Disagreement About Monetary Policy

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Abstract

Why do markets and central banks systematically hold different beliefs about the path of policy and the economy? I use a simple signal extraction model to contrast predictions based on three mechanisms: asymmetric information, heterogeneous beliefs about the policy rule, and heterogeneous use of common information. I test these predictions using US data since 1995 and find the following combination of results which are most consistent with the third mechanism: lagged upticks in opinion-aggregating public signals predict that (i) markets are surprised by monetary tightening in future FOMC meetings; (ii) output exceeds professional forecasts thereof; and (iii) these forecasts are revised upward with a delay. The model, when calibrated to match these moments, implies a sizable causal effect of market-to-Fed disagreement about the value of data on the market’s macro beliefs, but essentially no causal effect of Fed persuasion through its actions. A structural vector auto-regression (SVAR) model, identified using the theory, reveals that predictable, data-driven disagreements arise in response to quantitatively import demand shocks; by contrast, disagreements driven by monetary noise have negligible effects on policy or outcomes.

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1. Introduction

Markets and the central banks regularly hold different beliefs, or disagree, about where the economy is heading and how monetary policy will respond. Indeed if they did not, central bank communications would be redundant proclamations of common knowledge instead of, in the words of former Federal Reserve Chair Ben Bernanke, “one of the most powerful tools” in the central bank arsenal for moving market opinion (2015). Yet relatively little is known about the root causes of disagreements between markets in central banks, particularly in the modern era of abundant public information about macro activity. Understanding these root causes is, in turn, critical for (i) determining the channels through which central bank communication move market beliefs and (ii) economically interpreting “unexpected” monetary policy actions and their effects on the economy.

This paper develops a theoretical and empirical framework to study these issues. It first shows in a simple signal-extraction model how three mechanisms—asymmetric information about fundamentals, mis-perception of the monetary rule, and mis-use of public information—can each cause central-bank-to-market disagreement, but differ in their predictions for how forecasts and forecast errors respond on average to public information. Implementing the theory’s suggested empirical tests on US data since 1995 reveals that good news in forward-looking public signals (e.g., consumer sentiment surveys or published consensus forecasts) systematically predicts surprise monetary tightening, measured using “high-frequency shocks” in interest rate futures markets (as studied, for instance, by Kuttner, 2001; Bernanke and Kuttner, 2005; Nakamura and Steinsson, 2018); market pessimism about real activity, measured using forecasts in the Blue Chip Economic Indicators survey; and delayed upward revisions in the same forecasts over subsequent months. Further analysis of dynamic, cross-variable patterns in a structural vector auto-regression (SVAR) model, identified via the theory, reveals that true “noise” in monetary policy explains essentially no macro dynamics, while systematic disagreement via the mechanisms described above is among the many endogenous effects of a demand shock that explains a sizable fraction of all nominal interest rate variation. The empirical results, by themselves, reveal a market slow to reach consensus in contrast to a more decisive Fed over the studied period.

Used as calibration targets for the theory, the same results structurally imply a significant role for market under-estimation the value of public signals, a small but perceptible role market under-estimation of the Fed’s response to the same information, and essentially no role for private information within the Fed. This calibration has the following three unifying implications about the informational role of monetary policy. First, clarity about the monetary rule is neither necessary nor sufficient to eliminate the most consequential disagreements between central banks and markets. That role is instead played by heterogeneity in interpreting common data. Second, the Fed’s direct control over market beliefs is mainly limited to the policy path. This finding sharply contrasts with a recent quantitative literature on the signaling channel of short-run policy and long-run forward guidance in New Keynesian models (Campbell, Evans, Fisher, and Justiniano, 2012; Campbell, Fisher, Justiniano,
and Melosi, 2016; Melosi, 2016; Nakamura and Steinsson, 2018) and a theoretical literature on the effects of public information in informational games involving central banks and markets (e.g., Morris and Shin, 2002, and much follow-up work). The distinction follows from this paper’s proposing, and empirically justifying, a model of heterogeneous priors rather than a model of purely Bayesian disagreement created by asymmetric information. Finally, the perhaps infeasible counterfactual of harmonizing the market’s and central bank’s model of the world would make the former’s beliefs much more sensitive to fundamentals. This suggests that the market’s perception that the Fed is over-stabilizing business cycles could, via Keynesian cross or financial accelerator channels, become partially self-fulfilling and meaningfully dampen the effects of demand shocks.

Model. Toward these conclusions, this paper’s analysis begins with a signal extraction model which allows a tractable comparison of several models of belief disagreement. There are two players, a representative monetary authority (“the Fed”) and a representative investor (“the Market”); three periods, indexed by \( t \in \{0, 1, 2\} \); and a single exogenous fundamental, which can be thought of as an aggregate demand shock and/or the natural rate of interest. At \( t = 0 \), both the Fed and the Market observe a public signal of the fundamental, and the former observes also a private signal of the fundamental. The Fed sets interest rates equal to its forecast of the fundamental. The Market attempts to forecast policy, or makes a forecast of the Fed’s forecast. At \( t = 1 \), the policy is announced and a monetary surprise, or Market forecast error in predicting the policy, is realized. At \( t = 2 \), the Market obtains additional private information about fundamentals and an additional variable, output or employment, is realized. Output depends positively on fundamentals and negatively on policy and serves as an additional variable that both the Fed and Market forecast in each preceding period.\(^1\)

In a familiar benchmark that maintains that all parties are rational and Bayesian, asymmetric information is the only possible explanation for Market to Fed disagreement about policy or outcomes. Such a benchmark puts tight restrictions on how much disagreement can survive interaction (more specifically, in the model, the policy announcement at \( t = 1 \)). To accommodate richer predictions of persistently “agreeing to disagree,” which are anecdotally characteristic of Market and Fed interactions, I augment the model with two possibilities for the market to mis-specify the economic environment. The first such possibility is that the markets are incorrect about how the Fed uses information, or mis-estimate the Fed’s “reaction function” relating policy to data sources. The second such possibility allows the markets to mis-perceive the public signal’s precision, while holding constant their beliefs about the Fed’s use of the signal.

I show how the Bayesian asymmetric information model by itself precludes public information from predicting monetary surprises, while either of the models of mis-specification allow this possibility (Proposition 1). In particular, under-estimating the Fed’s confidence in the public signal or

\(^1\)For simplicity, I ignore modeling the endogeneity of outcomes to market beliefs. In a realistic calibration, this would involve taking a stand on the relative importance of market beliefs and unmodeled “general public beliefs” (i.e., those that enter the majority of individuals’ consumption rules), the latter of which are not likely so sensitive to bleeding-edge data releases or the subtleties of Fed signaling. Nonetheless the present model can be thought of as a reduced form for such considerations.
having low confidence directly in the public signal are consistent with the (ultimately empirically relevant) case of good news correlating with surprise monetary tightening. This single predictability test is a viable test of the null hypothesis of a purely Bayesian asymmetric information model against the composite alternative, but cannot powerfully distinguish among the specific alternatives.

I next show how to derive supplemental tests using forecasts of output that can distinguish between the different types of private-sector model mis-specification in an economically intuitive way. Most tellingly, if the market merely under-estimates policy response but efficiently uses public signals when forecasting fundamentals, it should over-estimate output when news in these public signals is good; whereas if the market under-weights the news content of public signals altogether, it would under-estimate output when news in the public signals is good (Proposition 2). Similar logic implies opposite behavior for forecast revisions after monetary announcements (Proposition 3). Finally, I show that both models prevent observers from interpreting the correlation between contemporaneous forecast revisions and monetary surprises as an “information effect,” as in Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018), but each case produces a different bias (Proposition 4). The established information effect in the literature may be either too high or too low depending on the underlying friction. In the first case, measuring belief revisions prevents the observer from picking up over-reactions to the Fed’s information that dissipate, or revert to the mean, as agents collect more outside information; in the second, the same makes the observer conflate learning from the monetary announcement with learning from outside sources, the latter of which appears like “momentum” in beliefs that had insufficiently adjusted in the first place.

Empirical Results. The next part of the paper devises empirical tests guided by these conclusions from the model, to get a sense of which “one-friction” model would best fit the data. The main empirical analysis treats the policy news shock of Nakamura and Steinsson (2018) as a summary of monetary surprises, or the extent of monetary disagreement resolved during announcements, from 1995 to the present. The policy news shock usefully combines many dimensions of interest rate news, cutting across the term structure, into a scalar. As representative forward-looking public signals, the paper focuses on (i) information about consumer sentiment from the University of Michigan Survey of Consumers; (ii) revisions to professional forecasts from the Blue Chip Economic Indicators survey; (iii) recent stock market performance; and (iv) sentiment about stock market direction from the American Association of Individual Investors survey.

The first main empirical finding is that all four measures are quantitatively meaningful, positive predictors of monetary surprises—that is, “good macro news” in any indicator predicts surprise monetary tightening. The result is strongest around recessions and valid even when using very stale (more than one month old) data. The main results for consumer and investor sentiment are independent from previously documented predictability by changes in the unemployment rate (Cieslak, 2018), total non-farm payrolls (Bauer and Swanson, 2020), and a broader average of macro indicators (Miranda-Agrippino, 2015; Miranda-Agrippino and Ricco, 2015), insofar as the results have a com-
parable magnitude in precision after controlling also for these factors. In the model, these results invalidate the Bayesian interpretation but are compatible with either main behavioral deviation.

I next turn to the three additional model predictions, described above as Propositions 2, 3, and 4, which offer distinguishing power about which of the two frictions jointly consistent with the previous result is quantitatively more important. The first checks whether lagged public signals at \( t-1 \) can predict errors in forecasts made at time \( t \) about economic activity. I operationalize this using consensus (negative) unemployment and real GDP growth forecasts from the Blue Chip Economic Indicators survey. I find that one basis point of predicted monetary tightening, based on realizations of the Michigan survey in month \( t-1 \), correlates with a statistically and economically significant under-estimation of real variables (e.g., a 15.3 basis point under-estimate of average unemployment over the next 3 quarters and 28.3 basis point under-estimate of average annualized growth over the same). The second test checks the relationship between public signal realizations in \( t-1 \) with forecast revisions between periods \( t+1 \) and \( t+2 \). I find a statistically significant positive correction that corrects only a small fraction of the observed forecast error (10-25%). The final test concerns the Fed information effect, or correlation of monetary surprises with the revision of consensus forecasts across a monetary announcement. Controlling for lagged public signals almost entirely eliminates the positive correlation between surprise tightening and upticks in output forecasts. The mis-specification-robust estimation of the true Fed information effect, or update in output forecasts directly attributable to the information in the Fed’s announcement, is positive, economically small, and statistically indistinguishable from zero.

Quantification and Broader Scope. The signs of the previous results, viewed through the lens of Propositions 2, 3, and 4, all point toward a model involving market under-weighting of public signals. I next show how to use the results’ magnitudes to fit the simple model and pinpoint the precise mechanism. My estimates imply that the predictable component in monetary surprises is due both to under-estimation of the monetary response to public signals and under-weighting the value of those signals. But the latter friction is quantitatively much bigger in terms of its contribution toward forecast errors about real variables, consistent with the earlier “sign test” intuition. The Fed’s internal information, on the other hand, is two orders of magnitude less precise than public information and hence asymmetric information has only a small role to play in the story.

An immediate implication of the last fact is that the implied information effects of persuasion through actions are quantitatively minuscule. This is formalized by showing in the calibrated model that the sensitivity of beliefs to fundamentals is affected by about 0.4% in a counterfactual scenario that turns off the signaling value of policy actions. This points a limited role for the Fed to sway public opinion via the signaling value of its actions. In practical terms, the Fed’s power of persuasion seems limited to the policy path—a fact that would improve the efficacy of standard stabilizing policy, which avoids counter-productively alerting the economy to upcoming (undesired) shocks. By contrast, disagreement itself does play an important role. In a counterfactual world in which the market shared
the Fed’s opinion about the usefulness of public data, the former’s beliefs would move 11.7% more in response to fundamentals.

Anecdotal evidence from FOMC meeting transcripts supports the story described above. Fed deliberations during the 2001 recession reveal (i) strong internal trust of sentiment data to reveal underlying demand conditions; (ii) clear public admission that sentiment data matter for the monetary rule; and (iii) recognition that professional forecasters are slower in incorporating the same information despite the Fed’s clarity about its own approach. This also highlights an angle that was ignored in the original, one-shock model and associated empirical analysis: that the mechanisms described above may be more or less active with respect to certain components of the business cycle, or underlying sources of variation in fundamentals.

The paper’s final section explores such issues in a semi-structural VAR model. I show how one can use timing restrictions combined with a “max-share” approach (as in Uhlig, 2004; Barsky and Sims, 2011; Angeletos, Collard, and Dellas, 2018a) to tease apart true trembles in monetary policy from rule-based fluctuations that trigger disagreement, in a way that is consistent with the simple, static model. The strategy uses only assumptions about the timing and extent of response in measured monetary surprises.

The first, “monetary noise” shock is associated with a small and transitory dip in stock prices, very small movements in Treasuries, and essentially no perceptible change in prices or output. This implies that the true noise component of monetary policy, unanticipated by markets and also unrelated to any systematic mistakes in markets’ reasoning, has essentially no effect on the macroeconomy. The second, “disagreement” shock, in sharp contrast, explains about 40% of all variation in nominal Treasury rates and sizable portions of variation in unemployment, consumption, and consumer prices. It is characterized in the short-run by sharp upticks in consumer sentiment and stock prices, and in the long run by a significant increase in activity and prices. These patterns resemble the identified news shocks of Beaudry and Portier (2006), Barsky and Sims (2011), and others. Thus disagreement about one of the most important shocks of the business cycle occurs in spite of Fed’s ostensible transparency about its actions and motives.

**Related Literature.** Miranda-Agrippino (2015), Miranda-Agrippino and Ricco (2015), Cieslak (2018), Bauer and Swanson (2020), and Karnaukh (2019) all explore how omitted variables explain monetary surprises and forecast revisions around monetary announcements. The former four focus on “hard data,” and their results might be explained variously by rational and non-rational theories that relax the combination of full information and rational expectations. The third, Bauer and Swanson (2020), includes original survey and anecdotal evidence that market professionals are very confident in their economic assessments, which is consistent with this paper’s findings. The last, contemporaneous work, Karnaukh (2019), demonstrates predictability by lagged Blue Chip output growth forecasts, which is part of this paper’s empirical focus, but also does not commit to a specific theoretical
Several studies draw additional conclusions based upon a specific interpretation in which markets are Bayesian and rational, the Fed wields additional internal information, and markets learn *ex post*. Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018) study “information effects” of persuasion through policy actions. Melosi (2016) presents a related model of monetary signaling focusing on an earlier time period (the 1970s and 80s) and not using the monetary surprises data. And early explorations of the monetary surprises data, including Kuttner (2001), Bernanke and Kuttner (2005), Gürkaynak, Sack, and Swanson (2005a), and Gürkaynak, Sack, and Swanson (2005b), did not explicitly pre-suppose a rational model but mainly viewed their results through such a prism. This paper’s results have implications for interpreting all of these results.

