Public sentiment predicts movements in interest rate futures around Federal Reserve policy announcements ("monetary surprises"). When consumers are pessimistic, the Fed tends to forecast lower growth than private-sector professionals do and ease policy more than markets expect. This, plus anecdotal evidence from FOMC meeting minutes, suggests that the Fed has responded to sentiment more quickly than markets have in modern times (since 1995). Common causation by pre-announcement pessimism can explain why surprise rate cuts correlate with subsequent output contractions, stock market reversals, and negative forecast revisions. This requires no persuasion about fundamentals, which the data only weakly support. I contextualize these findings in a model in which Fed guidance is limited to explaining the policy path to a public initially overconfident in its assessment of fundamentals, but over time able to learn.

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1. Introduction

Markets move when the Federal Reserve speaks. Monetary policymakers recognize in turn that their words can directly affect the economy by influencing beliefs. Ben Bernanke, after his term as Federal Reserve Board Chair, opined that the ability to instantaneously shape expectations via carefully worded statements is “one of the most powerful tools the Fed has” (2015).

It is not entirely obvious, though, why this tool works. In an era of mostly systematic monetary policy and abundant economic data, what news remains to be revealed in policy announcements? And can the Fed make a surprise change in course without at least implicitly revealing “self-defeating” information about their own economic assessment?

This paper confronts both questions with direct empirical evidence and, in so doing, provides a new interpretation of the Fed’s capacity to surprise and persuade. It first shows that average public sentiment about where the economy is heading, measured in the months prior to an FOMC meeting from fairly coarse surveys (e.g., the University of Michigan Survey of Consumers), significantly predicts “high-frequency monetary surprises,” or implied revisions to interest rate forecasts from futures markets in narrow windows around policy announcements (Kuttner, 2001). When the public is pessimistic, markets are consistently surprised about the extent to which the Fed plans to cut rates. A variety of additional evidence links the previous fact with ex ante disagreement about the future path of the economy, both within the public and between the Fed and the public.

This evidence about how surprises come about suggests a sharpened question about self-defeating persuasion, related to the Fed’s ability to aggregate diverse considerations into a reasonably concise policy outlook. Could policy announcements be public signals that confirm latent, but unfocused feelings about a coming recession (or boom) in times of disagreement? I find limited direct evidence of such an effect. Holding fixed previous months’ sentiment, neither the unpredicted residual of surprises nor the presence of an FOMC meeting correlates with a significant response in financial-sector economists’ (professional forecasters’) average expectations for growth. Fed persuasion, perhaps for the better in this context, seems mostly limited to the future policy path.

The following scenario illustrates the main points. The Fed signals a willingness to cut rates substantially because it senses sluggish aggregate demand. Markets, having not fully internalized the demand headwinds, are surprised about the aggressive response but attribute it to an idiosyncratic whim of the Fed. On announcement day, stock prices go up because of this revision to interest rate forecasts. But over the next several weeks, as bad news percolates through the public, the stock gains are more than reversed (as in Bernanke and Kuttner, 2005) and professional forecasters revise their future outlook downward (as in Campbell et al., 2012, 2016; Nakamura and

For instance, after the June 20, 2019, FOMC meeting, the Wall Street Journal reported the link from policy to stock prices as essentially causal: “The Federal Reserve’s decision to leave rates unchanged this week while signaling readiness to cut them if the economic outlook doesn’t improve soon sent stocks to new highs.” (“Analysis: Five Takeaways From the June Fed Meeting,” June 21 Edition, by Nick Timiraos).
Steinsson, 2018). Common causation—pervasive pessimism induces immediate Fed action and, with some delay, market and forecaster revisions—masquerades as the Fed’s delivering bad news to the public. A good example of this pattern is the gradual slowing of aggregate demand in early 2001 and aggressive monetary response. In several cases, this policy surprised markets in its intensity, but evidently did not accelerate their perception of a recession.

