Policymakers' Uncertainty

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Deviations from a policy rule underpin empirical identification of monetary policy shocks. We cast light on how deviations arise by analyzing internal policy deliberations of the Federal Open Market Committee (FOMC). We show that policymakers' beliefs about higher-order moments of economic distributions—specifically perceptions of uncertainty and skewness—significantly impact policy stance beyond economic forecasts typically used in rule estimates. To capture those otherwise unobservable decision-making features, we construct text-based proxies for policymakers' uncertainty, sentiment, and policy stance from the FOMC meeting transcripts over the 1987–2015 period. Heightened uncertainty generally amplifies the policymakers' response to the macroeconomy. However, while an increased uncertainty about the real economy drives an easier stance, inflation uncertainty leads to more hawkishness. We show that policymakers' inflation uncertainty is associated with their skewed beliefs about rising inflation, which do not materialize in our sample. The results depart from the certainty equivalence arising in classic monetary models and contrast with the frequently-referenced conservatism in policymaking under uncertainty. Instead, the evidence suggests that policymakers act aggressively to avoid low-probability costly outcomes which are endogenous to their policy actions.

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I. Introduction

Alan Greenspan famously said, "(...) uncertainty is not just a pervasive feature of the monetary policy landscape; it is the defining characteristic of that landscape" (Greenspan, 2004). Yet, despite the ubiquitous emphasis on uncertainty in central bankers' speeches and statements, we know little about how policymakers' uncertainty and, more broadly, their beliefs about higher-order moments of economic outcomes affect policy decisions. The classic foundation for the Taylor rules leaves no room for the effects of uncertainty. In a world where policymakers minimize quadratic deviations of inflation and output from their targets and the state of the economy is linear with additive shocks, the certainty equivalence result implies that policy only reacts to the macro variables or their expected values. While policymakers use such models as a starting point for guiding their decisions, they do not follow them exactly. We cast light on how deviations from such rules occur by analyzing internal policy deliberations of the Federal Open Market Committee (FOMC). We show that policymakers' perceptions of uncertainty and skewness significantly impact the policy stance over and above economic forecasts.

Understanding the effects of uncertainty on policymaking comes with theoretical and empirical challenges. A frequently-quoted theoretical result to describe how policymakers should behave under uncertainty goes back to Brainard (1967), who postulated a more conservative stance. However, the theoretical predictions are highly model-specific: depending on the assumptions about the structure of the economy and policymakers' preferences, uncertainty can induce more or less aggressive optimal policy response or no response at all. On the empirical front, the challenges pertain to both measuring policymakers' perceptions of uncertainty and disentangling their effect from other confounders, most importantly, the first-moment beliefs about the state of the economy.

Our empirical approach relies on analyzing the deliberations of the Federal Open Market Committee (FOMC) recorded in the transcripts of the scheduled FOMC meetings between 1987 and 2015. Given the wealth of information that is available, the FOMC setting is well-suited to study the impact of uncertainty on decision-making. At each meeting, we observe nearly verbatim statements by individual FOMC members and the Federal Reserve Board staff. This content allows us to construct three kinds of measures to describe the policymaking process: policymakers' uncertainty, their sentiment capturing their directional views on the economy, and their resulting policy stance. We can attribute the language describing economic outcomes to actual decision-makers and tie it to their policy stance, both at the level of the committee and an individual FOMC member. In addition, through the Greenbook (now Tealbook) forecasts prepared by the staff prior to each meeting, we also gain access to the baseline macroeconomic projections that policymakers are equipped with before they enter the meeting.

We exploit the typical structure of the FOMC meetings to derive the above measures. With minor exceptions, the meetings during our sample are comprised of two rounds, each serving different objectives. In the first round, which we refer to as the economy round, policymakers discuss the economic and financial market developments and the baseline outlook. This step lays the foundation for the second round—the policy round—which contains discussions about the appropriate policy choice and during which the policy decision takes place. We thus study how uncertainty and sentiment manifest in the first round affect policy stance communicated in the second round.

Policymakers' uncertainty is a multifaceted object. Its various dimensions pertain to the distinction between risk and uncertainty as well as to the specific economic concepts toward which uncertainty is directed. We use the term "uncertainty" in a broad sense, which reflects the practical challenges associated with identifying and measuring uncertainty. The challenges we face as econometricians parallel those encountered by decision-makers, as depicted by Greenspan (2004): "In practice, one is never quite sure what type of uncertainty [Knightian uncertainty or risk] one is dealing with in real time, and it may be best to think of a continuum ranging from well-defined risks to the truly unknown."

To reflect these complexities, we adopt a two-pronged approach to characterize the properties of policymakers' uncertainty. In the first step, we measure overall uncertainty expressed in the economy round of the meetings using word embeddings—a tool from computational linguistics—for terms "risk" or "risks" and "uncertainty" or "uncertain." Our baseline policymakers' uncertainty index, which we label as the PMU, is a count of phrases related to risk and uncertainty relative to the overall count of tokens in the economy round of a given meeting. As such, it depicts the intensity with which policymakers express uncertainty when discussing the economic situation. Importantly for our subsequent analysis, in a second step, we separate the uncertainty language into topic categories, distinguishing uncertainty about inflation, real economy, financial markets, models and forecasts, and a residual unclassified ("other") category. For a precise attribution to a topic, we develop a set of algorithms that match uncertainty phrases with topic-specific phrases at a sentence level.

Uncertainty is a non-directional concept that should describe perceived breadth of possible unknown outcomes. Different models (which we discuss below) introduce uncertainty in different ways as, for example, stochastic volatility of disturbances or a variance around unknown parameters. However, there is no guarantee that when policymakers talk about uncertainty in the meeting, they actually think in this non-directional way, as opposed to expressing concerns about particularly undesirable outcomes. To cast light on this issue, we therefore complement the PMU indices with topic-specific measures of directional language, reflecting policymakers' views about the path of inflation, real economy, and financial markets. We refer to the directional language as sentiment. To the extent that Greenbooks represent modal projections, the sentiment serves to control for the variation in the conditional means and higher-order moments of the distributions (in particular, skewness) that policymakers pay attention to.

We first confirm Greenspan's claim by establishing that policymakers' perceptions of "risk" comove closely with their perceptions of "uncertainty." Therefore, for most of our analysis, we do not attempt to disentangle the two concepts. We then show that uncertainties related to inflation, real economy, and financial markets account for the vast portion of uncertainty mentioned in the transcripts. The correlations between the topic-specific PMU indices are low across the board (e.g., inflation and real economy PMUs have a correlation of 0.07), suggesting that our classification distinguishes largely orthogonal aspects of policymakers' uncertainty.

To analyze the effects of policymakers' beliefs about the economy on policy, we develop a new textual measure of policy stance based on the balance of hawkish and dovish language—the hawk-dove score—of the FOMC members in the policy round of the meeting. This approach allows us to span the entire 1987–2015 sample, including the zero-lower-bound period. We document that the hawk-dove score varies in an intuitive way and is a highly significant predictor of the federal funds rate (FFR) target. Importantly, its predictive power for the FFR is not subsumed by the Greenbook forecasts that are usually included in estimated Taylor rules, which implies that the policy stance derived from the text reflects in large part deviations from the rule. Accordingly, we show that the hawk-dove score alone explains about a quarter of the variation of the Romer and Romer (2004) shocks, a widely-used measure of monetary policy surprises. Its information content, however, goes beyond the current policy stance. Consistent with a forward-looking nature of policy discussions in the meetings, the hawk-dove score has significant explanatory power for high-frequency monetary policy surprises based on market interest rates, and it predicts FFR target changes several meetings ahead. Given those properties, we use the hawk-dove score as the dependent variable describing the FOMC members' policy stance and estimate various specifications of text-based policy rules.

With the measures of the policymakers' beliefs and their policy stance, we provide new insights about the drivers of the decision-making at the FOMC. Uncertainty and sentiment in the economy round of the meetings predict policy stance when controlling for the Greenbook forecasts, and as such, drive a wedge between the estimated rules and the actual decision making. The key new insights stem from our ability to distinguish between the types of uncertainty, which have distinct effects on policy. A higher PMU for the real economy and financial markets both predict an easier policy stance. To the extent that these types of uncertainty influence the economy akin to a negative demand shock, this result is broadly consistent with the real options channel of uncertainty (e.g., Bloom, 2009). However, because the effect is not subsumed by the Greenbook controls, it also indicates that the staff forecasts do not fully take the impact of uncertainty on board. The explanatory power of inflation uncertainty for policy stance reveals a new and separate channel at work that has not been widely discussed in the literature. In contrast to the real-economy PMU, higher inflation PMU predicts a more hawkish policy tilt.

To tie these empirical facts more closely to theoretical predictions from models of optimal policy under uncertainty, we estimate a version of a policy rule in which we allow uncertainty to affect the strength of the policy response to projected inflation and growth. We find that uncertainty leads to an amplification of the policy response to fluctuations in economic forecasts. An increase in the inflation PMU from the 5th to the 95th percentile leads to a tripling of the policymakers' response to the inflation forecast. The amplifying effect of uncertainty on the FOMC's reaction contrasts with the oft-referenced conservatism principle of Brainard (1967). It is, however, consistent with models in which policymakers face uncertainty about structural inertia in the inflation process (e.g., Söderström, 2002) or display robustness concerns (e.g., Giannoni, 2002). As a benchmark for our empirical estimates, we illustrate the implications of leading models in the literature and conclude that, for standard calibrations, their predicted impact of uncertainty on optimal policy remains economically small relative to our empirical findings.

Analyzing the properties of policymakers' beliefs, we argue both theoretically and empirically that the uncertainty that is relevant for understanding policymaking cannot be gleaned from the objective measures of volatility or from the public perceptions of uncertainty. Contrary to various measures of public uncertainty, policymakers' uncertainty does not fluctuate in an evidently countercyclical manner. The inflation PMU is, in fact, strongly procyclical. The fact that policymakers become uncertain about inflation when the economy is doing well suggests that they are concerned with demand-driven deviations of inflation from the target. Likewise, the highest readings of the real-economy PMU precede the global financial crisis by about a year, coinciding with a still depressed VIX and a strong stock market.

Examining the drivers of policymakers' uncertainty, we establish several results. First, we fail to find a clear relationship between the PMU and the Greenbook forecasts or forecast revisions. However, inflation uncertainty increases after Greenbook forecast errors have been particularly large, suggesting that policymakers become more uncertain about inflation as their models fail. Indeed, we find that inflation PMU correlates positively with model uncertainty discussed in the meeting. Second, we document a tight link between uncertainty and the directional language—the sentiment in the meeting—which reveals an important asymmetry: Uncertainty is strongly associated with views about the economy that policy-makers' would traditionally consider unfavorable or costly. Real-economy PMU comoves with the negative real sentiment (i.e., perceptions of weakening economy) more than it does with the positive sentiment (i.e., perceptions of strengthening economy). Likewise, inflation PMU comoves much more closely with the positive inflation sentiment (i.e., perceptions of rising inflation) in the meeting than it does with the negative sentiment (i.e., perceptions of declining inflation). We interpret this finding as policymakers' uncertainty reflecting concern about low-probability but costly outcomes. We show that neither inflation sentiment nor PMU in the meeting predict future inflation outcomes. While sentiment predicts policy stance beyond Greenbook forecasts, in line with policymakers' placing weight on particular tail events they fear, its explanatory power for policy is subsumed by the inflation PMU. As such, policymakers' inflation beliefs in the meeting are an expression of worry that does not materialize in the sample we study.

The remainder of the paper proceeds as follows. In Section II, we lay out the different theoretical channels proposed in the literature through which uncertainty can affect monetary policy and illustrate the effects of uncertainty on policy in a simple static framework. In Section III, we discuss our empirical strategy, the measurement of policymakers' uncertainty (PMU), sentiment and policy stance from FOMC transcripts. In Section V, we analyze the effect of uncertainty and sentiment on policy stance. In Section VI, we study the properties of policymakers' perceptions and

II. Uncertainty and Optimal Monetary Policy

Suppose the central bank adjusts interest rates in reaction to economic conditions Ω_t in order to achieve its objectives. A typical way to represent the policy behavior is as a reaction function

$$i_t = \beta' \Omega_t + m_t, \tag{1}$$

where i_t is the policy instrument, β is a vector of coefficients capturing the response of the policymakers to the state of the economy, and m_t represents a monetary policy shock.[2] In economic models, Ω_t is often a function of past economic conditions (Ω_{t-1}) as well as newly-realized structural shocks (such as demand shocks, price-markup shocks).

[2] The theory does not provide much guidance as to what the policy shock should be (Ramey, 2016). Some frequently discussed possibilities are shifts in policymakers' preferences (perhaps due to shifting weight given to unemployment and inflation), or power changes within the committee (Christiano, Eichenbaum, and Evans, 1999).

II.A. Channels

The literature has highlighted several theoretical channels of how uncertainty could affect policymaking. The starkest prediction is that uncertainty does not matter at all. This result, known as the certainty equivalence, emerges in many classic monetary models and is a standard property of a linear-quadratic environment: the structure of the economy is linear (with additive shocks to Ω_t) and the policymaker's loss function is quadratic. As such, the central bank reacts to its assessment of the economy in the same way (i.e.., with the same β) no matter if uncertainty is high or low (see, e.g., Blinder (1999)).

A channel emphasized by a growing macro literature pertains to how uncertainty affects economic agents outside the central bank. While specific theoretical mechanisms differ, rising uncertainty generally acts akin to a negative demand shock, causing a rapid drop, rebound, and overshoot in employment, output, and productivity growth (e.g., Bloom, 2009; Basu and Bundick, 2017; Leduc and Liu, 2016). Since such uncertainty manifests itself as a structural shock, the central bank in line with its mandate reacts as it would to other demand shocks: A positive uncertainty shock worsens its assessment of the economy, Ω_t, which in turn leads to policy accommodation. This logic does not overturn the certainty equivalence in that the optimal policy response coefficients do not change, but rather, uncertainty now has an effect on policy because it is itself a source economic fluctuations reflected in Ω_t.

There are two broadly-studied classes of models, in which uncertainty matters directly for policymaking by altering the optimal reaction function (β parameters). These models specialize the general principle that, to break certainty equivalence, policy needs to affect the variance of the state variables.

The first class of models emphasizes policymakers' incomplete information about model parameters. In a classic example of Brainard (1967), the policy multiplier, which determines how policy affects the economy, is stochastic and a Bayesian policymaker only knows the distribution from which it is drawn. In this scenario, optimal policy should be less aggressive relative to policy pursued in a certain world—a result known as the Brainard conservatism principle. However, conservatism is not a uniform property of optimal policy. Söderström (2002) challenges it by showing that while uncertainty about the policy impact on the economy leads to a less aggressive stance (consistent with Brainard), uncertainty about the economic dynamics does not. Specifically, uncertainty about inflation persistence induces the policymaker to become *more* aggressive in their policy. The intuition is as follows: When the dynamics of inflation are uncertain, the amount of uncertainty facing policymakers is greater, the further away the inflation rate is from its target. Consequently, to reduce the uncertainty about the future path of inflation, the optimal policy pushes inflation closer to the target more strongly than in the certainty case.

The second class of models emphasizes the policymakers' desire for robustness: the policymaker is uncertain about their economic model and seeks a policy that is robust to the worst possible form of misspecification (Hansen and Sargent, 2001, 2008; Giordani and Söderlind, 2004; Giannoni, 2007). Rather than specifying a particular form of uncertainty, the robust policymaker solves for an optimal policy by selecting the minimum loss in the version of the distorted model that causes maximum expected loss (subject to limits on how distorted the alternative model can be). Certainty equivalence fails because, even with a linear-quadratic setup, the coefficients of the optimal policy function depend on the variance of the structural shocks. Generally, uncertainty manifests itself through a more aggressive reaction function (larger policy coefficients β).

We illustrate the effects of the parameter uncertainty and preference for robustness in several standard model calibrations in the online Appendix D. Below, we lay out the general principle of how uncertainty could affect policymaking with a simple framework.

II.B. A simple static framework of policy choice

To clarify the impact that uncertainty might have on monetary policy choices, we introduce a simple static framework, in which a policymaker must choose an interest rate $r \in \{r_0, r_1\}$ where $r_0 < r_1$. Without uncertainty, under r_0, the prevailing levels of inflation and output are known to be π_0 and y_0, respectively, while under r_1 they are $\pi_0 - \delta$ and $y_0 - \phi$, respectively, with $\delta, \phi > 0$. That is, under the higher interest rate, both inflation and output are lower.

The policymaker's loss function over inflation and output has the standard quadratic form:

$$L(\pi, y) = (\pi - \pi^*)^2 + \lambda\,(y - y^*)^2\,, \tag{2}$$

where π^* is the inflation target and y^* is the medium-term potential output, which is known. Let L_0 (L_1) be the loss from choosing r_0 (r_1). It is straightforward to show that

$$L_1 < L_0 \Longleftrightarrow \delta(\pi_0 - \pi^*) + \lambda\phi(y_0 - y^*) > \frac{\delta^2 + \lambda\phi^2}{2}. \tag{3}$$

When the linear combination of the deviation of inflation from target and the deviation of output from its potential level is sufficiently high under the accommodative policy r_0, the policymaker will end up choosing the tighter policy, r_1. Let

$$X_1^C = \{(\pi_0, y_0) \mid L_1 < L_0\}$$

be the set of inflation and output levels under accommodation for which the policymaker chooses r_1 (over r_0) when there is certainty.

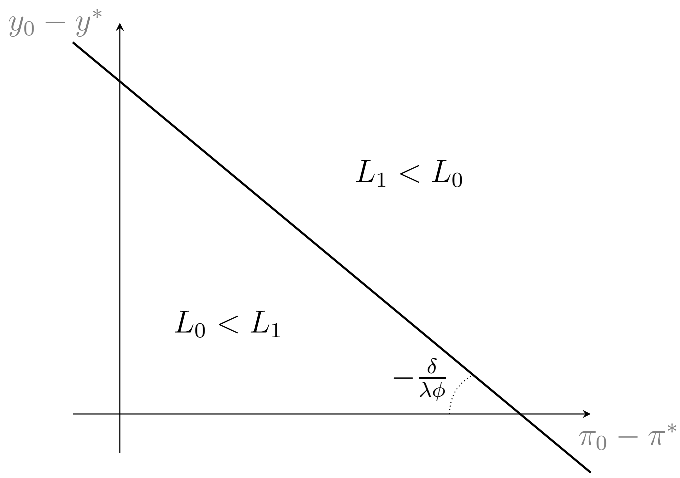

Figure 1. Decision boundary for certainty case

Figure 1 depicts a graphical representation of the decision rule using an indifference curve. Points to the northeast (southwest) of the line represent combinations of inflation and output deviations under accommodation such that the policymaker will choose r_1 (r_0). The slope of the decision boundary is determined by the relative sensitivity of output and inflation to the higher interest rate, as well as the weight λ that the policymaker attaches to output. To take an extreme case, suppose that the policymaker cares only about inflation so that $\lambda = 0$. Then, the curve in Figure 1 becomes vertical through $(\frac{\delta}{2}, 0)$, and r_1 is chosen whenever the inflation rate under accommodation is further from its target value than half the effect of changing rates ($\pi_0 - \pi^* > \delta/2$).

II.C. Effects of uncertainty

To see when uncertainty about outcomes will, and will not, matter, we introduce uncertainty into the outcome distributions, so that $\pi \sim G_\pi$ and $y \sim G_y$. We assume these distributions G are unimodal with finite variance. Let $\overline{x}_j$, $\hat{x}_j$, $\sigma^2_{x,j}$ denote the mean, mode, and variance of the distribution of outcome variable $x \in \{y, \pi\}$ under interest rate r_j. In line with the setup under certainty, we assume that $\overline{\pi}_1 = \overline{\pi}_0 - \delta$ and $\overline{y}_1 = \overline{y}_0 - \phi$.

Decisions now depend on expected losses $\overline{L}_0$ and $\overline{L}_1$. Basic computations yield

$$\overline{L}_1 < \overline{L}_0 \iff \delta(\overline{\pi}_0 - \pi^*) + \lambda\phi(\overline{y}_0 - y^*) > \frac{\delta^2 + \lambda\phi^2}{2} - \underbrace{(\sigma^2_{\pi,0} - \sigma^2_{\pi,1})}_{\equiv\ \Delta\sigma^2_\pi} - \lambda \underbrace{(\sigma^2_{y,0} - \sigma^2_{y,1})}_{\equiv\ \Delta\sigma^2_y} \quad (4)$$

One can observe an effect of uncertainty by comparing (3) with (4). When interest rate r_0 generates additional (less) volatility in inflation or output relative to r_1, r_1 becomes more (less) attractive.[3] Below, we discuss examples in which such endogenous outcome variance might arise.

In practice, empirical decision rules estimated in the monetary literature are often formulated in terms of numeric forecasts of outcomes variables. Importantly, in the FOMC context, as for other central banks, numeric inflation and output forecasts are modal projections associated with the most likely outcome. As Bernanke (2016) describes the FOMC's Summary Economic Projections (SEP), "SEP projections are explicitly of the 'most likely' or modal outcomes rather than the range of possible scenarios." Likewise, the New York Fed forecast "is referred to as the 'modal' forecast in that it is intended to be the most likely of a wide range of potential outcomes" (Alessi, Ghysels, Onorante, Peach, and Potter, 2014).

Given the ubiquity of estimating monetary policy rules using modal forecasts, we characterize the policymaker's decision problem in terms of the modes $(\hat{\pi}_0, \hat{y}_0)$. The decision rule in (4) can be easily reformulated as

$$\delta(\hat{\pi}_0 - \pi^*) + \lambda\phi(\hat{y}_0 - y^*) > \frac{\delta^2 + \lambda\phi^2}{2} - \Delta\sigma_\pi^2 - \lambda\Delta\sigma_y^2 - \delta\underbrace{(\overline{\pi}_0 - \hat{\pi}_0)}_{\equiv s_\pi} - \lambda\phi\underbrace{(\overline{y}_0 - \hat{y}_0)}_{\equiv s_y}. \tag{5}$$

Let

$$X_1^U = \left\{(\hat{\pi}_0, \hat{y}_0) \mid \overline{L}_1 < \overline{L}_0\right\}$$

be the set of modal outcomes under accommodation for which the policymaker prefers r_1 over r_0. *Certainty equivalence* is the case when $X_1^C = X_1^U$, i.e., when the introduction of uncertainty in output or inflation does not change the set of modal outcomes for which the policymaker prefers r_1 over r_0. This definition leads to the following result.

