Disagreement About Monetary Policy

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Abstract

Using US data since 1995, I document that “bad macroeconomic news” in public signals predicts market over-estimation of interest rates, excessive market optimism about employment, and delayed correction in these forecasts. In a stylized model that can accommodate such patterns via three leading mechanisms—asymmetries between the market and central bank in their signals about fundamentals, beliefs about the monetary rule, and confidence in public data—I show that the last is the most empirically relevant. The calibrated model implies that the market’s relative under-reaction to news substantially dampens the response of asset prices to fundamentals, while the central bank’s signaling through actions or “information effect” has almost no role.

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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, in the words of former Federal Reserve Chair Ben Bernanke, “one of the most powerful tools” in the central bank arsenal (2015). But what actually 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 study these issues. It first shows via a simple model how to distinguish three leading mechanisms for disagreement: asymmetric information about fundamentals (private signals), different beliefs about the monetary rule (forecasting with different model equations), and different confidence in public data (heterogeneous priors). The model generates simple conditions under which specific mechanisms are necessary to explain the data, as well as a method for recovering the extent of each mechanism by matching moments. In a nutshell, pure asymmetric information is rejected if pre-determined public data can predict forecast biases; and the relative extent of disagreement about the monetary rule versus differential confidence in public data can be identified by comparing biases in interest rate and real activity forecasts.

I implement the model’s suggested tests on US data since 1995, using the predictions embedded in interest rate futures prices and average forecasts about unemployment in the Blue Chip Economic Indicators Survey as proxies for aggregate market expectations about interest rates and real activity, respectively. I find that “bad macroeconomic news” in leading indicators of the business cycle, like depressed consumer confidence, bearish professional forecasts, or low stock returns, systematically predicts market over-estimation of interest rates and employment. At face value, the results show how markets are a half-step behind the Federal Reserve in anticipating both the business cycle and the systematic monetary response. Via the model, they pinpoint different confidence in public data or heterogeneous priors as the most quantitatively relevant of the three aforementioned mechanisms.

The model, when calibrated to match the data, generates the following two main conclusions. First, central bank communication works almost entirely by altering market beliefs about policy instead of market beliefs about fundamentals. This conclusion contrasts with recent studies which use the coincidence of surprise monetary tightening with upward revisions in real activity forecasts to infer a quantitatively important signaling channel of monetary policy, or information effect (Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018). My theoretical framework clarifies how slow learning with heterogeneous priors could appear like persuasion in correlational data, and how incorporating additional empirical tests can reject a pure asymmetric-information model and its prediction of large signaling effects. Second, heterogeneous priors are quantitatively large by the following metric: if the Fed shared the market’s under-confidence in leading indicators, and the market knew this, stock prices would be 25% more sensitive to fundamentals. This effect is 47
times larger than the corresponding reduction in belief sensitivity were signaling and asymmetric information removed from the model. Thus, the market’s perception that the Fed over-reacts to news meaningfully dampens financial fluctuations at the onset of the business cycle, while information effects do not meaningfully amplify these fluctuations.

**Theoretical Framework.** Toward these conclusions, this paper begins with a simple signal extraction model that structures the identification exercise. There are two agents, a representative monetary authority (“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 leading indicator of the business cycle), and the former observes also a private signal of the fundamental (e.g., internal research). The Fed sets interest rates equal to its possibly mis-specified forecast of the fundamental. The Market attempts to forecast policy, or makes a forecast of 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 $t = 2$, the Market observes an additional signal of fundamentals. Afterward, an additional variable, employment, is realized. Employment depends positively on fundamentals and negatively on policy, with slopes that encode the assumption that policy incompletely stabilizes shocks in expectation.

In the model, the Fed’s and Market’s beliefs about interest rates and employment may differ for three reasons. First, as mentioned above, the Fed has private information. Second, markets may mis-estimate the Fed’s policy reaction to the public signal. And third, the Market and Fed may have different confidence in the public signal, generating heterogeneous priors. I call a case of the model with only the first element a “Bayesian, asymmetric-information model,” which is broadly speaking the standard approach in the monetary signaling literature following Morris and Shin (2002).\footnote{Similar models are also standard in the literature on the trade-offs between disclosure and action following Cukierman and Meltzer (1986) and commitment versus flexibility with private information following Athey, Atkeson, and Kehoe (2005). These connections add more context for my results, though I do not study either issue directly.}

I first show that a pure asymmetric information model precludes public information from predicting monetary surprises, while either of the other two non-Bayesian mechanisms allow this possibility. In particular, under-estimating the Fed’s confidence in the public signal or having low confidence directly in the public signal are consistent with the (ultimately empirically relevant) case of bad news correlating with surprise monetary loosening.

I next show how the two non-Bayesian mechanisms can be distinguished from one another by their predictions for employment forecasts. Stated informally, 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. A market that under-estimates the monetary response to news, but correctly uses public information, expects interest rates to remain high and therefore under-predicts employment. A market that under-regards the fundamental shift, but correctly specifies the
monetary rule, over-predicts interest rates; but, on net, they also over-estimate employment under
the assumption that the policy rule incompletely stabilizes shocks. My formal result generalizes this
logic to other cases that blend the mechanisms and/or flip their signs.

My results, together, show how a series of “sign tests” can illuminate what mechanisms are
necessary to explain the data. They also provide a blueprint for how to use multiple estimated
moments to identify the best-fitting combination of frictions. I will pursue both strategies in the
paper in sequence.

**Empirical Results.** The next part of the paper takes the model to the data. I treat the *policy news
shock* of Nakamura and Steinsson (2018) as a summary of monetary surprises from 1995 to the
present. The policy news shock combines many dimensions of interest rate news into a scalar
summary, simplifying analysis.² As representative signals that are leading indicators of the business
cycle, I focus on (i) consumer sentiment from the University of Michigan Survey of Consumers; (ii)
revisions to professional forecasts 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.

The first main empirical finding is that all four measures are positive predictors of monetary
surprises—that is, bad news in any indicator predicts surprise monetary loosening. The result
is strongest around recessions and valid even when using data that was collected more than one
month prior. The main results for consumer and investor sentiment confirm, along an independent
dimension, predictability documented in other studies using changes in the unemployment rate
(Cieslak, 2018), total non-farm payrolls (Bauer and Swanson, 2020), and a broader average of macro
indicators (Miranda-Agrippino, 2015; Miranda-Agrippino and Ricco, 2021). In the theory, this result
invalidates the Bayesian, asymmetric-information case but does not pinpoint the correct alternative.

I next turn to the model’s additional predictions for real activity forecasts to distinguish the
two non-Bayesian mechanisms. I first check whether lagged public signals at \( t - 1 \) can predict
errors in forecasts made at time \( t \) about economic activity. I operationalize this using errors in
consensus (negative) unemployment and real GDP growth forecasts from the Blue Chip Economic
Indicators survey. I find that lagged upticks in consumer confidence correlate with a significant
under-estimation of real variables at all horizons.³ Next, I study the relationship between the same
public signal realizations in \( t - 1 \) with forecast revisions between months \( t + 1 \) and \( t + 2 \). I find a
statistically significant positive response to upticks that corrects only 10-25% of the predicted forecast
error. I finally check the relationship between the same public signal realizations with the difference
between the Fed’s real activity forecasts in the Greenbook with the Blue Chip forecasts. I find that
predictable surprise tightening correlates with the Fed’s being systematically more optimistic than

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²I conduct robustness checks with expectations of individual interest rates.
³When the regressor is re-scaled to predict one basis point of surprise monetary tightening, it correlates with a 15.3
basis point over-estimate of average unemployment over the next 3 quarters and 28.3 basis point under-estimate of average
annualized growth over the same.
markets, with a magnitude equal to 30-70% of the aforementioned forecast errors depending on variable and horizon.\(^4\)

The previously described under-reaction and delayed learning may remind of the argument by Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) that the coincidence of surprise monetary tightening and positive updates to employment forecasts implies a persuasion channel of monetary policy. I return to my model to show how either non-Bayesian mechanism breaks the connection between this correlation and the model-consistent definition of persuasion, and how controlling for public signals removes this bias. In the data, I find that the model-consistent estimation of the Fed information effect is positive but statistically indistinguishable from zero. This result illustrates how slow learning and “agreeing to disagree” can be appear like persuasion without more model structure.

**Quantification and Interpretation.** I finally fit the model to the empirical estimates via method-of-moments to quantify each mechanism’s importance via explore counterfactual experiments. In the empirically calibrated model, the Fed’s private information is two orders of magnitude less precise than public information. An immediate implication of the previous is that the implied information effects of persuasion through actions are quantitatively minuscule. I formalize this by showing that, if the Fed’s private signal is completely 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 shared the market’s (under-) confidence in public data, the sensitivity of the latter’s post-announcement beliefs to fundamentals would increase by 25%. The ratio of this 25% change to the aforementioned 0.5% change implies that, in normalized units, disagreement is about 47 times (up to rounding) more important than signaling.\(^5\)

Two additional exercises corroborate and contextualize the quantitative model’s story. First, policy deliberations at the onset of the 2001 recession provide a revealing case study of how the Fed and markets can see the same data very differently. Second, a semi-structural VAR model identified by the theory shows that disagreement consistently arises in response to a demand shock that explains 40% of all variation in nominal Treasury rates and sizable portions of variation in unemployment, consumption, and consumer prices. Thus disagreement about one of the most important shocks of the business cycle occurs in spite of Fed’s ostensible transparency about its actions and motives.

**Other Related Literature.** The idea that central banks and markets are engaged in an informational tug-of-war has inspired considerable research in macroeconomics and finance. A specific literature starting from Morris and Shin (2002) has studied communication and persuasion in Bayesian, rational-

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\(^4\) In response to these shocks, the Fed’s forecast is more “accurate” or has smaller predictable errors. This “conditional accuracy” is a different moment than the “unconditional accuracy” (e.g., forecast error variance) measured by Romer and Romer (2000) or Bauer and Swanson (2020).