This paper provides a new, empirically grounded story on where disagreements between the Fed and the informed public, which are both salient to policymakers and potentially relevant for optimal policy conduct (as in Caballero and Simsek, 2019; Vissing-Jorgensen, 2019), may come from. More broadly, this paper’s results provide a new justification for business cycle theories in which uncertainty about others’ beliefs and/or persistent disagreement play a key role despite abundantly available information.²

There is a parallel implication for macroeconomic identification and measurement. If disagreements between the markets and the Fed have an interpretable structure, or relationship with past beliefs and economic activity, conventional arguments about markets’ informational efficiency may not justify using monetary surprises as instruments for primitive deviations from the policy rule.³ At least historically, much of what markets have perceived as aberrant monetary policy has been both systematic and systematically known to other agents in the economy on average.

Detailed findings. This paper starts with the “policy news” monetary surprise construction of Nakamura and Steinsson (2018). This one-dimensional statistic aggregates jumps in futures prices for various-horizon Federal Funds rates and Eurodollar (inter-bank) rates. It is measured in 30-minute windows around scheduled FOMC announcements since 1995. My main empirical result correlates this surprise with the average outlook about future unemployment in the University of Michigan Survey of Consumers from the past several months. Three lags of a simple “unemployment sentiment” variable predict “policy news” (both size and magnitude) with an $R^2$ of 15.2%.

The magnitude of surprises is also predicted by the extent of disagreement measured from the same survey question.

This market under-reaction to aggregate beliefs is pervasive throughout the sample but especially at the onset of recessions (e.g., 2001 and 2007). The result is robust to many different sentiment constructions (including independent data on firm and investor expectations) and shock constructions (varying window size and interest rate choice).

²For the former, see Woodford (2003), Lorenzoni (2009), and Angeletos and La’O (2013); for the latter, Caballero and Simsek (2017).
³For example, Nakamura and Steinsson (2018) state the following to justify the high-frequency approach for identifying monetary shocks:

All information that is public at the beginning of the 30-minute window is already incorporated into financial markets, and, therefore, does not show up as spurious variation in the monetary shock … A major strength of the high-frequency identification approach we use is how cleanly it is able to address the endogeneity concern.
The same sentiment variables reliably predict Fed target rate changes, even conditional on more traditional macro indicators (output and price growth, recent stock market performance, and credit spreads). A case study of rate cuts in 2001 substantiates the claim that the Fed closely watches consumer and firm sentiment data and, in particular, uses them to monitor the downside risk of transitioning to recession. More generally, sentiment measured before FOMC meetings (for instance, in the Michigan survey) explains much of the gap between Fed (Greenbook) forecasts and their financial-sector (Blue Chip survey) counterparts.

Separating two components of the monetary surprise, one predicted by sentiment (a “demand shock”) and the other not (a “monetary tremble”), reveals a striking dichotomy ex post. The first correlates with a prolonged boom in output and prices and commensurate monetary response. The second is a very transitory rate change that traces out the conventional negative output response, albeit very imprecisely.

On the announcement day, equities uniformly fall and bond yields uniformly rise in response to the two different “types” of surprise tightening. Each market takes several weeks to separate the two cases, with the former leading to sustained stock market gains and higher yields. For fixed interest rate expectations, this is inconsistent with any model in which the Fed unambiguously communicates (expected) future conditions in its forward guidance. But it does make sense if the Fed and market initially agree to disagree, but the latter eventually comes around as it independently collects data. My findings, taken all together, thus provide a different context for the puzzling “asset price reversals” in response to high-frequency surprises reported since Bernanke and Kuttner (2005).

The correlation between monetary surprises and Blue Chip forecasters’ revisions about real GDP growth, taken as evidence of persuasion effects in previous studies (Campbell et al., 2012, 2016; Nakamura and Steinsson, 2018), is mostly driven by the predictable shocks. That is, it can be spanned by information in beliefs measured before the FOMC meeting. I find only limited evidence that the correlation between sentiment and professional revisions is higher in months with an FOMC meeting, suggesting a limited role for the Fed to influentially “broadcast” this information about what others believe.4

Interpretation and broader scope. In the penultimate section of the paper, I contextualize these key findings in a very simple Keynesian cross model. To explain the facts, and match the narrative of my “case studies,” the model assumes that agents have (i) heterogeneous expectations about future income, (ii) uncertainty about what others think, and (iii) some inability to invert monetary policy to produce a signal about these average expectations. The first and second conditions, which