Proposition 1. *Certainty equivalence holds when the variance in outcomes is exogenous to the policy choice, and when outcomes are symmetrically distributed.*

These conditions are typically present in monetary models. For example, π and y are typically assumed to be normally distributed, which implies that $\hat{x} = \overline{x}$. Moreover, outcomes are usually subject to exogenous shocks independent of the policy choice.

If certainty equivalence holds, FOMC members would not even need to discuss their worries, concerns, or uncertainty about the economy. Instead, they would just express the expected values of economic variables. Of course, in this case, uncertainty language could be a linguistic tool they use to describe distributions and explain how they form expectations. However, such uncertainty should have no independent role policy beyond economic forecasts.

[3]This effect is akin to the idea of a risk management approach to monetary policy as described in Greenspan (2004).

With endogenous variance or skewed distributions, however, certainty equivalence typically does not hold. We formalize this statement in our next result.

Proposition 2. *Suppose $\Delta\sigma_\pi^2, \Delta\sigma_y^2, s_\pi, s_y \geq (\leq) 0$ with one inequality strict. Then certainty equivalence does not hold and $X_1^C \subset (\supset) X_1^U$.*

Figure 2 illustrates the effect of uncertainty on the decision rule. The curve for which $\Delta\sigma_\pi^2, \Delta\sigma_y^2, s_\pi, s_y = 0$ corresponds to the decision boundary in Figure 1. When accommodation generates uncertainty or outcomes are right-skewed, the decision boundary shifts downwards and the policymaker prefers r_1 for a larger range of modal forecasts.[4]

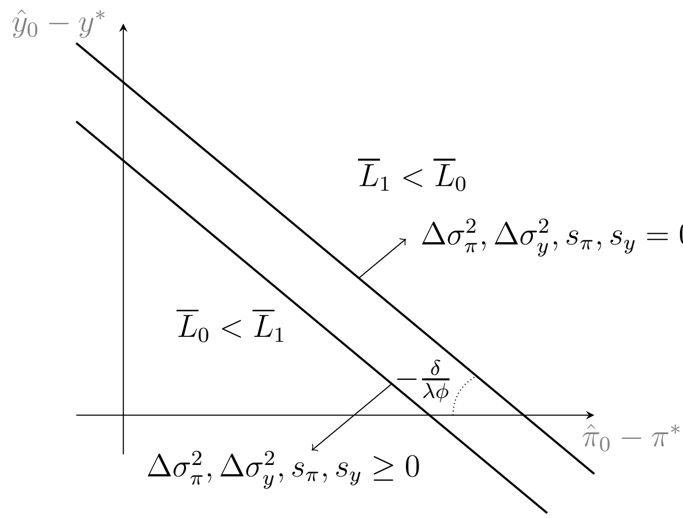

Figure 2. Effect of uncertainty on the decision boundary

When accommodative monetary policy generates additional outcome uncertainty—or upside risks in the form of right-skewed output or inflation outcomes—an additional incentive exists to choose the higher interest rate compared to the case with no uncertainty. Under the reverse inequalities, uncertainty instead increases the incentive to choose the lower interest rate. In these circumstances, FOMC discussions should reveal these risks and these risks should influence their policy decisions.[5]

A key implication is that uncertainty only matters when it is endogenous to policy. If the variance of outcomes that does *not* depend on policy, then $\Delta\sigma_\pi^2 = \Delta\sigma_y^2 = 0$. In this case, it

[4] The curve is drawn assuming that s_π, s_y are held constant when $\hat{\pi}_0, \hat{y}_0$ change.

[5] The Söderström (2002) anti-conservatism result is an example of this effect. When the dynamics of inflation are uncertain, the amount of uncertainty facing policymakers is greater, the further away the inflation rate is from its target. So a policy which brings inflation closer to target, actually reduces the uncertainty around future inflation outcomes. Therefore, the optimal policy is more aggressive and pushes inflation closer to the target more strongly than in the certainty case.

is reasonable for policymakers to not adjust their policy choice because of uncertainty they face.

While our model is static, it is natural to imagine the conditions under which certainty equivalence breaks down to depend on the business cycle. For example, if upside inflation and output outcomes are more likely during expansions, and downside outcomes more likely during contractions, uncertainty generates a pro-cyclical tendency to choose higher rates. This effectively creates state-dependent preferences without the need to adopt asymmetric preferences in the utility function (2). We provide an illustrative example below to highlight these effects.

II.D. Example: Inflation scares

The above framework clarifies situations in which uncertainty can alter policymakers' decision rules within a stylized environment. Here, we provide a specific example of how uncertainty effects can arise: the potential for "inflation scares" as initially described in Goodfriend (1993). The idea is that when policymakers do not act sufficiently aggressively against inflation, there is a small chance of a loss of the central bank's credibility that leads to a large inflation realization and losses.

To capture this phenomenon, we assume that, under the more aggressive policy r_1, inflation and output are known to be $\pi_0 - \delta'$ and $y_0 - \phi$. Under the less aggressive policy r_0, output is y_0 but inflation becomes a random variable:[6]

$$\pi \mid r_0 = \begin{cases} \pi_0 & \text{w.p. } 1-p \\ \pi_0 + \zeta & \text{w.p. } p \end{cases}$$

where p is the probability of a large price increase. Typically p is small but ζ is large due to the loss of credibility, de-anchoring of inflation expectations, etc. The modal outcomes under r_0 are y_0 and π_0 given that p is small. In terms of the previous framework, $\delta = \delta' + p\zeta$. That is, under inflation scares, raising interest rates has an additional effect of reducing the probability of losing the nominal anchor to zero.

Under these assumptions, both effects of inflation and skewness we emphasize above are simultaneously present. Choosing r_0 over r_1 generates additional uncertainty in inflation by moving variance from 0 to $p(1-p)\zeta^2$. It also induces a skewed inflation distribution for which the mean lies $p\zeta$ above the mode. Overall, the wedge generated by inflation scares relative to the certainty equivalent rule is, by substituting into (5),

[6] All outcome distributions could be perturbed by exogenous noise without affecting the conclusions, per the discussion above.

$$(\delta' + p\zeta)p\zeta + p(1-p)\zeta^2 = p\zeta(\delta' + \zeta) \tag{6}$$

The size of this wedge is higher whenever the inflation scare p is perceived as more likely and when the associated cost ζ is higher. As such, low probability but high-cost outcomes associated with r_0 generate a tendency to choose r_1, i.e., act more aggressively.

II.E. Mapping to empirics

In our empirical specifications below, we test whether FOMC members' assessments of higher moments of economic distributions affect their policy stance beyond the modal Greenbook forecasts. Our main source of information is the language they use when discussing economic conditions. Market-based or survey measures of uncertainty are unlikely to proxy well the uncertainty relevant for policymaking because such measures already condition on the expected FOMC behavior. An important message from the preceding discussion is that the evolution of uncertainty *across* policy choices can be an important driver of policy. The language policymakers use as they discuss economic conditions in the context of policy choices is more likely to reflect the important drivers.

The framework above highlights the importance of the variance and skewness of payoff-relevant outcomes for quantifying the impact of uncertainty on policy choices. We construct their language-based analogues in the next section. In practice the same "deep" parameters may drive both uncertainty and skewness (e.g., the ζ term in the inflation scares example), which makes cleanly separating language about second and third moments difficult. We therefore do not attempt to test whether variance and skewness have separate effects on policy choices, but rather whether language broadly related to uncertainty and tail realizations of outcomes impacts policy. We now introduce our specific measures.

III. Measuring Policymakers' Uncertainty and Policy Stance with Text

Our main goal in the remainder of the paper is to determine which channels highlighted above operate on the FOMC. Evaluating these empirically requires quantifying three relevant phenomena: first, policymakers' uncertainty in general and uncertainty about specific concepts; second, directional beliefs about payoff-relevant economic variables to capture expected values or skewness; third, a measure of policy stance to assess the impact higher-order moments on actual decision-making.

Since FOMC members' views on uncertainty and higher moments of outcome distributions are not recorded in structured surveys over our whole sample period, text provides the most direct information about those otherwise unobserved factors affecting policymaking.[7] Text also provides rich information about the resulting policy stance. While the FOMC's policy decision is of course available every meeting, it is less informative about members' policy stances than those they directly express in language. First, policy views expressed in text are related to the future path of interest rates beyond the immediate decision (as we show below). Second, as there is little individual formal dissent on the FOMC, one must resort to the content of deliberations to understand members' true views.[8] Finally, the textual approach allows us to evaluate the policy stance in a consistent fashion over a long sample that includes the zero-lower-bound period.

III.A. Transcript data

The main textual source we draw from is the nearly verbatim transcripts of Federal Open Market Committee meetings, available online.[9] These transcripts contain a fully attributed, statement-by-statement account of meetings with very light editing, for example to remove the names of specific banks with which the Fed conducts open market operations. The sample period we consider consists of the 228 meetings from August 1987 (the first meeting of Alan Greenspan's chairmanship) through December 2015 (the last meeting for which a transcript was available at the time of data processing).[10] Regular FOMC meetings occur eight times per year, with occasional special meetings convened via conference call during times of macroeconomic turbulence. Since the format of these calls is somewhat irregular, we only consider regular meetings in our analysis.

The typical composition of the FOMC consists of 19 members, of which twelve are regional Fed Presidents and seven are Governors. During our sample, a total of 75 unique FOMC members appear in the transcripts in at least one meeting. A number of Fed staff economists also participate in the meetings.

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[7] Beginning in 2007, individual member views on inflation, output, and employment are recorded in Summary of Economic Projections conducted every other meeting. One role of the SEP is to communicate the FOMC's views to the public, so forecasts have a signaling role. In contrast, transcripts are released with a five-year lag and so also better capture private views.

[8] Alternatively, one could use the voting records of individual FOMC members. However, it is known that despite differing views on the committee, the dissents have been rare over the period we study (Meade and Stasavage, 2008; Thornton and Wheelock, 2014). Meade (2005) pioneers the use of FOMC transcripts to codify the expressed policy preferences about the short-term interest rate. Bordo and Istrefi (2021) use a classification scheme of FOMC members based on narrative records in the public media discussing policy preferences of individual FOMC members.

[9] See https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm

[10] Only a small part of the May 1988 meeting was transcribed, so we treat it as a missing observation.

The first step in preprocessing the transcripts is to break each statement by each speaker into separate sentences using a standard sentence tokenizer. This yields 559,709 total sentences, which form the basic units of linguistic analysis for the algorithms we propose below.

III.A.1. Exploiting the structure of the FOMC meetings

Our framework is focused on uncertainty about the economic outcomes that enter the policymakers' loss function. Hence, it is important to isolate the part of the meeting in which FOMC members discuss economic conditions—as opposed to the appropriate policy response—to build language-based uncertainty measures. To this end, we exploit the regular structure of FOMC meetings, all of which follow a similar agenda during our sample period.

The first core part of the FOMC meetings is the *economy round*, making up 43% of the total sentences in the transcripts. The Fed staff economists first present their forecasts of economic activity (contained in Greenbooks/Tealbooks) along with supporting contextual information. Each FOMC member in turn presents his or her views on economic developments, which can differ from the views of the staff. These developments can be discussed in the context of alternative interest rate paths—which our framework shows can be an important part of evaluating uncertainty—but FOMC members do not advocate for particular policy choices. It is this part of meeting we use for constructing text-based measures of outcome distributions as perceived by the FOMC.

The second core part of the meeting is the *policy round*, accounting for 24% sentences in the overall transcripts.[11] This round begins with the staff laying out different policy alternatives, after which FOMC members debate on which alternative to adopt before proceeding to a final vote. This section also includes a discussion of the public statement released along with the policy announcement. We use the policy round to derive text-based measures of policy stances.

While uncertainty language might appear in the policy round in discussion of economic conditions related to policy stance, it also reflects other factors such as hesitance about the correct policy stance, or how to communicate uncertainty to the public. In practice, separating out these distinct forms of uncertainty is a formidable challenge and, for this

[11] The remainder of the transcripts, which we do not use, is largely made up of staff discussion of financial market conditions and discussion of special topics in monetary policy. The sectioning of meetings is done manually by us. One outlier in meeting structure is the September 2009 meeting, for which the policy and economic rounds were merged into one round. In this case, we manually classify sentences as either belonging to the economy round or the policy round. For further details on the structure of FOMC meetings and the composition of the committee, see Hansen, McMahon, and Prat (2018).

reason, we do not use uncertainty language in the policy round to measure uncertainty about economic conditions.

III.B. Constructing policymakers' uncertainty (PMU) indices

III.B.1. Obtaining risk and uncertainty terms from word embeddings

Our measurement strategy begins with the construction of term lists that denote risk and uncertainty. According to Greenspan (2004), as quoted in the introduction, both notions are relevant for the FOMC, and accounting for each is important.[12] We consider mentions of the terms 'risk' and 'risks' to be associated with objective probabilities and mentions of the terms 'uncertain' and 'uncertainty' to be associated with uncertainty in the Knightian sense.

To obtain other terms that convey similar meanings as the four root terms, we rely on a word embedding model to estimate a vector space representation of different terms, within which we compute the nearest neighbors of the roots.[13] Specifically, we use the Continuous Bag-of-Words (CBOW) model (Mikolov, Chen, Corrado, and Dean, 2013) estimated on the set of FOMC sentences contained in the economy round to obtain a vector representation of each unique term.[14] Tables A-1 and A-2 in Appendix A contain the fifty nearest neighbors for each of the roots, where similarity is computed using cosine similarity.[15]

The nearest neighbors of risk and uncertainty appear in large part to reflect worries and concerns of policymakers: terms like 'threat', 'fear', 'doubts', 'tension', 'wary', and 'anxiety' abound. This suggests that, when FOMC members discuss risk and uncertainty, they do so in the context of perceived losses arising from unknown economic conditions rather than forming pure variance estimates. This is consistent with the framework in which uncertainty becomes relevant for decisionmakers when it generates larger expected losses.

[12] Similarly, Bloom (2014) writes: "I'll refer to a single concept of uncertainty, but it will typically be a stand-in for a mixture of risk and uncertainty."

[13] This approach follows an recent studies by Hanley and Hoberg (2019), Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020), Davis, Hansen, and Seminario-Amez (2020), and Bloom, Hassan, Kalyani, Lerner, and Tahoun (2021).

[14] We preprocess each sentence following standard steps of tokenization and stop word removal. We also replace a limited number of bigrams with a single term, e.g., 'downside risk' and 'upside risk.' We then remove all sentences that do not contain at least five terms from the estimation corpus. The embedding model is estimated with 200-dimensional embedding vectors and a window size of five, which are typical defaults in the natural language processing literature.

[15] The cosine similarity is the cosine of the angle formed by two vectors in a vector space. So, if two vectors point in the same direction, and have a zero angle between them, the cosine similarity is 1. If they point in opposite directions, and have an angle of 180 degrees, the cosine similarity is -1. Mathematically, the formula is the dot product of two vectors normalized to have unit length.

Another interesting feature is that the neighbors for 'risk' and 'risks' contain terms one would associate with the quantification of known probability distributions such as 'probability', 'likelihood', and 'odds'. Likewise, neighbors for 'uncertain' and 'uncertainty' include 'murky', 'unclear', 'skepticism', and 'anxiety' which suggest unquantifiable uncertainty and associated concerns. Still, the distinction is not perfect and all lists contain a mix of relevant and generic terms. We therefore further organize the lists using our domain expertise and, for each word in each list, explicitly assign it to either a risk or uncertainty term set, or remove it from the analysis altogether. The final sets include 18 terms that denote the general concept of risk, and 60 terms that denote uncertainty.[16]

III.B.2. Overall PMU index

Denote by $\mathcal{U}$ the list of phrases identified as pertaining to risk and uncertainty derived from the word embeddings approach. The most basic measure of policymakers' uncertainty aggregates the counts of terms in $\mathcal{U}$ from the economy round in each FOMC meeting t, and scales them by the number of total terms in the economy round of meeting t. More formally, let $\mathbf{w}_{t,s} = (\mathbf{w}_{t,s,1}, \ldots, \mathbf{w}_{t,s,N_{t,s}})$ be the list of terms in the sth sentence of meeting t; $u_{t,s} = \sum_n \mathbb{1}(\mathbf{w}_{t,s,n} \in \mathcal{U})$ is then the sentence-level count of risk/uncertainty terms and policymakers' uncertainty (PMU) is

$$PMU_t = \frac{\sum_s \mathbf{u}_{t,s}}{\sum_s N_{t,s}}. \tag{7}$$

PMU_t is based on all sentences in the economy round, including those spoken by Fed staff in their opening presentation. This is because the Fed's staff internal assessment of economic conditions potentially informs policymakers' views in addition to their own personal views. Additionally, we construct analogous PMU at the speaker level, PMU_t^i, in which case we scale the number of uncertainty words by the total number of words spoken by speaker i in meeting t.

III.B.3. Topic-specific PMU indices

While overall PMU is a useful starting point for characterizing the uncertainty perceived by the FOMC, breaking it down into subcomponents is necessary to explore the various channels through which uncertainty matters for policy stance. In line with the framework above, we define three potentially relevant types of uncertainty: those that act as negative demand shocks, either via the real economy or financial markets; inflation uncertainty, which

[16] Some of these terms are antonyms such as 'confident.' In these cases, we count appearances of such terms as indicative of risk/uncertainty when they are immediately preceded by a negation phrase, which is one of {'less', 'no','not', 'little', 'don't', 'doesn't', 'hasn't', 'haven't', 'won't', 'shouldn't', 'didn't'}.

policymakers might fear could lead to a credibility loss; and model uncertainty, which limits policymakers' ability to understand the evolution of the economy.

The basic strategy for building these subcomponents uses the local co-occurrence of risk and uncertainty terms with terms that denote specific topics.[17] More specifically, we identify sentences in which terms in $\mathcal{U}$ co-occur with terms that lie in three distinct sets: inflation (search phrases contained in Appendix Table A-3); real economy (Tables A-4 through A-6) / financial markets (Tables A-7 through A-10); and models (Table A-11).[18] As we show below, these components capture the bulk of uncertainty-related mentions in the transcripts and display significant heterogeneity in their variation over time.

For each of these topics, we construct topic-specific uncertainty counts using the following procedure. For each sentence in each FOMC meeting:

1. Increase the topic k uncertainty count by $u_{t,s}$ if sentence s contains any term in the list associated with topic k. Thus, if a term from more than one topic set appears in sentence s, $u_{t,s}$ can be assigned to more than one topic.
2. If no term from any set of topic words appears in sentence s, assign $u_{t,s}$ to topic k if a topic-k term appears in sentence $s-1$ or sentence $s+1$ (whenever these sentences are uttered by the same speaker of sentence s).
3. If no topic k term appears in sentences $s-1$, s, or $s+1$ then leave $u_{t,s}$ unassigned.

As with PMU_t, we then normalize the topic-specific counts by the total number of terms in the economy round of the meeting. We denote policymakers' perceived inflation uncertainty in meeting t as InfPMU_t; real economic uncertainty as EcoPMU_t; financial market uncertainty as MktPMU_t; uncertainty about models as ModPMU_t; and unclassified uncertainty as OthPMU_t.[19] Figure 3 presents the distribution of economic terms in each uncertainty topic.

[17] The use of local co-occurrence patterns to build text-based proxies for economic phenomena has been pioneered by Mikael and Blix (2014) in the monetary policy context and by Hassan, Hollander, van Lent, and Tahoun (2019) to measure specific types of uncertainty in a corporate context. Our innovation is to apply these ideas to analyze the impact of perceived risk and uncertainty on policy preferences.

[18] Here, we rely on a purely manual approach to phrase construction rather than the partially automated approach used to obtain risk/uncertainty synonyms. The reason is that the topical terms are largely made up of phrases, and sequence embeddings are substantially more complex to build than single word embeddings.

[19] Note that, in general, $\mathit{InfPMU}_t + \mathit{EcoPMU}_t + \mathit{MktPMU}_t + \mathit{ModPMU}_t + \mathit{OthPMU}_t > PMU_t$, since the same risk/uncertainty term is associated with multiple topics whenever a trigger phrase for more than one topic is present in the same sentence as the risk/uncertainty term.

Figure 3. Distribution of phrases in topic-specific PMU indices. The figure presents key economic terms within each topic-specific PMU index. The size of the phrase reflects is relative frequency. All topic-specific PMU indices are obtained from the economy round of the FOMC meetings. The sample period is 1987:08–2015:12

III.B.4. Descriptive statistics for PMU

To set the stage for subsequent analysis, we provide descriptive statistics for the PMU and its components. Figure 4 plots the overall PMU measure per meeting as well as an eight-meeting moving average. The PMU reaches its highest point at the onset of the US-led invasion of Iraq in March 2003, when the risk- and uncertainty-related terms in $\mathcal{U}$ make up 2.5% of all terms (after pre-processing) spoken in the economy round. PMU also features notable spikes in August 1991 on general uncertainty about the type of recession recovery, in the late 1998 and in the month preceding the 2008 global financial crisis on financial market uncertainty.

Figure 5 Panel A stacks the PMU categories as fractions of all uncertainty related mentions in the economy round. On average across the entire sample, we are able to classify 87% of mentions of terms in $\mathcal{U}$ into topics. Real economy, inflation, and markets PMU account for the bulk of uncertainty mentions, with the model PMU contributing relatively little. This already provides evidence that the primary driver of uncertainty on the FOMC does not come via model uncertainty, which stands in contrast to the academic literature in which this channel has received the most attention. Panel B shows the time series for the three

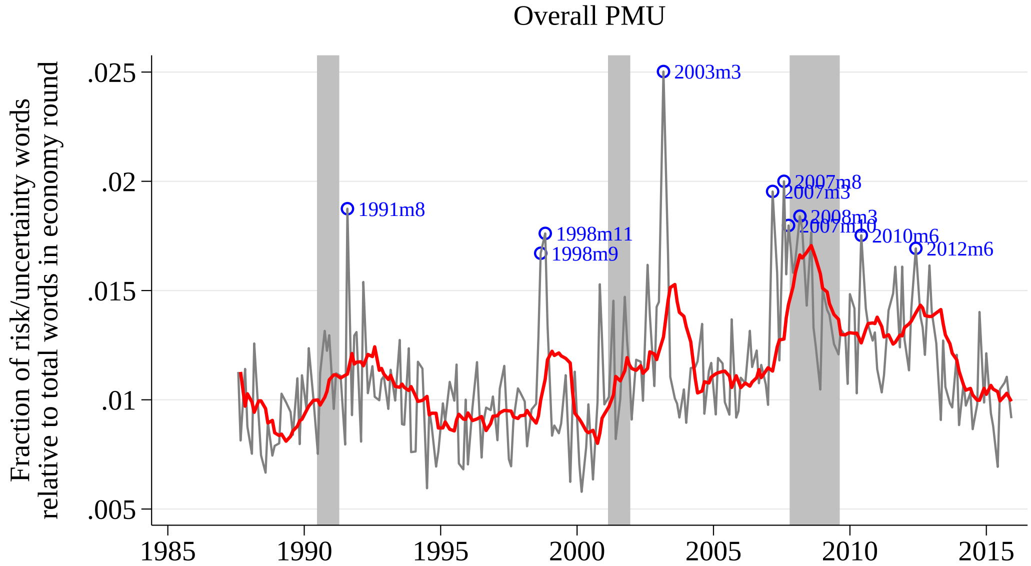

Figure 4. Policymakers' uncertainty index (PMU). The figure displays the PMU index obtained from the economy round of the FOMC meeting. The smoothed index is a moving average over the last eight meeting. The y-axis is expressed as the fraction of words contained in our risk/uncertainty dictionaries $\mathcal{U}$ relative to total words (after pre-processing) in the economy round of each FOMC meeting.

largest PMU categories. The summary statistics for these series are reported in Appendix Table A-12.

