,t}$	10089	62.978	21.326	54.507	61.141	67.868
$\text{Loans/dep}_{b,t}$	10085	92.071	22.410	82.117	92.318	100.672
$\text{ROA}_{b,t}$	10218	0.876	1.743	0.715	1.030	1.318
$\text{LLP}_{b,t}$	10218	0.145	0.332	0.019	0.056	0.134
Federal Fund rate_t	10907	1.609	1.709	0.250	1.000	2.250
$\text{inflation}_t(QoQ)$	10907	0.578	0.435	0.349	0.512	0.708
GDP $\text{growth}_t(QoQ)$	10907	0.531	1.482	0.321	0.612	0.886
$\log(\text{SP500})_t$	10907	7.551	0.487	7.137	7.562	7.961
employment_t	10907	147909.452	7159.519	141526.000	146241.000	153786.000

Notes. The first two rows present summary statistics for bank attention $MPAtt_{b,t}$ and uncertainty $MPUn_{b,t}$ about monetary policy. $MPAtt_{b,t}$ is the number of time banks mention a monetary policy bigrams in their earnings calls, while $MPUn_{b,t}$ is the number of synonyms of risk and uncertainty within 10 words of a monetary policy bigrams. Bank controls include the log of total assets ($\log(\text{Size})_{b,t}$), total equity over total assets ($\text{Eq/TA}_{b,t}$), provisions for loan losses over total gross loans ($\text{LLP}_{b,t}$), the cost to income ratio ($\text{Cost/inc}_{b,t}$), the return-on-assets ($\text{ROA}_{b,t}$) and the net loans over total deposits ($\text{Loans/dep}_{b,t}$). The last five variables are used in Appendix I Table 13. Federal Fund rate_t is the US federal fund target rate, inflation_t is quarter-on-quarter growth of the CPI, GDP growth_t is quarterly real GDP growth, $\log(\text{SP500})_t$ is the log of the SP500 and employment_t is the US total civilian employment.

7.4 Appendix C: Dealscan descriptive statistics

Table 9: Summary Statistics Dealscan

	N	Mean	SD	p25	p50	p75
Tranche controls						
AISD	37656	2.181	1.275	1.250	2.000	2.750
Log Tranche	39745	5.707	1.475	4.828	5.858	6.780
Log Maturity	39485	3.747	0.588	3.584	4.043	4.094
Secured	550137	0.040	0.196	0.000	0.000	0.000
Covenant	550137	0.044	0.205	0.000	0.000	0.000
Performance Pricing	543301	0.019	0.136	0.000	0.000	0.000
Number Lead Arrangers	39766	3.586	3.157	1.000	2.000	5.000
Relation Loan	550137	0.001	0.030	0.000	0.000	0.000
Borrower characteristics						
Log Total Assets	514247	7.563	2.413	5.976	7.616	9.289
Fixed Assets	329130	0.627	0.466	0.258	0.539	0.902
Market Leverage	510859	1.769	6.894	0.568	1.250	2.416
ROA	513075	0.053	5.145	-0.229	0.904	1.974
Interest Coverage	457610	8.873	44.974	-0.201	1.946	6.749
Listed	515984	0.972	0.165	1.000	1.000	1.000
Bank characteristics						
Log Total Assets	36558	20.635	1.135	20.355	21.057	21.282
Equity-to-assets	36558	9.354	1.671	8.316	9.298	10.553
Cost-to-income	41209	61.451	8.580	57.250	59.856	64.543
Loans/dep	36558	78.089	17.825	65.772	74.593	88.593
ROA	41629	0.982	0.598	0.786	1.046	1.340
LLP	35677	0.243	0.267	0.091	0.157	0.302
Sentiment Indices						
MPU	44762	0.000	0.000	0.000	0.000	0.000
MPSent	44762	0.001	0.001	0.000	0.000	0.001
Sent	38734	0.099	0.030	0.081	0.101	0.121
Un	44762	0.004	0.002	0.003	0.003	0.004
Analyst MPU	44762	0.000	0.000	0.000	0.000	0.000

Notes. The first rows present summary statistics for tranche controls. Log Tranche is the log of the Tranche Amount in USD, Log Maturity is the log of the loan maturity, Secured is a dummy for secured loans and Covenants is a dummy for covenant loans. Performance Pricing is a dummy for the presence of performance pricing, the number of Lead lenders and Relation Loan, a dummy equal to 1 if the bank has lent to the firm in the last three years. Borrower characteristics include the log of Total Assets, the fixed asset ratio (Property Plan and Equipment over Total Assets, leverage (assets - total equity over total equity), ROA, interest coverage ratio (EBIT/interest expenses) and Listed (a listed dummy). Bank characteristics are the log of total assets ($\log(\text{Size})_{b,t}$), total equity over total assets ($\text{Equity-to-assets}_{b,t}$), provisions for loan losses over total gross loans ($\text{LLP}_{b,t}$), the cost to income ratio ($\text{Cost-to-income}_{b,t}$), the return-on-assets ($\text{ROA}_{b,t}$) and the net loans over total deposits ($\text{Loans/dep}_{b,t}$). Sentiment indices include MPU (Bank monetary policy uncertainty), MPSent (Bank Sentiment about monetary policy), Sent (Bank sentiment) and Un (total uncertainty of the earnings calls).

7.5 Appendix D: Loan Pricing - Robustness

Table 10: Relationship between Lending Conditions and bank monetary policy uncertainty - Robustness

	(1) AISD	(2) AISD	(3) AISD	(4) AISD	(5) AISD	(6) AISD	(7) AISD
MPU	271.436**	297.098**	298.922**	314.830**	282.220***	282.220***	202.685***
	(112.389)	(129.188)	(141.703)	(141.116)	(92.036)	(94.133)	(41.457)
MPSent	7.399	14.932	-5.464	19.839	3.728	3.728	7.340
	(14.559)	(17.312)	(13.386)	(20.254)	(14.582)	(14.864)	(9.514)
Sent	-1.318	-1.413	-1.067	-1.168	-1.219	-1.219	-0.528
	(0.833)	(0.983)	(0.916)	(0.723)	(0.994)	(0.904)	(0.324)
Un	-24.013**	-27.983*	-22.795***	-29.257***	-24.997**	-24.997**	-4.604
	(11.077)	(13.920)	(7.008)	(7.729)	(11.654)	(10.922)	(5.782)
Analyst MPU	-206.982***						
	(71.360)						
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tranche Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Tranche Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	No
Bank FE	No	No	No	No	No	No	No
Firm x Year FE	No	No	No	No	No	No	No
robustness		P-weight	F-weight	Lag controls	Bank-Time Clustering	Bank-Firm Clustering	ISLT
N	19,564	19,564	36,848	19,375	19,564	19,564	17,276
R2	0.458	0.436	0.466	0.471	0.458	0.458	0.819