\(^5\) I find a similar magnitude if I consider the “agreement” counterfactual with the market sharing the Fed’s viewpoint: market beliefs move 20% more or 37 times more than in the case shutting off the information effect.

A recent literature studies the informational effects of surprise central bank actions via models of asymmetric information (Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018). Melosi (2016) presents a related model of monetary signaling using different data on expectations inertia. A variety of other studies using the monetary surprises data mostly view their results through the prism of a rational-expectations, asymmetric-information model (e.g., Kuttner, 2001; Bernanke and Kuttner, 2005; Gürkaynak, Sack, and Swanson, 2005). This paper suggests an alternative interpretation for many of these results, which de-emphasizes asymmetric information and prioritizes instead different interpretation of common information.

This paper’s empirical findings regarding how omitted variables explain monetary surprises and forecast revisions confirm and complement those in studies by Miranda-Agrippino (2015), Miranda-Agrippino and Ricco (2021), Cieslak (2018), Bauer and Swanson (2020), and Karnaukh (2019). The first four focus on statistical releases. Bauer and Swanson (2020) also include original survey and anecdotal evidence that market professionals are very confident in their economic assessments, and mainly interpret their findings in terms of market mis-estimation of the monetary rule. Karnaukh (2019) shows that Blue Chip output growth forecasts predict monetary surprises. This paper investigates more closely what departure from the full-information, rational-expectations benchmark best explains the empirical patterns, and how identifying the “correct” model matters for counterfactual analysis.

Finally, recent work on modeling expectations emphasizes the importance of subjective modeling errors to explain the data (Bordalo, Gennaioli, Ma, and Shleifer, 2020; Broer and Kohlhas, 2018; Angeletos, Huo, and Sastry, 2021). This paper shows how heterogeneity in biases across groups (e.g., market professionals versus Fed economists) leads to a particular, consequential form of disagreement.

Outline. Section 2 describes the organizing theoretical framework. Section 3 describes the data. Section 4 presents the main empirical results. Section 5 provides additional theory and evidence regarding the Fed information effect, or signaling via actions. Section 6 presents a quantification of the model and explores counterfactual scenarios. Section 7 reviews additional evidence corroborating the model mechanism. And Section 8 concludes.


7An exception is Bernanke and Kuttner’s (2005) observation that mean reversion in the stock market response to monetary surprises resembles a pattern of over-reaction and correction. This paper’s findings would rationalize over-reaction in a heterogeneous priors story: markets predictably under-estimate one component of the business cycle and the monetary response, and delayed movements in stock prices reflect delayed learning about fundamentals.
2. Model

In this section, I embed three mechanisms for disagreement between central banks and markets—asymmetric information, asymmetric beliefs about the policy rule, and asymmetric confidence in public information—in a model and contrast their predictions for measurable moments of beliefs. The goal of the model is to derive a series of simple empirical tests to guide joint identification of the three mechanisms in the data.

2.1 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, we use the notation \( \mathbb{E}_{X,t}[Y] \) to denote the expectation of agent \( X \in \{F, M\} \) at time \( t \) of a random variable \( Y \).

At \( t = 0 \), the Fed sets the (real) interest rate \( r \) equal to its expectation of the shock. That is, \( r = \mathbb{E}_{F,0}[\theta] \). 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 \( \varepsilon_z \sim N(0, \tau_{\varepsilon_z}^{-1}) \) and \( \varepsilon_F \sim N(0, \tau_{\varepsilon_F}^{-1}) \) are independent from each other and all other variables. The public signal may represent the statistical releases, opinion aggregators, and asset prices that are forward-looking indicators of the business cycle, while the private signal may represent the Federal Reserve Board’s internal research.\(^8\)

The Market also predicts the monetary policy action at \( t = 0 \). The prediction \( P \) equals the market’s belief of interest rates at \( t = 0 \), 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.\(^9\)

The interest rate is revealed at \( t = 1 \). I define the error or revision in the market prediction as \( \Delta = r - P \). Given again that the interest rate is a forecast of \( \theta \), \( \Delta \) is a Market error in forecasting the Fed’s belief about fundamentals.

At \( t = 2 \), everyone observes an additional public signal \( S = \theta + \varepsilon_S \) with independent noise \( \varepsilon_S \sim N(0, \tau_{\varepsilon_S}^{-1}) \). 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 monetary policy does not over-stabilize the business cycle in expectation. All the aforementioned timing is summarized in Figure 1.

Micro-foundations. I abstract from detailed derivations of these model equations to keep the analysis concise, but provide more detail in OnlineAppendix B. First, Appendix B.1 derives the expressions for \( r \) and \( Y \) in a simple, rigid-price New Keynesian model. The fundamental \( \theta \) is a consumer discount-rate shock; \( Y \) and \( r \) are respectively percent deviations from steady-state for employment (or output)

\(^8\)This research may include non-public statistical releases or the qualitative data incorporated in the Beige Book. It may also include “expertise,” as highlighted by both Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018).

\(^9\)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 \( Z \).
and interest rates. The monetary rule stabilizes, in expectation, fraction $1/a \leq 1$ of the shock. 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.\(^\text{10}\) This admits a model-consistent interpretation of $P$ as the (re-scaled) price of an interest rate futures contract and $\Delta$ as the revision in that price as a result of a monetary policy announcement.

### 2.2 Beliefs

I now complete the model by describing the mapping from sources of information to beliefs.

The Fed uses Bayes rule to form its beliefs, but subject to a potentially mis-specified notion of the news content of public signals. In particular, I assume the Fed’s posterior expectation about $\theta$ at $t = 0$, which is also its policy action, is the following

$$E_{F,0}[\theta] = \delta^F_F (\delta^F_Z - q^F)Z$$

where $\delta^F_F := \frac{\tau_F}{\tau_F + \tau_Z + \tau_0}$ and $\delta^F_Z := \frac{\tau_Z}{\tau_F + \tau_Z + \tau_0}$ are the appropriate objective precision weights and $q^F$ is an additive “distortion” relative to the latter precision weight.\(^\text{11}\) 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 $\tau_Z - q^F (\tau_Z + \tau_F + \tau_0)$ and the precision of the fundamental to be $\tau_0 + q^F (\tau_Z + \tau_F + \tau_0)$.\(^\text{12}\) As will become clear, allowing $q^F \neq 0$ affords flexibility in matching the observed reaction of monetary policy to news but is not crucial for either of the main results.

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\(^\text{10}\)The Gaussianity of beliefs will be verified in due course. The assumption of a representative market corresponds to each agent having an identical subjective belief operator.

\(^\text{11}\)I have also used the conjecture (which will be verified) that the futures price contains no information about $\theta$ that is not already spanned by $Z$.

\(^\text{12}\)These “compensating errors” in the total precision $\tau_0 + \tau_Z + \tau_F$ are convenient for deriving analytical results, though not essential for the main conclusions.
The market applies Bayes rule subject to two deviations in modeling the economic environment. The first is analogous to the Fed’s: each market participant may over- or under-weight the importance of the public signal for fundamentals. In particular, the Market’s fundamental belief at $t = 0$ is

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

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.

Second, the market may mis-specify the weight on $Z$ in the policy rule. Market beliefs about $r$ are

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

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 $\theta$. Such a friction may be justified by having the Market attribute under- or over-reaction to the Fed (depending on the value of $q^{F} + w$). It may also reflect, in reduced form, difficulty in learning the monetary rule.

To summarize, the model accommodates disagreement between the Market and Fed along three dimensions. The first is the Fed’s private signal $F$, or asymmetric information. The second is the Market’s mis-perception $-wZ$ for the monetary rule, or forecasting with an incorrect model equation. The third is the Market’s and Fed’s potentially different confidence in the public signal as captured by $q$ and $q^{F}$, or heterogeneous priors after the public signal is realized.

### 2.3 Result: Predicting Monetary Surprises

I now explore 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). This gives

$$
\Delta = \delta_{F}^{r} \left( F - \mathbb{E}_{M,0}^{R}[\theta] \right) + \delta_{F}^{r} q Z + w Z
$$

where I have defined $\mathbb{E}_{M,0}^{R}[\theta] := \delta_{Z}^{M} Z$ is the rational Bayesian expectation of $\theta$.

The first term in (4) is the error the Market would make with an “objectively optimal” (lowest mean-squared-error) guess of the Fed’s internal information. This term cannot be predicted by $Z$, which is fully incorporated into $\mathbb{E}_{M,0}^{R}[\theta]$. The second term is the bias in the Market forecast of $F$, grounded in its biased forecast of $\theta$. The third term is the mistake due to mis-estimating the Fed’s
response to Z. The Fed’s information-use distortion $q^F$ does not show up in (4), 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 $\Delta$ and $Z$, or component of monetary surprises that may be predicted by public data:

**Proposition 1 (Monetary Surprises and Public Signals).** The following three properties hold for $\text{Cov}[\Delta, Z]$:

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

The proof in the Appendix A is a step-by-step derivation of (4) and the informal argument above.

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 behavioral biases 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 no unambiguous 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 representative public signals and changes in the market forecasts about monetary policy around FOMC meetings embedded in interest rate futures prices (e.g., as pioneered by Kuttner, 2001). But, by itself, it is not a powerful test for determining the “right” model for disagreement 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 one’s prediction for real outcomes.

I first state my main 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:

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13The literal translation from forecast error to forecast revision requires only the re-interpretation of $r$ as an announced future path of policy rather than an interest rate that “immediately” goes into effect.
Proposition 2 (Forecast Errors and Revisions). The following properties hold:

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

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

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

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 them.

The proof of Proposition 2 in Appendix A verifies the results via direct calculations. Here, I provide a proof sketch which fully details the argument for the Market’s forecast error at \( t = 0 \) and sketch, via examples, the logic of the additional results.