One concern might be that our topic-specific PMU indices are related to a common factor and, therefore, do not capture independent dimensions of variation. As seen in Appendix Table A-12, though, the partial correlations between each series are never higher than 0.33 in absolute value. Inflation PMU in particular shows low correlation (0.07) with economy and market PMU. A principal components decomposition of the five time series also delivers the same message, with the first two components each explaining 31% of total variance and remaining components explaining at least 10%. In short, the topic-specific PMU measures appear to capture distinct dimensions of uncertainty, which we will explore in the remainder of the paper.

PMU can be disaggregated to the speaker-level, which we exploit in parts of the analysis that follows. Figure 6 shows speaker-level averages of overall PMU compared to the meeting-level averages of PMU in the meetings, in which those speakers served. Here again, one observes substantial heterogeneity, with some FOMC members referring much more frequently to terms in $\mathcal{U}$ than their colleagues.

Finally, we can construct separate PMU indices based on phrases associated with "risk" and "uncertainty." Although policymakers may draw a distinction between the two, in practice,

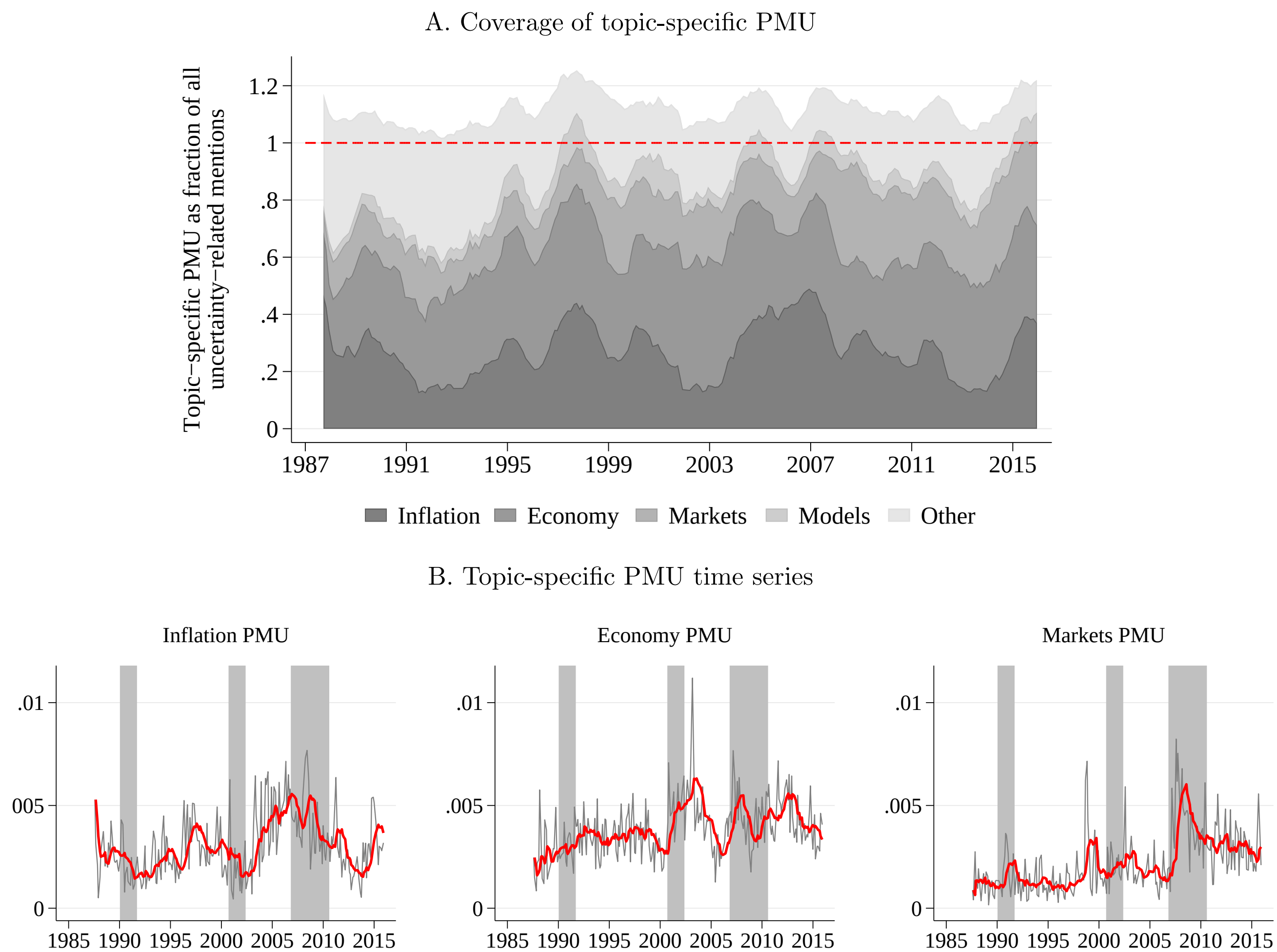

Figure 5. Topic-specific PMU. Panel A displays the topic-specific uncertainty-related mentions as a fraction of all uncertainty-related mentions in the economy round of the FOMC meeting. The fractions are smoothed over the last eight meeting and stacked. The numbers do not necessarily sum up to one because one mention can belong to more than one topic. Panel B displays the PMU index obtained from the economy round of the FOMC meeting disaggregated into topics. The smoothed index is a moving average over the last eight meeting. The y-axis is expressed as the fraction of words contained in our risk/uncertainty dictionaries $\mathcal{U}$ classified into a particular topic relative to total words in the economy round of each FOMC meeting.

as Greenspan (2004) claims "one if never quite sure what type of uncertainty on is dealing with in real time." We decompose topic-specific PMUs into the two components in Appendix Figure A-1 using nonoverlapping sets of phrases associated with risk and uncertainty. The main conclusion is that risk and uncertainty indices are highly correlated with each other in the time series and appear with a similar frequency in policy deliberations. The largest discrepancies are visible for the *EcoPMU* for which mentions referring to uncertainty are 50% more frequent than those referring to risk. Overall, however, their overlap is consistent with the statement by Greenspan that the two notions are closely related and challenging

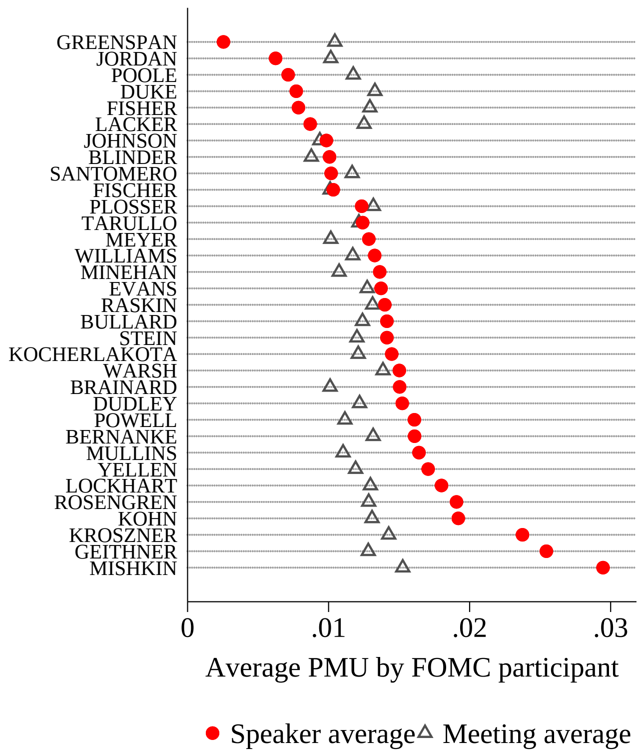

Figure 6. Speaker-level uncertainty. The figure presents the average speaker-level PMU. The index is the fraction of uncertainty-related phrases mentioned by a speaker relative to the overall number of words by that speaker in the economy round of the FOMC meeting. Circles represent speaker-specific average PMU. For reference, the triangles indicate the overall meeting-level PMU averaged across the meetings in which the speaker was present. The plot includes only those participants who were present in at least 8 meetings over our sample from 1987:08 to 2015:12, and who have spoken average number of words per meeting that is above the median.

to disentangle in practice. Therefore, in most of our subsequent analysis, we use the overall PMU indices encompassing both risk- and uncertainty-related mentions.

III.C. Sentiment based on directional views about the economy

As our framework makes clear, skewness as well as variance is relevant for policy decisions under uncertainty. How to measure higher-order-moments from language is not immediately obvious. The approach we take is to account for the perceived direction of relevant economic variables. The attention paid to outcomes evolving in certain directions should proxy for the worries attached to tail risks.

We refer to these directional measures as sentiment (following Hassan, Hollander, van Lent, and Tahoun, 2019 and Shapiro and Wilson, 2022) and build them for inflation, the real economy, and financial markets.[20] As a convention, we label the discussions of falling inflation as indication of negative inflation sentiment (*InfNeg*), discussions of weakening economic activity as negative sentiment about real economy (*EcoNeg*), and discussion of deteriorating financial conditions as negative market sentiment (*MktNeg*). We reverse those relations for the positive sentiment (*InfPos*, *EcoPos*, and *MktPos*). As a proxy for the overall sentiment, we define balance measures as the difference between the positive and negative sentiment, e.g., for inflation $\mathit{InfSent}_t = \mathit{InfPos}_t - \mathit{InfNeg}_t$. Increases in the balance indicate a positive tilt in views about a given variable.

Appendix B.1 details the construction of the sentiment indices. The basic idea is to count the frequency with which topic-specific terms (which generally overlap with those used for the topic-specific uncertainty) are preceded or followed by direction words that indicate positive or negative sentiment, respectively. In analogy to the PMU, we derive the sentiment proxies from the economy round of the meeting and scale the sentiment count by the number of total words in that round. Importantly, to avoid a mechanical relationship between PMU and sentiment, in sentiment construction we exclude all sentences that we use to obtain the PMU indices.

III.D. Measuring policy stance with text

So far, we have focused on measuring policymakers' perceptions of economic conditions discussed in the economy round of the meeting that serve as inputs into the policy decision. To quantify the outcome of the deliberations—the policy stance—we use FOMC members' statements during the policy round.

In each meeting, we measure the frequency of occurrence of the language indicating hawkishness and dovishness, scaled by the overall length (number of words) of the policy round. Here, however, to glean the policy views of actual decision makers, we exclude statements made by the staff. Our classification of the hawkish and dovish language takes into consideration both conventional policy as well as the unconventional tools during the zero-lower-bound period. Appendix B.2 describes the details of the construction.

We denote the resulting scores in meeting t as Hawk_t and Dove_t, respectively, and summarize the overall policy stance by taking the difference:

[20] Shapiro and Wilson (2022) construct a measures of policymakers' losses from negative sentiment expressed in the meeting to estimate the implicit inflation target. Their sentiment measure relies on Loughran and McDonald (2011) dictionary who construct lists of negative and positive words curated for financial texts. Our measurement approach differs from theirs in that we extract sentiment in the economy round of the meeting pertaining to specific variables based on the Fed-specific dictionary that we develop. Our objective is also different as we use text to isolate sentiment and PMU as the inputs to the policy decision from the resulting policy stance.

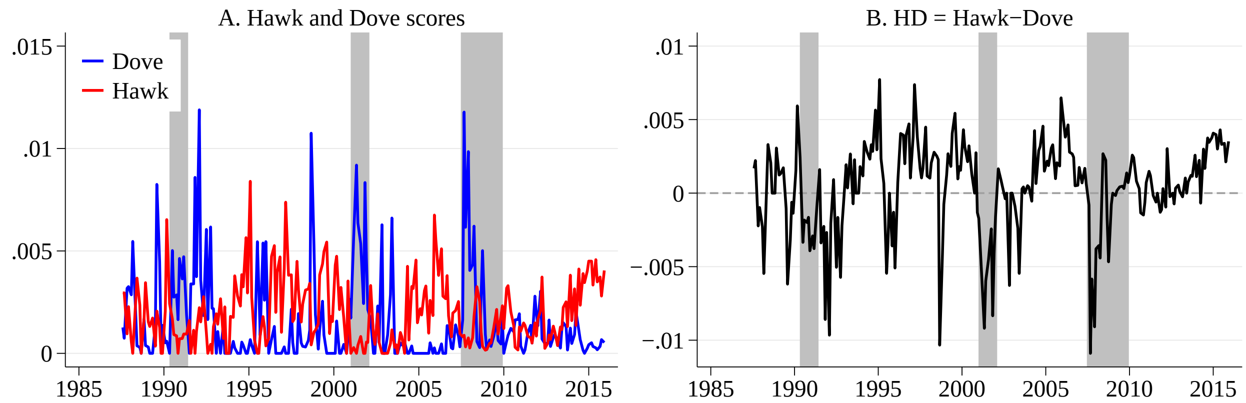

Figure 7. Textual measures of policy stance. The figure presents textual measures of policy preferences derived from the statements of FOMC members during the policy round of the FOMC meetings.

$$HD_t = Hawk_t - Dove_t. \tag{8}$$

Thus, HD_t reflects the tilt in the policy stance that emerges during the meeting. As with the PMU, the HD score can also be obtained to describe the stance of an individual FOMC member. We denote a member's i score as HD_{it}.

Figure 7 presents the time series of the $Hawk_t$ and $Dove_t$ scores, and their balance HD_t. The dynamics of these variables display intuitive properties, with the $Dove_t$ becoming elevated around recessions and in periods of financial turmoil, and the $Hawk_t$ increasing in expansions. Importantly, policy stance derived from the text show substantial variation in the post-2008 sample when short-term nominal interest rates are constrained at zero.

IV. Validation of textual measures

In this section, we provide validity checks for our interpretation of the text-based measures developed above as capturing policy stance, policymakers' uncertainty, and the directional views about the economy (sentiment), respectively.

IV.A. HD score as a measure of policy stance

To validate the *HD* score as describing the policy stance, in Table I, we analyze its relationship with proxies in the literature: deviations of the policy rate from a Taylor rule and high-frequency monetary policy surprises obtained from changes in market interest rates around FOMC announcements. All regressions in Table I are estimated at the FOMC meeting frequency.

In Table I, panel A, we first project *HD* on typical variables included in the estimates of a policy rule. This specification, reported in column (1), serves as a benchmark to describe the systematic component of policy reflected in language. The explanatory variables include the Greenbook forecasts and forecast revisions for inflation and the real GDP growth, as well as a trend inflation variable, τ_t, to account for a slow-adjustment in the inflation target over our sample.[21] Most loadings in column (1) are highly significant and have expected signs: higher expected growth and higher expected deviation of inflation from the target predict a more hawkish tilt in the policy language. At the same time, the regression $\bar{R}^2$ of 29% leaves more than two-thirds of the variation in the policy language unexplained by the rule.

Columns (2)–(5) focus on explaining changes in the actual policy instrument—the federal funds rate (FFR) target—with the policy language. Although our textual proxies are available until 2015:12, we estimate these regressions through 2008:12, given that the FFR is at the zero-lower bounds thereafter. The estimates show a strong explanatory power of the policy language. A more hawkish (dovish) language predicts a FFR target increase (decrease) (column (2)). The *HD* variable contains essentially the same information (column (3)) as the *Hawk* and *Dove* scores considered separately. A one standard deviation increase in *HD* is associated with approximately 0.5 standard deviation increase in the FFR target (about 14 basis points) with a t-statistic of 6.8. Given results in column (1), the significance of *HD* could simply reflect the policy rule as opposed to the deviation from it. However, column (5) shows that this is not the case. Also with a full set of controls, the *HD* score remains economically and statistically significant with a one-sigma increase in *HD* corresponding to a 0.3-sigma increase in the target (t-statistic of 5.3).

In columns (6)–(8), we present analogous results using a widely-adopted measure of monetary policy shocks proposed by Romer and Romer (2004).[22] Since Romer-Romer shocks are constructed from changes in the policy rate at each meeting purged of Fed's information (Greenbooks), it is not surprising that the results in column (6)–(8) are very similar to those based on FFR target in columns (3)–(5). The *HD* language alone explains a quarter of variation in Romer-Romer shocks.

[21] Following Coibion and Gorodnichenko (2012), as Greenbook controls, we use longer-term CPI inflation forecasts (four quarters ahead, $F_t(\pi_4)$), and current quarter real GDP growth forecast (nowcast, $F_t(g_0)$). We also add forecast revisions between meetings ($FR_t(\pi_3), FR_t(g_1)$), following Romer and Romer (2004) to account for changes in forecasts in addition to levels. The trend inflation variable τ_t is constructed as the discounted moving average of past core inflation following Cieslak and Povala (2015). Including trend inflation allows the regression to capture the effect of deviations of expected inflation from the target on the policy rate.

[22] We obtain the Romer-Romer shock series from the data set accompanying Valerie Ramey's handbook chapter on propagation of macro shocks (Ramey, 2016). The shocks are available during the pre-zero-lower-bound sample 1987:08–2007:12.

A. FFR target changes and Romer-Romer shocks

	(1) HD_t	(2) ΔFFR_t	(3) ΔFFR_t	(4) ΔFFR_t	(5) ΔFFR_t	(6) RR_t	(7) RR_t	(8) RR_t
$Hawk_t$			0.287***			0.253**		
			(4.07)			(2.54)		
$Dove_t$			-0.316***			-0.359***		
			(-6.42)			(-3.70)		
HD_t				0.497***	0.334***		0.506***	0.601***
				(6.83)	(5.30)		(4.95)	(5.04)
$F_t(\pi_4)$	0.613***	0.684***			0.523***			0.115
	(3.64)	(3.79)			(2.97)			(0.73)
$F_t(g_0)$	0.382***	0.546***			0.456***			-0.085
	(2.99)	(6.60)			(5.75)			(-1.14)
τ_t	-0.695***	-0.374***			-0.226**			0.043
	(-3.81)	(-3.30)			(-2.06)			(0.26)
$FR_t(\pi_3)$	0.073	0.051			0.022			0.088
	(1.43)	(0.86)			(0.39)			(1.30)
$FR_t(g_1)$	0.152***	0.136**			0.092			-0.168**
	(2.79)	(2.30)			(1.32)			(-2.55)
L.FFR_t		0.587	1.807***	1.766***	-0.091			
		(1.14)	(3.35)	(3.18)	(-0.15)			
L2.FFR_t		-0.875*	-1.851***	-1.801***	-0.159			
		(-1.84)	(-3.64)	(-3.40)	(-0.29)			
$\bar{R}^2$	0.29	0.52	0.45	0.45	0.59	0.25	0.25	0.30
N	227	169	169	169	169	163	163	163

B. Market-based measures of monetary policy surprises

	(1) GSS target	(2) GSS path	(3) GK MP0	(4) GK ED12m	(5) NS news
HD_t	0.169	0.178***	0.382***	0.409***	0.290**
	(1.33)	(2.74)	(4.00)	(4.92)	(2.33)
R^2	0.028	0.032	0.15	0.17	0.084
N	196	196	190	199	154

Table I. Validity of textual measures of policy preferences. The table reports regressions of various measures of monetary policy stance on textual *Hawk*, *Dove*, and *HD* variables. The textual measures are derived from the policy round of the FOMC meeting transcripts. Panel A reports regressions of changes in the FFR target and Romer-Romer shocks on the textual proxies, with and without Greenbook controls (forecasts $F_t(\cdot)$ and forecast updates $FR_t(\cdot)$). The τ_t variable controls for the perceived inflation target. Columns (2)–(5) are based on the 1987:08–2008:12 sample, i.e., excluding the zero-lower bound episode. Columns (6)–(8) are based on the 1987:08–2007:12 sample, when Romer-Romer shocks are available from Ramey (2016). HAC t-statistics with eight lags are reported in parentheses. The sample period is 1987:08–2015:12. Panel B reports regressions of monetary policy surprises on the *HD* variable. Columns (1) and (2) contain high-frequency target and path surprises following the approach of Gürkaynak, Sack, and Swanson (2005) as updated by Swanson (2018) (1991:07–2015:10 sample). Columns (3) and (4) use shocks from Gertler and Karadi (2015) obtained from the current month fed fund futures (MP0, sample 1988:11–2012:06) and 12-month ahead Eurodollar futures (ED12m, sample 1987:08–2012:06). Column (5) is based on surprises from Nakamura and Steinsson (2018) (sample 1995:02–2014:03). Robust t-statistics are reported in parentheses. All regressions are estimated at the frequency of FOMC meetings. The coefficients are standardized.

Dependent variable: Change in FFR target over subsequent h meetings, $\Delta FFR_{t+h,t} = FFR_{t+h} - FFR_t$

	(1) $h=1$	(2) $h=2$	(3) $h=3$	(4) $h=4$	(5) $h=5$	(6) $h=6$	(7) $h=7$	(8) $h=8$
HD_t	0.326***	0.311***	0.335***	0.330***	0.290***	0.234***	0.194**	0.188**
	(3.45)	(3.02)	(3.08)	(3.28)	(3.23)	(2.83)	(2.35)	(2.30)
GB controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.40	0.40	0.38	0.41	0.44	0.46	0.48	0.50
N	170	170	170	170	170	170	170	170

Table II. Validity of textual measures of policy preferences. The table reports predictive regressions of changes in the FFR target rate over h meetings ahead by the textual measure of policy stance *HD*. The regressions are estimated at the frequency of FOMC meetings, controlling for Greenbook forecasts and trend inflation τ_t and two lags of the FFR target (same controls as in Table I). All explanatory variables (except the lagged FFR target) are measured as of meeting t. The dependent variables (future changes in the FFR target) span the horizon from the next meeting up to eight meetings ahead. The coefficients are standardized. HAC standard errors to account for overlapping data are reported in parentheses. The maximum sample uses data over the 1987:08–2009:12 period.