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4All my analysis is based on historical small deviations. It cannot constitute not a “global” argument that monetary policy could never backfire via signaling channels, or that policy need not be gradual. There may be dynamic considerations — socially optimal or not — supporting gradual policy as a general principle. See Coibion and Gorodnichenko (2012b) and Stein and Sunderam (2018) for more discussion of these topics. A full reconciliation of these ideas with my results on signaling about fundamentals would be an interesting angle for future research.
are natural if important information (about consumer demand, labor markets, etc.) is dispersed, generate predictability and the potential for learning. The third is more behavioral but seems necessary to match the evidence of limited persuasion about fundamentals, even when monetary surprises on average include valuable information.

The very last section discusses how to apply the lessons of this paper to the “empirical practice” of using monetary surprises as instrumental variables for unobserved monetary shocks. A broad take-away is that neither Fed actions nor market forecast errors are likely uncorrelated from other macro shocks, the former because the Fed acts for a reason and the latter because there is some structure to aggregate belief inertia. For estimating causal effects at “macro horizons” (i.e., more than one month out), it may be necessary to provide a full structural model of both demand shocks, potentially originating in beliefs, and their (mis-) perception by markets. These structural requirements may defeat the hoped-for “elegance” of the external instruments approach.

Roadmap. Section 2 reviews related literature. After a short discussion of measurement in Section 3, Section 4 reports the main predictability result. Section 5 provides direct evidence of the role sentiment data play in Fed decisionmaking. Section 6 demonstrates, ex post, that sentiment-predicted monetary surprises look like demand shocks. Section 7 looks more closely at the responses of markets and professional forecasts. Section 8 organizes the findings in a simple model. Section 9 discusses applications to shock identification questions in macro and finance. Finally, Section 10 concludes.

2. Relation to the Literature

This paper relates to multiple works in the literature, which are summarized below.

Persuasion and the information effect. Campbell et al. (2012, 2016) and Nakamura and Steinsson (2018) show a positive relationship between monetary surprises and “surprise-sign” responses in beliefs (e.g., negative revisions after surprise accommodation). Both sets of authors take this as potential evidence of Federal Reserve persuasion via rules-based monetary policy. My paper clarifies further why the Fed can surprise along the monetary rule and exactly what counterfactual without Fed communication one should compare with. On the second point, in particular, I suggest that “baseline belief inertia” explains the original fact without an obvious role for Fed persuasion.

My model framework links to the theoretical literature on Central Bank communication and transparency. In particular there is relevant work on how signaling potentially undermines intended direct effects (Baeriswyl and Cornand, 2010; James and Lawler, 2011; Melosi, 2016).

Finally, the emphasis on persistent disagreement dovetails with a recent literature highlighting challenges for optimal policy in the face of an “opinionated” public (Caballero and Simsek, 2019;
Interpreting monetary surprises. This paper relates also to a literature that tries to more closely interpret the “economic content” of monetary surprises, starting with early contributions by Bernanke and Kuttner (2005) and Rigobon and Sack (2004). Most relevant is a newer literature proposing empirical methods to decompose “informational” and “non-informational” monetary policy shocks, often under the primitive assumption that the main identification threat are the persuasive forces described by the previously summarized literature.

Andrade and Ferroni (2016), Jarocinski and Karadi (2018), and Cieslak and Schrimpf (2019) condition on ex-post financial responses to disentangle the two effects. My results, in contrast, suggest may not be particularly informative because markets themselves sluggishly incorporate information from central bank announcements.

Miranda-Agrippino and Ricco (2015) and Miranda-Agrippino (2015) identify that surprises are predictable based on lagged macro aggregates and suggest an empirical remedy based on the gap between Fed and professional output and inflation forecasts. My paper instead identifies predictability based on lagged beliefs, which has a theoretically more precise interpretation—someone knows the relevant information, but it is only sluggishly incorporated into aggregate policy forecasts. Moreover it also provides a theory for where disagreements between the Fed and professionals come from.