2.4.1 Forecast Errors at \( t = 0 \): A Direct Calculation

The Market’s forecast error \( t = 0 \) is a linear combination of forecast errors about fundamentals and about 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:

\[
Y - \mathbb{E}_{0,M}[Y] = \left( a - \delta_{F}^{x} \right) \left( \theta - \mathbb{E}_{M,0}^{R} [\theta] \right) + \delta_{F}^{x} \varepsilon_{F} - wZ + \left( a - \delta_{F}^{x} \right) qZ
\]  

(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” \( Z < 0 \) contributes 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 \( \delta_{F}^{x} \)). Under the stated conditions \( a \geq 1 > \delta_{F}^{x} \), which correspond to the Fed’s not over-stabilizing the business cycle and the Fed’s not perfectly knowing \( \theta \), this term has the same sign as \( qZ \). To illustrate, \( q > 0 \) and the same “bad news” \( Z < 0 \) contributes to under-estimating output.

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

To illustrate Proposition 2’s additional results, it is easiest to sketch two extreme cases which isolate each friction. The mathematical arguments in Appendix A make these arguments “continuous” as a function of parameters $w$ and $q$ to derive the corresponding components of Proposition 2.

In the first case, we 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 $F_{CE}$). 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 hinted at an identification strategy for $(q, w)$, which I now make more explicit. Define the “regression coefficients” of $Z$ on monetary surprises and forecasts errors as, respectively,

$$b^\Lambda := \frac{\mathbb{E}[\Lambda, Z]}{\text{Var}[Z]} = \delta_F^F q + w$$

$$b_{FCE} := \frac{\mathbb{E}[Y - \mathbb{E}_0, M[Y], Z]}{\text{Var}[Z]} = (a - \delta_F^F) q - w$$

(6)
Conditional on knowing $a$, the slope of output in $\theta$, and $\delta_F^F$, the relative precision of the Fed’s information, the following inverse mapping recovers $q$ and $w$:

$$
q = \frac{1}{a} \left( b^{\text{FCE}} + b^\Delta \right) \quad \text{and} \quad w = b^\Delta - \frac{\delta_F^F}{a} \left( b^{\text{FCE}} + b^\Delta \right)
$$

(7)

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

This process is visualized in Figure 2, a version of which illustrates the sign cases for $(q, w)$ as a function of $(b^\Delta, b^{\text{FCE}})$. One could determine a “best-fit, one-friction model” by merely identifying a quadrant of Figure 2, 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 exercis could jointly identify $(q, w)$ using the point estimates of $(b^\Delta, b^{\text{FCE}})$, and moreover use additional informative moments to learn other relevant model parameters (e.g., $a$, $q^F$, $\tau_F$, $\tau_Z$, and $\tau_S$). I will pursue this in Section 6.

2.6 Remarks and Extensions

But before proceeding to the empirical analysis, I discuss a few relevant extensions of the model.

**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

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

(8)

where $\mathbb{E}^{R,F}_{F,0}[\theta] := \delta_F^F + \delta_Z^FZ$ is the Fed’s as-if rational expectation. Two remarks 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.\(^{15}\) Conditional on other measurements of the Market’s bias (for instance, based on the logic in Figure 2), 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, generally observed with significant 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 information $F$.\(^{16}\) Such regressions, while interesting to interpret in combination with the other moments discussed above, do not in isolation distinguish

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\(^{14}\)Analogous expressions can be derived at $t = 1$ and $t = 2$, but are omitted for brevity.

\(^{15}\)Observe that $\mathbb{E}^{R,F}_{F,0}[\theta] - \mathbb{E}^{R,M}_{M,0}[\theta]$ is orthogonal to $Z$ again based on an argument with the law of iterated expectations, conditioning down on the realization of $Z$.

\(^{16}\)This point relates to predictability tests using Fed forecasts discussed by Gertler and Karadi (2015) and Ramey (2016).
between mechanisms controlling disagreement.

**Belief Updates at \( t = 1 \).** Proposition 2 did not sign belief updates at \( t = 1 \), or the Fed’s signaling through actions. This is due to the fact that the monetary announcements jointly reveal information about fundamentals and policy, as is commonly observed on the literature on monetary signaling. Nonetheless, the model can be used to provide a structural decomposition of information effects in the presence of the two behavioral biases and, in particular, clarify whether correlations of belief updates and monetary news really map to “persuasion.” I return to this topic in Section 5.

**Fed Reaction to Market Expectations.** Both Propositions 1 and 2 would hold as stated in a variant model in which the Fed responded directly to the market’s expectations of \( r, \theta, \) or \( Y \), as might be natural in a richer model of the term structure of interest rates, the Keynesian cross, and/or optimal dynamic policy with some notion of “credibility”. The reason is that each of these objects is spanned by \( Z \), and the exact loading on \( Z \) was not relevant in either proof.

### 3. Data and Descriptives

#### 3.1 Monetary Surprises

I use data on interest rate surprises from Nakamura and Steinsson (2018). These data cover January 1995 to April 2014.\(^7\) 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 announcement (10 minutes before and 20 minutes after).\(^8\)

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.\(^9\) Finally, the policy news

\(^7\)Unlike Nakamura and Steinsson (2018), I do not exclude 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.

\(^8\)See Appendix A of Nakamura and Steinsson (2018) for the details for data construction.

\(^9\)See also a related argument in Section I.F of Bernanke and Kuttner (2005) that shocks to the “level” of Fed policy captured in longer-horizon expectations, rather than the “timing” of short-rate changes, may be more macroeconomically

13
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 Public Signals

I focus on a subset of public signals which are forward-looking opinion aggregators and the consequently easiest to interpret as leading indicators of demand shocks and the business cycle.\(^2\) I consider four main such indicators reviewed below.

**Consumer sentiment about economic performance.** These data are taken from the Michigan Survey of Consumers, which is administered monthly to a nationally representative sample of 500 individuals via telephone every month. Appendix D.1 prints the exact questions and answers that are used in the analysis. All aggregate measures are survey-weighted averages. 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. The measure, which will be referred to as “unemployment sentiment” throughout the paper, is the difference between the fraction who believe unemployment will go down (the positive response) versus the fraction who believe unemployment will go up.

I focus on sentiment for two related reasons. First, empirical research corroborates that the Michigan survey provides forward-looking information particularly about consumption and spending (Carroll, Fuhrer, and Wilcox, 1994; Barsky, Basu, and Lee, 2015).\(^1\) Second anecdotal evidence about policymaking, including the FOMC transcripts reviewed in Section 7.1, suggest 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 because it has the clearest interpretation for assessing labor market conditions, as is relevant in the model.\(^2\) Tellingly, in the case study of Section 7.1, it is also singled out by Fed economists as a particularly useful indicator.

**Professional forecasts of future economic activity.** These data are from the Blue Chip Economic Indicators Survey, which 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.\(^3\) The analysis focuses on the consensus forecasts for unemployment and real GDP growth. The BCEI forecast for month \(t\) is conducted in the first week of that month, informative.

\(^2\)Of course, in economic models, all economic actions are necessarily functions of the beliefs of the agents who made them, and therefore would also count as public signals at this level of abstraction. I return to this point in Section 2.3.

\(^1\)Appendix Figure 9 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.

\(^3\)It also has very high correlation with other in-survey measures of economic optimism as well as the University of Michigan’s expectations and confidence indices (respectively, 0.45 and 0.46 on my sample).

\(^2\)This quotation is taken from the landing page: https://lrus.wolterskluwer.com/store/blue-chip-publications/.
Recent returns of the S&P 500. This analysis uses closing prices of the S&P500 at the monthly frequency. Previous research has suggested that recent stock returns are a major determinant of policy in the modern era (Cieslak and Vissing-Jorgensen, 2018).

Public sentiment about stock performance. These data are taken from the weekly survey of the American Association of Individual Investors, aggregated to a monthly average when appropriate. This metric captures the sentiment of small-scale investors about future stock returns. 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 fraction of Bullish and Bearish respondents (i.e., in analogy to the similar diffusion measure of unemployment sentiment from the Michigan survey). Greenwood and Shleifer (2014) show that the AAII results are a statistical predictor of future excess returns.

4. MAIN EMPIRICAL RESULTS

In this section, I present my main empirical results. I first establish 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, via the “sign test” logic of the model, these results identify market under-response to public signals as the quantitatively most important driver of imperfect expectations.

4.1 Predicting Monetary Surprises

I first study the predictability of monetary surprises by public signals. I estimate the following univariate regression models relating the monetary surprise $\Delta_t$ with the previous-month realizations of each predictor $X_{t-1}$:

$$\Delta_t = \beta X \cdot X_{t-1} + \epsilon_t$$

The variables are normalized, in sample, to have zero mean and unit standard deviation. This allows easy comparability of coefficient magnitudes across measures. The units of $\Delta_t$ are such that

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24The newsletter also contains individual forecasts for variables related to, but not exactly the same as, the ones I study, like average growth rates or unemployment rates for the next calendar year.


26The de-meaning also removes the requirement for a constant in the regression.
Figure 3: Predicting Monetary Surprises.
Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). 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.

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 $\beta_X$ are of a one-standard-deviation outcome on percentage points for interest rates. The sample consists of 153 scheduled FOMC meetings.

A value of $\beta_X \neq 0$ implies statistical predictability of monetary surprises and hence a rejection of the rational model as per Proposition 1f. $\beta_X > 0$ implies that positive values of the predictors correlate with unexpected monetary tightening. Insofar as each $X$ is normalized to be unconditional “good news” about the economy, like the public signal $Z$ in the model, this prediction would be implied by case 2 in Proposition 1. The complementary possibility $\beta_X < 0$ would be implied by case 3.

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 prior to the announcement.

Figure 3 shows the estimates of $\beta_X$ 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.

Before proceeding to the rest of the empirical analysis, I review a number of extensions and robustness checks of this result.

Timing. An additional dimension of interest, not explored in specification (9), is timing. The theoretical predictions hold for any signals realized before the FOMC meeting and ideally give
consistent results for different choices of lags before the meeting. Appendix D.2 explores this at the monthly frequency for the Michigan sentiment measure and the weekly frequency for the AAII survey, and confirms that (i) information older than one month prior can also predict monetary surprises but (ii) the largest effects are concentrated at the one-month lag.

