Disagreement About Monetary Policy

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Abstract

Using a model of monetary policymaking with belief distortions, I propose tests to distinguish among three leading hypotheses for explaining disagreement between markets and central banks: asymmetric information, different beliefs about the monetary rule, and different confidence in public signals. Implementing these tests in US data, I find that bad macroeconomic news predicts market over-estimation of both interest rates and employment relative to realizations and Federal Reserve forecasts. I show that different confidence in public signals is necessary to explain these findings and that, quantitatively, this mechanism significantly dampens market beliefs' responsiveness to fundamentals. Central-bank signaling has much smaller effects.

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1 Introduction

Markets and central banks regularly hold different beliefs about where the economy is heading and how monetary policy will respond. Indeed, if they did not, central bank communications would be redundant proclamations of common knowledge instead of potentially, in the words of former Federal Reserve Chair Ben Bernanke, "one of the most powerful tools" in the central-bank arsenal (2015). But what induces such disagreements in a world of abundant public data and constant discussion about policy? And what does the answer to the previous question imply about the power—or futility—of central bank communication as a tool for moving markets?

This paper develops a theoretical and empirical framework to answer these questions. The analysis has three parts. First, I introduce a simple model of policymaker and market interactions in which disagreements between the two agents can arise from three possible mechanisms: asymmetric information about unknown fundamentals, asymmetric beliefs about the policymaker's reaction to public signals, and asymmetric confidence in those signals. The model generates testable conditions under which specific mechanisms are necessary to explain belief data. Second, I implement these tests in the US data since 1995. I find evidence that rejects models with only asymmetric information or only policy-rule mis-perception, and points toward a significant role for asymmetric confidence (i.e., "agreeing to disagree"). Third, I use my estimates to identify the model's parameters and quantitatively compare the importance of all three proposed mechanisms for disagreement. In the calibration, the market's perception that the Fed over-reacts to news significantly dampens belief fluctuations over the business cycle. By contrast, the "information effect," or phenomenon of central banks' signaling their information about fundamentals through policy actions, does not meaningfully amplify them.

Model. I begin by presenting the model that structures the empirical analysis and its interpretation. There are two agents, a central bank ("the Fed") and a representative investor ("the Market"); three periods, indexed by $t \in \{0, 1, 2\}$; and a single exogenous fundamental, an aggregate demand shock. At $t = 0$, both the Fed and the Market observe a public signal of the fundamental (e.g., a statistical indicator), and the former observes also a private signal of the fundamental (e.g., internal research). The Fed sets interest rates equal to its forecast of the fundamental.[1] The Market attempts to forecast policy, or forecast the Fed's forecast. At $t = 1$, the policy is announced and a *monetary surprise*, or Market forecast error in predicting the policy, is realized. At $t = 2$, everyone observes a second public signal of fundamentals. Afterward, an additional variable, employment or output, is realized. Employment depends positively on fundamentals and negatively on policy, with slopes encoding the assumption that fundamental shocks have a positive effect on employment net of the policy response, on average.

[1] Allowing for a Fed reaction to Market expectations is nested in the basic set-up (see Section 2.6).

The Fed's and the Market's beliefs about fundamentals, interest rates, and employment may differ for three reasons. First, as mentioned above, the Fed has private information ("Mechanism 1"). Second, markets may mis-estimate the Fed's policy reaction to the public signal ("Mechanism 2"). And third, the Market and Fed may have different confidence in the public signal, generating heterogeneous priors ("Mechanism 3").[2]

I first show that a pure asymmetric information model (e.g., as hypothesized by Romer and Romer, 2000) precludes public information from predicting monetary surprises. By contrast, either of the other two mechanisms allows for this possibility. In particular, under-estimating the Fed's confidence in the public signal or having low confidence in the public signal is consistent with the (ultimately empirically relevant) case in which markets are surprised by the extent of monetary loosening following bad news and monetary tightening after good news.

I next show how mis-estimation of the monetary rule and heterogeneous confidence in public data can be distinguished by their predictions for employment forecasts. The result, stated informally, is that mis-specification of the policy rule pushes interest rate and employment forecast errors (or revisions) to have opposite signs, while over- or under-reaction to public information pushes these forecast errors (or revisions) to have the same sign. The logic is best illustrated by describing how a Market agent would respond to bad news in the public signal under two polar cases for its belief distortion. The first case is a Market that under-estimates the monetary response to news but correctly interprets the news' informativeness about fundamentals (e.g., as hypothesized by Bauer and Swanson, 2020). The market over-predicts interest rates in response to the bad news and, if it understands that monetary policy has negative real effects, therefore under-predicts employment (i.e., is pessimistic). The second case is a Market that under-estimates the news' informativeness about fundamentals but correctly specifies the monetary response to news. This version of the Market also over-predicts interest rates, because it expects the Fed's private signal to align with its own more optimistic beliefs about fundamentals. But, under the assumption that shocks have a positive effect on employment net of the policy response, the Market *over*-estimates employment (i.e., is optimistic)—its optimism about fundamentals dominates any countervailing pessimism from expecting high interest rates.

The results, taken together, show how multiple joint "sign tests" can show what mechanisms are necessary to explain the data. The remainder of the paper conducts these tests and interprets their results via the model.

Empirical Analysis. I treat the *policy news shock* of Nakamura and Steinsson (2018) as a summary of monetary surprises across the term structure since 1995. I focus on the following leading indicators of the business cycle as representative public signals: (i) consumer sentiment from the University of Michigan Survey of Consumers; (ii) revisions to professional forecasts

[2] An equivalent interpretation, if the Market and Fed are both objectively under-confident in the signal, is that the two parties are differentially inattentive to the signal.

from the *Blue Chip Economic Indicators* survey; (iii) recent stock market performance; and (iv) stock-market sentiment from the American Association of Individual Investors survey.

My first main empirical finding is that all four measures are positive predictors of monetary surprises—that is, good (bad) news in any indicator predicts surprise monetary tightening (loosening). This result confirms and complements predictability documented in other studies using changes in the unemployment rate (Cieslak, 2018), total non-farm employment (Bauer and Swanson, 2020), and a broader average of macro indicators (Miranda-Agrippino, 2015; Miranda-Agrippino and Ricco, 2021). In the theory, the result invalidates the pure asymmetric-information case but does not pinpoint an alternative model that generates disagreements.

I next test three model predictions about the correlation between realizations of public signals at month $t-1$ and forecasts and realizations of real activity at or after month t. My first finding is that good news from $t-1$, associated with surprise monetary tightening according to my previous results, correlates with professional forecasters' over-predicting unemployment and under-predicting real GDP growth in the Blue Chip Economic Indicators survey at month t. My second finding is that the same lagged good news correlates with optimistic Blue Chip forecast revisions between month t and $t+1$, which partially corrects the predictable component of the time-t forecast error. My third finding is that lagged good news correlates with the Fed's being systematically more optimistic than markets, comparing Greenbook or Tealbook forecasts to the Blue Chip forecasts within the same month. The magnitude equals 30-70% of the aforementioned forecast errors depending on the variable (unemployment or real GDP growth) and forecast horizon.[3]

I finally show how these patterns of belief under-reaction and delayed correction around policy announcements relate to the empirical analysis used by Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) to justify a signaling or "information effect" channel of monetary policy. I show in the model how departing from a purely rational-expectations framework breaks the connection between the aforementioned papers' key moment, the correlation of monetary surprises and forecast revisions about real activity, and their key model mechanism, monetary signaling about fundamentals. In particular, public signal realizations are an omitted variable predicting both monetary surprises and future forecast revisions. I find in the data that the model-consistent estimation of the Fed information effect, controlling for public signal realizations, is positive but statistically indistinguishable from zero. This result illustrates how slow learning and "agreeing to disagree" can appear like signaling if interpreted in a purely Bayesian, asymmetric-information model.

Quantification. In a last section, I fit the model to the empirical estimates to quantify each mechanism's importance. In the empirically calibrated model, the Fed's private information is

[3] This "conditional accuracy" in response to specific shocks is a different moment than the "unconditional accuracy" (e.g., forecast error variance) measured by Romer and Romer (2000) or Bauer and Swanson (2020).

two orders of magnitude less precise than public information. This suggests that the implied information effects of persuasion through actions may be quantitatively small. I formalize this by showing that, if the Fed's private signal were counterfactually removed, the sensitivity of the Market's post-announcement beliefs (which correspond also to the appropriate notion of a stock price) to fundamentals is reduced by only 0.5%. By contrast, disagreement itself does play an important role. If the Fed counterfactually had the Market's (lower) confidence in public data, the sensitivity of the latter's post-announcement beliefs to fundamentals would increase by 25% because policy would respond less aggressively to the same data. If the Market shared the Fed's (higher) confidence, the same beliefs would be 20% more sensitive due to the Market's quicker response to news. In these units of "belief responsiveness," disagreement from heterogeneous priors therefore has 40 to 50 times larger effects than asymmetric information.

Related Literature. A literature stemming from Morris and Shin (2002) has studied central bank communication and persuasion in Bayesian, rational-expectations models with asymmetric information.[4] Campbell, Evans, Fisher, and Justiniano (2012), Nakamura and Steinsson (2018), and Melosi (2017) use models in this tradition to quantitatively study the signaling effects of US monetary policy. These settings are stylized in my model as "Mechanism 1." In my empirical analysis, I find that such models fit the data less well than alternatives based around heterogeneous priors ("Mechanism 3"). In Section 5, I elaborate on how my different economic conclusion is fully consistent with the empirical analysis of the "information-effect" literature. In Section 6, I show how a quantification fully consistent with the information-effect evidence, but under a different structural interpretation, implies small causal effects of monetary signaling.

My empirical finding that monetary surprises are predictable relates to those in studies by Miranda-Agrippino (2015), Miranda-Agrippino and Ricco (2021), Cieslak (2018), Karnaukh and Vokata (2022), and Bauer and Swanson (2020). Contemporaneously, Bauer and Swanson (2020) show that pre-determined economic news predicts monetary surprises and, when controlled for, attenuates the relationship of surprises with private-sector forecasts.[5] The authors interpret these findings via a model in which market participants under-estimate the Fed's reaction to publicly available economic news in the monetary rule (this paper's "Mechanism 2"). My paper, by contrast, considers a broader class of models, tests additional model predictions about the relationship between interest-rate and real-activity forecasts, and concludes that mis-estimation of the monetary rule needs to be accompanied by heterogeneous priors to explain the facts.

By focusing on heterogeneous priors ("Mechanism 3"), this paper relates to a large literature on disagreement in measured expectations (e.g., Mankiw, Reis, and Wolfers, 2003; Andrade and Le Bihan, 2013; Andrade, Crump, Eusepi, and Moench, 2016; Andrade, Gaballo, Mengus,

[4]For example, Walsh (2007), James and Lawler (2011), Baeriswyl and Cornand (2010), and Kohlhas (2020).

[5]The authors include original survey evidence indicating Blue Chip forecasters' confidence in their own assessment relative to the Fed's. Such evidence is also consistent with this paper's heterogeneous-priors interpretation.

and Mojon, 2019). Caballero and Simsek (2022) study optimal policy when policymakers and the public disagree about aggregate demand, a scenario that is consistent with my findings.

This paper finally relates to existing studies of "imperfections" in macroeconomic expectations that are at odds with full-information, rational-expectations models (e.g., Carroll, 2003; Coibion and Gorodnichenko, 2012, 2015; Broer and Kohlhas, 2021; Kohlhas and Walther, 2021; Bordalo, Gennaioli, Ma, and Shleifer, 2020; Bianchi, Ludvigson, and Ma, 2022; Angeletos, Huo, and Sastry, 2021). This paper's findings show how differences in forecast biases across groups can generate systematic, cyclical belief disagreement.

Outline. Section 2 describes the theoretical model and results. Section 3 describes the data. Section 4 presents the main empirical results. Section 5 explains the consistency of my findings with the measured "Fed information effect." Section 6 introduces a model calibration and studies counterfactuals. Section 7 concludes.

2 Model

In this section, I write a model that embeds three mechanisms for disagreement between central banks and markets—asymmetric information, asymmetric beliefs about the policy rule, and asymmetric confidence in public information. I contrast these mechanisms' predictions to derive empirical tests that can identify the underlying disagreement mechanisms in the data.

2.1 Set-up: Timing, Actions, and Sources of Information

There are three periods denoted by $t \in \{0, 1, 2\}$ and two agents, the "Fed" (F) and the "Market" (M). There is a single fundamental $\theta \sim N(0, \tau_\theta^{-1})$, which shifts policy and outcomes. Throughout, I use the notation $\mathbb{E}_{X,t}[A]$ to denote the expectation of agent $X \in \{F, M\}$ at time t of a random variable A.

At $t = 0$ the Fed sets the (real) interest rate r equal to its expectation of the shock, or $r = \mathbb{E}_{F,0}[\theta]$. The Fed's beliefs at $t = 0$ are measurable in a public signal $Z = \theta + \varepsilon_z$ and a private signal $F = \theta + \varepsilon_F$, where the noise terms $\varepsilon_z \sim N(0, \tau_z^{-1})$ and $\varepsilon_F \sim N(0, \tau_F^{-1})$ are independent from each other and all other variables. The public signal represents asset prices, opinion aggregators, and statistical releases that are forward-looking indicators of the business cycle. The private signal represents the Federal Reserve's internal research or any publicly unobservable components of "expertise."[6,7]

[6] The "literal" interpretation of research may include non-public statistical releases or the qualitative data incorporated in the Beige Book. The "figurative" interpretation of expertise, as highlighted by both Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018), may include non-public details about the Fed's macroeconomic models.

[7] The assumption that market participants have no (aggregate or dispersed) private information source of

The Market at $t = 0$ makes a prediction P equal to its expectation of interest rates, or $P = \mathbb{E}_{M,0}[r]$. In light of the monetary rule, this is an expectation of the Fed's expectation of fundamentals, or $P = \mathbb{E}_{M,0}[\mathbb{E}_{F,0}[\theta]]$. The Market's beliefs at $t = 0$ are measurable only in the public signal.[8]

The interest rate is revealed to the Market at $t = 1$. The error or revision in the market prediction is defined as $\Delta = r - P$. Given again that the interest rate is a forecast of θ, the error Δ is a Market error in forecasting the Fed's belief about fundamentals.

At $t = 2$, both agents observe an additional public signal $S = \theta + \varepsilon_S$, with independent noise $\varepsilon_S \sim N(0, \tau_S^{-1})$. Finally, after $t = 2$, employment (or output) Y is realized as $Y = a\theta - r$ for some $a \geq 1$. The restriction is sufficient to imply that fundamental shocks have a positive effect on employment net of the policy response, as is empirically realistic.

I abstract from detailed derivations of these model equations in the main text to keep the main analysis concise, but provide more detail in Online Appendix B. First, Appendix B.1 derives the model structure in a simple rigid-price New Keynesian model. The fundamental θ is a consumer discount-rate shock; Y and r are respectively percent deviations from steady-state for employment (or output) and interest rates. The monetary rule stabilizes, in expectation, fraction $1/a \leq 1$ of the shock, because of rational confusion between supply and demand shocks. Output is the equilibrium outcome of a "Keynesian cross" formed by the Euler equation. Second, Online Appendix B.2 derives P as the price of an asset that pays off in proportion to r at $t = 1$ in the canonical asset pricing setting in which traders have constant absolute risk aversion (CARA) preferences, and fundamentals and signals are Gaussian. This admits a model-consistent interpretation of P as the (re-scaled) price of an interest rate futures contract and Δ as the revision in that price as a result of a monetary policy announcement.

2.2 Set-up: Beliefs

The Fed's Beliefs. The Fed uses Bayes rule to form its beliefs, but have a potentially mis-specified notion of the news content of public signals. In particular, I assume the Fed's posterior expectation about θ at $t = 0$, which is also its policy action, is the following linear combination of signals F and Z:

$$\mathbb{E}_{F,0}[\theta] = \delta_F^F F + (\delta_Z^F - q^F) Z \tag{1}$$

their own at $t = 0$ is merely simplifying and could be dispensed with for the main insights, provided that auxiliary assumptions are made to prevent the futures price from perfectly aggregating information (e.g., noise traders as in Grossman, 1976; Grossman and Stiglitz, 1980).

[8] Of course, one may also assume that the Fed and Market observe P contemporaneously at $t = 0$; but as will be formalized shortly, this reveals no additional information beyond what is summarized in Z.

where $\delta_F^F := \frac{\tau_F}{\tau_F+\tau_Z+\tau_\theta}$ and $\delta_Z^F := \frac{\tau_Z}{\tau_F+\tau_Z+\tau_\theta}$ are the objective precision weights from Gaussian signal extraction and q^F is an additive "distortion" relative to the latter.[9] In particular, $q^F > 0$ encodes under-reaction to or under-confidence in public information relative to a Bayesian benchmark and $q^F < 0$ encodes over-reaction or over-confidence. This is modeled, in a way that is consistent with optimal forecasting *conditional* on mistaken confidence in Z, by having the Fed perceive the precision of the public signal to be $\tau_Z - q^F(\tau_Z + \tau_F + \tau_\theta)$ and the precision of the fundamental to be $\tau_\theta + q^F(\tau_Z + \tau_F + \tau_\theta)$.[10] The under-reaction case of $q^F > 0$ can also be interpreted as a reduced form for rational inattention toward the signal (e.g., as in Sims, 2003) or biased, "cognitively discounted" perception of the signal (Gabaix, 2014, 2020).

The Market's Beliefs. The Market applies Bayes rule subject to two deviations in modeling the economic environment. The first is analogous to the Fed's: the Market may over- or under-weight the importance of the public signal for fundamentals. In particular, the Market's fundamental belief at $t = 0$ is

$$\mathbb{E}_{M,0}[\theta] = \left(\delta_Z^M - q\right) Z \tag{2}$$

where the coefficient $\delta_Z^M = \frac{\tau_Z}{\tau_Z+\tau_\theta}$ corresponds with the objective signal-to-noise ratio for Z, and q measures the market's under-utilization of the public signal. Similarly to the discussion above, $q > 0$ and $q < 0$ respectively correspond to under-reaction and over-reaction, and the underlying model has the Market perceive precision $\tau_Z - q(\tau_Z + \tau_\theta)$ for the public signal and $\tau_\theta + q(\tau_Z + \tau_\theta)$ for the fundamental. Also similarly to the above, under-reaction in this model may be a reduced-form for rational inattention or cognitive discounting.

Second, the market may mis-specify the policy rule's coefficient on Z. Market expectations about r are

$$\mathbb{E}_{M,0}[r] = \mathbb{E}_{M,0}\left[\delta_F^F F + (\delta_Z^F - q^F - w)Z\right] \tag{3}$$

where the term in brackets is a perceived monetary rule, which contrasts with the rule (1) via the newly introduced parameter w. The case $w > 0$ (respectively, $w < 0$) corresponds to under-estimating (over-estimating) the Fed's reliance on Z. Varying w affects how the Market *thinks the Fed uses information*, or the Market's second-order belief about the fundamental θ. Such a friction may be justified by having the Market attribute under- or over- reaction to the Fed, depending on the value of $q^F + w$. The parameter w may also reflect, in reduced form, imprecision arising from learning the monetary rule.

Summary and Relation to the Literature. To summarize, the model accommodates disagreement between the Market and Fed due to three mechanisms, each of which is prominently

[9]I have also used the conjecture (which will be later verified) that the futures price contains no information about θ that is not already spanned by Z.

[10]These "compensating errors" in the total precision $\tau_\theta + \tau_Z + \tau_F$ are convenient for deriving analytical results, though not essential for the main conclusions.

hypothesized in the literature as a source of empirically observed disagreements between markets and central banks. Mechanism 1 is the Fed's private signal F, or asymmetric information. This accommodates the hypothesis that the Federal Reserve in reality has an "informational advantage" over markets, as articulated for instance by Romer and Romer (2000) or Nakamura and Steinsson (2018). Mechanism 2 is the Market's mis-perception $-wZ$ in the monetary rule, or forecasting with an incorrect model equation. This possibility is raised recently by Bauer and Swanson (2020), Bauer, Pflueger, and Sundaram (2022), and Schmeling, Schrimpf, and Steffensen (2020).[11] Mechanism 3 is the Market's and Fed's potentially different confidence in (or attention toward) the public signal as captured by q and q^F. This mechanism, which generates heterogeneous priors after the public signal is realized, is consistent with Caballero and Simsek's (2022) hypothesis of "opinionated markets" that interpret public data differently than the policymaker.