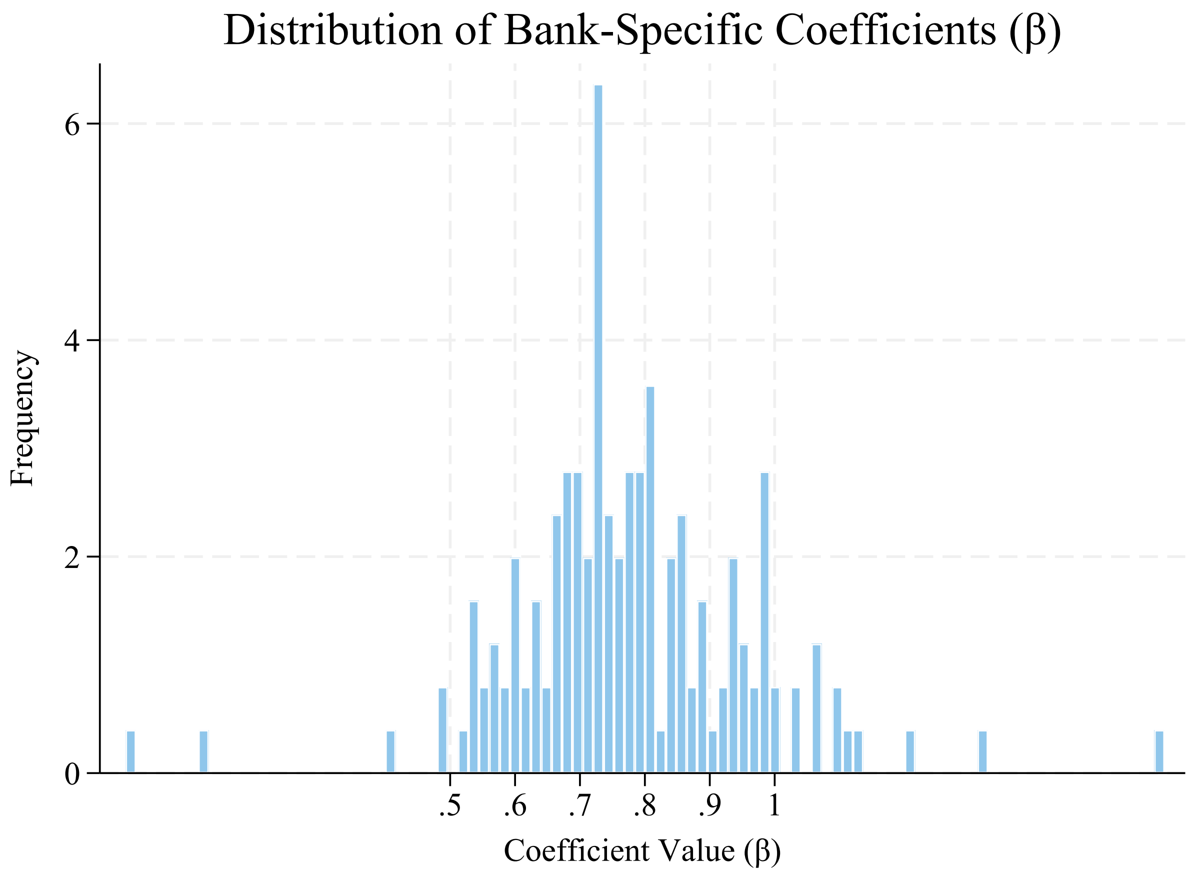
Notes. The table shows the OLS estimates from regressions of the All-In-Spread-Drawn (AISD) on bank monetary policy uncertainty, tranche firm, and bank controls. The weights are the inverse of the Lender-Share and the number of lead lenders (when Lender share is not available) the Bank monetary policy attention is the count of monetary policy bigrams in earnings calls. Bank monetary policy uncertainty is computed looking at 10 words before and after the monetary policy words, and counting synonyms of risk words. The sample runs from Q1 2002 until Q4 2023 for US banks lending to US firms. The data is obtained merging our sentiment dataset and the syndicate loan market, and Compustat. We only retain observations where the bank is always the lead bank. The bank controls are log(Size), Equity-to-assets ratio, Return-on-assets (ROA), Loans-to-deposit and loan-loss-provisions. Tranche controls are log(Tranche Amount in USD), a secured and covenants dummy, a dummy for the presence of performance pricing, the number of lenders and a dummy equal to 1 if the bank has lent to the firm in the last five years. Firm Controls include log(Total Assets), fixed asset ratio, leverage, ROA, interest coverage ratio and a listed dummy. All variables are winzorized at the 1% level. Standard errors (in parentheses) allow for clustering at the bank level. ***, ** and * refer to significance at the 1%, 5% and 10%.

This section discusses different robustness tests to the main specification in Table 5. The first column in Table 10 controls for analyst perceived monetary policy uncertainty Analyst MPU. To build this index at the bank-level, I separate parts of the Q&A where analysts speaks from parts where manager speak. Analyst MPU is an important control to remove the possibility of bank managers catering to analyst by increasing their perceived monetary policy uncertainty (Simpson, 2013). Bank monetary policy uncertainty is still significant and the economic magnitude is roughly the same.

Column (2) and (3) addresses the unique high-dimensional nature of the Dealscan data. Indeed, Dealscan is reported at the tranche-participant level. This means that each tranche has one row for each bank participating in the syndicate. Tranches with a lot of participants are thus over-represented in the sample. The baseline regression in Table 10 deals with this issue by controlling for the number of lead arrangers. This robustness test goes one step further with a Weight-Least-Square strategy. Column (2) conducts WLS with sampling weights equal to the lender share in decimals and 1 over the number of lenders when lender share is not available. Observations where banks have a bigger say in the lending conditions of the syndicate (with a bigger share of the syndicate) are thus over-weighted in the estimation. Column (3) adopts a more straightforward approach with a frequency weight equal to the inverse of the number of lenders. The magnitude of the impact increases for both specifications which suggests that the results are robust to adopting different weighting techniques.

Following Ma et al. (2021) and Degryse et al. (2023), I run a specification lagging both lenders and firm controls. In column (4), firm characteristics are a state variable observed by the lender before choosing lending conditions. The relationship between bank monetary policy uncertainty is robust to lagging firm and bank controls. The next two columns vary the clustering of standard errors. While standard errors in column (5) allow for correlation within banks due to macro-economic shocks hitting the banking sectors, the standard errors in column (5) are robust to standard errors being correlated at the bank-firm relationship due to bank specialization in some firms. Finally, column (7) adopts a different strategy than Khwaja and Mian (2008) to control for credit demand. One of the limitations of firm-time fixed effects is that they limit the sample to multi-bank firms who borrow from many banks. These firms may not representative of the whole sample because they have easier access to finance. The solution is to control for credit demand without restricting the sample to multi-bank firms. Therefore, column (7) forms buckets of firms with similar industry, size, location and year and compares the lending of two banks lending to the same group within the same year. The assumption is only that firms located in the same US State, in the same total asset decile and sic industry (with 2 digits) have a similar credit demand. The results are robust to considering single-bank relationship firms when controlling for credit demand.

Figure 8: Stickiness in Forecast Errors



Notes. The figure displays the distribution of regression coefficients of the forecast error ($i_t - E_t[i_t]$) on the forecast revision ($E_t[i_t] - E_{t-1}[i_t]$). Banks need to participate at least 10 times in the survey and submit at least two different forecasts in the sample.