**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. The following model provides an empirical horse race of the survey and market variables $X_t$ against other possible predictors $W_{t-1}$:

$$
\Delta_t = \alpha + \beta_M \cdot X_{t-1} + W'_{t-1} \Sigma + \epsilon_t
$$

(10)

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 4 shows estimates of (10) 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. 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. These patterns, together, build confidence that the empirical results in this section are both consistent with the literature and representative of an important, complementary channel of predictability.

**Different sample periods.** Appendix Figure 13 re-estimates the main specification (9) excluding data including and after 2008. This eliminates the Great Recession as well as the lengthy spell at the zero lower bound, at which we may expect the mechanics of forward guidance and monetary policy to operate much differently. The coefficient estimates are very stable for each predictor.

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27 An important exception to this in the literature is Karnaukh (2019) who studies the predictive power of consensus Blue Chip forecasts, which was one of the baseline predictors in this paper.

28 Results are very similar if instead of using employment growth in months $t-1$ and $t-2$, we use 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.

29 The multivariate VAR analysis in Section 7.2 reveals similar patterns: while economic activity does seem to move before predictable surprises, by far the quantitatively larger and more striking patterns involve changes in beliefs and stock prices.
To zoom in either further on sub-sample robustness, Appendix Figure 14 re-estimates (9) for unemployment sentiment from the Michigan survey using windows of observations within the last 48 months (4 years). The prediction is the strongest in the early and late 2000s owing to the respective recessions and rate cuts. But it is positive for almost the entire sample, excepting the much more recent experience at or near the ZLB.

**Different surprise measures.** Appendix Figure 11 recreates the analysis of Figure 3 for three individual futures contracts which are notable 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. Such results suggest that the forecasting biases identified in this paper are most relevant for the “level” instead of the “timing” of monetary policy, to use the language of Bernanke and Kuttner (2005).

**Individual events.** Appendix Figure 12 shows the scatterplot of monetary surprises against realizations of the previous month’s unemployment sentiment. At a glance, and in corroboration of the rolling regression results, the aforementioned recessions provide influential observations for fitting the trend. In Section 7.1 I will provide a more detailed case-study of rate cuts in 2001, which is a salient example.

**Pseudo-out-of-sample forecasting.** Appendix D.3 explores a pseudo-out-of-sample forecasting exercise for each of the four main predictors, to explore how relevant these results are as a real-time “market failure.” Unsurprisingly the predictive power for each variable is quite a bit lower, though for the key unemployment sentiment variable it remains positive. I calculate also a feasible, pseudo-out-of-sample Sharpe Ratio for portfolios that invest based on the predicted sign of policy news. These are all positive but reasonably low, between 0.15 and 0.30, reflecting the substantial risk attached to exploiting this trade. This builds confidence both that the observed market failures are not extreme, while the patterns of interest are robust. The latter is ultimately more relevant to the paper’s stated goals, which are to explain average imperfections in market and central-bank beliefs and not to shed light on “market failures” *per se*.

### 4.2 Predicting Forecast Errors

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 $\tilde{X}_{t-1}$:

$$\Delta_t = \alpha + \tilde{X}_{t-1}' \Gamma + \epsilon_t$$

(11)
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 and could plausibly be incorporated into any forecast made at time \( t \); together, they explain 14.8% of the variation in the monetary surprise. I take estimates of (11) over the entire sample and construct fitted values \( \hat{Z}_{t-1} = \hat{\alpha} + \hat{X}'_{t-1} \hat{\Gamma} \), an empirical estimate of the model’s public signal, and residuals \( \hat{\Delta}_{t} \), 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 \( \hat{\Delta}_{t} \) 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; and final-release macro data. The full sample consists of 288 months.

I estimate the following empirical model:

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

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. A complementary interpretation of the same regression equation, relative to the literature on measuring information frictions via the dynamics of professionals’ forecast errors, is that \( \beta^{FCE} > 0 \) and \( \beta^{FCE} < 0 \) correspond to the aggregate under- and over- reaction to shocks that have been variously documented in modern US data depending on the driving shock process and horizon (see, e.g., Broer and Kohlhas, 2018; Angeletos, Huo, and Sastry, 2021).

Figure 4 plots the estimates of \( \beta^{FCE} \), with 90% and 95% confidence interval bars, for each variable and horizons. 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.

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30Note that, according to the results of Appendix D.2, there is predictive power in both the level and growth rate of lagged sentiment. This motivates the empirical specification that flexibly includes both, instead of restricting the coefficients to enter via their difference. The coefficient estimates are 0.18 (SE: 0.05) on the first lag and -0.11 (SE: 0.04) on the second lag. The estimate for the sum of coefficients is 0.08 (SE: 0.02), validating the approach.

31To 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. The full SVAR analysis of Section 7.2, which will flexibly allow for both sentiment variables and a variety of real and nominal outcomes to predict monetary surprises at any lag, gives a comparable extent of prediction.

32Note that this regression does not require restricting the analysis to overlap with the availability of the monetary surprise data. Adding such a restriction, which reduces the sample size, does not meaningfully change the quantitative findings.

33Observe that these predictions in the model are robust to when forecasts are made relative to Fed announcements.
Figure 4: Market Forecast Errors and Public Signals.
Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (12), 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.

\( (p\text{-value less than } 5\%) \) 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.

For unemployment, in particular, the magnitudes are large. The median absolute error over the sample period is 27 basis points, while a one-standard-deviation variation in \( \hat{Z} \) (1.46 basis points) correlates according to (12) with a 22.4 basis-point error. The predictive \( R^2 \) is correspondingly quite large (23%).

Four additional results, printed in the Appendix, probe robustness. Appendix Figure 15 re-creates Figure 4 for two different outcomes, the growth rate of personal consumption expenditures (PCE) and predictions for the three-month Treasury rate. In both cases, we find a similar sign pattern. The result for PCE provides robustness for the main test of Proposition 2, while the result for Treasury rates provides a corroboratation of the main findings of Section 2.3 without relying on market-derived expectations. Appendix Figure 16 re-creates Figure 4 using first-release macro data, as is often common in the literature assessing forecast efficiency.\(^{34}\) It shows broadly similar patterns, although they are much noisier when output growth is the outcome. These results are interesting for assessing the “real time feedback” regarding forecasting errors, but to be clear are not necessarily the most relevant in terms of assessing the underlying economic theory.

Appendix Figure 17 re-creates Figure 4, 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 \( \beta_{PCE} \) reveal that the highlighted bias is present across the entire distribution.

Finally, Appendix Figure 18 shows rolling regressions using the last 48 months (4 years) of data separately for this quarters’ unemployment rate and the (nine months prior) three-quarter ahead forecast from the Blue Chip survey on \( \hat{Z}_{t-9} \), the public signal available just before that forecast. It

\(^{34}\)See, for instance, discussion in Bordalo, Gennaioli, Ma, and Shleifer (2020) and Angeletos, Huo, and Sastry (2021).
Figure 5: Post-Announcement Forecast Revisions and Public Signals. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (13). The units for the coefficients are basis points of forecast revision per basis point of expected monetary surprise.

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.\(^{35}\)

4.3 Predicting Post-Announcement Drift

The second test documented in Proposition 2 concerns forecast updates after the monetary announcement. To implement it, I take the revision in the consensus Blue Chip forecast (again, about real GDP or real PCE growth, at various horizons) 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:

\[
E_{B,t+2}[Y_{q(t+1)+h}] - E_{B,t+1}[Y_{q(t+1)+h}] = \alpha + \beta^{Dr} \cdot \hat{Z}_{t-1} + \epsilon_t \tag{13}
\]

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 \( t + 2 \), well after the monetary announcement. The prediction \( \beta^{Dr} > 0 \), according to Proposition 2, corresponds with under-estimating the predictive value of the public signals; the prediction \( \beta^{Dr} < 0 \) corresponds with under-estimating the monetary authority’s reliance on the public signal, and hence over-reacting to the public signal’s realization. Regression (13), apart from its justification in the theory, is also a good empirical complement to the earlier test of forecast errors because it does not require any data on final outcomes—it

\(^{35}\)The last can be read either as evidence of learning over time (especially for correcting large errors during the Great Recession) or a discontinuity in results when policy at the Zero Lower Bound begins to dominate the estimation sample. Either possibility is quite interesting, though outside the scope of the present analysis.
merely checks whether forecasters predictably change their mind more than a month after certain data is released.

Figure 5 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.

Appendix D.4 outlines an additional model test based on the drift of stock prices after high realizations of $\hat{Z}_{t-1}$ (as well as $\hat{\Delta}^⊥$). 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 private signals) is being revealed that corrects the public’s original mis-assessment of the economy. This result resembles, at a much shorter time horizon, an important result in Bernanke and Kuttner (2005) of delayed positive expected returns in the response to surprise monetary tightening.

4.4 Fed Forecasts and Measured Disagreement

The bias in the Fed’s forecast was inessential to the model’s predictions in Proposition 2 mapping biases to predictions for forecast errors and revisions. Nonetheless, it is important to quantify this bias to directly check to what extent, if at all, the market’s bias in forecasting fundamentals generates predictable disagreement with the Fed.