2.3 Result: Predicting Monetary Surprises

I first analyze what explains monetary surprises in the model. I calculate the surprise, $\Delta = r - P$, by plugging fundamental beliefs (2) into the perceived monetary rule (3), and subtracting this from the actual rule (1). After re-arranging terms and defining $\mathbb{E}^R_{M,0}[\theta] := \delta^M_Z Z$ as the rational Bayesian expectation of θ, I derive the following:

$$\Delta = \delta^F_F \left(F - \mathbb{E}^R_{M,0}[\theta] \right) + \delta^F_F q Z + wZ \tag{4}$$

The first term in the above equation is the error that the Market would make with a rational Bayesian, but noisy, guess of the Fed's internal information. This term cannot be predicted by Z, which is fully incorporated into $\mathbb{E}^R_{M,0}[\theta]$. The second term is the bias in the Market forecast of F, grounded in its biased forecast of θ. The third term is the mistake due to mis-estimating the Fed's response to Z. The Fed's own information-use distortion q^F does not show up in this term, because it is fully accounted for in the market's model of the Fed up to the deviation w.

The following Proposition uses the previous logic to sign the covariance between Δ and Z, or the component of monetary surprises that may be predicted by public data:

Proposition 1 (Monetary Surprises). *The following three properties hold for $Cov[\Delta, Z]$:*

1. *If $w = q = 0$, then $Cov[\Delta, Z] = 0$.*
2. *If $w \geq 0$ and $q \geq 0$, then $Cov[\Delta, Z] \geq 0$.*
3. *If $w \leq 0$ and $q \leq 0$, then $Cov[\Delta, Z] \leq 0$.*

[11] A similar idea appears, for a different reason, in the theoretical literature about equilibrium determinacy when agents learn monetary rules (e.g., Bullard and Mitra, 2002).

Point 1 demonstrates that public information will *not* predict monetary surprises when the Market rationally incorporates Z into their forecast and correctly models how the Fed will act. This result does not require the Fed to act rationally, as long as the Market is fully aware of the Fed's bias and accounts for it in their prediction. Points 2 and 3 show in what direction the other, non-Bayesian mechanisms push $\text{Cov}[\Delta, Z]$, when these biases line up to produce an unambiguous sign prediction. As stated, case 2 corresponds to the Market's both under-reacting to information in Z and under-estimating the Fed's reaction, leading to a positive correlation between "bad news" in Z and un-expected monetary loosening; while case 3 corresponds to the Market's over-reacting to Z and over-estimating the Fed's reaction, leading to a negative correlation of the same. In the remaining sign cases for (q, w), there is an ambiguous sign prediction for $\text{Cov}[\Delta, Z]$ due to the possibly offsetting effects.

The test embedded in Proposition 1 can be implemented given data on public signals and changes in the market forecasts about monetary policy around FOMC meetings embedded in interest rate futures prices. But, by itself, it is not a powerful test for determining the "right" model for disagreement, and crucially the one relevant for comparative statics and counterfactuals, due to the pooling of predictions for $w \neq 0$ and $q \neq 0$.

2.4 Result: Identifying the Mechanism for Disagreement

I now describe how to use data on the errors in and revisions of employment forecasts to differentiate the two mechanisms for disagreement. The core idea is that, if monetary tightening has a negative real effect, under-estimating the monetary response to a fundamental shock (i.e., $w > 0$) versus under-estimating the magnitude of that fundamental shock (i.e., $q > 0$) should have opposite effects on the Market's prediction for real outcomes, which contrasts with their shared prediction for the Market's prediction of interest rates.

I first state my formal result that maps sign cases for the parameters (q, w) to the signs of (i) the covariance of Z with forecast errors of Y at each horizon and (ii) the covariance of Z with forecast revisions of Y after the announcement:

Proposition 2 (Employment Forecast Errors and Revisions)**.** *The following properties hold:*

1. *If $w = q = 0$, then $Cov[Y - \mathbb{E}_{M,t}[Y], Z] = 0$ for $t \in \{0, 1, 2\}$ and $Cov[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] = 0$.*

2. *If $w \leq 0$ and $q \geq 0$, then $Cov[Y - \mathbb{E}_{M,t}[Y], Z] \geq 0$ for $t \in \{0, 1, 2\}$ and $Cov[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] \geq 0$.*

3. *If $w \geq 0$ and $q \leq 0$, then $Cov[Y - \mathbb{E}_{M,t}[Y], Z] \leq 0$ for $t \in \{0, 1, 2\}$ and $Cov[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] \leq 0$.*

With no biases, public signals cannot predict subsequent forecast errors or revisions; with over-estimation of the monetary response or under-reaction to news, positive realizations of the public signal predict positive forecast errors and revisions; and with under-estimation of the monetary response or over-reaction to news, positive realizations of the public signal predict negative forecast errors and revisions. The relevant moments can be measured with data on the beliefs of the market, or informed professional forecasters who may reasonably stand in for the Market.

The proof of Proposition 2 in Appendix A verifies the results via direct calculations. Here, I provide a proof sketch that fully details the argument for the Market's forecast error at $t = 0$ and uses examples to describe the logic of the additional results.

Forecast Errors at $t = 0$: A Direct Calculation. The Market's forecast error $t = 0$ is a linear combination of forecast errors about both fundamentals and the policy response. Using the previous expressions for the Market's beliefs of each, and combining terms, I can write this forecast error as the following:

$$Y - \mathbb{E}_{0,M}[Y] = \left(a - \delta_F^F\right)\left(\theta - \mathbb{E}_{M,0}^R[\theta]\right) + \delta_F^F \varepsilon_F - wZ + \left(a - \delta_F^F\right) qZ \tag{5}$$

The first two terms, respectively proportional to the rational forecast error and the idiosyncratic noise in the Fed's assessment, are orthogonal to Z for the same reasons argued in the proof of Proposition 1. The third term describes the market's tendency to expect a diluted monetary response to Z whenever $w > 0$ and an exaggerated monetary response if $w < 0$. To illustrate, $w > 0$ and "bad news" $Z < 0$ contribute to a positive forecast error, or under-estimation of output, on account of the Market's expecting the Fed to under-react to news and keep policy too tight. The fourth term captures the Market's under-reaction to Z, which has a direct effect (loaded onto a) and an indirect effect from the mistaken conjecture of the Fed's private information (loaded onto δ_F^F). Under the stated conditions $a \geq 1$ (the Fed's not over-stabilizing the business cycle) and $\delta_F^F < 1$ (the Fed's not perfectly knowing θ), this term has the same sign as qZ. To illustrate, $q > 0$ and the same "bad news" $Z < 0$ contribute to *under*-estimating output, on account of the Market's not taking the bad news fully seriously.

Using (5) to calculate $\mathbb{E}[Y - \mathbb{E}_{0,M}[Y], Z] = \text{Var}[Z] \cdot \left(\left(a - \delta_F^F\right) q - w\right)$, it is straightforward to verify claims 1, 2, and 3 of Proposition 2 for the forecast error at $t = 0$.

Sketching the Remainder of the Argument. To illustrate Proposition 2's additional results, it is easiest to sketch two extreme cases which isolate each mechanism; the proof makes these arguments "continuous" as a function of parameters w and q. In the first extreme case, I set $w > 0$ and $q = 0$ and continue the thought experiment of "bad news" or $Z < 0$. At $t = 1$, the Market is surprised by the Fed's loosening and rationalizes this by assuming the Fed has made a very pessimistic idiosyncratic assessment (a low F). Taking this information into account in their new employment forecast at $t = 1$, the Market is again overly pessimistic due to this mis-interpretation. When new data arrive at $t = 2$ in the form of the second public signal S, the Market's beliefs partially mean-revert to offset the over-reaction.

In a second extreme case, the Market is correct about the Fed's reaction function ($w = 0$) but under-reacts to news in the public signal ($q > 0$). At $t = 0$, the Market is optimistic about employment because they do not take the bad news so seriously. At $t = 1$ and $t = 2$, respectively, they are surprised by the extent of monetary loosening (and the implied pessimism of the Fed's assessment) and the badness of the second public signal. Their optimism partially erodes after the announcement, as beliefs slowly and inertially converge to the correct story.

2.5 Identification: Sign Tests and Moment Matching

The calculations underlying Propositions 1 and 2 suggest an identification strategy for (q, w) based on comparing belief patterns for interest rates and employment. I now make this strategy more explicit. Define the "regression coefficients" of Z on monetary surprises and forecasts errors as, respectively,

$$b^{\Delta} := \frac{\mathbb{E}[\Delta, Z]}{\mathrm{Var}[Z]} = \delta_F^F q + w \qquad b^{\mathrm{FCE}} := \frac{\mathbb{E}[Y - \mathbb{E}_{0,M}[Y], Z]}{\mathrm{Var}[Z]} = \left(a - \delta_F^F\right) q - w \tag{6}$$

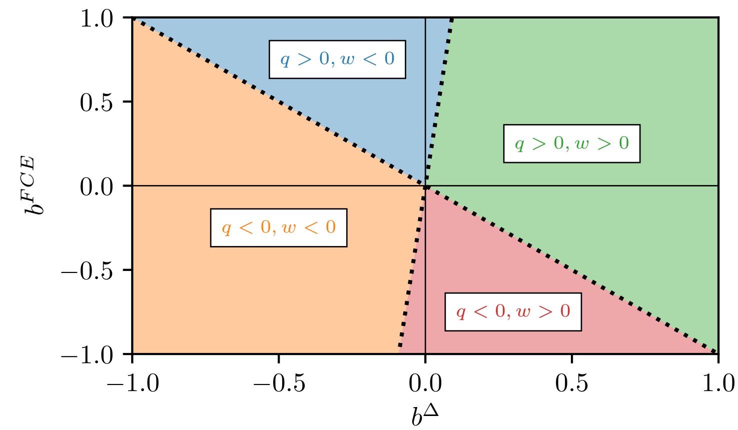
Conditional on knowing a, the slope of output in θ, and δ_F^F, the relative precision of the Fed's information, the following inverse mapping recovers q and w:

$$q = \frac{1}{a}\left(b^{\mathrm{FCE}} + b^{\Delta}\right) \qquad w = b^{\Delta} - \frac{\delta_F^F}{a}\left(b^{\mathrm{FCE}} + b^{\Delta}\right) \tag{7}$$

By knowing the predictable errors for r and Y and the slope of Y in θ and r, one can identify the predictable error for θ. Then one can identify the required mis-specification of the monetary rule that rationalizes the predictable error for interest rates.

This process is visualized in Figure 1, a version of which illustrates the sign cases for (q, w) as a function of $(b^{\Delta}, b^{\mathrm{FCE}})$. One could determine a "best-fit, one-friction model" by merely identifying a quadrant of Figure 1, or the sign of each moment, and assuming the correct model lay on the dotted lines (on which either $q = 0$ or $w = 0$). A more exact exercise can jointly identify (q, w) using the point estimates of $(b^{\Delta}, b^{\mathrm{FCE}})$ and use additional informative moments to learn the other model parameters. In the empirical analysis, I will pursue both the simple, "sign-test" strategy (Section 4) and the more exact, but structurally demanding, moment-matching exercise (Section 6).

Figure 1: Parameter Cases for (q, w)



Notes: This illustration sets $a = 1$ and $\delta_F^F = 0.10$. Each colored region indicates a sign case for (q, w), and the dotted lines indicate borders between these regions.

2.6 Remarks and Extensions

Before proceding to the empirical analysis, I cover three additional topics.

Measured Disagreements in Forecasts of Y. In the model, the Fed's forecast about output at $t = 0$ differs from the Market's due both to (i) the Fed's different forecast of fundamentals and (ii) the Fed's knowledge of its own information and interest rate choice. In particular, the difference in Fed and Market beliefs is the following:[12]

$$\mathbb{E}_{F,0}[Y] - \mathbb{E}_{M,0}[Y] = a(\mathbb{E}^R_{F,0}[\theta] - \mathbb{E}^R_{M,0}[\theta]) + a(q - q^F)Z - \Delta \tag{8}$$

where $\mathbb{E}^R_{F,0}[\theta] := \delta_F^F F + \delta_Z^F Z$ is the Fed's as-if rational expectation. Two conclusions are immediate from this expression. First, the public signal Z can predict this disagreement going both through fundamental disagreement, or $q \neq q^F$, and the previously discussed predictable component of the policy forecast error.[13] Conditional on other measurements of the Market's bias (for instance, based on the logic in Figure 1), the predictability of Market-to-Fed disagreement therefore provides direct insight into the Fed's relative forecasting biases. Second, the Fed's beliefs about real variables and their difference from Market beliefs, observed with delay in published Greenbooks (or Tealbooks), may predict monetary surprises even in the *absence* of biases (i.e., with $q = q^F = w = 0$) owing to their partial revelation of the Fed's internal

[12] Analogous expressions can be derived at $t = 1$ and $t = 2$, but are omitted for brevity.

[13] Observe that $\mathbb{E}^R_{F,0}[\theta] - \mathbb{E}^R_{M,0}[\theta]$ is orthogonal to Z again based on an argument with the law of iterated expectations, conditioning down on the realization of Z.

information F. Such regressions (e.g., as in Gertler and Karadi, 2015; Ramey, 2016) do not in isolation distinguish between mechanisms controlling disagreement.

Fed Reaction to Market Expectations. One might consider a variant model in which the Fed's reaction function, Equation 1, included terms spanned by the market's expectations of r, θ, or Y. This is not natural in the New Keynesian microfoundation presented in Appendix B.1, but it may be realistic if the Fed has an explicit objective to stabilize financial markets and/or avoid surprising the public. In a variant of my model that adds terms to Equation 1 linear in the aforementioned expectations, both Propositions 1 and 2 hold as stated. The reason is that each of these objects is spanned by the public signal Z, and the exact loading on Z was not relevant in either proof. This variant model requires interpreting q^F, previously interpreted as parameterizing the Fed's under-reaction to the public signal, as the Fed's explicit correction to the hypothesized monetary policy function to respond to market expectations.

Belief Updates at $t = 1$. The cases described in Proposition 2 do not immediately translate into sign predictions for the correlation between Z and $\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y]$, the Market's forecast revision about employment or output during the monetary announcement. For this correlation, the model's prediction depends on the relative magnitudes of the Market's belief update about interest rates and its belief update about fundamentals, and not just their sign. In Section 5, I return to this topic as part of a theoretical and empirical analysis of the "information effect," or signaling channel of monetary policy, and its measurement in the presence of belief frictions (Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018).

3 Data and Measurement

3.1 Monetary Surprises

To measure the market's interest-rate forecast revisions, I use data on futures-market interest rate surprises ("high-frequency monetary shocks") from Nakamura and Steinsson (2018). These data cover January 1995 to April 2014.[14] I restrict attention to surprises corresponding to scheduled FOMC meetings, since the timing of unscheduled meetings is usually a direct response to economic conditions. Like Nakamura and Steinsson (2018), I study revisions to market-implied expectations of the Federal Funds Rate and the US BBA LIBOR ("Eurodollar") rate at different horizons. The surprise component is defined as the change in the price-implied-expectation over a 30-minute window circumscribing the timing of an FOMC interest rate

[14] Unlike Nakamura and Steinsson (2018), I include data from the financial crisis (July 2008 to June 2009) in my main sample. Throughout the empirical analysis, I explore sample splitting and rolling regressions that indicate that my estimates are not unduly sensitive to including this period.

announcement (10 minutes before and 20 minutes after).[15]

For the main analysis, I use Nakamura and Steinsson's (2018) *policy news shock* measure, a linear combination of surprises to futures for the following five rates: the Federal Funds rate in the same month of the meeting, the Federal Funds rate in the month of the next scheduled meeting, and Eurodollar futures at quarterly horizons 2, 3, and 4. The linear weights are chosen to maximize, up to normalization, the explained variance for interest rate surprises in these rates over the same 30-minute afternoon window in daily data since 1995 (i.e., the first principal component of the data). The focus on longer-term rates follows the observation of Gürkaynak, Sack, and Swanson (2005) and Campbell, Evans, Fisher, and Justiniano (2012) that much of the relevant monetary policy news in the US regards future interest rates, rather than the short-term policy rate; and it is an appropriate match to the model, which focuses on one "most important" dimension of the policy announcement.[16] The policy news shock is defined only up to scale, so I follow the methodology of Nakamura and Steinsson (2018) to normalize the variable to have a one-percentage-point, or 100 basis-point, impact on the one-year Treasury yield on the day of the announcement.

3.2 Beliefs About Real Variables

To measure "Market" forecasts about real variables, I use consensus forecasts from the Blue Chip Economic Indicators (BCEI) survey. The BCEI survey is administered each month to more than 50 economists "employed by some of America's largest and most respected manufacturers, banks, insurance companies, and brokerage firms" according to the publisher.[17] These forecasts are widespread in the macroeconomics and finance literatures for proxying expert private-sector opinion. I use forecasts of unemployment and real GDP growth as measures of forecasted real activity. In robustness checks, I study the reported tails of the forecast distribution (averages of the top and bottom 10 forecasts) to explore whether patterns are consistent throughout the forecast distribution; and I use aggregate (S&P 500) stock prices as a higher frequency, but less precise, proxy for aggregate market beliefs about fundamentals.

To measure the "Fed's" macro beliefs, I use the Board of Governors staff's Greenbook or Tealbook forecasts for all available months from 1995 to 2012. I take the first prediction made in the month when there are multiple. The imperfect alignment of Blue Chip and Greenbook

[15]See Appendix A of Nakamura and Steinsson (2018) for the details of data construction.

[16]In the rigid-price New Keynesian model used in Appendix B.1 to micro-found the main model, expected future interest rates would enter the studied period's Keynesian cross in an identical, linear fashion to the current period's interest rate. In this way, it is consistent within the model to combine current policy actions with "forward guidance." The same reasoning also justifies jointly studying patterns at and away from the zero-lower-bound.

[17]This quotation is taken from the landing page: https://lrus.wolterskluwer.com/store/blue-chip-publications/.

(Tealbook) forecast dates poses well-documented issues for comparing their unconditional accuracy (see, e.g., Romer and Romer, 2000; Bauer and Swanson, 2020).[18] In my dataset, 114 of the 152 Greenbook forecasts take place after the 10th of the month, the date on which the Blue Chip forecast data are generally released. Thus, when interpreting my subsequent analysis through the lens of the model, any within-month economic data that arrives between the Blue Chip survey and the FOMC meeting would be interpreted as the Fed's private signal. I further discuss this choice, and the robustness of my results to alternatives, in Section 4.4.

3.3 Public Signals

I focus on public signals which are forward-looking opinion aggregators, since these are easiest to interpret as leading indicators of demand shocks in the model. I consider four such indicators.

The first indicator is consumer sentiment about economic performance from the Michigan Survey of Consumers. The main sentiment measure considered in this paper is based on a question asking individuals whether they believe unemployment rates will go up, stay the same, or go down over the next twelve months.[19] The measure, which will be referred to as "Unemployment Sentiment" throughout the paper, is the balance score defined by Curtin (2019): the difference between the fraction who believe unemployment will go down (the positive response) versus the fraction who believe unemployment will go up (the negative response). I focus on sentiment for two related reasons. First, previous empirical work corroborates that Michigan-survey aggregates predict consumption and spending (Carroll, Fuhrer, and Wilcox, 1994; Barsky, Basu, and Lee, 2015; Curtin, 2019).[20] Second anecdotal evidence about policymaking, including the FOMC transcripts reviewed in Online Appendix E, suggests the Federal Reserve is highly attentive to consumer sentiment as a leading indicator of the business cycle. I focus on the specific unemployment-based measure, among the possible measures in the Michigan survey, because it has the clearest interpretation for assessing labor market conditions, as is relevant in the model. Tellingly, in the case study of Online Appendix E, it is also singled out by Fed economists as a particularly useful indicator.

The second indicator is consensus unemployment forecasts from the Blue Chip Economic Indicators survey. I treat the BCEI consensus forecast in the previous month as a public signal available in the current month, in the form of the BCEI newsletter which is typically released

[18] My timing convention differs from the one used by Bauer and Swanson (2020), who link a Blue Chip forecast with the Greenbook forecast that is closest in time. I revisit this issue in Section 4.4.

[19] Appendix D.1 prints the exact questions and answers that are used in the analysis. All aggregate measures are survey-weighted averages.

[20] Appendix Figure A1 shows, on the left scale, the unemployment sentiment index, from 1995 to the present with the US unemployment rate on the right scale. At a glance, this suggests some predictive power of the Michigan variable for observed labor market dynamics, as the former turns pessimistic before unemployment peaks in 1995, 2002, and 2009.

on the 10th.[21]

The third indicator is recent returns of the S&P 500, based on end-of-month closing prices. Previous research has suggested that recent stock returns are a major determinant of policy in the modern era (Cieslak and Vissing-Jorgensen, 2020).

The fourth indicator is investor sentiment about future stock performance from the weekly survey of the American Association of Individual Investors. Respondents may indicate whether they are "Bullish," "Bearish," or "Neutral" about stock market performance over the next six months. As a summary indicator, I take the difference in the fraction of Bullish and Bearish respondents, averaged over the month. Greenwood and Shleifer (2014) show that bullishness in survey indicators of stock market beliefs correlates with contemporaneous mutual fund inflows, validating their relevance for measuring individual investors' "expectations of returns."