Section 2.6 shows that past absolute forecast errors and monetary policy uncertainty are correlated. Therefore, changes in lending rates in the syndicated loan market could reflect a correction towards the correct interest rates after a large absolute error in forecast. The correlation between high monetary policy uncertainty and lending rates would only reflect the impact of past absolute errors in perceived uncertainty and forecast corrections. Indeed, if agents are rational, they should change their interest rate forecasts after a large error to include all past available information. Agents would not systematically under or overreact to the information in their forecasts and we would not observe systematic errors in forecasts. We can test the Full Information Rational Agent hypothesis on bank forecast data following Coibion and Gorodnichenko (2015):

$$i_t - E_{b,t}[i_t] = \beta_0 + \beta_1 E_{b,t}[i_t] - E_{t-1}[i_t] + \epsilon_{b,t} \tag{7}$$

In the regression i_t is the Federal Fund Rate and the expectation operation $E_t[i_t]$ gives the forecast of bank b at quarter t. In this regression, $\beta_1 > 0$ signals under-reacting to incoming news, which is often called a sticky information bias. Figure 8 illustrates that all bank-level coefficients are above 0. This indicates that banks forecasts of interest rates are sticky and banks often do not change their forecast enough after incoming information to reduce their forecast errors. The pooled OLS coefficient of 0.77 highlights an elevated level of stickiness, in line with estimates of 0.71 and 0.67 in the Survey of Professional Forecasters and Bluechip data (Bordalo et al., 2020) Furthermore, despite the great heterogeneity in bank-level coefficients, most estimates are between 0.5 and 1, which strengthens the idea that banks slowly adjust their belief about monetary policy interest rates. A systematic reaction in lending rates due to past forecast errors is thus not likely to drive the positive correlation between monetary policy uncertainty and lending conditions. To conclude, Coibion and Gorodnichenko (2015) regressions document that banks are are prone to the sticky information bias found elsewhere in the behavioral economics literature (Bouchaud et al., 2019; Bordalo et al., 2019, 2018) and therefore do not correct their lending rates after absolute forecast errors.

7.6 Appendix E: FOMC meetings descriptive statistics

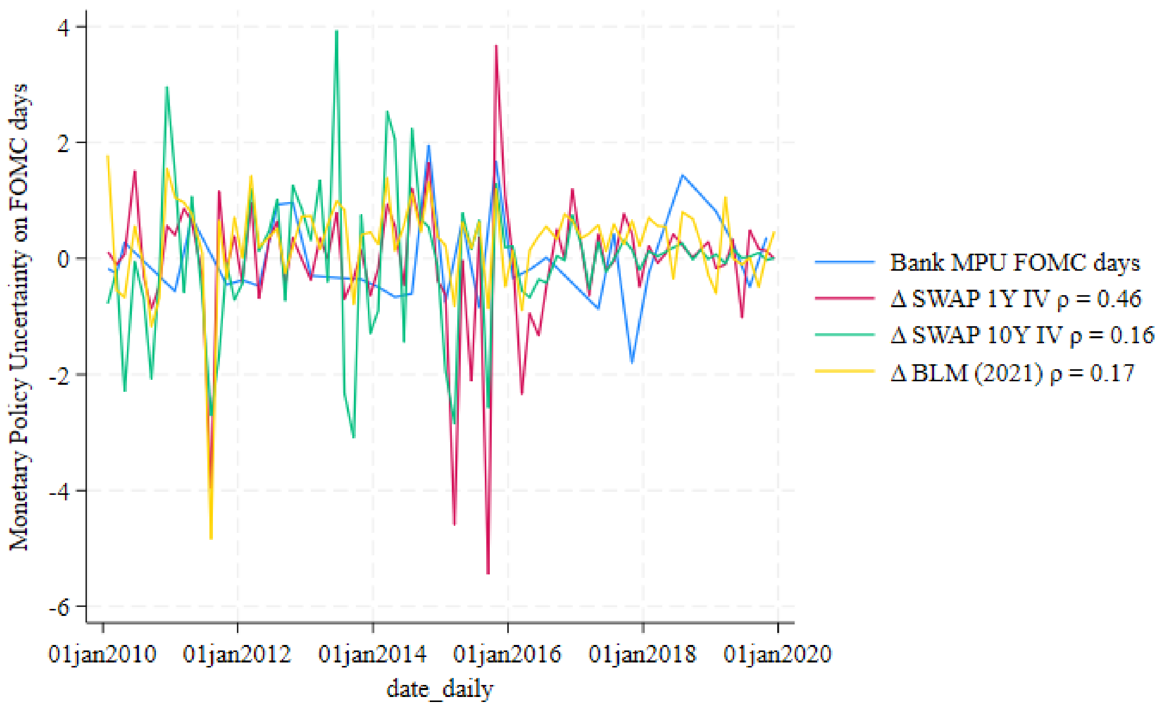
Table 11: Summary Statistics - FOMC level

	N	Mean	SD	p25	p50	p75
$\hat{\epsilon}_t$	49	-0.000003	0.00004	-0.00003	-0.00002	0.00001
BankMPU$_{FOMC,b,t}$	60	0.000040	0.00004	0.00000	0.00004	0.00007
US MPU	160	118.624979	63.03241	79.61288	104.13634	137.70456
Target	160	-0.002796	0.03902	-0.00553	0.00000	0.00500
ED4s	160	0.000000	0.05668	-0.02506	0.00320	0.02949
TNOTE10s	160	0.000000	0.03009	-0.01000	-0.00151	0.01178
Num Banks$_t$	60	7.033333	6.27334	1.50000	4.50000	11.50000
Num Banks$_{t-1}$	54	7.055556	4.78369	2.00000	7.50000	11.00000

Notes. This table depicts the summary statistics of the variables used in FOMC-level regressions. $\hat{\epsilon}_t$ is the average residuals of a regression of bank monetary policy uncertainty on its fundamentals and analyst monetary policy uncertainty. BankMPU$_{FOMC,b,t}$ is monetary policy uncertainty measured on FOMC days. US MPU is market-based monetary policy uncertainty from Bauer et al. (2021). Target measures the surprise change in the current or next-month federal funds futures responses. ED4s, the forward guidance surprises, is computed as the residuals of the fourth Eurodollar futures contract on the target surprise. The asset purchase surprise (TNOTE10s) is residual of the change in ten-year yield over the target surprises and the forward guidance surprises. All surprises are from Bauer and Swanson (2022) and use a 30-min window around FOMC annoucements. Num Banks$_t$ is the number of banks presenting earnings calls on FOMC days.

Table 11 describes the descriptive statistics of the index orthogonal to bank fundamentals. Out of 160 FOMC announcement since Q2 2002 for which Husted et al. (2020) measures monetary policy uncertainty, I am able to measure monetary policy uncertainty for 60 FOMC meetings. Once controlling for bank fundamentals, this number goes down to 49 FOMC announcements. There are on average 7 banks revealing their earnings calls on that day. While the coverage in terms of FOMC meetings is limited, the number of banks for each meeting supports to the idea that the index is representative of the banking sector.