Cieslak (2018) highlights the correlation between forecast errors about aggregate activity and interest rates. Closely related work by Karnaukh (2019), contemporaneous to this paper, shows that professional growth forecasts can predict future monetary surprises and connects this with the interpretation of persuasion and “information effects” in the literature. Relative to both papers, this paper identifies and theoretically motivates the specific importance of consumer and firm beliefs. This provides a more parsimonious theory of disagreements and, in quantitative “horse races,” a better-fitting predictive model for monetary surprises.5

Belief dynamics and information frictions across groups. My paper integrates with the large literature using forecast data to explore information rigidity and/or non-rational expectations in macroeconomics (e.g., Coibion and Gorodnichenko, 2012a, 2015; Bordalo et al., 2018) and finance (e.g., Greenwood and Shleifer, 2014; Adam et al., 2017).

This paper’s message specifically relates to Carroll et al.’s (1994) research on the information content of consumer sentiment and Carroll’s (2003) study of information transmission across

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5 Older related references in the same vein are Romer and Romer’s (2000) classic contribution on the Fed’s potential “informational advantage” and Faust et al.’s (2004) contrasting perspective on the same issues. The latter authors argue there is no specific evidence that futures-market-measured monetary surprises correlate with very high-frequency macro forecast revisions. My point is complementary but also explains why there are correlations with revisions at lower frequencies.
groups. My results are essentially opposite to Carroll’s (2003) claim that general-public (e.g., Michigan) expectations are well-modeled as “trailing” the professionals, as if they are learning from experts with some delay. In contrast, and more consistently with my findings, Coibion and Gorodnichenko (2012a) conclude from similar data that Michigan and professional inflation forecasts exhibit similar inertia in response to shocks; and Kohlhas and Broer (2018) find broad evidence of professional forecasters’ “relative over-confidence” that their information is superior to other individuals’.

3. Data

3.1 Interest rate futures

My data on interest rate surprises come from Nakamura and Steinsson (2018), who themselves directly collected data from the CME Group. These data cover 1995-2014.

Market surprises come from interest rate futures. 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.\footnote{See \url{https://www.cmegroup.com/trading/interest-rates/stir/30-day-federal-fund_contract Specifications.html} for details.} 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.\footnote{See Appendix A of Nakamura and Steinsson (2018) for the details.} Changes in this re-scaled measure are thus in units of forecast revisions. Like Nakamura and Steinsson (2018), I focus on contracts expiring at the end of the current month and the month of the next scheduled FOMC meeting. I have the surprise in 30-minute windows (10 minutes before and 20 minutes after FOMC announcements) and 24-hour windows.

I also have implied interest rate surprises from Eurodollar markets. The Eurodollar futures contract pays, at the end of the quarter, 100 minus the contemporaneous US Dollar BBA LIBOR rate. Again following Nakamura and Steinsson (2018), I refer to the “$n$-quarter ahead” or “$nQ$” Eurodollar contract as the $n$th next contract to expire.\footnote{In February, the $n = 1$ contract expires on March 31, and the $n = 2$ contract expires on June 30.} The inclusion of the longer-horizon Eurodollar futures also improves my ability to pick up longer-term forward guidance effects of monetary announcements.

Sample choice. I focus on scheduled FOMC meetings, excluding the window around 9/11/2001 and a 1 year period of “financial distress” from July 2008 to June 2009. The former constraint avoids the issue that timing of emergency FOMC meetings could be endogenous to economic conditions. The latter avoids attributing the obvious large swings in economic activity at those times to monetary policy, absent using more sophisticated stochastic volatility or fat-tail-shock effects.
models that would naturally down-weight those observations. It is not essential for the main results.

**Policy news shock.** For most of the paper, I use Nakamura and Steinsson’s (2018) preferred 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). I refer to this, like the original authors do, as the “policy news shock.”

### 3.2 Public sentiment

My main source of consumer sentiment data is the University of Michigan Survey of Consumers, 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 A.1 prints the exact questions questions and answers that I use in my analysis. All aggregate measures are survey-weighted averages.

The Michigan survey 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. 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.  