4 Main Empirical Results

I now present my main empirical results, which test the model's predictions. I first establish that monetary surprises are predictable by public signals, in the direction of "bad news" correlating with surprise loosening. I next study the predictability of forecast errors, forecast revisions, and Fed-to-Market disagreements regarding employment and real GDP growth. I find evidence that the same "bad news" corresponds with the market's over-estimating real variables, slowly revising these forecasts, and being more optimistic than the Fed. I describe how these results, when interpreted via the model, identify market under-response to public signals as the quantitatively most important driver of imperfect expectations.

4.1 Predicting Monetary Surprises

Empirical Model. Following Proposition 1, I estimate the following regression models relating the monetary surprise Δ_t with lagged realizations of each public-signal predictor X_{t-1}:

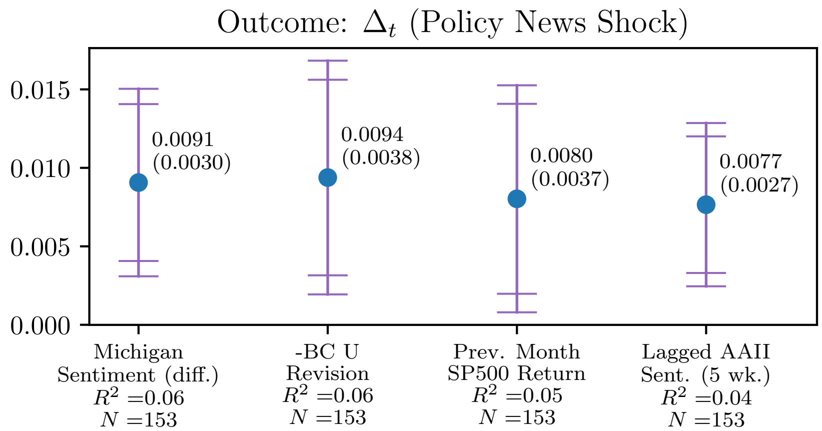
$$\Delta_t = \beta_X \cdot X_{t-1} + \varepsilon_t \tag{9}$$

The variables are normalized, in sample, to have zero mean and unit standard deviation.[22] This allows easy comparability of coefficient magnitudes across measures. The units of Δ_t are such that a unit increase corresponds to a one-percentage-point or 100-basis-point same-day increase in 1-year Treasury rates, so the units of β_X are of a one-standard-deviation outcome on percentage points for interest rates. The sample consists of 153 scheduled FOMC meetings.

[21] Ottaviani and Sørensen (2006) and Broer and Kohlhas (2021) emphasize that this consensus information is very salient to forecasters who read the newsletter.

[22] The de-meaning also removes the requirement for a constant in the regression.

Figure 2: Predicting Monetary Surprises



Notes: Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (9), and each estimate corresponds to a separate univariate regression. The units for the coefficients are implied percentage points of monetary surprise per one-standard-deviation outcome of the regressor.

A value of $\beta_X \neq 0$ implies statistical predictability of monetary surprises and hence a rejection of the asymmetric-information model as per Proposition 1. Positive or negative β_X would be consistent with the sufficient conditions in Proposition 1, and would reflect some combination of under- or over-confidence in the public signal and imperfect perception of the monetary rule.

The four main predictors studied, as reviewed above, are the following: (i) the lag difference (i.e., $t-2$ to $t-1$ change) in the Michigan unemployment sentiment variable; (ii) the negative average revision to unemployment forecasts (at horizons $q \in \{1, 2, 3\}$) in the previous month's Blue Chip forecast; (iii) the cumulative return over the previous month for the S&P500; (iv) and the average Bull-Bear spread in the AAII survey over the five weeks before the announcement.

Results. Figure 2 shows the estimates of β_X for each aforementioned predictor. The broad pattern is that lagged public information does predict monetary surprises. All estimates go in the direction of $\beta_X > 0$. The magnitudes are all in the corridor of 0.7 to 1 basis points of predictable surprise per one-standard-deviation outcome in the predictor. Through the lens of the model, these results require at least one of (i) market under-confidence in each public signal or (ii) market under-estimation of the monetary reaction to each public signal.

Sensitivity and Robustness. Appendix Figure A2 recreates the analysis of Figure 2 for three individual futures contracts which are components of the policy news surprise: the Fed Funds futures corresponding to the current meeting, the Fed Funds futures corresponding to the next scheduled meeting (i.e., 1-2 months in the future), and the 4-quarter-ahead Eurodollar future. The broad pattern, across each predictive variable, is stronger predictability (in terms of magnitudes and t-statistics) for the longer-horizon contracts.

I explore the sensitivity of the main result to sub-samples and individual events in three ways. First, Appendix Figure A3 shows the scatterplot of monetary surprises against the previous month's unemployment sentiment. At a glance, rate cuts during recessions provide the most influential observations. This is also consistent with anecdotal evidence regarding the origin of Market-Fed disagreements reviewed in Online Appendix E. Second, Appendix Figure A4 re-estimates the main specification (9) excluding data including and after 2008. These results are quantitatively similar to the main results, suggesting that the pattern is not driven by "unconventional" experiences at or near the Zero Lower Bound. Third, Appendix Figure A5 re-estimates (9) for unemployment sentiment from the Michigan survey using windows of observations within the last 48 months. The prediction is the strongest in the early and late 2000s, periods of recessions and rate cuts. But it is positive for almost the entire sample.

Three other extensions are summarized in the Online Appendix. First, Online Appendix D.2 explores the timing of predictability at the monthly frequency for the Michigan sentiment measure and the weekly frequency for the AAII survey. I find (i) that information older than one month prior can also predict monetary surprises but (ii) that the largest effects are concentrated at the one-month lag. Second, Online Appendix D.3 compares the predictive power of the public signals studied in this paper with those studied in other work. I find that consumer sentiment, in particular, measures an independent channel of predictability beyond what is found in non-farm employee statistics (Bauer and Swanson, 2020) and principal-component summaries of recent macro data (McCracken and Ng, 2016; Miranda-Agrippino and Ricco, 2021). Third, Online Appendix D.4 presents a pseudo-out-of-sample forecasting exercise for each of the four main predictors. Out-of-sample predictive power is much lower than in-sample predictive power, and feasible Sharpe Ratios are low (between 0.15 and 0.30). This builds confidence that the observed market failures are not extreme, while the pattern of predictability is robust.

4.2 Predicting Forecast Errors

Empirical Model. I now study the predictability of market forecast errors by the public signal, as guided by Proposition 2 of the model. In light of the previous section's evidence that multiple data series meet the criteria of public signals in the model, I construct a scalar summary $\hat{Z}_t$ in the following way. I run the following regression which resembles the predictive equation (9) but with a vector of predictors $\vec{X}_{t-1}$:

$$\Delta_t = \alpha + \vec{X}_{t-1}'\Gamma + \varepsilon_t \tag{10}$$

Based on the results of the previous section, I use the first two lags of the Michigan unemployment sentiment variable to take into account both level and growth rate effects. These variables are importantly pre-determined at the beginning of the month t and could plausibly be incorporated into any forecast made at time t; together, they explain 14.8% of the variation in the monetary surprise.[23] I take estimates of (10) over the entire sample and construct fitted values $\hat{Z}_{t-1} = \hat{\alpha} + \vec{X}'_{t-1}\hat{\Gamma}$, an empirical estimate of the model's public signal, and residuals $\hat{\Delta}_t^{\perp}$, an empirical estimate of the orthogonal component of the monetary surprise. Through the lens of the model, $\hat{Z}_{t-1}$ corresponds exactly to the terms spanned by Z in the monetary surprise expression (4) and $\hat{\Delta}_t^{\perp}$ exactly to their complement.

Next, as proxies for market beliefs about relevant outcomes, I take the consensus Blue Chip forecast in month t for negative unemployment (i.e., the employment rate) and real GDP growth. I use data on horizons 1, 2, and 3 quarter-ahead forecasts, as well as the average of all three. I use final-release macro data for the main analysis, and first-release macro data for robustness checks. The full sample consists of 288 months.

I estimate the following regression equation:

$$Y_{Q(t)+h} - \mathbb{E}_{B,t}[Y_{Q(t)+h}] = \alpha + \beta^{FCE} \cdot \hat{Z}_{t-1} + \varepsilon_t \tag{11}$$

where t indexes times in months; $Q(t)$ returns the quarter index of month t; and $Q(t)+h$ indexes the outcome h quarters ahead of the current quarter. I estimate this model for each choice of horizon h and forecasted variable Y. According to Proposition 2, and the previous evidence for *at least one* of under-confidence or under-estimation of monetary reaction to $\beta^{FCE} > 0$ is consistent with under-confidence in the public signal and $\beta^{FCE} < 0$ is consistent with under-estimation of the Fed's response to the public signal.

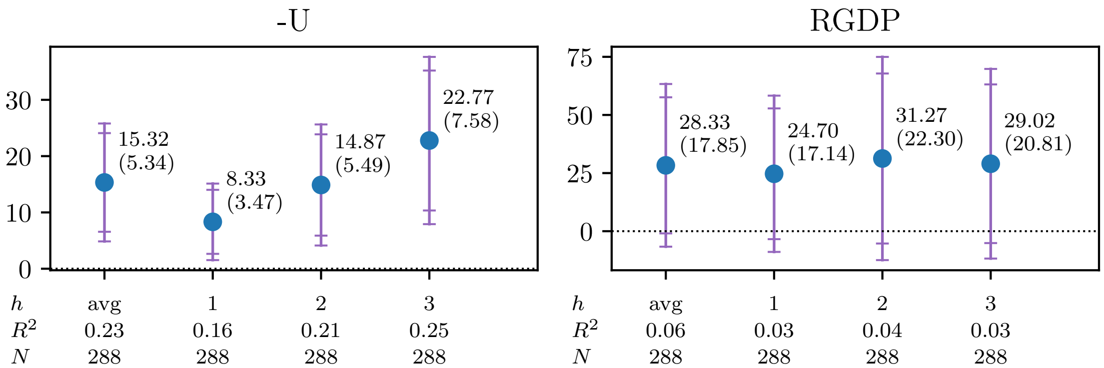
Results. Figure 3 plots the estimates of β^{FCE}, with 90% and 95% confidence interval bars, for each variable and horizon. There is consistent evidence across specifications of $\beta^{FCE} > 0$, favoring under-confidence in public signals as the correct model. This evidence is strongly statistically significant (p-value less than 5%) at all horizons for unemployment as the outcome, and weakly significant (across specifications, at the 10% or 15% level) for real GDP growth as the outcome. These findings are consistent in the model with under-confidence in the public signal. These findings are also consistent with findings in the literature of sluggish adjustment aggregate macroeconomic expectations (Coibion and Gorodnichenko, 2012, 2015).

For unemployment, in particular, the magnitudes are large given the variable's persistence

[23] To give a sense of the "sufficiency" of these two variables, the R^2 of the predictive equation increases only to 16.2% after adding the lagged average forecast revision about GDP growth from the Blue Chip survey, the lagged level of AAII sentiment, and the lagged growth rate of the S&P 500. Results for all subsequent regression specifications in Sections 4 and 5 are similar using the expanded set of predictor variables, but are not reported for brevity.

Figure 3: Market Forecast Errors and Public Signals

Outcome: $Y_{Q(t)+h} - \mathrm{E}_{B,t}[Y_{Q(t)+h}]$



Notes: Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (11), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per basis points of expected monetary surprise.

and predictability. The median absolute error (at the "average" horizon) over the sample period is 27 basis points, while a one-standard-deviation variation in $\hat{Z}$ (1.46 basis points) correlates according to the regression model with a 22.4 basis-point error. The predictive R^2 is 23%.

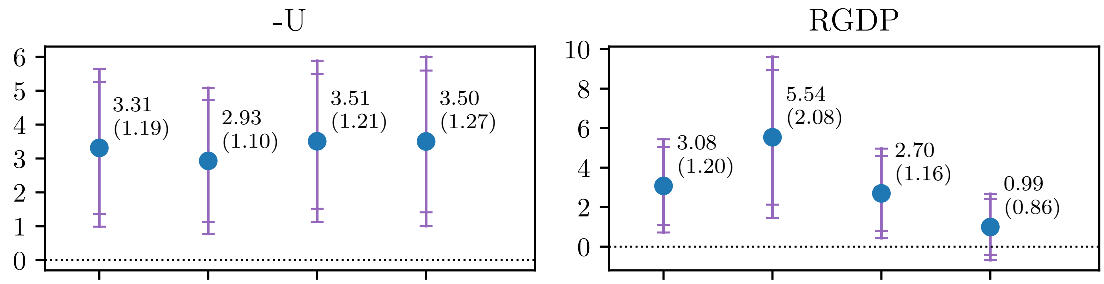
Sensitivity and Robustness. Appendix Figure A6 re-creates Figure 3 for two different outcomes, the growth rate of personal consumption expenditures (PCE) and predictions for the three-month Treasury rate. In both cases, I find a similar sign pattern. The result for PCE provides robustness for the main test of Proposition 2, while the result for Treasury rates corroborates the main findings of Section 4.1 without relying on market-derived expectations. Appendix Figure A7 re-creates Figure 3 using first-release macro data. It shows similar, but noisier, patterns to the main analysis.

Appendix Figure A8 re-creates Figure 3, but instead of using the consensus (mean) forecast uses the reported mean unemployment forecast among the 10 highest (i.e., most pessimistic) and lowest (i.e., most optimistic) in the Blue Chip survey. The consistent estimates of β^{FCE} reveal that the highlighted bias is present across the entire distribution.

Finally, Appendix Figure A9 shows rolling regressions using the last 48 months (4 years) of data separately for this quarter's unemployment rate and the (nine months prior) three-quarter ahead forecast from the Blue Chip survey on $\hat{Z}_{t-9-1}$, the public signal available just before that forecast. It shows that the market has consistently under-estimated the impact of $\hat{Z}$ on outcomes; the deviation between each group's forecast is most prominent in the two major recessions in sample; and that predictive power has diminished in the most recent five years.

Figure 4: Post-Announcement Forecast Revisions and Public Signals

Outcome: $\mathrm{E}_{B,t+2}[Y_{Q(t+1)+h}] - \mathrm{E}_{B,t+1}[Y_{Q(t+1)+h}]$



h	avg	1	2	3	h	avg	1	2	3
R^2	0.13	0.11	0.13	0.14	R^2	0.10	0.09	0.08	0.02
N	116	116	116	116	N	116	116	116	116

Notes: Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (12), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast revision per basis point of expected monetary surprise.

4.3 Predicting Post-Announcement Drift

Empirical Model. I now implement the second test described in Proposition 2, which concerns forecast updates after the monetary announcement. To implement it, I take the revision in the consensus Blue Chip forecast between the first Blue Chip Survey *after* a given monetary announcement and the *subsequent* month. The same sample restrictions outlined above result in 116 observations from 1995 to 2014. The empirical model is the following:

$$\mathbb{E}_{B,t+2}[Y_{Q(t+1)+h}] - \mathbb{E}_{B,t+1}[Y_{Q(t+1)+h}] = \alpha + \beta^{Dr} \cdot \hat{Z}_{t-1} + \varepsilon_t \tag{12}$$

where the left-hand-side variable is the forecast revision about an h-quarter ahead outcome between months $t+1$ and $t+2$. To re-iterate, the news encapsulated in $\hat{Z}_t$ was determined in month $t-1$; the monetary announcement occurs in month t, after month t's Blue Chip survey is completed; and the outcome variable concerns revisions made between $t+1$ and $t+2$. The logic for the sign cases of β^{Dr} is the same as outlined for β^{FCE} in the previous subsection. The prediction $\beta^{Dr} > 0$ is consistent with under-confidence in the public signal, and the previous finding of $\beta^{FCE} > 0$, while the prediction β^{Dr} is consistent with under-estimating the Fed's response to the public signal. Regression (12), apart from its justification in the theory, is also a potentially useful empirical complement to the earlier test of forecast errors because it does not require any data on final outcomes—it merely checks whether forecasters predictably change their minds more than a month after certain data is released.

Results. Figure 4 illustrates the coefficient estimates for each variable and horizon, with standard errors. There is consistent evidence of $\beta^{Dr} > 0$. This result demonstrates that forecasters continue to adjust up their forecasts after positive realizations of $\hat{Z}$ three months in the past. And, in the context of the model, it is consistent with forecasters slowly, upon arrival of new information, fixing their original mistake in forecasts.

Online Appendix D.5 outlines an additional model test based on the drift of stock prices after high realizations of $\hat{Z}_{t-1}$. It shows that stock prices tend to drift upward for the next month after surprise monetary tightening that is spanned by $\hat{Z}_{t-1}$, suggesting that good news (i.e., additional signals) is being revealed that corrects the public's original mis-assessment of the economy. This result resembles, at a shorter time horizon, the finding in Bernanke and Kuttner (2005) of delayed positive expected returns after surprise monetary tightening.

4.4 Fed Forecasts and Measured Disagreement

Empirical Model. To study potential bias in Fed forecasts, and its relationship with potential Market biases, I collect Greenbook forecasts for all months from 1995 to 2012. I take the first prediction made in the month when there are multiple, and sub-set to months with a scheduled FOMC meeting that occurred after the Blue Chip forecast (i.e., outside the first 10 days of the month). This results in a sample of 107 observations. I first re-create model (11), for forecast-error predictability, using Greenbook forecast errors as the outcome. Appendix Figure A10 shows the results. The point estimates for (negative) unemployment are significantly positive, but smaller than their counterparts in Figure 3; those for real GDP growth are mostly positive but statistically insignificant. By a logic essentially identical to the one underpinning Proposition 2, these results are indicative of $q^F > 0$ or Fed under-confidence in the relevant public signals.

To directly test whether the market's and Fed's errors are asymmetric on a common sample, or whether public signals drive market-to-Fed disagreement, I estimate the following model with the Greenbook-to-Blue-Chip forecast gap as the dependent variable:

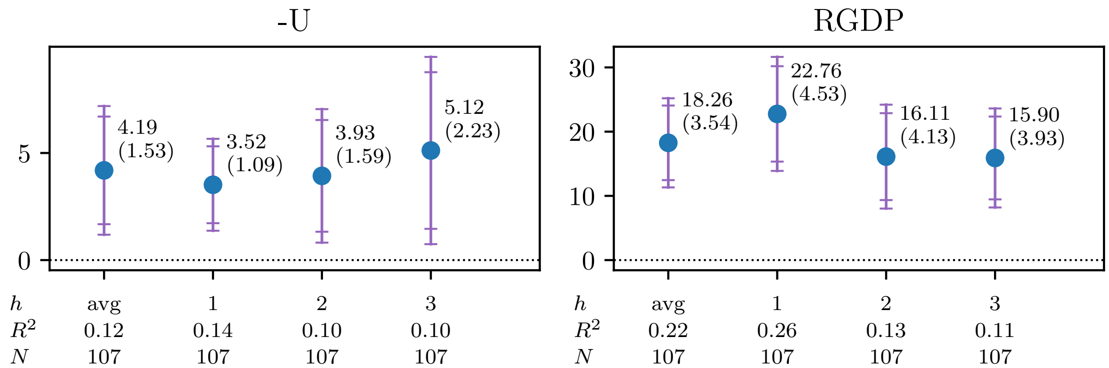
$$\mathbb{E}_{G,t}[Y_{Q(t)+h}] - \mathbb{E}_{B,t}[Y_{Q(t)+h}] = \alpha + \beta^{Di} \cdot \hat{Z}_{t-1} + \varepsilon_t \tag{13}$$

This regression operationalizes Equation 8 and the subsequent discussion in Section 2. This approach for understanding systematic differences in the shock-response of Fed and Market forecasts contrasts with that of Romer and Romer (2000) and Bauer and Swanson (2020), who test for asymmetry in Fed and Market forecasts by comparing their unconditional accuracy.

Results. Figure 5 confirms that $\beta^{Di} > 0$, with high statistical significance, for both variables and all prediction horizons. Moreover, the constructed public signal proxy, by itself, explains

Figure 5: Forecast Disagreements and Public Signals

Outcome: $\mathrm{E}_{G,t}[Y_{Q(t)+h}] - \mathrm{E}_{B,t}[Y_{Q(t)+h}]$



Notes: Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (13), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast disagreement per basis point of expected monetary surprise.

10% and 26% of all variation in disagreement between the Blue Chip forecasters and the Fed about unemployment or growth, depending on specification. Thus, Fed forecasts are more responsive than Market forecasts to the news contained in the studied public signals, and that this additional responsiveness explains a significant fraction of the disagreement.