Figure 9: Monetary policy uncertainty and Market-based Measures

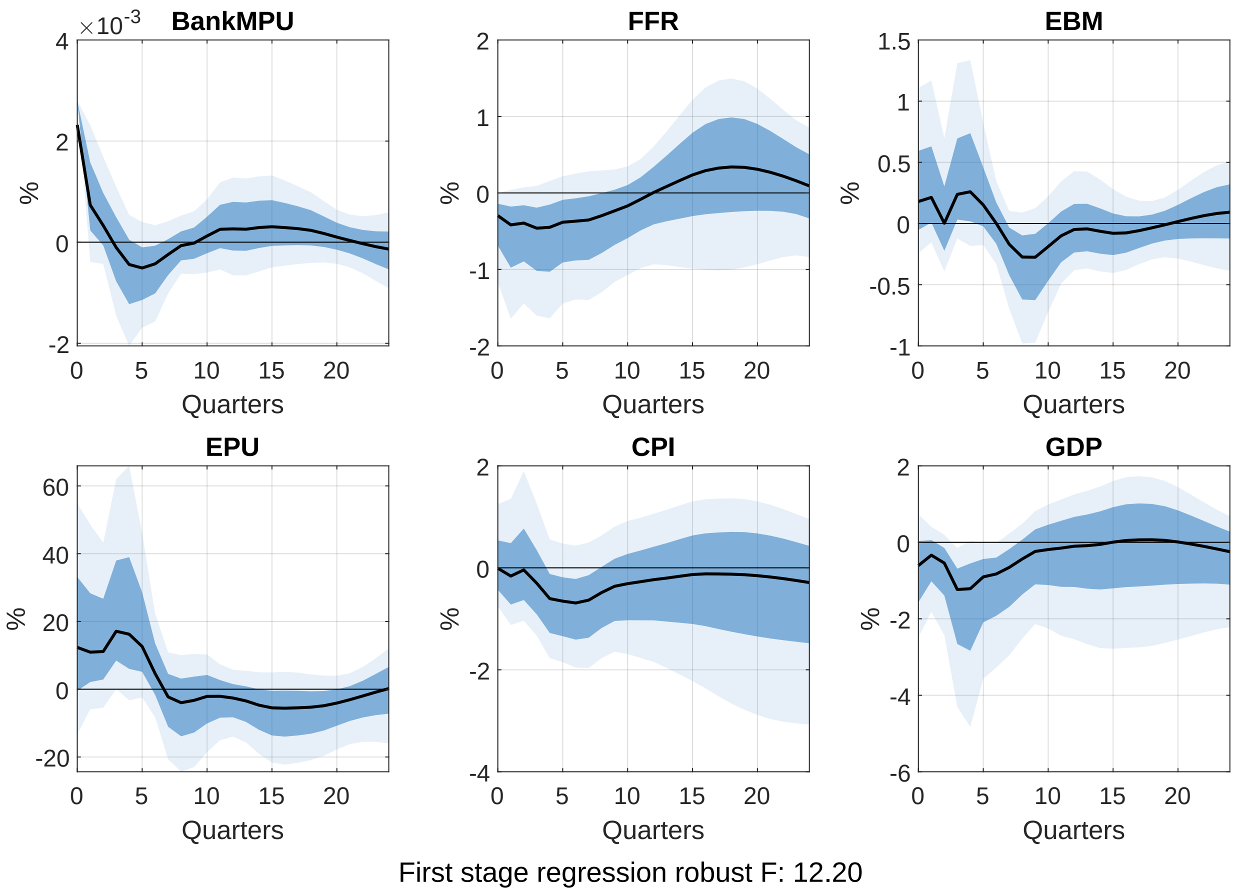


Notes. The graph depicts the correlation between market-based measures of monetary policy uncertainty and average monetary policy uncertainty in the banking sector on FOMC days from Jan 2010.. Bank MPU FOMC days is $\hat{\epsilon}$, the residual of eq (4). $\Delta SWAP1YIV$ is the daily variation of an implied volatility of a one year swap rate contract and $\Delta SWAP10YIV$ is the same volatility with a ten year-ahead contract. Both swap contract have an horizon of one month. $\Delta BLM(2021)$ is the daily variation of the market-based monetary policy uncertainty measure presented in Bauer et al. (2021). All variables are standardized to facilitate comparison.

7.7 Appendix F: Robustness VAR

7.7.1 Appendix F.1: Robustness VAR Specification

Figure 10: Uncertainty and economic activity: Impulse Response Function - Not orthogonalizing with bank fundamentals

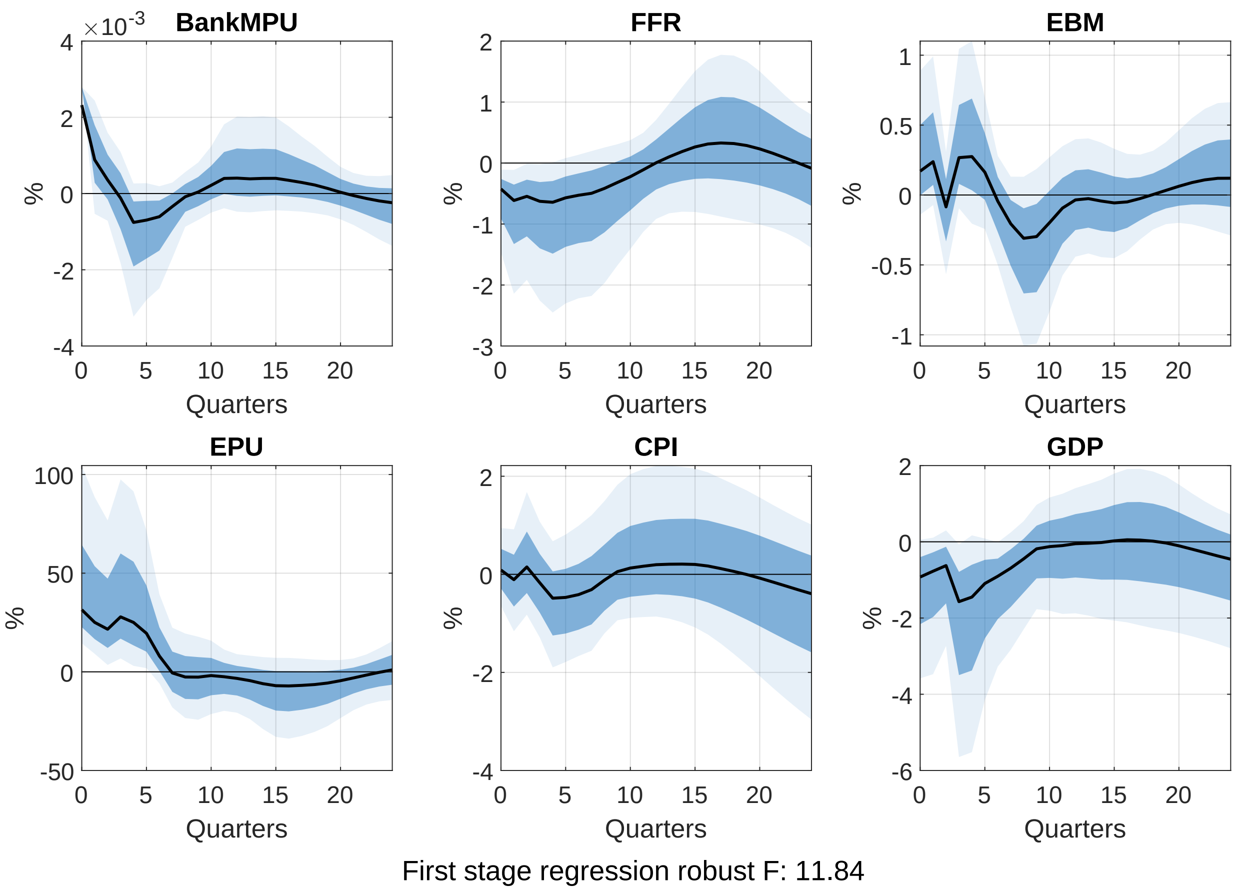


Notes. The figure displays the IRFs to a monetary policy uncertainty shock identified from an estimated quarterly SVAR using a US macroeconomic data. The identification strategy relies on high-frequency instrument using monetary policy uncertainty using earnings calls occurring on FOMC days only, where at least 5 banks conduct earnings calls. The daily uncertainty index is then orthogonalized with respect monetary policy decisions. The scheme follows Husted et al. (2020) and Fasani et al. (2023). The response are shown in percentage and the unit of the shock is one standard deviation. The sample is from Q1 2002 until Q4 2023. 68% (dark blue) and 90% (light blue) errors bands are computed using bootstrap standard errors.