I collect Greenbook forecasts for all months from 1995 to 2012, taking the first prediction made in the month when there are multiple, and sub-setting 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 (12) using Greenbook forecast errors as the
Figure 7: **Forecast Disagreements and Public Signals.**

Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (14). The units for the coefficients are basis points of forecast disagreement per basis point of expected monetary surprise.

outcome. Figure 6 shows the results. The point estimates for unemployment are significantly positive, but smaller than their counterparts in Figure 4; those for real GDP growth are mostly positive but statistically insignificant. By a logic similar to the one underpinning Proposition 2, with the obvious adjustment that the Fed knows its own monetary rule, 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:

\[
E_{G,t}[Y_{Q(t)+h}] - E_{B,t}[Y_{Q(t)+h}] = \alpha + \beta^{Di} \cdot Z_{t-1} + \epsilon_t \tag{14}
\]

This regression operationalizes Equation 8 and the subsequent discussion in Section 2. Relative to the literature, it relates first to studies by Carroll (2003) and Coibion and Gorodnichenko (2012) on the heterogeneity in forecasting biases across groups. And it contrasts with the approach of Romer and Romer (2000) and Bauer and Swanson (2020), who test for asymmetry in Fed and Market forecasts by comparing their unconditional accuracy instead of their response to specific shocks. Figure 7 confirms that \( \beta^{Di} > 0 \), and that these estimates are highly statistically significant for both variables and at all horizons. Moreover, the constructed public signal proxy, by itself, explains 10% and 26% of all variation in disagreement between the Blue Chip forecasters and the Fed about unemployment or growth, depending on specification. This builds confidence that markets under-react to the fundamental content of news relative to the Fed.
5. ADDITIONAL RESULTS: THE INFORMATION EFFECT

The empirical evidence in the last section, taken together, points toward inertial response to news among market participants contrasted with quicker uptake of news by the Fed. But it did not directly address a question which has animated a recent literature on monetary policy communication: does the Fed’s assessment of the economy, revealed via policy choices and/or communication, cause large changes in markets’ beliefs about fundamentals?

I first revisit the model from Section 2 to characterize such persuasion effects. I show that the main informative observable moment that Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) take as informative about these effects could be biased upward or downward relative to its “true” model counterpart in the presence of the non-Bayesian mechanisms, and that an unbiased estimate can be recovered by controlling for the realizations of public signals. I next show that, in the data, the former case is the relevant one: controlling for the realizations of public signals reduces the measured information effect to a much lower level which is statistically indistinguishable from zero. The model interpretation is that the market’s sluggish correction of an original mistake in forecasting both fundamentals and policy masquerades as the Fed’s signaling through actions.

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

\[
   i := \frac{\text{Cov} [\Delta, E_{M,1}[Y] - E_{M,0}[Y]]}{\text{Var} [\Delta]}
\]

(15)

Note that this moment combines revelation of the interest rate \( r \) with indirect signaling about the fundamental \( \theta \), or the Fed’s assessment thereof. This tension for monetary communication is front-and-center in the literature on monetary signaling: aggressive central bank response to shocks can backfire by alerting the public to the severity of those shocks.\(^{36}\)

The moment which Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) take as informative about the previous phenomenon, and appropriate translations of model object \( i \), is the covariance of monetary surprises \( \Delta \) 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 nested in the model

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\(^{36}\)For theoretical analysis of these issues, see, for instance: James and Lawler (2011); Baeriswyl and Cornand (2010); Campbell, Evans, Fisher, and Justiniano (2012); Melosi (2016); Nakamura and Steinsson (2018).
as the forecast revision from $t = 0$ to $t = 2$. The following Corollary emphasizes that this covariance does correspond with $i$ only in the 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

$$i^F := \frac{\text{Cov} [\Delta, E_{M,2}[Y] - E_{M,0}[Y]]}{\text{Var}[\Delta]} \tag{16}$$

be an estimator of the information effect defined in (15). 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 $\text{Cov} [\Delta, Z] > 0$, then $B \geq 0$.
3. If $w \geq 0$, $q \leq 0$, and $\text{Cov} [\Delta, Z] > 0$, then $B \leq 0$.

The bias, as illustrated in the proof in Appendix A, is directly proportional to the covariance between $\Delta$ and the forecast revision from period 1 to period 2. In the rational model, this covariance is zero because the information in $\Delta$ 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 $\Delta$ 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 2.3.

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.\(^{37}\)

A fortunate implication of the model, however, is that the bias term is entirely spanned by $Z$ and therefore may be purged by direct 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 $\Delta$ can be written as $\Delta = \Delta^\perp + (q^F + w)Z$, where $\text{Cov} [\Delta^\perp, Z] = 0$. Moreover, the population estimator

$$i^\perp = \frac{\text{Cov} [\Delta^\perp, E_{M,2}[Y] - E_{M,0}[Y]]}{\text{Var}[\Delta^\perp]} \tag{17}$$

corresponds with the true information effect $i$.

\(^{37}\)This case is the one prioritized by Bauer and Swanson (2020) in their interpretation of related empirical results.
**Figure 8:** Cross-Meeting Forecast Revisions and Monetary Surprises.
Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (18). The units for the coefficients are basis points of forecast revision per basis point of (expected or unexpected) monetary surprise.

### 5.2 In the Data

We 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:

$$E_{B,t+1}[Y_{Q(t)+h}] - E_{B,t}[Y_{Q(t)+h}] = \alpha + \beta^Z \cdot \hat{Z}_{t-1} + \beta^\Delta \cdot \hat{A}^\perp_t + \epsilon_t \quad (18)$$

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 $\beta^\Delta$ is an unbiased estimate of $i$ as per Corollary 2.

Figure 8 shows the results. 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, to use the language from the previous subsection. Second, there is limited statistical evidence across variables and horizons of $\beta^\Delta > 0$, although point estimates are uniformly positive. In particular, estimates with unemployment forecasts as the outcome are uniformly insignificant and estimates with GDP forecasts as the outcome are significant only at the shortest forecast horizon.

### 6. Quantification and Counterfactuals

I now synthesize the empirical findings by fitting the model of Section 2 to the measured moments. This allows precise quantification of the relative strength of each of the three main mechanisms...
(asymmetric information, asymmetric beliefs about the policy rule, and asymmetric response to public information). I then use the calibrated model to explore informative counterfactual scenarios.

### 6.1 Methods and Results

To do so, I commit to following mapping of the theory to the data. The unconditional forecast error regression (12), which for the purposes of sign predictions we could treat as a prediction at any \( t \in \{0, 1, 2\} \), corresponds to \( t = 0 \) in the model; the monetary announcement is \( t = 1 \); and the beginning of the next month corresponds to \( t = 2 \).

The model has seven parameters, listed in Table 1. I target seven moments. Six are described and reported above: the \( R^2 \) of predicting monetary surprises with \( \hat{Z}_t \); the coefficient and \( R^2 \) of regressing \( \hat{Z}_t \) on market forecast errors (Figure 4); the coefficient of regressing the same on Greenbook forecast errors (Figure 6); and the coefficients of regressing \( (\hat{Z}_t, \hat{\Delta}_t) \) on forecast revisions (Figure 8). The last is the regression coefficient of \( \hat{Z}_{t-1} \) on the outcome, or a regression estimator of \( \beta^Y \) in

\[
Y_{Q(t)+h} = \alpha + \beta^Y \cdot \hat{Z}_{t-1} + \epsilon_t
\]

This helps evaluate the predictive power of the public signal for the relevant outcome, or “unpack” the separate effects on forecasts and outcomes when combined with the prediction of forecast errors.

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 formulas for each moment in terms of model parameters. The moments are fit exactly up to algorithmic precision.

The following three findings can be read directly from the parameter estimates. First, we observe \( q > w > 0 \) (i.e., the top-right region of Figure 2). In common units of “under-weighting,” the Market’s error in using the information embedded within the signal \( Z \) is much larger than its error in estimating

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Table 1: **Method of Moments Calibration.**

Parameters are fit to minimize the sum of squared deviations of model moments from targets.

<table>
<thead>
<tr>
<th>Moment</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ( R^2 ) from predicting surprises</td>
<td>0.15</td>
<td>( q )</td>
<td>0.121</td>
</tr>
<tr>
<td>2 ( \beta^{FCE} ) for BC</td>
<td>15.32</td>
<td>( q^F )</td>
<td>0.089</td>
</tr>
<tr>
<td>3 ( R^2 ) for FCE reg. (BC)</td>
<td>0.23</td>
<td>( w )</td>
<td>0.007</td>
</tr>
<tr>
<td>4 ( \beta^{FCE} ) for GB</td>
<td>12.06</td>
<td>( \tau_Z )</td>
<td>20.99</td>
</tr>
<tr>
<td>5 ( \beta^Z ) for BC Revisions</td>
<td>3.69</td>
<td>( \tau_F )</td>
<td>0.194</td>
</tr>
<tr>
<td>6 ( \beta^\Delta ) for BC Revisions</td>
<td>0.10</td>
<td>( \tau_S )</td>
<td>6.849</td>
</tr>
<tr>
<td>7 ( \beta^Y ) from (19)</td>
<td>22.69</td>
<td>( a )</td>
<td>1.100</td>
</tr>
</tbody>
</table>

---

38This 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 (two months after the monetary announcement).

39The remaining free parameter, the precision or variance of the fundamental, is normalized to one. This is a normalization with no bearing on the calibration.
the coefficient on $Z$ in the monetary rule. This confirms the intuition of the “sign test” interpretation of all the previous results while also accommodating an error in modeling the monetary rule.

Second, $q^F + w < q$. The market is correct that the Fed uses the signal $Z$ more than they do, but misses about $100 \cdot \frac{w}{q-q^F} = 22\%$ of this effect.

Finally, $(\tau_Z, \tau_S) \gg \tau_F$: 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 $\tau_F / (\tau_F + \tau_F + \tau_Z) = 0.01$, 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.

### 6.2 Counterfactual Scenarios

I now use the model to decompose forecast errors into different constituent frictions, and study how errors would change if specific frictions were shut down.

To this end, I conduct the following three counterfactual exercises that change the values of $(q, q^F, w)$, the three parameters controlling deviations from the Bayesian model. In the first scenario, which I call “agree to disagree,” the market makes no error in predicting the Fed’s use of information ($w = 0$) but both the market and Fed continue their (ex post mistaken) treatment of public information. The second and third models, respectively the “Fed’s viewpoint” and the “Market’s viewpoint,” has consensus about the policy rule ($w = 0$) and consensus about the use of information ($q = q^F$), at either the Fed’s or market’s level. The final scenario, “correct specification,” gives both the Fed and the market shuts down all mis-specification, or sets $q = q^F = q = 0$.