### 4. Sentiment Predicts Surprises

A monetary surprise around an FOMC meeting in month $t$ positively correlates with the level of sentiment in the previous few months. To show this fact, I will report the estimates $\beta_j$ from the following regression of a sentiment variable in month $t + j$ on the surprise in month $t$:

$$\text{Sentiment}_{t+j} = \alpha_j + \beta_j \cdot \text{Surprise}_t + \epsilon_{t+j}$$ (4.1)

Each coefficient $\beta_j$ equals the covariance between past (or future) sentiment with the monetary surprise, normalized by the latter’s variance. The full sequence of coefficients from $J$ months prior to $J$ months after the shock, $(\beta_j)_{j=-J}^J$, traces out these covariances over time. Differences between coefficients are covariances with sentiment growth.

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9This was confirmed from direct communication with the Michigan Survey Research Center.
As discussed in the last section, I will present main results using Nakamura and Steinsson’s (2018) policy news shock as Surprise, and remove the height of the financial crisis (July 2008 to June 2009) from my sample. I use as the primary outcomes four different “sentiment measures” from the Michigan survey of Consumers.\footnote{The exact indicators are the following: (i) proportion (e.g., 1 = 100%) respondents who think unemployment will go down in 12 months minus percentage who think up; (ii) proportion respondents who think business conditions over the next 12 months will be (very or slightly) good minus (very or slightly) bad; (iii) the Michigan consumer expectations index constructed from three different survey questions; and (iv) proportion of respondents who think interest rates will go up (over next 12 months) minus percentage who think down. The second to last is constructed based on the business conditions question plus two others, not separately reported here, about household financial status and long-run (5-year) economic outlook.}

Figure 1 demonstrates substantial predictive power for all of these variables in months prior to the FOMC announcement. The two main indicators of general economic outlook, sentiment about how unemployment and business conditions will evolve in the next year, spike the month before to the monetary shock. The former is generally elevated, signaling labor market optimism, for several months prior to a positive monetary surprise.

The bottom left panel, using Michigan’s standard published “expectations index,” suggests this is not a function of merely drawing very specific data from the survey. The bottom right panel, quite strikingly, suggests that the general public on average expects interest rates to go up before...
markets are surprised in that direction.\footnote{The question (Appendix A.1) is vague about what interest rates it refers to. But it is a safe inference that respondents would be thinking about consumer and real estate loans.}

To provide a sense of scale, the regression coefficient of the monetary shock on the first lag of the unemployment sentiment has a \( \sigma \)-on-\( \sigma \) slope of 0.305: one standard deviation of sentiment, away from its long-run mean, correlates with a 0.305-standard-deviation surprise (of 1.1 basis points in the units of one-year Treasury responses on announcement day).

Taken together, this evidence contradicts any conventional model in which a representative investor prices risk-neutrally using all of their information. This information set, even if it lacked certain macro data releases, would necessarily include average public beliefs.

\subsection*{4.1 Alternative sentiment measures}

I corroborate the previous story with three complementary sentiment data sources in Appendix B.1: (i) the weekly survey of the American Association of Individual Investors, (ii) the monthly survey of the National Federation for Independent Businesses, and (iii) the monthly Conference Board consumer survey. I find similar results in all cases. This suggests there is some independent \textquotedblleft signal\textquotedblright{} in my results, evident in different measures of sentiment, instead of just Michigan-specific \textquotedblleft noise.\textquotedblright{} This signal is also not localized to one sector of the economy: it's evident also among small-scale investors (who respond to the AAII survey) and small firms (who respond to the NFIB survey).

\subsection*{4.2 Extent of predictability}

How much variation in the monetary surprise is spanned by sentiment variables in total? I regress different constructions of the shock on three lags each of the following two variables. The first is the aforementioned \textquotedblleft unemployment sentiment\textquotedblright{} variable constructed in the Michigan survey. The second is a variable from the National Federation of Independent Businesses (NFIB) survey that measures the proportion of surveyed firms that think their own sales (in real terms) will go up in the next six months minus the fraction who think sales will go down. This second measure, among the non-Michigan-survey alternatives I consider, has one of the largest predictive powers (as documented in Appendix A.3) and also adds the angle of measuring business confidence, which is anecdotally quite important to policymakers.