Recent advancements in the literature on modeling survey expectations have emphasize the importance of behavioral biases to explain imperfect expectations (Bordalo, Gennaioli, Ma, and Shleifer, 2018; Broer and Kohlhas, 2018; Angeletos, Huo, and Sastry, 2020). This paper shows how heterogeneity in biases across groups (here, the professionals in the Fed) leads to a particular form of dogmatic disagreement with important macro consequences.

Finally, the idea that central banks and markets are engaged in an informational tug-of-war is a classic one in theoretical macro, finance, and information economics. This paper’s results suggest that an array of more “classical” results based on rational expectations equilibria (e.g., Morris and Shin, 2002; James and Lawler, 2011; Baeriswyl and Cornand, 2010; Amador and Weill, 2010) may miss the essential role of heterogeneous models. Recent contributions by Andrade, Gaballo, Mengus, and Mojon (2019) and Caballero and Simsek (2019) capture exactly these forces in their theoretical analysis. The latter, in particular, posits (and independently justifies with survey data) a market over-confidence channel that is very similar to the one uncovered in this paper. Its theoretical premise also matches this paper’s finding that most monetary disagreement arises in response to important demand shocks that drive the business cycle and which have footprints in measured expectations and asset prices.

**Organization.** Section 2 presents a theoretical model. Section 3 describes the data. Section 4 presents the main results on predicting monetary surprises. Section 5 presents the main results on predicting forecast revisions, errors, and disagreements. Section 6 presents a quantification of the model and explores counterfactual scenarios. Section 7 provides additional evidence for the

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2 Older contributions by Piazzesi and Swanson (2008) and Hamilton (2009) test for evidence of *market efficiency* in futures markets overall, including both announcement and non-announcement days.

3 Relatedly, Jarocinski and Karadi (2018), Andrade and Ferroni (2016), and Cieslak and Schrumpf (2019) build identification strategies for types of monetary communication based on *ex post* financial response under a Bayesian model.

4 An exception is Bernanke and Kuttner’s (2005) observation that mean reversion in the stock market response to monetary surprises resembled a pattern of over-reaction and correction.

5 This builds upon, and contrasts with, earlier contributions that emphasized mainly noisy observation of fundamentals in an otherwise rational environment (Colibioni and Gorodnichenko, 2012, 2015).

6 Another interesting related contribution is Carroll’s (2003) study of expectations heterogeneity between households and professionals. That paper finds that a model in which households learn slowly from professionals fit the data. This is at odds with this paper’s finding that innovations in household beliefs may predict professionals’ eventual errors.
proposed mechanism. Section 8 presents an SVAR model that contextualizes the findings. And Section 9 concludes.

2. Model

This section presents a simple model of the forecasting problem faced by investors and the Fed. The main goal is to suggest empirical tests that can tease apart conceptually distinct hypotheses for how and why the Fed disagrees with markets. The theoretical results will structure the paper’s empirical analysis.

2.1 Primitives

There are three periods denoted by \( t \in \{0, 1, 2\} \) and two agents, the “Fed” (\( F \)) and the “Market” (\( M \)). There is a single fundamental \( \theta \sim N(0, \tau_{-1}) \), which can be interpreted as a demand shock and a shifter of optimal policy.

The monetary authority (“Fed,” denoted by the letter \( F \)) chooses a (real) interest rate \( r \) at \( t = 0 \), the period corresponding to policymaking. It sets this rate equal to the expected shock:

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

(2.1)

where \( \mathbb{E}_{F,0}[\cdot] \) is an operator that gives the Fed’s belief at \( t = 0 \) (which will be modeled shortly).

The “Market,” denoted by \( M \), predicts the monetary policy action at \( t = 0 \). Let \( P \) denote this prediction, or

\[
  P = \mathbb{E}_{M,0}[r] = \mathbb{E}_{M,0}[\mathbb{E}_{F,0}[\theta]]
\]

(2.2)

where \( \mathbb{E}_{F,0}[\cdot] \) gives individuals’ subjective beliefs and \( \mathbb{E}_{M,0}[\cdot] \) is defined to give the market’s aggregate (average) subjective belief. The Fed and Market observe prediction \( P \) contemporaneously at \( t = 0 \).

The interest rate is itself revealed at \( t = 1 \). Denote the implied error in (or revision to) the market prediction as

\[
  \Delta := r - P = \mathbb{E}_{F,0}[\theta] - \mathbb{E}_{M,0}[\mathbb{E}_{F,0}[\theta]]
\]

(2.3)

Note that this is not directly a disagreement between the Market and Fed about the value of \( \theta \). It is instead a disagreement about what the latter thinks is the value of \( \theta \).

At \( t = 2 \), output \( Y \) is realized as

\[
  Y = a\theta - r
\]

(2.4)

for some \( a \geq 1 \). Output plays no other instrumental role in the model but provides a target for all agents in the model to forecast.

Micro-foundations and interpretations. Appendix B.1 shows how (2.1) and (2.4), the policy rule and expression for output, stylize how monetary policy would stabilize the economy in a simple
Keynesian cross model. The fundamental $\theta$ corresponds to the sum of two shocks: a demand shock, which the central bank wants to have no effect on output, and a supply shock, which the central bank wants to efficiently pass through to output. By assumption, the former has a larger variance than the latter so “news about positive economic shocks,” or news about high $\theta$, translates into a desire to tighten monetary policy. The monetary rule (2.1) is a feasible approximation to the optimal policy when the central bank obtains signals only of this sum of shocks. And relationship (2.4) corresponds to the expected equilibrium outcome of a Keynesian cross. The parameter $a$ decreases in the relative variance of demand to supply shocks, as the central bank becomes unconditionally more interested in stabilizing the economy against $\theta$.

Appendix B.2 re-casts (2.2), the market prediction, as the price of an asset that pays off in proportion to $r$ at $t = 1$, in the canonical asset pricing setting in which traders have constant absolute risk aversion (CARA) preferences and fundamentals and signals are Gaussian.\(^7\) This admits a model-consistent interpretation of $P$ as the (re-scaled) price of an interest rate futures contract and $\Delta$ as the error or revision in that contract as a result of a monetary policy announcement. These mappings will be crucial in our empirical application.

### 2.2 Subjective Beliefs

**Sources of information.** At $t = 0$, there are three sources of information. First there is a public signal $Z = \theta + \varepsilon_z$, where $\varepsilon_z \sim N(0, \tau_z^{-1})$ is noise.\(^8\) Second, each agent observes the futures price $P$. And finally, the Fed also receives a private signal $F = \theta + \varepsilon_F$, where $\varepsilon_F \sim N(0, \tau_F^{-1})$ is private noise.

At $t = 1$, as stated above, all agents including the market participants observe $r$.\(^9\) Finally, at $t = 2$, each investor observes an additional public signal $S$ with precision $\tau_S > 0$.

These sources of information are purposefully described in an abstract way, and the following varied interpretations are valid. First, the public signal may itself be an outcome of a process that aggregates unspecified additional private information—for instance, a market price or the result of an opinion survey. Second, the assumption that market participants have no other common or private information at $t = 0$ is merely simplifying and could be dispensed with for the main insights below.\(^10\) Finally, none of the results will require any specific ranking for the relative precision of these signals, so as long as all three are strictly positive.

**The Fed’s Beliefs and Decision Rule.** The Fed applies Bayes rule to form its beliefs. Its posterior belief about $\theta$ at $t = 0$ is the following

$$\mathbb{E}_{F,0}[\theta] = \delta^F \mathbb{E} + \delta^F Z$$

\(^7\)The Gaussianity of beliefs, which of course cannot be verified now, will be verified in due course.

\(^8\)Here, “noise” is shorthand for a Gaussian random variable that is independent from all others in the state space.

\(^9\)Since the agents already know $P$, this is tantamount to observing $\Delta$.

\(^10\)The only caveat is whether the futures price $P$ becomes perfectly revealing about $\theta$. This problem is easily solved by allowing the futures price $P$ to itself be contaminated with noise from the the result of background liquidity trading, as familiar from the classic analysis of Grossman (1976) and Grossman and Stiglitz (1980).
where \( \delta^F_F := \frac{\tau_F}{\tau_F + \tau_Z + \tau_0} \) and \( \delta^F_Z := \frac{\tau_Z}{\tau_F + \tau_Z + \tau_0} \) are the appropriate objective precision weights, and I have used the conjecture (which will be verified) that the futures price contains no information about \( \theta \) that is not already spanned by \( Z \). As will become clear shortly, the assumption that the Fed’s beliefs are Bayesian or “correct” is mostly simplifying, and (2.5) could be replaced with any mis-calibrated monetary rule with strictly positive coefficients.

**The Market’s Beliefs.** The market applies Bayes rule subject to two mistakes in modeling the economic environment.

First, each market participant may over- or under-weight the importance of the public signal. This is parametrized by letting each market participant’s belief at \( t = 0 \) be given by the following:

\[
E_{i,0}[\theta] = \left( \delta^M_Z - q \right) Z
\]

where the coefficient \( \delta^M_Z = \frac{\tau_Z}{\tau_Z + \tau_0} \) corresponds with the objective signal-to-noise ratio for \( Z \), and \( q \) measures the market’s under-utilization of the public signal. This is the result of agents’ perceiving the precision of the public signal to be \( \tau_Z - t \tau_0 \) and the precision of the fundamental to be \( \tau_Z + t \tau_0 \), where \( \tau_0 := \tau_Z + \tau_0 \) is the objective posterior precision at \( t = 0 \). These distortions in perceived precision are maintained at \( t = 1 \) and \( t = 2 \), as market participants use Bayes rule to incorporate additional information.

Second, the market may mis-specify the weight on \( Z \) in the monetary rule. Each market participant believes monetary policy is set by the following rule:

\[
E_{i,0}[r] = E_{i,0} \left[ \delta^F_Z \right] + \left( \delta^F_Z - w \right) Z
\]

The case \( w > 0 \) (respectively, \( w < 0 \)) corresponds to under-estimating (respectively, over-estimating) the monetary authority’s reliance on \( Z \). This distortion affects both how agents predict monetary policy and how they incorporate information revealed by it, as will become clear in due course.

**Discussion of Assumptions.** Varying \( q \) affects how market participants use the information embedded within the public signal \( Z \), or the market’s first-order belief about the fundamental \( \theta \). One might interpret \( q > 0 \), or under-emphasis on the public signal, as a form of the sparsity or cognitive discounting introduced by Gabaix (2014, 2016), and the complementary possibility of \( q < 0 \) as a behavioral over-reaction in the same spirit. Alternatively, one may take \( q \neq 0 \) as reduced form for a more complex model in which agents need to learn the precision of signals, or their true predictive relationship with the fundamental \( \theta \), using finite histories of observations (Kohlhas and Robertson, 2020). Finally, there is a close mapping of \( q > 0 \) to a model in which agents observe noisy Gaussian signals of \( Z \), as in the canonical rational inattention model of Sims (2003) or the classic imperfect

\[ 11 \text{That is, } \delta_X = \frac{\tau_X}{\tau_F + \tau_Z + \tau_F + \tau_0}. \]
information model of Woodford (2003).\textsuperscript{12} I abstract from these more specific micro-foundations in order to make the analysis simpler.

Varying \( w \) affects how the Market thinks the Fed uses information, or the Market’s second-order belief about the fundamental \( \theta \). Such a friction may be justified by having the Market believe any of the just-described frictions to apply to the Fed’s decisionmaking, instead of (or in addition to) their own. It may also reflect, in reduced form, difficulty in learning the monetary rule via repeated observation of policy actions.

2.3 Predictable Monetary Surprises: Testing for Behavioral Bias

I now outline the model’s sign prediction for various moments relating monetary surprises, belief updates, and the public signal.

The first step is to characterize the monetary surprise itself. The following Lemma summarizes how monetary surprises arise in the model:

**Lemma 1** (Monetary Surprises). The monetary surprise \( \Delta \) can be written as

\[
\Delta = \delta^F_1 \epsilon_F + \delta^F_1 \left( \theta - \mathbb{E}^R_{M,0} [\theta] + q Z \right) + w Z
\]

where \( \mathbb{E}^R_{M,0} [\theta] := \delta^M_1 Z \) is the rational average expectation of \( \theta \).

**Proof.** See Appendix A. \( \square \)

Equation (2.8) shows how to write the monetary surprise as the sum of three terms. The first is a true, idiosyncratic error in the Fed’s assessment of the economy. The second reflects the market’s attempt to forecast the variation in the policy rule spanned by the Fed’s internal information. It is split into the “as-if rational” average expectation of \( \theta \), that efficiently incorporates information about \( Z \), and an additional bias term that is proportional to \( q \), the market’s under-response to the signal \( Z \). The third and final term is the under-estimation of \( Z \) in the monetary rule.

Observe that the error in the Fed’s signal and the “as-if rational” expectation are orthogonal to the public signal—the former by construction, and the latter by the law of iterated expectations. A key implication of the characterization in Lemma 1, then, is that a public signal can only predict monetary surprises if one of the two behavioral biases is present, The following Proposition formalizes this result:

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

1. \( \text{Cov}[\Delta, Z] = 0 \) in the rational benchmark with \( w = q = 0 \).

\textsuperscript{12}If individuals observe \( Z_i = Z + \epsilon_i^Z \), where the latter is iid Gaussian noise of precision \( \tau_{iZ} \), then average beliefs are \( \mathbb{E}^R_{M,0} [\theta] = \frac{(\tau_{Z}^{-1}+\tau_{iZ}^{-1})^{-1}}{(\tau_{iZ}^{-1})^{-1}+\tau_{iZ}} \). This prediction agrees with the average beliefs implied by (2.6) for \( \frac{\tau_{iZ}}{\tau_{iZ}+\tau_{\theta}} = \frac{(\tau_{Z}^{-1}+\tau_{iZ}^{-1})^{-1}}{(\tau_{Z}^{-1}+\tau_{iZ}^{-1})^{-1}+\tau_{iZ}} > 0 \).
2. \( \text{Cov}[\Delta, Z] \geq 0 \) if \( w \geq 0 \) and \( q \geq 0 \).