In Table I, panel B, we further explore the relationship between language and monetary policy surprises identified from high-frequency changes in interest rates around the FOMC announcements. As these surprises differ in construction details (maturities of interest rates and sample periods), we consider proxies from several recent studies: Swanson (2018) who extends and updates the estimates of target and path factors in Gürkaynak, Sack, and Swanson (2005, GSS), Gertler and Karadi (2015, GK), and Nakamura and Steinsson (2018, NS). Across the board, we find a positive relationship with the *HD* score, whereby the relationship is generally stronger for surprises identified from longer-term interest rates. Accordingly, in Table II, we use *HD* to forecast the path of policy rates. The *HD* variable remains a significant predictor of FFR target changes up to eight meetings ahead, controlling for the meeting-t Greenbook forecasts.

In sum, the FOMC deliberations summarized in the *HD* variable reveal to a significant degree the content of policy surprises (deviation of policy stance from a rule). The language in the policy round encompasses forward-looking views by policymakers that pertain not only to the current decision but also to the intended policy path.

IV.B. PMU indices as measures of uncertainty

A challenge for empirically identifying the effects of higher-order moments on policy is that they tend to correlate with the current or expected future state of the economy. Additionally, it is possible that when policymakers express views about risk or uncertainty they do not refer to second moments of a distribution, but rather to a particular directional outcome they fear or are concerned about (i.e., skewness).

To verify that our textual measures do not simply capture policymakers' first-moment beliefs about the economy, in Table III, we study their predictive power for future realization of inflation and real GDP growth. To make sure that the macro realizations are aligned with the schedule of the FOMC meetings, we use the future Greenbook nowcasts for inflation and real GDP growth, $F_{t+h}(\pi_0)$ and $F_{t+h}(g_0)$, up to eight meetings ahead as the dependent variables, for $h = \{1, ..., 8\}$. We project the time-$t+h$ nowcast onto PMU and sentiment observed in meeting t. The regressions control for meeting-t Greenbook forecasts (average of forecasts for horizons between current quarter up to four quarters ahead).

The main observation from Table III is that PMU does not predict future outcomes at any horizon. This finding holds true both for inflation and real GDP growth forecasts.[23] It is therefore unlikely that PMU proxies for policymakers' first-moment beliefs. The second takeaway is that the sentiment predicts inflation and growth over and above the Greenbook forecasts (growth at all forecast horizons and inflation up to two meetings ahead), implying that the deliberations contain information not captured by the staff forecasts. To the extent that the Greenbooks focus on the most likely scenarios (modes), the additional predictive content suggests that the directional language in the meeting reflects policymakers' perceptions of skewed, potentially undesirable, outcomes.

V. (How) Does Uncertainty Affect Policy Stance?

We now explore the relationship between the uncertainty policymakers perceive and their policy stance. Since all PMU and sentiment indices are constructed from the economy round of the FOMC meeting, they are predetermined by the time the policy round begins, and from which we derive policy stance of the FOMC members.

V.A. Meeting-level results

Table IV reports the predictability of the policy stance with the PMU and the sentiment in the transcripts, with and without controlling for the Greenbook forecasts. In column (1), we project *HD* on the overall *PMU* index, following much of the literature that focuses on uncertainty in general, without separating the type. More uncertainty expressed in the economy round of the meeting forecasts relatively more dovishness in the policy round. Overall PMU explains about 8% of the variation in the *HD* score. Column (2) illustrates

[23] The result is not sensitive to whether or not we include sentiment and Greenbook variables in the regression. Univariate predictive regressions with just PMU are in Appendix Table A-13.

A. Dependent variable: Greenbook CPI inflation nowcast h meetings ahead, $F_{t+h}(\pi_0)$

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
$InfPMU_t$	0.039	-0.038	-0.042	0.011	-0.107	-0.070	0.038	0.044
	(0.62)	(-0.48)	(-0.38)	(0.08)	(-0.69)	(-0.42)	(0.27)	(0.45)
$InfNeg_t$	-0.260***	-0.164*	0.012	0.093	0.086	0.010	-0.058	-0.025
	(-3.49)	(-1.87)	(0.18)	(1.30)	(1.04)	(0.17)	(-0.98)	(-0.39)
$InfPos_t$	0.173***	0.144***	0.025	-0.131	-0.100	-0.120	-0.169*	-0.138
	(3.81)	(2.67)	(0.38)	(-1.32)	(-0.97)	(-1.42)	(-1.80)	(-1.47)
$\overline{F}_t(\pi)$	0.560***	0.457***	0.378***	0.351***	0.319***	0.321***	0.337***	0.335***
	(8.46)	(6.91)	(4.30)	(3.39)	(2.82)	(2.90)	(3.73)	(4.01)
$\bar{R}^2$	0.50	0.30	0.13	0.11	0.11	0.11	0.12	0.10
N	226	225	224	223	222	221	220	219

B. Dependent variable: Greenbook real GDP growth nowcast h meetings ahead, $F_{t+h}(g_0)$

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
$EcoPMU_t$	-0.081	-0.058	0.032	0.069	0.029	-0.001	0.087	0.113
	(-1.60)	(-1.15)	(0.69)	(1.03)	(0.36)	(-0.02)	(1.01)	(1.23)
$EcoNeg_t$	-0.150***	-0.163**	-0.220***	-0.275***	-0.313***	-0.226**	-0.238**	-0.237**
	(-2.92)	(-2.40)	(-2.65)	(-3.00)	(-4.29)	(-2.28)	(-2.05)	(-2.32)
$EcoPos_t$	0.116**	0.127**	0.147**	0.149*	0.151*	0.193**	0.203**	0.190**
	(2.39)	(2.17)	(2.07)	(1.68)	(1.72)	(2.25)	(2.30)	(2.14)
$\overline{F}_t(g)$	0.623***	0.553***	0.401***	0.287***	0.227**	0.174	0.112	0.075
	(7.20)	(5.78)	(5.03)	(3.20)	(2.12)	(1.31)	(0.80)	(0.51)
$\bar{R}^2$	0.56	0.48	0.35	0.28	0.26	0.19	0.16	0.13
N	226	225	224	223	222	221	220	219

Table III. Predicting macro variables with textual measures of uncertainty and sentiment. The table reports predictive regressions of inflation and real GDP growth by textual PMU and sentiment indices derived from the economy round of the FOMC meeting transcripts. The regressions are estimated at the FOMC meeting frequency with the forecast horizon ranging from the next meeting ($h = 1$) up to eight meetings ahead ($h = 8$). To make sure that the timing of the depend variable is consistent with the timing of the meetings, we use Greenbook nowcasts at future meetings as the dependent variable. The regression is $F_{t+h}(\pi_0) = \beta_0 + \beta_1 InfPos_t + \beta_2 InfNeg_t + \beta_3 InfPMU_t + \beta_4 \overline{F}_t(\pi) + \varepsilon_{t+h}$, where $F_{t+h}(\pi_0)$ is the CPI inflation nowcast at meeting $t+h$, and $\overline{F}_t(\pi)$ is the average forecast (across horizons) given at meeting t. We estimate analogous regressions for the real GDP growth. The coefficients are standardized. HAC standard errors to account for the overlap are reported in parentheses. The sample period is 1987:08–2015:12.

the importance of disaggregating the sources of uncertainty by introducing the topic-specific PMU for inflation and the real economy. As the main empirical fact, inflation and real-economy PMU predict policy stance with opposite signs, both are highly significant, and explain 15% of the *HD* variance. A one-sigma increase in *InfPMU* is associated with a 0.3-sigma increase in the *HD* score (t-statistic = 3.39); in contrast, a one-sigma increase in *EcoPMU* leads to 0.24 sigma decrease in the *HD* score (t-statistic = −3.97).

In columns (3)–(6) we test whether the uncertainty effect on policy stance can be subsumed by the variation in the first-moment beliefs as captured by the Greenbook forecasts or by the

Dependent variable: HD_t policy stance score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PMU_t	-0.288***							
	(-3.66)							
$InfPMU_t$		0.341***			0.281***	0.184**	0.235***	0.223***
		(3.39)			(3.89)	(2.54)	(3.03)	(3.21)
$EcoPMU_t$		-0.238***			-0.151***	-0.221***	-0.139**	-0.126**
		(-3.97)			(-3.10)	(-3.21)	(-2.26)	(-2.30)
$InfSent_t$			0.204**	0.134***	0.085			0.074
			(2.54)	(2.72)	(1.17)			(1.03)
$EcoSent_t$			0.498***	0.421***	0.471***			0.397***
			(5.71)	(4.79)	(5.91)			(5.00)
$MktPMU_t$							-0.197*	-0.092
							(-1.71)	(-0.86)
$ModPMU_t$							0.155***	0.153***
							(3.35)	(3.87)
$OthPMU_t$							-0.262***	-0.122*
							(-4.21)	(-1.84)
GB controls	No	No	No	Yes	No	Yes	No	No
$\bar{R}^2$	0.079	0.15	0.30	0.40	0.38	0.34	0.28	0.41
N	227	227	227	227	227	227	227	227

Table IV. Predicting policy stance with PMU at the meeting-level. The table reports regressions of the policy stance score *HD* on topic-specific PMU indices as well as Greenbook forecasts and textual sentiment controls. The *HD* variable is derived from the statements of FOMC members in the policy round of the FOMC meeting, while the PMU indices are based on the statements by the staff and FOMC members in the economy round of the meeting. All regressions are estimated at the frequency of FOMC meetings. The sentiment measures are defined in Section III.C. The coefficients are standardized. HAC t-statistics with eight lags are reported in parentheses. The sample period is 1987:08–2015:12.

sentiment in the meeting. As a first step, columns (3) and (4) establish that the sentiment is strongly predictive for the policy stance beyond the Greenbooks. Importantly, however, *InfPMU* and *EcoPMU* preserve their significance either with the sentiment (column (5)) or the Greenbook controls (column (6)). Of note is the fact that inflation PMU drives out the significance of the inflation sentiment. This suggests that increased inflation PMU correlates with policymakers' discussions of rising inflation. Table III has already established that inflation sentiment does not predict actual realizations of inflation except at very short horizons. Taken together, the results thus suggest that inflation sentiment is likely to reflect policymakers' worry about inflation getting out of control, but that worry does not materialize in our sample. This evidence is consistent with the inflation scares example in Section II.D, whereby a low-probability but costly event can influence the decision making. We explore this interpretation further in Section VI. In contrast, uncertainty and sentiment about the real economy contain largely independent information: Views of stronger economy lead to hawkishness, while increased uncertainty about the economy produces a more dovish stance.

Accounting for the remaining uncertainty categories (markets *MktPMU*, models *ModPMU*, and the unclassified category *OthPMU*) in columns (7) and (8) partially reduces the economic significance of inflation and real-economy PMU. This is not surprising in that PMU indices are not orthogonal and can load on common factors. However, the distinct directional effects suggest that uncertainty affects policy via at least two channels. Like *InfPMU*, also model uncertainty (*ModPMU*) predicts more hawkishness. Combined with the fact that *InfPMU* and *ModPMU* are positively correlated, this suggests that inflation PMU stems in part from policymakers' concern with model misspecification. Similar to the real-economy PMU, the market and the residual PMUs, are instead associated with relatively more dovishness. As such, these uncertainty types affect policy akin to a negative demand shock, leading to an easier stance. With a full suite of PMU indices in column (8), *MktPMU* and *OthPMU* become marginally significant, suggesting they have little independent role over and above inflation and real-economy PMU. Thus, in subsequent analysis, we focus on these two main uncertainty types.

V.B. Individual-level results

The analysis so far focuses on the meeting-level outcomes, where the uncertainty and sentiment aggregate the views of both the FOMC members and the staff in the economy round. One consideration in interpreting the results is that they could arise from a disagreement among members as opposed to the common perceptions on the committee. We thus turn to estimating the language-based reaction functions at the individual FOMC-member level exploiting the granularity of the textual data. The results show that it is the common perception of uncertainty that affects the policy stance.

In Table V, the dependent variable is the policy stance of member i in meeting t, HD_{it} (using the policy-round statements), and the explanatory variables are the corresponding uncertainty and sentiment scores of that member (using the economy-round statements). The goal is to study how a policymaker's own expression of uncertainty predicts their individual policy stance. All regressions include member fixed effects, and so the estimates represent the within-individual reaction functions. Column (1) shows that, similar to the meeting-level results, also within-member inflation uncertainty is associated with more hawkishness, while real-economy uncertainty with more dovishness (although this effect is weaker than that of inflation). The impact of inflation uncertainty on policy stance is not driven by the member-specific sentiment (column (2)).

To study the role of common perceptions on the committee vis-á-vis heterogeneity, column (3) additionally includes aggregate meeting-level PMU indices, and column (4) includes the

Dependent variable: Individual FOMC member policy stance at meeting t, HD_{it}

	(1)	(2)	(3)	(4)	(5)	(6)
$InfPMU_{it}$	0.12***	0.12***	-0.0044	-0.011	0.11**	-0.0097
	(2.86)	(2.82)	(-0.10)	(-0.30)	(2.62)	(-0.25)
$EcoPMU_{it}$	-0.074	-0.058	0.014	0.012	-0.041	0.011
	(-1.65)	(-1.43)	(0.36)	(0.30)	(-1.03)	(0.29)
$\overline{InfPMU}_t$			0.98***			
			(4.70)			
$\overline{EcoPMU}_t$			-0.84***			
			(-3.86)			
$MktPMU_{it}$					-0.16***	0.011
					(-2.70)	(0.25)
$ModPMU_{it}$					-0.071	-0.15
					(-0.64)	(-1.38)
$OthPMU_{it}$					-0.19***	-0.11**
					(-4.20)	(-2.40)
Sentiment	No	Yes	No	Yes	Yes	Yes
Meeting FE	No	No	No	Yes	No	Yes
Member FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.028	0.048	0.055	0.26	0.059	0.26
N	3925	3925	3925	3925	3925	3925

Table V. Predicting policy stance with PMU at the individual-meeting-level. The table reports regressions of individual FOMC member i policy stance at meeting t, HD_{it}, with individual PMU indices at meeting t. Inflation and real-economy sentiment are also measured at the member-meeting level. $\overline{InfPMU}_t$ and $\overline{EcoPMU}_t$ are the meeting-level PMU indices. Standard errors are double-clustered at the meeting and member level.

time fixed effects. As both specifications render the member-level PMU insignificant, the explanatory power of uncertainty comes entirely from the time-series variation rather than from cross-sectional dispersion of views across members.

Finally, column (5) includes the full set of individual-level PMU indices. Individual member policy views are sensitive to the market uncertainty, with increased $MktPMU_{it}$ associated with an easier stance, supporting the demand-shock interpretation of market uncertainty. However, this effect reflects common rather than member-specific variation and is subsumed by the meeting fixed effects in column (6). Two additional differences from the meeting-level results in Table IV are worth highlighting. First, $ModPMU_{it}$ is not significant at the individual level, implying that it stems primarily from the staff discussions of model uncertainty, which then influence inflation uncertainty of the members. Second, $OthPMU_{it}$ predicts easier policy stance even with time fixed effects, suggesting that idiosyncratic uncertainty perceptions do influence individual policy views but their effect on the overall policy stance of the committee is weak (given results in Table IV column (8)).

V.C. *Does uncertainty strengthen or weaken policymakers' reaction to the state of the economy?*

The classic approach to introduce a role of uncertainty in policymaking in the literature is by allowing uncertainty to affect the optimal response coefficients in a policy rule. Policy parameters thus become a function of the policymaker's uncertainty. Different models have different predictions as to whether uncertainty induces a more or less aggressive response to economic conditions.[24] Likewise, it remains an open empirical question whether uncertainty strengthens or weakens the policymakers' response, and whether its effects differ across state variables policymakers care about.

To cast light on these questions, we study the role of interactions between macro variables and the PMU indices in explaining policy stance using the following specification estimated at the meeting level:

$$\begin{aligned} HD_t = {} & \beta_0 + \beta_1 \tau_t + \beta_2 F_t(\pi_4) + \beta_3 F_t(g_0) \\ & + \delta_1 (F_t(\pi_4) \times \mathit{InfPMU}_t) + \delta_2 (F_t(g_0) \times \mathit{InfPMU}_t) \\ & + \delta_3 (F_t(\pi_4) \times \mathit{EcoPMU}_t) + \delta_4 (F_t(g_0) \times \mathit{EcoPMU}_t) \\ & + \gamma_1 \mathit{InfSent}_t + \gamma_2 \mathit{EcoSent}_t + \varepsilon_t. \end{aligned} \tag{9}$$

One can interpret equation (9) as a forward-looking policy rule with time-varying loadings that change with the degree of policymakers' uncertainty. The coefficients on the interaction terms describe how the sensitivity of policy stance (measured with the *HD* score as before) to inflation and real growth changes when uncertainty changes.

We report the estimates in Table VI. For reference, column (1) displays results when interactions are not included, only allowing for direct effects of uncertainty, as in Table IV. Column (2) adds sentiment. The new results are in columns (3) and (4) which interact each of the Greenbook forecasts with PMU indices, with and without sentiment. All variables are expressed in units of standard deviations. The conditional character of the interaction regressions makes the interpretation of the individual coefficients challenging.[25] Thus, we present the main marginal effects of interest graphically in Figure 8. The estimates, obtained with the delta method, illustrate how the slope coefficient on a given variable changes with the level of another variable. The graph contains 95% confidence bounds for the null hypothesis that each of the coefficients is different from zero.

[24] We summarize those models in Section II.A and provide illustrative calibrations in Appendix D.

[25] With interactions, the direct effect coefficients (βs and γs in equation (9)) capture the effect of a variable when keeping other variables it is interacted with at zero. As such, the direct effects may not be economically interesting or meaningful when considered on their own.

The main finding is that the policymakers' response to the inflation forecast increases with the level of inflation uncertainty. The interaction term on $F_t(\pi_4) \times InfPMU_t$ is positive and significant. Panel A of Figure 8 shows the change in the HD_t score given one unit change in $F_t(\pi_4)$ at different levels of $InfPMU_t$. The increasing pattern of the slope coefficients shows that policymakers tend to display relatively more hawkishness in reaction to inflation when inflation forecast is accompanied by high uncertainty. When uncertainty is very low, the effect of inflation is not statistically different from zero. This result holds also when we account for the sentiment expressed in the meeting.

The real-economy PMU likewise tends to strengthen the Fed's reaction to real GDP growth, visible in Figure 8 panel B. The positive coefficient on $F_t(g_0) \times EcoPMU_t$ in Table VI means that policy stance becomes relatively more dovish when the economy is doing poorly and uncertainty is high. In contrast to inflation, however, the amplification due to uncertainty weakens when controlling for the sentiment.

Complementary to the above results, the bottom panels of Figure 8 depict the impact of uncertainty on policy stance at different levels of expected inflation and growth, respectively. By extending the baseline linear specification in column (1) of Table VI, these estimates help assess when, i.e., in which economic states, the effect of uncertainty on policy is likely to be the strongest. Inflation PMU is associated with a more hawkish stance when inflation forecast is high, while real-economy PMU is associated with a more dovish stance when growth is weak. The cross-effects, i.e., inflation PMU altering the policy response to the real economy, and economy PMU altering the response to inflation, are economically and statistically small (and are not reported in the graph). Thus, while inflation uncertainty tends to amplify the response to inflation, it does not affect the response to growth, and vice-versa.

V.D. Implications for models of optimal policy choice with uncertainty

Our evidence helps cast light on which theoretical mechanisms discussed in Section II.A are likely to be born out by the actual policymakers' deliberations. The main finding of Table VI—the amplifying effect of uncertainty on the inflation and growth response—goes against the Brainard's conservatism principle, and could arise from uncertainty about inflation persistence and/or desire for decision making to avoid costly outcomes. This interpretation also aligns with view expressed by policymakers themselves, e.g., Bernanke (2007) states: "Indeed, intuition suggests that stronger action by the central bank may be warranted to prevent particularly costly outcomes."[26] However, while the amplification is qualitatively

[26] More recently, Praet (2018) elaborates: "A more aggressive monetary policy response (...) is warranted when there is clear evidence of heightened risks to price stability, i.e. when it is established that the degree of

Dependent variable: HD_t policy stance score

	(1)	(2)	(3)	(4)
$F_t(\pi_4)$	0.39***	0.55***	0.090	0.48**
	(2.74)	(3.95)	(0.40)	(2.32)
$F_t(g_0)$	0.38***	0.15**	-0.060	-0.14
	(5.67)	(2.14)	(-0.31)	(-0.80)
τ_t	-0.53***	-0.59***	-0.52***	-0.58***
	(-3.84)	(-4.72)	(-3.64)	(-4.40)
$F_t(\pi_4) \times \mathit{InfPMU}_t$			0.20***	0.15***
			(3.47)	(2.88)
$F_t(g_0) \times \mathit{InfPMU}_t$			-0.016	-0.030
			(-0.33)	(-0.65)
$F_t(g_0) \times \mathit{EcoPMU}_t$			0.18***	0.13**
			(2.99)	(2.49)
$F_t(\pi_4) \times \mathit{EcoPMU}_t$			-0.024	-0.085
			(-0.42)	(-1.55)
InfPMU_t	0.19***	0.19***	-0.21	-0.087
	(3.50)	(3.73)	(-1.28)	(-0.59)
EcoPMU_t	-0.24***	-0.13**	-0.43***	-0.14
	(-4.11)	(-2.22)	(-2.84)	(-1.02)
$\mathit{InfSent}_t$		0.063		0.090**
		(1.45)		(2.11)
$\mathit{EcoSent}_t$		0.41***		0.39***
		(5.74)		(5.55)
R^2	0.34	0.45	0.39	0.48
$\bar{R}^2$	0.33	0.43	0.36	0.45
N	227	227	227	227

Table VI. Effect of uncertainty on policy stance. The table reports estimates of regression (9), allowing for interactions between PMU indices and the Greenbook forecasts. The sample period is 1987:08–2015:12. All variables are scaled by their standard deviations. Robust t-statistics are in parentheses.

consistent some theoretical specifications, its economic magnitude (visible in Figure 8) is hard to generate in standard settings. We illustrate the different mechanisms proposed in the literature in Appendix D. Using standard calibrations, even very large changes in uncertainty lead to small changes in the coefficients of the reaction function.