Robustness and Sensitivity. My preferred timing for the Greenbook forecast relative to the Blue Chip forecast generates, in the mapping to the model, a consistent convention for the Fed's policy choice to occur "just after" the private sector forecast. In this mapping to the model, the Fed's private signal F can encompass pieces of *public* information revealed in the interim (e.g., as emphasized by Bauer and Swanson, 2020). But in a reduced-form test, this timing convention may overstate the Fed's relative responsiveness to data by giving the Fed more time to respond to *new* data correlated with past data, to which the Fed may have initially under-reacted.[24] To alleviate this concern, I re-estimate Equation 13 after matching Blue Chip forecasts with the *closest* Greenbook forecast within 30 days, as in Bauer and Swanson (2020). This procedure results in 143 observations, 60 of which have the Greenbook survey precede the Blue Chip survey. Appendix Figure A11, in comparison to Figure 5, verifies that coefficient

[24] To see this in the model, note from Equation 8 and the accompanying discussion that there is zero predictable disagreement about fundamentals if $q = q^F$. But the condition for the Market and Fed to have the same perception of the public signal's precision is $q = \frac{\tau_\theta + \tau_Z + \tau_F}{\tau_\theta + \tau_Z} q^F$. Thus, if $q^F > 0$ or the Fed under-reacts to Z, then $q > q^F$ in this equal-confidence scenario. In this case, the realization of Z predicts the Fed's response to the new information in F (e.g., statistical releases in the interim between the Blue Chip survey and FOMC meeting), pushing toward a positive estimate of β^{Di} in Equation 13.

estimates and R^2 values are very similar under this alternative timing convention. This finding offers direct evidence that forecast timing alone cannot explain the patterns of predictable disagreement. More substantially, it suggests that predictable Fed to Greenbook disagreements are not driven by the revelation of new data before the FOMC meeting.

Appendix Figure A12 re-estimates Equation 13 using Blue Chip forecasts of three-month Treasury rates and Greenbook point forecasts from the "Financial Assumptions" for the Greenbook forecast. There is strong evidence (p-value less than 5%) of $\beta^{di} > 0$ at the four-quarter horizon, and weaker evidence at the two- and three-quarter horizon. This is consistent with the earlier findings that good news in public signals predicted news about monetary tightening in futures markets, especially at longer horizons.

5 Additional Results: Revisiting the Information Effect

The findings from the last section, interpreted via the model, suggested that a necessary mechanism to explain disagreements between the Market and Fed was the former's slower uptake of public information. In this section, I show explicitly how to reconcile my results with findings in the literature of "information effects" of monetary policy, or signaling about fundamentals via policy actions (Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018). I show how heterogeneous confidence in public information biases the literature's empirical estimates of "information effects," and how a corrected estimator that controls directly for confounding public news suggests small effects.

5.1 In the Theory: Identifying and Removing Bias

At time period $t = 1$ in the model, the only piece of information revealed is the interest rate r. The market's forecast revision about employment at $t = 1$ thus isolates the effect of monetary signaling. I define the covariance of the monetary surprise with the update of beliefs about Y, normalized by the variance of the monetary surprise, as the "true" information effect:

Definition 1. *The information effect is*

$$i := \frac{Cov[\Delta, \mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y]]}{Var[\Delta]} \tag{14}$$

The moment which Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) take as informative about the aforementioned phenomenon is the covariance of monetary surprises Δ with forecast revisions about employment (or real GDP) *bracketing* the announcement. This choice is due to convenience, as sufficiently precise forecasts are not available in high frequencies around monetary announcements, and may be nested in the model as the forecast revision from $t = 0$ to $t = 2$. The following Corollary emphasizes that this covariance does correspond with i *only* in the noisy rational expectations benchmark, but otherwise includes a bias term which can be signed as a function of the deviation from rationality:

Corollary 1 (Bias in the Information Effect)**.** *Let*

$$i^F := \frac{Cov[\Delta, \mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y]]}{Var[\Delta]} \tag{15}$$

be an estimator of the information effect defined in (14)*. This estimator can be written as* $i^F = i + B$ *where*

1. *If* $w = q = 0$*, then* $B = 0$*.*
2. *If* $w \leq 0$*,* $q \geq 0$*, and* $Cov[\Delta, Z] > 0$*, then* $B \geq 0$*.*
3. *If* $w \geq 0$*,* $q \leq 0$*, and* $Cov[\Delta, Z] > 0$*, then* $B \leq 0$*.*

The bias, as illustrated in the proof in Appendix A, is directly proportional to the covariance between Δ and the forecast revision from period 1 to period 2. In the rational model, this covariance is zero because the information in Δ is fully and efficiently incorporated into beliefs at $t = 1$. This recovers the informal argument that “market efficiency” justifies the empirical strategy in Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018). But the logic breaks down as soon as there is a deviation from all agents’ rationally incorporating the information in Δ and, in particular, Z. Claims 2 and 3 follow directly from the related arguments in Proposition 2 about post-announcement forecast revisions, combined with a fixed sign for $\text{Cov}[\Delta, Z]$ which is consistent with the empirical findings in Section 4.1.

A more heuristic interpretation of Claims 2 and 3 is the following. Under the conditions for Claim 2, there is “belief momentum” between periods 2 and 3: markets sluggishly fix their errors of under-reacting to the public signal and/or the Fed’s signal as revealed through the monetary announcement. Under the conditions for Claim 3, there is “belief mean-reversion” as markets sluggishly fix their errors of over-reacting to the same pieces of information.

A fortunate implication of the model, however, is that the bias term is entirely spanned by Z and therefore may be purged by directly controlling for the effect of Z on forecast revisions. The validity of this approach is formalized below and proved in Appendix A.

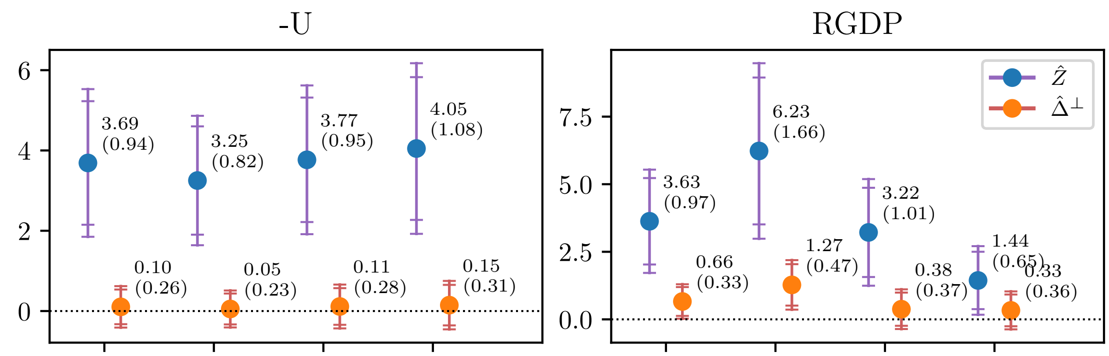
Corollary 2 (Corrected Information Effect Regression)**.** *The monetary shock* Δ *can be written as* $\Delta = \Delta^{\perp} + (q\delta_F^F + w)Z$*, where* $Cov[\Delta^{\perp}, Z] = 0$*. Moreover, the population estimator*

$$i^{\perp} := \frac{Cov[\Delta^{\perp}, \mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y]]}{Var[\Delta^{\perp}]} \tag{16}$$

corresponds with the true information effect i*.*

Figure 6: Cross-Meeting Forecast Revisions and Monetary Surprises

Outcome: $\mathrm{E}_{B,t+1}[Y_{Q(t)+h}] - \mathrm{E}_{B,t}[Y_{Q(t)+h}]$



h	avg	1	2	3
R^2	0.22	0.19	0.21	0.22
N	116	116	116	116
t^D	3.88	3.74	4.00	3.77

h	avg	1	2	3
R^2	0.14	0.18	0.09	0.05
N	116	116	116	116
t^D	2.91	3.00	2.67	1.69

Notes: Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (17) , and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast revision per basis point of (expected or unexpected) monetary surprise. The t^D row reports the t-statistic for the difference of coefficients.

5.2 In the Data: An Attenuated Information Effect

Empirical Model. I now operationalize these tests in the data. The outcome variable of interest is forecast revisions from t to $t+1$. The sample is restricted to months with scheduled FOMC meetings after the 10th, to ensure that month t's FOMC meeting occurs after month t's Blue Chip survey. Thus these forecast revisions bracket the FOMC meeting. The timing is identical to that in Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018). The estimating equation is the following:

$$\mathbb{E}_{B,t+1}[Y_{Q(t)+h}] - \mathbb{E}_{B,t}[Y_{Q(t)+h}] = \alpha + \beta^Z \cdot \hat{Z}_{t-1} + \beta^{\Delta} \cdot \hat{\Delta}_t^{\perp} + \varepsilon_t \tag{17}$$

In the language of the theory, the term $\beta^Z \cdot \hat{Z}_{t-1}$ spans the bias B. The cases $\beta^Z > 0$ and $\beta^Z < 0$ respectively span cases 2 and 3 of Corollary 1. And the coefficient β^{Δ} is an unbiased estimate of i as per Corollary 2.

Results. Figure 6 shows the estimated coefficients. First, there is robust evidence of $\beta^Z > 0$, or the predicted component of the surprise correlating with future revisions. This points to significant "belief momentum" around announcements. Second, there is limited statistical evidence across variables and horizons of $\beta^{\Delta} > 0$, although point estimates are uniformly positive. In particular, at the 5% significance level, estimates with unemployment forecasts as the outcome are uniformly insignificant and estimates with GDP forecasts as the outcome are significantly different from zero only at the shortest forecast horizon. This finding underscores the extent to which the large, positive reduced-form information effect in the literature reflects a delayed response to pre-determined public signals.

That said, the near-zero estimates of β^{Δ} can reject hypotheses of quantitatively large negative effects. Positive but small effects are consistent with the model, which predicts a (potentially small) information effect from the noise component of the Fed's expectations.[25] I return to this point in the Quantification.

6 Quantification

In this section, I fit the model of Section 2 to the empirical findings. This allows more precise quantification of the relative importance of each of the three main mechanisms—asymmetric information, asymmetric beliefs about the policy rule, and asymmetric response to public information—via counterfactual scenarios that switch each mechanism on and off. A key finding, formalized via these counterfactual experiments, is that heterogeneous priors drive a larger fraction of fundamental variance in beliefs than information effects.

6.1 Methods and Calibrated Parameters

Mapping the theory to the data requires committing to a specific timing and definition of model variables. I proceed in the following way. A given month's Blue Chip survey, which is administered in the first week of the month, corresponds to $t = 0$ in the model; that month's subsequent monetary announcement is $t = 1$; and the beginning of the next month corresponds to $t = 2$.[26] The model public signal Z is the constructed signal $\hat{Z}$ from the empirical analysis, based on lagged consumer sentiment about the labor market from the Michigan Survey of Consumers (Section 4.2). The model interest rate r is the linear combination of contemporaneous and future Federal Funds Rates and Eurodollar rates that corresponds to the policy news shock (Nakamura and Steinsson, 2018) forecast. And the outcome Y is the average negative unemployment rate over the subsequent three quarters.

The model has seven parameters, listed in Table 1.[27] I match seven moments. Six have been described and reported in Sections 4 and 5: the R^2 of predicting monetary surprises with

[25] More specifically, the population estimate of β^{Δ} is $i^{\perp} = a - 1$ as derived in Appendix C.

[26] This allows me to map the empirical results of Sections 4.2 and 5.2 directly to the model, but does not use the results of Section 4.3 which correspond to a different time horizon.

[27] The remaining free parameter, the precision or variance of the fundamental, is set to one. This is a normalization with no bearing on the calibration, since I do not focus on matching the variance of business-cycle fluctuations in interest rates or employment.

Table 1: Method of Moments Calibration

	Matched Moment	Reference	Value	Parameter	Value
1	R^2 from predicting surprises	Section 4.2, in text	0.15	q	0.121
2	β^{FCE} for BC	Section 4.2, Figure 3	15.32	q^F	0.089
3	R^2 for predicting FCE (BC)	Section 4.2, Figure 3	0.23	w	0.007
4	β^{FCE} for GB	Section 4.4, Figure A10	12.06	τ_Z	20.99
5	β^Z, for BC Revisions	Section 5.2, Figure 6	3.69	τ_F	0.194
6	β^Δ for BC Revisions	Section 5.2, Figure 6	0.10	τ_S	6.849
7	β^Y from (18)	Section 6.1, in text	22.69	a	1.100

Notes: The seven matched moments are fit exactly by the model, given the indicated parameter values.

$\hat{Z}_t$; the coefficient and R^2 of regressing $\hat{Z}_t$ on market forecast errors; the coefficient of regressing the same on Greenbook forecast errors; and the coefficients of regressing $(\hat{Z}_t, \hat{\Delta}_t^\perp)$ on forecast revisions. The last is the regression coefficient of $\hat{Z}_{t-1}$ on Y, or β^Y in the model

$$Y_{Q(t)+h} = \alpha + \beta^Y \cdot \hat{Z}_{t-1} + \varepsilon_t \tag{18}$$

This moment isolates the relative effect of $\hat{Z}$ on both forecasts and outcomes.

To fit the model, I minimize the sum of squared deviations of the model prediction from each moment. The targeted moments and estimated parameters are summarized in Table 1. Appendix C provides exact formulae for each moment in terms of model parameters.

The moment-matching exercise clarifies three points about the relative strength of each mechanism for disagreement, which go beyond the "sign-test" interpretation of findings in Sections 4 and 5. First, $0 < w << \ll q$: the data require some Market under-estimation of public data in the monetary rule, and much more Market under-reaction to the fundamental information in these data. In the context of Figure 1, which outlined the cases for identifying (q, w) in a simplified environment from "regression coefficients" of public signals on employment and interest rate forecast errors, the empirically relevant case is the top-right (green) quadrant.

Second, $0 < q^F < q$: the Fed under-reacts to the fundamental content of public data, but to a lesser extent than the market. This is consistent with findings in the literature of forecast error inertia for both professional and central-bank forecasts in response to shocks (Coibion and Gorodnichenko, 2012), and it also suggests that shocks induce systematic disagreements between the groups. Moreover, the gap between under-reactions is larger than the mis-specification of the monetary rule, or $q - q^F > w$. Loosely speaking, the Market "knows" that the Fed uses the signal Z more than they do, but misses $100 \cdot \frac{w}{q-q^F} = 22\%$ of this effect.

Third, $(\tau_Z, \tau_S) \gg \tau_F$, or the non-private sources of information in the economy are much more precise than the private information. The precision weight on the Fed's signal in the monetary rule is $\tau_F/(\tau_\theta + \tau_F + \tau_Z) = 0.01$, which is itself about 98 times smaller than the Fed's weight on the public signal. This foreshadows the limited role played by asymmetric information in the model, which is formalized in counterfactual experiments below.

A final relevant property of the calibration is the relative precision of Market and Fed forecasts. In the model, Market forecast errors of employment have 9.6% higher variance, or 4.7% more root-mean-squared-error (RMSE), than Fed forecasts. Over the studied sample period, I find in the data that Blue Chip forecasts of average unemployment over the next three quarters have 20.1% higher variance or 9.6% higher RMSE, using the timing convention for matching Board of Governors and private-sector forecasts introduced in Section 3.2.[28] In counterfactual experiments, I will be able to decompose this (modest) difference in forecasting quality into margins explained by the availability of additional information for the Fed, more effective use of public information, and knowledge of the policy rule.

6.2 Decomposing the Margins for Disagreement

I now use the model to explore the contribution of each model mechanism toward observed patterns of beliefs. In each counterfactual, I focus on the changes, relative to the baseline calibration, for six statistics summarizing the economy's response to shocks and the quality of forecasts. The first two are the sensitivity of the market's beliefs to fundamentals at $t = 0$ and $t = 2$, respectively. In Online Appendix B.1.3, I show how Market beliefs about Y correspond to a notion of a stock price. In this sense, changes in the sensitivity of $\mathbb{E}_{M,t}[Y]$ to shocks can be interpreted as changes in the sensitivity of stock prices to shocks holding fixed risk premia. The third studied statistic is the sensitivity of interest rates to fundamentals, which depends in turn on the Fed's confidence in assessing aggregate demand. The fourth and fifth are the variance of the Market's and Fed's forecast errors about output at $t = 0$. And the sixth and last is their ratio, which measures the Fed's forecasting "advantage."

I first study the effect of removing the Market's mis-specification of the monetary rule, or setting $w = 0$ and fully allowing the Market and Fed to "agree to disagree" about fundamentals. The results of this experiment are summarized in Row 1 of Table 2. The so-called "Agree to disagree" scenario leads to modest reductions in the sensitivity of output forecasts to fundamentals, because it removes the market's under-estimation of monetary response at $t = 0$ and the market's tendency to over-extrapolate at $t = 2$. The change slightly increases forecast errors about output (by 2.7%), because the Market's perception of policy under-reaction to shocks compensates for its own error in under-estimating the fundamental impact of those shocks.

Next, I study the effect of additionally shifting the Market's response to public data to

[28] These results are also consistent with those reported in Bauer and Swanson (2020) under a comparable timing convention which uses Fed forecasts that occur after the Blue Chip survey within the same month.

Table 2: Counterfactual Predictions

	Scenario Name	Parameter Case	Percent Change from Baseline					
			$\frac{d\mathbb{E}_{M,0}[Y]}{d\theta}$	$\frac{d\mathbb{E}_{M,2}[Y]}{d\theta}$	$\frac{dr}{d\theta}$	$\mathbb{V}[\text{FCE}^Y_{M,0}]$	$\mathbb{V}[\text{FCE}^Y_{F,0}]$	$\frac{\mathbb{V}[\text{FCE}^Y_{M,0}]}{\mathbb{V}[\text{FCE}^Y_{F,0}]}$
1	Agree to disagree	$w = 0$	-11.8	-5.9	0.0	2.7	0.0	2.7
2	Fed's viewpoint	$q = q^F = \hat{q}^F$, $w = 0$	45.5	20.0	0.0	-9.0	0.0	-9.0
3	Market's viewpoint	$q = q^F = \hat{q}$, $w = 0$	40.7	25.1	-3.6	2.7	13.0	-9.1
4	No errors	$q = q^F = w = 0$	59.1	5.3	10.3	-23.0	-15.6	-8.7
5	No Fed Info	$\tau_F \downarrow 0$	-1.8	-0.5	0.0	1.1	0.7	0.3

Notes: The units are percentage differences from the baseline calibration. In the "Parameter Case" column, hats denote the calibrated value of each parameter.

coincide with the Fed's (Row 2). This "Fed's viewpoint" scenario leaves the monetary rule unchanged, but significantly increases the Market's sensitivity to fundamentals both before and after the monetary announcement, by 45.5% and 20.0% respectively.[29] It moreover erodes about half of the difference in relative forecast error variance between the two parties. This shows how heterogeneous responsiveness to public data drives differences in forecast quality.

I also study the complementary "Market's viewpoint" experiment of giving the Fed the bias of the market (Row 3). This worsens the Fed's forecast of output and lessens its policy responsiveness to shocks. But it has very similar impacts to the previous experiment on the sensitivity of market beliefs to shocks. This underscores the importance of heterogeneous priors or responsiveness to public data, above and beyond the level of that responsiveness, as a determinant of business cycle beliefs. In particular, there are close to symmetric effects on the economy at $t = 2$ of having the Market respond *more* to news in its beliefs of fundamentals, or having the Fed respond *less* to news via its interest rate choice.

To benchmark fully the effect of all biases in combination, I next study the effect of setting $q = q^F = w = 0$ and reducing the model to its Bayesian, asymmetric-information core (Row 4). Market and Fed output forecasts are considerably better, with 23.0% and 15.6% lower variance respectively. The monetary rule is more responsive to the demand shock. The movement of market beliefs is more "front-loaded" in response to the fully-processed news at $t = 0$, instead of requiring a substantial update at $t = 2$.

In a final, "No Fed Info" experiment, I make internal information infinitely imprecise (Row 5).[30] In particular, this scenario implies that the Fed neither leans on the internal signal for

[29]This method for equating the biases of the Market and Fed would remove predictable disagreement in forecasts about fundamentals at $t = 0$. An alternative method would equate the two parties' perceived precision of the public signal, or set $q = \hat{q}^F \cdot \frac{\tau_\theta + \tau_Z + \tau_F}{\tau_\theta + \tau_Z}$. Evaluated with the calibrated parameters, this would set $q = 1.009 \cdot \hat{q}^F$ and lead to almost identical counterfactual predictions—for example, changes in belief responsiveness of 45.5% and 19.3% at $t = 0$ and $t = 2$, respectively.