The exact estimated equation, for lags \( \ell \in \{1, 2, 3\} \), is

\[
\text{Surprise}_t = \alpha + \sum_{\ell=1}^{3} \left( \beta_{M,\ell} \cdot \text{MichUnempSent}_{t-\ell} + \beta_{N,\ell} \cdot \text{NFIBSalesUp}_{t-\ell} \right) + \varepsilon_t \quad (4.2)
\]

The first row of Table 1 reports this regression's \( R^2 \) for the policy news variable (16.7\%). The second
<table>
<thead>
<tr>
<th>Measure</th>
<th>Surprise</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Policy news factor (30 min.)</td>
<td>0.167</td>
<td>0.180</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>2 Fed Funds (this meeting)</td>
<td>0.066</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>3 Fed Funds (next meeting)</td>
<td>0.145</td>
<td>0.069</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>4 Eurodollar (2Q)</td>
<td>0.144</td>
<td>0.094</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>5 Eurodollar (3Q)</td>
<td>0.163</td>
<td>0.119</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>6 Eurodollar (4Q)</td>
<td>0.159</td>
<td>0.102</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>7 Orthogonal to FF</td>
<td>0.124</td>
<td>0.196</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>8 Policy news factor (1 day)</td>
<td>0.130</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.044)</td>
</tr>
</tbody>
</table>

Table 1: $R^2$ from surprise predictability regression (4.2). Numbers in parenthesis are standard errors.

column shows that results are similar if one just uses the sign of the policy news surprise as the outcome, which adds some confidence that a few outliers of the outcome variable are not driving the result. Numbers in parentheses are bootstrapped standard errors from re-sampling all data points with replacement. Almost every $R^2$ is significantly different from 0.

**Different rates.** Rows 2-6 of Table 1 re-estimate the predictability exercise separately for different interest rate futures. Predictability is stronger for the longer maturity interest rates. These are the surprises that are most likely to correspond to long-run policy news instead of small deviations in timing of an interest rate change (as stressed, in particular, by Bernanke and Kuttner, 2005). Along the same lines, an interest rate factor orthogonalized from the current meeting’s Fed Funds rate future, to isolate the news about the yield curve in the spirit of Gürkaynak et al. (2005), is also highly predictable (row 7).

Finally row 8 shows, at least for the policy news construction, that using 30-minute versus 1-day windows does not matter. This is consistent also for the other rates (omitted for brevity).

**In dollar terms.** Consider a replicating portfolio that pays in proportion to the policy news shock across each announcement.\(^{12}\) The cost of this portfolio would be about 100 dollars each time, so payouts equal (percentage point unit) returns.\(^{13}\) Buying and holding this portfolio across all announcements in the sample would given an average return of essentially zero (0.129 basis

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\(^{12}\)Because the policy news shock is a linear combination of interest rate futures shocks, this is feasible to construct.

\(^{13}\)Since futures pay out at $100 - r$ given an interest rate $r$. 

10
points). Conditioning the decision to buy or sell on the ex post (i.e., hindsight-based) prediction of the regression (4.2) would produce an average return of 1.24 basis points, but with a standard deviation of 3.32 basis points. This makes the Sharpe ratio quite low (0.373).

4.3 Additional results and robustness

More disagreement predicts larger surprises. All the predictability results so far have used first moments. In Appendix B.2 I run a complementary regression of the cross-sectional dispersion in the unemployment sentiment variable, a measure of disagreement, on the absolute value of the policy news shock. This correlation is large and positive (Figure A4). Moreover this response is quite flat across the announcement day, suggesting that policy does not “resolve” much of this disagreement.

“Turning points” matter the most. Figure 2 shows the scatter-plot for the regression of the policy news shock on the first lag of the sentiment variable. I use different colors to differentiate meetings at which the Fed’s target Fed Funds rate changed and label a few notable observations. At a glance, (i) negative shocks and (ii) meetings at which the Fed Funds target are changed seem to matter more. Re-running previous regressions with interaction coefficients conditioned on the sign of the surprise or a change in the target rate confirms this (Appendix B.7). My later interpretation, which
emphasizes the special difficulty of predicting policy in recessions and inertia in market beliefs, will speak to both results.