In each counterfactual, I focus on the change in the market’s and Fed’s beliefs using the following statistics from the model: the sensitivity of the market’s beliefs to fundamentals at $t = 0$ and $t = 2$, the sensitivity of interest rates to fundamentals, and the variance of market forecast errors regarding both output and interest rates at $t = 0$. In Appendix B.1.3, I show how market beliefs at $t = 2$ correspond to a notion of a “stock price” (i.e., expected value of dividend $Y$ discounted by rate $r$ and adjusted for a discount rate shock proportional to $\theta$). In this sense, changes in the sensitivity of $E_{M,2}[Y]$ to shocks can be read one-for-one as changes in the sensitivity of stock prices to shocks.

The results are summarized in the first four rows of Table 2. The 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 it removes a compensating error in the market’s reasoning. The second and third rows reveal the effects of harmonizing the Fed’s and Market’s models for how valuable is the public signal. Each counterfactual results in a remarkably similar increase in the sensitivity of beliefs to fundamentals (46% or 41% at $t = 0$, and 20% or 25% at $t = 2$), while only the former improves the accuracy of output forecasts. Finally, the fourth row reveals that removing biases entirely has the largest effects.
on improving forecast accuracy.\footnote{It turns out to have a limited impact on increasing the sensitivity of output to beliefs because of compensating forces—the public is much more alert to shocks, but the monetary authority is also much more aggressive in its response.}

The bottom line is that market and Fed disagreements about how to respond to public data have an outsize effect on market expectations relative even to the levels of these responses. The reason, illuminated through the model, is that these disagreements translate directly to the component of fundamental variation the markets do not expect the central bank to stabilize. Harmonizing the market’s and Fed’s model removes the former’s persistent belief that the latter is over-stabilizing the business cycle, either by increasing the Market’s perception of the demand shock (row 2) or decreasing the policy response to match the Market’s own viewpoint (row 3). Exactly which of the two scenarios is pursued matters comparatively little for the sensitivity of beliefs to outcomes, while it understandably matters more for the accuracy of forecasts.

The model’s low emphasis on Fed private information suggests a limited effect for the signaling channel of monetary policy. To make this clear, I consider a counterfactual exercise in which the Fed has vanishingly small internal information—neither does it lean on such information in its decision, nor does it reveal that information in its announcement.\footnote{Formally, as long as \( w \neq 0 \), the case with \( \tau_F = 0 \) is not well defined as the Market cannot rationalize any forecast error regarding policy. As such, I consider a limit as \( \tau_F \) gets arbitrarily small; but the core conclusion would be the same comparing a model with \( w = 0 \) and \( \tau_F \) with the counterfactual model with \( w = 0 \).} The fifth line of Table 2 reveals that this alteration has a very small effect on both the policy rule and the Market’s \( t = 2 \) 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 the information effect.

These numbers rule out large information effects, or causal effects of Fed persuasion on public beliefs and hence, in more sophisticated models that endogenize real outcomes as a function of beliefs, the transmission of business-cycle demand shocks. This is a more precise, within-model analogue to the discussion in Section 5 regarding the interpretation of monetary signaling in Campbell, Evans,
Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018). The difference in conclusions lies in this paper’s further investigation of predictability in forecast revisions and errors of both policy and outcomes, additional moments that are highly informative (as revealed in the model) about the precise distortion in market beliefs. These beliefs are by contrast essentially a free parameter in the main analysis of Nakamura and Steinsson (2018), who assume a very large information asymmetry in their illustrative counterfactual exercise. In my calibration, by contrast, model mis-specification is sufficient to drive quantitatively realistic patterns in disagreements, forecast errors, and forecast revisions without significant scope for asymmetric information.

7. Additional Evidence

In this final section, I review two supplemental sources of evidence for my main conclusions: a case study of the Fed’s early response to (what would become) the 2001 recession, and an SVAR analysis of what cross-variable patterns correlate with market-to-Fed disagreement.

7.1 A Case Study: Fed Policy in 2001

Here, 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. In this sense, the Fed’s concern about a specific type of forward-looking signal (sentiment indicators) was well telegraphed to the markets.

In 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. Mr. Slifman remarked directly that, among the Michigan survey indicators, “the one about unemployment expectations” consistently has the most predictive power. This is the most robustly predictive sentiment indicator in Section 2.3 and subsequent analysis. Philadelphia Fed President Anthony Santomero

42The authors, more specifically, assume the Fed has full information about the one-step-ahead innovation in productivity while the private sector, absent monetary signaling, erroneously assumes productivity is a random walk. See Section 6 of that paper (“The Causal Effect of Monetary Shocks”) for more discussion.
43Taken from the online archive of the Washington Post, accessible at https://www.washingtonpost.com/wp-srv/business/greenspan012501.htm.
Table 3: \textit{Sentiment, Beliefs, and Surprises in Early 2001.}

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 \textit{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. Markets had almost completely priced in the possibility of a rate cut 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. At the center of the disparity was, again, 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:

\begin{quote}
[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.
\end{quote}

The Fed ultimately adopted a pessimistic stance that surprised markets (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 more difficult to model) 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.” The real-time forecasting problem is, at least by the policymakers’ admission, exceptionally difficult and equally an art of prioritizing different narratives and data sources as a science of quantitatively incorporating that information in models. And regardless of whether the precise axis of disagreement regarding sentiment and aggregate demand is a generalizable feature beyond this studied case, the broader theme of evolution and disagreement in modeling “macro fundamentals” is potentially more permanent.

7.2 SVAR Analysis: What Shocks Drive Predictable Disagreement?

The previous subsection hinted that disagreement arises in response to quantitatively important fluctuations. In Online Appendix E, I study this issue further using a structural vector autoregression model identified in a way that is consistent with the theory. In particular, I take a theoretically agnostic view 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” akin to the shock in the Fed’s private information in the model. The empirical implementation leverages the “max-share” approach of Uhlig (2004), Barsky and Sims (2011), and Angeletos, Collard, and Dellas (2020).

I find that “monetary trembles” explain about 1% of total variation in unemployment and nominal interest rates, while “disagreement shocks” explain respectively 23% and 40% (in the posterior median estimates). 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.

8. Conclusion

This paper studies disagreement about monetary policy in the US since 1995 and why it persists despite abundant and precise public information. It shows, in a simple signal-extraction model, how to differentiate first between theories of asymmetric and heterogeneous models and then next between two leading cases of heterogeneous models (mis-specifying the monetary rule or disagreeing about the value of public information). Its main empirical results demonstrate that opinion-aggregating public signals have significantly predicted surprises about monetary policy as well as large forecast errors in the private sector and disagreements between the private sector and Fed about the future path of real variables. Through the lens of the model, these patterns imply a significant role for mis-specifying the value of public information, a small role for mis-specifying monetary response to that information, and an almost negligible role for asymmetric information. Such a calibration implies a large causal effect of market to Fed disagreement on the former’s beliefs but an essentially negligible causal effect of Fed persuasion about fundamentals.
Apart from the above conclusions, an additional practical take-away is that monetary surprises are not valid instruments for true “monetary shocks,” defined as unexpected and non-fundamental deviations from a policy rule. This paper’s simple model was precise about why: monetary surprises conflate true deviations, which come from idiosyncrasies in the central bank’s information, with the persistent bias in private sector forecasts. The SVAR model in Appendix E offers one perspective on how to ameliorate this issue by controlling for lagged macroeconomic variables.44

The same caveat does not apply to studies with high-frequency outcome variables, on which monetary surprises have sharp effects (e.g., Gürkaynak, Sack, and Swanson, 2005; Bernanke and Kuttner, 2005). If estimates of high-frequency Fed persuasion are limited, as established in this paper’s quantitative model, monetary surprises may be treated primarily as news about interest rates at high frequencies even if they are driven by business-cycle shocks. But researchers must use caution, as surprises correlate with news about fundamentals revealed within one month or less of the original policy announcement.

Finally, this paper did not study optimal policy conduct in light of the patterns highlighted within. Caballero and Simsek (2019) study optimal monetary policy in a similar environment, in which markets disagree with the Fed about the path of fundamentals, and the Fed designs policy around “agreeing to disagree.” An exploration of this topic in a realistic empirical calibration is an important topic for future research.

44This also accords with the recommendation of Miranda-Agrippino and Ricco (2021), who propose a “partialed out” variant of futures-based monetary surprises as a valid instrument for monetary shocks.
REFERENCES


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Appendices

A. OMMITED PROOFS

Proposition 1

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

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

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

\[ P = \mathbb{E}_{M,0}[r] = (\delta^Z_Z - q^Z + w)Z + \delta^Z_F(\delta^M_M - q)Z \tag{20} \]

These beliefs apply the conjecture that the market price \( P \) reveals no independent information about the state \( \theta \); 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 (20) from this is

\[ \Delta = \delta^F_F(F - \delta^M_M Z) + \delta^F_z q Z + w Z \tag{21} \]

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

We next calculate the covariance between \( Z \) and the rational forecast error of \( \theta \). This simplifies to

\[ \mathbb{E} \left[ Z \left( \theta - \mathbb{E}^R_{M,0}[\theta] \right) \right] = \mathbb{E} \left[ \mathbb{E}^R_{0,M} \left[ Z \left( \theta - \mathbb{E}^R_{M,0}[\theta] \right) \right] \right] = \mathbb{E}[0] = 0 \tag{22} \]

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

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

\[ \text{Cov}[\Delta, Z] = \text{Cov}[\delta^F_F \varepsilon_F, Z] + \delta^F_Z \text{Cov}[\theta - \mathbb{E}^R_{M,0}[\theta], Z] + \left( \delta^F_F + w \right) \text{Cov}[Z, Z] \tag{23} \]

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

\[ \text{Cov}[\Delta, Z] = \left( \delta^F_F q + w \right) \text{Var}[Z] \tag{24} \]

which is (i) 0 if \( q = w = 0 \); (ii) positive if \( q > 0 \) and \( q > 0 \); (iii) negative if \( q < 0 \) and \( q < 0 \). These verify the stated properties.
Proposition 2