[30]Formally, as long as $w \neq 0$, the case with $\tau_F = 0$ is not well defined as the Market cannot rationalize any

its decisions nor reveals a useful signal via its actions. This alteration has a very small effect on both the policy rule and the Market's beliefs about fundamentals. In percentage terms, the differences from the baseline in the two models that eliminate disagreement (rows 3 and 4) have respectively 37 and 47 times larger of an effect on the sensitivity of $t = 2$ beliefs, which as noted previously correspond to a notion of the model's stock price, to fundamentals. In these units, disagreement is considerably more influential for the observed pattern of beliefs than any signaling effects which are necessarily removed in the "No Fed Info" scenario.[31]

These numbers suggest very small *information effects*, or causal effects of Fed persuasion on public beliefs. The difference in conclusions, relative to studies by Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018), lies in this paper's consideration of a larger set of models beyond the pure asymmetric information model, and use of additional moments for identification in the larger class of models. This allows my analysis, in particular, to pinpoint exactly the extent of asymmetric information required to rationalize the data; this asymmetry is by contrast essentially a free parameter in the main analysis of Nakamura and Steinsson (2018).[32] The low estimated asymmetric information, despite sizable observed belief differences, reflects the extent to which a heterogeneous-priors model better fits the data.

7 Conclusion

This paper studies the causes and consequences of disagreement about monetary policy. I first develop a model that accommodates market and policymaker disagreement due to asymmetric information, asymmetric knowledge of the monetary rule, and asymmetric confidence in public signals. I derive simple "sign tests" under which each mechanism is necessary to explain measurable patterns of market and central-bank beliefs. I next turn to US data since 1995 to test the model's predictions. I find that upticks in opinion-aggregating public signals predict surprise monetary tightening, private-sector pessimism about real variables, delayed correction of private-sector forecasts, and relative Fed optimism about real variables. Interpreted via the model, the empirical findings imply a significant role for mis-specifying the value of public information, a small role for mis-specifying the monetary response to that information, and an almost negligible role for asymmetric information. After calibrating the model to match the

forecast error regarding policy. As such, I consider a limit as τ_F gets arbitrarily small; but the core conclusion would be the same comparing a model with $w = 0$ and τ_F with the counterfactual model with $w = 0$.

[31] Because of the changing variance of output and the interaction of asymmetric information with expectational biases, removing the Fed's signal can make the Fed's forecasting edge over markets slightly worse.

[32] The authors, in their main model and counterfactual exercise, assume that the private sector forms its beliefs about the natural rate of interest on the basis of monetary announcements. Absent announcements, the private sector assumes the natural rate is a random walk. Regarding this counterfactual behavior of beliefs, the authors write: "One could consider other counterfactuals. We don't have any data to precisely pin down the counterfactual."

data, I validate that disagreement between markets and the Federal Reserve about the precision of public information has a large effect on market beliefs, relative to a counterfactual world in which both parties treated information symmetrically. I find that central bank signaling about fundamentals, by contrast, has a comparatively small effect on market beliefs. Taken together, these findings reconcile the idea that central banks' power over beliefs is mostly restricted to the policy path with the ubiquity of disagreement and uncertainty about fundamentals.

I finish by discussing additional analysis contained within the Online Appendix.

Case Study Analysis: Fed Policy in 2001. In Online Appendix E, I review anecdotal evidence from FOMC transcripts to illustrate market-to-Fed disagreement in practice. I focus on surprise rate cuts in 2001, which appeared as influential observations in my empirical analysis (see Section 4.1). According to the transcripts of the January and May 2001 meetings, Fed economists were aware that they were considerably more pessimistic than markets about the medium-term outlook. They identified a more serious reaction to measured consumer and firm pessimism as a mechanism for the disagreement. These observations are consistent with this paper's more systematic empirical findings.

SVAR Analysis: What Shocks Drive Predictable Disagreement? In Online Appendix F, I use a structural vector autoregression model to study how disagreement evolves over the business cycle. For identification, the model assumes that a composite "disagreement shock" spans variation in monetary surprises that is predictable by lagged macro data, while the residual is a true "monetary tremble" corresponding to the shock in the Fed's private information in the model. I find that "monetary trembles" explain about 1% of the total variation in unemployment and nominal interest rates, while "disagreement shocks" explain respectively 23% and 40%. Thus, trembles are essentially irrelevant for explaining real activity, while systematic disagreement driven by heterogeneous models is associated with one of the largest shocks driving the business cycle. My results also provide an alternative explanation for previous studies' findings that plausibly identified "information effects" propagate through the economy like demand shocks (Miranda-Agrippino and Ricco, 2021; Jarociński and Karadi, 2020; Acosta, 2021). My results are consistent with an interpretation that these "information-effect" shocks are demand shocks with non-monetary causes, about which markets and central banks systematically disagree. That said, my analysis suggests that even this business-cycle-disagreement component of monetary surprises may have an approximately correct interpretation as a pure shock to interest rate expectations in the very short run (e.g., when studying announcement-day effects on asset prices). My results suggested very little monetary signaling that could drive high-frequency revisions in market forecasts of fundamentals. The model instead implied slow convergence toward market-and-Fed consensus about real activity, which takes on the order of months and may contribute only negligible drift to high-frequency financial outcomes.

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A Omitted Proofs

Proposition 1

I first derive (4), which expresses the monetary surprise in terms of primitive shocks. The market's average expectation of monetary policy is

$$P = \mathbb{E}_{M,0}[r] = (\delta_F^Z - q^F + w)Z + \delta_F^F(\mathbb{E}_{M,0}[\theta])$$

which, after substituting in average expectations from (2), is

$$P = \mathbb{E}_{M,0}[r] = (\delta_F^Z - q^F + w)Z + \delta_F^F(\delta_Z^M - q)Z \tag{19}$$

These beliefs apply the conjecture that the market price P reveals no independent information about the state θ; this is readily verified by noting that P must be linear in Z, provided that beliefs are linear in P and Z.

Now observe that the interest rate is given by the Fed's belief (1). The difference of (19) from this is

$$\Delta = \delta_F^F(F - \delta_Z^M Z) + \delta_F^F qZ + wZ \tag{20}$$

which re-arranges to (4) upon definition of $\mathbb{E}^R_{M,0}[\theta] := \delta_Z^M Z$.

I next calculate the covariance between Z and the rational forecast error of θ. This simplifies to

$$\mathbb{E}\left[Z\left(\theta - \mathbb{E}^R_{M,0}[\theta]\right)\right] = \mathbb{E}\left[\mathbb{E}^R_{0,M}\left[Z\left(\theta - \mathbb{E}^R_{M,0}[\theta]\right)\right]\right] = \mathbb{E}[0] = 0 \tag{21}$$

where the first equality applies the law of iterated expectations and the second simplifies.

Consider now $\mathrm{Cov}[\Delta, Z]$. Using expression (4) for Δ, this can be written as the following sum of terms

$$\mathrm{Cov}[\Delta, Z] = \mathrm{Cov}[\delta_F^F \varepsilon_F, Z] + \delta_F^F \mathrm{Cov}[\theta - \mathbb{E}^R_{M,0}[\theta], Z] + \left(\delta_F^F + w\right)\mathrm{Cov}[Z, Z] \tag{22}$$

The first term is 0 by definition of the price and monetary observation shocks; the second is 0 by the aforementioned argument. Hence

$$\mathrm{Cov}[\Delta, Z] = \left(\delta_F^F q + w\right)\mathrm{Var}[Z] \tag{23}$$

which is (i) 0 if $q = w = 0$; (ii) positive if $q > 0$ and $q > 0$; (iii) negative if $q < 0$ and $q < 0$.

Proposition 2

I split the proof for the claims about forecast errors and the claims about forecast revisions.

Forecast Errors. First, consider $t = 0$. The market's forecast error about r is Δ. Its forecast error about θ is

$$\theta - \mathbb{E}_{M,0}[\theta] = (\theta - \mathbb{E}^R_{M,0}[\theta]) + qZ \tag{24}$$

where $\mathbb{E}^R_{M,0}[\theta]$ is the previously defined "rational average" forecast and $\tau_0 = \tau_\theta + \tau_Z$ is the initial (subjective) posterior precision. The forecast error for Y is therefore

$$\begin{aligned} Y - \mathbb{E}_{M,0}[Y] &= a(\theta - \mathbb{E}_{M,0}[\theta]) - (r - \mathbb{E}_{M,0}[r]) \\ &= (a - \delta_F^F)(\theta - \mathbb{E}_{M,0}[\theta]) + (a - \delta_F^F)qZ - wZ \end{aligned} \tag{25}$$

The covariance with Z is

$$\begin{aligned} \mathrm{Cov}[Y - \mathbb{E}_{M,0}[Y] &= (a - \delta_F^F)\,\mathrm{Cov}[(\theta - \mathbb{E}_{M,0}[\theta]), Z] + \left((a - \delta_F^F)q - w\right)\mathrm{Var}[Z] \\ &= \left((a - \delta_F^F)q - w\right)\mathrm{Var}[Z] \end{aligned} \tag{26}$$

where the simplification uses the point, established in the proof of Proposition 1, that the rational forecast error has no covariance with Z. The desired properties follow given the observation that $(a - \delta_F^F) > 0$, given $a \geq 1$ (assumed) and $\delta_F^F < 1$ (directly observable from the expression $\delta_F^F = \tau_F/(\tau_\theta + \tau_Z + \tau_F)$ in which all constants are positive).

Next, consider $t = 1$ and $t = 2$. Since all agents know that the monetary announcement r is linear in Z and F, and all agents have observed the former, observing the monetary announcement is treated by each agent as observing the signal

$$\hat{F} = \frac{1}{\delta_F^F}(r - (\delta_Z^F - q^F - w)Z) = F + \frac{w}{\delta_F^F}Z \tag{27}$$

which is "correctly" equal to F if the market participants know the monetary rule, over-weights Z if the market under-estimates the weight on Z in the rule, and under-weights Z if the market over-estimates the weight on Z in the rule.

The forecast of θ in each period $t \in \{1, 2\}$ can be constructed using the standard Bayesian formula. The forecast error for θ is

$$\theta - \mathbb{E}_{M,t}[\theta] = (\theta - \mathbb{E}_{M,t}^R[\theta]) + \frac{\tau_0}{\tau_t}qZ - \frac{\delta_{F,t}^M}{\delta_F^F}wZ \tag{28}$$

with the following definitions. $\mathbb{E}_{M,t}^R[\theta]$ is the "rational" average expectation of θ, defined by

$$\begin{aligned} \mathbb{E}_{M,1}^R[\theta] &= \frac{\tau_Z}{\tau_\theta + \tau_Z + \tau_F}Z + \delta_{F,1}^M F \\ \mathbb{E}_{M,2}^R[\theta] &= \left(1 - \frac{\tau_S}{\tau_1 + \tau_S}\right)\mathbb{E}_{M,1}^R[\theta] + \frac{\tau_S}{\tau_1 + \tau_S}S \end{aligned} \tag{29}$$

and the coefficients $(\delta_{F,t}^M)_{t\in\{1,2\}}$ are

$$\begin{aligned} \delta_{F,1}^M &= \frac{\tau_F}{\tau_\theta + \tau_Z + \tau_F} = \delta_F^F \\ \delta_{F,2}^M &= \frac{\tau_F}{\tau_\theta + \tau_Z + \tau_F + \tau_S} \end{aligned} \tag{30}$$

Observe that the forecast error for Y can be written as

$$Y - \mathbb{E}_{M,t}[Y] = a(\theta - \mathbb{E}_{M,t}[\theta]) \tag{31}$$

as r is now known. Plugging in (28), taking the covariance with Z, and noting the zero covariance with the average rational expectation gives

$$
\begin{aligned}
\mathrm{Cov}[Y - \mathbb{E}_{M,t}[Y], Z] &= a\mathrm{Cov}[(\theta - \mathbb{E}^R_{M,t}[\theta]), Z] + a\left(\frac{\tau_0}{\tau_t}q - \frac{\delta^M_{F,t}}{\delta^F_F}w\right)\mathrm{Var}[Z] \\
&= a\left(\frac{\tau_0}{\tau_t}q - \frac{\delta^M_{F,t}}{\delta^F_F}w\right)\mathrm{Var}[Z]
\end{aligned}
\tag{32}
$$

The desired properties are immediate from the second line and the observations that $a > 0$, $\tau_0/\tau_1 > 0$, and $\delta_{F,t} > 0$ for all t.

Forecast Revisions. Observe from (28) and (29) that the average forecast revision from $t = 1$ to $t = 2$ for θ can be written as

$$
\mathbb{E}_{M,2}[\theta] - \mathbb{E}_{M,1}[\theta] = \mathbb{E}^R_{M,2}[\theta] - \mathbb{E}^R_{M,1}[\theta] - \left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right)qZ + \left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right)\frac{w\tau_F}{\delta^F_F}Z \tag{33}
$$

The revision for Y is a rescaling of this, or $\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y] = a(\mathbb{E}_{M,2}[\theta] - \mathbb{E}_{M,1}[\theta])$. Taking the covariance with Z, and noting the zero covariance of the rational revision with Z, gives

$$
\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] = a\left(\frac{1}{\tau_1} - \frac{1}{\tau_2}\right)\left(q - \frac{\tau_F}{\delta^F_F}w\right)\mathrm{Var}[Z] \tag{34}
$$

The desired properties are immediate after noting $a > 0$ and $\tau_2 > \tau_1 > 0$.

Corollary 1

Observe that the covariance between Δ and $\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y]$ can be written as the sum of two terms corresponding to one-period updates:

$$
\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y], \Delta] = \mathrm{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta] + \mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta] \tag{35}
$$

Mechanically, then, the bias term is

$$
B := \frac{\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta]}{\mathrm{Var}[\Delta]} \tag{36}
$$

Observe further that $\Delta = \Delta^R + \left(\delta^F_F q + w\right)Z$, where Δ^R is the forecast error obtained under rational expectations. By application of the law of iterated expectations, Δ^R has zero covariance with either the rational update from 1 to 2 or Z. Hence, I can re-write B as

$$
B = \left(\delta^F_F q + w\right)\frac{\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z]}{\mathrm{Var}[\Delta]} \tag{37}
$$

Applying the expression (34) from the proof of Proposition 2 simplifies further to

$$B = \left(\delta_F^F q + w\right)\left(q - \frac{\tau_F}{\delta_F^F} w\right) \cdot \left(\frac{1}{\tau_1} - \frac{1}{\tau_2}\right) a \frac{\mathrm{Var}[Z]}{\mathrm{Var}[\Delta]} \tag{38}$$

The first term captures the effects of biases, while the second collects positive constants. The restriction to $\mathrm{Cov}[\Delta, Z] > 0$ restricts to $\left(\delta_F^F q + w\right) > 0$, and from here the properties are immediate.

Corollary 2

See from (4), the model decomposition of the monetary surprise, that $\Delta = \delta_F^F(F - \mathbb{E}^R_{M,0}[\theta]) + (q\delta_F^F + w)Z$. By this definition, $\delta^\perp = \delta_F^F(F - \mathbb{E}^R_{M,0}[\theta])$.

The "true" information effect i is defined by (14) in Definition 1, reprinted here:

$$i := \frac{\mathrm{Cov}[\Delta, \mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y]]}{\mathrm{Var}[\Delta]} \tag{39}$$

Our goal is to show that

$$i = i^\perp := \frac{\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y], \Delta^\perp]}{\mathrm{Var}[\Delta^\perp]} \tag{40}$$

I start by simplifying the numerator of the right-most expression in (40). Note that this numerator can be separated into two terms, for each incremental revision:

$$\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y], \Delta^\perp] = \mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta^\perp] + \mathrm{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta^\perp]$$

Let us start with the first of the two terms. Note that $\Delta^\perp$ is the agent's forecast revision about r under the rational model, which is contained in a rational agent's information set at $t = 1$. Therefore, by the standard law of iterated expectations argument,

$$\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta^\perp] = 0 \tag{41}$$

Combining this with (40) gives the following expression for $i^\perp$:

$$i^\perp = \frac{\mathrm{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta^\perp]}{\mathrm{Var}[\Delta^\perp]} \tag{42}$$

which, combined, with the definition of i, means our goal is now to show

$$\frac{\mathrm{Cov}[\Delta, \mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y]]}{\mathrm{Var}[\Delta]} = \frac{\mathrm{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta^\perp]}{\mathrm{Var}[\Delta^\perp]} \tag{43}$$

Next, observe that the forecast update about θ at $t = 1$, after observing Δ, can be written in the following way:

$$\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta] = \frac{\hat{\mathrm{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\mathrm{Var}}[\Delta]} \cdot \Delta \tag{44}$$

where the numerator and denominator of the scaling factor are perceived covariances and variances, and Δ is the (average) forecast error about r. The covariance of this revision with Δ and $\Delta^{\perp}$ is respectively

$$\begin{aligned}
\mathrm{Cov}[\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta], \Delta] &= \frac{\hat{\mathrm{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\mathrm{Var}}[\Delta]} \cdot \mathrm{Var}[\Delta] \\
\mathrm{Cov}[\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta], \Delta^{\perp}] &= \frac{\hat{\mathrm{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\mathrm{Var}}[\Delta]} \cdot \mathrm{Var}[\Delta^{\perp}]
\end{aligned} \tag{45}$$

which again uses the fact that $\Delta^{\perp}$ is the rational forecast error. Combining (45) with (43) gives

$$\frac{1}{\mathrm{Var}[\Delta]} \cdot \frac{\hat{\mathrm{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\mathrm{Var}}[\Delta]} \cdot \mathrm{Var}[\Delta] = \frac{1}{\mathrm{Var}[\Delta^{\perp}]} \frac{\hat{\mathrm{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\mathrm{Var}}[\Delta]} \cdot \mathrm{Var}[\Delta^{\perp}] \tag{46}$$

which, after canceling out like divisors, reduces to the following which verifies the claim:

$$\frac{\hat{\mathrm{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\mathrm{Var}}[\Delta]} = \frac{\hat{\mathrm{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\mathrm{Var}}[\Delta]} \tag{47}$$

Online Appendix

for "Disagreement About Monetary Policy" by Sastry

B Model Micro-foundations

This section provides a micro-foundation for the abstract model introduced in the main text.

B.1 Policy and Output: A Simple New Keynesian Model

Here, I provide a micro-foundation for the abstract model's policy rule,

$$r = \mathbb{E}_{F,0}[\theta] \tag{48}$$

and expression for output,

$$Y = a\theta - r \tag{49}$$

in expectation in a New Keynesian model with preference (demand) shocks.

B.1.1 Primitives

Time is indexed by $h \in \{0, 1, 2, 3 \ldots\}$. All of the abstract model's time periods, $t \in \{0, 1, 2\}$, are sub-periods of $h = 0$.

There is a representative household with the following preferences over consumption C_t and labor supply N_t:

$$\exp(a\theta)\left(\log C_0 - \frac{N_0^2}{2}\right) + \sum_{h=1}^{\infty} \beta^h \left(\log C_h - \frac{N_h^2}{2}\right) \tag{50}$$

where $\beta \in (0, 1)$ is a discount factor, θ is a demand shock known to the household, and $a \geq 1$ is a scaling factor. The household has the standard flow budget constraint

$$C_t + R_{t+1}B_t \leq w_t N_t + B_{t-1} \tag{51}$$

where w_t denotes the wage, B_t denotes savings in a bond and R_{t+1} is the real interest rate from t to $t + 1$.

A representative firm produces output with the technology $Y_t = N_t$. It charges a constant price, normalized to one, and commits to meeting demand by hiring sufficient labor at a supply-determined wage w_t.

A monetary policymaker sets the nominal interest rate, which, given full rigidity in prices, corresponds with the real interest rate. For $h \geq 1$, the policymaker sets $R_t = 1/\beta$ which corresponds with the natural rate. At $h = 0$, the policymaker sets $1/\beta \cdot \exp(r)$ for some perturbation $r \in \mathbb{R}$.

B.1.2 Equilibrium

For $t \geq 1$, the Euler equation implies

$$\beta R_{t+1} \frac{C_t}{C_{t+1}} = 1 \tag{52}$$

Since $R_{t+1} = 1/\beta$, then $C_t = C_{t+1}$ for all $t \geq 1$. As is conventional, I will assume that when policy replicates the natural rate for $t \geq 1$, the first-best outcome is implemented and $C_t = Y_t \equiv 1$.

At $t = 0$, the same condition is

$$\beta \cdot \exp(-a\theta) R_1 \frac{C_0}{C_1} = 1 \tag{53}$$

Substituting in the monetary rule $R_1 = 1/\beta \cdot \exp(r)$, this re-arranges to $C_0 = \exp(a\theta - r)C_1$. Substituting in $C_1 = 1$, this becomes, in logs,

$$\log C_0 = a\theta - r \tag{54}$$

which corresponds exactly to abstract equation (49) when $Y = \log C_0$. One recovers the monetary rule (48) by assuming that r is set to the policymaker's expectation of θ. See that this stabilizes the (log) output gap, in expectation, when $a = 1$; otherwise, the policymaker tolerates, in expectation, a positive effect of a positive demand shock on today's output. Such a feature is common for empirically plausible monetary rules and might be justified by adding additional constraints on or objectives for monetary policy, like financial stability.

