

Supplemental Appendix for “Disagreement About Monetary Policy” by Sastry

B Model Micro-foundations

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

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

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

$$r = \mathbb{E}_{F,0}[\theta] \tag{1}$$

and expression for output,

$$Y = a\theta - r \tag{2}$$

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

B.1.1 Primitives

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

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

$$\exp(a\theta) \left(\log C_0 - \frac{N_0^2}{2} \right) + \sum_{h=1}^{\infty} \beta^h \left(\log C_h - \frac{N_h^2}{2} \right) \tag{3}$$

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

$$C_t + R_{t+1}B_t \leq w_tN_t + B_{t-1} \tag{4}$$

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

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

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

B.1.2 Equilibrium

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

$$\beta R_{t+1} \frac{C_t}{C_{t+1}} = 1 \quad (5)$$

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

At $t = 0$, the same condition is

$$\beta \cdot \exp(-a\theta) R_1 \frac{C_0}{C_1} = 1 \quad (6)$$

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

$$\log C_0 = a\theta - r \quad (7)$$

which corresponds exactly to abstract equation (2) when $Y = \log C_0$. One recovers the monetary rule (1) by assuming that r is set to the policymaker's expectation of θ . See that this stabilizes the (log) output gap, in expectation, when $a = 1$; otherwise, the policymaker tolerates, in expectation, a positive effect of a positive demand shock on today's output. Such a feature is common for empirically plausible monetary rules and might be justified by adding additional constraints on or objectives for monetary policy, like financial stability.

B.1.3 Stock Prices

It is useful, for interpretations of the numerical model, to introduce a model-consistent notion of a stock price. Introduce Q as the stock price, which I will define as the expected present-discounted value of output *adjusted by the demand shock* under a different Market agent's beliefs

$\mathbb{E}_M[\cdot]$, or

$$Q = \mathbb{E}_M \left[\exp(a\theta)C_0 + \sum_{h=1}^{\infty} \frac{C_h}{\exp\left(\prod_{k=1}^h R_k\right)} \right] \quad (8)$$

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

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

$$q = (1 - \beta)\mathbb{E}_M[\log C_0] - \beta(\mathbb{E}_M[r] - a\mathbb{E}_M[\theta]) \quad (9)$$

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

$$q = a\mathbb{E}_M[\theta] - \mathbb{E}_M[r] \quad (10)$$

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

B.2 Futures Prices: A Simple Trading Model

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

$$P = \mathbb{E}_{M,0}[r] \quad (11)$$

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

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

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

$$-\exp(-\alpha W) \quad (12)$$

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

The investor's optimization problem is therefore

$$\max_{p \mapsto x_i \in \mathbb{R}} -\mathbb{E}_i [\exp(-\alpha(E + x_i(r - P)))] \quad (13)$$

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

$$\max_{p \mapsto x_i \in \mathbb{R}} \mathbb{E}_i[E + x_i(r - P)] - \frac{\alpha}{2} \mathbb{V}_i[E + x_i(P - r)] \quad (14)$$

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

$$x_i(P) = \frac{\mathbb{E}_i[r] - P}{\alpha \mathbb{V}_i[r]} \quad (15)$$

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

$$\int_i x_i(P) \, di = 0 \quad (16)$$

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

$$P = \int_i \mathbb{E}_i[r] \, di \quad (17)$$

If all investors share the same information, or $\mathbb{E}_i[\cdot] \equiv \mathbb{E}_M[\cdot]$ for all i (where M denotes the “market”), then (17) reduces to (11). More generally, when there is not a single information set, (17) says that price equal population average beliefs.

C Solution of Model

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

Monetary surprises are

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

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

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

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

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

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

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

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

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

and hence the regression coefficient is

$$\beta_F^{FCE} = \frac{aq^F}{w + \delta_F^F q^M} \quad (\text{M4})$$

Similarly, for the market,

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

and hence the regression coefficient is

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

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

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

and then observe that, because Z is uncorrelated with the rational forecast error, $\text{Var}[\text{FCE}_{M,0}^Y] =$

$\text{Var}[(Y - \mathbb{E}_{M,0}^R[Y])] + \text{Var}[\beta_M^{FCE}Z]$. Using this, we calculate

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

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

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

from which it is immediate that

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

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

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

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

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

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

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

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

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

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

$$\beta^\Delta = a - 1 \quad (\text{M6})$$

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

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

D Additional Analysis

D.1 Pseudo-out-of-sample Fit

In this section I measure whether observing certain variables would have aided in real time forecasting of high-frequency monetary shocks. Let X_{t-1} be a predictor variable. For each scheduled FOMC meeting month s , greater than a burn-in period of the first 48 meetings in the data, I run a linear regression of (i) previous surprises and (ii) the sign of previous surprises on X_{t-1} for all data up to month $s - 1$. I calculate the mean squared error for all these out of sample projections. Then, to put this in units of an “approximate R^2 ,” I calculate reduction in MSE as

$$\text{ReductionMSE} = 1 - \frac{\text{MSE}_{\text{POOS}}}{\text{MSE}_{\text{naive}}} \quad (18)$$