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

Forecast Errors

First, consider $C = 0$. The market’s forecast error about $A$ is $\Delta = E_{\text{rational}}' - 0$. The forecast error about $B$ is $E_{\text{rational}}'' - E_{\text{rational}}' = (E_{\text{rational}}'' - E_{\text{rational}}') + \tau_0 = \tau_0 + \tau_Z$. The forecast error for $A$ is therefore

$$\theta - \bar{E}_{M,0}[\theta] = (\theta - \bar{E}_{M,0}^{R}[\theta]) + qZ$$

(25)

where $\bar{E}_{M,0}^{R}[\theta]$ 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

$$Y - \bar{E}_{M,0}[Y] = a(\theta - \bar{E}_{M,0}[\theta]) - (r - \bar{E}_{M,0}[r])$$

$$= (a - \delta_F^\theta)(\theta - \bar{E}_{M,0}[\theta]) + (a - \delta_F^\theta)qZ - wZ$$

(26)

The covariance with $Z$ is

$$\text{Cov}[Y - \bar{E}_{M,0}[Y]] = (a - \delta_F^\theta)\text{Cov}[(\theta - \bar{E}_{M,0}[\theta]), Z] + \left((a - \delta_F^\theta)q - w\right)\text{Var}[Z]$$

$$= \left((a - \delta_F^\theta)q - w\right)\text{Var}[Z]$$

(27)

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 $(a - \delta_F^\theta) > 0$, given $a \geq 1$ (assumed) and $\delta_F^\theta < 1$ (directly observable from the expression $\delta_F^\theta = \tau_F / (\tau_\theta + \tau_Z + \tau_F)$ 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

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

(28)

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

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

(29)
with the following definitions. $E_{M,1}^R[\theta]$ is the “rational” average expectation of $\theta$, defined by

$$
E_{M,1}^R[\theta] = \frac{\tau_Z}{\tau_0 + \tau_Z + \tau_F} Z + \delta_{F,1}^M F
$$

$$
E_{M,2}^R[\theta] = \left(1 - \frac{\tau_S}{\tau_1 + \tau_S}\right) E_{M,1}^R[\theta] + \frac{\tau_S}{\tau_1 + \tau_S} S
$$

(30)

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

$$
\delta_{F,1}^M = \frac{\tau_F}{\tau_0 + \tau_Z + \tau_F}
$$

$$
\delta_{F,2}^M = \frac{\tau_F}{\tau_0 + \tau_Z + \tau_F + \tau_S}
$$

(31)

Observe that the forecast error for $Y$ can be written as

$$
Y - E_{M,t}[Y] = a(\theta - E_{M,t}^R[\theta])
$$

(32)

as $r$ is now known. Plugging in (29), taking the covariance with $Z$, and noting the zero covariance with the average rational expectation gives

$$
\text{Cov}[Y - E_{M,t}[Y], Z] = a \text{Cov}[(\theta - E_{M,t}^R[\theta]), Z] + a \left(\frac{\tau_0}{\tau_t} q - \delta_{F,t}^M \frac{w}{\delta_F} \right) \text{Var}[Z]
$$

$$
= a \left(\frac{\tau_0}{\tau_t} q - \delta_{F,t}^M \frac{w}{\delta_F} \right) \text{Var}[Z]
$$

(33)

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 (29) and (30) that the average forecast revision from $t = 1$ to $t = 2$ for $\theta$ can be written as

$$
E_{M,2}[\theta] - E_{M,1}[\theta] = E_{M,2}^R[\theta] - E_{M,1}^R[\theta] - \left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right) q Z + \tau_F \tau_0 \left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right) \frac{w}{\delta_F} Z
$$

(34)

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

$$
\text{Cov}[E_{M,2}[Y] - E_{M,1}[Y], Z] = a \left(\frac{1}{\tau_1} - \frac{1}{\tau_2}\right) \left(q - \frac{\tau_F w}{\delta_F}\right) \text{Var}[Z]
$$

(35)

The desired properties are immediate after noting $a > 0$ and $\tau_2 > \tau_1$, which implies $1/\tau_1 - 1/\tau_2 > 0$.
Corollary 1

Observe that the covariance between $\Delta$ 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:

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

(36)

Mechanically, then, the bias term is

$$
B := \frac{\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta]}{\text{Var}[\Delta]} \quad (37)
$$

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

$$
B = \left(\delta^F_t q + w\right) \frac{\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z]}{\text{Var}[\Delta]} \quad (38)
$$

Applying the expression (35) from the proof of Proposition 2 simplifies further to

$$
B = \left(\delta^F_t q + w\right) \left(q - \frac{\tau_t}{\delta^F_t} w\right) \cdot \left(\frac{1}{\tau_1} - \frac{1}{\tau_2}\right) \frac{\text{Var}[Z]}{\text{Var}[\Delta]} \quad (39)
$$

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

Corollary 2

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

The “true” information effect $i$ is defined by (15) in Definition 1, reprinted here:

$$
i := \frac{\text{Cov}[\Delta, \mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y]]}{\text{Var}[\Delta]} \quad (40)
$$

Our goal is to show that

$$
i = i^+ := \frac{\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y], \Delta^+]}{\text{Var}[^+]} \quad (41)
$$

We start by simplifying the numerator of the right-most expression in (41). Note that this numerator can be separated into two terms, for each incremental revision:

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

40
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,

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

(42)

Combining this with (41) gives the following expression for $i^\perp$:

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

(43)

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

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

(44)

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

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

(45)

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

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

(46)

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

(46)

which again uses the fact that $\Delta^\perp$ is the rational forecast error. Combining (46) with (44) gives

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

(47)

which, after canceling out like divisors, reduces to

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

(48)

which is true and verifies the claim.
Online Appendices

B. Model Micro-foundations

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

This section micro-founds the abstract model’s policy rule,

\[ r = E_F[\theta] \]  \hspace{1cm} (49)

and expression for output,

\[ Y = a \theta - r \]  \hspace{1cm} (50)

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 \( N_t \):

\[
\exp(a \theta) \left( \log C_0 - \exp \frac{N^2_0}{2} \right) + \sum_{h=1}^{\infty} \beta^h \left( \log C_h - \frac{N^2_h}{2} \right) \]  \hspace{1cm} (51)

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

\[ C_t + R_{t+1} B_t \leq w_t N_t + B_{t-1} \]  \hspace{1cm} (52)

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

$$\beta R_{t+1} \frac{C_t}{C_{t+1}} = 1 \quad (53)$$

Since $R_{t+1} = 1/\beta$, then $C_t = C_{t+1}$ for all $t \geq 1$. As is conventional, we 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

$$\beta \cdot \exp(-a\theta)R_1 \frac{C_0}{C_1} = 1 \quad (54)$$

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,

$$\log C_0 = a\theta - r \quad (55)$$

which corresponds exactly to abstract equation (50) when $Y = \log C_0$. We recover the monetary rule (49) if we assume that $r$ is set to the policymaker’s expectation of $\theta$. 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 we will define as the expected present-discounted value of output adjusted by the demand shock under the a different Market agent’s beliefs $\mathbb{E}_M[\cdot]$, or

$$Q = \mathbb{E}_M \left[ \exp(a\theta)C_0 + \sum_{h=1}^{\infty} \frac{\exp(C_h)}{\exp \left( \prod_{k=1}^{k} R_k \right)} \right] \quad (56)$$

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

We set $q = \log Q - \log \overline{Q}$, 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

$$q = (1-\beta)\mathbb{E}_M[\log C_0] - \beta(\mathbb{E}_M[r] - a\mathbb{E}_M[\theta]) \quad (57)$$

Let us now map $\mathbb{E}_M[\cdot]$ in (57) with $\mathbb{E}_{M,2}[\cdot]$ in the abstract model, or market beliefs after the monetary announcement. Then, because the interest rate $r$ is known to the market, the previous reduces to

$$Q = a\mathbb{E}_{M,2}[\theta] - r \quad (58)$$
which is of course the same as $\mathbb{E}_{M,2}[Y]$ in the abstract model.

**B.2 Futures Prices: A Simple Trading Model**

In this section, a micro-foundation is provided for the market’s average prediction of the interest rate equaling the value of a traded asset paying off in proportion to the interest rate’s value, or the model equation

$$P = \mathbb{E}_{M,0}[r]$$  \hspace{1cm} (59)

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:

$$-\exp(-\alpha W)$$  \hspace{1cm} (60)

and submit limit orders, or contingent demands of $x_i$ that depend on the price $P$. We 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

$$\max_{p \to x_i \in \mathbb{R}} -\mathbb{E}_i[-\exp(-\alpha(E + x_i(r - P)))$$  \hspace{1cm} (61)

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

$$\max_{p \to x_i \in \mathbb{R}} \mathbb{E}_i[E + x_i(r - P)] - \frac{\alpha}{2} \mathbb{V}_i[E + x_i(P - r)]$$  \hspace{1cm} (62)

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

$$x_i(P) = \frac{\mathbb{E}_i[r] - P}{\alpha \mathbb{V}_i[r]}$$  \hspace{1cm} (63)

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

$$\int x_i(P) \, di = 0$$  \hspace{1cm} (64)
See that this is satisfied, for all \( \alpha \) and values of the common subjective variance, when

\[
P = \int_i \mathbb{E}_i[r] \, di
\] (65)

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 (65) reduces to (59). More generally, when there is not a single information set, (65) says that price equal population average beliefs.
Below, the numbered equations (M1) to (M7) refer to the moments used in the numerical calculation, numbered by their appearance in the left panel of Table 1, but not their appearance in the calculations.

As in the main model, monetary surprises are

$$\Delta = (w + \delta^F_t q)Z + \delta^F_t (F - \delta^M_t Z)$$

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

The Fed’s policy rule is given by the following

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

which is the same expression as (1) with the additional bias in the Fed’s expectations. The Fed’s expectation of output is

$$\mathbb{E}_{F,0} [Y] = a \mathbb{E}_{F,0} [\theta] - r$$
$$= (a - 1) \left( \delta^F_t F + (\delta^F_t - q^F)Z \right)$$
$$= \mathbb{E}^R_{F,0} [Y] - a q^F Z$$

where the rational expectations are $\mathbb{E}^R_{F,0} [\theta] = \delta^F_t F + \delta^F_t Z$, $\mathbb{E}^R_{F,0} [r] = r$, and $\mathbb{E}^R_{F,0} [Y] = a \mathbb{E}^R_{F,0} [\theta] - \mathbb{E}^R_{F,0} [r]$.