7.7.2 Appendix F.2: Robustness Monetary Policy dictionary

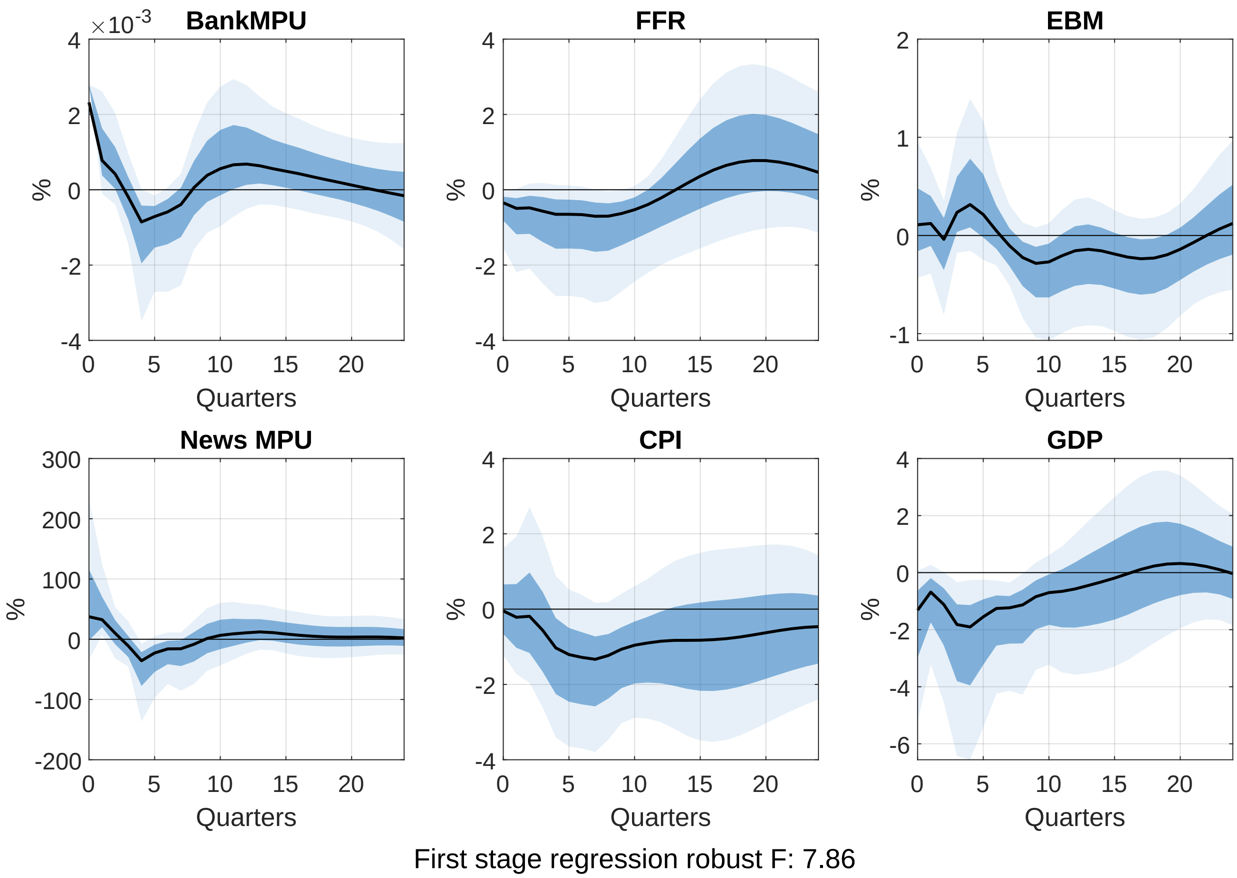
In this section, I test the robustness of the results to choices in the dictionary construction. In the baseline dictionary, I make several choices that could impact the results of the index

Figure 11: Uncertainty and economic activity: Impulse Response Function - all banks



Notes. The figure displays the IRFs to a monetary policy uncertainty shock identified from an estimated quarterly SVAR using a US macroeconomic data. The identification strategy relies on high-frequency instrument using monetary policy uncertainty using earnings calls occurring on FOMC days only. The daily uncertainty index is then orthogonalized with respect monetary policy decisions. The scheme follows Husted et al. (2020) and Fasani et al. (2023). The response are shown in percentage and the unit of the shock is one standard deviation. The sample is from Q1 2002 until Q4 2023. 68% (dark blue) and 90% (light blue) errors bands are computed using bootstrap standard errors.

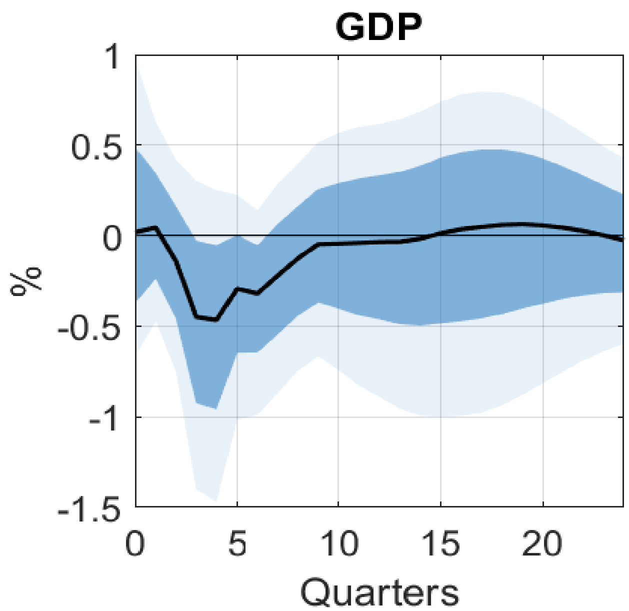
Figure 12: Uncertainty and economic activity: Impulse Response Function - News MPU



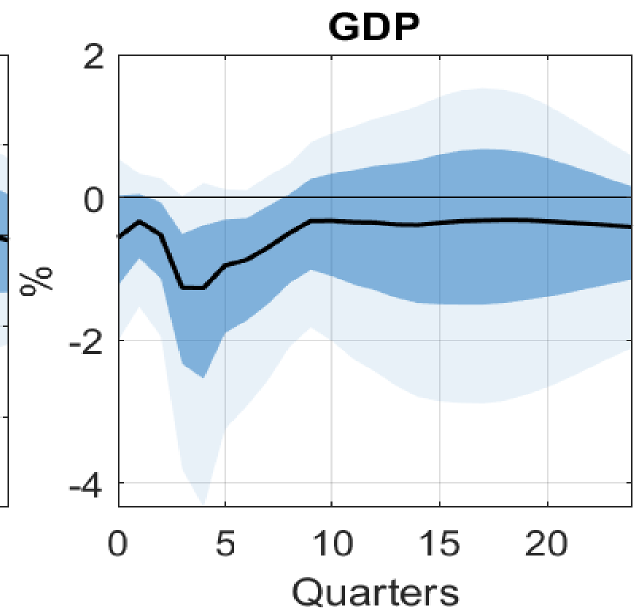
Notes. The figure displays the IRFs to a monetary policy uncertainty shock identified from an estimated quarterly SVAR using a US macroeconomic data and the news-based index of Husted et al. (2020). The identification strategy relies on high-frequency instrument using monetary policy uncertainty using earnings calls occurring on FOMC days only, where at least 5 banks conduct earnings calls. The daily uncertainty index is then orthogonalized with respect to bank fundamentals and monetary policy decisions. The scheme follows Husted et al. (2020) and Fasani et al. (2023). The response are shown in percentage and the unit of the shock is one standard deviation. The sample is from Q1 2002 until Q4 2023. 68% (dark blue) and 90% (light blue) errors bands are computed using bootstrap standard errors.