3. \( \text{Cov}[\Delta, Z] \leq 0 \) if \( w \leq 0 \) and \( q \leq 0 \).

\textit{Proof.} See Appendix A. \qed

Point 1 demonstrates that public information will \textit{not} predict monetary surprises when the Market rationally incorporates \( Z \) into their forecast and correctly models how the Fed will act. The following two remarks clarify the strength of this result. First, this benchmark still allows for the Fed’s private signal \( F \), as revealed for instance in later-released internal forecasts, or the realized fundamental \( \theta \), as revealed by retrospective macro data, to predict surprises. Each is a data source that is not available to the market and hence never fully incorporated into the forecast.\(^{12}\) Second, the proof of the result relies only the Fed placing some positive weights on \( F \) and \( Z \) in the monetary rule, and not that those weights are the “correct” ones corresponding with a Bayesian expectation of \( \theta \). More practically, the neutrality result would remain true if the market and Fed disagreed about the precision of the public signal \textit{provided that the market knew the Fed’s subjective assessment correctly}. It would also hold if the Fed responded \textit{directly} to the market’s expectations of \( r, \theta \), or \( Y \), each of which is spanned by \( Z \), as would be natural in a richer and more strategic model of either the term structure of interest rates or a Keynesian cross (as in Caballero and Simsek, 2019).

The second and third points of Proposition 1 make clear how each introduced friction signs the predictability. If markets under-estimate the Fed’s reliance on \( Z \) or under-estimate the precision of \( Z \) themselves, then positive realizations of \( Z \) correlate with markets’ underestimating monetary tightening. The former scenario corresponds with market’s under-estimating the Fed’s sensitivity to incoming macro-financial data embodied in \( Z \). The latter corresponds with the market’s systematically underestimating the information contained within \( Z \), which causes the market to systematically under-estimate the component of the monetary rule (i.e., the part that loads on \( F \)) which they cannot re-construct with public information.

This test embedded in Proposition 1 is easily implemented given data on representative public signals and changes in the market forecasts about monetary policy around FOMC meetings embedded in interest rate futures prices (e.g., as pioneered by Rudebusch, 1998; Kuttner, 2001).\(^{14}\) Such a test is carried out in Section 4.

### 2.4 Output Forecasts: Testing the Mechanism

Proposition 1 makes clear that measuring \( \text{Cov}[\Delta, Z] \) allows an observer to test the rational model against the compound alternative of the non-rational models. But it cannot, by itself, distinguish between the two proposed cases of model mis-specification. This subsection outlines three additional

\(^{12}\)The former point relates to predictability tests using Fed forecasts discussed by Gertler and Karadi (2015) and Ramey (2016), and the latter point to tests discussed by Miranda-Agrippino (2015) using lagged macro data.

\(^{14}\)The literal translation from forecast error to forecast revision requires only the re-interpretation of \( r \) as an announced future path of policy rather than an interest rate that “immediately” goes into effect.
tests, using data on output forecasts, that allow an observer to tease those two models apart with simple sign predictions.

2.4.1 Predictable Forecast Errors

Consider first the errors that the public makes in forecasting output, or \( Y - \mathbb{E}_{M,t}[Y] \) for \( t \in \{0, 1, 2\} \). Under the Bayesian model, of course, these errors are never correlated with the public signal realization \( Z \), as this information is efficiently incorporated into each individual’s forecast from \( t = 0 \).

If agents under-estimate the precision of the public signal, as is consistent with \( \text{Cov}[\Delta, Z] > 0 \), then they will also under-estimate the extent to which a high \( Z \) portends good news about output. This property is true in all three periods of the model.

If agents under-estimate the weight on \( Z \) in the monetary rule, as is also consistent with \( \text{Cov}[\Delta, Z] > 0 \), the model’s predictions are opposite. At \( t = 0 \), the market efficiently uses \( Z \) in its forecast of \( \theta \), but under-estimates the monetary response to high \( Z \). As such, they will systematically over-estimate output when \( Z \) is high. A similar result is obtained at \( t = 1 \) and \( t = 2 \) for a slightly different reason.

Now the market knows what monetary policy is, but they erroneously assume that the public signal contains important, independent information (i.e., coming from the Fed’s signal \( F \)) instead of an affirmation of the already known public signal. This induces the market to doubly-react to the news embedded in \( Z \), and \textit{ex-post} tests would reveal over-reaction to positive realizations of \( Z \).

The following result summarizes the predictions:

**Proposition 2 (Forecast Errors).** The following three properties hold for \( \text{Cov}[Y - \mathbb{E}_{M,t}[Y], Z] \) for \( t \in \{0, 1, 2\} \):

1. \( \text{Cov}[Y - \mathbb{E}_{M,t}[Y], Z] = 0 \) in the rational benchmark with \( w = q = 0 \).
2. \( \text{Cov}[Y - \mathbb{E}_{M,t}[Y], Z] \geq 0 \) if \( w \leq 0 \) and \( q \geq 0 \).
3. \( \text{Cov}[Y - \mathbb{E}_{M,t}[Y], Z] \leq 0 \) if \( w \geq 0 \) and \( q \leq 0 \).

**Proof.** See Appendix A. \( \square \)

Compared to Proposition 1, points (ii) and (iii) in particular offer an exhaustive criterion to differentiate two “pure” models encapsulating each of the frictions.\(^{15}\) That is, a model in which \( q = 0 \) but \( w \neq 0 \), or pure mis-estimation of the monetary rule, predicts \textit{opposite signs} for the covariance of public signals with monetary surprises and forecast errors; whereas a model in which \( q \neq 0 \) but \( w = 0 \) predicts the same sign. Practically, Proposition 2 can be tested with data on the beliefs of the market, or informed professional forecasters who may reasonably stand in for them. Such a test will be implemented in Section 5.1.

\(^{15}\)Usefully, the sign prediction is true at any of the model’s sub-periods, so a test does \textit{not} need to be careful about when beliefs are measured relative to the monetary announcement.
2.4.2 Post-Announcement Drift

Building off the same intuition, an additional test may be derived based on behavior of beliefs right after the announcement. If agents initially under-estimate the value of the public signal $Z$, they will continue to correct their mistake as new private information is made available at $t = 2$. Their beliefs should drift up conditional on positive $Z$, or loosely speaking exhibit “momentum.” If agents erroneously over-react to the public signal $Z$ by under-estimating its importance for monetary policy, they will also correct their mistake with private information but to the opposite effect: their beliefs should drift down conditional on positive $Z$, or loosely speaking exhibit “mean reversion.” This is summarized in the following Proposition:

**Proposition 3** (Post-announcement Drift). The following three properties hold for $\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z]$:

1. $\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] = 0$ in the rational benchmark with $w = q = 0$.
2. $\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] \geq 0$ if $w \leq 0$ and $q \geq 0$.
3. $\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], Z] \leq 0$ if $w \geq 0$ and $q \leq 0$.

*Proof.* See Appendix A. □

Testing Proposition 3 requires data on beliefs, either directly extracted from market prices or reported in surveys, in periods after the monetary announcement. I will implement two versions of the test, one of which uses professional forecast data and resembles the aforementioned studies of forecast revision predictability (Section 5.2) and a second which uses the drift of the stock market and recalls discussion of long-run mean reversion in the original study of Bernanke and Kuttner (2005) (Appendix C.4).

2.4.3 Long-run Revisions and the “Fed Information Effect”

A final prediction of the model relates to the correlation of monetary surprises with beliefs across the announcement window. Observe first that, at $t = 1$, the only piece of information revealed in the economy is $r$ (or, equivalently, $\Delta$). Let us define the change in public beliefs about $Y$ at $t = 1$, then, as a measure of the causal effect of Fed announcements on beliefs; and the covariance thereof with the monetary surprise as the “Fed information effect,” in units of the policy surprise:

**Definition 1.** The Fed information effect is

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

(2.9)

Observe from combining representation (2.9) with the definition 2.4 that the Market is both learning the direct effect of $r$ and trying to filter out information about the fundamental $\theta$ from the announcement. The former “signaling channel of monetary policy” may in richer models run counter
to the monetary authority’s goal of stabilizing output and inflation, insofar as it directly affects private sector actions and asset prices.

To measure effect $i$, researchers often use data on belief revisions bracketing the monetary announcement, or in our language from $t = 0$ to $t = 2$, for convenience: it is exceptionally difficult to instantaneously measure beliefs at $t = 1$. The following Corollary emphasizes that this covariance corresponds with $i$ only in the rational expectations benchmark, and otherwise includes a bias term which can be signed as a function of the deviation from rationality:

**Proposition 4** (Bias in the Information Effect). Let

$$i^F := \frac{\text{Cov}[\Delta_2, \mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,0}[Y]]}{\text{Var}[\Delta]}$$

be a feasible estimator of the information effect defined in (2.9). This estimator can be written as

$$i^F = i + B$$

where

1. $B = 0$ in the rational benchmark with $q = w = 0$.
2. $B \geq 0$ if $w \leq 0$, $q \geq 0$, and $\text{Cov}[\Delta, Z] > 0$.
3. $B \leq 0$ if $w \geq 0$, $q \leq 0$, and $\text{Cov}[\Delta, Z] > 0$.

**Proof.** See Appendix A.

The bias, as illustrated in the proof, is directly proportional to the covariance between $\Delta$ and the forecast revision from period 1 to period 2. In the rational model, this covariance is zero because the information in $\Delta$ is fully and efficiently incorporated into beliefs at $t = 1$. This breaks down as soon as there is a deviation from all agents’ rationally incorporating the information in $\Delta$ and, in particular, $Z$. Properties 2 and 3 follow directly from the related arguments in Proposition 3 about post-announcement drift, combined with a fixed sign for $\text{Cov}[\Delta, Z]$.

Proposition 4 suggests that the interpretation of “information effects” in *Campbell, Evans, Fisher, and Justiniano (2012)* and *Nakamura and Steinsson (2018)* is relatively fragile, and these authors’ regression coefficient $i^F$ confounds a true effect of persuasion with persistence in forecasting biases.

The model, however, suggest a simple fix: to control directly for the effect of $Z$. The following result affirms that such a procedure correctly recovers $i$:

**Corollary 1** (Corrected Information Effect Regression). The monetary shock $\Delta$ can be written as $\Delta = \Delta^+ + aZ$, where $\text{Cov}[\Delta^+, Z] = 0$. Moreover, the population estimator

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

(2.12)
corresponds with the true information effect $i$.

Proof. See Appendix A. $\square$

The joint of Proposition 4 and Corollary 1 suggests the following test. Regressing long-run forecast revisions on the monetary shock after partalling out, or controlling for, the public signal $Z$ gives a feasible estimator of $i$, and doing the same without controls gives an estimator for $i^F$. We can compare $i$ and $i^F$, or estimates of $B$, to test directly the implications of Proposition 4. Such an exercise will be carried out in Section 5.3.

2.5 Summary

The previous section outlined a simple model that could distinguish different models of monetary disagreement. The key predictions, summarized in Propositions 1, 2, 3, and 4, provide simple “sign tests” for whether a departure from rationality is required and, if so, which single departure from rationality matches the data. The next part of the paper implements these tests in the data.

3. Data and Descriptives

3.1 Monetary Surprises

The data on interest rate surprises are identical to those used by Nakamura and Steinsson (2018). These data cover January 1995 to April 2014.

The Fed Funds futures contract for a given month $m$ pays off $100 - \bar{r}_m$, where $\bar{r}_m$ is the average daily effective rate in the month. A linear transformation of this, to adjust for the number of days remaining, provides the implied expected average interest rate for the remainder of the month under the assumption of risk-neutral pricing. Similarly, Eurodollar futures contracts pay, at the relevant horizon, 100 minus the contemporaneous US Dollar BBA LIBOR rate, and a linear transformation of the price also reveals an expected future interest rate. The “$n$-quarter ahead” or “$nQ$” Eurodollar contract is the $n$th next contract to expire. The surprise component for each of these market-derived expectations is defined as the change in the price-implied-expectation over a 30-minute window circumscribing the timing of an FOMC interest rate announcement (10 minutes before and 20 minutes after).

Surprises can be defined separately for each interest rate with an associated futures contract. As a scalar summary of these surprises, throughout most of the paper, I use Nakamura and Steinsson’s

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15These authors directly collected data from the CME Group.
18See Appendix A of Nakamura and Steinsson (2018) for the details for data construction.
(2018) preferred policy news shock measure, a linear combination of surprises to futures for the following five rates: the Federal Funds rate in the same month of the meeting, the Federal Funds rate in the month of the next scheduled meeting, and Eurodollar futures at quarterly horizons 2, 3, and 4. The linear weights are chosen to maximize, up to normalization, the explained variance for interest rate surprises in these rates over the same 30-minute afternoon window in daily data since 1995 (i.e., the first principal component of the data). The focus on longer-term rates follows the observation of Gürkaynak, Sack, and Swanson (2005a) and Campbell, Evans, Fisher, and Justiniano (2012) that much of the relevant monetary policy news in the US regards future interest rates, rather than the current short-term policy rate.

Finally, the policy news shock is defined only up to scale, so I follow the methodology of Nakamura and Steinsson (2018) to normalize the variable to have unit impact on the one-year Treasury rate on the day of the announcement.

3.2 Public Signals

The analysis will focus on a subset of public signals which are forward-looking opinion aggregators, and therefore easiest to interpret as sources of news about fundamentals over the relevant horizon, which is the next twelve months.\footnote{Of course, in economic models, all economic actions are necessarily functions of the beliefs of the agents who made them, and therefore would also count as public signals at this level of abstraction. I return to this point in Section 4.2.} I consider four main such indicators which have a priori merits. The following reviews, in each case, the (i) relevant data source, (ii) potential relevance for forecasting and policy, and (iii) extent of “publicity” associated with each.

**Consumer sentiment about economic performance.** These data are taken from the Michigan Survey of Consumers, which is administered monthly to a nationally representative sample of 500 individuals via telephone every month. The survey asks a variety of questions about economic expectations. Appendix C.1 prints the exact questions questions and answers that are used in the analysis. All aggregate measures are survey-weighted averages.

The main sentiment measure considered in this paper is based on a question asking individuals whether they believe unemployment rates will go up, stay the same, or go down over the next twelve months. The measure, which will be referred to as “unemployment sentiment” throughout the paper, is the difference between the fraction who believe unemployment will go down (the positive response) versus the fraction who believe unemployment will go up. This measure is chosen because it has the clearest interpretation for assessing business cycle conditions.