The market’s beliefs about fundamentals are given by

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

and of the policy rate by

$$\mathbb{E}_{M,0} [r] = (\delta^F_t - q^F - w + \delta^F_t \delta^Z_M - q)Z$$

which means the market beliefs about output are

$$\mathbb{E}_{M,0} [Y] = a \mathbb{E}_{M,0} [\theta] - \mathbb{E}_{M,0} [r]$$
$$= a \mathbb{E}^R_{M,0} [\theta] - \mathbb{E}^R_{M,0} [r] + ((\delta^F_t - a)q + w)Z$$

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

$$\text{FCE}_{0,F}^Y = (Y - \mathbb{E}^R_{0,F} [Y]) + a q^F Z$$
and hence the regression coefficient is

$$\beta_{F}^{RCE} = \frac{aq^{F}}{w + \delta_{F}^{2}q}$$  \hspace{1cm} (M4)$$

Similarly, for the market,

$$FCE_{0,M} = (Y - \mathbb{E}_{0,M}^{R}[Y]) + ((a - \delta_{F}^{2})q - w)Z$$

and hence the regression coefficient is

$$\beta_{M}^{RCE} = \frac{(a - \delta_{F}^{2})q - w}{w + \delta_{F}^{2}q}$$  \hspace{1cm} (M2)$$

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

$$\text{Var} \left[ (Y - \mathbb{E}_{0,M}^{R}[Y]) \right] = (a - \delta_{F}^{2})^{2} \frac{1}{\tau_{Z} + \tau_{\theta}} + (\delta_{F}^{2})^{2} \frac{1}{\tau_{F}}$$

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

$$R_{FCE,\theta,M}^{2} = \frac{(\beta_{M}^{FCE})^{2}(w + \delta_{F}^{2}q)^{2}(\tau_{Z}^{-1} + \tau_{\theta}^{-1})}{(\beta_{M}^{FCE})^{2}(w + \delta_{F}^{2}q)^{2}(\tau_{Z}^{-1} + \tau_{\theta}^{-1}) + (a - \delta_{F}^{2})^{2} \frac{1}{\tau_{Z} + \tau_{\theta}} + (\delta_{F}^{2})^{2} \frac{1}{\tau_{F}}}$$  \hspace{1cm} (M3)$$

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

$$Y = a\theta - \delta_{F}^{E}F - (\delta_{Z} - q^{E})Z$$

from which it is immediate that

$$\beta_{Y}^{RCE} = \frac{(a - \delta_{F}^{E})\delta_{Z}^{R} - \delta_{Z} + q^{E}}{w + \delta_{F}^{E}q}$$  \hspace{1cm} (M7)$$

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

$$\text{Var}[\delta_{F}^{R}(F - \mathbb{E}_{0,M}^{R}\theta)] = (\delta_{F}^{R})^{2}\left(\tau_{F}^{-1} + \frac{1}{\tau_{\theta} + \tau_{Z}}\right)$$

The $R^{2}$ of regressing $Z$, or any linear transformation thereof, on $\Delta$ is

$$R_{\Delta}^{2} = \frac{(w + \delta_{F}^{E}q)^{2}(\tau_{\theta}^{-1} + \tau_{Z}^{-1})}{(w + \delta_{F}^{E}q)^{2}(\tau_{\theta}^{-1} + \tau_{Z}^{-1}) + (\delta_{F}^{2})^{2}\left(\tau_{F}^{-1} + \frac{1}{\tau_{\theta} + \tau_{Z}}\right)}$$  \hspace{1cm} (M1)$$
We finally calculate market beliefs at $t = 2$. As in the main model, beliefs of the fundamental are given by

$$E_{2,M}[\theta] = \left(\frac{\tau Z}{\tau_2} - q \frac{\tau_0}{\tau_2} + w \frac{\tau_1}{\tau_2}\right) Z + \frac{\tau_F}{\tau_2} F + \frac{\tau_S}{\tau_2} S$$

$$= E_{2,M}^{R}[\theta] + \left(\frac{-q \tau_0}{\tau_2} + w \frac{\tau_1}{\tau_2}\right) Z$$

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

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

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

$$\beta_{\Delta} = a - 1 \quad (M6)$$

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

$$\beta^Z = a \frac{q \left(1 - \frac{\tau_0}{\tau_2}\right) + w \frac{\tau_1}{\tau_2}}{w + \delta^F q} - 1 \quad (M5)$$
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](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 \(\Delta X_t\) by horizon:

\[
\Delta_t = \alpha + \beta_h \cdot X_{t+h} + \varepsilon_{t+h}^X
\]  

(66)

For \(h < 0\), \(\beta_h\) measures prior predictability. For \(h > 0\), \(\beta_h\) measures correlation stretching into the future, or the statistical inference about \(X\) that is possible after observing \(\Delta_t\). 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 10 plots \(\beta_h\) from model (66) 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 10 plots \(\beta_h\) from model (66) 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 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

$$\text{Reduction MSE} = 1 - \frac{\text{MSE}_{\text{POOS}}}{\text{MSE}_{\text{naive}}}$$

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 Table 5 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 return to standard deviation thereof. These Sharpe ratios, in the third column of Table 5, all lie between 0.15 and 0.30.

D.4 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), we 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:

\[ R_{W(t)} = \alpha + \beta Z \cdot \hat{Z}_{t-1} + \beta^A \hat{\Delta}^A_{t} + \varepsilon_{W(t)} \]  

(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 20. 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. This is consistent with the model but in sharp contrast to the claim of Jarociński and Karadi (2020) that one may distinguish monetary trembles from “information shocks” by contemporaneous stock market reaction.

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. SVAR Model

This Appendix describes an SVAR model, compatible with our theory, which can shed 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.

E.1 Empirical Model and Identification Strategy

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

$$y_t = \sum_{\ell=1}^{L} A_{\ell} y_{t-\ell} + A_{0}^{-1} \nu_t$$

where each $A_{\ell}$ is an $N \times N$ matrix and $\nu_t$ is an $N \times 1$ vector of independent, Gaussian innovations. The matrix $A_{0}^{-1}$ controls the contemporaneous impact of $\nu_t$ 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. 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 shock captures variation spanned by the error in the monetary authority’s information. 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

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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.

The method also relates to the suggestion of Plagborg-Møller and Wolf (2019) 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.
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.47

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

### E.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 19, 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, we 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 we assume 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 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.48 These results imply substantial effects on disagreement about macro outcomes as a result of shocks spanned by past and present public data at $t = 0$.

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

48 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.
E.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 one unidentified shock up to a feasible lag truncation. 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.

E.4 Identification and Posterior Sampling

This subsection fills in methodological details.

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

$$y_t = \sum_{l=1}^{L} A_l y_{t-l} + v_t$$

(70)

where $v_t := A_0^{-1} v_t$ are now the one-step-ahead forecast errors. Given the original assumption that $v_t \sim N(0, I)$, 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 reduced-form covariance matrix for the one-step-ahead forecast errors.

E.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 $\Sigma$ 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

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49These are calculated, as a feasible numerical approximation, to the horizon of 48 months.
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. We 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 \( \Sigma \).** I impose a Wishart prior on \( \Sigma^{-1} \) (or an inverse-Wishart prior on \( \Sigma \)) centered around variance 0.01 in each equation.

### E.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 \( \Sigma \) and the \( (B_t)^p_{t=1} \) 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 \( \text{Var}[u_t] = I \), so the variance of \( \Delta_t \) can be written as the sum of vectors \( \delta_i \), 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:

$$\max_{w \in \mathbb{R}^N} w'[b_2b_2' + b_3b_3' + b_4b_4']w$$

s.t. $w'w = 1$

$$w'e_1 = 0$$

(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 $A_0^{-1}(A_0^{-1})^{-1} = \Sigma$. 
### Additional Tables and Figures

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<thead>
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Table 4: **Predictive Value of Sentiment, Holding Fixed Recent Data.**
The regression equation is (10). The four predictors are described in Section 4.1 and the control variables in Section 4.1, paragraph “Comparison with other predictors.”

<table>
<thead>
<tr>
<th>Predictor</th>
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Table 5: **Pseudo-out-of-sample Fit.**
Values are fraction MSE reduction calculated as in (67). The methodology is described in Appendix D.3.
Figure 9: **Labor Market Sentiment: Time Series Patterns.** 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 10: **Event Study of Sentiment.** Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (66). The units for the coefficients are implied percentage points of monetary surprise per one (non-normalized) unit of the regressor.
Figure 11: Predictability for Different Assets.
Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). Each graphic is an analogue of Figure 3 with a different outcome variable.
Figure 12: **Scatter Plot of Surprises vs. Sentiment.**
Selected points are labeled with the date of meeting. Meetings at which the short-rate target were changed are labeled in orange.

Figure 13: **Predicting Monetary Surprises, Pre 2008.**
This figure replicates the analysis of Figure 3, 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). 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 14: **Rolling Estimation of Predictive Regression.**
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).

Figure 15: **Forecast Errors and Public Signals, Alternative Outcomes.**
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). The regression equation is (12), 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 16: Forecast Errors and Public Signals, First-Release Data.
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). The regression equation is (12), 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 17: Forecast Errors and Public Signals, Upper and Lower Tails.
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). The regression equation is (12), 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 18: Rolling Estimation of Forecast and Outcome Prediction. 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 \( y_t = \beta \cdot \hat{y}_t + \alpha + \epsilon_t \), 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).

Figure 19: Impulse Response Functions. 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.
Figure 20: **Predictable Surprises and Stock-Price Drift.**
The estimating equation is (68). Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth).