# Disagreement About Monetary Policy

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**Abstract**

This paper studies why central banks and markets hold different beliefs. I introduce a model that formalizes three mechanisms for disagreement: asymmetric information about fundamentals, different perceptions of the policy rule, and different confidence in public signals. I show how to separately identify these mechanisms using their predictions for beliefs about multiple variables. In US data, negative macroeconomic news predicts market over-estimation of interest rates and employment relative to realizations and Federal Reserve forecasts. The estimates imply that markets slightly misspecify the monetary rule and are significantly under-confident in public information. Central-bank private information and "information effects" are quantitatively negligible.

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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 "one of the most powerful tools" in the central-bank arsenal (Bernanke, 2015). But what induces such disagreements in a world of abundant public data and constant discussion about policy? And what does the answer to the previous question imply about the power—or futility—of central bank communication as a tool for moving market opinion?

This paper links theory and data to study these questions. Theoretically, I introduce a model of policymaker and market interactions in which belief differences can arise for three reasons: asymmetric information about unknown fundamentals, asymmetric beliefs about the policymaker's reaction to public data, and asymmetric confidence in the informativeness of those data. I show how these mechanisms are separately identified based on their joint predictions for beliefs about both policy instruments and macroeconomic outcomes. Empirically, implementing model-derived tests in US data from 1988 to 2019, I find evidence that rejects models with only asymmetric information or only policy-rule mis-perception and implies a significant role for asymmetric confidence. That is, markets and the Fed systematically "agree to disagree" about what incoming data imply about the economy. Quantitatively, when I use my empirical findings to calibrate the model, I find that the market's perception that the Fed overreacts to news significantly dampens belief fluctuations over the business cycle. By contrast, the "information effect," or phenomenon of central banks' signaling their information about fundamentals through policy actions, does not significantly amplify them.

**Model.** I begin with a stylized model of interactions between a central bank ("the Fed") and a representative investor ("the Market"). There are four periods, indexed by $t \in \{0, 1, 2, 3\}$, and a single exogenous fundamental, which represents the state of aggregate demand. At $t = 0$, both the Fed and the Market observe a public signal of the fundamental (e.g., a macroeconomic statistic). The Fed also observes a private signal of the fundamental, representing internal research. The Fed takes an action equal to its forecast of the fundamental. The Market attempts to forecast the policy action. This is equivalent to forecasting the Fed's forecast of economic fundamentals. At $t = 1$, the policy is announced and a *monetary surprise*, or Market forecast error in predicting the policy, is realized. At $t = 2$, everyone observes a second public signal of fundamentals. At $t = 3$, a macroeconomic outcome ("employment") is realized. Employment depends positively on fundamentals and negatively on policy, such that fundamental shocks have a positive effect net of the policy response in expectation.

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

I first show that a model with only asymmetric information precludes public information from predicting monetary surprises. Either of the other two mechanisms allows for this possibility. Thus, testing for predictability of surprises can reject Mechanism 1 but not distinguish between Mechanisms 2 and 3.

I next show how mis-estimation of the monetary rule and heterogeneous confidence in public data can be distinguished by their predictions for employment forecasts. The result, stated informally, is that misspecification 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 opposite cases. The first case is a Market that under-estimates the monetary response to news but correctly interprets the news' informativeness about fundamentals. The market over-predicts interest rates in response to the bad news and, if it understands that monetary policy has negative real effects, therefore is pessimistic about employment. The second case is a Market that under-estimates the news' informativeness about fundamentals but correctly specifies the monetary response to news. In this case, the Market again over-predicts interest rates, but for a different reason: it expects the Fed's private signal to align with its optimistic beliefs about fundamentals. But, if shocks have a positive effect on employment net of the policy response, the Market *over*-estimates employment—its optimism about fundamentals dominates any countervailing pessimism from expecting high interest rates.

In further results, I show that both mis-perception of the rule and heterogeneous confidence can generate systematic deviations in what the Market and Fed believe over the business cycle. They can also generate deviations between what the Fed does and what the Market thinks it *ought to do*: that is, a reason that Markets may think the Fed is generally "behind (or ahead) of the curve". Finally, I show how the presence of belief distortion complicates empirical methods for measuring the signaling content of monetary policy announcements ("information effects").

The theoretical results, taken together, show how to use data on multiple dimensions of forecasting to identify specific mechanisms for disagreement. This, in turn, has implications for how disagreements evolve over the business cycle and whether they are significantly affected by central banks' signaling their beliefs via actions.

**Empirical Analysis.** I treat the *monetary policy surprise* of Bauer and Swanson (2023b) as a summary of monetary surprises across the term structure from 1988 to 2019. I focus on the following leading indicators of the business cycle as representative public signals: (i) consumer sentiment about the labor market 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; (iv) stock-market sentiment from the American Association of Individual Investors survey; and (v) the surprise component of the nonfarm payrolls estimate of employment growth (as studied by Bauer and Swanson, 2023a).

I first find that all five measures are positive predictors of monetary surprises—that is, good (bad) news in any indicator predicts surprise monetary tightening (loosening). In the theory, the result invalidates the pure asymmetric-information case. But, as observed above, this result in isolation does not identify *which* of the second two mechanisms is present—or even rule out a significant role for asymmetric information in *combination* with those mechanisms.

I next test three model predictions about the relationship between lagged realizations of public signals and forecasts of subsequent macroeconomic outcomes. My first finding is that lagged good news in leading indicators, associated with surprise monetary tightening according to my previous results, correlates with professional forecasters' over-predicting unemployment and under-predicting real GDP growth. My second finding is that the same lagged good news correlates with optimistic Blue Chip forecast revisions between month $t$ and $t+1$, which partially but do not fully correct the aforementioned forecast error. My third finding is that lagged good news correlates with the Fed's being systematically more optimistic than markets, comparing Greenbook or Tealbook forecasts to the Blue Chip forecasts within the same month.

I finally show how these patterns of belief under-reaction and delayed correction around policy announcements relate to the empirical analysis used by Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) to justify an "information effect" of monetary policy. All of the positive information effect of surprise monetary tightening on forecast revisions is explained by the correlation between lagged public news from prior to both survey waves. Theoretically, this is to be expected if public signal realizations are an omitted variable predicting both monetary surprises and future forecast revisions.

**Quantification.** To measure the relative importance of different mechanisms underlying disagreement, I fit the model to the empirical estimates. Both the Market and Fed under-react to the public signal, consistent with previous observations of "sluggish expectations" for both groups (Coibion and Gorodnichenko, 2012). The Market recognizes that the Fed responds more to news, but does not adjust its expectations enough. That is, on net, the Market underestimates the Fed's response to news, consistent with the hypothesis of Bauer and Swanson (2023a). By quantifying the relative strength of these mechanisms, I can show that they explain about equal shares of interest rate forecast errors (monetary surprises). But under-reaction to fundamental signals explains almost all of the predictable component of employment forecast errors, while mis-estimation of the monetary rule has a negligible effect. Finally, the Fed's internal information is an order of magnitude less precise than public information. Thus, the component of "internal information" (Romer and Romer, 2000; Nakamura and Steinsson, 2018) due to (conditionally) independent information contributes very little to belief differences.

To formally gauge the effect of central-bank signaling on public beliefs, I use the model to study a counterfactual in which the Fed's private signal is removed. In this case, the sensitivity of the Market's post-announcement beliefs to fundamentals is reduced by only 2%. By contrast, if the Fed counterfactually had the Market's (lower) confidence in public data, the sensitivity of the latter's post-announcement beliefs to fundamentals would increase by 12% because policy would respond less aggressively to the same data. If the Market shared the Fed's (higher) confidence, the same beliefs would be 14% more sensitive due to the Market's quicker response to news. In these units, disagreement from heterogeneous priors therefore has 7 to 8 times larger effects than asymmetric information.

**Extensions and Robustness.** I pursue four main extensions of the empirical analysis which, although not necessary for matching the theory to the data, provide further context for my findings. First, I show that the monetary surprise predictability results are qualitatively and quantitatively similar for interest rate futures of different horizons and for survey forecasts of interest rates. Second, I show that news about inflation also predicts monetary surprises and that inflation forecast errors and disagreements also exhibit cylical patterns. Third, I show that *real-time* forecast error predictability is considerably lower than *ex post* predictability, consistent with the general findings of Bianchi, Ludvigson, and Ma (2022) regarding biases in macroeconomic beliefs. Moreover, while implementable investment strategies in futures markets *can* generate returns on average, their variance is large relative to standard benchmarks (e.g., "rules of thumb" for acceptable Sharpe ratios). Thus, from this perspective, the *ex post* forecasting biases uncovered in this paper would be relatively difficult to detect or exploit in real time. Finally, I provide suggestive evidence that the Fed's interpretation of data is not crucial for "fixing" the Market's forecasting errors: forecast error predictability is just as pronounced in Blue Chip forecasts after an FOMC meeting as opposed to before.

**Related Literature.** My finding that monetary surprises are predictable relates to findings in studies by Miranda-Agrippino (2015), Miranda-Agrippino and Ricco (2021), Cieslak (2018), Karnaukh and Vokata (2022), and Bauer and Swanson (2023a). Bauer and Swanson (2023a), the most related of these studies, show that pre-determined economic news predicts monetary surprises and, when controlled for, attenuates the relationship of surprises with private-sector forecasts.[1] The authors interpret these findings via a model in which market participants under-

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

estimate the Fed's reaction to publicly available economic news in the monetary rule while also under-reacting to information, a combination of this paper's "Mechanism 2" and "Mechanism 3." My paper focuses on how to use additional pieces of evidence and model structure to separate these mechanisms. I conclude that mis-estimation of the monetary rule needs to be accompanied by heterogeneous priors to explain the facts and I quantify the importance of these mechanisms relative to asymmetric information.

A large literature studies central bank policy and communication in rational-expectations models with asymmetric information. Campbell, Evans, Fisher, and Justiniano (2012), Nakamura and Steinsson (2018), and Melosi (2017) use models in this tradition to quantitatively study the signaling effects of US monetary policy. In my empirical and quantitative analysis, I find that such models fit the data less well than alternatives based on heterogeneous priors. I discuss how to reconcile the sets of findings in greater detail in Sections 4.5 (Revisiting the Information Effect) and 5 (Quantification). I further discuss the relationship between this paper's three proposed Mechanisms with the broader literature on central-bank information, communication, and conduct at the end of Section 2.1.

More generally, this paper relates to a large literature on disagreement in measured expectations (e.g., Mankiw, Reis, and Wolfers, 2003; Andrade and Le Bihan, 2013; Andrade, Gaballo, Mengus, and Mojon, 2019). I depart by casting focus on disagreements between the public and central banks, a topic studied theoretically by Caballero and Simsek (2022). Finally, this paper finally relates to existing studies of "imperfections" in macroeconomic expectations that are at odds with full-information, rational-expectations models (e.g., Carroll, 2003; Coibion and Gorodnichenko, 2012; Bianchi, Ludvigson, and Ma, 2022). This paper's findings show how differences in forecast biases across groups can generate systematic, cyclical belief disagreement.

# 2 Model

I first present a stylized model that embeds three mechanisms for disagreement between central banks and markets: asymmetric information, asymmetric beliefs about the policy rule, and asymmetric confidence in public information. I contrast these mechanisms' predictions and derive tests that can distinguish among them in the data.

## 2.1 Set-up

**Timing and Fundamentals.** There are four periods denoted by $t \in \{0, 1, 2, 3\}$ and two agents, the "Fed" ($F$) and the "Market" ($M$). There is an exogenous fundamental $\theta \sim N(0, \tau_\theta^{-1})$ that represents the state of aggregate demand. Throughout, I use $\mathbb{E}_{X,t}[A]$ to denote the expectation of agent $X \in \{F, M\}$ at time $t$ of a random variable $A$.

At $t = 0$, both agents observe a public signal $Z = \theta + \varepsilon_z$, where $\varepsilon_z \sim N(0, \tau_z^{-1})$ is a noise term independent from all other exogenous variables. The Fed additionally observes a private signal $F = \theta + \varepsilon_F$, where $\varepsilon_F \sim N(0, \tau_F^{-1})$ is an independent noise term. The Fed takes a policy action $r$ that corresponds to its expectation of the shock, or $r = \mathbb{E}_{F,0}[\theta]$. The Market makes a prediction $P$ equal to its expectation of interest rates, or $P = \mathbb{E}_{M,0}[r]$. At $t = 1$, the policy action is revealed to the Market. At $t = 2$, both agents observe an additional public signal $S = \theta + \varepsilon_S$, with independent noise $\varepsilon_S \sim N(0, \tau_S^{-1})$. At $t = 3$, output $Y$ is realized as $Y = a\theta - r$ for some $a \geq 1$. This restriction ensures that higher aggregate demand ($\theta$) correlates with higher output, despite the Fed's reaction.

Appendix B micro-founds the model. The variables map to a New Keynesian environment in which $\theta$ is a consumer discount-rate shock, $Y$ is a percent deviation from steady-state employment, and $r$ is a percent deviation from the steady-state interest rate. The prediction $P$ is the price of an asset that pays off in proportion to $r$ at $t = 1$ in a setting in which traders have constant absolute risk aversion (CARA) preferences and beliefs are Gaussian.

**The Fed's Beliefs.** The Fed uses Bayes rule to form its beliefs but potentially misspecifies the news content of public signals. In particular, the Fed perceives the public signal to have precision $\tau_Z - q^F(\tau_Z + \tau_F + \tau_\theta)$ and the fundamental to have precision $\tau_\theta + q^F(\tau_Z + \tau_F + \tau_\theta)$, where $q^F$ measures the Fed's under-confidence in the data.[2] The Fed's belief at $t = 0$ is

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

where $\delta_F^F := \frac{\tau_F}{\tau_F + \tau_Z + \tau_\theta}$ and $\delta_Z^F := \frac{\tau_Z}{\tau_F + \tau_Z + \tau_\theta}$ are the objective precision weights from Gaussian signal extraction. Viewed this way, $q^F > 0$ encodes under-reaction to public information relative to a Bayesian benchmark and $q^F < 0$ encodes over-reaction.

**The Market's Beliefs.** The Market, like the Fed, may misspecify the news content of the public signal. Specifically, the Market perceives the public signal to have precision $\tau_Z - q^M(\tau_Z + \tau_\theta)$ and the fundamental to have precision $\tau_\theta + q^M(\tau_Z + \tau_\theta)$, where $q^M$ directly measures the Market's under-confidence in the data. Thus, the Market's fundamental belief at $t = 0$ is

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

where the coefficient $\delta_Z^M = \frac{\tau_Z}{\tau_Z + \tau_\theta}$ corresponds with the objective signal-to-noise ratio for $Z$. The cases $q^M > 0$ and $q^M < 0$ respectively correspond to under-reaction and over-reaction.

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

The market may also misspecify the policy rule's coefficient on $Z$. That is,

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

The case $w > 0$ (respectively, $w < 0$) corresponds to under-estimating (over-estimating) the Fed's reliance on $Z$ relative to the ground truth. The parameter $q^F + w$ measures the Market's perception of the Fed's reaction to news. Varying $q^F + w$ affects how the Market *thinks the Fed uses information about the economy*: that is, it moves second-order beliefs about fundamentals.

**Mechanisms for Disagreement and Their Relationship to the Literature.** The model accommodates disagreement between the Market and the Fed due to three mechanisms.

Mechanism 1 is asymmetric information arising from the signal $F$. This assumption is ubiquitous in work on communication and transparency (e.g., Moscarini, 2007; Baeriswyl and Cornand, 2010; Kohlhas, 2020), signaling (e.g., Ellingsen and Söderström, 2001; Melosi, 2017), and agency problems (e.g., Cukierman and Meltzer, 1986; Athey, Atkeson, and Kehoe, 2005). The idea that a central bank has access to and could reveal new information about economic fundamentals is also the premise for a large literature on the social value of public information (e.g., Morris and Shin, 2002; Svensson, 2006; Angeletos and Pavan, 2007).[3]

Mechanism 2 is the Market's mis-perception of the monetary rule, or the mapping from the Fed's information to its action. This possibility is raised by Bauer and Swanson (2023a), Bauer, Pflueger, and Sundaram (2022), and Schmeling, Schrimpf, and Steffensen (2022) via the justification of slow learning about the Fed's conduct.

Mechanism 3 is the Market's and Fed's potentially different confidence in, attention toward, or economic interpretation of the public signal as captured by $q^M$ and $q^F$. Under-reaction or over-reaction to public information ($q^M, q^F \neq 0$) would be consistent with various strands of the large literature on imperfect macroeconomic expectations (see, e.g., Angeletos, Huo, and Sastry, 2021). Under-reaction to news ($q^M, q^F > 0$) would, in particular, be consistent with findings of sluggish updates in professional and policy forecasts by Coibion and Gorodnichenko (2012, 2015). *Differences* in confidence, or $q^M \neq q^F$, would be consistent with Caballero and Simsek's (2022) hypothesis of "opinionated markets" that interpret public data differently than the policymaker, leading to systematic disagreements about fundamentals.

## 2.2 Predicting Monetary Surprises

I first analyze what explains monetary surprises $\Delta = r - P$, or the difference between predicted and realized policy actions. To calculate the surprise, I plug fundamental beliefs (2) into the

[3] See p. 449-450 of Svensson (2006) for a discussion of the practical interpretation of public information disclosure in these models and the relationship with empirical evidence (e.g., Romer and Romer, 2000).

perceived monetary rule (3) and subtract this from the actual rule (1). These calculations yield:

$$\Delta = \delta_F^F \left(F - \mathbb{E}_{M,0}^R[F]\right) + \delta_F^F q^M Z + wZ \tag{4}$$

where, throughout, $\mathbb{E}_{X,t}^R[A]$ denotes the correctly specified ("rational") expectation of random variable $A$ using the information available to agent $X \in \{F, M\}$ at time $t$. The first term in Equation 4 is the error that the Market would make with a correctly specified, Bayesian forecast of the Fed's internal information. This term has zero covariance with $Z$ due to the law of iterated expectations. Intuitively, a correctly specified Bayesian forecast cannot be improved by variables on which it already conditions. 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 latter two terms are both proportional to the public signal realization. Note that the Fed's information-use distortion $q^F$ does not show up in this expression, because it is fully accounted for in the Market's thinking up to the deviation $w$.

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

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

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

Proofs for this and all other results are given in Appendix A.

Case 1 shows that public information will *not* predict monetary surprises when the Market correctly incorporates $Z$ into their forecast and correctly models how the Fed will act. This result does not require the Fed to be correctly specified, as long as the Market is fully aware of any Fed bias. Case 2 shows that Market under-reaction to information in $Z$ and market under-estimation of the Fed's reaction to $Z$ both point toward a positive correlation: that is, the Fed tightens (loosens) more than expected when $Z$ reveals good (bad) news about demand. Case 3 shows that Market over-reaction to information or over-estimation of the Fed's reaction has the opposite prediction. More generally, there is an ambiguous sign prediction for $\text{Cov}[\Delta, Z]$ due to the possibly offsetting effects of the distortions embodied by $w$ and $q^M$.

## 2.3 Identifying the Mechanism for Disagreement

The test embedded in Proposition 1 does not perfectly discriminate between two models for disagreement: mis-perception of the monetary rule and mis-perception of the informativeness of news about fundamentals. I now show that the two mechanisms for disagreement have differing, testable implications for the errors in and revisions of forecasts about $Y$.

The result below formalizes the relationship between sign cases for the parameters $(q^M, w)$ and the signs of (i) the covariance of $Z$ with forecast errors of $Y$ and (ii) the covariance of $Z$ with forecast revisions of $Y$ after the policy announcement:

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

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

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

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

With no biases, public signals cannot predict subsequent forecast errors or revisions; with over-estimation of the monetary response or under-reaction to news, positive news in $Z$ predicts positive forecast errors and revisions; and with under-estimation of the monetary response or over-reaction to news, positive news in $Z$ predicts negative forecast errors and revisions.

To understand this result, consider the Market's forecast error at $t = 0$:

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

The first term, proportional to the rational forecast error, is orthogonal to $Z$ because of the law of iterated expectations. The second term, proportional to the Fed signal's noise, is orthogonal to $Z$ by construction. The third term describes the market's tendency to expect a diluted monetary response to $Z$ whenever $w > 0$ and an exaggerated monetary response if $w < 0$. To illustrate, $w > 0$ and "bad news" $Z < 0$ contribute to a positive forecast error, or under-estimation of output. This is because the Market expects the Fed to under-react to news, keep policy too tight, and therefore lower output. 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 $\delta_F^F$). Under the stated conditions $a \geq 1$ (the Fed responds to shocks less than one-for-one) and $\delta_F^F < 1$ (the Fed does not perfectly know $\theta$), this term has the same sign as $q^M Z$. To illustrate, $q^M > 0$ and the same "bad news" $Z < 0$ contribute to *under*-estimating output. This is due to the the direct channel of under-estimating aggregate demand. Using Equation 5 to calculate $\mathbb{E}[Y - \mathbb{E}_{M,0}[Y], Z] = \mathrm{Var}[Z] \cdot \left(\left(a - \delta_F^F\right) q^M - w\right)$, it is straightforward to verify the claims regarding the covariance of $Z$ with the date 0 forecast error.

To illustrate Proposition 2's additional results, it is easiest to sketch two extreme cases that isolate each mechanism. As a first extreme case, consider what happens if the Market is correct about the Fed's reaction function ($w = 0$) but under-reacts to news in the public signal ($q^M > 0$). 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 negativity of the second public signal. Their optimism partially erodes after the announcement, as beliefs slowly and inertially converge toward the truth. This story would be consistent with the overall inertia in macroeconomic expectations documented, among others, by Coibion and Gorodnichenko (2012, 2015) and Angeletos, Huo, and Sastry (2021). An important subtlety is that the predictability of slow forecast revisions by lagged *public* data requires some bias in the interpretation of those data.[4]

As a second extreme case, consider what happens in response to "bad news" ($Z < 0$) if $w > 0$ and $q^M = 0$. At $t = 1$, the Market is surprised by the Fed's loosening and rationalizes this by assuming the Fed has made a very pessimistic idiosyncratic assessment (a low $F$). Taking this information into account in their new employment forecast at $t = 1$, the Market is again overly pessimistic due to this mis-interpretation. When new data arrive at $t = 2$, the Market's beliefs mean-revert (in expectation) to offset the over-reaction. This over-reaction and delayed correction would be consistent, for example, with the findings of Kohlhas and Walther (2021) regarding macroeconomic expectations over the business cycle.

In summary, qualitatively different patterns of forecast errors and revisions surrounding monetary announcements help distinguish between mechanisms for disagreement. Moreover, either pattern is *ex ante* reasonable in light of existing evidence on the behavior of macroeconomic expectations. This underscores the importance of taking the question to the data.

## 2.4 Implications: Disagreements and Signaling Effects

I next study the model's implications for Fed-Market disagreements and the signaling role of monetary policy announcements.

**Disagreements about $Y$.** 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 the policy action. The difference in Fed and Market beliefs at $t = 0$ is:

$$\mathbb{E}_{F,0}[Y] - \mathbb{E}_{M,0}[Y] = a(\mathbb{E}^R_{F,0}[\theta] - \mathbb{E}^R_{M,0}[\theta]) + a(q^M - q^F)Z - \Delta \tag{6}$$

[4] By contrast, the models of Coibion and Gorodnichenko (2015) and Angeletos, Huo, and Sastry (2021) assume that all information is *private* and therefore do not address this issue.

where $\mathbb{E}^R_{F,0}[\theta] := \delta^F_F F + \delta^F_Z Z$ is the Fed's as-if rational expectation. This expression has three interesting implications. First, the public signal $Z$ can predict this disagreement through both fundamental disagreement ($q^M \neq q^F$) and the previously discussed predictable component of the policy forecast error.[5] Second, the Fed's beliefs about real variables and their difference from Market beliefs, observed with delay in published Greenbooks (or Tealbooks), may predict monetary surprises even in the *absence* of biases (i.e., with $q^M = q^F = w = 0$) owing to their partial revelation of the Fed's internal information $F$. Such regressions (e.g., as in Gertler and Karadi, 2015; Ramey, 2016) do not by themselves distinguish between mechanisms controlling disagreement. Third, central-bank and public forecasts may differ from one another and therefore be differentially informative about macroeconomic outcomes. Thus, through the lens of this model, the empirical test of Romer and Romer (2000) for "inside information" is not uniquely associated with one mechanism.

**Positive versus Normative Disagreements.** Throughout, I have used the term "disagreement" to refer to any difference in the forecast of a random variable. In that sense, such disagreements are purely *positive*. It is also often true in practice that Markets have a different view than the Fed about what *ought* to be done, which one might refer to as a *normative disagreement*. To understand this phenomenon in the model, we can calculate the policy rule that the Market agent would use if it were in the Fed's position and had access to the signal $F$. Since the Fed and Market agree about the precision of the signal $F$, this is a linear combination of the Market's belief (without $F$) and the signal $F$ with weights $1 - \delta^F_F$ and $\delta^F_F$:

$$r^M = (1 - \delta^F_F)(\mathbb{E}_{M,0}[\theta]) + \delta^F_F F = (\delta^F_Z - (1 - \delta^F_F) q^M) Z + \delta^F_F F \tag{7}$$

where the second equality plugs in the Market's beliefs. Under the Market's view of the world, the difference between this and what the Market assumes the Fed to do (Equation 3) is

$$\Delta^N := (\delta^F_F Z + (\delta^F_Z - q^F - w) Z) - r^M = ((1 - \delta^F_F) q^M - q^F - w) Z \tag{8}$$

If $w = (1 - \delta^F_F) q^M - q^F$, then the Market expects the Fed to use information exactly as it would. Moreover, from Equation 4, the predictable component of surprises is $\Delta = (q^M - q^F) Z$ and $\mathrm{Cov}[\Delta, Z]$ has the same sign as $q^M$. If $w > (1 - \delta^F_F) q^M - q^F$, then the Market thinks the Fed is "behind the curve" or acting too passively in response to demand shocks. If the opposite holds, then the Market thinks that the Fed is "ahead of the curve" or acting too agressively. These predictions hinge crucially on the *relative* value of $q^M$, $q^F$, and $w$. I revisit them in the quantitative analysis (Section 5.2).

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

**Signaling or Information Effects.** At $t = 1$, the Market incorporates information revealed from the policy announcement into its beliefs. One implication of the model is that isolating the effect of the Fed's signaling is not possible without additional information on forecasting biases. To illustrate this, I can use the model to study an empirical technique used in the literature (e.g., Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018) that infers signaling power from the relationship between monetary surprises and forecast revisions between survey periods after and before the announcement (i.e., $\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y]$). The measured covariance between these forecast revisions and monetary surprises decomposes into the component capturing revisions from $t = 0$ to $t = 1$ when $r$ is revealed and a component capturing revisions from $t = 1$ to $t = 2$ when the additional macro observation $S$ is revealed:

$$\begin{aligned} \text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y], \Delta] &= \text{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta] + \text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta] \\ &= (a-1)\text{Var}[\Delta] + \text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta] \end{aligned} \tag{9}$$

If beliefs are formed using Bayes rule with correct specification, the second term is zero: a prior forecast error cannot predict a future forecast revision. Otherwise, the second term can lead a researcher to over- or under-state the effect of policy announcements on macroeconomic beliefs:

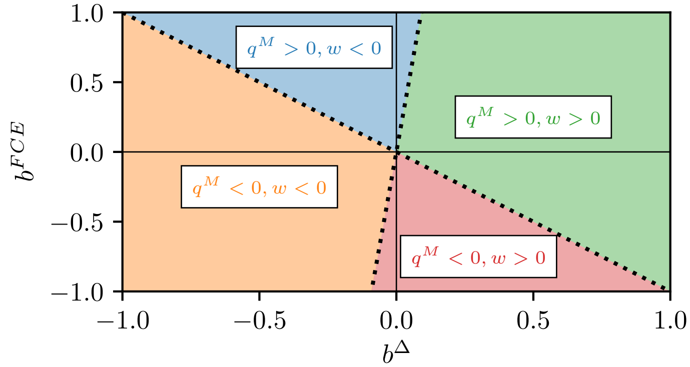
**Corollary 1** (Bias in Measuring the Information Effect)**.** *The following statements are true:*

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

Under the conditions for part 2, there is "belief momentum" between periods 2 and 3 as markets slowly remedy their initial under-reaction. A researcher that looks at the relationship between monetary surprises and belief revisions would over-state the effect of monetary communication on beliefs because of a common causation bias: positive (negative) macroeconomic news predicts both monetary surprises and sluggish updating of macroeconomic forecasts. Under the conditions for part 3, there is "belief mean-reversion" as markets sluggishly fix their errors of over-reacting to the same pieces of information. An analyst would over-state the true effect of monetary surprises on macroeconomic beliefs in this case.[6]

[6] Moreover, even under Case 1 of Proposition 1, the regression of belief updates on monetary surprises identifies $a - 1$ (see Equation 9) but not the precision of the Fed's information. That is, the moment of interest does not identify how impactful Fed signalling is for Market beliefs. I return to this point in Section 5.

**Figure 1:** Parameter Cases for $(q^M, w)$




*Notes*: This figure illustrates sign cases for the Market's under-reaction $q^M$ and the Market's mis-estimation of the monetary rule $w$, as a function of statistics $b^{\Delta}$ and $b^{FCE}$ defined in Equation 10, conditional on $a = 1$ and $\delta_F^F = 0.10$. Each colored region indicates a sign case for $(q^M, w)$ and the dotted lines indicate borders between these regions.

### 2.5 Identification: Sign Tests and Moment Matching

The calculations underlying Propositions 1 and 2 suggest an identification strategy for $(q^M, w)$ that uses the relationship of public signals with forecasts of both policy actions and macroeconomic outcomes. I now make this strategy more explicit. Define the regression coefficients of monetary surprises and forecast errors on $Z$ as

$$b^{\Delta} := \frac{\mathbb{E}[\Delta, Z]}{\mathrm{Var}[Z]} = \delta_F^F q^M + w \qquad b^{\mathrm{FCE}} := \frac{\mathbb{E}[Y - \mathbb{E}_{M,0}[Y], Z]}{\mathrm{Var}[Z]} = \left(a - \delta_F^F\right) q^M - w \tag{10}$$

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 $q^M$ and $w$:

$$q^M = \frac{1}{a}\left(b^{\mathrm{FCE}} + b^{\Delta}\right) \qquad w = b^{\Delta} - \frac{\delta_F^F}{a}\left(b^{\mathrm{FCE}} + b^{\Delta}\right) \tag{11}$$

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 misspecification of the monetary rule that rationalizes the predictable error for interest rates.

This logic is visualized in Figure 1, which maps values of $(b^{\Delta}, b^{\mathrm{FCE}})$ to sign cases for $(q^M, w)$ One could determine the best "one-friction model" by identifying the sign of each moment (i.e., quadrant of Figure 1) and assuming the correct model lay on the dotted lines (on which either $q^M = 0$ or $w = 0$). I will reference this "sign-test" logic in Section 4. A more exact exercise can jointly identify $(q^M, w)$ using the point estimates of $(b^{\Delta}, b^{\mathrm{FCE}})$ and use additional informative moments to learn the other model parameters. I pursue this approach in Section 5.

# 3 Data

## 3.1 Monetary Surprises

To measure the market's interest-rate forecast revisions ("$\Delta$"), I use data on futures-market interest rate surprises ("high-frequency monetary shocks") from Bauer and Swanson (2023b). The data cover 321 FOMC announcements from 1988 to 2019.[7] I use the original authors' measure of a one-dimensional "Monetary Policy Surprise (MPS)" calculated as the first principal component of shocks to the one, two, three, and four-quarter Eurodollar contracts in 30-minute windows bracketing monetary announcements. This decision is consistent with findings in the literature that revisions to longer-term expectations play a dominant role in affecting financial markets (Gürkaynak, Sack, and Swanson, 2005) and that a one-dimensional summary of these revisions is empirically predictive of key outcomes (Nakamura and Steinsson, 2018). In light of the theory, focusing on average interest rate expectations for the next year may help pick up the persistent policy changes that are more likely to have measurable real effects.

## 3.2 Beliefs About Macroeconomic Variables

To measure "Market" forecasts about macroeconomic variables, I use consensus forecasts from the Blue Chip Economic Indicators (BCEI) survey from 1988 to 2019. The BCEI survey is administered each month to more than 50 economists "employed by some of America's largest and most respected manufacturers, banks, insurance companies, and brokerage firms" according to the publisher (Wolters Kluwer, 2024). I use forecasts of unemployment and real GDP growth as baseline proxies of forecasted real activity ("$Y$"). In additional analyses, I also study forecasts of 3-month Treasury rates and Consumer Price Index (CPI) inflation.

To measure the "Fed's" macro beliefs, I use the Board of Governors staff's Greenbook or Tealbook forecasts from 1988 to 2018. Finally, I also use data on the FOMC staff's forecasts for the 3-month Treasury rate from the Greenbook (Tealbook) Financial Assumptions.

## 3.3 Public Signals

I consider four variables to proxy for the model's public signal about aggregate demand.

The first is consumer sentiment about labor market performance from the Michigan Survey of Consumers, based on a question asking individuals whether they believe unemployment 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 balance score defined

[7] Following Bauer and Swanson (2023a), I drop the FOMC meeting on September 17, 2001, due to its proximity with the 9/11 terrorist attacks. Results for all analyses are similar with this observation included.

by Curtin (2019): the difference between the fraction who believe unemployment will go down (the positive response) versus the fraction who believe unemployment will go up (the negative response). I focus on sentiment for two related reasons. First, previous empirical work corroborates that Michigan-survey aggregates predict consumption and spending (Carroll, Fuhrer, and Wilcox, 1994). Second anecdotal evidence about policymaking, including the FOMC transcripts reviewed in Online Appendix D.2, suggests the Federal Reserve is highly attentive to consumer sentiment as a leading indicator of the business cycle.

The second indicator is consensus unemployment forecasts from the Blue Chip Economic Indicators survey. The BCEI consensus is printed in that month's newsletter, generally published on the 10th of the month. I treat the BCEI consensus forecast in the previous month as a public signal available in the current month. The third indicator is recent returns of the S&P 500, based on end-of-month closing prices. Previous research has suggested that recent stock returns are a major determinant of policy in the modern era (Cieslak and Vissing-Jorgensen, 2020). The fourth indicator is investor sentiment about the stock market from the weekly survey of the American Association of Individual Investors. Respondents may indicate whether they are "Bullish," "Bearish," or "Neutral" about stock market performance over the next six months. As a summary, I measure the difference in the fraction of Bullish and Bearish respondents. Greenwood and Shleifer (2014) show that bullishness in survey indicators of stock market beliefs is informative about both individual investor behavior and stock market movements.

Finally, to capture a primary component of economic news and allow comparability with the analysis of Bauer and Swanson (2023a), I measure the surprise component of the monthly non-farm payrolls (NFP) release of the (change) in number of workers in the US economy. I measure the surprise as the difference between the first-release NFP figures and the median pre-release expert forecast reported by Haver Analytics' Money Market Service.

# 4 Empirical Results

I now present my main empirical results. I first establish that public signals predict monetary surprises: in particular, "bad news" correlates with 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 that "bad news" correlates with the market's overestimating real variables, slowly revising these forecasts, and being more optimistic than the Fed. Finally, I show that controlling for lagged public signals significantly attenuates measured "information effects," in line with the model's predictions.

## 4.1 Predicting Monetary Surprises

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

$$\Delta_t = \beta_X \cdot X_{t-1} + \varepsilon_t \tag{12}$$

I normalize the predictors to have zero mean and unit standard deviation in the regression sample. The units of $\Delta_t$ are such that a unit increase corresponds to a one-percentage-point increase in four-quarter Eurodollar rates, so the units of $\beta_X$ are of a one-standard-deviation outcome on percentage points for interest rates. When there are multiple FOMC meetings (and therefore surprises) in the same month, I sum over them. This avoids double-counting observations that correspond to the same realizations of the predictors and is also consistent with the treatment of these data in other macroeconomic contexts (see, e.g., Ramey, 2016).

The five predictors 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) the average Bull-Bear spread in the AAII survey over the five weeks before the month's first announcement; and (v) the surprise component of the non-farm payroll release in the current month.[8]

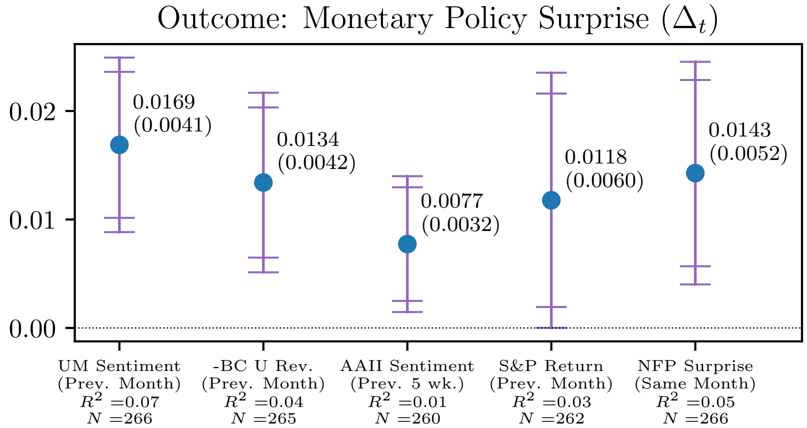
The null hypothesis $\beta_X = 0$, under which monetary surprises are unpredictable by lagged news, is consistent with the asymmetric information model with correctly specified Bayesian inference or with a knife-edge departure from that model in which forecasting biases exactly cancel out. The alternative hypothesis $\beta_X \neq 0$ is consistent only with models with some departure from the Bayesian benchmark.

**Results.** For all predictors, I find statistically significant evidence that $\beta_X > 0$ (Figure 2). The magnitudes are all in the range of 0.7 to 2.0 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. These findings are consistent with the observations that various macroeconomic variables predict monetary surprises in studies by Cieslak (2018), Miranda-Agrippino (2015), and Bauer and Swanson (2023a).[9]

[8]The NFP release for data pertaining to month $t-1$ occurs on the first Friday of the following month. If the monetary announcement takes place before this, I use the previous month's release.

[9]To help visualize what observations drive this result, Appendix Figure A1 shows the scatterplot of monetary surprises against the previous month's unemployment sentiment. At a glance, rate cuts during recessions provide the most influential observations. This is consistent with anecdotal evidence regarding the origin of disagreements in Online Appendix D.2.

**Figure 2:** Predicting Monetary Surprises




*Notes*: The regression equation is Equation 12. Each estimate corresponds to a separate univariate regression. The units for the coefficients are implied percentage points of monetary surprise per one-standard-deviation outcome of the regressor. The error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

## 4.2 Predicting Forecast Errors

**Empirical Model.** I next study the relationship between public signals and market forecast errors, guided by Proposition 2 of the model. The previous section's results suggested that multiple variables satisfy the description of a public signal which predicts monetary surprises. For the main analysis, I use a re-scaling of the first predictor, lagged labor-market sentiment in the Michigan survey. Specifically, I take $\hat{Z}_{t-1} = \hat{\beta} X_{t-1}$ where $\hat{\beta}$ is the regression coefficient from my estimate of Equation 12. The rescaling allows for a simple interpretation of coefficients below in terms of their relationship to a predictable one percentage point interest rate surprise. I review results for this (and other) regressions with different choices of $X$ in Section 4.6.

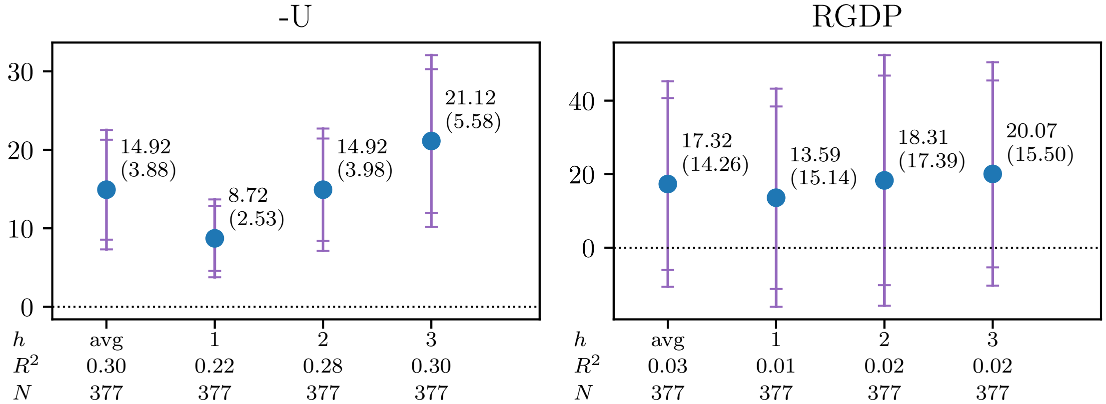
As proxies for market beliefs about real macroeconomic outcomes, I take the consensus Blue Chip forecast in month $t$ for the negative unemployment rate (i.e., the employment rate) and real GDP growth. I use data on horizons 1, 2, and 3 quarter-ahead forecasts, as well as the average of all three. I use final-release macro data for the main analysis and later study first-release macroeconomic data as a robustness check. The full sample consists of 377 months from 1988 to 2019. This exceeds the number of observations above because this test is also possible in months that do not have an FOMC meeting.

I estimate the following regression equation for each predictor $Y$ and horizon $h$:

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

**Figure 3:** Market Forecast Errors and Public Signals

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




*Notes*: The regression equation is Equation 13, and each estimate corresponds to a different univariate regression. The outcome is the negative forecast error of unemployment (left panel) or the forecast error of real GDP growth (right panel) at the indicated horizon from the Blue Chip survey. The "avg" outcome is the average of the one-, two-, and three-quarter-ahead forecast errors. The units for the coefficients are basis points of forecast error per basis points of expected monetary surprise. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

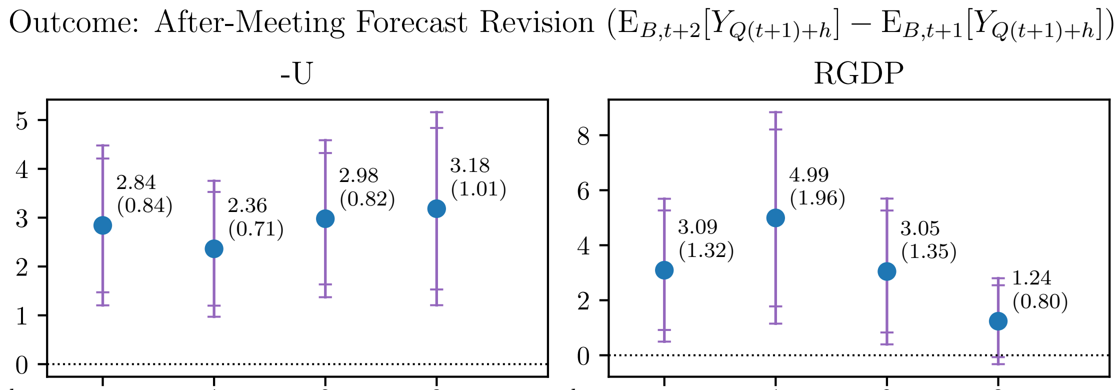
where $t$ indexes times in months; $Q(t)$ returns the quarter index of month $t$; and $Q(t) + h$ indexes the outcome $h$ quarters ahead of the current quarter.

Proposition 2 provides an economic interpretation for the possible cases for $\beta^{FCE}$. We obtain a sharper picture when conditioning on the result above (Figure 2), which through the lens of the model implies *at least one* of under-confidence or under-estimation of monetary reaction. From this perspective, $\beta^{FCE} > 0$ implies that there is under-confidence in the public signal and $\beta^{FCE} < 0$ implies that there is under-estimation of the Fed's response to the public signal.

**Results.** I find consistent evidence that $\beta^{FCE} > 0$ (Figure 3) This evidence is strongly statistically significant ($p$-value less than 5%) at all horizons for unemployment as the outcome, and similarly signed but not statistically significant for real GDP growth as the outcome. As mentioned above, these findings are consistent in the model with under-confidence in the public signal. They are also consistent with findings in the literature of sluggish adjustment aggregate macroeconomic expectations (Coibion and Gorodnichenko, 2012, 2015).

For unemployment, in particular, the magnitudes are large. The standard deviation of forecast errors (at the "average" horizon) over the sample period is 46 basis points, while a one-standard-deviation variation in $\hat{Z}$ (1.7 basis points) predicts a 26 basis-point change in the error. The $R^2$ of the same regression is 30%.

**Figure 4:** Post-Announcement Forecast Revisions and Public Signals




| $h$ | avg | 1 | 2 | 3 | $h$ | avg | 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|---|---|
| $R^2$ | 0.16 | 0.11 | 0.15 | 0.16 | $R^2$ | 0.11 | 0.10 | 0.09 | 0.03 |
| $N$ | 240 | 240 | 240 | 240 | $N$ | 240 | 240 | 240 | 240 |

*Notes*: The regression equation is Equation 14, and each estimate corresponds to a different univariate regression. The outcome is the negative forecast revision for unemployment (left panel) or the forecast revision for real GDP growth (right panel) at the indicated horizon from the Blue Chip survey in the following month. The "avg" outcome is the average of the one-, two-, and three-quarter-ahead revisions. The units for the coefficients are basis points of forecast revision per basis point of expected monetary surprise. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

### 4.3 Predicting Post-Announcement Forecast Revisions

**Empirical Model.** I now implement the second test described in Proposition 2, which concerns forecast updates after the monetary announcement. To implement this test, I take the revision in the consensus Blue Chip forecast between the first Blue Chip Survey after a given monetary announcement and the *subsequent* month. The empirical model is

$$\mathbb{E}_{B,t+2}[Y_{Q(t+1)+h}] - \mathbb{E}_{B,t+1}[Y_{Q(t+1)+h}] = \alpha + \beta^{Rev} \cdot \hat{Z}_{t-1} + \varepsilon_t \tag{14}$$

where the left-hand-side variable is the forecast revision about an $h$-quarter ahead outcome between months $t+1$ and $t+2$. Because of the restriction to months $t$ with a monetary announcement and to announcements which take place after the Blue Chip survey's data collection, this analysis has a sample of 240 observations.

The prediction $\beta^{Rev} > 0$ is consistent with under-confidence in the public signal, and the previous finding of $\beta^{FCE} > 0$, while the prediction $\beta^{Rev}$ is consistent with under-estimating the Fed's response to the public signal. Equation 14, apart from its justification in the theory, is also a potentially useful empirical complement to the earlier test of forecast errors because it does not require any data on final outcomes.

**Results.** I find consistent evidence of $\beta^{Rev} > 0$ (Figure 4). That is, forecasters adjust up their forecasts after positive realizations of $\hat{Z}$ three months in the past. In the model, this is consistent with forecasters fixing their original mistake in forecasts as new information arrives.

Consistent with the previous subsection's findings, the predicted forecast revisions in this model are economically large. The standard deviation of forecast revisions for unemployment (averaging over horizons) is 12 basis points, and the predicted change induced by a one-standard-deviation change in $\hat{Z}_t$ is 5 basis points.

## 4.4 Predicting Disagreement

**Empirical Model.** To study how public signals induce disagreement between the public and the Fed, I estimate the following model to predict the Greenbook-to-Blue-Chip forecast gap:

$$\mathbb{E}_{G,t}[Y_{Q(t)+h}] - \mathbb{E}_{B,t}[Y_{Q(t)+h}] = \alpha + \beta^{Di} \cdot \hat{Z}_{t-1} + \varepsilon_t \tag{15}$$

This regression operationalizes Equation 6 and the subsequent discussion. This approach for understanding systematic differences in the shock-response of Fed and Market forecasts contrasts with that of Romer and Romer (2000) and Bauer and Swanson (2023a), who test for asymmetry in Fed and Market forecasts by comparing their unconditional accuracy.

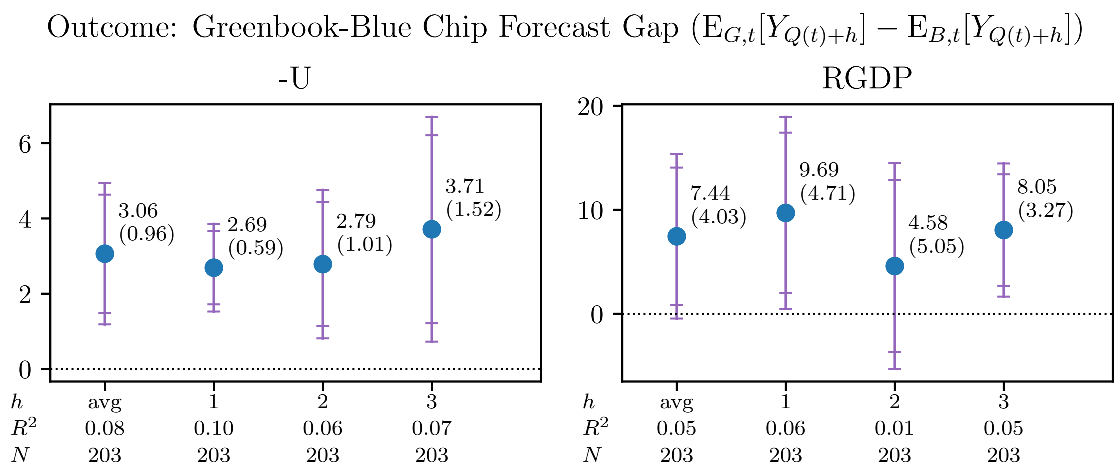
**Results.** Figure 5 confirms that $\beta^{Di} > 0$ for both variables and all prediction horizons. The signal proxy, by itself, explains about 10% between the Blue Chip consensus and the Fed staff forecast about unemployment over each horizon. The implication is that, over this sample period, markets and the Fed systematically disagree through the business cycle due to differential responsiveness to economic news.

## 4.5 Revisiting the Information Effect

**Empirical Model.** The previous findings suggest that professional forecasts slowly absorb information in public signals about aggregate demand. Through the lens of Corollary 1, this generates a prediction that standard empirical techniques designed to measure monetary signaling effects (Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018) will *over*-state the influence of monetary surprises on private-sector beliefs about real outcomes. Good news about aggregate demand predicts both monetary surprises and subsequent slow learning from other information sources, a form of common-causation bias.

I now test this prediction 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 second business day of the month, to ensure that month $t$'s FOMC meeting occurs after month $t$'s Blue Chip survey concludes. Thus these forecast revisions bracket the FOMC meeting: the

**Figure 5:** Forecast Disagreements and Public Signals




*Notes*: The regression equation is Equation 15, and each estimate corresponds to a different univariate regression. The outcome is the difference in Greenbook and Blue Chip forecasts for the negative unemployment rate (left panel) or real GDP growth (right panel) at the indicated horizon. The "avg" outcome is the average of the one-, two-, and three-quarter-ahead forecast differnces. The units for the coefficients are basis points of forecast disagreement per basis point of expected monetary surprise. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

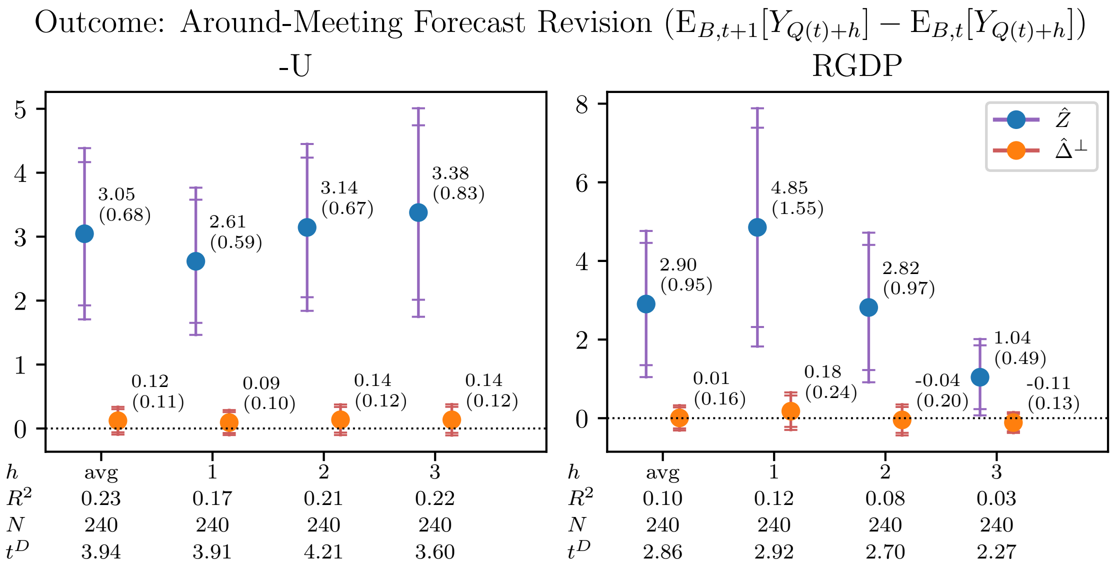
first survey takes place before the meeting and the second survey takes place after the meeting. The timing is identical to that in Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018). The estimating equation is the following:

$$\mathbb{E}_{B,t+1}[Y_{Q(t)+h}] - \mathbb{E}_{B,t}[Y_{Q(t)+h}] = \alpha + \beta^Z \cdot \hat{Z}_{t-1} + \beta^\Delta \cdot \hat{\Delta}_t^\perp + \varepsilon_t \tag{16}$$

where we define the new regressor $\hat{\Delta}_t^\perp := \Delta_t - \hat{Z}_{t-1}$ that isolates the component of the monetary surprise that is *not* spanned by the public signal predictor. Corollary 2, stated and proven in Appendix A, shows that this regression that controls for lagged public signals isolates the "true" information effect, defined as the component of the Market (Blue Chip) forecast revision explained by the revised expectations about monetary actions, via the coefficient $\beta^\Delta$. The coefficient $\beta^Z$ absorbs the bias that arises from common causation, as described above.

**Results.** I find statistically strong evidence of $\beta^Z > 0$ and $\beta^\Delta \approx 0$. That is, the positive correlation between monetary surprises and forecast revisions around monetary announcements (Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018) can be explained by public information that is revealed *before* both the monetary announcement and the initial Blue Chip survey. This is consistent with the empirical approach and main findings of Bauer and Swanson (2023a).

**Figure 6:** Revisiting the Information Effect




*Notes*: The regression equation is Equation 16 , and each estimate corresponds to a different univariate regression. The outcome is the negative forecast revision for unemployment (left panel) or the forecast revision for real GDP growth (right panel) at the indicated horizon from the Blue Chip survey. The "avg" outcome is the average of the one-, two-, and three-quarter-ahead revisions. The units for the coefficients are basis points of forecast revision per basis point of (expected or unexpected) monetary surprise. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The $t^D$ row reports the t-statistic for the difference of coefficients.

Through the lens of the model, this is consistent with Market under-reaction to the public signal (see, e.g., Case 2 of Corollary 1) and "belief momentum" after monetary announcements. Note that it is insufficient for there merely to be additional information revealed between the Blue Chip survey and the monetary announcement (e.g., a jobs report) conditional on correct specification of precisions ($q^M = w = 0$), as such information sources could be nested in the model as part of the Fed signal $F$. Instead, it must additionally be the case that the Market under-reacts to older pieces of information that may well be correlated with the apparent "surprise" component of newer information.

## 4.6 Additional Analysis

In Section 5, I will interpret the empirical estimates via the model to quantify the relative importance of central bank private information and forecasting biases. Before continuing to this step, I review several robustness exercises and extensions of the main analysis. These are not strictly necessary for the quantification, but they help contextualize the empirical findings and address hypotheses outside the scope of the model.

**Survey Forecasts of Interest Rates.** I treated interest rate surprises derived from futures markets as a measure of $\Delta$ to be as precise as possible about the timing of forecasts around monetary announcements and to be consistent with a large literature studying the properties of these high-frequency shocks (following Kuttner, 2001). To expand upon the latter point, note that "low-frequency monetary surprises" from monthly frequency surveys are subject to many of the same interpretational issues as "low-frequency macroeconomic forecast revisions" as highlighted in the analysis of the Fed information effect (Corollary 1 and Section 4.5). Nonetheless, it is interesting to revisit the analysis of both predictable forecast errors and predictable disagreements using predictions of the 3-month Treasury rate from the Blue Chip survey and the Fed's Greenbook (Tealbook).[10] I find that the public signal is a statistically significant positive predictor of both Blue Chip forecast errors and the Greenbook-Blue Chip gap between one and three quarters out (Figure A2). That is, good news about demand predicts that the Blue Chip respondees under-estimate future interest rates and that their predictions are below the Fed's assumptions. This is directionally consistent with the main findings above.

**Alternative High-Frequency Forecasts.** Among the possible measures for high-frequency surprises, I focused on the first principal component of the one, two, three, and four-quarter Eurodollar futures following Bauer and Swanson (2023a,b). In Appendix Figure A4, I separately show the analysis of predictability (Section 2.2) for each asset. The results are quantitatively similar for each outcome.

**Alternative Public Signals.** From Section 4.2 onward, I studied a single variable (lagged sentiment in the Michigan survey) as the public signal. Figure A4 re-estimates the main regression results (Figures 3, 4, 5, and 6) using each candidate signal from Section 2.2. While precise magnitudes vary between the cases, the qualitative take-aways and statistical significance of the results are robust.

**News About Inflation.** The main analysis focused on real variables. This choice is motivated by the studied sample period, which saw relatively controlled inflation. But, of course, it is also of interest to understand the extent to which these predictions extend to news about and forecasts of inflation. Figure A5 recreates the surprise predictability analysis of Section 4.1 using three public signals that encode news about inflation: the past month's median inflation expectation in the Michigan Survey, the change between last month and the prior month in the same, and the average (across one-, two-, and three-quarter forecast) revision to CPI expectations in the previous month's Blue Chip survey. All three variables predict surprise monetary tightening, the latter two with comparable magnitude and statistical significance to the baseline

[10] The Greenbook (Tealbook) "forecasts" in this case correspond to the financial assumptions used for modeling.

predictors studied in Section 4.1. Figure A6 recreates the analysis of predicting forecast errors and the Greenbook-Blue Chip gap, keeping the definition of the public signal consistent with the main analysis. Directionally, positive news in this signal predicts a positive CPI forecast error, although this is imprecisely estimated. The same news predicts a significantly *negative* Greenbook-Blue Chip gap. This would be consistent with both Markets and the Fed perceiving a relatively low direct pass-through of aggregate demand shocks to inflation via the labor market but a relatively high pass-through of monetary actions to inflation. This logic could rationalize the findings that markets, relative to the Fed, under-predict output (employment), under-predict interest rates, and over-predict inflation after positive demand shocks.

**First-Release Macro Data.** The main analysis used current ("final release") macroeconomic data to calculate forecast errors. Economically, this correctly captures inaccuracy in forecasting economic conditions. Nonetheless, the literature on forecast error accuracy commonly also considers comparisons to first-release macroeconomic data. Appendix Figure A7 recreates the analysis of Section 4.2 using first-release macroeconomic data. The results are noisier than, but consistent with, the main findings.

**Real-time Forecasting.** The main analysis studies *ex post* predictability of forecast errors and revisions. In the model, these *ex post* measurements are most informative about underlying forecasting biases. That said, they may give a misleadingly strong impression that forecasters or futures market participants are making corectable *mistakes* in real time (see also discussion by Bianchi, Ludvigson, and Ma, 2022). To further investigate these issues, I study three extensions.

First, to understand whether predictability patterns are stable over the sample, I study *rolling regression* counterparts to the main analyses predicting monetary surprises (Figure A8) and Blue Chip forecast errors (Figure A9). In the former case, the rolling estimates are positive for 70% of time periods averaging across predictors. Nonetheless, there is significant real-time uncertainty about the value of each predictor. In the latter case, there is also a consistent overall sign pattern, but also clear periods (most notably, the Great Recession and recovery) in which the pattern is significantly more pronounced.

Second, to quantify the potential profitability of exploiting predictability in the Fed Funds futures markets, I conduct a pseudo-out-of-sample forecasting exercise that corresponds to the analysis of Section 4.1. I describe the analysis in fuller detail in Online Appendix D.1 and summarize two main take-aways here. First, the pseudo-out-of-sample $R^2$ for predicting the magnitude of surprises is very low, ranging from 0.000 to 0.016 across predictors, compared to 0.01 to 0.07 in sample. Second, simple portfolios that condition on the predicted direction of monetary surprises from real-time regressions achieve Sharpe Ratios of 0.2 to 0.3, which is extremely poor by standard benchmarks. That is, in practical terms, the *variance* inherent in exploiting these relationships in real time is very high.

Third, I re-create the forecast error predictability analysis of Section 4.2 using the *machine efficient benchmarks* of Bianchi, Ludvigson, and Ma (2022). These authors train a machine learning algorithm to make forecasts using real-time data and argue that this is a more fair reference point to define "belief distortions." I focus on four-quarter ahead forecasts of real GDP growth, the primary real-activity forecast studied by these authors. In Figure A11, I estimate Equation 13 (predicting forecast errors with $\hat{Z}_t$) using the relative-to-data forecast error, relative-to-machine forecast error (machine prediction minus Blue Chip forecast), and the gap between data and machine. I find considerably more predictability with errors relative to *ex post* data compared to errors relative to the machine benchmark, and moderate predictability of the data-to-machine gap. This further suggests that the properties of beliefs uncovered above, while quantitatively significant *ex post*, would not be easy to detect in real time.

**Does the Fed Teach the Markets How to Learn?** A possibility which was not formalized in my analysis is that the Federal Reserve influences public beliefs by shifting their perceptions of which statistical indicators contain valuable news. That is, "the Fed teaches the Market how to learn." It is difficult to test all variations of this hypothesis empirically. At low frequencies, the general trend over time toward lower forecast error predictability (Figures A8 and A9) is consistent with this hypothesis, but also with many others, including statistical learning about variances and random chance. Moreover, there are pronounced and persistent gaps between Greenbook and Blue Chip forecasts for unemployment, real GDP growth, and CPI inflation throughout the sample (Figure A10), suggesting that systematic differences in how these groups read economic data do not completely disappear over time.

At a month-to-month frequency, a more direct test of the hypothesis is possible. If Fed announcements are crucial for the public to understand the value of public signals, then it seems reasonable that public signals have less predictive value for forecast errors from months *after* FOMC meetings and announcements. To test this, I estimate the regression model

$$\begin{aligned} Y_{Q(t+1)+h} - \mathbb{E}_{B,t+1}[Y_{Q(t+1)+h}] = \alpha &+ \beta_{NM} \cdot (X_{t-1} \times \text{No Meeting}_t) \\ &+ \beta_M \cdot (X_{t-1} \times \text{Meeting}_t) + \gamma \cdot \text{Meeting}_t + \varepsilon_t \end{aligned} \tag{17}$$

where $X_{t-1}$ are the public signals studied in Section 4.1 and $\text{Meeting}_t$ is an indicator for whether there is an FOMC meeting in month $t$, which is the case for 261 of the 377 months in the main sample. If Fed announcements help the public understand the economic relevance of the signals $X_{t-1}$ (i.e., lower the $q^M$ with which they are processed), then we predict $\beta_{NM} > \beta_M$: forecast error predictability is higher in months with no policy announcement to help the public interpret the data. If meetings and associated communications are sufficient to fully mitigate the belief distortion, then we predict that $\beta_M = 0$. What we find is strong statistical evidence that $\beta_M > 0$ for all candidate signals and no statistically strong evidence that $\beta_{NM} > \beta_M$ (Figure

A12).[11] In fact, for the NFP surprise, we find instead strong evidence that $\beta_{NM} < \beta_M$. While this test is far from conclusive, it is consistent with the idea that public interpretation of news is (at least in the short run) relatively insenstive to monetary announcements.

# 5 Quantification

In this section, I fit the model of Section 2 to the empirical findings. This allows more precise quantification of the relative importance of each of the main mechanisms—asymmetric information, asymmetric beliefs about the policy rule, and asymmetric response to public information.

## 5.1 Methods

To map the theory to the data, I adopt the following conventions. A given month's Blue Chip survey, which is administered in the first week of the month, corresponds to $t = 0$ in the model; that month's subsequent monetary announcement is $t = 1$; and the beginning of the next month corresponds to $t = 2$. The model public signal $Z$ is the constructed signal $\hat{Z}$ from the empirical analysis, based on lagged consumer sentiment about the labor market from the Michigan Survey of Consumers (Section 4.2). The model interest rate $r$ is the linear combination of interest rates that corresponds to the Monetary Policy Surprise (Bauer and Swanson, 2023a). The outcome $Y$ is the average negative unemployment rate over the subsequent three quarters.

The model has seven parameters, listed in Table 1.[12] I match seven moments. Six have been described and reported in Section 4: the $R^2$ of predicting monetary surprises with $\hat{Z}_t$; the coefficient and $R^2$ of regressing Blue Chip forecast errors on $\hat{Z}_t$; the coefficient of regressing Greenbook-Blue Chip forecast gap on the same; and the coefficients of regressing $(\hat{Z}_t, \hat{\Delta}_t^{\perp})$ on forecast revisions. The last is the regression coefficient of $\hat{Z}_{t-1}$ on $Y$, or $\beta^Y$ in the model

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

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

To fit the model, I minimize the sum of squared deviations of the model prediction from each moment. Appendix C provides exact formulas for each moment in terms of model parameters. The moments are matched exactly.

[11] Figure A13 performs the same analysis where the outcome variable is the forecast revision between months $t$ and $t + 1$. This empirical design is parallel to the one used to the Fed Information effect in Section 4.5. In this case, the "Fed teaches the markets" hypothesis would be associated with $\beta_M > \beta_{NM}$: predictable revisions are larger when the FOMC meeting occurs between survey rounds. I find no evidence for this except when the predictor is the lagged stock retur. Nonetheless, even in this case, the difference $\beta_M - \beta_{NM}$ is small compared to the predictable component of the forecast error (Figure A12).

[12] The remaining free parameter, the precision or variance of the fundamental, is set to one. This is a normalization with no bearing on the calibration.

**Table 1:** Model Calibration

Panel A: Moments

| | Matched Moment | Reference | Value |
|---|---|---|---|
| 1 | $R^2$ from predicting surprises | Section 4.2 | 0.07 |
| 2 | $\beta^{FCE}$ for BC | Section 4.2 | 14.92 |
| 3 | $R^2$ for predicting FCE (BC) | Section 4.2 | 0.30 |
| 4 | $\beta^{Di}$ for predicting GB-BC gap | Section 4.4 | 3.06 |
| 5 | $\beta^{Z}$ for BC Revisions | Section 4.5 | 3.05 |
| 6 | $\beta^{\Delta}$ for BC Revisions | Section 4.5 | 0.12 |
| 7 | $\beta^{Y}$ from Equation 18 | Section 5.1 | 31.21 |

Panel B: Parameters

| Parameter | Value |
|---|---|
| $q^M$ | 0.08 |
| $q^F$ | 0.06 |
| $w$ | 0.003 |
| $\tau_Z$ | 69.0 |
| $\tau_F$ | 2.4 |
| $\tau_S$ | 17.9 |
| $a$ | 1.12 |

*Notes*: Panel A prints the seven targeted moments. The moments are fit exactly by the model. Panel B prints the estimated parameters.

## 5.2 Measuring Belief Distortions and Fed Information

The moments and estimated parameters are summarized in Table 1. The findings clarify several points about the relative strength of each mechanism for disagreement, which go beyond the "sign-test" interpretation of findings in Sections 4 and 4.5.

**Under-reaction and Mis-perception are Both Required to Fit the Data.** First, $q^M > 0$ and $w > 0$: the data require Market under-estimation of public data in the monetary rule and Market under-reaction to public data. Through the lens of Figure 1, which outlined the cases for identifying $(q^M, w)$, the empirically relevant case is the top-right quadrant.

**Both Matter Equally for Errors about $r$, but Under-reaction Matters More for Errors about $Y$.** By combining information on forecast errors about interest rates ($r$) and real outcomes ($Y$) to uncover multiple mechanisms for forecast bias, we can structurally decompose Market forecast errors about both variables. For interest rates, we apply Equation 4 and use the uncorrelatedness of the public signal $Z$ with the correctly-specified-Bayesian ("rational") forecast error to calculate

$$\mathrm{Var}[r-\mathbb{E}_{M,0}[r]] = \underbrace{\mathrm{Var}[\delta_F^F(F-\mathbb{E}^R_{M,0}[F])]}_{\substack{\text{Rational Component}\\=93.3\%}} + \underbrace{\mathrm{Var}[\delta_F^F q^M Z]}_{\substack{\text{Under-reaction}\\=1.4\%}} + \underbrace{\mathrm{Var}[wZ]}_{\substack{\text{Mis-perception}\\=1.9\%}} + \underbrace{2\mathrm{Cov}[\delta_F^F q^M Z, wZ]}_{\substack{\text{Interaction}\\=3.3\%}} \quad (19)$$

where the labels interpret each term and the percentages correspond to each term's contribution to Var[$\Delta$] under the calibration. By direct calibration (line 1 of Table 1A), 93.3% of the surprise is unpredictable and corresponds to the forecast error that a "rational" Market would make if updating beliefs with Bayes rule under correct specification. Within the predictable component, under-reaction and mis-perception have close to equal contributions. Removing the former would reduce the predictable covariance by $\frac{1.4\%+3.3\%}{1.4\%+1.9\%+3.3\%} = 71.2\%$, and removing the latter would reduce the predictable covariance by $\frac{1.9\%+3.3\%}{1.4\%+1.9\%+3.3\%} = 78.5\%$.

For unemployment, we apply Equation 5 and calculate

$$\begin{aligned}\text{Var}[Y - \mathbb{E}_{M,0}[Y]] = &\underbrace{\text{Var}[(Y - \mathbb{E}^R_{M,0}[Y])]}_{\substack{\text{Rational Component} \\ =70.0\%}} + \underbrace{\text{Var}[q^M(a - \delta^F_F)Z]}_{\substack{\text{Under-reaction} \\ =32.2\%}} + \underbrace{\text{Var}[-wZ]}_{\substack{\text{Mis-perception} \\ =0.04\%}} + \\ &\underbrace{2\text{Cov}[q^M(a-\delta^F_F)Z, -wZ]}_{\substack{\text{Interaction} \\ =-2.2\%}}\end{aligned} \tag{20}$$

Again by direct calibration (line 3 of Table 1), 70.0% of of the forecast error is unpredictable and "rational." Within the predictable component, mis-perception of the monetary rule has an almost negligible effect that partially offsets under-reaction to the public signal. When news in the public signal is positive, the Market slightly under-estimates the monetary response and therefore, via this channel, is slightly too optimistic about employment; but this channel is quantitatively dominated by under-reaction to the public signal. This comparison of magnitudes reveals why we did not observe a negative correlation between public signals and forecast errors, which was a theoretical possibility raised in Case 3 of Proposition 2. More concretely, this decomposition suggests that Market mis-perception of the monetary rule is not quantitatively important for explaining imprecision and inertia in macroeconomic expectations (Coibion and Gorodnichenko, 2012, 2015; Angeletos, Huo, and Sastry, 2021).

**The Fed Also Under-reacts, but to a Lesser Extent.** Third, $0 < q^F < q^M$: the Fed under-reacts to public data, but to a lesser extent than the market. This is consistent with previous findings of forecast error inertia for both professional and central-bank forecasts in response to shocks (Coibion and Gorodnichenko, 2012). This result also result implies that shocks to public signals can induce systematic disagreements between the groups.

Moreover, I can quantitatively verify that the gap is large enough to sustain "normative agreements" as described in Section 2.4 (Equation 8):

$$\begin{aligned}\frac{\mathrm{d}\Delta^N}{\mathrm{d}Z} &= (1-\delta^F_F)q^M - q^F - w \\ &= 0.97 \cdot 0.08 - 0.06 - 0.003 = 0.015 > 0\end{aligned} \tag{21}$$

That is, the Market thinks that the Fed over-reacts to news, or that it tightens too fast after strong news about demand and loosens too quickly after weak news about demand. This is consistent with an interpretation of the "Fed Response to News" channel introduced by Bauer and Swanson (2023a) as well as the anecdotal evidence from case studies in Appendix D.2.

**The Fed Has Very Little Additional Information.** Fourth, $(\tau_Z, \tau_S) \gg \tau_F$, or the non-private sources of information in the economy are much more precise than the private information. The precision weight on the Fed's signal in the monetary rule is $\tau_F/(\tau_\theta + \tau_F + \tau_Z) = 0.03$, which is itself about 27 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. Combined with the earlier finding of heterogeneous confidence in public data, limited Fed information is also consistent with the reality of there being persistent and cyclical gaps between Fed and Market forecasts (see, e.g., Figure A10), without very large differences in forecast accuracy (Faust, Swanson, and Wright, 2004; Bauer and Swanson, 2023a).

## 5.3 Beliefs under Counterfactual Scenarios

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

**Letting the Market Run the Fed (and Vice Versa).** I first study the counterfactual of giving the Fed the Market's (biased) viewpoint (Row 1). By construction, this loads all disagreements between the parties onto the Fed's signal $F$, and therefore removes all disagreement after $F$ has been revealed by the monetary announcement. This worsens the Fed's forecast of output and lessens its policy responsiveness to shocks. In turn, because of this diminished policy response, market beliefs are more sensitive to fundamentals (by 19.0% at $t = 0$ and 13.5% at $t = 2$).

I next study the opposite experiment of having the Market adopt the Fed's viewpoint. This does not change the monetary rule, but still increases the sensitivity of Market beliefs to fundamentals by making market beliefs about aggregate demand more responsive to fundamentals. This improves the variance of market forecast errors by 12%.

Together, these results underscore the importance of heterogeneous priors or responsiveness to public data, above and beyond the level of that responsiveness, as a determinant of business

**Table 2:** Counterfactual Predictions

| | Scenario Name | Percent Change from Baseline | | | | | |
|---|---|---|---|---|---|---|---|
| | | $\frac{\mathrm{d}\mathbb{E}_{M,0}[Y]}{\mathrm{d}\theta}$ | $\frac{\mathrm{d}\mathbb{E}_{M,2}[Y]}{\mathrm{d}\theta}$ | $\frac{\mathrm{d}r}{\mathrm{d}\theta}$ | $\mathbb{V}[\mathrm{FCE}^Y_{M,0}]$ | $\mathbb{V}[\mathrm{FCE}^Y_{F,0}]$ | $\frac{\mathbb{V}[\mathrm{FCE}^Y_{M,0}]}{\mathbb{V}[\mathrm{FCE}^Y_{F,0}]}$ |
| 1 | Market's viewpoint | 19.0 | 13.5 | -2.2 | 2.2 | 17.1 | -12.7 |
| 2 | Fed's viewpoint | 20.9 | 11.9 | 0.0 | -12.1 | 0.0 | -12.1 |
| 3 | No errors | 26.6 | 6.4 | 6.6 | -30.0 | -21.3 | -11.0 |
| 4 | No Fed Info | -2.8 | -1.6 | -0.1 | 4.2 | 2.7 | 1.5 |

*Notes*: The units are percentage differences from the baseline calibration. Each row corresponds to a different parameter case: (1) Market's viewpoint, which sets the Market's and Fed's perceived public signal precision to the calibrated value for the Market ($q^F = (1-\hat{\delta}^F_F)q^M$); (2) Fed's viewpoint, which sets the Market's and Fed's perceived public signal precision to the calibrated value for the Fed ($q^M = q^F/(1-\hat{\delta}^F_F)$); (3) No errors, which removes all belief distortions ($q^M = q^F = w = 0$); and (4) No Fed Info, which makes Fed Info arbitrarily uninformative ($\tau_F \downarrow 0$). Each column corresponds to a different statistic: (1) the sensitivity of market beliefs about $Y$ to the fundamental, (2) the sensitivity of Fed beliefs about $Y$ to the fundamental, (3) the sensitivity of the policy instrument to the fundamental, (4) the variance of the Market's forecast error about $Y$, (5) the variance of the Fed's forecast error about $Y$, and (6) the relative forecast error variance between the two agents (negative numbers mean that the Market's forecast gets relatively better).

cycle beliefs. Interestingly, there are close to symmetric effects on the economy at $t = 2$ of having the Market respond *more* to news in its beliefs of fundamentals, or having the Fed respond *less* to news via its interest rate choice.

**Quantifying Belief Distortions.** To fully benchmark the effect of all biases, I next study the effect of setting $q^M = q^F = w = 0$ and reducing the model to its Bayesian, asymmetric-information core (Row 3). Market and Fed output forecasts are considerably better, with 30.0% and 21.3% lower variance respectively. The monetary rule is more responsive to the demand shock. The movement of market beliefs is more "front-loaded" in response to the fully-processed news at $t = 0$, instead of requiring a substantial update at $t = 2$.

**Quantifying the Information Effect.** In a final, "No Fed Info" experiment, I make internal information infinitely imprecise (Row 4).[13] In particular, this scenario implies that the Fed neither leans on the internal signal for its decisions nor reveals a useful signal via its actions. This scenario has a very small effect on both the policy rule and the Market's beliefs about fundamentals. In percentage terms, the differences from the baseline in the two models that eliminate disagreement (rows 3 and 4) have respectively 7 and 8 times larger of an effect on the sensitivity of $t = 2$ beliefs, which as noted previously correspond to a notion of the model's

[13] 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.

stock price, to fundamentals. In these units, disagreement is considerably more influential for the observed pattern of beliefs than any signaling effects which are necessarily removed in the "No Fed Info" scenario.

These numbers suggest very small *information effects*, or causal effects of Fed persuasion on public beliefs. The difference in conclusions, relative to studies by Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018), lies in this paper's consideration of a larger set of models beyond the pure asymmetric information model, and use of additional moments for identification in the larger class of models. This allows my analysis, in particular, to pinpoint exactly the extent of asymmetric information required to rationalize the data; this asymmetry is by contrast essentially a free parameter in the main analysis of Nakamura and Steinsson (2018).[14] The low estimated asymmetric information reflects the extent to which a heterogeneous-priors model better fits the data.

# 6 Conclusion

This paper studies the causes and consequences of disagreement about monetary policy. I first develop a model that accommodates market and policymaker disagreement due to asymmetries in information, knowledge of the monetary rule, and confidence in public signals. I derive tests which differentiate these mechansims based on their predictions for market and central-bank beliefs. I next turn to US data from 1988-2019 to test the model's predictions. Good news in public signals predict surprise monetary tightening, private-sector pessimism about real variables, delayed correction of private-sector forecasts, and relative Fed optimism about real variables. The empirical findings imply a significant role for misspecifying the value of public information, a small role for misspecifying the monetary response to that information, and an almost negligible role for asymmetric information. Quantitatively, I validate that disagreement between markets and the Federal Reserve about the precision of public information has a large effect on market beliefs, relative to a counterfactual world in which both parties treated information symmetrically. I find that central bank signaling about fundamentals, by contrast, has a comparatively small effect on market beliefs. Taken together, these findings reconcile the idea that central banks' power over beliefs is mostly restricted to the policy path with the ubiquity of disagreement and uncertainty about fundamentals.

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

# A Omitted Proofs

## Proposition 1

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

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

which, after substituting in average expectations from Equation 2, is

$$P = (\delta_F^Z - q^F + w)Z + \delta_F^F(\delta_Z^M - q^M)Z \tag{22}$$

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 $Z$. The difference of $P$ (Equation 22) from the interest rate (Equation 1) is

$$\Delta = \delta_F^F(F - \delta_Z^M Z) + \delta_F^F q^M Z + wZ \tag{23}$$

which corresponds to Equation 4 upon definition of $\mathbb{E}_{M,0}^R[\theta] := \delta_Z^M Z$.

I next calculate $\text{Cov}[\Delta, Z]$. Using Equation 4 for $\Delta$, this can be written as

$$\text{Cov}[\Delta, Z] = \text{Cov}[\delta_F^F\varepsilon_F, Z] + \delta_F^F\text{Cov}[\theta - \mathbb{E}_{M,0}^R[\theta], Z] + \left(\delta_F^F + w\right)\text{Cov}[Z, Z] \tag{24}$$

The first term is 0 because $\varepsilon_F$ is independent of $Z$ by definition. The second is 0 because

$$\mathbb{E}\left[Z\left(\theta - \mathbb{E}_{M,0}^R[\theta]\right)\right] = \mathbb{E}\left[\mathbb{E}_{M,0}^R\left[Z\left(\theta - \mathbb{E}_{M,0}^R[\theta]\right)\right]\right] = \mathbb{E}[0] = 0 \tag{25}$$

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

$$\text{Cov}[\Delta, Z] = \left(\delta_F^F q^M + w\right)\text{Var}[Z] \tag{26}$$

which, given $\delta_F^F > 0$, is (i) 0 if $q^M = w = 0$; (ii) positive if $q^M > 0$ and $w > 0$; (iii) negative if $q^M < 0$ and $w < 0$.

## Proposition 2

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

**Forecast Errors.** First, consider $t = 0$. The market's forecast error about $r$ is $\Delta$. Its forecast error about $\theta$ is

$$\theta - \mathbb{E}_{M,0}[\theta] = (\theta - \mathbb{E}^R_{M,0}[\theta]) + q^M Z \tag{27}$$

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

$$\begin{aligned} Y - \mathbb{E}_{M,0}[Y] &= a(\theta - \mathbb{E}_{M,0}[\theta]) - (r - \mathbb{E}_{M,0}[r]) \\ &= (a - \delta^F_F)(\theta - \mathbb{E}_{M,0}[\theta]) + (a - \delta^F_F)q^M Z - wZ \end{aligned} \tag{28}$$

The covariance with $Z$ is

$$\begin{aligned} \operatorname{Cov}[Y - \mathbb{E}_{M,0}[Y] &= (a - \delta^F_F)\operatorname{Cov}[(\theta - \mathbb{E}_{M,0}[\theta]), Z] + \big((a - \delta^F_F)q^M - w\big)\operatorname{Var}[Z] \\ &= \big((a - \delta^F_F)q^M - w\big)\operatorname{Var}[Z] \end{aligned} \tag{29}$$

where the simplification uses the point, established in the proof of Proposition 1, that the rational forecast error has no covariance with $Z$. The desired properties follow given the observation that $(a - \delta^F_F) > 0$, given $a \geq 1$ (assumed) and $\delta^F_F < 1$ (immediate from the definition $\delta^F_F = \tau_F/(\tau_\theta + \tau_Z + \tau_F)$).

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

$$\hat{F} = \frac{1}{\delta^F_F}(r - (\delta^F_Z - q^F - w)Z) = F + \frac{w}{\delta^F_F}Z \tag{30}$$

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

$$\theta - \mathbb{E}_{M,t}[\theta] = (\theta - \mathbb{E}^R_{M,t}[\theta]) + \frac{\tau_0}{\tau_t}q^M Z - \frac{\delta^M_{F,t}}{\delta^F_F}wZ \tag{31}$$

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

$$\begin{aligned} \mathbb{E}^R_{M,1}[\theta] &= \frac{\tau_Z}{\tau_\theta + \tau_Z + \tau_F}Z + \delta^M_{F,1}F \\ \mathbb{E}^R_{M,2}[\theta] &= \left(1 - \frac{\tau_S}{\tau_1 + \tau_S}\right)\mathbb{E}^R_{M,1}[\theta] + \frac{\tau_S}{\tau_1 + \tau_S}S \end{aligned} \tag{32}$$

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

$$\begin{aligned} \delta^M_{F,1} &= \frac{\tau_F}{\tau_\theta + \tau_Z + \tau_F} = \delta^F_F \\ \delta^M_{F,2} &= \frac{\tau_F}{\tau_\theta + \tau_Z + \tau_F + \tau_S} \end{aligned} \tag{33}$$

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

$$Y - \mathbb{E}_{M,t}[Y] = a(\theta - \mathbb{E}_{M,t}[\theta]) \tag{34}$$

as $r$ is now known. Plugging into Equation 31, taking the covariance with $Z$, and noting the zero covariance with the average rational expectation gives

$$\begin{aligned} \mathrm{Cov}[Y - \mathbb{E}_{M,t}[Y], Z] &= a\mathrm{Cov}[(\theta - \mathbb{E}^R_{M,t}[\theta]), Z] + a\left(\frac{\tau_0}{\tau_t} q^M - \frac{\delta^M_{F,t}}{\delta^F_F} w\right) \mathrm{Var}[Z] \\ &= a\left(\frac{\tau_0}{\tau_t} q^M - \frac{\delta^M_{F,t}}{\delta^F_F} w\right) \mathrm{Var}[Z] \end{aligned} \tag{35}$$

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 (31) and (32) that the average forecast revision from $t = 1$ to $t = 2$ for $\theta$ can be written as

$$\mathbb{E}_{M,2}[\theta] - \mathbb{E}_{M,1}[\theta] = \mathbb{E}^R_{M,2}[\theta] - \mathbb{E}^R_{M,1}[\theta] - \left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right) q^M Z + \left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right) \frac{w\tau_F}{\delta^F_F} Z \tag{36}$$

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

$$\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] = a\left(\frac{1}{\tau_1} - \frac{1}{\tau_2}\right)\left(q^M - \frac{\tau_F}{\delta^F_F} w\right) \mathrm{Var}[Z] \tag{37}$$

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

## Corollary 1

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:

$$\mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y], \Delta] = \mathrm{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta] + \mathrm{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta] \tag{38}$$

Hence the desired statements concern the sign of

$$\mathrm{Cov}[\mathbb{E}_{M,2}[Y]-\mathbb{E}_{M,0}[Y],\Delta]-\mathrm{Cov}[\mathbb{E}_{M,1}[Y]-\mathbb{E}_{M,0}[Y],\Delta]=\mathrm{Cov}[\mathbb{E}_{M,2}[Y]-\mathbb{E}_{M,1}[Y],\Delta] \tag{39}$$

Next, note that $\Delta=\Delta^R+\left(\delta_F^F q^M+w\right)Z$, 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 write

$$\mathrm{Cov}[\mathbb{E}_{M,2}[Y]-\mathbb{E}_{M,1}[Y],\Delta]=\left(\delta_F^F q+w\right)\mathrm{Cov}[\mathbb{E}_{M,2}[Y]-\mathbb{E}_{M,1}[Y],Z] \tag{40}$$

Using Equation 37 from the proof of Proposition 2,

$$\mathrm{Cov}[\mathbb{E}_{M,2}[Y]-\mathbb{E}_{M,1}[Y],\Delta]=\left(\delta_F^F q^M+w\right)\left(q^M-\frac{\tau_F}{\delta_F^F}w\right)\cdot\left(\frac{1}{\tau_1}-\frac{1}{\tau_2}\right)a\mathrm{Var}[Z] \tag{41}$$

The restriction to $\mathrm{Cov}[\Delta,Z]>0$ ensures that $\left(\delta_F^F q^M+w\right)>0$. Moreover, by definition $(1/\tau_1-1/\tau_2)>0$ and $a>0$. The statements follow from sign cases for $\left(q^M-\frac{\tau_F}{\delta_F^F}w\right)$.

## Statement and Proof of Corollary 2

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

$$i^{\perp}:=\frac{Cov[\Delta^{\perp},\mathbb{E}_{M,2}[Y]-\mathbb{E}_{M,0}[Y]]}{Var[\Delta^{\perp}]} \tag{42}$$

*corresponds with the true information effect*

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

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

Toward proving the second statement, I first simplify the numerator of Equation 42:

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

Let us start with the first of the two terms. Note that $\Delta^{\perp}$ is the agent's forecast revision about $r$ under the rational model, which is contained in a rational agent's information set at $t=1$. Therefore, by the law of iterated expectations, $\mathrm{Cov}[\mathbb{E}_{M,2}[Y]-\mathbb{E}_{M,1}[Y],\Delta^{\perp}]=0$. Combining this with (42) gives the following expression for $i^{\perp}$:

$$i^{\perp} = \frac{\text{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta^{\perp}]}{\text{Var}[\Delta^{\perp}]} \tag{44}$$

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

$$\frac{\text{Cov}[\Delta, \mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y]]}{\text{Var}[\Delta]} = \frac{\text{Cov}[\mathbb{E}_{M,1}[Y] - \mathbb{E}_{M,0}[Y], \Delta^{\perp}]}{\text{Var}[\Delta^{\perp}]} \tag{45}$$

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

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

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

$$\begin{aligned} \text{Cov}[\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta], \Delta] &= \frac{\hat{\text{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\text{Var}}[\Delta]} \cdot \text{Var}[\Delta] \\ \text{Cov}[\mathbb{E}_{M,1}[\theta] - \mathbb{E}_{M,0}[\theta], \Delta^{\perp}] &= \frac{\hat{\text{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\text{Var}}[\Delta]} \cdot \text{Var}[\Delta^{\perp}] \end{aligned} \tag{47}$$

which again uses the fact that $\Delta^{\perp}$ is the rational forecast error. Combining (47) with (45) gives

$$\frac{1}{\text{Var}[\Delta]} \cdot \frac{\hat{\text{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\text{Var}}[\Delta]} \cdot \text{Var}[\Delta] = \frac{1}{\text{Var}[\Delta^{\perp}]} \frac{\hat{\text{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\text{Var}}[\Delta]} \cdot \text{Var}[\Delta^{\perp}] \tag{48}$$

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

$$\frac{\hat{\text{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\text{Var}}[\Delta]} = \frac{\hat{\text{Cov}}[\Delta, \mathbb{E}_{M,0}[\theta]]}{\hat{\text{Var}}[\Delta]} \tag{49}$$

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# Online Appendix

for "Disagreement About Monetary Policy" by Sastry

# B Model Micro-foundations

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

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

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

$$r = \mathbb{E}_{F,0}[\theta] \tag{50}$$

and expression for output,

$$Y = a\theta - r \tag{51}$$

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

### B.1.1 Primitives

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

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

$$\exp(a\theta)\left(\log C_0 - \frac{N_0^2}{2}\right) + \sum_{h=1}^{\infty} \beta^h \left(\log C_h - \frac{N_h^2}{2}\right) \tag{52}$$

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

$$C_t + R_{t+1}B_t \leq w_t N_t + B_{t-1} \tag{53}$$

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

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

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

### B.1.2 Equilibrium

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

$$\beta R_{t+1} \frac{C_t}{C_{t+1}} = 1 \tag{54}$$

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

At $t = 0$, the same condition is

$$\beta \cdot \exp(-a\theta) R_1 \frac{C_0}{C_1} = 1 \tag{55}$$

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

$$\log C_0 = a\theta - r \tag{56}$$

which corresponds exactly to abstract equation (51) when $Y = \log C_0$. One recovers the monetary rule (50) by assuming 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 I will define as the expected present-discounted value of output *adjusted by the demand shock* under a different Market agent's beliefs $\mathbb{E}_M[\cdot]$, or

$$Q = \mathbb{E}_M \left[ \exp(a\theta) C_0 + \sum_{h=1}^{\infty} \frac{C_h}{\exp\left(\prod_{k=1}^{h} R_k\right)} \right] \tag{57}$$

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

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

$$q = (1-\beta)\mathbb{E}_M[\log C_0] - \beta(\mathbb{E}_M[r] - a\mathbb{E}_M[\theta]) \tag{58}$$

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

$$q = a\mathbb{E}_M[\theta] - \mathbb{E}_M[r] \tag{59}$$

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

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

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

$$P = \mathbb{E}_{M,0}[r] \tag{60}$$

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

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

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

$$-\exp(-\alpha W) \tag{61}$$

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

The investor's optimization problem is therefore

$$\max_{p \mapsto x_i \in \mathbb{R}} -\mathbb{E}_i\left[\exp(-\alpha(E + x_i(r - P)))\right] \tag{62}$$

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

$$\max_{p \mapsto x_i \in \mathbb{R}} \mathbb{E}_i[E + x_i(r - P)] - \frac{\alpha}{2}\mathbb{V}_i[E + x_i(P - r)] \tag{63}$$

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

$$x_i(P) = \frac{\mathbb{E}_i[r] - P}{\alpha \mathbb{V}_i[r]} \tag{64}$$

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

$$\int_i x_i(P)\,\mathrm{d}i = 0 \tag{65}$$

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

$$P = \int_i \mathbb{E}_i[r]\,\mathrm{d}i \tag{66}$$

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 (66) reduces to (60). More generally, when there is not a single information set, (66) says that price equal population average beliefs.

# C Solution of Model

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

Monetary surprises are

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

This implies that $\tilde{Z}$, or the best-fit prediction of $\Delta$ with $Z$, is $(w + \delta_F^F q^M) Z$.

The Fed's policy rule is $\mathbb{E}_{F,0}[\theta] = \delta_F^F F + (\delta_Z^F - q^F) Z$, which is the same expression as (1). The Fed's expectation of output is

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

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

The market's beliefs about fundamentals are given by $\mathbb{E}_{M,0}[\theta] = (\delta_M^Z - q^M) Z$ and of the policy rate by $\mathbb{E}_{M,0}[r] = (\delta_Z^F - q^F - w + \delta_F^F(\delta_M^Z - q^M))Z$. Thus, the market beliefs about output are

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

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

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

and hence the regression coefficient is

$$\beta_F^{FCE} = \frac{aq^F}{w + \delta_F^F q^M} \tag{M4}$$

Similarly, for the market,

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

and hence the regression coefficient is

$$\beta_M^{FCE} = \frac{(a - \delta_F^F)q^M - w}{w + \delta_F^F q^M} \tag{M2}$$

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

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

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

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

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

$$Y = a\theta - \delta_F^F F - (\delta_Z^F - q^F)Z$$

from which it is immediate that

$$\beta^Y = \frac{(a - \delta_F^F)\delta_Z^M - \delta_Z^F + q^F}{w + \delta_F^F q^M} \tag{M7}$$

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

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

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

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

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

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

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

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

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

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

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

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

# D Additional Analysis

## D.1 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 48 meetings in the data, I run a linear regression of (i) previous surprises and (ii) the sign of previous surprises on $X_{t-1}$ for all data up to month $s-1$. I calculate the mean squared error for all these out of sample projections. Then, to put this in units of an "approximate $R^2$," I calculate reduction in MSE as

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

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

The first two columns of A1 gives the results. As mentioned in the main text, real time prediction of the surprises themselves is fairly poor. Only for the unemployment sentiment and stock market variables is it positive; the other two predictors (Blue Chip revisions and AAII sentiment) perform worse than the naive strategy of assuming zero surprise. Prediction of the sign of the surprise, which is still informative about real-time failures of rational expectations (and the potential for an exploitative trading strategy), is better. All four variables beat the naive strategy of assuming surprises are equally likely to have either sign.

Next, to give these results a more practical unit, I calculate the return and volatility for a portfolio based on each sign prediction regression. I assume that the investor could run the regression pseudo-out-of-sample, calculate a probability $\hat{p}$ that there will be surprise tightening, and construct a portfolio that pays off $\hat{p}$ dollars if policy tightens (the policy news shock is positive) and $1-\hat{p}$ otherwise, at the risk-neutrally fair price of \$0.50. Over such small horizons the risk-free rate is essentially zero, so I summarize the security by its Sharpe Ratio, or ratio of the expected return to the standard deviation. These Sharpe ratios, in the third column of Table A1, all lie between 0.15 and 0.30.

## D.2 Case Study Analysis: Fed Policy in 2001

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

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

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

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

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

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

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

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

In the data, the confidence break was indeed severe: the Michigan labor-market sentiment variable plunged by 13%. The Fed had a more pessimistic labor market outlook than the Market: while the Blue Chip revised its unemployment forecast up by 8 basis points (averaged over 1, 2, and 3 quarters ahead), the Fed's Greenbook forecast increased by 62 basis points. The monetary policy surprise was -12.5 basis points, one of the largest recorded in the dataset.

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

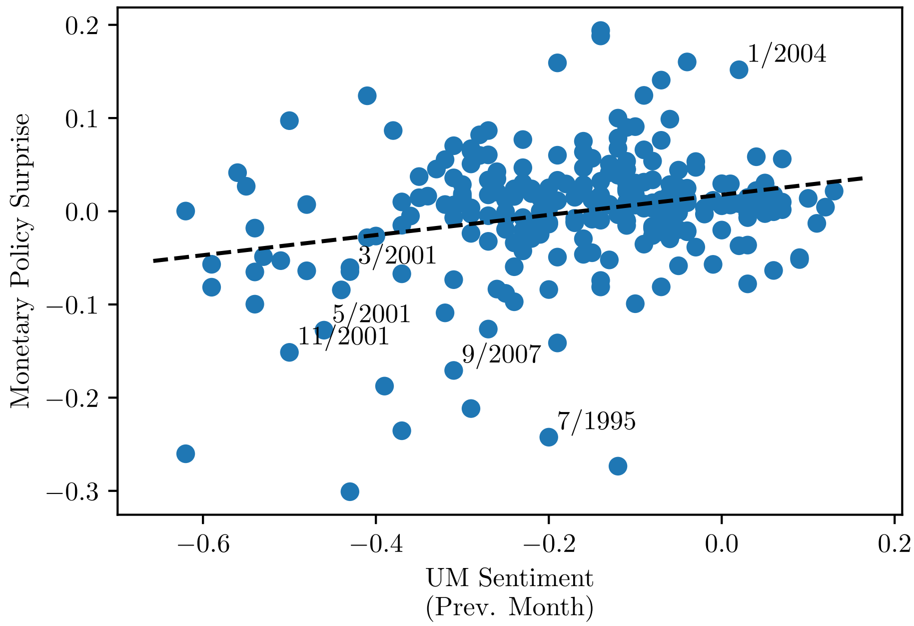
> [O]ne can take a look at the pattern of forecast errors around recessions, and it is almost always the case that the recessions are steeper than models can explain. So, the recession often occurs because there is a collapse of confidence that accompanies them. [. . . ] Our models, at least, are not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

The Fed ultimately adopted a pessimistic stance that surprised markets, which continued to also be more optimistic about the labor market. In particular, the Fed's upward revision of unemployment forecasts (again, averaging over the next three quarters) was 43 basis points higher than the revision in the Blue Chip survey. The monetary surprise was a further -12.7 basis points.