Previous research suggests that the Michigan survey provides forward-looking information particularly about consumption and spending (Carroll, Fuhrer, and Wilcox, 1994). Appendix Figure 7 shows, on the left scale, the aforementioned sentiment index, from 1995 to the present with the US unemployment rate on the right scale. At a glance this suggests some predictive power of the Michigan variable for observed labor market dynamics, as the former turns pessimistic before unemployment...

The Michigan survey for month $t$ typically takes place over the entire month. Preliminary results, including summary statistics for the indices of conditions, sentiment, and expectations, are available by the middle of the same month based on the interviews completed to that point. Final results for major indices, as well as a detailed report with individual questions, are typically available by the first week of the next month. Detailed micro-data are released with a one-month delay to the general public, but immediately upon final release to selected media partners.\textsuperscript{21}

**Professional forecasts of future economic activity.** These data are from the *Blue Chip Economic Indicators Survey*, which is taken each month by 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.\textsuperscript{22} The analysis focuses on the consensus forecasts for unemployment and real GDP growth.

The BCEI survey, and its close cousin the *Blue Chip Financial Forecasts* survey, have been used to study expectational puzzles in monetary policy (e.g., Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018; Cieslak, 2018; Karnaukh, 2019; Caballero and Simsek, 2019) as well as broader puzzles regarding imperfect expectations (Bordalo, Gennaioli, Ma, and Shleifer, 2018; Angeletos, Huo, and Sastry, 2020). It is widely considered a reasonable summary of expert opinion among US financial firms.

The BCEI forecast for month $t$ is conducted in the first week of that month, and the results published in a newsletter dated typically on the 10th of that month. The BCEI newsletter prints the quantitative forecasts of individual participants for the current month, so past individual and consensus forecasts are conceivably common knowledge to all participants. Ottaviani and Sørensen (2006) and Broer and Kohlhas (2018) emphasize that this information is also very salient to forecasters.

**Recent returns of the S&P 500.** This analysis uses closing prices of the S&P500 at the monthly frequency. Previous research has suggested that recent stock returns are a major determinant of policy in the modern era (Cieslak and Vissing-Jorgensen, 2018). The relevance and publicity of the information needs no specific justification.

**Public sentiment about stock performance.** These data are taken from the weekly survey of the American Association of Individual Investors (aggregated to a monthly average when appropriate). This metric captures the sentiment of small-scale investors about future stock returns.\textsuperscript{23} Respondents may indicate whether they are “Bullish,” “Bearish,” or “Neutral” about stock market performance over the next six months. As a summary indicator, I take the difference in fraction of Bullish and Bearish respondents (i.e., in analogy to the similar diffusion measure of unemployment sentiment

\textsuperscript{21}This was confirmed from direct communication with the Michigan Survey Research Center.

\textsuperscript{22}https://lrus.wolterskluwer.com/store/blue-chip-publications/

\textsuperscript{23}The financial press agrees, with the *Wall Street Journal* considering it a useful “barometer of American retail investor sentiment” (https://www.wsj.com/graphics/bear-market-signs/).
from the Michigan survey). Greenwood and Shleifer (2014) show that the AAII results are a statistical predictor of future excess returns and therefore it may matter for expectations and policy to the same extent that realized returns do. Results are available on the AAII’s website at the beginning of the subsequent week.

4. Predicting Monetary Surprises

This section investigates whether forward-looking opinion aggregators predict monetary surprises in the historical sample, or which case outlined in Proposition 1 is empirically relevant. The answer, across a variety of empirical specifications, is that monetary surprises are predictable, in the direction of “good news” correlating with surprise tightening.

These results invalidate the model of a fully Bayesian, rational market, even one that is not perfectly informed. They suggest that the informed public either fails to fully incorporate the information in data releases into its macro forecasts or consistently mis-models the Fed’s reaction function, possibilities that will be explored further in the following section.

4.1 Main Empirical Model and Results

To evaluate the test in Proposition 1 (“does public information predict surprises?”), the following univariate regression models are estimated relating the monetary surprise $\Delta_t$ with the previous-month realizations of each predictor $X_{t-1}$:

$$
\Delta_t = \beta_X \cdot \bar{X}_{t-1} + \epsilon_t
$$

The “check” denotes that the variables are normalized, in sample, to have zero mean and unit standard deviation. This normalization is used only in the present subsection, to allow easy comparability of coefficient magnitudes across measures. The units of $\Delta_t$ are such that a unit increase corresponds to a 1% point same-day increase in 1-year Treasury rates, so the units of $\beta_X$ are of a one-standard-deviation outcome on percentage points for interest rates. The sample consists of 153 scheduled FOMC meetings.

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

The four main predictors studied, as reviewed above, are the following: (i) the lag difference (i.e., $t - 2$ to $t - 1$ change) in the Michigan unemployment sentiment variable; (ii) the negative average revision to unemployment forecasts (at horizons $q \in \{1, 2, 3\}$) in the previous month’s Blue Chip

24The de-meaning also removes the requirement for a constant in the regression.
Figure 1: Predicting Monetary Surprises.
Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (4.1), and each estimate comes from a separate univariate regression. The units for the coefficients are implied basis points of monetary surprise per one-standard-deviation outcome of the regressor.

forecast; (iii) the cumulative return over the previous month for the S&P500; (iv) and the average Bull-Bear spread in the AAII survey over the five weeks prior to the announcement.

Figure 1 shows the estimates of $\beta_X$ for each aforementioned predictor. The broad pattern is that lagged public information does predict monetary surprises. All estimates, if statistically significant, go in the direction of $\beta_X > 0$. In the model, this suggests either market under-estimation of the Fed’s confidence in these indicators or under-confidence in these particular public signals.

An additional dimension of interest, not explored in specification (4.1), is timing. The theoretical predictions hold for any signals realized before the FOMC meeting and ideally give consistent results for different choices of lags before the meeting. Appendix C.2 explores this at the monthly frequency for the Michigan sentiment measure and the weekly frequency for the AAII survey, and confirms that (i) information older than one month prior can also predict monetary surprises but (ii) the largest effects are concentrated at the one-month lag.

4.2 Forward-looking Variables versus Lagged Activity

This paper’s theory and empirical results have, so far, emphasized the role of public signals that directly measure (expected) future fundamentals. But of course these signals are necessarily tied to activity today; and moreover, statistical releases about activity today often do constitute the most important news about fundamentals tomorrow. As such, it is worth checking whether we can empirically distinguish these subtly different explanations in the data: that policy forecasts under-react to news about tomorrow’s fundamentals, or that they under-react to data releases about today’s activity.
The following model provides an empirical horse race of the survey and market variables \( \hat{X}_{t-1} \) against other possible predictors \( Z_{t-1} \):

\[
\Delta_t = \alpha + \beta_M \cdot \hat{X}_{t-1} + Z'_{t-1} \Gamma + \epsilon_t
\]

(4.2)

I consider three sets of predictors, each of which has precedent in previous or contemporaneous studies of futures market belief anomalies:

1. The previous two months’ unemployment rates, as studied by Cieslak (2018).

2. The previous month’s growth rate in total non-farm employees, as studied by Bauer and Swanson (2020).

3. The previous two months’ value of the first two principal components in the FRED-MD database, constructed by McCracken and Ng (2016) to succinctly summarize a wealth of macro releases and used by Miranda-Agrippino (2015) and Miranda-Agrippino and Ricco (2015).

Appendix Table 5 shows estimates of (4.2) for the aforementioned control choices and the four predictive public signals. The point estimate and \( t \)-statistics for each predictor are virtually unchanged given the addition of unemployment data; the coefficients are unaffected for Michigan Sentiment and Blue Chip revisions, but attenuated for the stock market variables, when employment growth is added. The principal component control, the most conservative of the three, does not affect the sentiment estimate, but reduces the estimates using the Blue Chip revisions, market returns, and AAII sentiment.

The multivariate, VAR analysis in Section 8 will also hint at similar patterns: while economic activity does seem to move before predictable surprises, by far the quantitatively larger and more striking patterns involve changes in beliefs and stock prices.

These patterns, together, build confidence that this paper’s focus on forward-looking opinion aggregators, a focus that will be maintained in subsequent empirical analysis.

4.3 Different Surprise Measures

Appendix Figure 9 recreates the analysis of Figure 1 for three individual futures contracts which are notable components of the policy news surprise: the Fed Funds futures corresponding to the current meeting, the Fed Funds futures corresponding to the next scheduled meeting (i.e., 1-2 months in the future), and the 4-quarter-ahead Eurodollar future. The broad pattern, across each predictive variable, is augmented predictability (in terms of magnitudes and \( t \)-statistics) for the longer-horizon contracts.

The model itself abstracted entirely from the term structure of expectations or interest rates. But a rough mapping is that longer-horizon interest rates are determined by different forecasting problems
(i.e., identities of the random variable $\theta$), and these forecasting problems feature more significant behavioral distortions.

### 4.4 Sub-sample and Out-of-sample Performance

**Different sample periods.** Appendix Figure 10 re-estimates the main specification (4.1) excluding data including and after 2008. This eliminates the Great Recession as well as the lengthy spell at the zero lower bound, at which we may expect the mechanics of forward guidance and monetary policy to operate much differently. The coefficient estimates are very stable for each predictor.

To zoom in either further on sub-sample robustness, Appendix Figure 11 re-estimates (4.1) for unemployment sentiment from the Michigan survey using windows of observations within the last 48 months (4 years). The prediction is the strongest in the early and late 2000s owing to the respective recessions and rate cuts. But it is positive for almost the entire sample, excepting the much more recent experience at or near the ZLB.

**Individual events.** Figure 2 shows the scatterplot of monetary surprises against realizations of the previous month’s unemployment sentiment. At a glance, and in corroboration of the rolling regression results, the aforementioned recessions provide influential observations for fitting the trend. Building on this point, surprise predictability seems much stronger for meetings at which the Fed’s short-run interest rate target was changed (highlighted in orange). This builds confidence that, while the surprise measure does take into accounting implied changes to future policy (forward guidance), this
paper’s empirical finding has the most bite for changes in the immediate policy outlook.

**Pseudo-out-of-sample forecasting.** A reasonable question for judging these results as a market failure is whether sentiment information would have been as useful in real time to investors. Note that this question is not nearly as relevant for this paper’s stated aim, which is to uncover forecasting biases *ex post* and explore the macroeconomic consequences thereof. But it does provide a relatable barometer for the severity of the implied bias. Appendix C.3 explores a pseudo-out-of-sample forecasting exercise for each of the four main predictors. Unsurprisingly the predictive power for each variable is quite a bit lower, though for the key unemployment sentiment variable it remains positive. I calculate also a feasible, pseudo-out-of-sample Sharpe Ratio for portfolios that invest based on the predicted sign of policy news. These are all positive but reasonably low, between 0.15 and 0.30, reflecting the substantial risk attached to exploiting this trade. This buoyed confidence both that the observed market failures are not extreme, while the patterns of interest are robust.

5. **Testing the Mechanism: What Model Mis-specification?**

This section digs further into the mechanism for disagreement: in particular, does the public make a mistake in forecasting economic fundamentals or instead merely mis-understand the monetary rule? These hypotheses are pit against one another via empirical tests that operationalize Propositions 2, 3, and 4. In each case, the data support the first story about a bias in forecasting fundamentals.

The final subsection fits the model directly to the regression estimates to illuminate the quantitatively relevant combination of mechanisms that explains the data. Its broad conclusion, through the lens of the theory, is that under-reaction to news in public signals is the quantitatively “dominant” force.

5.1 **Forecast Errors**

The first test that distinguishes mechanisms, suggested by Proposition 2, concerns the predictability of private forecast errors by the public signal.

In light of the previous section’s evidence that multiple data series meet the criteria of public signals in the model, I construct a scalar summary $\hat{Z}_t$ in the following way. I run the following regression which resembles the predictive equation (4.1) but with a vector of predictors $\tilde{X}_{t-1}$:

$$\Delta_t = \alpha + \tilde{X}_{t-1}' \Gamma + \varepsilon_t$$  \hspace{1cm} (5.1)

Based on the results of the previous section, I use the first two lags of the Michigan unemployment sentiment variable to take into account both level and growth rate effects.\footnote{Note that, according to the results of Appendix C.2, there is predictive power in both the level and growth rate of lagged sentiment. This motivates the empirical specification that flexibly includes both, instead of restricting the coefficients to enter via their difference. The coefficient estimates are 0.18 (SE: 0.05) on the first lag and -0.11 (SE: 0.04) on the second lag.} These variables are
importantly pre-determined at the beginning of the month \( t \) and could plausibly be incorporated into any forecast made at time \( t \); together, they explain 14.8\% of the variation in the monetary surprise.\(^{26}\) I take estimates of (5.1) over the entire sample and construct fitted values \( \hat{Z}_{t-1} = \hat{\alpha} + \hat{X}_{t-1} \hat{\beta} \), an empirical estimate of the model’s public signal, and residuals \( \hat{\Delta} \), an empirical estimate of the orthogonal component of the monetary surprise. Through the lens of the model, the empirical objects \((\hat{Z}, \hat{\Delta})\) correspond exactly with the theoretical objects \((Z, \Delta)\) described in Corollary 1.\(^{27}\)

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

I estimate the following empirical model:

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

where \( t \) indexes times in months; \( Q(t) \) returns the quarter index of month \( t \); and \( Q(t) + h \) indexes the outcome \( h \) quarters ahead of the current quarter. I estimate this model for each choice of horizon \( h \) and forecasted variable \( Y \). According to Proposition 2, \( \beta^{FCE} > 0 \) is consistent with under-confidence in the public signal and \( \beta^{FCE} < 0 \) is consistent with under-estimation of the Fed’s response to the public signal.\(^{28}\)

Figure 3 plots the estimates of \( \beta^{FCE} \), with 90\% and 95\% confidence interval bars, across variables and horizons. There is consistent evidence across specifications of \( \beta^{FCE} > 0 \), favoring under-confidence in public signals as the correct model. This evidence is strongly statistically significant (p-value less than 5\%) at all horizons for unemployment as the outcome, and more weakly significant (across specifications, at the 10\% or 15\% level) for real GDP growth as the outcome.

For unemployment, in particular, the magnitudes are economically quite significant. The median absolute error over the sample period is 27 basis points, while a one-standard-deviation variation in \( \hat{Z} \) (1.46 basis points) correlates according to (5.2) with a 22.4 basis-point error. The predictive \( R^2 \) is correspondingly quite large (23\%).

**Robustness.** Four additional results, printed in the Appendix, probe robustness. Appendix Figure 12 re-creates Figure 3 for two different outcomes, the growth rate of personal consumption expenditures (PCE) and predictions for the three-month Treasury rate. In both cases, we find a similar

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\(^{26}\)To give a sense of the “sufficiency” of these two variables, the \( R^2 \) of the predictive equation increases only to 16.2\% after adding the lagged average forecast revision about GDP growth from the Blue Chip survey, the lagged level of AAII sentiment, and the lagged growth rate of the S&P 500. The full SVAR analysis of Section 8, which will flexibly allow for both sentiment variables and a variety of real and nominal outcomes to predict monetary surprises at any lag, gives a comparable extent of prediction.

\(^{27}\)A similar decomposition is used in contemporaneous work by Karnaukh (2019) to test the validity of the “information effect,” but without a corresponding theoretical analogue.

\(^{28}\)Observe that these predictions in the model are robust to when forecasts are made relative to Fed announcements.
sign pattern. The result for PCE provides robustness for the main test of Proposition 2, while the result for Treasury rates provides a corroboration of the main findings of Section 4 without relying on market-derived expectations. Appendix Figure 13 re-creates Figure 3 using first-release macro data, as is often common in the literature assessing forecast efficiency. It shows broadly similar patterns, although they are much noisier when output growth is the outcome. These results are interesting for assessing the “real time feedback” regarding forecasting errors, but to be clear are not necessarily the most relevant in terms of assessing the underlying economic theory.

Appendix Figure 14 re-creates Figure 3, but instead of using the consensus (mean) forecast uses the reported mean unemployment forecast among the 10 highest (i.e., most pessimistic) and lowest (i.e., most optimistic) in the Blue Chip survey. This reveals that the highlighted bias is present across the entire distribution. Moreover, more pessimistic forecasters seem consistently more data-sensitive, implying that good news shrinks within-private-sector disagreement while bad news exacerbates it. I will return to this observation in the multiple-equation analysis of Section 8.

Finally, Appendix Figure 15 shows rolling regressions using the last 48 months (4 years) of data separately for this quarters’ unemployment rate and the (nine months prior) three-quarter ahead forecast from the Blue Chip survey on $\hat{Z}_{t-9-1}$, the public signal available just before that forecast. It shows that the public has consistently under-estimated the impact of $\hat{Z}$ on outcomes; the deviation between each group’s forecast is most prominent in the two major recessions in sample; and that predictive power has largely disappeared in the most recent five years. The last can be read either as evidence of learning over time (especially for correcting large errors during the Great Recession) or a discontinuity in results when policy at the Zero Lower Bound begins to dominate the estimation sample.

Fed Forecasts and Measured Disagreement. Recall that the rationality of the Fed’s forecast was inessential to the model’s predictions, as long as the Fed followed some rule that put positive weight on the public signal and on internal information. Nonetheless, it is natural to take a slight detour from the menu of empirical tests regarding the market’s beliefs and ask whether the identified forecasting bias extends to the Fed’s outlook as well.

I collect Greenbook forecasts for all months from 1995 to 2012, taking the first prediction made in the month when there are multiple, and sub-setting to months with a scheduled FOMC meeting that occurred after the Blue Chip forecast (i.e., outside the first 10 days of the month) This results in a sample of 107 observations. I first re-create model (5.2) using Greenbook forecast errors as the outcome. Appendix Figure 17 shows the results. The point estimates for unemployment are significantly positive, but smaller than their counterparts in Figure 3; those for real GDP growth are mostly positive but statistically insignificant.

To directly test whether the market’s and Fed’s errors are asymmetric on a common sample, or whether public signals drive market-to-Fed disagreement, I estimate the following model with the

\[ \hat{Z}_{t-9-1} = \alpha + \beta \text{Unemployment Forecast} + \gamma \text{Real GDP Growth} + \epsilon \]

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

Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.2), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per one basis point of expected monetary surprise.

Greenbook-to-Blue-Chip forecast gap as the dependent variable:

\[
E_{G,t}[YQ(t+h)] - E_{B,t}[YQ(t+h)] = \alpha + \beta^{Di} \cdot \hat{Z}_{t-1} + \varepsilon_t
\]

(5.3)

Appendix Figure 16 confirms that \(\beta^{Di} > 0\), and that these estimates are highly statistically significant for both variables and at all horizons. Moreover, the constructed public signal proxy, by itself, explains 10% and 26% of all variation in disagreement between the Blue Chip forecasters and the Fed about unemployment or growth, depending on specification.

Taken together, the conclusions of these joint tests for market and Fed forecast errors are threefold. First, there is robust evidence that the identified bias in forecasting is more prevalent for markets than the Fed. This directly proves that movements in the identified public signals drive market to Fed disagreement about the path of the economy. Second, insofar as we have nailed down the sign of these forecast errors, the previous suggests further that the Fed’s forecasts are systematically more accurate in response to the variation spanned by \(\hat{Z}_{t-1}\). The clarification is essential—as guided by the theory, we are assessing accuracy only in the response to specific shocks rather than unconditionally. Finally, there is significant evidence that the bias is non-zero for the Fed concerning forecasts of unemployment. This detail matters for a reasonable empirical calibration of the model. And it may also, more loosely, buoy confidence that the forecasting problem studied here is really quite hard—both sophisticated market participants and sophisticated policymakers make the same-signed mistake.
5.2 Post-Announcement Drift

The second test, documented in Proposition 3, concerns forecast updates after the monetary announcement. To implement it, I take the revision in the consensus Blue Chip forecast (again, about real GDP or real PCE growth, at various horizons) between the first Blue Chip Survey after a given monetary announcement and the subsequent month. The same sample restrictions outlined above result in 116 observations from 1995 to 2014. The empirical model is the following:

$$E_{B,t+2}[Y_{q(t+1)+h}] - E_{B,t+1}[Y_{q(t+1)+h}] = \alpha + \beta^{Dr} \cdot \hat{Z}_{t-1} + \varepsilon_t$$  \hspace{1cm} (5.4)

where the left-hand-side variable is the forecast revision about an \( h \)-quarter ahead outcome between months \( t + 1 \) and \( t + 2 \). To re-iterate, the news encapsulated in \( \hat{Z}_{t} \) was determined in month \( t - 1 \); the monetary announcement occurs in month \( t \), after month \( t \)'s Blue Chip survey is completed; and the outcome variable concerns revisions made between \( t + 1 \) and \( t + 2 \), well after the monetary announcement. The prediction \( \beta^{Dr} > 0 \), according to Proposition 3, corresponds with under-estimating the predictive value of the public signals; the prediction \( \beta^{Dr} < 0 \) corresponds with under-estimating the monetary authority’s reliance on the public signal, and hence over-reacting to the public signal’s realization. Regression (5.4), apart from its justification in economic theory, is also a good empirical complement to the earlier test of forecast errors because it does not require any data on final outcomes—it merely checks whether forecasters predictably change their mind more than a month after certain data is released.

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

**Additional Evidence from Stock Returns.** To first approximation, stock prices may provide an additional, higher-frequency proxy for public opinion about economic fundamentals. Appendix C.4 outlines an additional model test based on the drift of stock prices after high realizations of \( \hat{Z}_{t-1} \) (as well as \( \hat{\Delta} \)). It that stock prices tend to drift upward for the next month after surprise monetary tightening that is spanned by \( \hat{Z}_{t-1} \), suggesting that good news (i.e., additional private signals) is being revealed that corrects the public’s original mis-assessment of the economy.30

5.3 Long-run Revisions and the “Information Effect”

The final main model prediction was Proposition 4: that positive public signal realizations should predict forecast revisions across monetary announcements.

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30This result resembles, at a much shorter time horizon, an important result in Bernanke and Kuttner (2005) of delayed positive expected returns in the response to surprise monetary tightening.
Figure 4: **Post-Announcement Revisions and Public Signals.**
Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.4). The units for the coefficients are basis points of forecast revision per one basis point of expected monetary surprise.

Figure 5: **Cross-Meeting Forecast Revisions and Monetary Surprises.**
Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.5). The units for the coefficients are basis points of forecast revision per one basis point of (expected or unexpected) monetary surprise.
The outcome variable of interest is forecast revisions from \( t \) to \( t+1 \). Because the sample is restricted to ensure that month \( t \)'s FOMC meeting occurs after month \( t \)'s Blue Chip survey, these are forecast revisions that “bracket” the FOMC meeting. The timing is identical to that in Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018).

The estimating equation is the following:

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

(5.5)

Having established a deviation from the rational model, we expect \( \beta^Z \neq 0 \) and \( \beta^A \neq 0 \). In the language of Proposition 4 and Corollary 1, the term \( \beta^Z \cdot \hat{\Delta}_{t-1} \) spans the bias \( B \). \( \beta^Z > 0 \) corresponds with under-confidence in public signals while \( \beta^Z < 0 \) corresponds with under-estimating the role of public signals in the monetary rule. Meanwhile, by Corollary 1, \( \beta^A \) should be an estimator of the “pure” information effect \( i \) that is robust to either possibility of the behavioral distortion.

Figure 5 shows the results. First, there is robust evidence of \( \beta^Z > 0 \), or the predicted component of the surprise correlating with future revisions. This, like previous findings, points toward undervaluation of the informational content in \( Z \) as the main forecasting bias. Second, there is limited statistical evidence, across variables and horizons, of \( \beta^A > 0 \), although point estimates are uniformly positive. This result emphasizes the empirical fragility of the evidence underpinning the “information effect” in studies by Campbell, Evans, Fisher, and Justiniano (2012) and Nakamura and Steinsson (2018). This paper’s theoretical model underscores that the main moment studied in each paper, the correlation of monetary surprises with forecast revisions across the announcement, does not robustly identify the effect of Fed persuasion in models with additional behavioral distortions. And the empirical results in Figure 5 underscore that such distortions are an empirical reality, not just a theoretical curiosity.

6. Quantification and Counterfactual Analysis

The above facts, interpreted via Propositions 2, 3, and 4, resoundingly point to under-valuation of or inattention to the public signal as the dominant friction for explaining patterns of forecast errors and revisions. But it is possible to obtain a sharper friction by directly fitting the model to match the estimated moments, which may in principle (and, indeed, does in practice) incorporate both frictions. In this section, I exactly calibrate the model via a method-of-moments procedure and then use the model to explore informative counterfactual scenarios. The latter exercises crystallize this paper’s main lessons regarding monetary policy and its power to sway public opinion.

6.1 Methods and Results

To do so, I commit to following mapping of the theory to the data. The unconditional forecast error regression (5.2), which for the purposes of sign predictions we could treat as a prediction at any
\( t \in \{0, 1, 2\} \), corresponds to \( t = 0 \) in the model; the monetary announcement is \( t = 1 \); and the Blue Chip survey immediately after the monetary announcement corresponds to \( t = 2 \). This allows me to map the empirical results of Sections 5.1 and 5.3 directly to the model, but does not use the results of Section 5.2 which correspond to a different definition of \( t = 2 \). Next, I make an alteration to the Fed’s monetary rule (2.5) to accommodate a forecasting error on the part of the Fed regarding fundamentals. This is parametrized by a \( q^F \) which enters the monetary rule in analogy to \( q \) in the market’s beliefs, or the revised rule

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

This will allow us to fit a more realistic model for monetary policy, bearing in mind the monetary authority’s own predictable forecast errors. Finally, I define the outcome as negative average unemployment over the following three quarters, as in the baseline version of each of the above regressions.

The model has seven parameters, listed in Table 1.\(^{31}\) I target seven moments. Six are described and reported above: the \( R^2 \) of predicting monetary surprises with \( \hat{Z}_t \); the coefficient and \( R^2 \) of regressing \( \hat{Z}_t \) on market forecast errors (Figure 3); the coefficient of regressing the same on Greenbook forecast errors (Figure 17); and the coefficients of regressing \( (\hat{Z}_t, \hat{\Delta}_t^+) \) on forecast revisions (Figure 5). The last is the regression coefficient of \( \hat{Z}_{t-1} \) on the outcome, or \( \beta^Y \)

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

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

To fit the model, I minimize the sum of squared deviations of the model prediction from each moment. The targeted moments and estimated parameters are summarized in Table 1. The moments are fit exactly up to algorithmic precision.

Observe the following three facts which can be read directly from the parameter estimates. First, \( q \gg w \): in common units of “under-weighting,” the market’s error in using the information embedded within the signal \( Z \) is much larger than its error in estimating the coefficient on \( Z \) in the monetary rule. This confirms the intuition of the “sign test” interpretation of all the results in this section. Second, \( q^F + w < q \): the market is correct that the Fed uses the signal \( Z \) more than they do, but slightly under-estimates the extent to which that is true. Finally, \( (\tau_Z, \tau_S) \gg \tau_F \): the non-private sources of information in the economy are much more precise than the private information. The precision weight on the Fed’s signal in the monetary rule is \( \tau_F / (\tau_\theta + \tau_F + \tau_Z) = 0.01 \), which is itself about 96 times smaller than the Fed’s weight on the public signal. These findings foreshadow the formal counterfactual analysis in the next subsection.

\(^{31}\)The remaining free parameter, the precision or variance of the fundamental, is normalized to one. This is entirely a scaling choice with no bearing on the calibration.
Table 1: Method of Moments Calibration.
Parameters are fit to minimize the sum of squared deviations of model moments from targets. The fit is essentially exact.

<table>
<thead>
<tr>
<th>Moment</th>
<th>Value</th>
<th>Param.</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$ from predicting surprises</td>
<td>0.15</td>
<td>$q$</td>
<td>0.065</td>
</tr>
<tr>
<td>$\beta^{FCE}$ for BC</td>
<td>15.32</td>
<td>$q^F$</td>
<td>0.048</td>
</tr>
<tr>
<td>$R^2$ for FCE reg. (BC)</td>
<td>0.23</td>
<td>$w$</td>
<td>0.004</td>
</tr>
<tr>
<td>$\beta^{FCE}$ for GB</td>
<td>12.06</td>
<td>$\tau_Z$</td>
<td>86.91</td>
</tr>
<tr>
<td>$\beta^Z$, for BC Revisions</td>
<td>3.69</td>
<td>$\tau_F$</td>
<td>0.857</td>
</tr>
<tr>
<td>$\beta^\lambda$, for BC Revisions</td>
<td>0.10</td>
<td>$\tau_S$</td>
<td>23.29</td>
</tr>
<tr>
<td>$\beta^\gamma$ from (6.2)</td>
<td>22.69</td>
<td>$a$</td>
<td>1.100</td>
</tr>
</tbody>
</table>

6.2 Counterfactual Scenarios and Key Take-aways

The reduced-form exercise demonstrated that predictable forecast errors, or errors directly attributable to biases in interpreting information, were large. But the structural model allows one to more carefully decompose these errors into different constituent frictions.