Our second set of results pertains to the direct effects, whereby uncertainty may influence policy stance independently of its amplifying impact on the coefficients of the reaction function. Through the lens of the canonical linear-quadratic framework operating under certainty equivalence, additive uncertainty should have no effect on optimal policy. Thus, the fact that the direct effects are present suggests that policymakers systematically deviate from the linear-quadratic paradigm, for example, by overweighing particular outcomes which they

inflation persistence is likely to be high and risks disanchoring inflation expectations. In this case, a forceful, frontloaded monetary policy response to weak or excess inflation may become necessary to signal the central bank's commitment to its objective, and thus nudge inflation expectations towards that objective and make them less backward-looking."

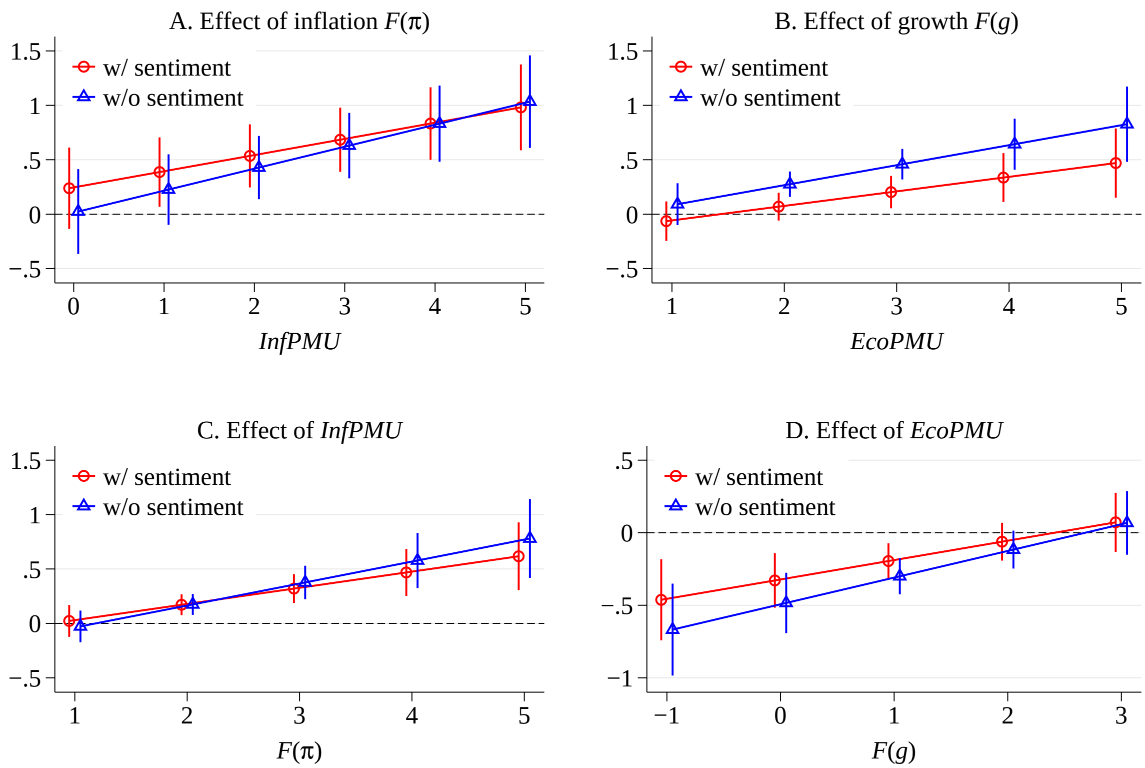

Figure 8. Marginal effects of PMU on policy stance. The figure presents the marginal effects based on the estimates in Table VI, columns (3) and (4). The dependent variable is the *HD* policy stance score. Panel A shows how the *HD* variable changes with a one unit change in Greenbook inflation forecast holding inflation PMU at different values (and all other covariates at their means). Analogous interpretation applies to the other panels. All variables are expressed in units of their standard deviations. The range of values for the variables depicted on the x-axis is constrained between their 5th and the 95th percentile.

view as costly. Likewise, the significance of uncertainty in the presence of the Greenbooks suggests that the staff forecasts customarily used in policy rule estimates do not fully account for the effects of uncertainty on the economy that FOMC members perceive.

VI. Properties of Policymakers' Uncertainty

The evidence so far shows that the uncertainty language in the meetings affects the FOMC's decision making. To further characterize its content, we analyze the variation in PMU over the business cycle, the relationship of the PMU measures with policymakers' skewed beliefs reflected in their sentiment, the Greenbook forecasts, and measures of public perceptions of uncertainty. The balance of evidence shows that policymakers' uncertainty provides new information about decision making that is not subsumed by variables typically used in policy analysis.

VI.A. PMU and sentiment over the business cycle

Figure 9 presents the time-series variation in PMU for inflation and the real economy, juxtaposing them against the positive and negative sentiment. For clarity of the graphs, we smooth all series with a moving average over the last eight meetings. A noteworthy feature of the PMU is a lack of a countercyclical behavior that is usually expected from uncertainty indicators (e.g., Bloom, 2014). Inflation PMU is strongly procyclical, suggesting that policymakers tend to express more uncertainty about inflation when the economy is doing well. Inflation concerns become prevalent from mid-2000s and reach their highest level in the first half of 2008. The procyclical inflation PMU is consistent with policymakers worrying primarily about the demand-driven increases in inflation. Indeed, inflation PMU comoves remarkably closely with the positive inflation sentiment expressed in the meetings (i.e., increasing inflation). Perhaps more surprisingly, the real-economy PMU also fails to display obviously countercyclical dynamics.[27] Compared to inflation, the economy PMU however shows a weaker correlation with the sentiment. For example, the economy PMU increases and remains persistently higher through the end of 2013, even when the negative sentiment about the economy subsides.[28]

Figure 9 points to an asymmetry: Elevated PMU coincides with views about the direction of the economy that policymakers would traditionally consider undesirable (rising inflation and weakening growth). To test the asymmetry more formally, in Table VII, we regress the PMU on the positive and negative sentiment. At the aggregate meeting level, in panel A, a one-sigma increase in positive inflation sentiment *InfPos* (referring to an increasing inflation) is associated with a 0.63-sigma increase in *InfPMU* (t-stat = 7.2); instead, a one-sigma increase in negative inflation sentiment *InfNeg* is associated with just 0.24-sigma increase in *InfPMU* (column (1)). A similarly asymmetric relationship is present for the real-economy PMU (column (2)), with *EcoNeg* (perception of a weakening economy) being about a three times stronger predictor of PMU than *EcoPos* (strengthening economy). The estimates also

[27] Its highest reading occurs during the March 18, 2003 meeting, driven by the uncertainty about the timing and extent of the Iraq war and about the underlying economic conditions. In another major episode, real-economy PMU becomes elevated in the first-half of 2007 before the start of the official NBER-dated recession. The transcripts of the March 21, 2007 meeting highlight rising concerns about growth outlook and heightened forecast uncertainty that are not yet associated with a direct downgrade of the economic forecasts. The uncertainty actually declines during the heights of the financial crisis even as the policymakers continue to express negative sentiment about the real economy.

[28] The market PMU is also strongly positively associated with the negative market sentiment expressed during the meetings (not shown in the figure for brevity). The market PMU reaches the highest level already in the early phases of the global financial crisis, in August 2007, preceding spike in the VXO (on October 29, 2008) by more than a year. As such, policymakers' uncertainty increases long before the full extent of the financial crisis can be appreciated.

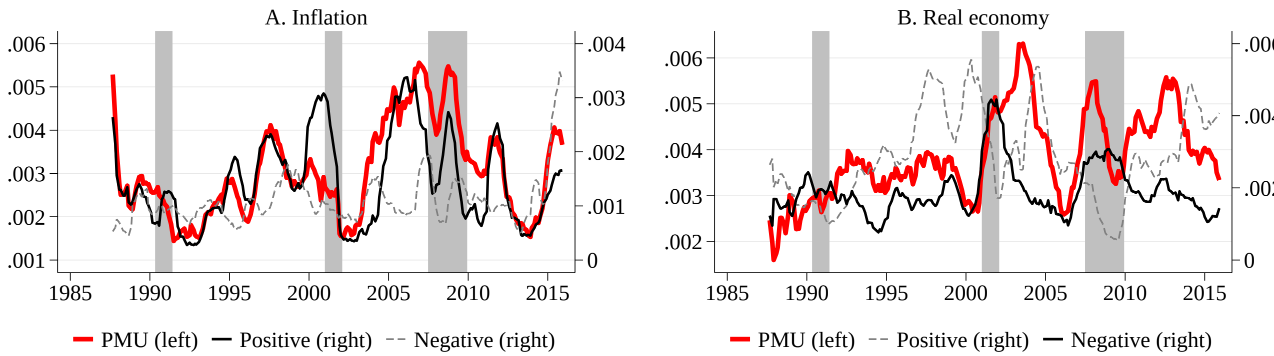

Figure 9. PMU over the business cycle. The figure presents topic-specific PMU indices superimposed against negative and positive sentiment. Positive (negative) sentiment indicates views of rising (declining) inflation or output. All text-based series are smoothed averages over the last eight FOMC meetings.

A. Meeting level

	(1) $InfPMU_t$	(2) $EcoPMU_t$
$InfPos_t$	0.623***	-0.195***
	(7.17)	(-2.98)
$InfNeg_t$	0.236***	-0.017
	(4.59)	(-0.30)
$EcoPos_t$	-0.154*	0.136*
	(-1.68)	(1.89)
$EcoNeg_t$	-0.063	0.344***
	(-1.10)	(6.22)
N	227	227
$\bar{R}^2$	0.41	0.13

B. Meeting-member level

	(1) $InfPMU_{it}$	(2) $InfPMU_{it}$	(3) $EcoPMU_{it}$	(4) $EcoPMU_{it}$
$InfPos_{it}$	0.21***	0.092**	-0.14***	-0.098***
	(5.06)	(2.28)	(-4.32)	(-3.97)
$InfNeg_{it}$	0.15***	0.12**	-0.050	-0.0079
	(3.18)	(2.64)	(-1.06)	(-0.16)
$EcoPos_{it}$	-0.053*	-0.038*	0.022	0.029
	(-1.89)	(-1.78)	(0.81)	(1.27)
$EcoNeg_{it}$	-0.032	-0.011	0.11***	0.062**
	(-1.35)	(-0.41)	(5.16)	(2.48)
Meeting FE	No	Yes	No	Yes
Member FE	Yes	Yes	Yes	Yes
N	3970	3970	3970	3970
R^2	0.15	0.27	0.16	0.25

Table VII. Relationship between uncertainty and sentiment. The table reports regressions of topic-specific PMU indices on the sentiment. Sentiment proxies are based on sentences that do not contain uncertainty phrases. Panel A presents the regressions at the meeting level, and panel B at the meeting-member level. All measures are derived from the economy round of the FOMC meeting. In panel A, the coefficients are standardized and HAC t-statistics with eight lags are reported in parentheses. In panel B, standard errors are double clustered at the meeting and member level. The sample period is 1987:08–2015:12.

indicate that the real-economy PMU declines when policymakers place more emphasis on rising inflation.

Panel B of Table VII presents analogous regressions at the meeting-member level. By including member fixed effects, we study how each a member's perception of uncertainty correlates with his or her directional views about the economy. A comparison of columns with and without time fixed effects indicates that asymmetric relationship between uncertainty and corresponding sentiment arises primarily from the business-cycle variation in policymakers' beliefs.

There are at least two possible interpretations of the correlations between PMU and sentiment. For one, policymakers may downgrade their sentiment in response to an increase in uncertainty they perceive. Thus, negative sentiment in the meeting could reflect policymakers' worry about undesirable developments which may not come true. Alternatively, negative shocks to expectations about the future could lead policymakers to express more uncertainty in the meeting. While in the latter case, one would expect negative sentiment to forecast future outcomes, in the former case, predictability is not warranted. The predictive regressions in Table III help cast light on these alternative interpretations. There, we establish that sentiment predicts real GDP growth but not inflation (except in a very short run). Thus, the close co-movement between inflation PMU and *InfPos* is likely to encapsulate policymakers' concerns about increases in inflation that do not come to fruition over our sample period.[29]

VI.B. Past forecast errors

The differences in the properties of inflation and real-economy PMU raise a broader question about the drivers of uncertainty in the meetings. It is natural to expect that uncertainty is affected by the magnitude of forecast errors, or the extent to which economic outcomes have diverged from the Fed's expectations. We therefore explore the relationship between uncertainty expressed in the meeting and the past forecast errors, using the Greenbook forecasts prepared by the Fed staff several days before the meeting. Table VIII reports regressions of PMU indices on the absolute and signed forecast errors for inflation and real GDP growth.[30]

The results in Table VIII panel A show that past absolute forecast errors (but not signed errors) are predictive of inflation PMU. Policymakers become more uncertain about inflation after experiencing large inflation surprises (in either direction). At the same time, inflation PMU is negatively related with absolute errors about the real GDP growth. The negative relationship is consistent with the procyclical variation in inflation PMU and the fact the

[29]The predictability results are unlikely to be endogenous to policy, given the known lagged effects of monetary policy on macro variables. The typical effect of policy on inflation takes about 18 months to unfold.

[30]The forecast error is defined as meeting-t nowcast minus meeting-$t-h$ forecast. The forecast errors $|\overline{FE}_t|$ are averages across horizons h from one-quarter-ahead to four-quarters-ahead. All errors are known at the time of the meeting t, but the forecast are formed at different meetings. In this way, we consider lookback period of up to one year. We do not include unemployment forecast errors in the regressions because of their high correlation with the forecast errors about the real GDP growth, making the interpretation of the coefficients less transparent.

A. Absolute forecast errors

	(1) $InfPMU_t$	(2) $EcoPMU_t$
$\lvert\overline{FE}_t(g)\rvert$	-0.308***	-0.013
	(-4.56)	(-0.15)
$\lvert\overline{FE}_t(\pi)\rvert$	0.382***	-0.038
	(4.82)	(-0.53)
$\bar{R}^2$	0.15	-0.0069
N	227	227

B. Forecast errors

	(1) $InfPMU_t$	(2) $EcoPMU_t$
$\overline{FE}_t(g)$	0.058	-0.205**
	(0.54)	(-2.14)
$\overline{FE}_t(\pi)$	0.150	0.144
	(1.26)	(1.60)
$\bar{R}^2$	0.021	0.041
N	227	227

Table VIII. Predicting uncertainty with past forecast errors. The table reports regressions of topic-specific PMU indices on past forecast errors in the Greenbooks. The coefficients are standardized. HAC t-statistics with eight lags are reported in parentheses. The sample period is 1987:08–2015:12.

real GDP growth errors are most pronounced in recessions. There is much less evidence of a systematic relationship between forecast errors and uncertainty about the real side of the economy. Policymakers tend to emphasize uncertainty about the real economy more when growth turns out lower and inflation higher than expected, but past forecast errors explain at most 4% of variation in the real-economy PMU. In summary, a significant part of PMU variation remains unexplained by the magnitude and direction of past surprises to Fed's macro expectations.

VI.C. Relationship of PMU with public perceptions of (policy) uncertainty

The illustrative framework in Section II indicates that policymakers' uncertainty expressed in the meeting is not equivalent to the objective conditional volatility of the macroeconomic variables. The inflation scares example shows how perceived uncertainty can be intertwined with policymakers' concerns about events that have low probability but are associated with large losses. The empirical properties of the PMU, and the link between PMU and sentiment, indeed suggest that PMU does not measure the objective physical volatility. As such, public perceptions of uncertainty should differ from the uncertainty relevant for policymaking, because they already condition on expected FOMC behavior.

To show this distinction more explicitly it worth connecting the PMU to measures of policy uncertainty proposed by Baker, Bloom, and Davis (2016) and Husted, Rogers, and Sun (2020).[31] These indices aim to reflect the degree of uncertainty that the public perceives

[31] Baker, Bloom, and Davis (2016, BBD) develop an index of economic policy uncertainty (EPU) based on the frequency of articles in ten leading newspapers that mention both uncertainty and economic policy. In addition, they also introduce sub-indices tailored for specific policies, including monetary policy. Husted, Rogers, and Sun (2020, HRS) adopt a related newspaper-based approach to construct a monetary policy uncertainty index (MPU) specific to the US monetary policy.

about general economic policy and more specifically Fed's policy actions and/or their consequences. Table IX presents regressions of the BBD and HRS indices on the overall PMU, PMU components, and the sentiment in the meeting. Here, in addition to the macro sentiment, we also include policymakers' directional views about financial markets ($MktSent$) given that public uncertainty generally rises at times of financial market stress.

The correlation between public and policymakers' uncertainty is positive (columns (1), (5) and (7)), but the significance of the relationship depends on the proxy. The disaggregated PMU indices reveal differences in signs of loadings across uncertainty types. The positive co-movement between policymakers' and public's uncertainty arises from the discussions of uncertainty about the real economy in the meeting, and in the case of the BBD indices, from other uncertainty ($OthPMU$) not subsumed by our explicit PMU categories.[32] In contrast, inflation PMU is strongly negatively related with the public's uncertainty. The negative loading reflects the fact that inflation PMU is procyclical while public uncertainty proxies are generally countercyclical (Bloom, 2014). Indeed, public uncertainty is high at times when policymakers express negative views about financial markets, as shown by the loadings on the sentiment measures.

Macroeconomic surveys of professional forecasters provide another useful comparison with the PMU. In Figure 10, we superimpose inflation and real-economy PMU with dispersion of forecast about inflation and real GDP growth in two Blue Chip surveys. One would expect the forecast dispersion to correlate with the uncertainty that public has about the path of the macroeconomy. The plots visualize the distinct features of policymakers' uncertainty. Peaks in PMU are not typically accompanied by an elevated dispersion of professional forecasts, and in fact, they precede periods of high dispersion. This supports the notion that uncertainty that is relevant for policymaking differs from public perceptions of macroeconomic uncertainty.

VII. Conclusions

We contribute to the literature by quantifying otherwise hard-to-measure factors driving monetary policymaking using texts of the FOMC deliberations. We show that policymakers' beliefs about the higher-order moments of the economic distributions affect the policy stance at the FOMC meetings during the 1987–2015 sample. Policymakers' perceptions of uncertainty and skewness about inflation and the real-economy drive a wedge between estimated policy rules using Greenbook forecasts and the actual decision-making of the committee. Uncertainty about the real-economy and inflation affect the policy stance in opposite ways.

[32] $OthPMU$ contains uncertainty mentioned in the context of other (i.e., not monetary) policy. As such, it includes mentions of fiscal policy in the meeting which is an important category in the BBD index.

	BBD EPU_t				BBD MPU_t		HRS MPU_t	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PMU_t	0.361***				0.372***		0.178	
	(3.35)				(4.35)		(1.51)	
$InfPMU_t$		-0.241***		-0.232***		-0.136**		-0.144
		(-4.46)		(-3.35)		(-2.21)		(-1.52)
$EcoPMU_t$		0.175*		0.196***		0.264***		0.233*
		(1.93)		(2.78)		(2.63)		(1.84)
$MktPMU_t$		0.115		-0.052		-0.091		-0.050
		(1.15)		(-0.57)		(-1.30)		(-0.39)
$ModPMU_t$		-0.036		-0.028		-0.048		0.140**
		(-0.78)		(-0.59)		(-1.21)		(2.05)
$OthPMU_t$		0.409***		0.315***		0.185**		-0.081
		(5.50)		(4.13)		(2.37)		(-0.78)
$InfSent_t$			-0.189**	-0.037		0.048		0.023
			(-2.42)	(-0.60)		(0.95)		(0.29)
$EcoSent_t$			-0.367***	-0.231***		-0.290***		-0.142
			(-4.10)	(-3.03)		(-4.64)		(-1.39)
$MktSent_t$			-0.198**	-0.209***		-0.288***		-0.211**
			(-2.41)	(-3.11)		(-4.02)		(-2.46)
R^2	0.13	0.38	0.27	0.47	0.14	0.41	0.032	0.15
$\bar{R}^2$	0.13	0.37	0.26	0.45	0.13	0.39	0.028	0.12
N	227	227	227	227	227	227	227	227

Table IX. Public perceptions of uncertainty. The table reports regressions of measures of public perceptions of policy uncertainty on PMU indices. BBD EPU is the economic policy uncertainty index from Baker, Bloom, and Davis (2016), BBD MPU is their subindex for monetary policy uncertainty, and HRS MPU is the monetary policy uncertainty index from Husted, Rogers, and Sun (2020). The sample period is 1987:08–2015:12. All variables are scaled by their standard deviations. HAC t-statistics with eight lags are reported in parentheses. The regressions are estimated at the frequency of the FOMC meetings.

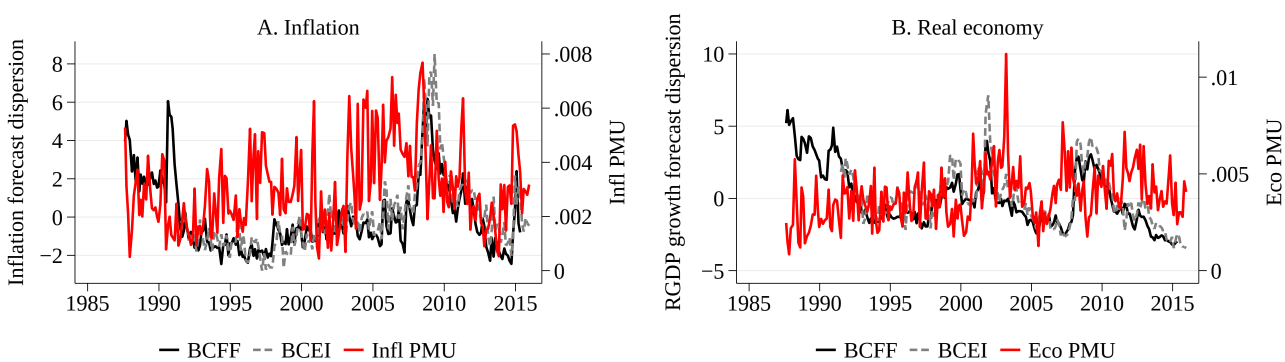

Figure 10. PMU vs. public disagreement. The figure compares PMU with measures of disagreement in survey forecasts of inflation and real GDP growth. The surveys are quarterly forecasts from the Blue Chip Economic Indicators (BCEI) and Blue Chip Financial Forecasts (BCFF). BCFF dispersion is measured as mean absolute deviation of forecasts across individuals. BCEI dispersion is the difference between the top 10th and bottom 10th percentile of forecasts (individual data is not available). We report the first principal component of forecast dispersions across horizons from the current quarter up to four quarters ahead.