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

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

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

D.2 Case Study Analysis: Fed Policy in 2001

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

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

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

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

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

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

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

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

In the data, the confidence break was indeed severe: the Michigan labor-market sentiment variable plunged by 13%. The Fed had a more pessimistic labor market outlook than the Market: while the Blue Chip revised its unemployment forecast up by 8 basis points (averaged

over 1, 2, and 3 quarters ahead), the Fed’s Greenbook forecast increased by 62 basis points. The monetary policy surprise was -12.5 basis points, one of the largest recorded in the dataset.

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

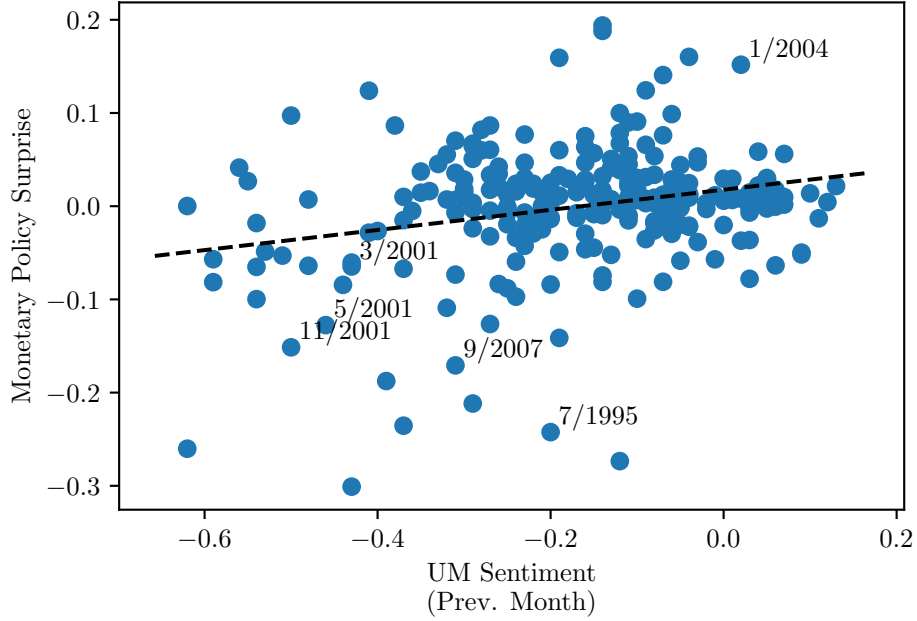
[O]ne can take a look at the pattern of forecast errors around recessions, and it is almost always the case that the recessions are steeper than models can explain. So, the recession often occurs because there is a collapse of confidence that accompanies them. [...] Our models, at least, are not able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

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

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

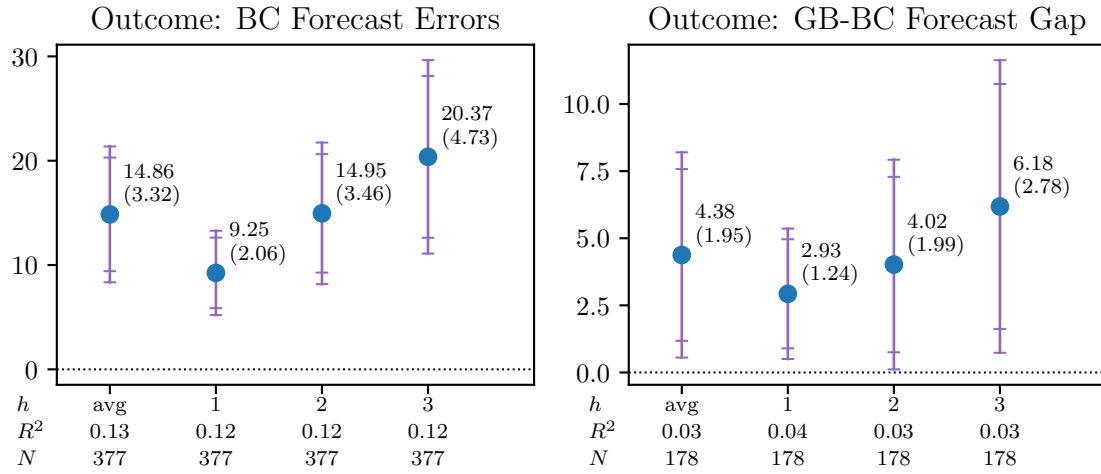
E Additional Tables and Figures

Figure A1: Scatter Plot of Surprises vs. Sentiment



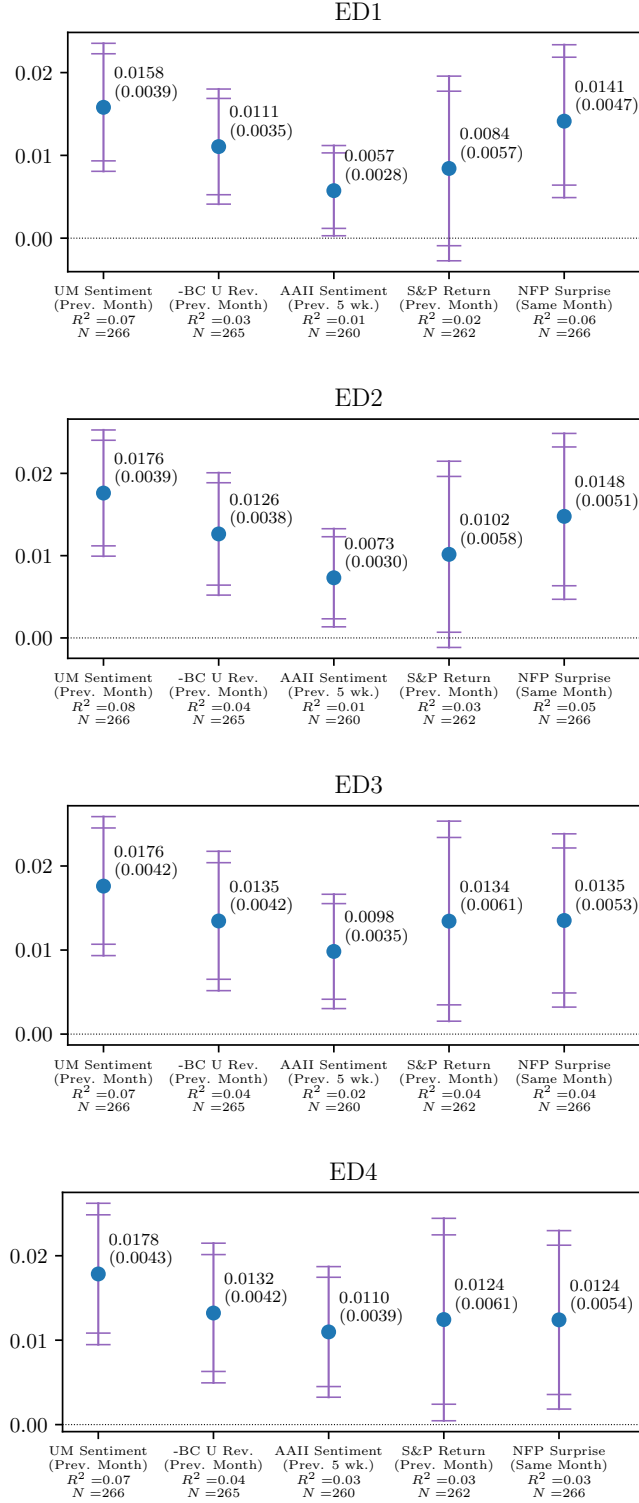
Notes: The scatterplot corresponds to the (non-normalized) estimation of Equation 12 and the results in the first panel of Figure 2. The horizontal axis variable is the labor-market sentiment in the Michigan survey, calculated as described in Section 3, in month $t - 1$. The vertical axis variable is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

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



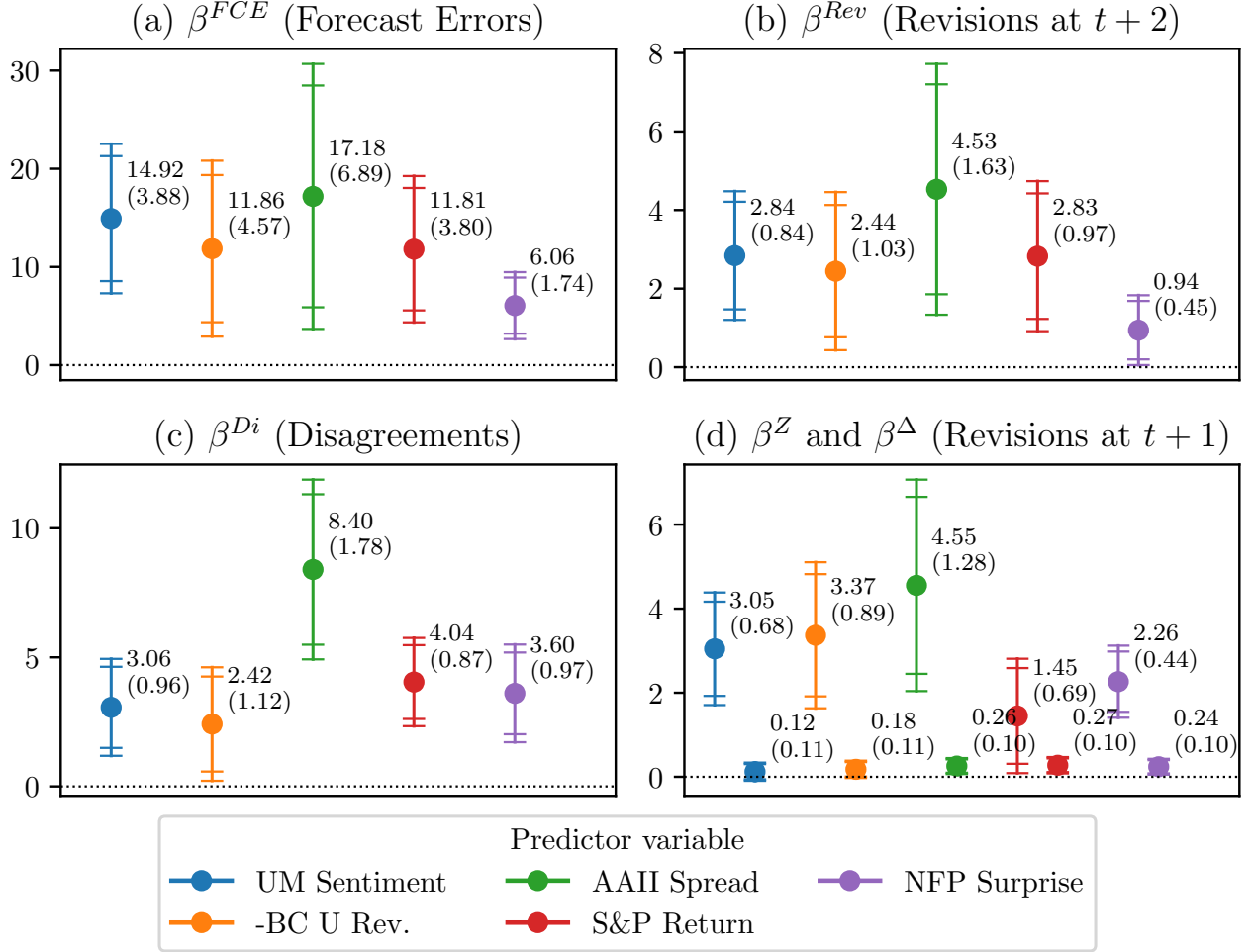
Notes: This Figure recreates the forecast error prediction analysis of Figure 3 (Equation 13) in the left panel and the forecast-gap prediction analysis of Figure 5 (Equation 15) in the right panel, where the forecasted variable is the 3-month Treasury rate (averaged over quarters). Errors bars are 90%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

Figure A3: Predictability for Different Monetary Surprise Measures



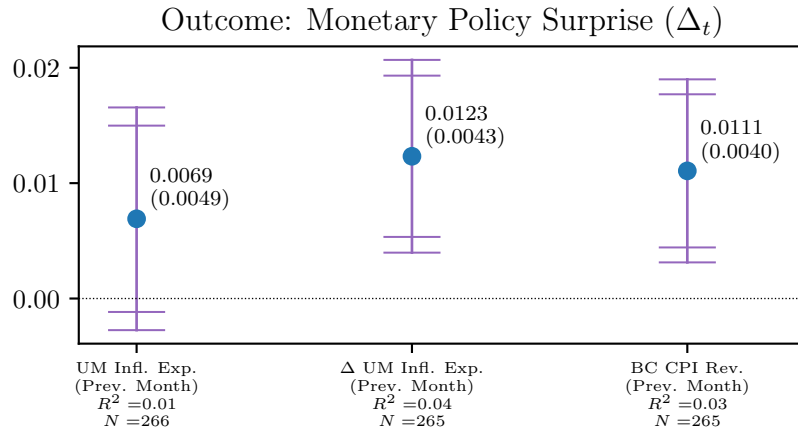
Notes: Each graphic is an analog of Figure 2 with a different outcome variable. Error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses.

Figure A4: Main Results for Different Public Signals



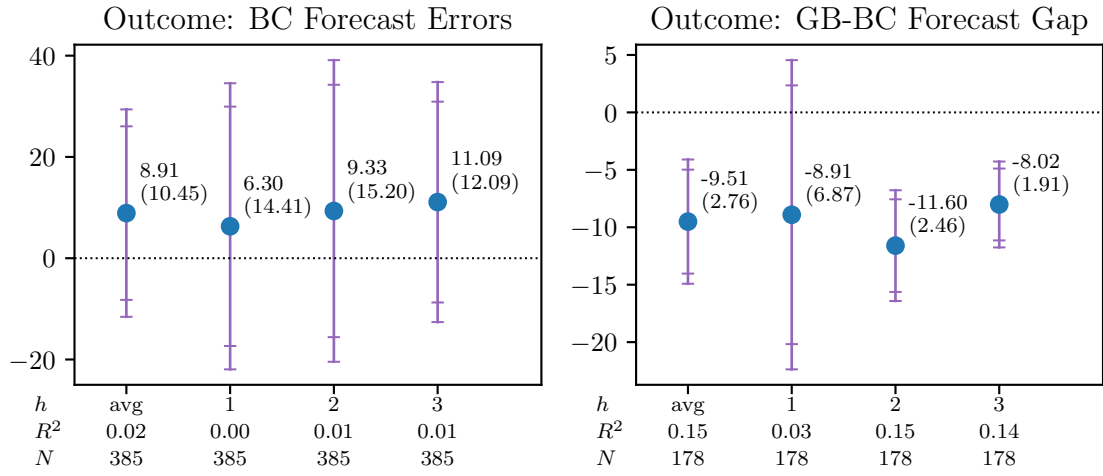
Notes: This plot shows results for the main analysis of Section 4 under different choice of predictor variables. Panel (a) corresponds to the analysis of Section 4.2 and Figure 3; panel (b) to Section 4.3 and Figure 4; panel (c) to Section 4.4 and Figure 5; and panel (d) to Section 4.5 and Figure 6.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

Figure A5: Predicting Monetary Surprises with News about Inflation



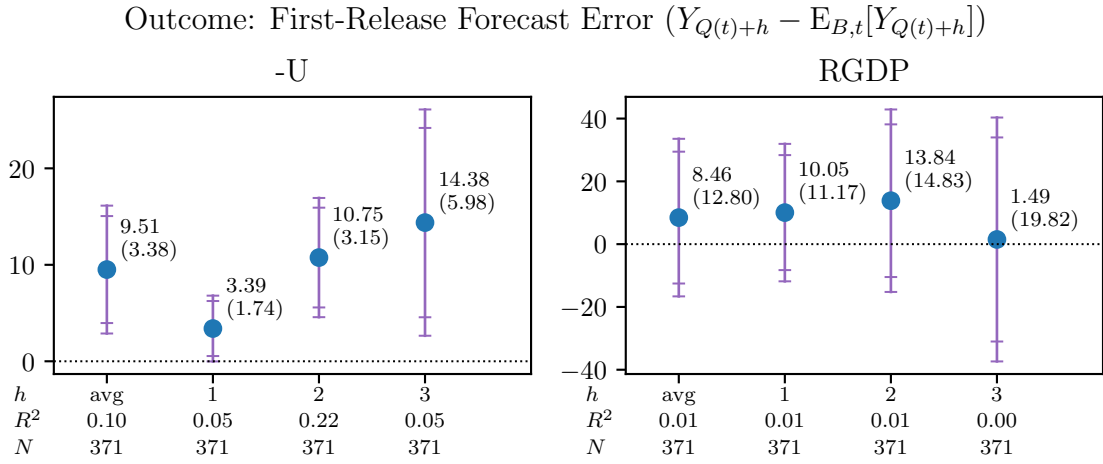
Notes: This Figure recreates the monetary surprise prediction analysis of Figure 2 (Equation 12) using predictors related to inflation. The first variable is the lagged median inflation forecast in the Michigan Survey of Consumers, the second is the lagged difference of the same, and the third is the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

Figure A6: Errors and Disagreements for CPI Forecasts



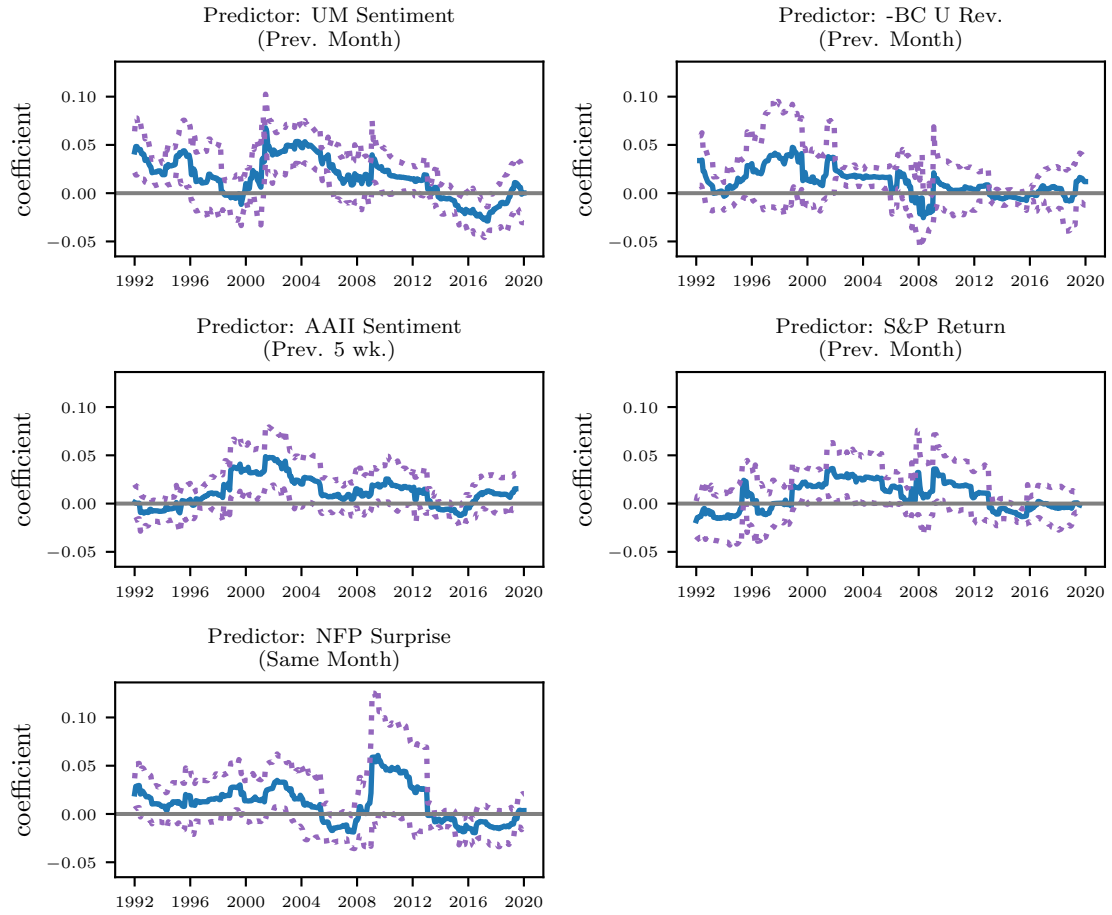
Notes: This Figure recreates the forecast error prediction analysis of Figure 3 (Equation 13) in the left panel and the forecast-gap prediction analysis of Figure 5 (Equation 15) in the right panel, where the forecasted variable is CPI inflation in annualized percentage points. Errors bars are 90% and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

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



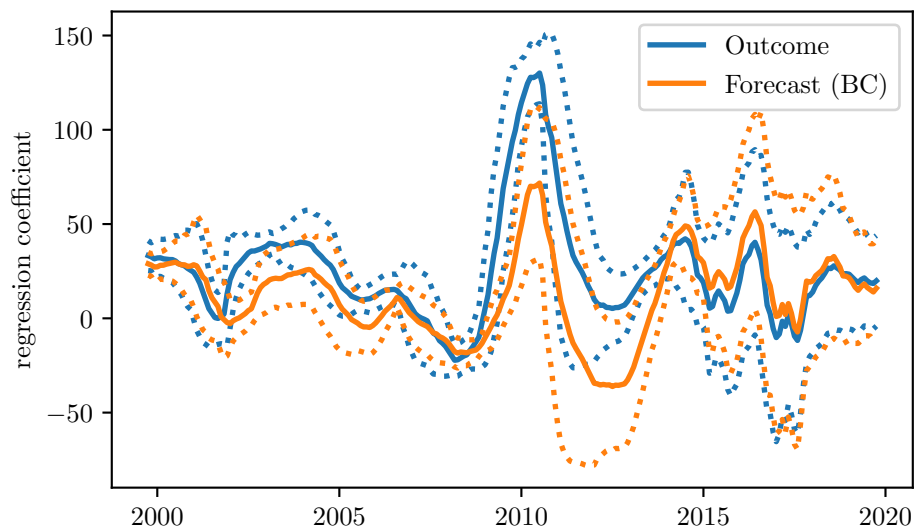
Notes: This Figure recreates the forecast error prediction analysis of Figure 3 (Equation 13), but measuring forecast errors relative to first-release macroeconomic outcomes. First-release macro data are taken from the Philadelphia Fed's real-time data center (<https://www.philadelphiafed.org/research-and-data/real-time-center>).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

Figure A8: Rolling Regressions Predicting Monetary Surprises



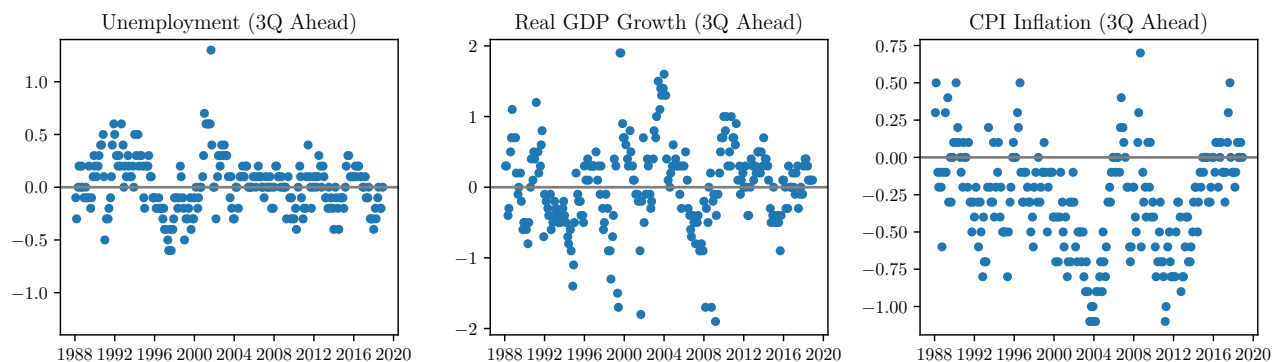
Notes: Each panel shows estimates from rolling regressions predicting the Monetary Policy Surprise (MPS) using the previous 48 months of data on the surprise and the indicated predictor. The empirical methodology, including the choice of predictors and their standardization (in z-score units), exactly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

Figure A9: Rolling Estimation of Forecast and Outcome Prediction



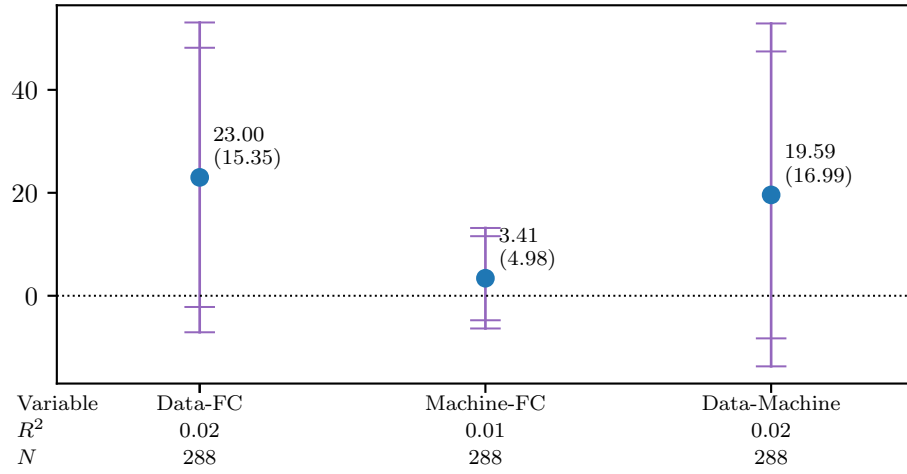
Notes: Each point is the coefficient in a feasible regression coefficient based on predictions made nine months ago or prior and measured unemployment rates. The regression is $Y_t = \beta \cdot \hat{Z}_t + \alpha + \varepsilon_t$, where Y_t is either the predicted or realized unemployment rate three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

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



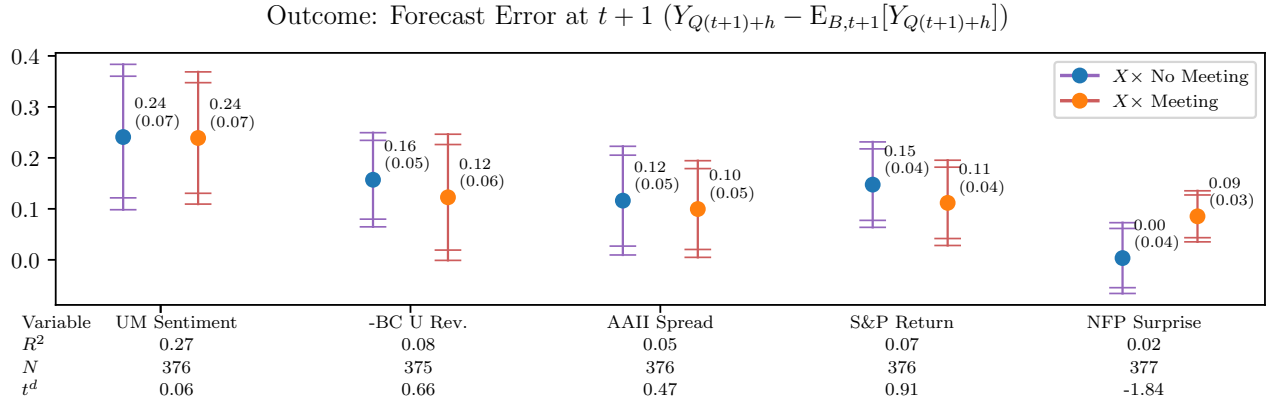
Notes: Each panel of this Figure shows differences between Greenbook and Blue Chip forecasts at the 3 quarter horizon for unemployment (left panel), real GDP growth (middle panel), and CPI inflation (right panel). Each dot corresponds to a month in which both Greenbook and Blue Chip forecasts are observed.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