Figure 13: Uncertainty and economic activity: Impulse Response Function - different dictonaries

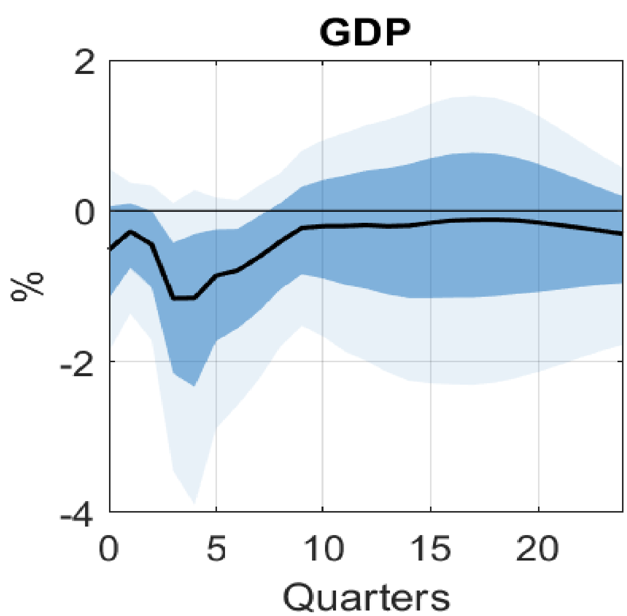
(a) Document-Frequency



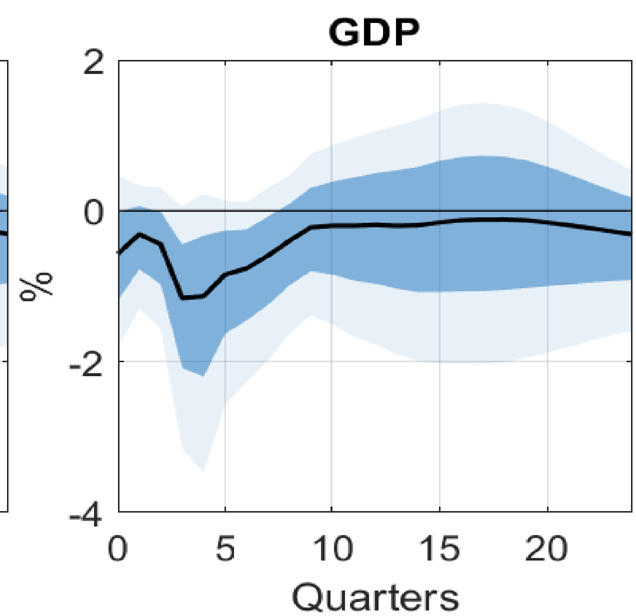
(b) Absolute Frequency



(c) TF-IDF matrix



(d) Inflation and Price



Notes. The figure displays the IRFs to a monetary policy uncertainty shock identified from an estimated quarterly SVAR using a US macroeconomic data. Panel (a) uses the document frequency matrix to select relevant monetary policy bi-grams. The algorithm in panel (b) only select 120 bigrams based on the absolute frequency. In panel (c), the algorithm selects the 100 most relevant words from monetary policy sections based on the TF-IDF matrix. Panel (d) deviates from the baseline by adding back the words "inflation" and "price" in the dictionary. In all specifications, the identification strategy relies on high-frequency instrument using monetary policy uncertainty using earnings calls occurring on FOMC days only, where at least 5 banks conduct earnings calls. 68% (dark blue) and 90% (light blue) errors bands are computed using bootstrap standard errors.

construction. The first choice made in the construction of the index relates to the threshold for a bi-gram to be relevant in the Tealbooks monetary policy section. In the baseline, I assume that a bi-gram has to appear at least in half of the Tealbooks to be relevant based on the absolute frequency. In the first robustness test in panel (a), I take another approach words to enforce this criteria. Instead of using the absolute count, I use the document frequency to select relevant words. The criteria is that bi-grams have to appear in at least 50% of the documents. This filtering is robust to the possibility that a terms appear a lot in one document and not others. The impulse response functions show that the reaction of GDP to an uncertainty shock is similar to the baseline specification.

Panel (b) selects words based on absolute frequency. A word has to appear at least two times per meeting. Since there are sixty meetings, the bi-gram has to have an absolute frequency of 120 words to be included in the dictionary. The results are robust to this alternative dictionary. The results are not driven by using the TF-IDF methods in the baseline.

In panel (c), the criteria for relevant monetary policy words is modified. As in the baseline, I use the TF-IDF algorithm to find relevant words as in Hassan et al. (2024). Words are ranked high if they appear a lot in a document while not appearing a lot in all documents. Once all words are ranked, I select the 100 most relevant words and built the dictionary as described in the baseline. This contrasts with the baseline using a TF-IDF criteria to select words. Figure 13 illustrates the stability of the results. The drop in GDP after a monetary policy uncertainty shock remains significant and of a similar magnitude.

Another important robustness test is to test whether the results are robust to keeping inflation words into the dictionary. In the baseline, I am interested in words that refer to monetary policy and not inflation. Words such as "inflation" and "price" are thus removed to the dictionary to reduce noise. In this robustness test, I evaluate the strength of the results by keeping these inflation bi-grams. Figure 13 panel (d) shows that the main result remain consistent.

To conclude, since the criteria of relevance for monetary policy bi-grams is somewhat arbitrary, this section selects relevant monetary policy bi-grams with different text-mining strategy. The impact of monetary policy beliefs on economic activity remains robust to alternative dictionary constructions.

7.8 Appendix G: First stage regression daily variations

Table 12: Monetary Policy Beliefs and Monetary Policy Surprises

	(1)	(2)
	$\Delta\hat{\epsilon}_t$	$\Delta\hat{\epsilon}_t$
Target	-0.000944**	-0.00118***
	(0.000406)	(0.000343)
ED4s RSW	0.000461***	
	(0.000142)	
TNOTE10s RSW	-0.0000892	
	(0.000280)	
ED4s		0.000522***
		(0.000155)
TNOTE10s		-0.000343
		(0.000569)
N	29	40
R2	0.398	0.372

Notes. This table shows regression of monetary policy uncertainty daily shocks on monetary policy surprises computed with Bauer and Swanson (2022) data. Target measures the surprise change in the current or next-month federal funds futures responses. The forward guidance surprises (ED4s) is computed as the residuals of the fourth Eurodollar futures contract on the target surprises. The asset purchase surprise (TNOTE10s) is residual of the change in ten-year yield over the target surprises and the forward guidance surprises. ED4s RSW is computed as the residuals of the fourth Eurodollar futures contract on the target surprises from Rogers et al. (2018). ONRUN101 is the residual of the change in ten-year yield over the target surprises and the forward guidance surprises from Rogers et al. (2018). Bauer and Swanson (2022) uses a 30-min window around FOMC annoucements while Rogers et al. (2018) computes the change from 15 min before FOMC annoucements to 1h 45 min afterwards. ***, ** and * refer to significance at the 1%, 5% and 10%.