An increase in the real-economy uncertainty works similar to a typical negative demand shock, consistent with the uncertainty channel postulated in recent macro models. Our key new results pertain to the effects of inflation uncertainty. Heightened inflation uncertainty leads to more hawkishness and strengthens the committee's reaction to inflation. We show that the uncertainty relevant for understanding the Fed decision-making deviates significantly from the public perceptions of uncertainty or objective measures of macroeconomic volatility. In particular, policymakers' uncertainty is associated with their skewed beliefs about increasing inflation. Consistent with models of inflation scares, policymakers place weight on low probability but costly and therefore salient events, but those events do not realize in our sample. Our results highlight the central role of policymakers' beliefs in understanding how deviations from policy rules occur. They also cast light on plausible mechanisms to be incorporated in models of optimal policy choice under uncertainty.

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Internet Appendix for:

Policymakers' uncertainty

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A. Dictionaries for Risk, Uncertainty, Topics, and Sentiment

risk			risks		
Term	Similarity	Count in Econ Discussion	Term	Similarity	Count in Econ Discussion
risks	0.691266	3183	downside risk*	0.737511	1118
downside risk*	0.59828	1118	upside risk*	0.704978	585
threat	0.594511	135	risk	0.691266	3236
upside risk*	0.522107	585	threat	0.52743	135
danger	0.502593	121	skewed	0.501801	101
probability	0.484233	524	uncertainties	0.48339	505
possibility	0.475492	1010	~~downside~~	0.449301	707
likelihood	0.469565	224	~~tilted~~	0.448698	119
vulnerability	0.439843	72	danger	0.445836	121
dangers	0.406005	28	dangers	0.439822	28
~~headwind~~	0.402709	38	fatter	0.434411	14
chances	0.386979	65	~~outcomes~~	0.420205	291
fragility	0.374305	106	probability	0.412639	524
~~risktaking~~	0.373512	50	skew	0.40086	29
~~challenges~~	0.348706	174	~~challenges~~	0.395508	174
~~prospect~~	0.347213	242	~~juncture~~	0.393311	114
~~unwelcome~~	0.345361	42	modal	0.391584	131
sensitivity	0.343196	82	~~headwinds~~	0.385167	288
probabilities	0.342825	87	vulnerabilities	0.378889	59
~~breakout~~	0.34249	39	probabilities	0.375555	87
uncertainty	0.341431	2317	concerns	0.374206	628
~~consequences~~	0.339106	367	~~breakout~~	0.372844	39
concern* that	0.33652	678	possibilities	0.369255	98
odds	0.332704	190	uncertainty	0.362784	2317
fatter	0.331849	14	vulnerability	0.355743	72
concern	0.326579	1047	~~directive~~	0.355738	29
potentially	0.322536	275	tensions	0.35208	51
concerns	0.318465	628	~~crosscurrents~~	0.350524	49
tension	0.313301	101	odds	0.343869	190
~~spiral~~	0.312127	69	threats	0.33815	36
possibly	0.309975	290	fragility	0.337531	106
~~costly~~	0.309472	63	~~symmetric~~	0.336238	57
~~challenge~~	0.307298	179	~~asymmetry~~	0.333936	25
~~urgency~~	0.303853	28	~~skews~~	0.33296	14
~~instability~~	0.303578	91	~~urgency~~	0.3309	28
unease	0.303215	25	skewness	0.330203	7
vulnerabilities	0.302247	59	tension	0.325514	101
fear	0.299544	194	~~headwind~~	0.323167	38
skewness	0.298903	7	~~vigilant~~	0.319233	55
~~trap~~	0.297911	58	~~drags~~	0.31894	75
~~overshoot~~	0.296446	53	~~costpush~~	0.318601	4
~~problem~~	0.295296	1221	possibility	0.318443	1010
skew	0.29475	29	~~balanced~~	0.317706	646
worries	0.294228	132	tails	0.31724	28
threats	0.294017	36	~~challenge~~	0.316888	179
~~repercussions~~	0.289451	23	likelihood	0.315145	224
skewed	0.287008	101	imponderables	0.31498	10
volatility	0.284335	360	~~considerations~~	0.311688	184
doubts	0.283668	65	~~consequences~~	0.306922	367
~~juncture~~	0.283524	114	~~leaning~~	0.305052	38

Table A-1. Nearest Neighbors of Risk and Risks in FOMC Word Embeddings. This table shows the fifty nearest neighbors to the terms 'risk' and 'risks' for a word embedding model estimated from the subcorpus formed of the economic situation discussion of the Federal Open Market Committee deliberations. For each neighbor term, we report the cosine similarity in the word embedding space and the count of the term in the subcorpus. For each term, we then assign it to a risk dictionary (black); to an uncertainty dictionary (blue); or remove it for being too generic.

uncertain			uncertainty		
Term	Similarity	Count in Econ Discussion	Term	Similarity	Count in Econ Discussion
!confident	0.460385	367	uncertainties	0.65845	505
fragile	0.455998	157	anxiety	0.515023	70
!sanguine	0.442406	101	angst	0.433309	24
murky	0.43732	24	skepticism	0.430759	68
unclear	0.436552	57	tension	0.427094	101
wary	0.428437	41	uncertain	0.426752	399
uncertainty	0.426752	2317	~~caution~~	0.423748	445
unsure	0.423955	14	downside risk*	0.418226	1118
~~poor~~	0.411094	194	~~challenges~~	0.414084	174
~~dependent~~	0.406995	119	pessimism	0.411988	179
apprehensive	0.404002	11	fragility	0.401378	106
vulnerable	0.401095	203	gloom	0.380074	65
stressed	0.397458	53	~~conflict~~	0.370107	47
~~challenging~~	0.391555	71	risks	0.362784	3183
~~bullish~~	0.38583	65	volatility	0.359692	360
bleak	0.385454	52	concerns	0.359599	628
skeptical	0.384238	169	!clarity	0.352539	89
~~attuned~~	0.383523	15	sensitivity	0.348326	82
uncertainties	0.383365	505	unease	0.347682	25
~~vigilant~~	0.382641	55	~~publicity~~	0.346734	31
~~cautious~~	0.378045	537	fog	0.343423	20
grim	0.376893	34	~~headwinds~~	0.341591	288
~~jury~~	0.376789	20	risk	0.341431	3236
agnostic	0.375537	31	~~surrounding~~	0.340727	163
!optimistic	0.372549	1249	worries	0.337692	132
~~muted~~	0.365712	87	!certainty	0.332492	91
unsettled	0.362423	22	doubts	0.328778	65
concern* about	0.361507	1634	concern	0.327687	1047
~~buoyant~~	0.360631	70	optimism	0.32465	498
~~disruptive~~	0.359961	50	~~pain~~	0.323275	31
~~depend~~	0.359918	198	ambiguity	0.322258	18
skittish	0.35904	18	error	0.320998	234
jittery	0.358658	11	skittishness	0.319675	9
precarious	0.357391	22	nervousness	0.319648	31
fog	0.357145	20	unknown	0.316516	32
fluid	0.357016	12	tensions	0.314929	51
!convinced	0.354622	173	imponderables	0.314825	10
pessimistic	0.354016	430	upside risk*	0.313048	585
!upbeat	0.352921	217	~~debate~~	0.312722	168
~~destabilizing~~	0.35242	22	~~awareness~~	0.312388	26
precise	0.352262	81	~~uncertaintyin~~	0.310427	3
uncomfortable	0.348358	102	~~disagreement~~	0.304366	57
~~assessing~~	0.345848	110	~~admits~~	0.302832	3
~~damaging~~	0.342869	39	~~science~~	0.29633	31
~~satisfactory~~	0.339921	66	~~apprehension~~	0.292553	16
anxious	0.33839	40	~~headwind~~	0.290777	38
~~worried~~	0.337316	410	~~instability~~	0.290598	91
ambiguous	0.335987	32	~~troubles~~	0.288294	35
problematic	0.33498	78	~~questions~~	0.288182	698
daunting	0.332674	19	~~worry~~	0.286513	402

Table A-2. Nearest Neighbors of Uncertain and Uncertainty in FOMC Word Embeddings. This table shows the fifty nearest neighbors to the terms 'uncertain' and 'uncertainty' for a word embedding model estimated from the subcorpus formed of the economic situation discussion of the Federal Open Market Committee deliberations. For each neighbor term, we report the cosine similarity in the word embedding space and the count of the term in the subcorpus. For each term, we then assign it to a risk dictionary (black); to an uncertainty dictionary (blue); or remove it for being too generic. An exclamation mark preceding a term indicates it is only associated with the dictionary when it is negated.

Nouns	Match w/ direction words		Direction words	
	Negative	Positive	Group 1	Group 2
commodity price*	1	2	abated	acceler*
consumer energy price*	1	2	adjust* downward	adjust* upward
consumer food price*	1	2	contract*	advanc*
consumer price index*	1	2	cool*	bolster*
consumer price index* cpi	1	2	deceler*	boost*
consumer price inflation	1	2	declin*	elevat*
consumer price*	1	2	decreas*	expand*
core consumer price inflation	1	2	down	fast*
core consumer price*	1	2	downturn	gain*
core cpi	1	2	downward	go* up
core cpi inflation	1	2	downward adjust*	heighten*
core inflation	1	2	downward revision	high*
core pce inflation	1	2	drop*	increas*
core pce price inflation	1	2	eas*	mov* higher
core pce price*	1	2	fall*	mov* up
core price inflation	1	2	fell	mov* upward
core producer price*	1	2	go* down	pick* up
cost basic material*	1	2	limit*	rais*
cost* goods and services	1	2	low*	rallied
cost* health care	1	2	moderate*	rally*
cost* labor	1	2	moderati*	rebound*
cost* living	1	2	mov* down	recoup*
cost* us goods and services	1	2	mov* downward	revis* up*
crude oil price*	1	2	mov* lower	rise*
disinflation*	2	1	pullback	rising
disinflation* pressure*	2	1	reduc*	rose
employment cost index*	1	2	revis* down*	run up
energy prices	1	2	slow*	runup
headline inflation	1	2	slow* down	stop decline
health care cost*	1	2	soft*	strength*
inflation*	1	2	stagnate*	strong*
inflation compensation	2	1	stall*	tick* up
inflation expectation*	1	2	subdu*	up
inflation level	1	2	tick* down	upward
inflation outlook	1	2	tight*	upward adjust*
inflation rate	1	2	weak*	upward revision
inflation wage*	1	2	weigh* on	went up
labor compensation	1	2	went down	
labor cost pressure*	1	2		
labor cost*	1	2		
long* run inflation expectation*	1	2		
long* term inflation expectation*	1	2		
manufacturing price*	1	2		
material price*	1	2		
near* term inflation expectation*	1	2		
oil price*	1	2		
pce price index*	1	2		
pressure* inflation	1	2		
pressure* wages	1	2		
price index*	1	2		
price inflation	1	2		
price level stability	2	1		
price stability	2	1		
prices of durable goods	1	2		
prices of durables	1	2		
prices of manufacturing	1	2		
prices of material*	1	2		
producer price ind*	1	2		
producer price*	1	2		
real oil price*	1	2		
unit labor cost*	1	2		
wage gains	1	2		
wage inflation	1	2		
wage pressure*	1	2		
wage price pressure*	1	2		
wages	1	2		
inflation* pressure*	1	2		
price pressure*	1	2		
deflation* force*	2	1		
deflation* pressure	2	1		
deflation*	2	1		
prices of durable goods	1	2		
prices of durables	1	2		
prices of manufacturing	1	2		
prices of material*	1	2		

Table A-3. Noun Phrases and Direction Words Related to Inflation and Wages. The first column displays the phrases we associate with inflation and wage discussion in the FOMC transcripts. The second to fifth columns relate to the construction of inflation sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
aggregate demand	2	1	*adjust* downward*	*acceler**
aggregate inventory sales ratio	1	2	*adverse*	*adjust* upward*
aggregate spending	2	1	*contract**	*advanc**
building activity	2	1	*cool**	*better*
business activity	2	1	*cut**	*bolster**
business capital spending	2	1	*deceler**	*boost**
business confidence	2	1	*declin**	*elevat**
business demand capital equipment	2	1	*decreas**	*encourag**
business equipment investment	2	1	*deteriorat**	*expand**
business equipment spending	2	1	*disappoint**	*fast**
business equipment spending	2	1	*down*	*favor**
business equipment spending and industrial production	2	1	*downturn*	*gain**
business expansion	2	1	*downward*	*go* up*
business expenditure*	2	1	*downward adjust**	*heighten**
business fixed investment	2	1	*downward revision*	*high**
business fixed investment and household spending	2	1	*drag**	*improv**
business inventory investment	2	1	*drop**	*increas**
business investment	2	1	*eas**	*mov* higher*
business investment spending	2	1	*fall**	*mov* up*
business outlay*	2	1	*fell*	*mov* upward*
business outlays capital equipment	2	1	*go* down*	*pick* up*
business output	2	1	*held down*	*rais**
business purchas*	2	1	*hold down*	*rallied*
business purchases of transporation equipment	2	1	*increas* at slow* rate*	*rally**
business sector	2	1	*limit**	*rebound**
business sentiment	2	1	*low**	*recoup**
business spending	2	1	*moderate**	*revis* up**
business spending capital equipment	2	1	*moderati**	*rise**
business spending of transporation equipment	2	1	*mov* down*	*rising*
capacity utilization	2	1	*mov* downward*	*rose*
capital investment	2	1	*mov* lower*	*run up*
capital spending	2	1	*pressur**	*runup*
capital spending plan*	2	1	*pullback*	*stop decline*
civilian unemployment rate	1	2	*reduc**	*strength**
claim* unemployment insurance	1	2	*revis* down**	*strong**
construction activity	2	1	*slow**	*tick* up*
consumer confidence	2	1	*slow* down*	*tight**
consumer sector	2	1	*soft**	*up*
consumer sentiment	2	1	*stagnat**	*upward*
consumer spending	2	1	*stall**	*upward adjust**
consumption	2	1	*strain**	*upward revision*
consumption spending	2	1	*stress**	*went up*
current account deficit			*subdu**	
current account surplus			*take* toll on*	
disposable income	2	1	*tension**	
domestic components of spending	2	1	*tick* down*	
domestic demand	2	1	*took toll on*	
domestic economy	2	1	*weak**	
domestic final demand	2	1	*weigh* down*	
domestic spending	2	1	*weigh* on*	
domestic spending components	2	1	*went down*	
durable equipment	2	1	*worse**	
economic activity	2	1		
economic development*	2	1		
economic expansion	2	1		
economic growth	2	1		
economic outlook	2	1		
economic performance	2	1		
economic recovery	2	1		
economic situation	2	1		
employment	2	1		
employment growth	2	1		
employment rate	2	1		
excess capacity	1	2		
factory output	2	1		

Table A-4. Noun Phrases and Direction Words Related to Economic Growth (1). The first column displays a subset the phrases we associate with economic growth discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of growth sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
final demand	2	1	*adjust* downward*	*acceler**
gdp growth	2	1	*adverse*	*adjust* upward*
global economic growth	2	1	*contract**	*advanc**
gross domestic product	2	1	*cool**	*better*
high tech equipment investment	2	1	*cut**	*bolster**
high tech equipment spending	2	1	*deceler**	*boost**
household spending and business fixed investment	2	1	*declin**	*elevat**
household* spending	2	1	*decreas**	*encourag**
housing activity	2	1	*deteriorat**	*expand**
housing construction	2	1	*disappoint**	*fast**
housing demand	2	1	*down*	*favor**
income growth	2	1	*downturn*	*gain**
industrial production	2	1	*downward*	*go* up*
inventories	2	1	*downward adjust**	*heighten**
inventory accumulation	1	2	*downward revision*	*high**
inventory investment	2	1	*drag**	*improv**
inventory liquidation	2	1	*drop**	*increas**
inventory sales ratio	1	2	*eas**	*mov* higher*
investment condition*	2	1	*fall**	*mov* up*
investment demand	2	1	*fell*	*mov* upward*
investment high tech equipment	2	1	*go* down*	*pick* up*
investment manufacturing	2	1	*held down*	*rais**
investment situation	2	1	*hold down*	*rallied*
investment spending	2	1	*increas* at slow* rate*	*rally**
job growth	2	1	*limit**	*rebound**
labor demand	2	1	*low**	*recoup**
labor force participation	2	1	*moderate**	*revis* up**
labor market*	2	1	*moderati**	*rise**
labor market condition*	2	1	*mov* down*	*rising*
labor market indicator*	2	1	*mov* downward*	*rose*
labor market slack	1	2	*mov* lower*	*run up*
labor productivity	2	1	*pressur**	*runup*
manufacturing activity	2	1	*pullback*	*stop decline*
manufacturing capacity utilization	2	1	*reduc**	*strength**
manufacturing output	2	1	*revis* down**	*strong**
manufacturing production	2	1	*slow**	*tick* up*
manufacturing sector	2	1	*slow* down*	*tight**
motor vehicle assembl*	2	1	*soft**	*up*
motor vehicle production	2	1	*stagnat**	*upward*
motor vehicle purchas*	2	1	*stall**	*upward adjust**
motor vehicle sales	2	1	*strain**	*upward revision*
motor vehicle sector	2	1	*stress**	*went up*
new construction	2	1	*subdu**	
new home sales	2	1	*take* toll on*	
new orders	2	1	*tension**	
nominal gdp	2	1	*tick* down*	
nonfarm business sector	2	1	*took toll on*	
nonfarm payroll employment	2	1	*weak**	
nonresidential construction	2	1	*weigh* down*	
nonresidential construction activity	2	1	*weigh* on*	
orders and shipments of nondefense capital goods	2	1	*went down*	
orders of nondefense capital goods	2	1	*worse**	
outlays business equipment	2	1		
outlays high tech equipment	2	1		
outlays transporation equipment	2	1		
outlook economic activity	2	1		
output gap				
output growth	2	1		
payroll employment	2	1		
pce	2	1		
personal consumption expenditure*	2	1		
personal income	2	1		
potential output	2	1		
potential output	2	1		
private expenditures business equipment	2	1		

Table A-5. Noun Phrases and Direction Words Related to Economic Growth (2). The first column displays a subset the phrases we associate with economic growth discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of growth sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
private nonfarm employment	2	1	adjust* downward	acceler*
private nonfarm payroll employment	2	1	adverse	adjust* upward
private sector investment	2	1	contract*	advanc*
private spending	2	1	cool*	better
productivity	2	1	cut*	bolster*
productivity growth	2	1	deceler*	boost*
purchas* of motor vehicle*	2	1	declin*	elevat*
real activity	2	1	decreas*	encourag*
real business spending	2	1	deteriorat*	expand*
real consumer spending	2	1	disappoint*	fast*
real disposable income	2	1	down	favor*
real disposable personal income	2	1	downturn	gain*
real gdp	2	1	downward	go* up
real gdp growth	2	1	downward adjust*	heighten*
real gnp	2	1	downward revision	high*
real personal consumption expenditure*	2	1	drag*	improv*
real spending	2	1	drop*	increas*
residential construction	2	1	eas*	mov* higher
residential construction activity	2	1	fall*	mov* up
residential investment	2	1	fell	mov* upward
resource use	2	1	go* down	pick* up
resource utilization	2	1	held down	rais*
retail trade	2	1	hold down	rallied
shipments of nondefense capital goods	2	1	increas* at slow* rate	rally*
spending and production	2	1	limit*	rebound*
spending business equipment	2	1	low*	recoup*
spending high tech equipment	2	1	moderate*	revis* up*
spending nonresidential structures	2	1	moderati*	rise*
spending transporation equipment	2	1	mov* down	rising
structural productivity	2	1	mov* downward	rose
total industrial production	2	1	mov* lower	run up
total nonfarm payroll employment	2	1	pressur*	runup
unemployment	1	2	pullback	stop decline
unemployment insurance claim*	1	2	reduc*	strength*
unemployment level	1	2	revis* down*	strong*
unemployment rate	1	2	slow*	tick* up
us economic activity	2	1	slow* down	tight*
us economy	2	1	soft*	up
outlook economy	2	1	stagnat*	upward
inventory level*	1	2	stall*	upward adjust*
fiscal			strain*	upward revision
deficit			stress*	went up
surplus			subdu*	
			take* toll on	
			tension*	
			tick* down	
			took toll on	
			weak*	
			weigh* down	
			weigh* on	
			went down	
			worse*	

Table A-6. Noun Phrases and Direction Words Related to Economic Growth (3). The first column displays a subset the phrases we associate with economic growth discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of growth sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
aaa spread*	1	2	*adjust* downward*	*acceler**
baa spread*	1	2	*contract**	*adjust* upward*
corporate bond spread*	1	2	*cool**	*advanc**
corporate spread*	1	2	*deceler**	*adverse*
cost of bank credit	1	2	*declin**	*bolster**
cost of bond financ*	1	2	*decreas**	*boost**
cost of capital	1	2	*down*	*deteriorat**
cost of credit	1	2	*downturn*	*edge* up**
cost of equity	1	2	*downward*	*elevat**
cost of external capital	1	2	*downward adjust**	*expand**
cost of funding	1	2	*drop**	*fast**
cost of raising capital	1	2	*eas**	*gain**
cost of raising capital through equity	1	2	*edge* down*	*go* up*
credit cost*	1	2	*encourag**	*heighten**
credit default swap*	1	2	*fall**	*high**
credit risk spread*	1	2	*favor**	*increas**
credit spread*	1	2	*fell*	*mov* higher*
debt securities spread*	1	2	*go* down*	*mov* up*
equity risk prem*	1	2	*improv**	*mov* upward*
expected real return equit*	1	2	*limit**	*pick* up*
expected return equit*	1	2	*low**	*pressure**
financing cost	1	2	*moderate**	*rais**
funding cost	1	2	*moderati**	*rebound**
risk prem*	1	2	*mov* down*	*recoup**
risk spread*	1	2	*mov* downward*	*revis* up**
risk spread* corporate bonds*	1	2	*mov* lower*	*rise**
spread* corporate bond*	1	2	*narrow**	*rising*
spread* investment grade bond*	1	2	*pullback*	*rose*
spread* speculative grade bond*	1	2	*reduc**	*run up*
			revis down**	*runup*
			*slow**	*stop decline*
			*soft**	*strain**
			*subdu**	*strength**
			take toll on*	*stress**
			tick down*	*strong**
			took toll on	*tension**
			*weak**	*tick* up*
			weigh on*	*up*
			went down	*upward*
				*upward adjust**
				went up
				*widen**
				*worse**

Table A-7. Noun Phrases Related to Financial Markets (1). The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
appetite* risk taking	2	1	*adjust* downward*	*acceler**
appetite* risk*	2	1	*adverse*	*adjust* upward*
appetite* risk* asset*	2	1	*contract**	*advanc**
appetite* risk* investment*	2	1	*cool**	*bolster**
appetite* taking risk*	2	1	*deceler**	*boost**
condition* credit market*	2	1	*declin**	*eas**
condition* financial market*	2	1	*decreas**	*elevat**
credit condition*	2	1	*deteriorat**	*encourag**
credit growth	2	1	*down*	*expand**
credit market*	2	1	*downturn*	*fast**
credit market condition*	2	1	*downward*	*favor**
credit market demand	2	1	*downward adjust**	*gain**
development financial market*	2	1	*downward revision*	*go* up*
financial condition*	2	1	*drop**	*high**
financial development*	2	1	*fall**	*improv**
financial instabilit*	1	2	*fell*	*increas**
financial market condition*	2	1	*go* down*	*loos**
financial market confidence	2	1	*limit**	*mov* higher*
financial market development*	2	1	*low**	*mov* up*
financial market index*	2	1	*moderate**	*mov* upward*
financial market indic*	2	1	*moderati**	*normaliz**
financial market pressure*	1	2	*mov* down*	*pick* up*
financial market price*	2	1	*mov* downward*	*rais**
financial market sentiment	2	1	*mov* lower*	*rallied*
financial market*	2	1	*pressure**	*rally**
financial situation	2	1	*pullback*	*rebound**
financial stability	2	1	*reduc**	*recoup**
investor* appetite*	2	1	*restrictive*	*revis* up**
investor* appetite* risk*	2	1	*revis* down**	*rise**
investor* confidence	2	1	*slow**	*rising*
investor* risk appetite*	2	1	*soft**	*rose*
investor* sentiment	2	1	*stagnate**	*run up*
investor* sentiment toward risk*	2	1	*stall**	*runup*
investor* sentiment toward risk* asset*	2	1	*strain**	*stop decline*
liquidity	2	1	*stress**	*strength**
pressure* financial market	1	2	*subdu**	*strong**
risk appetite*	2	1	*take a toll on*	*tick* up*
bank credit	2	1	*tension**	*up*
bank lending	2	1	*tick* down*	*upward*
banking supervision			*tight**	*upward adjust**
banking system	2	1	*took toll on*	*upward revision*
consumer credit	2	1	*turbulent*	*went up*
credit availability	2	1	*weak**	
credit quality	2	1	*weigh* on*	
domestic credit	2	1	*went down*	
domestic nonfinancial debt	2	1	*worsen**	
financial outlook	2	1		
financial system	2	1		
foreign exchange				
foreign exchange market*				
foreign exchange valu*				
household balance sheet*	2	1		
market exchange rate*				
market liquidity	2	1		
mortgage refinancing activity	2	1		
non market exchange rate*				
nonfinancial debt	2	1		
private credit	2	1		
private credit market*	2	1		
seasonal borrowing	2	1		
total domestic non financial debt	2	1		
total domestic nonfinancial debt	2	1		
us dollar				

Table A-8. Noun Phrases Related to Financial Markets (2). The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
aaa yield*	1	2	adjust* downward	acceler*
baa yield*	1	2	contract*	adjust* upward
bond yield*	1	2	cool*	advanc*
corporate bond yield*	1	2	deceler*	bolster*
corporate debt yield*	1	2	declin*	boost*
corporate yield*	1	2	decreas*	elevat*
debt yield*	1	2	down	encourag*
high grade corporate bond* yield*	1	2	downturn	expand*
interest rate*	1	2	downward	fast*
investment grade and speculative grade corporate bond* yield*	1	2	downward adjust*	gain*
investment grade corporate bond yield*	1	2	downward movement	go* up
long* term interest rate*	1	2	downward revision	heighten*
long* term rate*	1	2	drop*	high*
mortgage interest rate*	1	2	fall*	increas*
real long* term interest rate*	1	2	fell	mov* higher
real long* term rate*	1	2	go* down	mov* up
speculative grade corporate bond* yield*	1	2	limit*	mov* upward
yield* agency mortgage backed securities mbs	1	2	low*	pick* up
yield* corporate bond*	1	2	moderate*	rais*
yield* corporate bonds and agency mbs	1	2	moderati*	rallied
yield* mortgage backed securities	1	2	mov* down	rally*
yield* private sector debt securities	1	2	mov* downward	rebound*
comparable maturity treasury securities			mov* lower	recoup*
discount rate*	1	2	pullback	revis* up
long* term treasury securities			reduc*	revision upward
nominal treasury securities			revis* down	rise*
real interest rate*	1	2	slow*	rising
short* term interest rate*	1	2	soft*	rose
us government securities			stagnate*	run up
			stall*	runup
			subdu*	stop decline
			take* toll on	strength*
			tick* down	strong*
			tight*	tick* up
			took toll on	up
			weak*	upward
			weigh* on	upward adjust*
			went down	upward movement
				upward revision
				went up

Table A-9. Noun Phrases Related to Financial Markets (3). The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

Nouns	Match w/ direction words		Direction words	
	Positive	Negative	Group 1	Group 2
asset index*	2	1	adjust* downward	acceler*
asset indic*	2	1	adverse	adjust* upward
asset market*	2	1	burst*	advanc*
asset price index*	2	1	contract*	bolster*
asset price indic*	2	1	cool*	boost*
asset price*	2	1	deceler*	edge* up
asset valu*	2	1	declin*	elevat*
equities	2	1	decreas*	encourag*
equity and home price*	2	1	deteriorat*	expand*
equity and home valu*	2	1	down	fast*
equity and house price*	2	1	downturn	favor*
equity and housing price*	2	1	downward	gain*
equity index*	2	1	downward adjust*	go* up
equity indic*	2	1	downward movement	high*
equity market index*	2	1	downward revision	improv*
equity market indic*	2	1	drop*	increas*
equity market price*	2	1	eas*	mov* high*
equity market valu*	2	1	edge* down	mov* up
equity market*	2	1	fall*	mov* upward
equity price index*	2	1	fell	pick* up
equity price indic*	2	1	go* down	rais*
equity price measure*	2	1	limit*	rallied
equity price*	2	1	low*	rally*
equity valu*	2	1	moderate*	rebound*
equaity wealth	2	1	moderati*	recoup*
financial wealth	2	1	mov* down	revis* up*
home and equity price*	2	1	mov* downward	rise*
house and equity price*	2	1	mov* lower	rising
household wealth	2	1	plummet*	rose
household* net worth	2	1	pressure*	run up
housing and equity price*	2	1	pull* back	runup
price* of risk* asset*	2	1	pullback	stop decline
ratio of wealth to income	2	1	reduc*	strength*
risk* asset price*	2	1	revis* down*	strong*
s p 500 index	2	1	slow*	tick* up
stock index*	2	1	slow* down	up
stock indic*	2	1	soft*	upward
stock market index*	2	1	stagnate*	upward adjust*
stock market price*	2	1	stall*	upward movement
stock market wealth	2	1	strain*	upward revision
stock market*	2	1	stress*	went up
stock price indic*	2	1	subdu*	
stock price*	2	1	take* toll on	
stock prices index*	2	1	tension*	
stock val*	2	1	tick* down	
us stock market price*	2	1	tight*	
wealth effect*	2	1	took toll on	
wealth to income ratio	2	1	tumbl*	
			weak*	
			weigh* on	
			went down	
			worse*	

Table A-10. Noun Phrases Related to Financial Markets (4). The first column displays a subset the phrases we associate with financial market discussion in the FOMC transcripts (see other tables in sequence for other nouns). The second to fifth columns relate to the construction of market sentiment. An instance of positive sentiment occurs when a mention of one of the nouns with a 1 (2) recorded in the 'Positive' column is preceded or followed by a phrase from Group 1 (Group 2) within sub-sentences. Negative sentiment is constructed analogously. Nouns with no number recorded in the second and third columns are used to contextualize uncertainty language but not for the construction of sentiment.

parameter*
model*
measurement*
forecast error*
relationship*
error band*
nairu
trend
confidence interval*
uncertainty band*
confidence band*

Table A-11. Noun Phrases Related to Model. The table contains phrases we associate with model discussion in the FOMC transcripts.

B. Algorithms for Sentiment and Preference Construction

B.1. Sentiment construction

Here we describe the construction of sentiment for topic k (which corresponds to economic growth, inflation and wages, and financial markets). The algorithm follows closely that in **?** which use a similar approach to build a stock market sentiment index. Here we expand this to additional topics.

Sentiment is built exclusively using economy round language. We first remove any sentence in the economy round that either contains an uncertainty flag word, i.e. a term in the 'Term' columns of tables A-1 or A-2 that is not struck through, as well as sentences that immediately precede or follow such sentences. This ensures that sentiment is constructed using a different set of input words than the uncertainty measures, which avoids a mechanical relationship between the two.

The next step is to break all remaining sentences in the economy round into sub-sentences based on the presence of words in {'and', 'because', 'but',' if', 'or', 'so','that', 'when', 'where', 'while', 'although', 'however', 'though', 'whereas', 'despite'}. Let $\mathbf{p}_{t,s}$ be the sth phrase in meeting t generated by this rule.

As described in the tables above, each topic is associated with a set of nouns. Let $g_{k,m}$ be the mth noun associated with topic k. This noun will be associated with a set of positive words $\text{Pos}_{k,m}$ and a set of negative words $\text{Neg}_{k,m}$ according to the group definitions in the tables. The positive and negative sentiment measures in meeting t begin with the tabulations

$$\tilde{S}^{+}_{t,k} = \sum_{s}\sum_{m}\sum_{n} \mathbb{1}(w_{t,s,n} = g_{k,m}) \left[\mathbb{1}(w_{t,s,n-1} \in \text{Pos}_{k,m}) + \mathbb{1}(w_{t,s,n+1} \in \text{Pos}_{k,m})\right]$$
$$\tilde{S}^{-}_{t,k} = \sum_{s}\sum_{m}\sum_{n} \mathbb{1}(w_{t,s,n} = g_{k,m}) \left[\mathbb{1}\left(w_{t,s,n-1} \in \text{Neg}_{k,m}\right) + \mathbb{1}\left(w_{t,s,n+1} \in \text{Neg}_{k,m}\right)\right]$$

That is, we count the number of times topic-k words are immediately preceded or followed by (word-specific) positive and negative terms.[2] To obtain our final sentiment measure, we scale these counts by the number of total tokens in the economy round.

B.2. Preference construction

We now describe the algorithm for constructing the measures of hawkishness and dovishness used in the main text to capture policy preferences. For all meetings, we measure generic monetary policy preferences using the procedure detailed below. For meetings conducted in 2009 and onwards, we additionally measure preferences over the size of asset purchases as part of the Fed's quantitative easing program. The sentences we consider consist of those in the policy round since that is the section of the meeting pertaining to the articulation of preferences.

[2] Since in preprocessing we remove stop words, adjacency in this definition can include separation by stop words.

B.2.1. Generic monetary policy preferences

First, we exclude from the policy round any sentence in which the term 'increase' appears along with any of {cpi, inflation, yield*, treasury} to ensure we do not include language describing the direction of non-policy-related market prices and interest rates. We classify each remaining sentence as pertaining to monetary policy:

1. If it contains any phrase in the set {federal funds rate, funds rate, target rate, policy rate, interest rate, taylor rule, alternative a, alternative b, alternative c, directive, language, statement, symmetry, asymmetry, hawkish, dovish},
2. OR if 'policy' is in the sentence and NOT any phrase in the set {fiscal policy, supervisory policy, public policy, budget policy, tax policy, housing policy, regulatory policy, ecb policy, economic policy, government policy, inventory policy, health care policy, macro policy, macroeconomic policy, spending policy, legislation, law, regulation}.
3. OR if 'basis point' is found in the sentence AND any phrase in the set {[cut*, hik*, eas*, tight*, action*, moving, move, firming, recommendation, reduction, increase]}.

We define $Hawk_t'$ to be the count of terms in {tight*, hike*, increas*, hawkish, taper, liftoff} in policy sentences; and $Dove_t'$ to be the count of terms in {ease*, easing*, cut*, dovish, reduc*, decrea*} in policy sentences. Here we account for negation, and if any of the hawk (dove) terms is immediately preceded by one of {'less', 'no','not', 'little', 'don't', 'doesn't', 'hasn't', 'haven't', 'won't', 'shouldn't', 'didn't'}, it is counted as belonging to dove (hawk) set.

B.2.2. Quantitative easing preferences

We define policy round sentences beginning in 2009 as relating to quantitative easing whenever they contain the term 'purchase*' immediately preceded by a phrase in {mortgage backed securities, mbs, asset, treasur*, agency debt}.

We then define $Hawk_t''$ to be the count of terms in {reduc*, taper, stop, purchas*} within the set of QE sentences; and $Dove_t''$ to be the count of terms in {more, additional, further} within the set of QE sentences. We again account for negation.

B.2.3. Overall preference measure

Let NP_t be the overall number of terms in the policy round in meeting t. Our hawk measure is

$$Hawk_t = \begin{cases} \frac{Hawk_t'}{\mathrm{NP}_t} & \text{if meeting } t \text{ occurs prior to 2009} \\ \frac{Hawk_t' + Hawk_t''}{\mathrm{NP}_t} & \text{if meeting } t \text{ occurs during or after 2009} \end{cases}$$

and $Dove_t$ is defined analogously.

C. Additional Tables and Figures

C.1. Summary Statistics for PMU

A. Summary statistics for PMU indices

	Mean(%)	Median(%)	St.dev.(%)	P10(%)	P90(%)	AR(1)
PMU_t	1.126	1.078	0.293	0.787	1.529	0.461
$InfPMU_t$	0.302	0.276	0.153	0.131	0.529	0.550
$EcoPMU_t$	0.388	0.386	0.138	0.226	0.566	0.463
$MktPMU_t$	0.222	0.180	0.149	0.071	0.426	0.571
$ModPMU_t$	0.066	0.061	0.044	0.018	0.119	0.107
$OthPMU_t$	0.282	0.260	0.135	0.128	0.456	0.481

B. Correlations of topic-specific PMU indices

	InfPMU	*EcoPMU*	*MktPMU*	*ModPMU*
EcoPMU	0.0735			
MktPMU	0.1218	0.3754		
ModPMU	0.2218	0.1131	0.0957	
OthPMU	-0.3348	0.1319	0.1612	-0.2091

Table A-12. Descriptive statistics for PMU. The table reports summary statistics for the overall PMU and the topic-specific PMU indices. All PMU indices are obtained from the economy round of the FOMC meeting and represent the share of uncertainty-related mentions (by topic) relative to the total number of words in the economy round of the meeting. The sample period is 1987:08–2015:12, covering 227 meetings. Panel A expresses the summary statistics for PMU in percentages (e.g., the number 1.2 for the mean overall PMU implies that on average uncertainty-related mentions constitute 1.2% of all words in the economy round). Column "AR(1)" reports the first order autoregressive coefficient (at the meeting frequency). Panel B reports the pairwise correlations between topic-specific PMU indices.

C.2. Properties of Uncertainty, Sentiment, and Policy Stance Measures

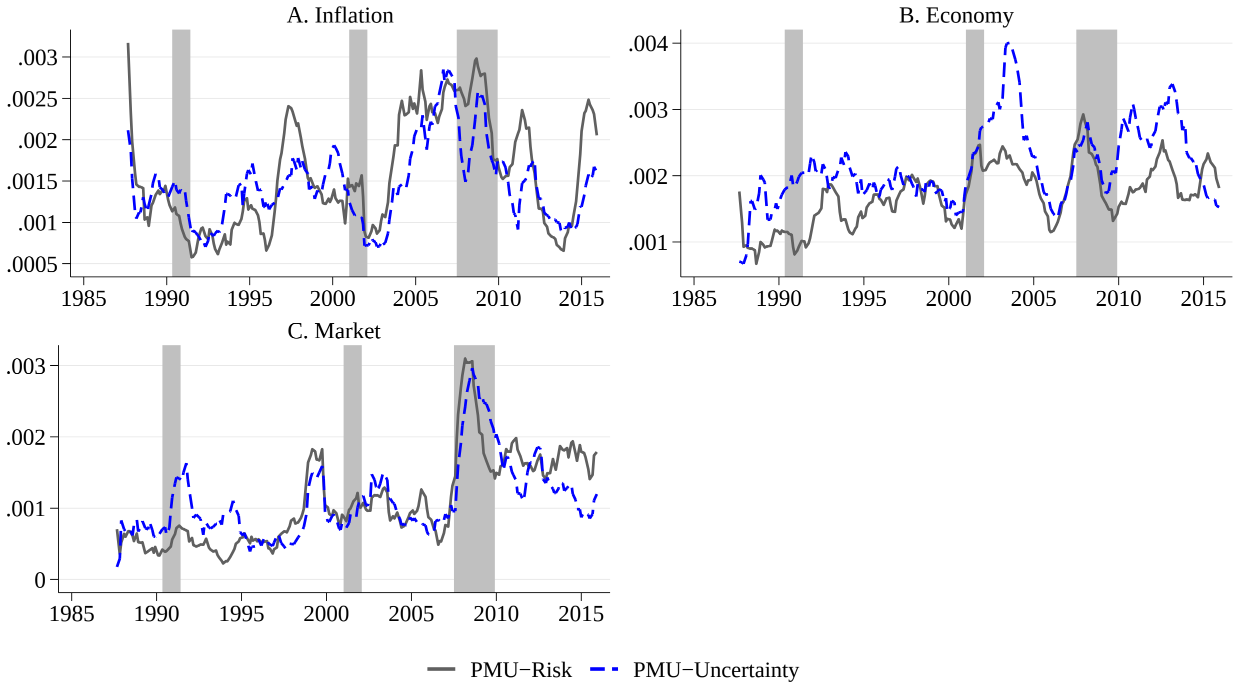

Figure A-1. Risk vs. uncertainty. The figure presents a decomposition of PMU indices (from Figure 5) into risk and uncertainty components. All text-based series are smoothed averages over the last eight FOMC meetings.

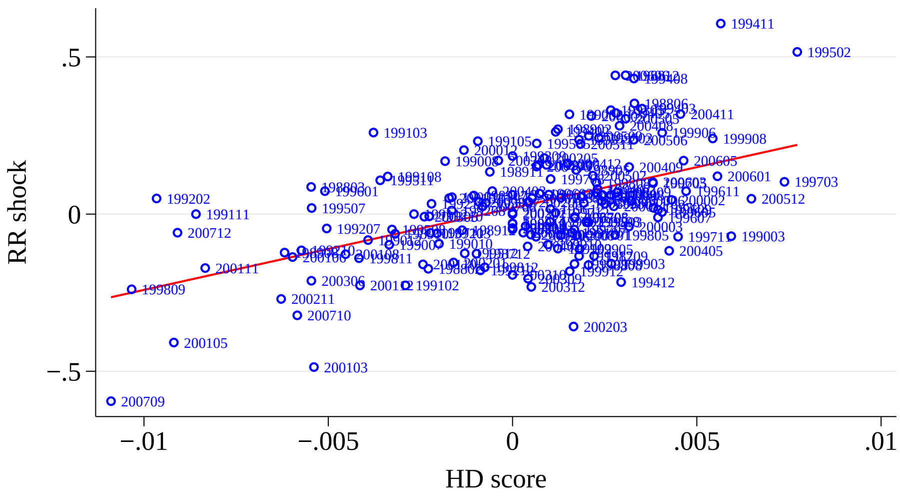

Figure A-2. *HD* measure of policy preferences vs. Romer-Romer shocks. The figure presents a scatter plot of the policy preferences *HD* against the Romer and Romer (2004) shocks. The *HD* measure is derived from the statements of the FOMC members during the policy round of the FOMC meeting.

A. Dependent variable: Greenbook CPI inflation nowcast h meetings ahead, $E_{t+h}(CPI)$

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
InfPMU_t	0.029	-0.035	-0.063	-0.083	-0.181	-0.173	-0.109	-0.073
	(0.33)	(-0.38)	(-0.63)	(-0.63)	(-1.27)	(-1.16)	(-0.91)	(-0.87)
$\bar{R}^2$	-0.0036	-0.0033	-0.00051	0.0024	0.028	0.025	0.0073	0.00081
N	226	225	224	223	222	221	220	219

B. Dependent variable: Greenbook real GDP growth nowcast h meetings ahead

	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	$h=7$	$h=8$
EcoPMU_t	-0.073	-0.059	-0.002	0.008	-0.050	-0.056	0.023	0.047
	(-0.92)	(-0.76)	(-0.03)	(0.09)	(-0.50)	(-0.52)	(0.21)	(0.39)
$\bar{R}^2$	0.00088	-0.00093	-0.0045	-0.0045	-0.0021	-0.0015	-0.0041	-0.0024
N	226	225	224	223	222	221	220	219

Table A-13. Predicting macro variables with textual measures of uncertainty and sentiment. The table reports predictive regressions of inflation and real GDP growth by textual PMU and sentiment indices derived from the economy round of the FOMC meeting transcripts. The regressions are estimated at the FOMC meeting frequency with the forecast horizon ranging from the next meeting ($h = 1$) up to eight meetings ahead ($h = 8$). To make sure that the timing of the depend variable is consistent with the timing of the meetings, we use Greenbook nowcasts at future meetings as the dependent variable. The regression is $E_{t+h,0q}(CPI) = \beta_0 + \beta_3 \mathit{InfPMU}_t + E_{t,0q}(CPI)$, and analogously for the real GDP growth. The coefficients are standardized. HAC standard errors to account for the overlap are reported in parentheses. The sample period is 1987:08–2015:12.

D. Illustrating effects of uncertainty in monetary models

Our empirical findings highlight an amplifying effect of uncertainty on how policy preferences react to the macroeconomy. Especially in the context of the inflation response, several facts are consistent with policymakers behaving as if they are unsure of the model that generates the data they observe. Inflation PMU increases following large forecast errors about inflation in the Greenbook and its predictive power for policy preferences goes in the same direction as the model PMU (more uncertainty about inflation and models is associated with more hawkishness).[3] As such, policymakers are likely to become more uncertain about inflation precisely at the time when their models fail, and concerns about changing economic structure become pertinent.

Below, we expand our discussion in Section V.D and revisit the theoretical literature on parameter uncertainty and preferences for robustness. We show how our empirical findings stand in contrast to the typical models of parameter uncertainty, though they are consistent with settings, in which policymakers face uncertainty about the persistence of inflation. Models with a desire for robustness more easily match the anti-conservatism response we find. However, even though the results are qualitatively similar, for standard calibrations the quantitative impact of uncertainty on optimal policy remains economically small relative to the empirical findings.