B.1.3 Stock Prices

It is useful, for interpretations of the numerical model, to introduce a model-consistent notion of a stock price. Introduce Q as the stock price, which I will define as the expected present-discounted value of output *adjusted by the demand shock* under a different Market agent's beliefs $\mathbb{E}_M[\cdot]$, or

$$Q = \mathbb{E}_M \left[\exp(a\theta) C_0 + \sum_{h=1}^{\infty} \frac{C_h}{\exp\left(\prod_{k=1}^{h} R_k\right)} \right] \tag{55}$$

This is the relevant notion of permanent income in the model, or the valuation for a claim on present and future consumption.

Let $q = \log Q - \log \overline{Q}$, where $\overline{Q} = \frac{1}{1-\beta}$ is the stock price in the steady-state with $\theta = r = 0$. Standard log-linearization arguments give gives

$$q = (1-\beta)\mathbb{E}_M[\log C_0] - \beta(\mathbb{E}_M[r] - a\mathbb{E}_M[\theta]) \tag{56}$$

I can substitute in the model equation $\log C_0 = a\theta - r$. Simplifying yields:

$$q = a\mathbb{E}_M[\theta] - \mathbb{E}_M[r] \tag{57}$$

This is the same as the market belief about Y in the abstract model, evaluated at either $t = 0$ or $t = 2$.

B.2 Futures Prices: A Simple Trading Model

In this section, I provide a a micro-foundation for the model equation

$$P = \mathbb{E}_{M,0}[r] \tag{58}$$

describing the market's "prediction" and interpreting it as a transformed futures-contract price.

There is a continuum of investors indexed by $i \in [0, 1]$ who are each endowed with E dollars at $t = 0$. They can invest a position x_i into a security with price P and payout proportional to the fundamental r, which is realized at $t = 1$ and is believed by each trader to be Gaussian with potentially investor-specific means but common variances. The security is in zero net supply. And the investor's wealth at $t = 1$ is given by $W = E + x_i(r - P)$.

Agents have preferences given by the following constant absolute risk aversion (CARA) form:

$$-\exp(-\alpha W) \tag{59}$$

and submit limit orders, or contingent demands of x_i that depend on the price P. I will take the limit as $E \to \infty$, or agents have "deep pockets" and can make arbitrarily large trades given any positive and finite price.

The investor's optimization problem is therefore

$$\max_{p \mapsto x_i \in \mathbb{R}} -\mathbb{E}_i\left[\exp(-\alpha(E + x_i(r - P)))\right] \tag{60}$$

where $\mathbb{E}_i[\cdot]$ returns the investor's beliefs. Standard formulae for the expectation of Gaussian random variables allows us to re-express this in the equivalent form

$$\max_{p \mapsto x_i \in \mathbb{R}} \mathbb{E}_i[E + x_i(r - P)] - \frac{\alpha}{2}\mathbb{V}_i[E + x_i(P - r)] \tag{61}$$

where $\mathbb{V}_i[\cdot]$ returns the investor's perceived variance. The solution to this program is

$$x_i(P) = \frac{\mathbb{E}_i[r] - P}{\alpha \mathbb{V}_i[r]} \tag{62}$$

for each investor i. Market clearing, when contracts are in zero net supply, requires that

$$\int_i x_i(P) \, \mathrm{d}i = 0 \tag{63}$$

See that this is satisfied, for all α and values of the common subjective variance, when

$$P = \int_i \mathbb{E}_i[r] \, \mathrm{d}i \tag{64}$$

If all investors share the same information, or $\mathbb{E}_i[\cdot] \equiv \mathbb{E}_M[\cdot]$ for all i (where M denotes the "market"), then (64) reduces to (58). More generally, when there is not a single information set, (64) says that price equal population average beliefs.

C Solution of Model

This Appendix provides exact expressions for the key objects in the model, as they are used in the method-of-moments exercise. Below, the numbered equations (M1) to (M7) refer to the moments used in the numerical calculation, numbered by their order of appearance in the left panel of Table 1. The results in this Section can also be used to provide alternative proofs of the main results, supplementing the more abstract arguments in Appendix A.

Monetary surprises are

$$\Delta = (w + \delta_F^F q)Z + \delta_F^F (F - \delta_Z^M Z)$$

This is unchanged by adding the Fed's bias term. This implies that $\tilde{Z}$, or the best-fit prediction of Δ with Z, is $(w + \delta_F^F q)Z$.

The Fed's policy rule is given by the following

$$\mathbb{E}_{F,0}[\theta] = \delta_F^F F + (\delta_Z^F - q^F)Z$$

which is the same expression as (1). The Fed's expectation of output is

$$\begin{aligned}
\mathbb{E}_{F,0}[Y] &= a\mathbb{E}_{F,0}[\theta] - r \\
&= (a-1)\left[\delta_F^F F + (\delta_Z^F - q^F)Z\right] \\
&= \mathbb{E}_{F,0}^R[Y] - aq^F Z
\end{aligned}$$

where the rational expectations are $\mathbb{E}_{F,0}^R[\theta] = \delta_F^F F + \delta_Z^F Z$, $\mathbb{E}_{F,0}^R[r] = r$, and $\mathbb{E}_{F,0}^R[Y] = a\mathbb{E}_{F,0}^R[\theta] - \mathbb{E}_{F,0}^R[r]$.

The market's beliefs about fundamentals are given by

$$\mathbb{E}_{M,0}[\theta] = (\delta_M^Z - q)Z$$

and of the policy rate by

$$\mathbb{E}_{M,0}[r] = (\delta_Z^F - q^F - w + \delta_F^F(\delta_M^Z - q))Z$$

which means the market beliefs about output are

$$\begin{aligned}
\mathbb{E}_{M,0}[Y] &= a\mathbb{E}_{M,0}[\theta] - \mathbb{E}_{M,0}[r] \\
&= a\mathbb{E}_{M,0}^R[\theta] - \mathbb{E}_{M,0}^R[r] + ((\delta_F^F - a)q + w)Z
\end{aligned}$$

The first moments of interest are the regression coefficients of $\tilde{Z}$ on the Fed's and Market's forecast errors about output. Observe that the Fed's forecast error is

$$\text{FCE}^Y_{0,F} = (Y - \mathbb{E}^R_{0,F}[Y]) + aq^F Z$$

and hence the regression coefficient is

$$\beta^{FCE}_F = \frac{aq^F}{w + \delta^F_F q} \tag{M4}$$

Similarly, for the market,

$$\text{FCE}^Y_{0,M} = (Y - \mathbb{E}^R_{0,M}[Y]) + ((a - \delta^F_F)q - w)Z$$

and hence the regression coefficient is

$$\beta^{FCE}_M = \frac{(a - \delta^F_F)q - w}{w + \delta^F_F q} \tag{M2}$$

To calculate the R^2 for this regression, we first calculate the variance of the market's rational forecast error:

$$\text{Var}\left[(Y - \mathbb{E}^R_{0,M}[Y])\right] = (a - \delta^F_F)^2 \frac{1}{\tau_Z + \tau_\theta} + \frac{(\delta^F_F)^2}{\tau_F}$$

and then observe that, because Z is uncorrelated with the rational forecast error, $\text{Var}[\text{FCE}^Y_{0,M}] = \text{Var}\left[(Y - \mathbb{E}^R_{0,M}[Y])\right] + \text{Var}\left[\beta^{FCE}_M Z\right]$. Using this, we calculate

$$R^2_{FCE,0,M} = \frac{(\beta^{FCE}_M)^2 (w + \delta^F_F q)^2 (\tau_\theta^{-1} + \tau_Z^{-1})}{(\beta^{FCE}_M)^2 (w + \delta^F_F q)^2 (\tau_\theta^{-1} + \tau_Z^{-1}) + (a - \delta^F_F)^2 \frac{1}{\tau_Z + \tau_\theta} + \frac{(\delta^F_F)^2}{\tau_F}} \tag{M3}$$

The final object of interest comes from the regression of $\tilde{Z}$ on Y. See that output Y can be written as

$$Y = a\theta - \delta^F_F F - (\delta^F_Z - q^F)Z$$

from which it is immediate that

$$\beta^Y = \frac{(a - \delta^F_F)\delta^M_Z - \delta^F_Z + q^F}{w + \delta^F_F q} \tag{M7}$$

We now return to the expression for the monetary surprise, $\Delta = (w + \delta^F_F q)Z + \delta^F_F (F - \mathbb{E}^R_{0,M}\theta)$. See first that $\delta^F_F (F - \mathbb{E}^R_{0,M}\theta)$ is uncorrelated with Z and has variance

$$\text{Var}[\delta^F_F (F - \mathbb{E}^R_{0,M}\theta)] = (\delta^F_F)^2 \left(\tau_F^{-1} + \frac{1}{\tau_\theta + \tau_Z}\right)$$

The R^2 of regressing Z, or any linear transformation thereof, on Δ is

$$R^2_\Delta = \frac{(w + \delta_F^F q)^2(\tau_\theta^{-1} + \tau_Z^{-1})}{(w + \delta_F^F q)^2(\tau_\theta^{-1} + \tau_Z^{-1}) + (\delta_F^F)^2 \left(\tau_F^{-1} + \frac{1}{\tau_\theta + \tau_Z}\right)} \tag{M1}$$

We finally calculate market beliefs at $t = 2$. As in the main model, beliefs of the fundamental are given by

$$\begin{aligned}
\mathbb{E}_{2,M}[\theta] &= \left(\frac{\tau_Z}{\tau_2} - q\frac{\tau_0}{\tau_2} + w\frac{\tau_1}{\tau_2}\right) Z + \frac{\tau_F}{\tau_2} F + \frac{\tau_S}{\tau_2} S \\
&= \mathbb{E}^R_{2,M}[\theta] + \left(-q\frac{\tau_0}{\tau_2} + w\frac{\tau_1}{\tau_2}\right) Z
\end{aligned}$$

where $\tau_0 = \tau_\theta + \tau_Z$, $\tau_1 = \tau_\theta + \tau_F + \tau_Z$ and $\tau_2 = \tau_\theta + \tau_F + \tau_Z + \tau_S$, and the rational expectation is defined as usual. The market's forecast revision from $t = 0$ to $t = 2$ is therefore

$$\mathbb{E}_{2,M}[Y] - \mathbb{E}_{2,0}[Y] = a\left(\mathbb{E}^R_{2,M}[Y] - \mathbb{E}^R_{2,0}[Y] + \left(q\left(1 - \frac{\tau_0}{\tau_2}\right) + w\frac{\tau_1}{\tau_2}\right) Z\right) - \Delta$$

Observe that the regression coefficient of $\delta_F^F(F - \mathbb{E}_{0,M}[\theta])$ is 1 on the rational revision from 0 to 1 and 0 on the rational revision from 1 to 2. Thus

$$\beta^\Delta = a - 1 \tag{M6}$$

Next, to get the regression coefficient of $\tilde{Z}$, we simply separately consider the projection on the revision for θ and the revision for r. This gives

$$\beta^Z = a\frac{\left(q\left(1 - \frac{\tau_0}{\tau_2}\right) + w\frac{\tau_1}{\tau_2}\right)}{w + \delta_F^F q} - 1 \tag{M5}$$

D Additional Empirical Details

D.1 Original Survey Questions

Michigan Survey of Consumers

Question: How about people out of work during the coming 12 months–do you think that there will be more unemployment than now, about the same, or less?
Answers: 1. MORE UNEMPLOYMENT; 3. ABOUT THE SAME; 5. LESS UNEMPLOYMENT
Coding: (Share == 5) - (Share == 1)
Aggregation: Average using survey weights

AAII Survey

Historical AAII survey data are available at: https://www.aaii.com/sentimentsurvey/sent_results. The survey asks organization members whether they are "Bullish," "Neutral," or "Bearish" about "what direction members feel the stock market will be in next 6 months [sic]."

D.2 Event Studies

The following empirical model explores more closely the *timing* of the relationship between public signals and monetary surprises. The following model, estimated separately for each $-H \leq h \leq H$, decomposes the relationship of a predictor X_t and the surprise Δ_t by horizon:

$$\Delta_t = \alpha + \beta_h \cdot X_{t+h} + \varepsilon^X_{t+h} \tag{65}$$

For $h < 0$, β_h measures prior predictability. For $h > 0$, β_h measures correlation stretching into the future, or the statistical inference about X that is possible after observing Δ_t. I estimate the model for the level of the Michigan unemployment sentiment variable, for which the time-step h is a month, and for the AAII Bull-Bear spread, for which the time-step is a week.

The left panel of Figure A13 plots β_h from model (65) where the indicator X_{t+h} is the unemployment sentiment variable from the Michigan survey and the frequency is monthly. The variable tends to be at an elevated level for several months prior to a positive monetary surprise, and to spike slightly in the prior month. This suggests that there is information both in the growth rate of sentiment, emphasized in the earlier results, and the level of sentiment. Furthermore, there is no obvious visual evidence of a trend break occurring at the announcement event. If anything, there is smooth reversion back to the mean.

The right panel of Figure A13 plots β_h from model (65) where the indicator X_{t+h} is the fraction of bullish investors in the AAII survey. This indicator is elevated 4-5 weeks prior to a positive surprise and seems to steadily decline as if reverting to a long-run mean.

Together, these results emphasize that (i) predictability of monetary surprises in the data is possible with fairly old data but (ii) the most significant effects are concentrated about one month prior to the announcement.

D.3 Comparison With Other Predictors

This paper's theory funneled attention toward forward-looking public signals related to demand conditions, although the exact "identity" of public signal was immaterial to the main results. Here, I compare my results with evidence of surprise predictability in the literature as measured via lagged economic activity.[33] The following model provides an empirical horse race of the survey and market variables X_{t-1} against other possible predictors W_{t-1}:

$$\Delta_t = \alpha + \beta_M \cdot X_{t-1} + W'_{t-1}\Xi + \varepsilon_t \tag{66}$$

I consider three sets of predictors W_{t-1}. The first is the previous two months' unemployment rates, as studied by Cieslak (2018). The second is the previous two month's growth rate in total non-farm employees, as studied by Bauer and Swanson (2020). The third is the previous two months' value of the first two principal components in the FRED-MD database, constructed by McCracken and Ng (2016) to succinctly summarize a wealth of macro releases and used by Miranda-Agrippino (2015) and Miranda-Agrippino and Ricco (2021).

Appendix Table A1 shows estimates of (66) for the aforementioned control choices and the four predictive public signals. The point estimate and t-statistics for each predictor are virtually unchanged given the addition of unemployment data; the coefficients are unaffected for Michigan Sentiment and Blue Chip revisions, but attenuated for the stock market variables, when employment growth is added.[34] The principal component control, the most conservative of the three, does not affect the sentiment estimate, but reduces the estimates using the Blue Chip revisions, market returns, and AAII sentiment.[35] These patterns, together, build confidence that the empirical results in this section are both consistent with the literature and

[33] An exception is Karnaukh and Vokata (2022) who studies the predictive power of consensus Blue Chip forecasts, which was one of the baseline predictors in this paper.

[34] Results are very similar if instead of using employment growth in months $t-1$ and $t-2$, one uses employment growth in months t and $t-1$, and restrict to monetary announcements that occur after the 10th of the month (which in almost all cases should be after the BLS NFP announcement). Representatively, the coefficient for the Michigan Sentiment variable is 0.0098 and the t statistic is 2.69.

[35] The multivariate VAR analysis in Online Appendix F reveals similar patterns: while activity does seem to move before predictable surprises, the quantitatively larger and more striking patterns involve changes in beliefs and stock prices.

representative of a complementary channel of predictability.

D.4 Pseudo-out-of-sample Fit

In this section I measure whether observing certain variables would have aided in real time forecasting of high-frequency monetary shocks. Let X_{t-1} be a predictor variable. For each scheduled FOMC meeting month s, greater than a burn-in period of the first 24 meetings in the data, I run a linear regression of (i) previous surprises and (ii) the sign of previous surprises on X_{t-1} for all data up to month $s-1$. I calculate the mean squared error for all these out of sample projections. Then, to put this in units of an "approximate R^2," I calculate reduction in MSE as

$$\text{ReductionMSE} = 1 - \frac{\text{MSE}_{\text{POOS}}}{\text{MSE}_{\text{naive}}} \tag{67}$$

where the naive forecast is uniformly 0 for the surprises and 1/2 for the sign of the surprise. Note that reduction in MSE can, and will be, negative for models that are overfit.

The first two columns of A2 gives the results. As mentioned in the main text, real time prediction of the surprises themselves is fairly poor. Only for the unemployment sentiment and stock market variables is it positive; the other two predictors (Blue Chip revisions and AAII sentiment) perform worse than the naive strategy of assuming zero surprise. Prediction of the sign of the surprise, which is still informative about real-time failures of rational expectations (and the potential for an exploitative trading strategy), is better. All four variables beat the naive strategy of assuming surprises are equally likely to have either sign.

Next, to give these results a more practical unit, I calculate the return and volatility for a portfolio based on each sign prediction regression. I assume that the investor could run the regression pseudo-out-of-sample, calculate a probability $\hat{p}$ that there will be surprise tightening, and construct a portfolio that pays off $\hat{p}$ dollars if policy tightens (the policy news shock is positive) and $1-\hat{p}$ otherwise, at the risk-neutrally fair price of \$0.50. Over such small horizons the risk-free rate is essentially zero, so I summarize the security by its Sharpe Ratio, or ratio of the expected return to the standard deviation. These Sharpe ratios, in the third column of Table A2, all lie between 0.15 and 0.30.

D.5 Monetary Surprises and Stock Prices

Under the model-consistent interpretation that belief fluctuations about Y map one-to-one to stock prices (Appendix B.1.3), one can operationalize tests of Proposition 2 regarding forecast revisions using cumulative returns of the stock market around monetary announcements.

I estimate the following empirical equation:

$$R_{W(t)} = \alpha + \beta^Z \cdot \hat{Z}_{t-1} + \beta^\Delta \hat{\Delta}_t^\perp + \varepsilon_{W(t)} \tag{68}$$

where t denotes the day of the relevant FOMC meeting and $R_{W(t)}$ is the cumulative return (sum of log returns) in a window $W(t)$ on or after t. I run the regression separately for returns on the day of the announcement, and then in bins of five trading days after the announcement.

The results are plotted in Figure A14. First, on the day of the announcement, there is no statistically significant difference between the response of stock prices to either the predicted or unpredicted components of the monetary surprise.

Next, over longer horizons (and, in particular, 11-20 trading days after the announcement), there is weak statistical evidence of an upward drift in stock prices. This would be consistent with an upward drift in expectations of fundamentals, holding fixed expectations of future interest rates. It corroborates the test in the main text (Section 4.3) of the revisions predictions in Proposition 2, and demonstrates that much of the correction in expectations may occur within one month of the monetary announcement.

E Case Study Analysis: Fed Policy in 2001

In this Appendix, I provide anecdotal evidence from the early stages of the 2001 recession that makes the scope for heterogeneous interpretation of public data more concrete.

On January 25, speaking before Congress, Fed Chairman Alan Greenspan described plunging sentiment as an important bellwether for a recession:

> The crucial issue [...] is whether that marked decline [in GDP growth] breaches consumer confidence, because there is something different about a recession from other times in the economy. It is not a continuum from slow growth into negative growth. Something happens. (Washington Post, 2001)

In this sense, the Fed's concern about a specific type of forward-looking signal, consumer confidence indicators, was well telegraphed to the markets.

In the following week's FOMC meeting, after initial presentations of the Central Bank outlook, Governor Edward Gramlich and staff economist Lawrence Slifman had an extended discussion about whether plunging consumer confidence signals that headwinds will be persistent (Federal Open Market Committee, 2001a). Slifman highlighted the downside risk:

> MR SLIFMAN: [...] We don't envision a severe confidence break that is long lasting. But that's clearly a risk to the forecast[.], and it's the reason we included an alternative simulation in Part I of the Greenbook with a greater near-term loss of confidence.

Later, Slifman remarks that, among the Michigan survey indicators, "the one about unemployment expectations" consistently had the most predictive power. This is the most robustly predictive sentiment indicator in this paper's main analysis.

Philadelphia Fed President Anthony Santomero reiterated the connection between pessimism in the data and the risk of a crash: "[G]iven the deterioration in consumer and business sentiment that we have seen so far, certainly there is reason to continue to be concerned about the downside risks to the economy." Governor Gramlich mentioned, as a contrast to these negative anecdotes, that the Blue Chip survey of professional forecasters remains relatively optimistic about growth prospects. While he did not "take that forecast literally" in levels, given its generally slow and "stodgy" adjustment, he was concerned by its negative trend of revisions.

The first column of Table 3 gives an *ex post* report of the rate decision and its relation with beliefs. The confidence break in the data, as alluded to in the minutes, was indeed severe; and the Fed had a more pessimistic labor market outlook than the Blue Chip survey, despite the latter's upward revision. Markets had almost completely priced in the possibility of a rate cut

Table 3: Sentiment, Beliefs, and Surprises in Early 2001

Variable	January 2001	May 2001
Target rate change	-0.5%	-0.5%
Michigan Sentiment, change	-13%	-3%
Consensus Blue Chip Revision, U (Q1-Q3 Average)	0.08	0.03
Greenbook Minus Blue Chip: U (Q1-Q3 Average)	0.54	0.43
Futures surprise, Eurodollar (4Q)	-0.04	-0.15
Futures surprise, policy news factor	0.00	-0.09

in the same month but, after the meeting, significantly revised downward their expectations of future rates.