7.9 Appendix H: Bank MPU and Macro-economic Variables

Table 13: Relationship between managers' and analysts' sentiment

	(1) $\text{MPAtt}_{b,t}$	(2) $\text{MPUn}_{b,t}$
Federal Fund rate_t	0.0976^{***}	0.0178^{**}
	(0.0130)	(0.00885)
inflation_t	0.0458^{***}	0.0184^{*}
	(0.0109)	(0.00947)
GDP growth_t	-0.0158^{***}	0.0171^{***}
	(0.00451)	(0.00390)
$\log(\text{SP500})_t$	-0.0143	-0.185^{***}
	(0.0656)	(0.0490)
$\log(\text{emp})_t$	-0.566	-0.306
	(0.592)	(0.471)
Husted et al.$(2020)_t$	0.00175^{***}	0.00108^{***}
	(0.000141)	(0.000128)
Time FEs	No	No
Bank FEs	Yes	Yes
N	10349	10349
R2	0.349	0.199

Notes. This table shows regression of bank managers' attention and uncertainty index computed on their earning calls. Bank monetary policy attention is the count of monetary policy bigrams in earnings calls. Bank monetary policy uncertainty is computed looking at 10 words before and after the monetary policy words, and counting synonyms of risk words. All controls are winsorized at the first and 99th percentile. Attention and Uncertainty are winsorized at the 99th percentile only. Standard errors (in parentheses) are clustered at the bank-level and ***, ** and * refer to significance at the 1%, 5% and 10%.

7.10 Appendix I: The impact of Monetary Policy Uncertainty - Local Projections

This appendix looks at the dynamics of the impact of monetary policy uncertainty on investment decisions. Using firm-level data from 2004 Q1 until 2024 Q1, I run the following local projections over h horizons:

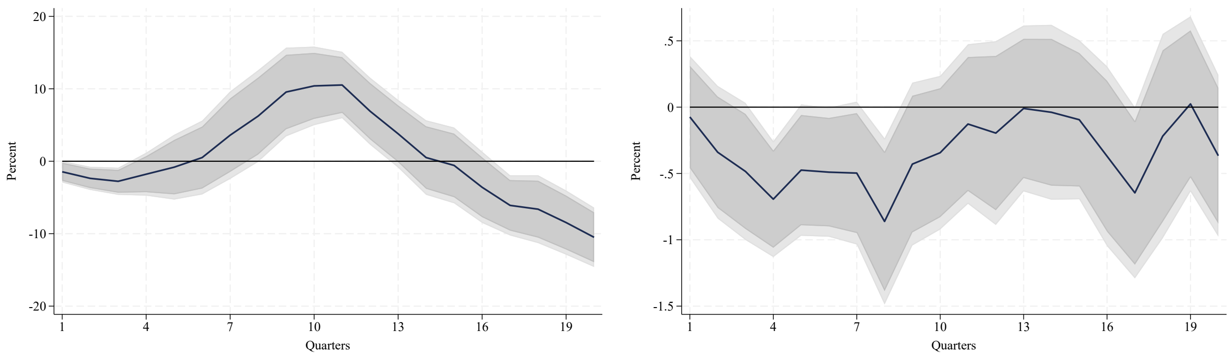
$$log(ik_{i,t+h}) = \gamma_i + \theta_t + \beta_1 BankMPU_t + \beta_3 Q_{i,t-1} + \beta_4 \frac{\text{CF}_{i,t}}{\text{TA}_{i,t-1}} + \beta_5 \text{SG}_{i,t} + \beta_6 M_{t-1} + \beta_7 log(ik_{i,t-1}) + \varepsilon_{i,t} \tag{8}$$

where the dependent variable $log(\frac{\text{CAPX}_{i,t}}{\text{PPENT}_{i,t-1}})$ measures the investment ratio of firm i at quarter t, as in (Caldara and Iacoviello, 2022). $BankMPU_t$ is the monetary policy uncertainty index, $Q_{i,t-1}$ is the Tobin's Q while $\frac{\text{CF}_{i,t}}{\text{TA}_{i,t-1}}$ and $\text{SG}_{i,t}$ are the cash flows and sales growth following Husted et al. (2020). $M_{i,t-1}$ are the same as in Husted et al. (2020) and include GDP growth, the Economic Policy Uncertainty Index of Baker et al. (2016), the expected GDP growth over the next 6 months, Consumer Confidence and the Expected Business Condition index from the University of Michigan. The macroeconomic variables control for macroeconomic conditions and expectations about future investment profitability which impact investment decisions. Finally, γ_i and θ_t are a firm fixed effects and a fiscal quarter fixed effect. The fixed effects control for time-invariant unobservables at the firm level and seasonality in investment.

Local projections in Table 14 compare the 95% (dark gray) and 90% (light gray) confidence interval of the response of the $log(ik_{i,t+h})$ to a one standard deviation shock in uncertainty. Panel (a) illustrates that most of the impact of monetary policy uncertainty in the banking sector on firm investment occurs within the first year of an uncertainty shock. The strong rebound in investment after the first year nevertheless shows some wait-and-see dynamics. After a year of pausing investment due to elevated uncertainty about rates, firms appear to have postponed their investment decisions as in Baker et al. (2016). When uncertainty resolves, firms invests leading to an investment boom. Panel (b) documents that monetary policy uncertainty at the firm level also predicts falls in investment. However, the effect is

Figure 14: Local-Projections of firm-level Investment on aggregate Monetary Policy Uncertainty and firm Monetary policy Uncertainty

(a) Bank MPU **(b)** Firm MPU



Notes. The left panel outlines the dynamic response of investment following a one standard deviation shock in aggregate monetary policy uncertainty in the banking sector. The right panel depicts the dynamic response of investment after a one standard deviation shock in firm-level monetary policy uncertainty. The shaded areas describe 90 and 95 percent confidence intervals. Standard errors are clustered at the firm and quarter level.

long-lived and can lasts up to two years after an uncertainty shocks. The economic magnitude of the impact between bank and firm monetary policy uncertainty differs. A one standard deviation increase in monetary policy uncertainty in the banking sector predicts a fall in investment of 2.86% over the next two quarters while the same impact diminishes investment by -0.488% for firm monetary policy uncertainty. Overall, the local projections indicate that the magnitude of monetary policy uncertainty in the banking sector is much greater than firms' monetary policy uncertainty. While the main message of the static regressions remains, local projections also highlight that firm-level beliefs have a lasting impact on investment.

References

Aikman, D., F. Monti, and S. Zhang (2024). In the Fed we trust? Measuring trust in central banking and its effects on the macroeconomy. *CEPR Discussion Paper DP19811*.

Baker, S. R., N. Bloom, and S. J. Davis (2016, November). Measuring Economic Policy Uncertainty*. *The Quarterly Journal of Economics 131*(4), 1593–1636.

Bauer, M. D., A. Lakdawala, and P. Mueller (2021). Market-based Monetary Policy Uncertainty. *the economic journal 132*, 1290–1308.

Bauer, M. D., C. E. Pflueger, and A. Sunderam (2023). Perceptions about Monetary Policy.

Bauer, M. D. and E. T. Swanson (2022). A Reassessment of Monetary Policy Surprises and High-Frequency Identification. *NBER Macroeconomics Annual*.

Berg, T., A. Saunders, S. Steffen, and D. Streitz (2017, March). Mind the Gap: The Difference between U.S. and European Loan Rates. *The Review of Financial Studies 30*(3), 948–987.

Bianchi, F., C. L. Ilut, and M. Schneider (2018, April). Uncertainty Shocks, Asset Supply and Pricing over the Business Cycle. *The Review of Economic Studies 85*(2), 810–854.

Blinder, A. S., M. Ehrmann, J. De Haan, and D.-J. Jansen (2024, June). Central Bank Communication with the General Public: Promise or False Hope? *Journal of Economic Literature 62*(2), 425–457. Publisher: American Economic Association.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica 77*(3), 623–685.

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer (2020). Overreaction in macroeconomic expectations. *American Economic Review 110*(9), 2748–82.

Bordalo, P., N. Gennaioli, R. L. Porta, and A. Shleifer (2019). Diagnostic Expectations and Stock Returns. *The Journal of Finance 74*(6), 2839–2874.