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

In each counterfactual, I focus on the change in the market’s and Fed’s beliefs using the following statistics: the sensitivity of the market’s beliefs to fundamentals at $t = 0$ and $t = 2$, the sensitivity of interest rates to fundamentals, and the variance of market forecast errors regarding both output and interest rates at $t = 0$. These statistics, together, summarize responsiveness to the business cycle and forecast accuracy. The first four rows of Table 2 summarize the results, reported in units relative to the baseline calibration.

Transparency. A great deal of emphasis in the applied literature on central bank communication has focused on transparency, which here may be narrowly defined as clear description of the monetary rule.\(^{32}\) The present model underscores very vividly why common knowledge of the broad policy objective ("minimize distance from $\theta$" or "lean this much into business cycles") is not sufficient to generate common knowledge of the policy rule when there is room to disagree about the informativeness of specific signals about the economy, but the empirical calibration revealed that the gap between the actual and perceived monetary rule was very small. To make more concrete what “small” means economically, row 1 of Table 2 reveals that the effect of achieving complete transparency about the

\(^{32}\)For a representative review of this applied literature, see Blinder, Ehrmann, Fratzscher, De Haan, and Jansen (2008).
monetary rule or counterfactually setting $w = 0$ amounts to a 3-5% decrease in the sensitivity of beliefs to output and a 15% increase in the precision of monetary policy forecasts. This change actually increases market forecast errors about output by 2%, because it removes a compensating error to the market’s under-estimation of the shock’s direct effect. These results underscore that while confusion about the monetary rule is an important contributor to forecast errors about policy, it is not the main story in terms of (possibly more consequential) expectations of real variables.

**Modeling public information.** By implication, the more important friction is heterogenous valuation of public information. The next three calculations quantify exactly how much this friction affects observed beliefs.

The second and third rows reveal the effects of harmonizing the Fed’s and Market’s models for how valuable is the public signal, while realistically maintaining that they may continue to be mis-specified at either the Fed’s or Market’s level. Each counterfactual results in a remarkably similar increase in the sensitivity of beliefs to fundamentals (17% or 18% at $t = 0$, and 12% or 14% at $t = 2$), while only the former improves the accuracy of forecasts. Starting from either of these points, completely removing the mis-specification in both the Market’s and Fed’s beliefs has a comparatively smaller marginal effect on the belief sensitivity, while it has a much larger effect on forecast accuracy (row 4).

The bottom line is that market and Fed disagreements about how to respond to public data have an outsize effect on market expectations relative even to the levels of these responses. The reason, illuminated through the model, is that these disagreements translate directly to the component of fundamental variation the markets do not expect the central bank to stabilize. Harmonizing the market’s and Fed’s model removes the former’s persistent belief that the latter is over-stabilizing the business cycle, either by increasing the Market’s perception of the demand shock (row 3) or decreasing the policy response to match the Market’s own viewpoint (row 4).

**The Information Effect.** The model’s low emphasis on Fed private information, and heavy emphasis on model mis-specification and heterogeneity, suggests a limited effect for the signaling channel of monetary policy. To make this clear, I consider a counterfactual exercise in which the Fed has vanishingly small internal information—neither does it lean on such information in its decision, nor

Table 2: **Counterfactual Analysis.**

The units are ratios to the baseline calibration. Each counterfactual is described in column 2, in which hats denote the calibrated value of each parameter.

<table>
<thead>
<tr>
<th>Scenario Name</th>
<th>Parameter Case</th>
<th>$\frac{d}{dt}E_0[Y]$</th>
<th>$\frac{d}{dt}E_2[Y]$</th>
<th>$\frac{d}{dt}F$</th>
<th>$\mathbb{V}[FCE_{Y,0}]$</th>
<th>$\mathbb{V}[FCE_{r,0}]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Agree to disagree</td>
<td>$w = 0$</td>
<td>0.953</td>
<td>0.966</td>
<td>1.000</td>
<td>1.023</td>
<td>0.854</td>
</tr>
<tr>
<td>2 Fed’s viewpoint</td>
<td>$q = q^F = \hat{q}, w = 0$</td>
<td>1.184</td>
<td>1.117</td>
<td>1.000</td>
<td>0.903</td>
<td>0.853</td>
</tr>
<tr>
<td>3 Market’s viewpoint</td>
<td>$q = q^F = \hat{q}, w = 0$</td>
<td>1.165</td>
<td>1.141</td>
<td>0.982</td>
<td>1.029</td>
<td>0.854</td>
</tr>
<tr>
<td>4 No errors</td>
<td>$q = q^F = w = 0$</td>
<td>1.238</td>
<td>1.049</td>
<td>1.051</td>
<td>0.752</td>
<td>0.851</td>
</tr>
<tr>
<td>5 No Fed Info</td>
<td>$\tau_F \downarrow 0$</td>
<td>0.992</td>
<td>0.996</td>
<td>1.000</td>
<td>1.012</td>
<td>0.109</td>
</tr>
</tbody>
</table>
does it reveal that information in its announcement. The fifth line of Table 2 reveals that this alteration essentially does not change the policy rule and it changes the Market’s \( t = 2 \) beliefs about fundamentals only slightly, amounting to a 0.4% change from the baseline.

These numbers rule out large information effects, or causal effects of Fed persuasion on public beliefs and hence, in more sophisticated models that endogenize real outcomes as a function of beliefs, the transmission of business-cycle demand shocks. This finding contrasts sharply with those of Nakamura and Steinsson (2018), who interpret the correlation of monetary surprises with subsequent upward revisions in forecasts about real variables (specifically, real GDP growth) as evidence of Fed persuasion about fundamentals. The difference in conclusions lies in this paper’s further investigation of predictability in forecast revisions and errors of both policy and outcomes, additional moments that are highly informative (as revealed in the model) about the precise distortion in market beliefs. These beliefs are by contrast essentially a free parameter in the main analysis of Nakamura and Steinsson (2018), who assume a very large information asymmetry. In my calibration, by contrast, model misspecification is sufficient to drive quantitatively realistic patterns in disagreements, forecast errors, and forecast revisions without significant scope for asymmetric information.

7. Anecdotal Evidence: Rate Changes in 2001

Is the story outlined in the quantitative model reasonable? This section provides anecdotal evidence from the early stages of the 2001 recession, which makes the scope for heterogeneous models and their connection with public data more concrete.

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

The crucial issue [. . .] is whether that marked decline [in GDP growth] breaches consumer confidence, because there is something different about a recession from other times in the economy. It is not a continuum from slow growth into negative growth. Something happens. In this sense, the Fed’s concern about a specific type of forward-looking signal (sentiment indicators) was well telegraphed to the markets in advance.

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. Mr. Slifman

\[^{33}\text{Formally, as long as } w \neq 0, \text{ the case with } \tau_F = 0 \text{ is not well defined as the Market cannot rationalize any forecast error regarding policy. As such, I consider a limit as } \tau_F \text{ gets arbitrarily small; but the core conclusion would be the same comparing a model with } w = 0 \text{ and } \tau_F \text{ with the counterfactual model with } w = 0.\]

\[^{34}\text{The authors, more specifically, assume the Fed has full information about the one-step-ahead innovation in productivity while the market has no information absent Fed signaling.}\]

\[^{35}\text{Taken from the online archive of the Washington Post, accessible at } \text{https://www.washingtonpost.com/wp-srv/business/greenspan012501.htm.}\]

\[^{36}\text{Mr. Slifman highlights the downside risk:}\]
January 2001 | May 2001
---|---
Target rate change | -0.5 | -0.5
Public Signals | Michigan Sentiment (change) | -13% | -3%
| Avg. Blue Chip Rev., U | 0.08 | 0.03
Fed-Blue-Chip Disagreement | U: 1-3Q Avg. | 0.54 | 0.43
| RGDP Growth: 1-3Q Avg. | -0.53 | -0.13
Futures Surprise | Eurodollar: 4Q | -0.04 | -0.15
| Policy News Factor | 0.00 | -0.09

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

remarked directly that, among the Michigan survey indicators, “the one about unemployment expectations” consistently has the most predictive power. This is the most robustly predictive sentiment indicator in Section 4 and subsequent analysis. Philadelphia Fed President Anthony Santomero reiterated the connection between pessimism in the data and the risk of a crash: “[G]iven the deterioration in consumer and business sentiment that we have seen so far, certainly there is reason to continue to be concerned about the downside risks to the economy.” Governor Gramlich mentioned, as a contrast to these negative anecdotes, that the Blue Chip survey of professional forecasters remains relatively optimistic about growth prospects. While he did not “take that forecast literally” in levels, given its generally slow and “stodgy” adjustment, he was concerned by its negative trend of revisions.

The first column of Table 3 gives an *ex-post* report of the rate decision and its relation with beliefs. The confidence break in the data, as alluded to in the minutes, was indeed severe. Markets had almost completely priced in the possibility of a rate cut in the same month but, after the meeting, significantly revised downward their expectations of future rates.

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

\[O\]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

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.
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 (column 2 of Table 3).

These anecdotes shine additional light on how the mechanisms for persistent disagreement in the model play out in two specific ways. First, they illustrate how the model’s emphasis on heterogeneous valuation of specific signals might map to more specific, but of course higher-dimensional and much more difficult to empirically identify, differences in how each party models the world (e.g., the importance of “confidence-type effects” in models and the informativeness of survey data about such effects). Second, they illustrate how such disagreements may be most natural in the response to demand shocks which are necessary somewhat abstract (e.g., in standard models, changes in preferences, confidence, or outlook).

8. What Shocks Cause Disagreement: An SVAR Analysis

The previous section offered hints about how disagreement about monetary policy fits into the business cycle. More specifically, what do the structural shocks that empirically drive disagreement resemble when mapped to standard macroeconomic models? A natural follow-up question concerns how much these shocks affect the macroeconomy: does disagreement arise only in isolated, irrelevant instances or does it coincide with the main shocks driving the business cycle?

This section answers each question using a fully empirical, structural vector autoregression (SVAR) model, identified in a way that is consistent with the simple model of monetary surprises. Its overall conclusion is that the primitive source of most monetary disagreement is best characterized as a confidence-based demand shock that drives a considerable fraction of all variation in monetary policy. In this regard, disagreement about monetary policy is a feature of the portion of the business cycle that the monetary authority is most actively trying to stabilize, consistent with the demand-centric interpretation in Section 2, and the expectation not the norm in demand-led recessions.

8.1 Empirical Model and Identification Strategy

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

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

(8.1)

where each $A_{\ell}$ is an $N \times N$ matrix and $\nu_t$ is an $N \times 1$ vector of independent, Gaussian innovations. The matrix $A_{0}^{-1}$ controls the contemporaneous impact of $\nu_t$ and hence the economic identification of the different shocks. Each column of $A_{0}^{-1}$ represents a linear combination of one-step-ahead forecast errors that combine to constitute a structural shock.
The data components of \( y_t \), in order, are the following eight series: the policy news shock, unemployment, the log deflator of personal consumption expenditures (PCEPI), the Michigan “unemployment sentiment” variable, the Blue Chip expectation of unemployment six months hence, the spread in beliefs between the 10 most and least pessimistic Blue Chip forecasters about the same, the log level of the S&P500, and the 1-year Treasury rate. The first three variables need no introduction; the next four summarize different aspects of public beliefs; and the last is a reference for realized monetary policy.\(^{37}\) The estimation uses monthly data from January 1995 to April 2014.

The model has two identified shocks. The first is identified via short-run restrictions as the only shock that has a contemporaneous impact on the policy news variable, while remaining unpredictable by other lagged observables. Through the lens of the simple model, and in particular Lemma 1 and Corollary 1 defining the monetary surprise, this shock captures variation spanned by the error in the monetary authority’s information.\(^{38}\) I will refer to this in shorthand as a monetary noise shock.

The second shock is defined to maximize the variance contribution to the policy news variable at horizons between 1 and 3 months while remaining orthogonal to the identified monetary noise shock, in the max-share tradition of Uhlig (2004) and more recent applications by Barsky and Sims (2011) and Angeletos, Collard, and Dellas (2018a). Through the lens of the simple model, this shock would capture variation in the public signal. But relative to the empirical methods in Sections 4 and 5, which proxied with specific lagged observations of selected variables, the VAR method is more agnostic about (i) which lags and variables predict surprises and (ii) whether these patterns arise unconditionally or only in response to certain business-cycle shocks. I will refer to the identified shock in shorthand as a monetary disagreement shock.\(^{39}\)

Appendix D spells out the details in much more detail, including the Bayesian inference procedure and numerical implementation of the identification.

8.2 Impulse Response Functions: What Shocks?

To answer the first question (“what shocks drive disagreement?”), I first calculate the impulse response functions to the identified noise and disagreement shocks (Figure 6) and compare their patterns to standard model benchmarks.

The noise shock is associated with a transient spike in the policy news shock which translates into a short-term (2-3 month) and fairly imprecise increase in 1-year Treasury rates. This increase is roughly

\(^{37}\)The Blue Chip survey, while administered monthly, provides forecasts only for quarterly-frequency outcomes. To construct an expectation over the next six months, I take a weighted average of quarterly expectations. Specifically, if the current month is in the middle of the quarter (e.g., February), I assume the two-quarter-ahead forecast corresponds to exactly six months in the future; if the current month is the first in the quarter, I take a weighted average of the one-quarter (1/3) and two-quarter (2/3) forecasts; and if the current month is the last in the quarter, I take a weighted average of the three-quarter (1/3) and two-quarter (2/3) forecasts.

\(^{38}\)The method also relates to the suggestion of Plagborg-Møller and Wolf (2019) to estimate the impulse response to an identified shock by ordering that shock first in a recursive VAR. Here the logic is that the policy news shock is a valid instrument for the shock of interest conditional on observables, or after partialling out lagged macro indicators.

\(^{39}\)Technically the shock is defined only up to scale. An additional constraint, which is a normalization, is that the shock has a positive impact on the policy news shock at horizon 2.
Figure 6: Impulse Response Functions.

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

“one-for-one”: at the posterior median, the ratio of the maximum response of the policy news shock (in units of revisions to 1-year Treasury expectations) to the max response of one-year Treasuries is 0.67. The shock leads to a small, transitory decline in the price of the S&P 500 (posterior median: 0.6 percentage points or 0.006 log points) and a small decline in Michigan sentiment. The VAR picks up no significant effects on unemployment, consumption, or prices, though it is conceivable economically that a mean-reverting decline in stock market wealth. There is not strong statistical evidence to reject the standard hypothesis from New Keynesian models that truly noise-induced monetary tightening acts like a negative aggregate demand shock, but also no significant evidence for that hypothesis.