Four months later, in the May meeting, a more substantial disagreement had opened up about the state of the economy (Federal Open Market Committee, 2001b). At the center of the disparity was the interpretation of confidence indicators. Research and Statistics Division leader David Stockton clarified that his own pessimism was related to the "the real risk that confidence could deteriorate." He clarified further that it is both very important and very difficult to quantify this possibility:

> [O]ne can take a look at the pattern of forecast errors around recessions, and it is almost always the case that the recessions are steeper than models can explain. So, the recession often occurs because there is a collapse of confidence that accompanies them. [...] Our models, at least, are not able to fully capture the psychological effects and confidence-type effects that seem to play an important role in business cycles. That's not to say that we couldn't discover data sources or ways of measuring that going forward. But I don't know how we would do that currently.

The Fed ultimately adopted a pessimistic stance that surprised markets, which continued to also be more optimistic about the labor market (column 2 of Table 3).

These stories illustrate the tight connection between the more reduced-form idea of *trusting particular data* and a more fundamental, but complex, issue of *prioritizing different macroeconomic mechanisms*. The Fed's emphasis on forward-looking confidence indicators was based in a view that measured pessimism in surveys would translate into lower spending, which in their own admission required thinking outside their own baseline model. This also sheds light on how, with the benefit of hindsight, both the Fed and markets may seem to have made large "mistakes" on account of modeling uncertainty, which this paper's model captures via unknown precision of signals.

F SVAR Analysis: What Shocks Drive Predictable Disagreement?

This Appendix describes an SVAR model, consistent with the theory, which can shed on light on (i) what economic shocks cause disagreement and (ii) how much business cycle variation these shocks, and true "monetary trembles," explain. The results, overall, demonstrate that the primitive source of most monetary disagreement is best characterized as a confidence-based demand shock that drives a considerable fraction of all variation in monetary policy. In this regard, disagreement about monetary policy is a feature of the portion of the business cycle that the monetary authority is most actively trying to stabilize, consistent with the demand-centric interpretation in Section 2.

F.1 Empirical Model and Identification Strategy

The model is a vector auto-regression (VAR) with Gaussian errors. A $N \times 1$ vector of macro aggregates y_t evolves via the following process:

$$y_t = \sum_{\ell=1}^{L} A_\ell y_{t-\ell} + A_0^{-1} \nu_t \tag{69}$$

where each A_ℓ is an $N \times N$ matrix and ν_t is an $N \times 1$ vector of independent, Gaussian innovations. The matrix A_0^{-1} controls the contemporaneous impact of ν_t and hence the economic identification of the different shocks.

The components of y_t are the following eight series: the policy news shock, unemployment, the log deflator of personal consumption expenditures (PCEPI), the Michigan "unemployment sentiment" variable, the Blue Chip expectation of unemployment six months hence, the spread in beliefs between the 10 most and least pessimistic Blue Chip forecasters about the same, the log level of the S&P500, and the 1-year Treasury rate.[36] The estimation uses monthly data from January 1995 to April 2014.

The model has two identified shocks. The first is identified via short-run restrictions as the only shock that has a contemporaneous impact on the policy news variable, while remaining unpredictable by other lagged observables. Through the lens of the simple model, and in particular the representation Equation 4 and Corollary 2 defining the monetary surprise, this

[36] The Blue Chip survey, while administered monthly, provides forecasts only for quarterly-frequency outcomes. To construct an expectation over the next six months, I take a weighted average of quarterly expectations. Specifically, if the current month is in the middle of the quarter (e.g., February), I assume the two-quarter-ahead forecast corresponds to exactly six months in the future; if the current month is the first in the quarter, I take a weighted average of the one-quarter (1/3) and two-quarter (2/3) forecasts; and if the current month is the last in the quarter, I take a weighted average of the three-quarter (1/3) and two-quarter (2/3) forecasts.

shock captures variation spanned by the error in the monetary authority's information ε_F.[37] I will refer to this in shorthand as a *monetary noise shock*.

The second shock is defined to maximize the variance contribution to the policy news variable at horizons between 1 and 3 months while remaining orthogonal to the identified monetary noise shock, in the max-share tradition of Uhlig (2004) and more recent applications by Barsky and Sims (2011) and Angeletos, Collard, and Dellas (2020). Through the lens of the simple model, this shock would capture variation in the public signal Z. But relative to the empirical methods in Section 4, which proxied Z with specific lagged observations of selected variables, the VAR method is more agnostic about (i) which lags and variables predict surprises and (ii) whether these patterns arise unconditionally or only in response to certain business-cycle shocks. I will refer to the identified shock in shorthand as a *monetary disagreement shock*.[38]

The final Section F.4 spells out the details in much more detail, including the Bayesian inference procedure and numerical implementation of the identification.

F.2 Results: Impulse Response Functions

To answer the first question ("what shocks drive disagreement?"), I first calculate the impulse response functions to the identified noise and disagreement shocks. These are plotted in Appendix Figure A15, and the key results are summarized in text here. The noise shock is associated with a transient spike in the policy news shock which translates into a short-term (2-3 month) and fairly imprecise increase in 1-year Treasury rates. The shock leads to a small, transitory decline in the price of the S&P 500 (posterior median: 0.6 percentage points or 0.006 log points) and a small decline in Michigan sentiment. The VAR picks up no significant effects on unemployment, consumption, or prices. The disagreement shock, by contrast, significantly decreases unemployment and raises prices over medium horizons (1-4 years). Monetary policy leans into these shocks considerably, as one-year Treasury rates initially increase one-for-one with inflation before remaining elevated long after the price level has stabilized. The effects on real variables are led, by several months, by spikes in consumer sentiment and stock prices.

While it is impossible to include the Greenbook forecast in the VAR model since it is not observed in every month, one can use the model to provide a rough calculation of Market-to-Fed disagreement about unemployment. In the model, the Fed's beliefs about the outcome respond 26% more than the market's to a fundamental shock; if one assumes the IRF of the Fed's belief would be a uniform 26% larger than the market's, then the maximum response of Market-to-Fed

[37] The method also relates to the suggestion of Plagborg-Møller and Wolf (2021) to estimate the impulse response to an identified shock by ordering that shock first in a recursive VAR. Here the logic is that the policy news shock is a valid instrument for the shock of interest conditional on observables, or after partialling out lagged macro indicators.

[38] An additional constraint, which is a normalization, is that the shock has a positive impact on the policy news shock at horizon 2.

disagreement regarding unemployment six months ahead is -0.049 percentage points using the posterior median IRF. This is 29% of the maximum response of unemployment to the shock.[39] These results imply substantial effects on disagreement about macro outcomes as a result of shocks spanned by past and present public data at $t = 0$.

F.3 Results: Variance Decompositions

I now turn to quantifying how important the identified shocks are for explaining macro dynamics. Based on the moving average representation implied by the VAR dynamics, one can calculate in the model the total fraction of unconditional variance in the policy news variable attributed to each of the two identified shocks and the sum of all remaining unidentified shocks up to a feasible lag truncation.[40] In a posterior median estimate, 72% of variance of the policy news shock is explained by the noise shock; 14% by the disagreement shock; and the remaining 14% is unidentified. The fraction explained by the disagreement shock matches the R^2 of the bi-variate prediction equation in Section 4.2. In this sense, most of the monetary surprise variation in the multi-variate model remains related to the (very small) noise in the monetary authority's beliefs.

But of course the follow-up issue is how relevant this surprise variation is for explaining interest rate and real outcome (unemployment) variation. The noise shock explains merely 1% each of unemployment and nominal interest rate variation, compared to 23% and 40%, respectively, for the disagreement shock. This underscores the point that true monetary trembles are essentially irrelevant for explaining real activity, while systematic disagreement driven by heterogeneous models is associated with one of the largest shocks driving the business cycle.

F.4 Identification and Posterior Sampling

This subsection fills in methodological details.

The reduced-form representation of the model is (69), re-printed here:

$$y_t = \sum_{\ell=1}^{L} A_\ell y_{t-\ell} + v_t \tag{70}$$

where $v_t := A_0^{-1}\nu_t$ are now the one-step-ahead forecast errors. Given the original assumption that $\nu_t \sim N(0, \mathbb{I})$, it is also true that $v_t \sim N(0, A_0^{-1}(A_0^{-1})')$. Let $\Sigma := A_0^{-1}(A_0^{-1})'$ denote this

[39] The comparable figures for the response of *within* Blue Chip (or market pessimist to market optimist) disagreement, which is in the model, are -0.029 percentage points and 17%, indicating that the gap between optimists and pessimists habitually contracts in response to good news and widens in response to bad news owing to pessimist's greater sensitivity to news.

[40] These are calculated, as a feasible numerical approximation, to the horizon of 48 months.

reduced-form covariance matrix for the one-step-ahead forecast errors.

F.4.1 Priors and Inference

Let N be the number of variables and L be the number of lags, fixed to $L = 4$ in the main estimation. The model has $N \times N \times L$ reduced-form coefficient parameters in the $(A_j)_{j=1}^{L}$ and $N(N-1)$ covariance matrix parameters in Σ to estimate. I specify a proper prior on these parameters along the lines of the one suggested by Sims and Zha (1998) (henceforth, SZ). This is described below.

Reduced Form Coefficients A_j. As a minimal proper prior, I implement the "Minnesota prior" dummy observations described explicitly in SZ. These implement independent Gaussian priors for each coefficient, centered around 1 for own first lags and 0 for everything else, with prior precision increasing (prior variance decreasing) for further lags. The economic interpretation of the prior mean is an independent random walk for each variable. The "tightness" and "decay" for these dummy observations are uniform across equations. I choose values of 5 and 0.5, respectively, for these hyper-parameters (the precise meaning of which is described well in the SZ reference).

I add additional "unit root" dummy observations that, qualitatively, express belief that all variables would stay persistent at some mean levels. I estimate the prior mean as the sample mean from the lagged observations, which are not used on the left-hand-side of estimation. One observation expresses belief that *all* variables stay at the level, and another n observations express the belief that each *independently* stays at the level. Again, in the notation of the reference, I specify this with tightness 5 and persistence 2.

Covariance Matrix Σ. I impose a Wishart prior on Σ^{-1} (or an inverse-Wishart prior on Σ) centered around variance 0.01 in each equation.

F.4.2 Posterior Draws

Given the assumption that model errors are Gaussian, and the fact that the prior is conjugate, it is straightforward to sample from the posterior over Σ and the $(B_\ell)_{\ell=1}^{p}$ in closed form. Conditional on these reduced-form draws, the identification strategy provides a unique mapping to the structural shocks of interest and the impulse response functions thereof.

Let Q denote the unique lower-triangular matrix such that $QQ' = \Sigma$ (i.e., Cholesky decomposition). Based on the variable ordering specified in the main text, with the policy news shock ordered first, I take the first column of A_0^{-1} to be the first column of Q: that is, the first recursively-ordered shock. This is the monetary noise shock.

Next, I solve for the variance-maximizing disagreement shock. Define the implied Cholesky errors as $u_t := Q^{-1}v_t$ Let the policy news shock have the moving average representation in terms of the Cholesky errors

$$\Delta_t = \sum_{i\geq 0} b_i' u_{t-i} \tag{71}$$

Note that $\text{Var}[u_t] = \mathbb{I}$, so the variance of Δ_t can be written as the sum of vectors δ_i, the elements of which are the squared moving average coefficients in b_i:

$$\Delta_t = \sum_{i\geq 0} b_i' b_i = \sum_{i\geq 0} \text{Trace}[b_i b_i'] \tag{72}$$

I solve for the $N \times 1$, unit-length column vector w that maximizes its variance contribution for $i \in \{2, 3, 4\}$ without loading on the first shock, which is the identified monetary noise shock. This solves the following program:

$$\begin{aligned} \max_{w\in\mathbb{R}^N} \ & w'[b_2b_2' + b_3b_3' + b_4b_4']w \\ \text{s.t.} \ & w'w = 1 \\ & w'e_1 = 0 \end{aligned} \tag{73}$$

This is a standard eigenvector problem which can be solved easily in closed form. Note that it differs from the problem solved by Barsky and Sims (2011) because it does not normalize the denominator by the total variance in the period. That is, the units of this problem are in variance while the units of the Barsky and Sims (2011) problem are in variance shares.

I then take w as the second identified column in the matrix A_0^{-1}. The other columns are an arbitrary rotation such that $A_0^{-1}(A_0^{-1})^{-1} = \Sigma$.

G Additional Tables and Figures

Table A1: Predictive Value of Sentiment, Holding Fixed Recent Data

Predictor		No control	U Control	PC Control	NFP Control
Mich. Sentiment	β	0.0091	0.0092	0.0091	0.0092
	SE	(0.0030)	(0.0032)	(0.0028)	(0.0029)
	t-stat	2.97	2.91	3.31	3.14
BC U Rev.	β	0.0094	0.0074	0.0036	0.0042
	SE	(0.0038)	(0.0038)	(0.0050)	(0.0049)
	t-stat	2.47	1.95	0.71	0.87
S&P 500	β	0.0080	0.0077	0.0030	0.0050
	SE	(0.0037)	(0.0036)	(0.0027)	(0.0029)
	t-stat	2.18	2.20	1.40	1.74
AAII Sentiment	β	0.0077	0.0078	0.0030	0.0045
	SE	(0.0027)	(0.0026)	(0.0030)	(0.0027)
	t-stat	2.89	2.94	1.01	1.70

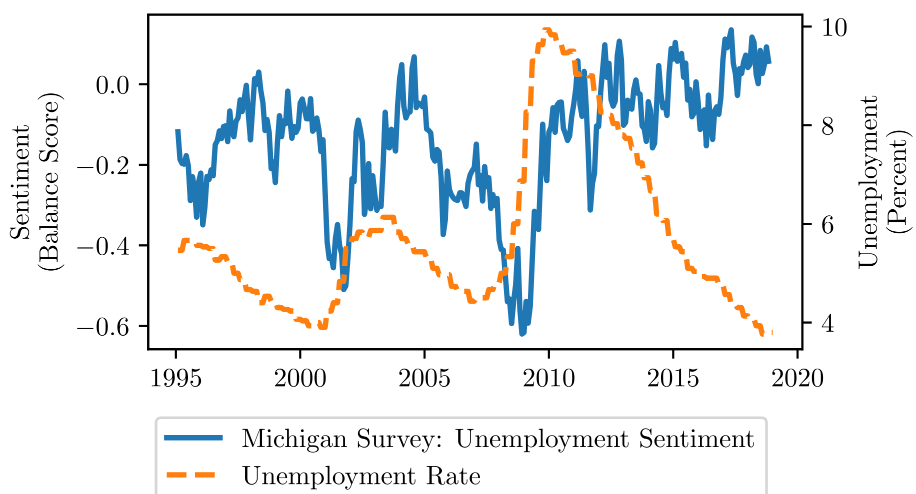
Notes: The regression equation is (66). The four predictors are described in Section 4.1 and the control variables in Section 4.1, paragraph "Comparison with other predictors."

Table A2: Pseudo-out-of-sample Fit

	Predictive R^2		Sharpe Ratio
Predictor	Magnitude	Sign	
Unemployment sentiment	0.042	0.076	0.29
Blue Chip Revision	-0.015	0.042	0.21
Stock Market jump	0.017	0.062	0.26
AAII Bull-Bear Spread	-0.027	0.034	0.20

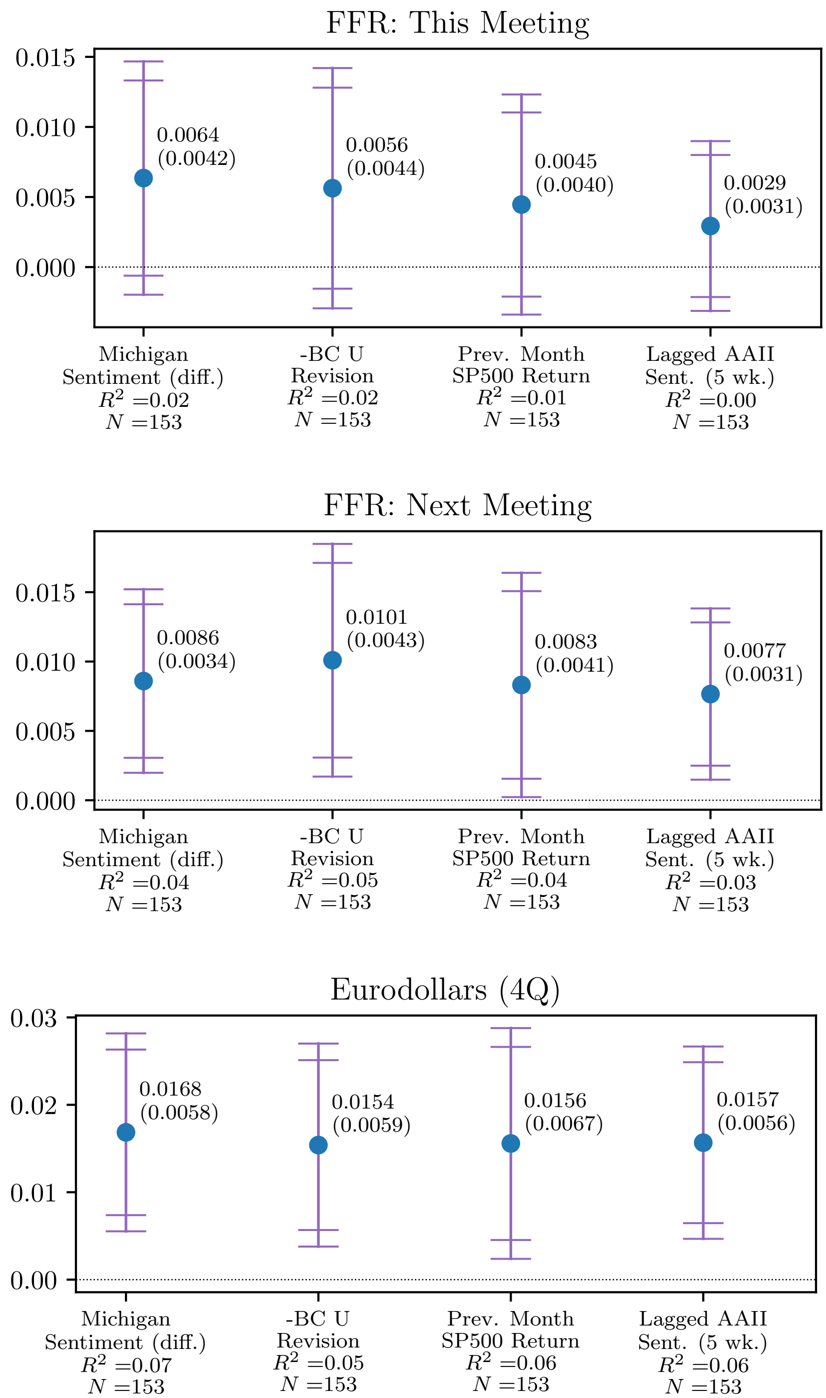
Notes: Values are fraction MSE reduction calculated as in (67). The methodology is described in Appendix D.4.

Figure A1: Labor Market Sentiment: Time Series Patterns



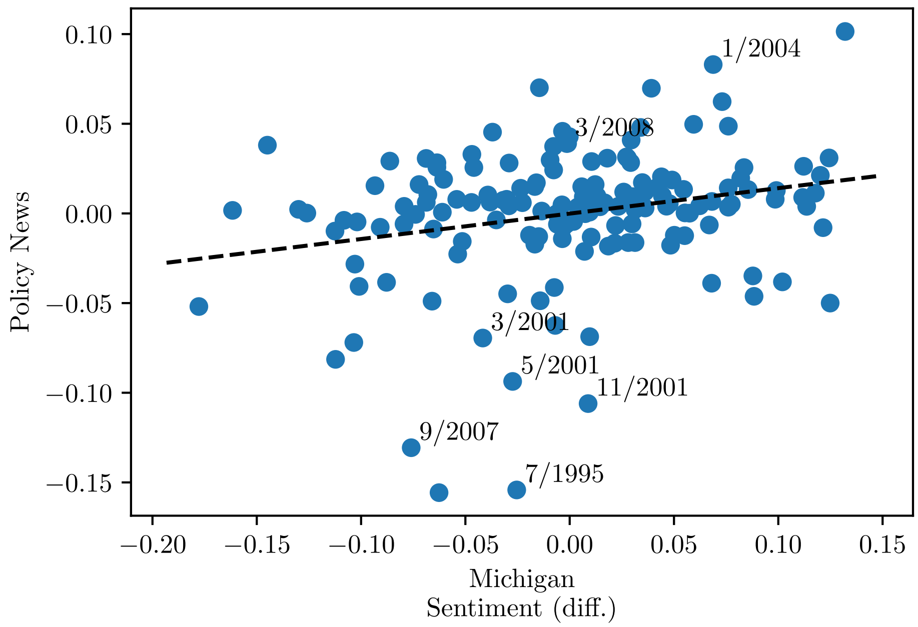
Notes: The left scale and solid blue line show the unemployment sentiment variable from the Michigan survey. The right scale and dotted orange line show the US unemployment rate.