Bordalo, P., N. Gennaioli, and A. Shleifer (2018). Diagnostic Expectations and Credit Cycles. *The Journal of Finance 73*(1), 199–227.

Bouchaud, J.-P., P. Krüger, A. Landier, and D. Thesmar (2019). Sticky Expectations and the Profitability Anomaly. *The Journal of Finance 74*(2), 639–674.

Bundick, B. and T. Herriford (2017, May). How Do FOMC Projections Affect Policy Uncertainty? *The Federal Reserve Bank of Kansas City Economic Review*. Publisher: Federal Reserve Bank of Kansas City.

Caldara, D. and M. Iacoviello (2022, April). Measuring Geopolitical Risk. *American Economic Review 112*(4), 1194–1225.

Cloyne, J., M. Froemel, C. Ferreira, and P. Surico (2023). Monetary Policy, Corporate Finance, and Investment. *Journal of the European Economic Association 21*(6), 2586–2634.

Coibion, O. and Y. Gorodnichenko (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review 105*(8), 2644–78.

Creal, D. D. and J. C. Wu (2017, November). MONETARY POLICY UNCERTAINTY AND ECONOMIC FLUCTUATIONS. *International Economic Review 58*(4), 1317–1354. Publisher: Wiley.

De Pooter, M., G. Favara, M. Modugno, and J. Wu (2021, June). Monetary policy uncertainty and monetary policy surprises. *Journal of International Money and Finance 114*, 102401. Publisher: Elsevier BV.

Degryse, H., O. De Jonghe, S. Jakovljević, K. Mulier, and G. Schepens (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation 40*, 100813.

Degryse, H., R. Goncharenko, C. Theunisz, and T. Vadasz (2023, February). When green meets green. *Journal of Corporate Finance 78*, 102355.

Dell'ariccia, G., L. Laeven, and G. A. Suarez (2017). Bank Leverage and Monetary Policy's Risk-Taking Channel: Evidence from the United States. *The Journal of Finance 72*(2), 613–654. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12467.

Ehrmann, M., D. Georgarakos, and G. Kenny (2025, August). Credibility gains from central bank communication with the public. *European Economic Review 177*, 105069. Publisher: Elsevier BV.

Elenev, V., T.-H. Law, D. Song, and A. Yaron (2024, March). Fearing the Fed: How wall street reads main street. *Journal of Financial Economics 153*, 103790.

Fasani, S., H. Mumtaz, and L. Rossi (2023, January). Monetary policy uncertainty and firm dynamics. *Review of Economic Dynamics 47*, 278–296.

Fernández-Villaverde, J. and P. A. Guerrón-Quintana (2020, August). Uncertainty shocks and business cycle research. *Review of Economic Dynamics 37*, S118–S146.

Florackis, C., C. Louca, R. Michaely, and M. Weber (2022, December). Cybersecurity Risk. *The Review of Financial Studies 36*(1), 351–407. Publisher: Oxford University Press (OUP).

Flynn, J. P. and K. A. Sastry (2023). Attention Cycles.

Gati, L. and A. Handlan (2021). Monetary Communication Rules.

Gertler, M. and P. Karadi (2015, January). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

Giannetti, M. and Y. Yafeh (2012, February). Do Cultural Differences Between Contracting Parties Matter? Evidence from Syndicated Bank Loans. *Management Science 58*(2), 365–383.

Gilchrist, S., J. W. Sim, and E. Zakrajšek (2014, April). Uncertainty, Financial Frictions, and Investment Dynamics. Working Paper 20038, National Bureau of Economic Research. Series: Working Paper Series.

Gilchrist, S. and E. Zakrajšek (2012, June). Credit Spreads and Business Cycle Fluctuations. *American Economic Review 102*(4), 1692–1720.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2019, November). Firm-Level Political Risk: Measurement and Effects*. *The Quarterly Journal of Economics 134*(4), 2135–2202.

Hassan, T. A., J. Schreger, M. Schwedeler, and A. Tahoun (2024, July). Sources and Transmission of Country Risk. *Review of Economic Studies 91*(4), 2307–2346. Publisher: Oxford University Press (OUP).

Hattori, M., A. Schrimpf, and V. Sushko (2016, April). The Response of Tail Risk Perceptions to Unconventional Monetary Policy. *American Economic Journal: Macroeconomics 8*(2), 111–136.

Heider, F., F. Saidi, and G. Schepens (2019, October). Life below Zero: Bank Lending under Negative Policy Rates. *The Review of Financial Studies 32*(10), 3728–3761.

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

Ilut, C. and H. Saijo (2021, January). Learning, confidence, and business cycles. *Journal of Monetary Economics 117*, 354–376.

Ilut, C. L. and M. Schneider (2014, August). Ambiguous Business Cycles. *American Economic Review 104*(8), 2368–2399.

Ilut, C. L. and M. Schneider (2022). Modeling uncertainty as ambiguity: A review. Publisher: National Bureau of Economic Research.

Istrefi, K. and S. Mouabbi (2018, November). Subjective interest rate uncertainty and the macroeconomy: A cross-country analysis. *Journal of International Money and Finance 88*, 296–313. Publisher: Elsevier BV.

Jamilov, R., H. Rey, and A. Tahoun (2023). The Anatomy of Cyber Risk. *NBER WORKING PAPER SERIES 28906*.

Khwaja, A. I. and A. Mian (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review 98*(4), 1413–42.

Kindleberger, C. P. (1978). *Manias, Panics and Crashes: A History of Financial Crises, Sixth Edition*. Palgrave Macmillan.

Lim, J., B. A. Minton, and M. S. Weisbach (2014, January). Syndicated loan spreads and the composition of the syndicate. *Journal of Financial Economics 111*(1), 45–69.

Ma, Y., T. Paligorova, and J.-L. Peydro (2021). Expectations and bank lending. *Work. Pap., Chicago Booth Sch. Bus., Chicago*.

Mertens, K. and M. O. Ravn (2013, June). The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States. *American Economic Review 103*(4), 1212–1247.

Montiel Olea, J. L., J. H. Stock, and M. W. Watson (2021, November). Inference in Structural Vector Autoregressions identified with an external instrument. *Journal of Econometrics 225*(1), 74–87.

Ottonello, P. and T. Winberry (2020). Financial Heterogeneity and the Investment Channel of Monetary Policy. *Econometrica 88*(6), 2473–2502.

Paligorova, T. and J. A. C. Santos (2017, April). Monetary policy and bank risk-taking: Evidence from the corporate loan market. *Journal of Financial Intermediation 30*, 35–49.

Rogers, J. H., C. Scotti, and J. H. Wright (2018, December). Unconventional Monetary Policy and International Risk Premia. *Journal of Money, Credit and Banking 50*(8), 1827–1850.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023, June). Firm-Level Climate Change Exposure. *The Journal of Finance 78*(3), 1449–1498. Publisher: Wiley.

Schwert, M. (2018). Bank Capital and Lending Relationships. *The Journal of Finance 73*(2), 787–830.

Shapiro, A. H., M. Sudhof, and D. J. Wilson (2022, June). Measuring news sentiment. *Journal of Econometrics 228*(2), 221–243.

Simpson, A. (2013). Does Investor Sentiment Affect Earnings Management? *Journal of Business Finance & Accounting 40*(7-8), 869–900.

Stock, J. H. and M. W. Watson (2018, May). Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments. *The Economic Journal 128*(610), 917–948.

Tillmann, P. (2020, June). Monetary Policy Uncertainty and the Response of the Yield Curve to Policy Shocks. *Journal of Money, Credit and Banking 52*(4), 803–833. Publisher: Wiley.