The disagreement shock, by contrast, significantly decreases unemployment and raises prices over medium horizons (1-4 years). Monetary policy leans into these shocks considerably, as one-year Treasury rates initially increase one-for-one with inflation before remaining elevated long after the price level has stabilized. The effects on real variables are led, by several months, by spikes in consumer sentiment and stock prices. In this regard the shock resembles an identified news shock, as in studies by Beaudry and Portier (2006), Barsky and Sims (2011), and Barsky, Basu, and Lee (2015), and various structural models calibrated to explain similar patterns (e.g., Angeletos, Collard, and Dellas, 2018b) with confidence-led demand shocks.

While it is non-trivial to include the Greenbook forecast in the VAR model since it is not observed in every month, we can use the model to provide a rough calculation. In the model, the Fed’s beliefs
Table 4: Unconditional Variance Contribution.
The outcome variables are the policy news shock and the 1-year Treasury rate. Variance contributions are based on estimating the moving-average form to horizon 48 months. Deviations from summing to 100 reflect rounding.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Noise</th>
<th>Disagreement</th>
<th>Unidentified</th>
</tr>
</thead>
<tbody>
<tr>
<td>Policy news</td>
<td>72</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>Unemployment</td>
<td>1</td>
<td>23</td>
<td>75</td>
</tr>
<tr>
<td>1-year Treasuries</td>
<td>1</td>
<td>40</td>
<td>57</td>
</tr>
</tbody>
</table>

about the outcome respond 18% more than the market’s to a fundamental shock; if we assume the IRF of the Fed’s belief would be a uniform 18% larger than the market’s, then the maximum response of Market-to-Fed disagreement regarding unemployment six months ahead is -0.034 at the posterior median; as a percentage of the maximum response of unemployment, this is 20% at the posterior median. The comparable figures for the response of within Blue Chip (or market pessimist to market optimist) disagreement, which is in the model, are -0.031 and 17%, indicating that the gap between optimists and pessimists habitually contracts in response to good news and widens in response to bad news owing to pessimist’s greater sensitivity to news. These results suggest substantial, and in the latter case verifiably persistent, effects on disagreement about macro outcomes as a result of shocks spanned by past and present public data at \( t = 0 \).

8.3 Variance Decomposition: Do the Shocks Matter?

I now turn to quantifying how important the identified shocks are for explaining macro dynamics. Based on the moving average representation implied by the VAR dynamics, one can calculate in the model the total fraction of unconditional variance in the policy news variable (which is almost certainly stationary) attributed to each of the two identified shocks and the one unidentified shock up to a feasible lag truncation. Table 4 shows the variance contributions of each of the three shocks to the policy news shock and to 1-year Treasury rates. In a posterior median estimate, 72% of variance is explained by the noise shock; 14% by the disagreement shock; and the remaining 14% is unidentified. The middle number closely matches the \( R^2 \) of the bi-variate prediction equation in Section 5.1. In this sense, most of the monetary surprise variation in the multi-variate model remains related to the (very small) noise in the monetary authority’s beliefs.

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

\(^{40}\)Appendix Figure 18 shows the forecast error variance decomposition (FEVD) for all variables in the model.
9. Conclusion

This paper studied disagreement about monetary policy in the US since 1995 and why it persists despite abundant and precise public information. It showed, in a simple signal extraction model, how to differentiate first between theories of asymmetric and heterogeneous models and then next between two leading cases of heterogeneous models (mis-specifying the monetary rule or value of public information). Its main empirical results demonstrated that opinion-aggregating public signals have significantly predicted surprises about monetary policy as well as large forecast errors in the private sector and disagreements between the private sector and Fed about the future path of real variables. Through the lens of the model, these patterns implied a significant role for mis-specifying the value of public information, a small role for mis-specifying monetary response to that information, and an almost negligible role for asymmetric information. Such a calibration implied a large causal effect of market to Fed disagreement on the former’s beliefs but an essentially negligible causal effect of Fed persuasion about fundamentals.

A semi-structural VAR revealed that the variation that causes most monetary disagreement resembles a confidence-driven demand shock to which the Fed has a large systematic response. This further deepens the story and suggests that monetary disagreement plays a role in the transmission of a significant driver of all economic fluctuations and a majority explainer of all Treasury rate variation.

Apart from the above conclusions, an additional practical take-away is that monetary surprises are not valid instruments for true “monetary shocks,” defined as unexpected and non-fundamental deviations from a policy rule. This paper’s simple model was precise about why: monetary surprises conflate true deviations, which come from idiosyncrasies in the central bank’s information, with the persistent bias in private sector forecasts. If anything, the impact of the disagreement shock is much more sharply identified in the business-cycle-frequency data than the impact of the (quantitatively minuscule) monetary noise shock.

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

Finally, this paper had little to say about optimal policy conduct in light of the patterns highlighted within. Caballero and Simsek (2019) study optimal monetary policy in a similar environment, in which markets disagree with the Fed about the path of fundamentals, and the Fed designs policy around “agreeing to disagree.” An exploration of this topic in a realistic empirical calibration is a fascinating topic for future research.
REFERENCES


CABALLERO, R. J., AND A. SIMSEK (2019): “Monetary Policy with Opinionated Markets,” miméo, MIT.


A. Omitted Proofs

Lemma 1

The market’s average expectation of monetary policy is

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

which, after substituting in average expectations from (2.6), is

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

(A.1)

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 \( Z \).

From here, the calculation is quite simple. Observe that the interest rate is given by the Fed’s belief (2.5). The difference of (A.1) from this is

\[ \Delta = \delta T(F - \delta M Z) + \delta F qZ + wZ \]

(A.2)

which re-arranges to (2.8) upon definition of \( \mathbb{E}^{R}_{M,0}[\theta] := \delta M Z \).

Proposition 1

Observe that the “rational expectation” \( \mathbb{E}^{R}_{M,0}[\theta] \) can be written as

\[ \mathbb{E}^{R}_{M,0}[\theta] = \int \mathbb{E}^{R}_{i,0}[\theta] d\theta \]

(A.3)

for fictitious individuals who observe \( Z \) and apply Bayes rule. By the law of iterated expectations, the objective covariance of each agent’s forecast error with \( Z \) is 0:

\[ \text{Cov}[\theta - \mathbb{E}^{R}_{i,0}[\theta], Z] = 0, \forall i \]

(A.4)

and hence \( \text{Cov}[\theta - \mathbb{E}^{R}_{M,0}[\theta], Z] = 0 \).

Consider now \( \text{Cov}[\Delta, Z] \). Using expression (2.8) for \( \Delta \), this can be written as the following sum of terms

\[ \text{Cov}[\Delta, Z] = \text{Cov}[\Delta, \delta F \epsilon_F] + \delta F \text{Cov}[\theta - \mathbb{E}^{R}_{M,0}[\theta], Z] + (\delta F + w) \text{Cov}[Z, Z] \]

(A.5)

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

\[
\text{Cov}[\Delta, Z] = (\delta_F^Z q + w) \text{Var}[Z] \tag{A.6}
\]

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

**Proposition 2**

These properties are established in turn for forecast errors in each time period.

First, consider \( C = 0 \). The market’s forecast error about \( A \) is \( \Delta \). Its forecast error about \( \theta \) is

\[
\theta - \mathbb{E}_{M,0}[\theta] = (\theta - \mathbb{E}_{M,0}^R[\theta]) + qZ \tag{A.7}
\]

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

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

\[
= (a - \delta_F^Z)(\theta - \mathbb{E}_{M,0}[\theta]) + (a - \delta_F^Z)qZ - wZ \tag{A.8}
\]

The covariance with \( Z \) is

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

\[
= ((a - \delta_F^Z)q - w) \text{Var}[Z] \tag{A.9}
\]

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 \( (a - b\delta_F^Z) > 0 \), given \( a \geq 1 \) (assumed) and \( \delta_F^Z \in (0,1) \) (directly observable from the expression \( \delta_F^Z = \tau_F / (\tau_0 + \tau_Z + \tau_F) \) in which all constants are positive).

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

\[
\hat{F} = \frac{1}{\delta_F^Z}(r - (\delta_F^Z - w)Z) = F + \frac{w}{\delta_F^Z}Z \tag{A.10}
\]

which is “correctly” equal to \( F \) if the market participants know the monetary rule, over-weights \( Z \) if the market under-estimates the weight on \( Z \) in the rule, and under-weights \( Z \) if the market over-estimates the weight on \( Z \) in the rule.
In both periods $t \in \{1, 2\}$, the forecast error for $\theta$ can be written as

$$\theta - \mathbb{E}_{M,t}[\theta] = (\theta - \mathbb{E}_{M,t}^R[\theta]) + \frac{\tau_0}{\tau_t}qZ - \frac{\delta_{F,t}^M}{\delta_F^t}wZ$$  \hfill (A.11)$$

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

$$\mathbb{E}_{M,1}^R[\theta] = \delta_{Z,1}^M Z + \delta_{F,1}^F$$

$$\mathbb{E}_{M,2}^R[\theta] = \left(1 - \frac{\tau_s}{\tau_1 + \tau_s}\right)\mathbb{E}_{M,1}^R[\theta] + \frac{\tau_s}{\tau_1 + \tau_s}S$$  \hfill (A.12)$$

and coefficients

$$\tau_1 := \tau_0 + \tau_Z + \tau_F$$  \hfill (A.13)$$

$$\delta_{X,1}^M := \frac{\tau_X}{\tau_1}$$  \hfill (A.14)$$

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

$$Y - \mathbb{E}_{M,t}[Y] = a(\theta - \mathbb{E}_{M,t}[\theta])$$  \hfill (A.15)$$

as $r$ is now known. Plugging in (A.11), taking the covariance with $Z$, and noting the zero covariance with the average rational expectation gives

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

$$= a\left(\frac{\tau_0}{\tau_t}q - \frac{\delta_{F,t}^M}{\delta_F^t}w\right)\text{Var}[Z]$$  \hfill (A.16)$$

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 $t$.

**Proposition 3**

Observe from (A.11) and (A.12) that the average forecast revision from $t = 1$ to $t = 2$ for $\theta$ can be written as

$$\mathbb{E}_{M,2}[\theta] - \mathbb{E}_{M,1}[\theta] = \mathbb{E}_{M,2}^R[\theta] - \mathbb{E}_{M,1}^R[\theta] - \left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right)qZ + \tau_F\tau_0\left(\frac{1}{\tau_2} - \frac{1}{\tau_1}\right)\frac{w}{\delta_F^t}Z$$  \hfill (A.17)$$
The revision for $Y$ is a rescaling of this, or $E_{M,2}(Y) - E_{M,1}(Y) = a(E_{M,2}(\theta) - E_{M,1}(\theta))$. Taking the covariance with $Z$, and noting the zero covariance of the rational revision with $\Delta$, gives

$$\text{Cov}[E_{M,2}(Y) - E_{M,1}(Y), Z] = a \left( \frac{1}{\tau_1} - \frac{1}{\tau_2} \right) (\tau_q - (\tau_F/\delta_F)w) \text{Var}[Z]$$  \hspace{1cm} (A.18)

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

**Proposition 4**

Observe that the covariance between $\Delta$ and $E_{M,2}(Y) - E_{M,0}(Y)$ can be written as the sum of two terms corresponding to one-period updates:

$$\text{Cov}[E_{M,2}(Y) - E_{M,0}(Y), \Delta] = \text{Cov}[E_{M,1}(Y) - E_{M,0}(Y), \Delta] + \text{Cov}[E_{M,2}(Y) - E_{M,1}(Y), \Delta]$$  \hspace{1cm} (A.19)

Mechanically, then, in expression (2.11), the bias term is

$$B := \frac{\text{Cov}[E_{M,2}(Y) - E_{M,1}(Y), \Delta]}{\text{Var}[\Delta]}$$  \hspace{1cm} (A.20)

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

$$B = (\delta_F q + w) \frac{\text{Cov}[E_{M,2}(Y) - E_{M,1}(Y), Z]}{\text{Var}[\Delta]}$$  \hspace{1cm} (A.21)

Applying the result from the proof of Proposition 3 simplifies further to

$$B = (\delta_F q + w) (q - (\tau_F/\delta_F)w) \left( \frac{1}{\tau_1} - \frac{1}{\tau_2} \right) a \frac{\text{Var}[Z]}{\text{Var}[\Delta]}$$  \hspace{1cm} (A.22)

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

**Corollary 1**

By the Frisch-Waugh-Lovell Theorem, it is sufficient to show

$$i = \frac{\text{Cov}[E_{M,2}(Y) - E_{M,0}(Y), \tilde{\Delta}]}{\text{Var}[\tilde{\Delta}]}$$  \hspace{1cm} (A.23)

where $\tilde{\Delta}$ is the residual of projecting $Z$ onto $\Delta$. Observe that $\tilde{\Delta} = \Delta^R$, or the forecast revision in the rational model, since $\Delta = \Delta^R + qZ$ for some $q \neq 0$ and $\text{Cov}[\Delta^R, Z] = 0.$
Next, observe that $\text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \hat{\Delta}] = \text{Cov}[\mathbb{E}_{M,2}[Y] - \mathbb{E}_{M,1}[Y], \Delta^R] = 0$ by the arguments used in the proof of Proposition 4.

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

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

(A.24)

where the numerator and denominator of the scaling factor are perceived covariances and variances and $\Delta$ is the (average) forecast error about $r$. Next, observe that the covariance of this revision with $\hat{\Delta}$ and $\tilde{\Delta}$ is respectively

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

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

(A.25)

which again uses the decomposition $\Delta = \Delta^R + qZ = \tilde{\Delta} + qZ$. This implies that

$$\hat{i} = \frac{\hat{\text{Cov}}[\Delta, \mathbb{E}_{i,0}[\theta]]}{\hat{\text{Var}}[\Delta]} \cdot \frac{(\text{Var}[\tilde{\Delta}] - \text{Var}[\zeta])}{\text{Var}[\tilde{\Delta}] \cdot \text{Var}[\tilde{\Delta}]} = i \cdot \frac{\text{Var}[\Delta]}{\text{Var}[\tilde{\Delta}]} \cdot \frac{\text{Var}[\tilde{\Delta}]}{\text{Var}[\tilde{\Delta}]} = i$$

where the last line verifies the result.
B. Micro-foundations

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

This section micro-founds conditions (2.1) and (2.4) in expectation in a New Keynesian model with both demand and supply shocks.

B.1.1 Primitives

Time is indexed by \( t = \{2, 3, \ldots\} \), to be consistent with the abstract model’s notation. All predictions of interest will relate to behavior at \( t = 2 \).