Figure A2: Predictability for Different Assets



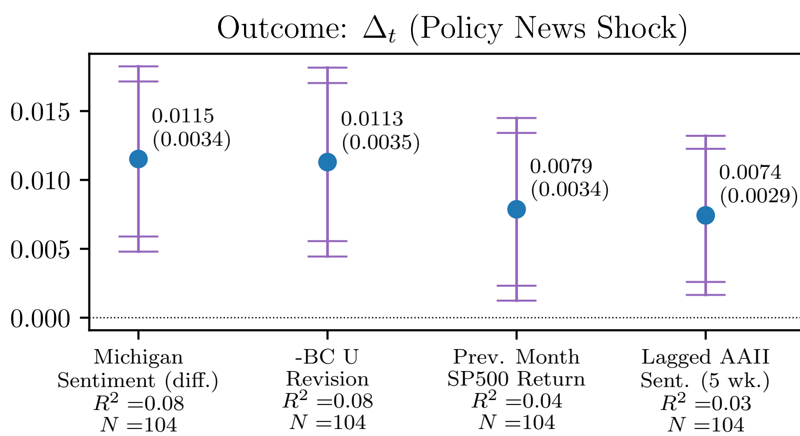
Notes: Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. Each graphic is an analogue of Figure 2 with a different outcome variable.

Figure A3: Scatter Plot of Surprises vs. Sentiment



Notes: Selected points are labeled with the date of meeting.

Figure A4: Predicting Monetary Surprises, Pre 2008



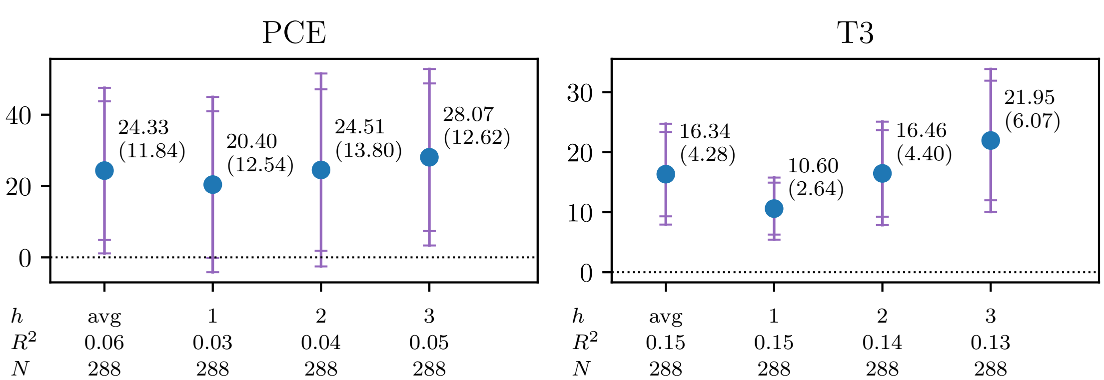
Notes: This figure replicates the analysis of Figure 2, but restricts the sample to 1995-2007. Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (9), and each estimate comes from a separate univariate regression. The units for the coefficients are implied percentage points of monetary surprise per one-standard-deviation outcome of the regressor.

Figure A5: Rolling Estimation of Predictive Regression

Notes: The regression specification is (9). The window is 48 months. Dotted lines are 95% CI based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

Figure A6: Forecast Errors and Public Signals, Alternative Outcomes

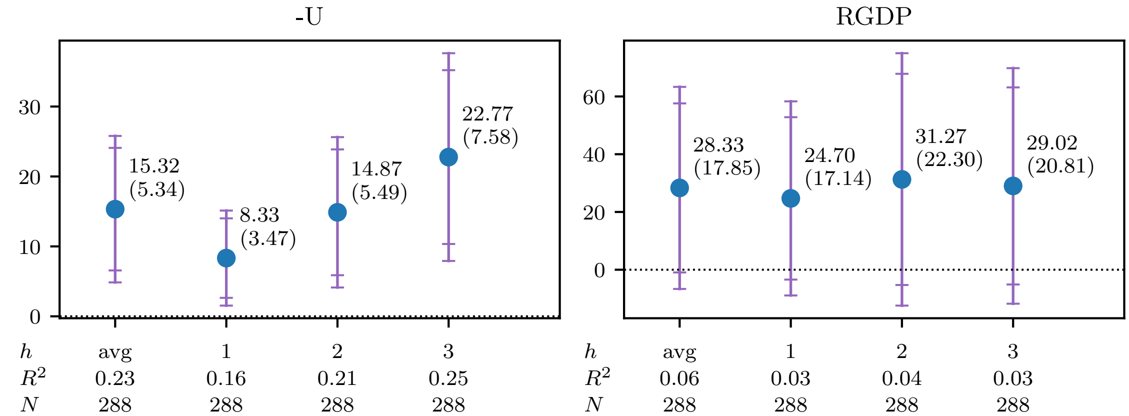
Outcome: $Y_{Q(t)+h} - \mathrm{E}_{B,t}[Y_{Q(t)+h}]$



Notes: The outcomes are Real PCE Growth (annualized) and 3-Month Treasury Rates (annualized, market average over quarter). Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (11), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per basis point of expected monetary surprise.

Figure A7: Forecast Errors and Public Signals, First-Release Data

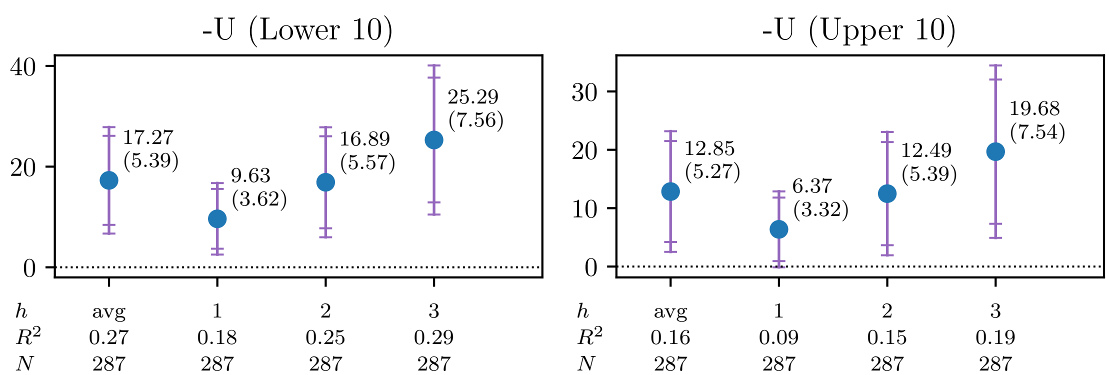
Outcome: $Y_{Q(t)+h} - \mathrm{E}_{B,t}[Y_{Q(t)+h}]$



Notes: First-release macro data are taken from the Philadelphia Fed's real-time data center (https://www.philadelphiafed.org/research-and-data/real-time-center). Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (11), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per basis point of expected monetary surprise.

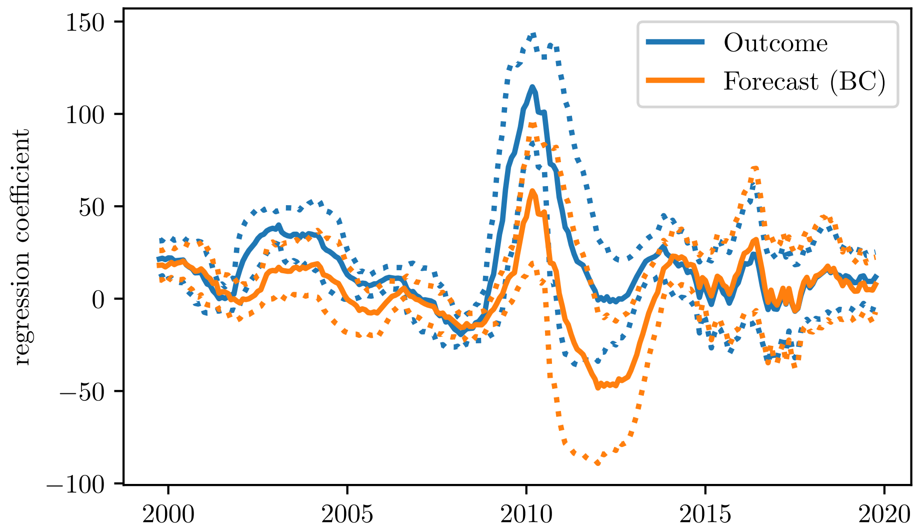
Figure A8: Forecast Errors and Public Signals, Upper and Lower Tails

Outcome: $Y_{Q(t)+h} - \mathrm{E}_{B,t}[Y_{Q(t)+h}]$



Notes: The forecasts are the average among the 10 highest (left) and 10 lowest (right) forecasts in that survey. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (11), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per basis point of expected monetary surprise.

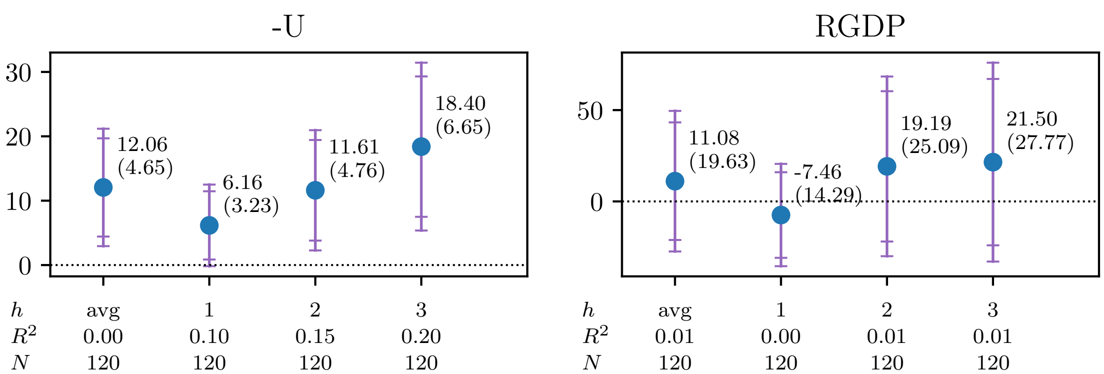
Figure A9: Rolling Estimation of Forecast and Outcome Prediction



Notes: Each point is the coefficient in a feasible regression coefficient based on predictions made nine months ago or prior and measured unemployment rates. The regression is $Y_t = \beta \cdot \hat{Z}_t + \alpha + \varepsilon_t$, where Y_t is either the predicted or realized unemployment rate three quarters hence. The window is 48 months and dotted lines are 95% CI based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

Figure A10: Greenbook Forecast Errors and Public Signals

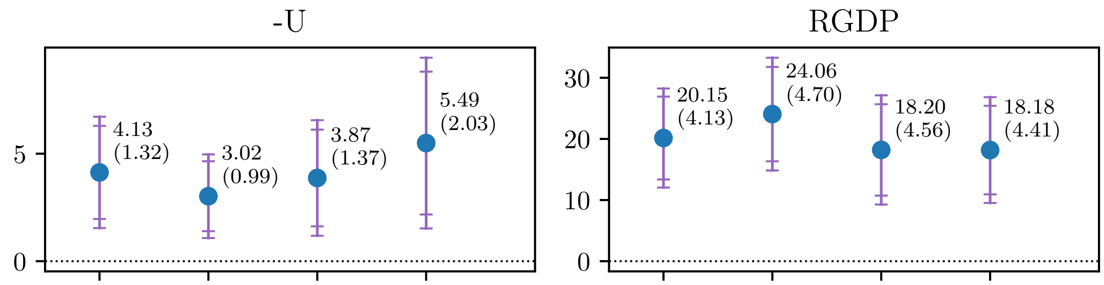
Outcome: $Y_{Q(t)+h} - \mathrm{E}_{G,t}[Y_{Q(t)+h}]$



Notes: Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (11), but the outcome is adjusted to be errors in the Fed's Greenbook forecasts, and the sample is smaller (see main text). The units for the coefficients are basis points of forecast error per basis point of expected monetary surprise.

Figure A11: Forecast Disagreements and Public Signals, Alternative Timing

Outcome: $\mathrm{E}_{G,t}[Y_{Q(t)+h}] - \mathrm{E}_{B,t}[Y_{Q(t)+h}]$

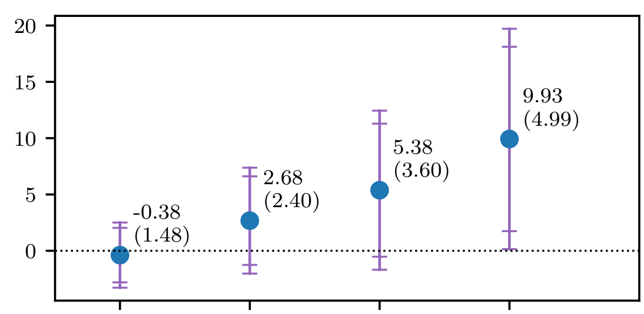


	-U				RGDP			
h	avg	1	2	3	avg	1	2	3
R^2	0.11	0.10	0.09	0.12	0.23	0.24	0.14	0.14
N	143	143	143	143	143	143	143	143

Notes: Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (13), with the alternative matching procedure for Blue Chip and Greenbook dates described in the main text. The units for the coefficients are basis points of forecast disagreement per basis point of expected monetary surprise.

Figure A12: Forecast Disagreements and Interest-Rate Disagreement

Outcome: $\mathrm{E}_{G,t}[R_{Q(t)+h}] - \mathrm{E}_{B,t}[R_{Q(t)+h}]$

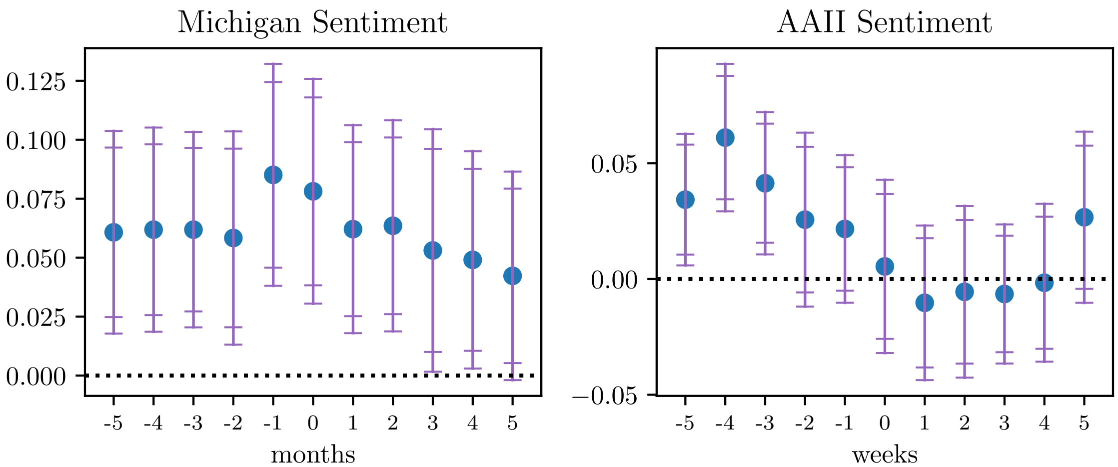


h	1	2	3	4
R^2	0.00	0.02	0.03	0.06
N	79	79	79	79

Notes: The analysis period is 1995-2008, the maximum period for which Greenbook Financial Assumptions are available. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (13), and the forecasted variable is the three-month Treasury rate. The units for the coefficients are basis points of forecast disagreement per basis point of expected monetary surprise.

Figure A13: Dynamic Relationship Between Sentiment and Surprises

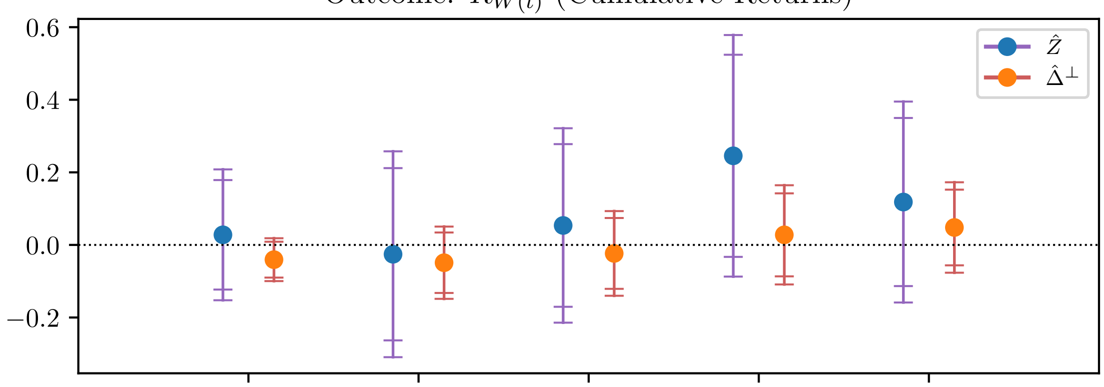
Outcome: Δ_t (Policy News Shock)



Notes: Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (65), and each estimate corresponds to a different estimating equation indexed by the horizon. The units for the coefficients are implied percentage points of monetary surprise per one (non-normalized) unit of the regressor.

Figure A14: Predictable Surprises and Stock-Price Drift

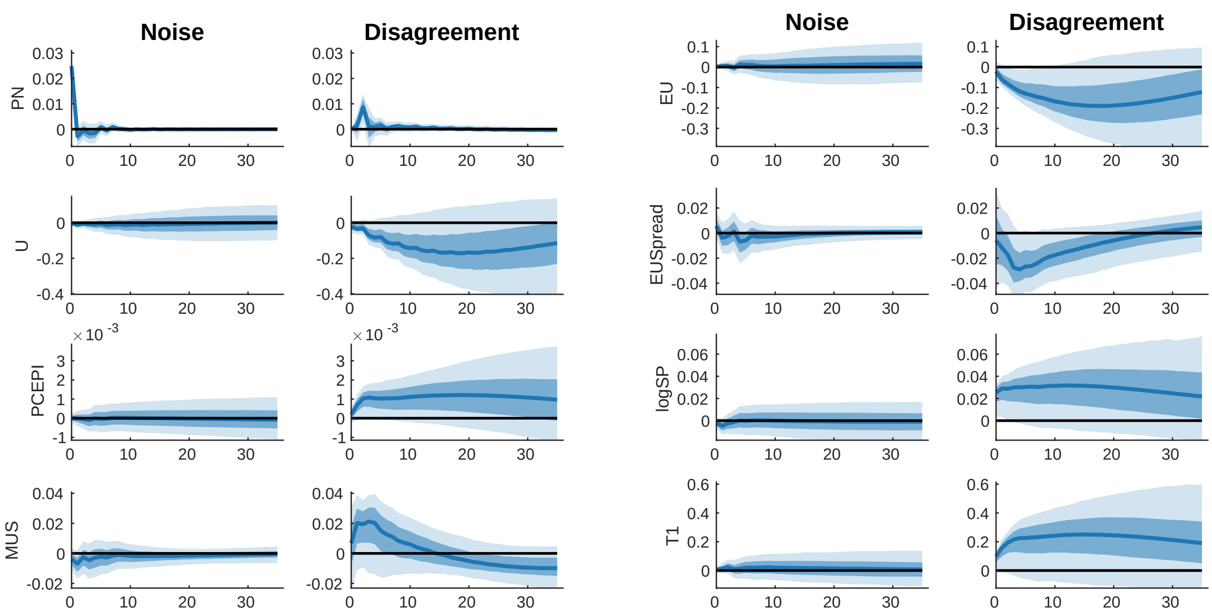
Outcome: $R_{W(t)}$ (Cumulative Returns)



h	0	1-5	6-10	11-15	16-20
R^2	0.01	0.01	0.00	0.01	0.01
N	153	153	153	153	153
t^D	0.72	0.16	0.65	1.22	0.54

Notes: The estimating equation is (68). Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth)

Figure A15: Impulse Response Functions



Notes: The response variables are, in order: the policy news shock, unemployment, PCE Deflator, Michigan Unemployment Sentiment, the Blue Chip expectation of the next six months' Real PCE growth, the spread between the high (top 10) and low (bottom 10) forecasts of the same, the S&P 500 Price, and the 1-Year Treasury Rate. Shaded bands are 68% and 95% high-posterior-density regions. The darkened central line is the posterior mode.

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