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

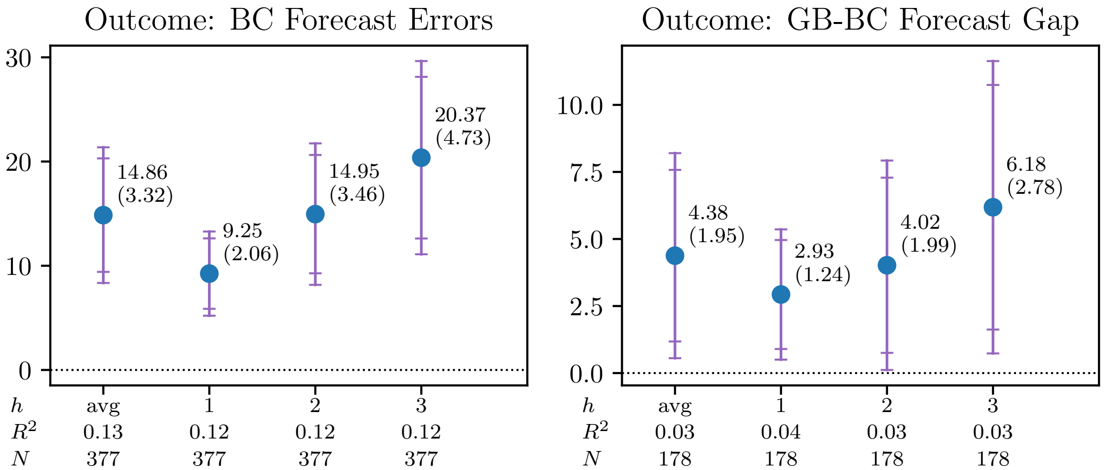
# E Additional Tables and Figures

**Figure A1:** Scatter Plot of Surprises vs. Sentiment



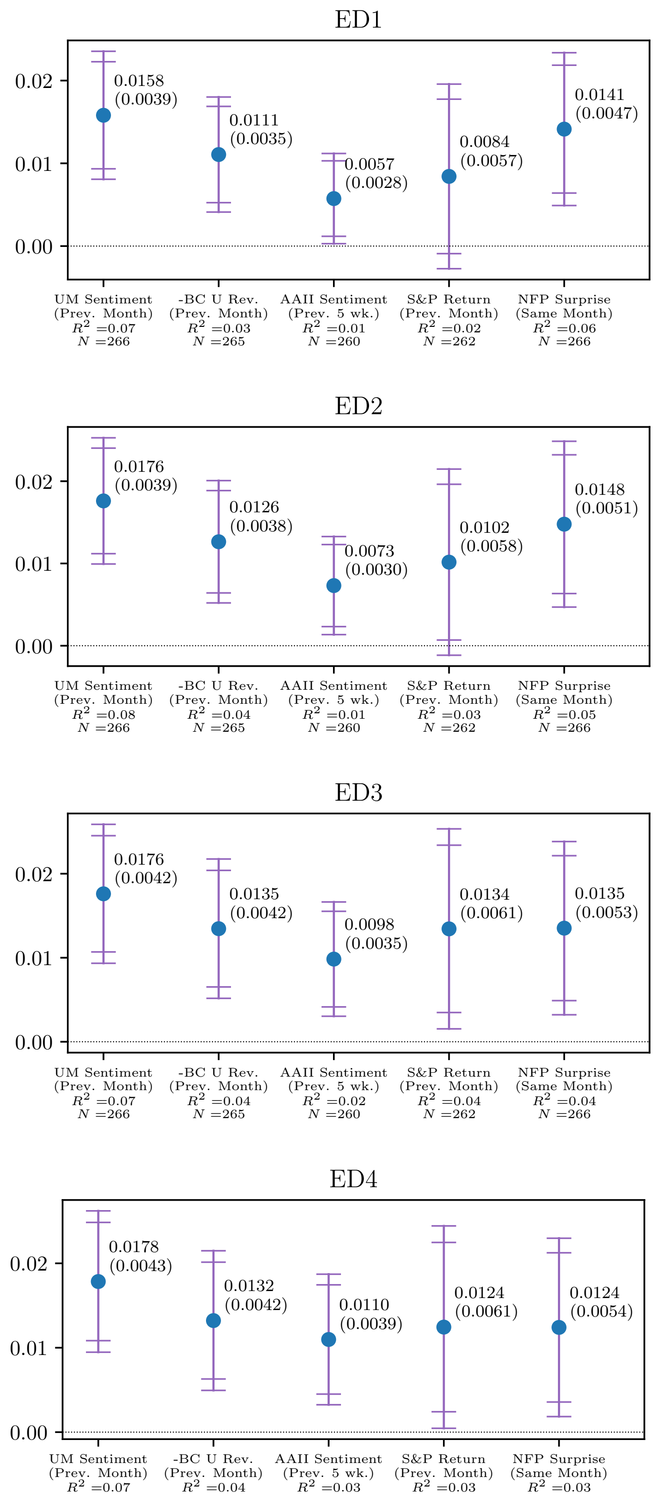

*Notes*: The scatterplot corresponds to the (non-normalized) estimation of Equation 12 and the results in the first panel of Figure 2. The horizontal axis variable is the labor-market sentiment in the Michigan survey, calculated as described in Section 3, in month $t-1$. The vertical axis variable is the (total) Monetary Policy Surprise of Bauer and Swanson (2023a) in month $t$. The dashed line is the linear regression fit. Selected points are annotated to the top right of the points.

**Figure A2:** Errors and Disagreements for 3-Month Treasury Forecasts



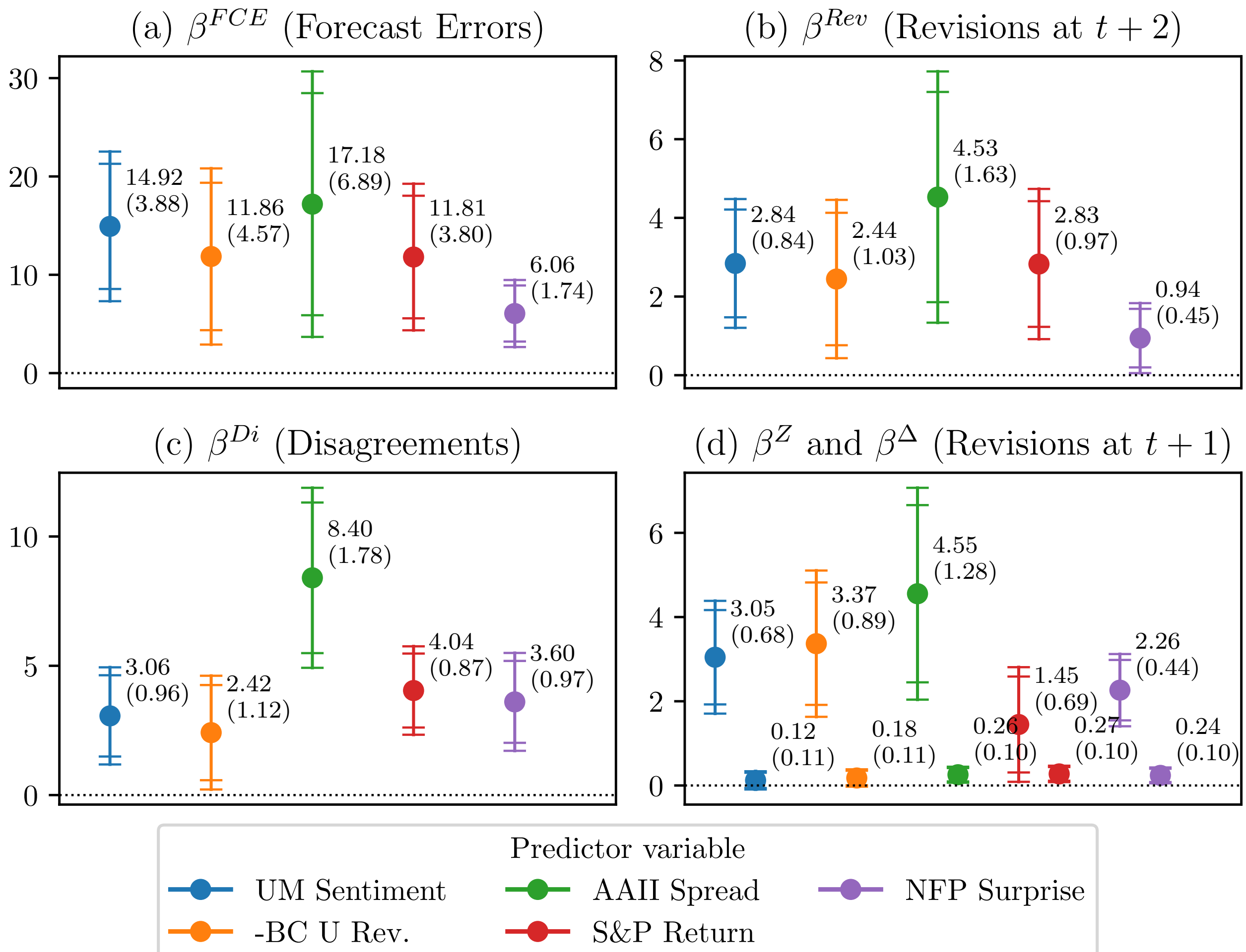

*Notes*: This Figure recreates the forecast error prediction analysis of Figure 3 (Equation 13) in the left panel and the forecast-gap prediction analysis of Figure 5 (Equation 15) in the right panel, where the forecasted variable is the 3-month Treasury rate (averaged over quarters). Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (13), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per basis points of expected monetary surprise.

**Figure A3:** Predictability for Different Monetary Surprise Measures



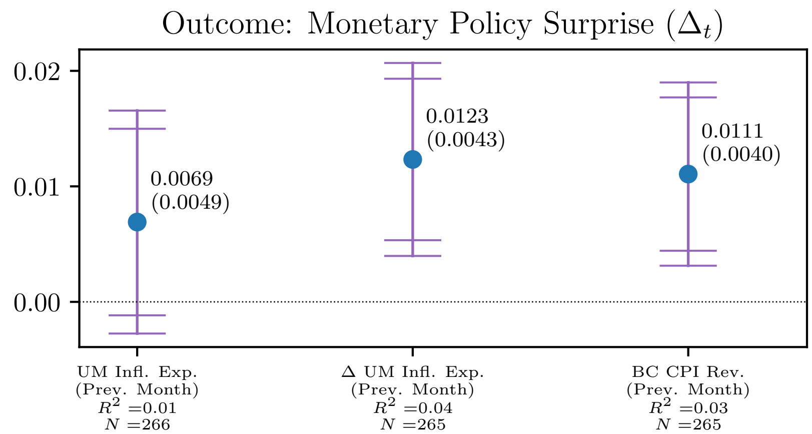

*Notes*: Each graphic is an analog of Figure 2 with a different outcome variable. Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

**Figure A4:** Main Results for Different Public Signals



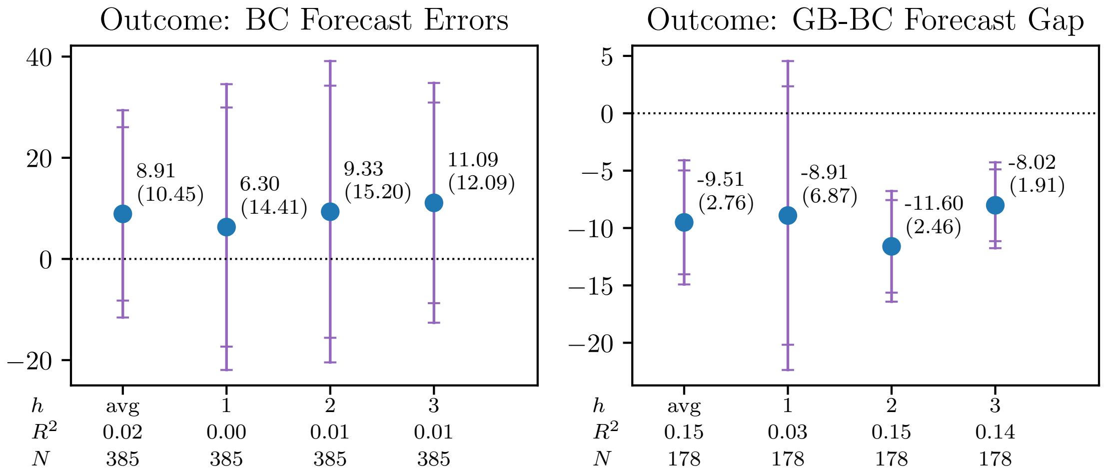

*Notes*: This plot shows results for the main analysis of Section 4 under different choice of predictor variables. Panel (a) corresponds to the analysis of Section 4.2 and Figure 3; panel (b) to Section 4.3 and Figure 4; panel (c) to Section 4.4 and Figure 5; and panel (d) to Section 4.5 and Figure 6. The empirical models and sample selection are as indicated in those sections. In each graph, the different color bars identified in the legend correspond to different choices of predictor variable. These are: unemployment sentiment from the Michigan survey in the previous month, the (negative) revision to Blue Chip unemployment forecasts in the previous month (averaged over the one-, two- and three-quarter horizons), the average Bull-Bear spread in the AAII survey in the previous month, the S&P 500 return in the previous month, and the NFP Surprise from in the current month (and corresponding to data from the previous month). In Figure (c), the left bar in each set corresponds to $\beta^Z$ and the right bar corresponds to $\beta^\Delta$. The error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

**Figure A5:** Predicting Monetary Surprises with News about Inflation



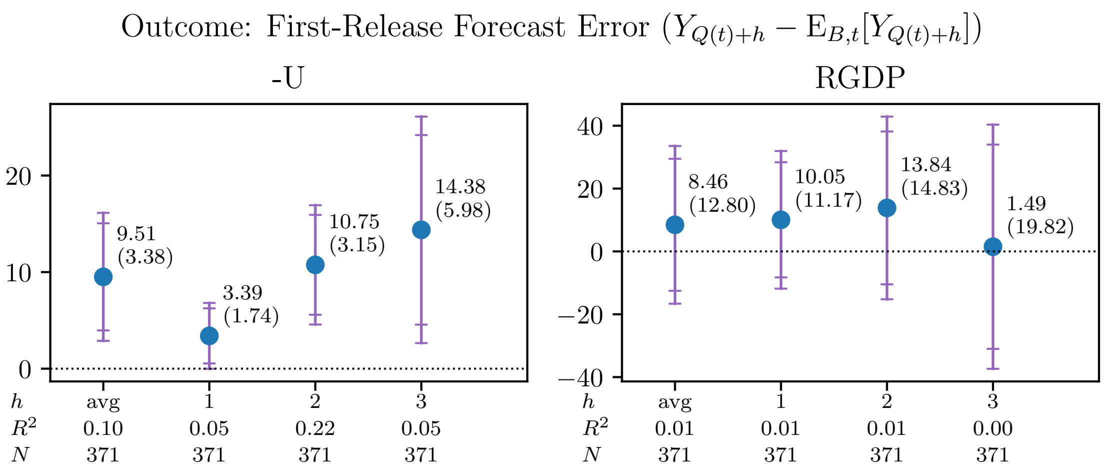

*Notes*: This Figure recreates the monetary surprise prediction analysis of Figure 2 (Equation 12) using predictors related to inflation. The first variable is the lagged median inflation forecast in the Michigan Survey of Consumers, the second is the lagged difference of the same, and the third is the average forecast revision (at horizons 1, 2, and 3 quarters) of CPI expectations in the previous month's Blue Chip survey. Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (12), and each estimate corresponds to a separate univariate regression. The units for the coefficients are implied percentage points of monetary surprise per one-standard-deviation outcome of the regressor.