D.1. Parameter uncertainty

In models where the policymaker lacks knowledge of the precise value of key structural parameters, the ϕ parameters of the policy rule (1) become a function of the parameter uncertainty. Typically, greater uncertainty reduces the ϕ loadings. To see this, consider a backward-looking Svensson (1999) type model with perfect knowledge of the parameter values $(\alpha, \beta, \delta, \gamma)$:

$$y_{t+1} = \alpha y_t - \beta\left(i_t - \pi_t\right) + \sigma_y \varepsilon^y_{t+1} \tag{A.10}$$

$$\pi_{t+1} = \delta \pi_t + \gamma y_t + \sigma_\pi \varepsilon^\pi_{t+1}, \tag{A.11}$$

where ε^y_{t+1} and ε^π_{t+1} are stochastic shocks. The central bank sets the optimal interest rate i_t by minimizing the following quadratic loss function:

$$\min_{\{i_{t+\tau}\}_{\tau=0}^{\infty}} E_t \sum_{\tau=0}^{\infty} \psi^\tau \left(\pi^2_{t+\tau} + \lambda_y y^2_{t+\tau}\right). \tag{A.12}$$

Optimal policy is a linear function of the current state variables:

$$i_t = \phi_y y_t + \phi_\pi \pi_t. \tag{A.13}$$

[3] As reported in Table A-12, model and inflation PMU have a correlation of 0.22 which is second highest among our measures.

The first row of Table A-14 shows the baseline parametrization of the model with the structural parameters known with certainty. The optimal policy coefficients ϕ_y, ϕ_π for $\lambda_y = 0.5$ and $\psi = 0.9$ are shown in the last two columns for the certainty case.

	$\bar{\alpha}$	$\bar{\beta}$	$\bar{\delta}$	$\bar{\gamma}$	σ^2_α	σ^2_β	σ^2_δ	σ^2_γ	ϕ_y	ϕ_π
Certainty	0.645	0.9	1	0.5	0	0	0	0	1.23	2.03
Baseline Uncertainty	0.645	0.9	1	0.5	0.0121	0.01	0.01	0.0169	1.20	1.98

Table A-14. Effect of parameter uncertainty

Uncertainty in this model is introduced following Söderström (2002): The policymaker does not know the specific parameters but is aware that the coefficients $(\alpha_{t+1}, \beta_{t+1}, \delta_{t+1}, \gamma_{t+1})$ are random variables drawn independently each period from normal distributions with known means and variances (e.g., $\alpha_{t+1} \sim N(\bar{\alpha}, \sigma^2_\alpha)$).[4]

Optimal policy remains a linear function of the current state variables as in equation (A.13). The model exhibits certainty equivalence in the sense that increasing volatility of the stochastic shocks (ε^y_{t+1} and ε^π_{t+1}) does not affect the ϕ coefficients. However, certainty equivalence fails in a different sense; the ϕ coefficients are a function of the uncertainty about the parameter values (such as σ_α). The second row of Table A-14 shows that the introduction of uncertainty about all parameters leads the ϕ coefficients to both decrease very slightly in line with the original Brainard's conservatism result. This is because we use the baseline variance of δ from the Söderström (2002) calibration ($\sigma^2_\delta = 0.01$); if we instead use a larger calibrated value considered in Söderström (2002) ($\sigma^2_\delta = 0.1$), the ϕ coefficients increase very slightly overall.

To connect the model predictions to our empirical findings, we explore how different levels of uncertainty about the paramaters (σ_δ, σ_γ, σ_α and σ_β) impact the policy reaction function. We analyze the effect of each of these parameter uncertainty measures varying from 0.4 to 3 times the baseline standard deviation (Table A-14 reports the variances) and present the evolution of the ϕ coefficients in Figure A-3. Two of the parameters directly affect inflation (δ and γ), and two directly affect output (α and β). We, therefore, analyse these together since our empirical measures do not distinguish whether higher uncertainty about inflation derives from uncertainty about δ or γ. The top row of Figure A-3, shows the effect of varying the uncertainty around the inflation parameters, and the bottom row shows the same for the output parameters. In each case, we consider the effect of uncertainty about each parameter separately as well as jointly with the other parameter.

Uncertainty about inflation can, in principle, drive the ϕ_π coefficient upward so long as it is uncertainty about the persistence of inflation (as in Söderström (2002)). Nonetheless, with a

[4] Specifically:

$$y_{t+1} = \alpha_{t+1} y_t - \beta_{t+1} (i_t - \pi_t) + \sigma_y \varepsilon^y_{t+1}$$
$$\pi_{t+1} = \delta_{t+1} \pi_t + \gamma_{t+1} y_t + \sigma_\pi \varepsilon^\pi_{t+1}$$

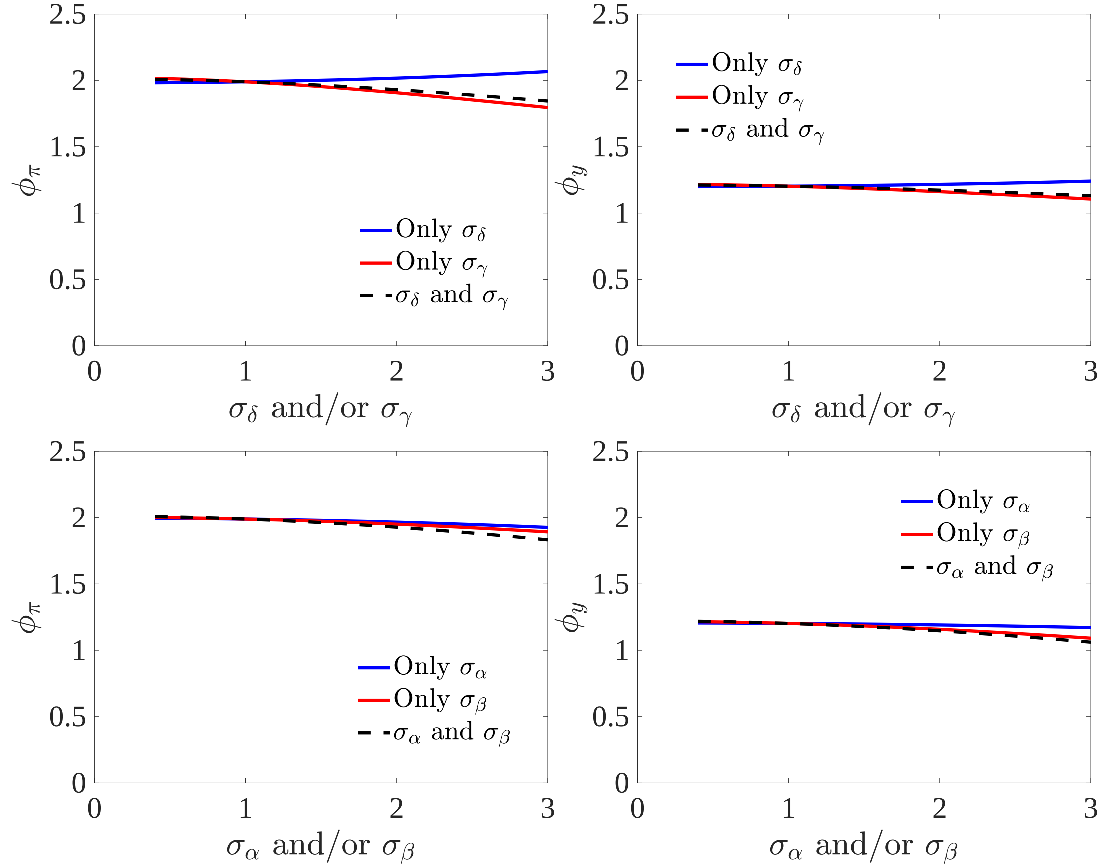

Figure A-3. The effect of parameter uncertainty. The figure presents the effect of parameter uncertainty on the optimal ϕ_π and ϕ_y in the backward looking monetary model. The top row shows the effect of varying uncertainty about the two parameters of the inflation equation (σ_δ and/or σ_γ), and the lower row shows the effect of varying uncertainty about output equation parameters (σ_α and/or σ_β). In each case, the dashed line shows the effect of changing both together.

threefold increase in σ_δ, the policy response ϕ_π only rises from 1.98 to 2.07. In the case of the other parameters, greater uncertainty leads to lower ϕ coefficients. Therefore, such a model of policymaker uncertainty has difficulties in explaining the amplifying impact of uncertainty on policy that we document empirically.

D.2. Robust control

As an alternative to parameter uncertainty, a policymaker may display a desire for robustness. That is, in the face of uncertainty about the correct model specification, the policymaker seeks a policy function that is robust to the worst possible form of misspecification (Hansen and Sargent, 2001, 2008; Giordani and Söderlind, 2004). The robust min-max approach to optimal policy involves two stages. First, an imagined evil agent distorts the model in the most damaging possible way (maximize losses); second, the policymaker minimizes losses subject to the distorted model of the economy. Specifically, in the model described above, the evil agent can use shocks, υ_t^y and υ_t^π, to distort the model. The distorted model is:

$$y_{t+1} = \alpha y_t - \beta\left(i_t - \pi_t\right) + \sigma_y(\upsilon^y_{t+1} + \varepsilon^y_{t+1}) \tag{A.14}$$

$$\pi_{t+1} = \delta\pi_t + \gamma y_t + \sigma_\pi(\upsilon^\pi_{t+1} + \varepsilon^\pi_{t+1}) \tag{A.15}$$

The υ shocks can be related to the endogenous variables allowing them to capture broad types of misspecification including the more traditional parameter uncertainty. The evil agent is constrained via a budget in how much they can distort the model and will always exhaust their budget. The parameter θ is inversely related to the budget: $\theta = \infty$ precludes distortions completely and corresponds to the rational expectations solution, while a low value of θ allows the evil agent distort the model in a significant way.[5]

The monetary authority minimizes the loss from inflation deviations and output deviations. The robust control literature finds that the policymaker's preference for interest rate smoothing can be important for model predictions. Therefore, we assume that the policymaker's loss function is given by:

$$L_t = \sum_{\tau=t}^{\infty} \psi^{\tau-t}\left(\pi_t^2 + \lambda_y y_t^2 + \lambda_i i_t^2\right) \tag{A.16}$$

where $\lambda_i > 0$ activates a preference for interest rate smoothing.[6]

Optimal policy is a linear solution of the predetermined state variables. Certainty equivalence fails because the optimal ϕ coefficients change with the variance of the structural shocks (σ_y^2 and σ_π^2). As volatility of the structural shocks increase, it becomes harder for the agent to distinguish their baseline model from the distorted model and they adjust their optimal policy to account for this uncertainty. Therefore, evaluating the effects of uncertainty in the robust control model is now directly related to examining the effect of σ_y^2 and σ_π^2 changing. There is no separate parameter uncertainty in this model.

In Figure A-4, we evaluate the optimal ϕ parameters as σ_π (top row) and σ_y (bottom row) vary. The baseline in this model is $\sigma_\pi^2 = \sigma_y^2 = 1$ and, therefore, the relative volatility increase or decrease is expressed in terms of additional standard deviations. This allows us to compare Figure A-3, Figure A-4, and our empirical results. Each line in Figure A-4 represents the effect of greater uncertainty for different key parameters; the basic calibration is the same as that in Table A-14.

Generally, in this environment, uncertainty manifests itself through a more aggressive reaction function (larger ϕ coefficients). Higher inflation uncertainty σ_π^2, increases both ϕ_π and ϕ_y. The increase is greater when the policymaker has a preference for interest rate smoothing ($\lambda_i = 0.15$), though even this effect is offset if the policymaker's preference for robustness (measured by the

[5]We do not present the evil agents optimisation problem in the interests of space.

[6]The theoretical justification for this welfare function is discussed in Woodford (2003, Chapter 6).

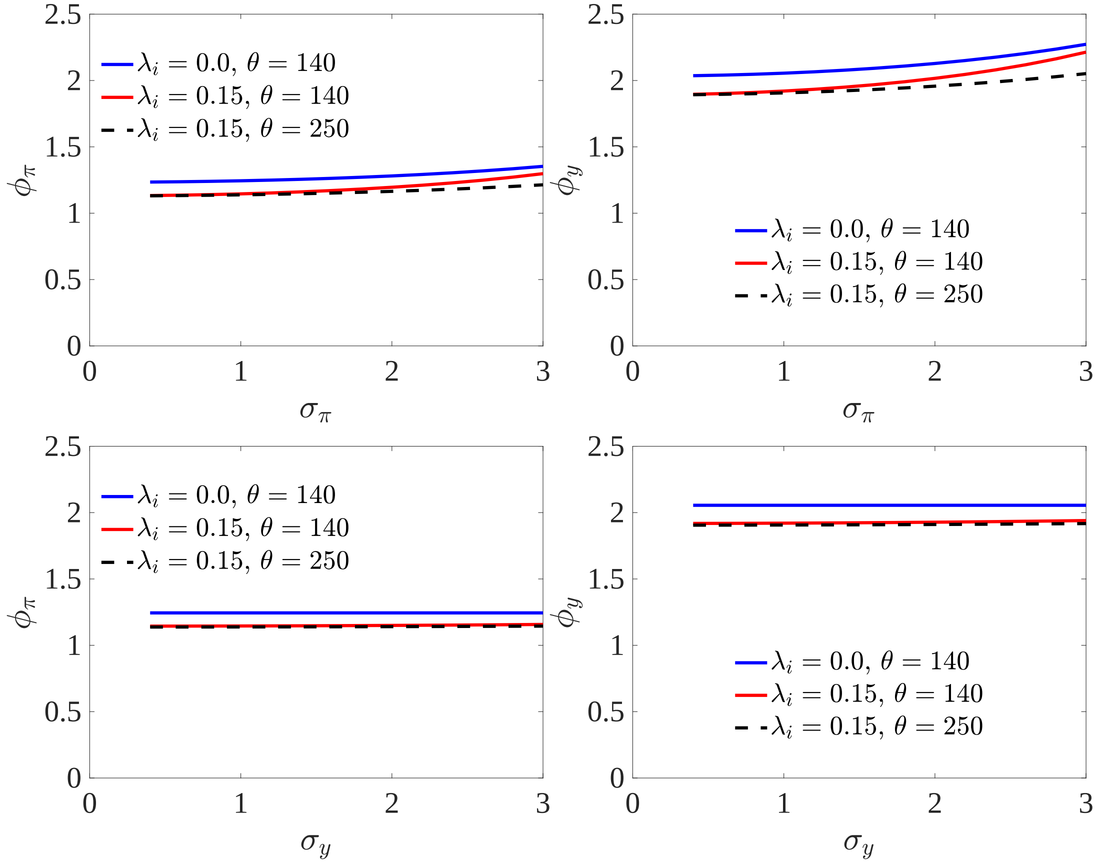

Figure A-4. Backward-looking robust control model. The figure presents the effect on the optimal ϕ_π and ϕ_y of a policymaker who has a preference for robustness in the backward looking monetary model. The top row shows the effect of varying σ_π (volatility of the inflation shocks), and the lower row shows the effect of varying σ_y (output equation shock volatility).

inverse of θ) is weaker. In contrast to inflation, the real uncertainty σ_y^2 has a negligible impact on the policy coefficients even when the smoothing motive is substantial.

D.2.1. A forward-looking model with robustness

One concern is that the model presented above is backward-looking and lacks greater persistence, which can be important in generating quantitatively meaningful effects of uncertainty. This simplicity is useful for obtaining tractable solutions for optimal policy. However, to show that the main conclusions persist in richer settings, we now analyze how robustness affects policy in a forward-looking New Keynesian model comprising an IS curve (A.17) and a Phillips curve (A.18) as in Clarida, Galí, and Gertler (1999) and Giordani and Söderlind (2004). Both equations are subject to persistent shocks, g_t and u_t respectively:[7]

[7]Ferrero, Pietrunti, and Tiseno (2019) present an analysis of optimal policy under parameter uncertainty in a forward-looking model similar to the one we consider. Their main finding is that the optimal response to uncertainty about the slope of the Phillips Curve depends on the the persistence of the cost-push shock. If

$$y_t = E_t y_{t+1} - \gamma (i_t - E_t \pi_{t+1}) + g_t \tag{A.17}$$

$$\pi_t = \alpha y_t + \beta E_t \pi_{t+1} + u_t \tag{A.18}$$

$$g_t = \rho_g g_{t-1} + \sigma_y \epsilon_t^y \tag{A.19}$$

$$u_t = \rho_u u_{t-1} + \sigma_\pi \epsilon_t^\pi \tag{A.20}$$

where $\epsilon_t^y \sim N(0,1)$ and $\epsilon_t^\pi \sim N(0,1)$ are i.i.d. disturbances. As before, the monetary authority minimizes the loss from inflation deviations, output deviations and, if $\lambda_i > 0$, interest rate level variation. The evil agent can use shocks, υ_t^y and υ_t^π, to distort the model.[8]

We solve this model under the assumption that the central bank cannot commit to a policy rule as in Giordani and Söderlind (2004).[9] This has the advantage that every period, the policymaker can assess uncertainty and choose an optimal response. As such, it is closer in spirit to the comparative statics exercise we perform, in which we change the volatility of structural shocks and solve for the optimal policy. The evil agent is similarly assumed to optimize every period and choose the worst-possible distortion. To simplify the solution, we follow Hansen and Sargent (2008) assuming that the private sector's loss function, reference model, and their degree of robustness are shared with the central bank.

The key parameters are the ρ_u and ρ_g persistence parameters, the degree of interest rate smoothing (λ_i), and the desire for robustness (θ). In Figure A-5, as before, we evaluate the optimal ϕ parameters as σ_π (top row) and σ_y (bottom row) vary for different values of the other key parameters. When the policymaker's utility from interest rate smoothing is low, the impact of uncertainty is imperceptible; the blue line in the figure show the effects for $\rho = \rho_\pi = \rho_x = 0$, but the effect is little changed if $\rho = \rho_\pi = \rho_x = 0.5$ (not shown). Adding a desire for smoothing but no persistence does generate an increasing relationship between the ϕ coefficients and the volatility of the shocks, albeit so slight that it does not appear visible in the graph (red line). It is only when there is a desire for smoothing, alongside persistence, that the upward relationship begins to emerge.[10]

In summary, across the models we consider, while policymakers' parameter uncertainty and preference for robustness can generate amplification of the policy reaction to the state of the macroeconomy, the economic magnitudes of this effect appear quantitatively small and are sensitive to

the shock is not persistent, policy caution is the optimal response; with persistent cost-push shocks, optimal policy is more aggressive.

[8]The distorted model is:

$$\begin{aligned} y_t &= E_t y_{t+1} - \gamma (i_t - E_t \pi_{t+1}) + \rho_g g_{t-1} + \sigma_y (\upsilon_t^y + \epsilon_t^y) \\ \pi_t &= \lambda y_t + \beta E_t \pi_{t+1} + \rho_u u_{t-1} + \sigma_\pi (\upsilon_t^\pi + \epsilon_t^\pi) \end{aligned}$$

[9]Giannoni (2002) solves a robust-control problem in the same type of model under the assumption of a commitment policy. We did not discuss this distinction when discussing the backward-looking model above as the discretion solution coincides with the commitment solution in that model.

[10]Although not plotted, increasing θ limits the budget of the evil agent and, as before, has a dampening effect on how higher volatility affects the ϕ coefficients.

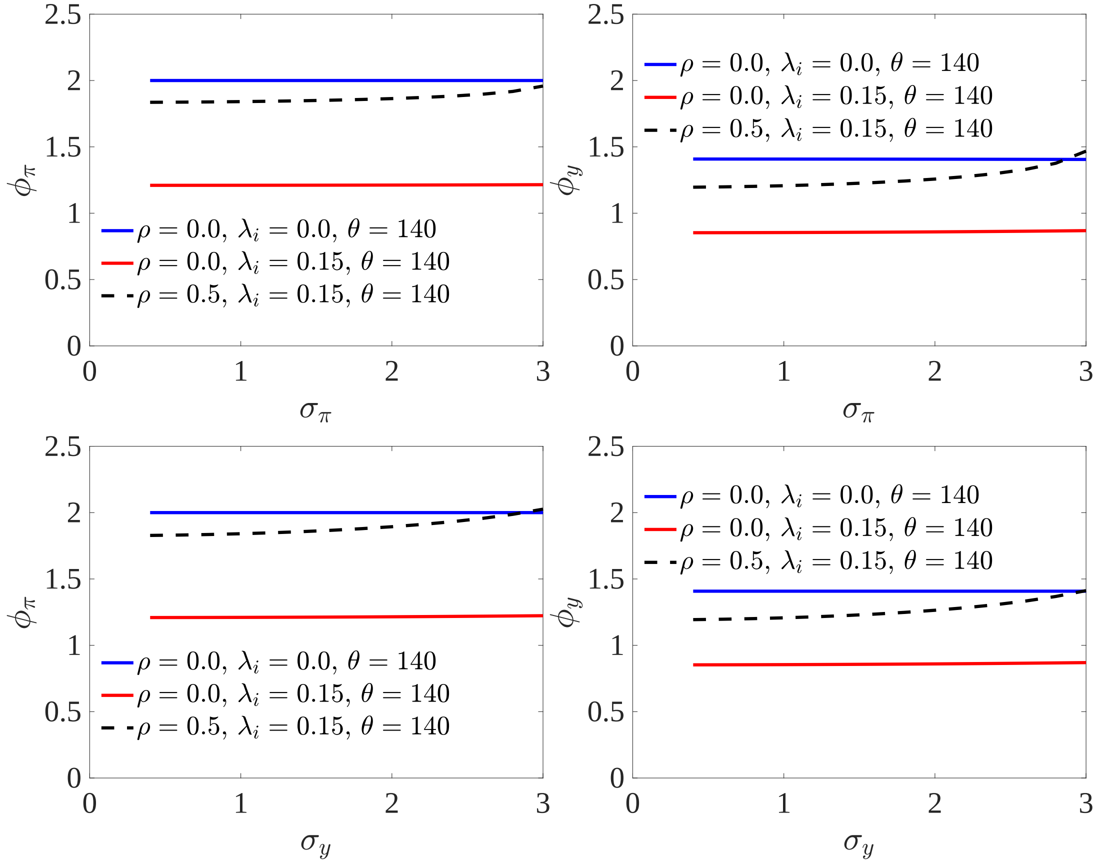

Figure A-5. Forward-looking robust control model. The figure presents the effect on the optimal ϕ_π and ϕ_y of a policymaker who has a preference for robustness in the forward-looking monetary model. The top row shows the effect of varying σ_π (volatility of the inflation shocks), and the lower row shows the effect of varying σ_y (output equation shock volatility).

specific model assumptions. This contrasts with the relatively sizeable effects of uncertainty on policy preferences we document empirically.