Figure A11: Predicting Belief Distortions Relative to Machine Benchmark



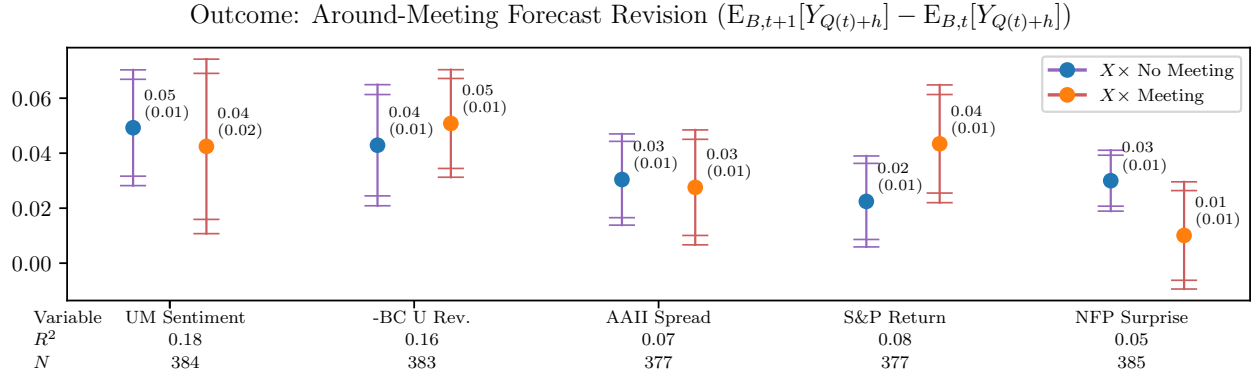
Notes: In each plot, the regressor is $\hat{Z}_t$, a rescaling of the $t - 1$ realization of labor market sentiment in the Michigan survey (constructed as described in Section 4.2), and the outcome is one of the following statistics for four-quarter ahead real GDP growth forecasts in the Blue Chip survey: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

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



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

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



$$\begin{aligned} \mathbb{E}_{B,t+1}[Y_{Q(t+1)+h}] - \mathbb{E}_{B,t}[Y_{Q(t+1)+h}] = & \alpha + \beta_{NM} \cdot (X_{t-1} \times \text{No Meeting}_t) \\ & + \beta_M \cdot (X_{t-1} \times \text{Meeting}_t) + \gamma \cdot \text{Meeting}_t + \varepsilon_t \end{aligned} \quad (19)$$

Notes: Each pair of bars corresponds to an estimation of Equation 19 for a different choice of predictor. Each predictor is standardized in Z-score units over the relevant sample. The plotted coefficients are the interaction of X_{t-1} with indicators for no FOMC meeting (blue) and at least one FOMC meeting (orange) in the month. The meeting indicator is included as a regressor but its coefficient is not plotted. The predictors are: unemployment sentiment from the Michigan survey in the previous month, the (negative) revision to Blue Chip unemployment forecasts in the previous month (averaged over the one-, two- and three-quarter horizons), the average Bull-Bear spread in the AAI survey in the previous month, the S&P 500 return in the previous month, and the NFP Surprise from in the current month (and corresponding to data from the previous month). The error bars are 90% and 95% confidence intervals based on HAC standard errors (Bartlett kernel, 5-month bandwidth), which are in parentheses. The t^d statistic is the t -statistic for the difference between the two interaction coefficients.

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

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

Notes: This table reports statistics related to real-time (pseudo-out-of-sample) trading strategies based on predicting the Monetary Policy Surprise using the indicated predictors, after a burn-in period of 48 observations. The predictor variables are the same ones used and described in Section 4.1. The first two columns report fraction MSE reduction calculated via Equation 18. The third column reports the Sharpe Ratio (expected return divided by standard deviation) based on a trading strategy that pays off $\hat{p}$ dollars if the monetary surprise is positive, where $\hat{p}$ is the predicted probability of a positive surprise, and $1 - \hat{p}$ otherwise, at a presumed price of \$0.50. The full methodology is described in Appendix D.1.

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