**Figure A6:** Errors and Disagreements for CPI Forecasts



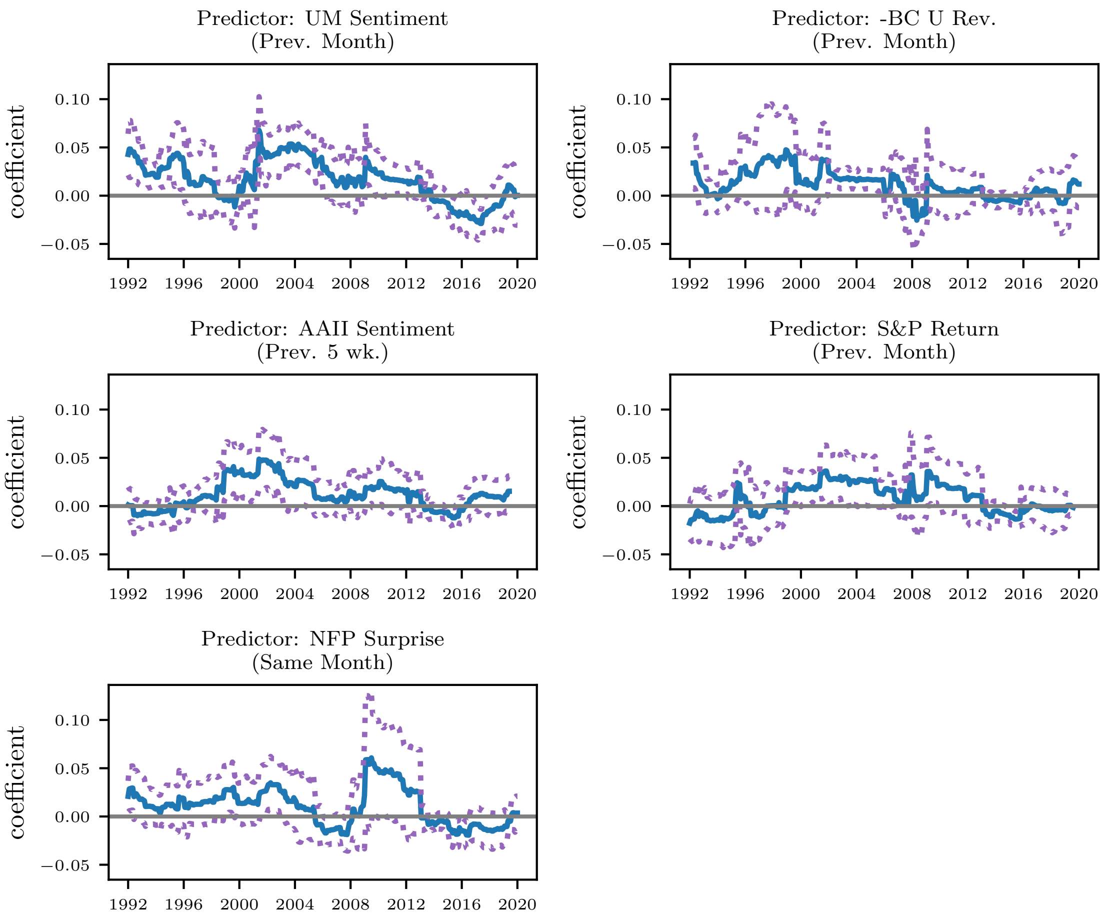

*Notes*: This Figure recreates the forecast error prediction analysis of Figure 3 (Equation 13) in the left panel and the forecast-gap prediction analysis of Figure 5 (Equation 15) in the right panel, where the forecasted variable is CPI inflation in annualized percentage points. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (13), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per basis points of expected monetary surprise.

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



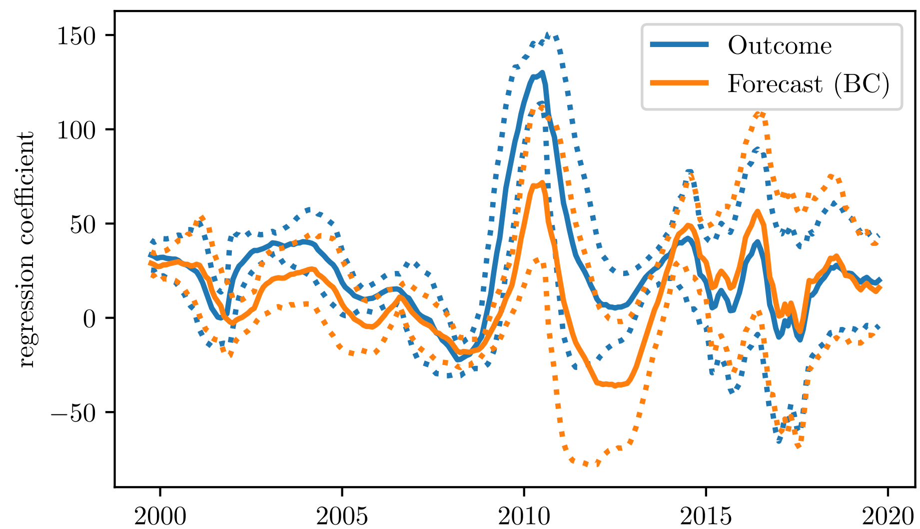

*Notes*: This Figure recreates the forecast error prediction analysis of Figure 3 (Equation 13), but measuring forecast errors relative to first-release macroeconomic outcomes. First-release macro data are taken from the Philadelphia Fed's real-time data center (https://www.philadelphiafed.org/research-and-data/real-time-center). Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The regression equation is (13), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per basis point of expected monetary surprise.

**Figure A8:** Rolling Regressions Predicting Monetary Surprises



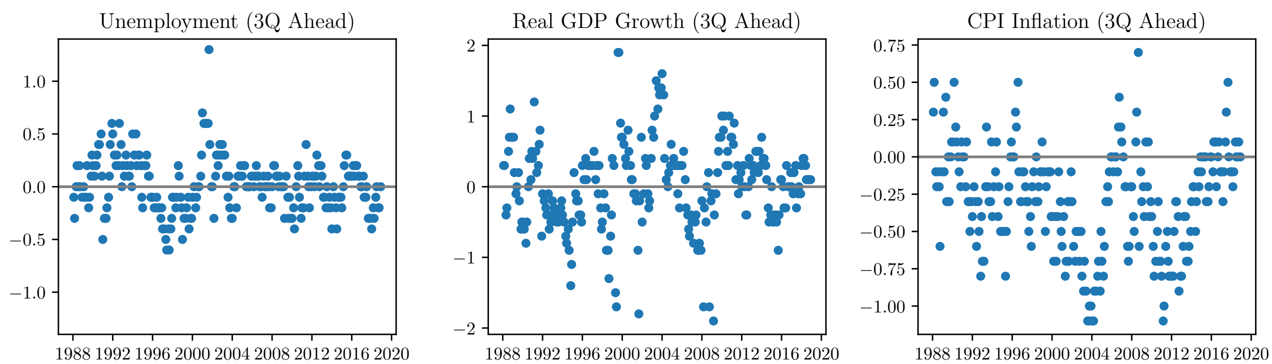

*Notes*: Each panel shows estimates from rolling regressions predicting the Monetary Policy Surprise (MPS) using the previous 48 months of data on the surprise and the indicated predictor. The empirical methodology, including the choice of predictors and their standardization (in z-score units), exactly follows the analysis in Section 4.1. The solid blue line shows the point estimates and the dashed purple lines are 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The solid grey line indicates a zero coefficient.

**Figure A9:** Rolling Estimation of Forecast and Outcome Prediction



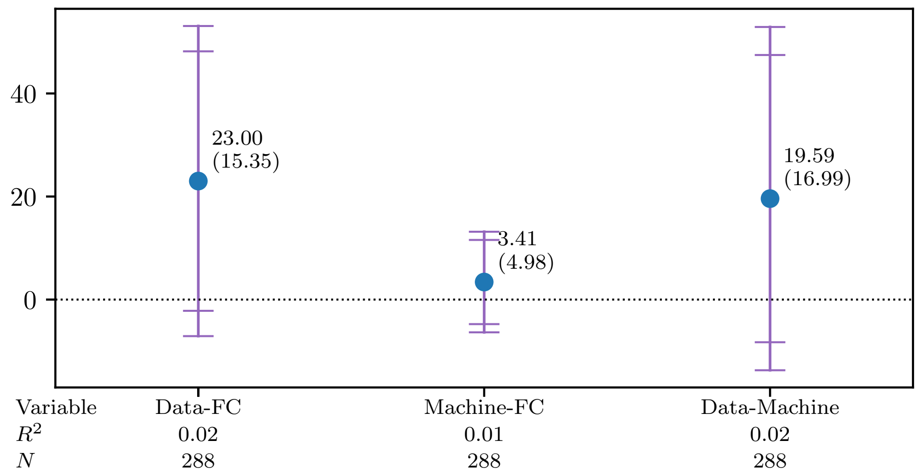

*Notes*: Each point is the coefficient in a feasible regression coefficient based on predictions made nine months ago or prior and measured unemployment rates. The regression is $Y_t = \beta \cdot \hat{Z}_t + \alpha + \varepsilon_t$, where $Y_t$ is either the predicted or realized unemployment rate three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

**Figure A10:** Time Series of Disagreement (Greenbook Minus Blue Chip)




*Notes*: Each panel of this Figure shows differences between Greenbook and Blue Chip forecasts at the 3 quarter horizon for unemployment (left panel), real GDP growth (middle panel), and CPI inflation (right panel). Each dot corresponds to a month in which both Greenbook and Blue Chip forecasts are observed. In months with multiple Greenbook forecasts (corresponding to multiple FOMC meetings), the measurement corresponds to the first of those meetings.

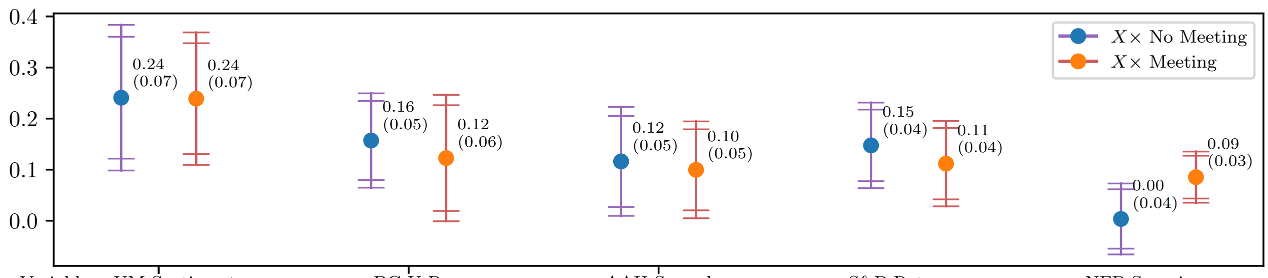
**Figure A11:** Predicting Belief Distortions Relative to Machine Benchmark




*Notes*: In each plot, the regressor is $\hat{Z}_t$, a rescaling of the $t-1$ realization of labor market sentiment in the Michigan survey (constructed as described in Section 4.2), and the outcome is one of the following statistics for four-quarter ahead real GDP growth forecasts in the Blue Chip survey: (i) the *ex post* forecast error, relative to observed data; the forecast error relative to the machine-efficient prediction of Bianchi, Ludvigson, and Ma (2022), based on a trained machine learning model using real-time data; and (iii) the difference between the *ex post* data and the machine prediction. The regressions are on a common sample from 1995 to 2019 based on availability of the machine benchmark. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

**Figure A12:** Forecast Error Predictability After Meeting and Non-meeting Months

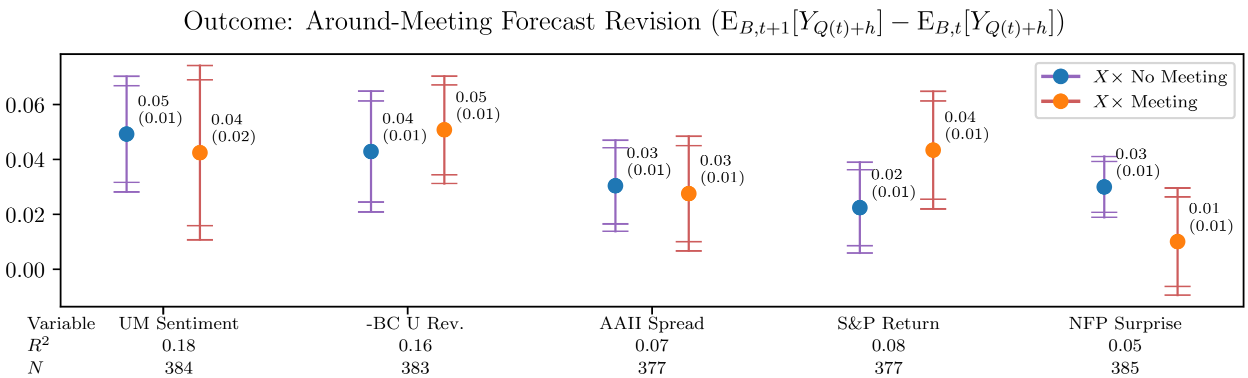
Outcome: Forecast Error at $t+1$ ($Y_{Q(t+1)+h} - \mathrm{E}_{B,t+1}[Y_{Q(t+1)+h}]$)




| Variable | UM Sentiment | -BC U Rev. | AAII Spread | S&P Return | NFP Surprise |
|---|---|---|---|---|---|
| $R^2$ | 0.27 | 0.08 | 0.05 | 0.07 | 0.02 |
| $N$ | 376 | 375 | 376 | 376 | 377 |
| $t^d$ | 0.06 | 0.66 | 0.47 | 0.91 | -1.84 |

*Notes*: Each pair of bars corresponds to an estimation of Equation 17 for a different choice of predictor. Each predictor is standardized in Z-score units over the relevant sample. The plotted coefficients are the interaction of $X_{t-1}$ with indicators for no FOMC meeting (blue) and at least one FOMC meeting (orange) in the month. The meeting indicator is included as a regressor but its coefficient is not plotted. The predictors are: unemployment sentiment from the Michigan survey in the previous month, the (negative) revision to Blue Chip unemployment forecasts in the previous month (averaged over the one-, two- and three-quarter horizons), the average Bull-Bear spread in the AAII survey in the previous month, the S&P 500 return in the previous month, and the NFP Surprise from in the current month (and corresponding to data from the previous month). The error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The $t^d$ statistic is the $t$-statistic for the difference between the two interaction coefficients.

**Figure A13:** Forecast Revision Predictability After Meeting and Non-meeting Months




$$\mathbb{E}_{B,t+1}[Y_{Q(t+1)+h}] - \mathbb{E}_{B,t}[Y_{Q(t+1)+h}] = \alpha + \beta_{NM} \cdot (X_{t-1} \times \text{No Meeting}_t) \\ + \beta_M \cdot (X_{t-1} \times \text{Meeting}_t) + \gamma \cdot \text{Meeting}_t + \varepsilon_t \tag{68}$$

*Notes*: Each pair of bars corresponds to an estimation of Equation 68 for a different choice of predictor. Each predictor is standardized in Z-score units over the relevant sample. The plotted coefficients are the interaction of $X_{t-1}$ with indicators for no FOMC meeting (blue) and at least one FOMC meeting (orange) in the month. The meeting indicator is included as a regressor but its coefficient is not plotted. The predictors are: unemployment sentiment from the Michigan survey in the previous month, the (negative) revision to Blue Chip unemployment forecasts in the previous month (averaged over the one-, two- and three-quarter horizons), the average Bull-Bear spread in the AAII survey in the previous month, the S&P 500 return in the previous month, and the NFP Surprise from in the current month (and corresponding to data from the previous month). The error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The $t^d$ statistic is the $t$-statistic for the difference between the two interaction coefficients.

**Table A1:** Pseudo-out-of-sample Fit and Investment Strategies

| Predictor | Predictive $R^2$ Magnitude | Predictive $R^2$ Sign | Sharpe Ratio for Sign Portfolio |
|---|---|---|---|
| Unemployment sentiment (previous month) | 0.002 | 0.063 | 0.29 |
| Blue Chip unemployment revision (previous month) | 0.010 | 0.045 | 0.22 |
| AAII Bull-Bear spread (previous five weeks) | 0.000 | 0.046 | 0.23 |
| S&P 500 return (previous month) | 0.007 | 0.008 | 0.20 |
| NFP surprise (most recent before announcement) | 0.016 | 0.031 | 0.21 |

*Notes*: This table reports statistics related to real-time (pseudo-out-of-sample) trading strategies based on predicting the Monetary Policy Surprise using the indicated predictors, after a burn-in period of 48 observations. The predictor variables are the same ones used and described in Section 4.1. The first two columns report fraction MSE reduction calculated via Equation 67. The third column reports the Sharpe Ratio (expected return divided by standard deviation) based on a trading strategy that pays off $\hat{p}$ dollars if the monetary surprise is positive, where $\hat{p}$ is the predicted probability of a positive surprise, and $1-\hat{p}$ otherwise, at a presumed price of \$0.50. The full methodology is described in Appendix D.1.