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

\[
\exp(\theta_d) \left( \log C_2 - \exp(-\theta_s) \frac{N_t^2}{2} \right) + \sum_{j=1}^{\infty} \beta^j \left( \log C_{t+j} - \frac{N_{t+j}^2}{2} \right)
\]

where \( \beta \in (0, 1) \) is a discount factor and \((\theta_d, \theta_s)\) are respectively demand and supply shocks, which are known to the household, and are each Gaussian with mean 0 and respective variances \((\sigma_d^2, \sigma_s^2)\).

The household has the standard flow budget constraint

\[
C_t + R_{t+1}B_t \leq w_t N_t + B_{t-1}
\]

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 some wage \( w_t \).

A monetary policymaker sets the nominal interest rate, which, given full rigidity in prices, corresponds with the real interest rate. The policymaker’s objective is to maximize the representative household’s utility (B.1).

B.1.2 Optimal Unconstrained Policy

It is simple to solve the planner’s problem in this economy to derive the optimal allocation \( Y_t = C_t = N_t \equiv 1 \) for all \( t \geq 3 \) and \( Y_t = C_t = N_t = \exp(\theta_s) \) for \( t = 2 \). That is, in the first period, the policymaker would like output to vary with the supply shock and to stabilize the demand shock.

The relevant constraints for implementation are the Euler equations between periods \( t \) and \( t + 1 \). First, for \( t \geq 3 \),

\[
\beta R_{t+1} \frac{C_{t+1}}{C_t} = 1
\]

from which it is easy to see that \( R_t \equiv 1/\beta \) implements the desired allocation. Next, at \( t = 2 \), the same
condition is
\[ \beta \exp(\theta_d) R_3 \frac{C_3}{C_2} = 1 \]  
(B.4)
from which it is clear that \( C_2 = \exp(\theta_s)C_3 \), as desired, is implemented when \( R_3 = 1/\beta \cdot \exp(\theta_s - \theta_d) \).

Finally, note that a transformation of (B.4) in logs, after substituting in \( C_t = Y_t \) and \( Y_3 = 1 \), is
\[ \log Y_2 = \theta_d - (\log(R_3) - \log \beta) \]  
(B.5)

### B.1.3 A Feasible Policy with Supply and Demand Confusion

I now introduce a frictional policy problem that captures the difficulty of differentiating supply shocks ("good shocks") and demand shocks ("bad shocks") in real time.

The central bank has an information set \( \mathcal{F}_t \), which comprises noisy signals of the sum of the two shocks: \( \theta_s + \theta_d \). Let \( r := \log R_3 - \log \beta \) denote the deviation of interest rates from the inverse discount rate. The central bank's objective, up to quadratic approximation, is to minimize the deviation of its policy from the unconstrained optimal policy \( r^* = \theta_s - \theta_d \):

\[ \mathcal{W} = -\mathbb{E} \left[ (r - r^*)^2 \mid \mathcal{F}_t \right] \]  
(B.6)
and the optimal feasible policy is
\[ r = \mathbb{E}[r^* \mid \mathcal{F}_t] \]  
(B.7)
By the law of iterated expectations, this can be re-written as
\[ r = \mathbb{E}[\mathbb{E}[r^* \mid \theta_s + \theta_d] \mid \mathcal{F}_t] \]
where the inner expectation conditions on the sum of shocks, and evaluates to the following
\[ r = \mathbb{E}[q(\theta_s + \theta_d) \mid \mathcal{F}_t] \]  
(B.8)
for \( q := \frac{\sigma_d^2 - \sigma_s^2}{\sigma_d^2 + \sigma_s^2} \leq 1 \). Under the assumption that \( \sigma_d^2 > \sigma_s^2 \), or demand shocks are higher variance than supply shocks, we have \( q \in (0, 1) \).

Finally, note that output at \( t = 2 \) can be written in expectation as
\[ \mathbb{E}[\log Y_2 \mid \theta_s + \theta_d, r] = \mathbb{E}[\theta_d \mid \theta_s + \theta_d, r] - r = p(\theta_s + \theta_d) - r \]  
(B.9)
for \( p := \frac{\sigma_s^2}{\sigma_d^2 + \sigma_s^2} \in (0, 1] \).
B.1.4 Mapping to the Abstract Model

The mapping to the abstract model is as follows. The abstract fundamental $\theta$ is the sum of the supply and demand shock scaled by $q \in (0, 1)$, or

$$\theta := q(\theta_s + \theta_d) \quad (B.10)$$

This is the “approximate natural rate of interest” when the central bank only observes the sum of the shocks. The outcome $Y$ is log output conditional on this sum of shocks, or

$$Y := \mathbb{E}[\log Y_2 \mid \theta_s + \theta_d] \quad (B.11)$$

and the coefficient $a$ is the ratio of how informative $\theta_s + \theta_d$ is about demand shocks versus the natural rate:

$$a := \frac{\sigma_d^2}{\sigma_d^2 - \sigma_s^2} \in [1, \infty) \quad (B.12)$$

Observe that $a$ strictly increases in $\sigma_d^2$ for fixed $\sigma_s^2$. That is, as supply shocks become more important in the economy, the central bank tries less in expectation to stabilize the economy against fluctuations in $\theta$.

B.2 Futures Prices: A Simple Trading Model

There are 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:

$$-\exp(-\alpha W) \quad (B.13)$$

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

The investor’s optimization problem is therefore

$$\max_{p \to x_i \in \mathbb{R}} -\mathbb{E}_i \left[ \exp(-\alpha(E + x_i(r - p))) \right] \quad (B.14)$$

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

$$\max_{p \to x_i \in \mathbb{R}} E_i[E + x_i(r - p)] - \frac{\alpha}{2} \mathbb{V}_i[E + x_i(p - r)]$$  (B.15)

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

$$x_i(p) = \frac{E_i[r] - p}{\alpha \mathbb{V}_i[r]}$$  (B.16)

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

$$\int_i x_i(p) \, di = 0$$  (B.17)

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

$$p = \int_i E_i[r] \, di$$  (B.18)

as postulated in (2.2)
C. ADDITIONAL EMPIRICAL DETAILS

C.1 Original Survey Questions

Michigan Survey of Consumers

**Question:** How about people out of work during the coming 12 months—do you think that there will be more unemployment than now, about the same, or less?

**Answers:** 1. MORE UNEMPLOYMENT; 3. ABOUT THE SAME; 5. LESS UNEMPLOYMENT

**Coding:** (Share == 5) - (Share == 1)

**Aggregation:** Average using survey weights

AAII Survey

Historical AAII survey data are available at: [https://www.aaii.com/sentimentsurvey/sent_results](https://www.aaii.com/sentimentsurvey/sent_results).

The survey asks organization members whether they are “Bullish,” “Neutral,” or “Bearish” about “what direction members feel the stock market will be in next 6 months [sic].”

C.2 Event Studies

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

$$\Delta_t = \alpha + \beta_h \cdot X_{t+h} + \epsilon_{t+h}^X$$  \hspace{1cm} (C.1)

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

The left panel of Figure 8 plots $\beta_h$ from model (C.1) where the indicator $X_{t+h}$ is the unemployment sentiment variable from the Michigan survey and the frequency is monthly. The variable tends to be at an elevated level for several months prior to a positive monetary surprise, and to spike slightly in the prior month. This suggests that there is information both in the growth rate of sentiment, emphasized in the earlier results, and the level of sentiment. Furthermore, there is no obvious visual evidence of a trend break occurring at the announcement event. If anything, there is smooth reversion back to the mean.

The right panel of Figure 8 plots $\beta_h$ from model (C.1) where the indicator $X_{t+h}$ is the fraction of bullish investors in the AAII survey. This indicator is elevated 4-5 weeks prior to a positive surprise and seems to steadily decline as if reverting to a long-run mean.
Together, these results emphasize that (i) predictability of monetary surprises in the data is possible with fairly old data but (ii) the most significant effects are concentrated about one month prior to the announcement.

C.3 Pseudo-out-of-sample Fit

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

\[
\text{Reduction MSE} = 1 - \frac{\text{MSE}_{\text{POOS}}}{\text{MSE}_{\text{naive}}} \tag{C.2}
\]

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 somewhat overfit.

The first two columns of Table 6 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 a possibly exploiting 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 actuarially fair price of $0.50. Over such small horizons the risk-free rate is essentially zero, so I summarize the security by its Sharpe Ratio or ratio of return to standard deviation thereof. These Sharpe ratios, in the third column of Table 6, all lie between 0.15 and 0.30.

C.4 Monetary Surprises and Stock Prices

Under the assumption that stock price fluctuations reflect changes in (the present discounted value of) expected fundamentals, we can operationalize tests of Proposition 3 using cumulative returns of the stock market around monetary announcements.
I estimate the following empirical equation:

\[ R_{W(t)} = \alpha + \beta Z \cdot \hat{Z}_{t-1} + \beta^A \hat{\Delta}_t^+ + \varepsilon_{W(t)} \]  \hspace{1cm} (C.3)

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

The results are plotted in Figure 19. First, on the day of the announcement, there is no statistically significant difference between the response of stock prices to either the predicted or unpredicted components of the monetary surprise. This is consistent with the model but in sharp contrast to the claim of Jarocinski and Karadi (2018) that one may distinguish monetary trembles from “information shocks” by contemporaneous stock market reaction.

Next, over longer horizons (and, in particular, 11-20 trading days after the announcement), there is weak statistical evidence of an upward drift in stock prices. This would be consistent with an upward drift in expectations of fundamentals, holding fixed expectations of future interest rates. It corroborates the test in the main text (Section 5.2) of Proposition 3, and demonstrates that much of the correction in expectations may occur within one month of the monetary announcement.
D. SVAR Model

The reduced-form representation of the model is (8.1), re-printed here:

\[ y_t = \sum_{\ell=1}^{L} A_{\ell} y_{t-\ell} + v_t \]  

(D.1)

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

D.1 Priors and Inference

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

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

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

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

D.2 Posterior Draws

Given the assumption that model errors are Gaussian, and the fact that the prior is conjugate, it is straightforward to sample from the posterior over \( \Sigma \) and the \( (B_\ell)^L_{\ell=1} \) in closed form. Conditional on these reduced-form draws, the identification strategy provides a unique mapping to the structural shocks of interest and the impulse response functions thereof.
Let $Q$ denote the unique lower-triangular matrix such that $QQ' = \Sigma$ (i.e., Cholesky decomposition). Based on the variable ordering specified in the main text, with the policy news shock ordered first, I take the first column of $A_0^{-1}$ to be the first column of $Q$: that is, the first recursively-ordered shock. This is the monetary noise shock.

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

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

(D.2)

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

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

(D.3)

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

$$\max_{w \in \mathbb{R}^N} w'[b_2 b_2' + b_3 b_3' + b_4 b_4']w$$

s.t. $w'w = 1$

$$w'e_1 = 0$$

(D.4)

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

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

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### Additional Tables and Figures

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<th>PC Control</th>
<th>NFP Control</th>
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<td>$t$-stat</td>
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<td>(0.0026)</td>
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Table 5: **Predictive Value of Sentiment, Holding Fixed Recent Data.**
The regression equation is (4.2). The four predictors are described in Section 4.1 and the control variables in Section 4.2.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Predictive $R^2$</th>
<th>Sharpe Ratio</th>
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<td>Sign</td>
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<td>Blue Chip Revision</td>
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<td>AAII Bull-Bear Spread</td>
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</table>

Table 6: **Pseudo-out-of-sample Fit.**
Values are fraction MSE reduction calculated as in (C.2).
Figure 7: Labor Market Sentiment: Time Series Patterns.
The left scale and solid blue line show the unemployment sentiment variable from the Michigan survey. The right scale and dotted orange line show the US unemployment rate.

Figure 8: Event Study of Sentiment.
Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (C.1). The units for the coefficients are implied basis points of monetary surprise per one (non-normalized) unit of the regressor.
Figure 9: Predictability for Different Assets.
Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). Each sub-figure is an analogue of Figure 1 with a different outcome variable.
Figure 10: **Predicting Monetary Surprises, Pre 2008.**
This figure replicates the analysis of Figure 1, but restricts the sample to 1995-2007. Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (4.1), and each estimate comes from a separate univariate regression. The units for the coefficients are implied basis points of monetary surprise per one-standard-deviation outcome of the regressor.

Figure 11: **Rolling Estimation of Predictive Regression.**
The window is 48 months and dotted lines are 95% CI.
Figure 12: Forecast Errors and Public Signals, Alternative Outcomes.
The outcomes are Real PCE Growth (annualized) and 3-Month Treasury Rates (annualized, market average over quarter).
Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.2), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per one basis point of expected monetary surprise.

Figure 13: Forecast Errors and Public Signals, First-Release Data.
First-release macro data are taken from the Philadelphia Fed’s real-time data center (https://www.philadelphiafed.org/research-and-data/real-time-center). Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.2), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per one basis point of expected monetary surprise.
Figure 14: Forecast Errors and Public Signals, Upper and Lower Tails.
The forecasts are the average among the 10 highest (left) and 10 lowest (right) forecasts in that survey. Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.2), and each estimate corresponds to a different univariate regression. The units for the coefficients are basis points of forecast error per one basis point of expected monetary surprise.

Figure 15: Rolling Estimation of Forecast and Outcome Prediction.
Each point is the coefficient in a feasible regression coefficient based on predictions made nine months ago or prior and measured unemployment rates. The regression is $Y_t = \beta \cdot \hat{Z}_t + \alpha + \epsilon_t$, where $Y_t$ is either the predicted or realized unemployment rate three quarters hence. The window is 48 months and dotted lines are 95% CI.
Figure 16: **Forecast Disagreements and Public Signals.**
Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.3). The units for the coefficients are basis points of forecast disagreement per one basis point of expected monetary surprise.

Figure 17: **Greenbook Forecast Errors and Public Signals.**
Errors bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The regression equation is (5.2), but the outcome is adjusted to be errors in the Fed’s Greenbook forecasts, and the sample is smaller (see main text). The units for the coefficients are basis points of forecast error per one basis point of expected monetary surprise.
Figure 18: Forecast Error Variance Decomposition.
The response variables are, in order: the policy news shock, unemployment, Real Personal Consumption Expenditures, PCE Deflator, Michigan Unemployment Sentiment, the Blue Chip expectation of the next six months’ Real PCE growth, the S&P 500 Price, and the 1-Year Treasury Rate. Shaded bands are 68% and 95% high-posterior-density regions.
Figure 19: Predictable Surprises and Stock-Price Drift.
Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth). The estimating equation corresponds with (C.3).