Table A5 in Appendix B.8 prints the 10 most influential observations (by the DFBETA measure) in the same regression. The influential observations, particularly in early 2001, generally bias the coefficient upward. But the result is qualitatively similar, and still statistically significant, when this period is dropped.\footnote{In the regression of the policy news shock on the first lag of unemployment sentiment, dropping the year 2001 (8 observations) reduces the coefficient from 0.083 to 0.055. This reduces the \( p \)-value from 0.001 to 0.026.}

It is difficult, though, to say whether removing these data is “correct.” Within the sample, 2001 is the most prevalent example of rate decreases \textit{and} non-standard consumer sentiment dynamics. The case study of rate cuts in 2001, which the next section will explore more thoroughly, is also indicative of the mechanism this paper has in mind: that policymakers may be unusually effective at spotting (and acting upon) trends in aggregate beliefs that market forecasts seem to miss.

\textbf{Sentiment beats other macro indicators.} Is this a feature of sentiment in particular, or is sentiment standing in for other correlated macro variables? I run a version of (4.2) with only the unemployment sentiment variable plus controls for lagged (3-month) growth of industrial production, lagged (3-month) growth of the CPI, the lagged unemployment rate, and a lagged credit spread measure (the excess bond premium of \textit{Gilchrist and Zakri\v{s}ek, 2012}). IP growth enters significantly at the 5\% level in the combined regression, with an incremental \( R^2 \) of 2.01\%. The three lags of the unemployment sentiment variable are significant with a \( p \)-value of 0.0004, and increase the \( R^2 \) very substantially from 7.8\% to 18.2\%. This suggests that forward-looking sentiment variables include substantial additional information.\footnote{To test a wider panel of possible macro correlates, and to compare with the predictability results of \textit{Miranda-Agrippino (2015)} and \textit{Miranda-Agrippino and Ricco (2015)}, I show in Appendix B.3 results controlling for the first several principal components of macro data (monthly frequency from 1992) from the \textit{McCracken and Ng (2016) FRED-MD} database. In general, macro factors by themselves also explain a significant (about 10\%) of variation in the policy news shock. Still, adding lagged Michigan sentiment as an additional control significantly boosts \( R^2 \).}

\textbf{Other checks.} Appendix B.4 describes an empirical Bayes approach that shrinks coefficients toward 0, which should naturally protect against over-fitting. This gives very similar results. Appendix B.5 presents a pseudo-out-of-sample forecasting exercise, which checks whether predictability also shows up in the rolling (real-time) sample. This is the harshest test, favoring sparse models, but it still implies that lagged sentiment has predictive power. Finally, Appendix B.6 checks via a simple (if crude) test that predictability is not entirely concentrated in model-derived changes in bond risk premia, providing some confidence that the main results really relate to physical-probability expectations.
5. **Policy Tracks Sentiment**

The previous section suggested that aggregate beliefs are an important omitted variable in the market’s interest rate forecasts. This section fills in the other side of the story with evidence that the Fed does consistently update its internal forecasts and make policy decisions using data on aggregate beliefs.

5.1 Case studies in 2001

A necessary condition for this hypothesis is that the Fed looks at expectations data. Anecdotally, this is true. I focus on two example rate cuts from the 2001 recession.

January. On January 25, speaking before Congress, Fed Chairman Alan Greenspan describes 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.\(^6\)

In following week’s FOMC meeting, after initial presentations of the Central Bank outlook, Governor Edward Gramlich and staff economist Lawrence Slifman have an extended discussion about whether plunging consumer confidence signals that headwinds will be persistent.\(^7\) Mr. Slifman remarks 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 this paper.

Philadelphia Fed President Anthony Santomero reiterates 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.”

Dallas Fed President Bob McTeer speaks extensively about how the Fed’s internal “soft data,” collected in its Beige Book report, is the most negative he has ever seen.\(^8\) Governor Gramlich

\(^6\)Taken from the online archive of the Washington Post, accessible at [https://www.washingtonpost.com/wp-srv/business/greenspan012501.htm](https://www.washingtonpost.com/wp-srv/business/greenspan012501.htm).

\(^7\)Mr. Slifman highlights 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.

\(^8\)The Beige Book, in the words of the Federal Reserve’s website, collects “anecdotal information on current economic conditions in its District through reports from Bank and Branch directors and interviews with key business contacts, economists, market experts, and other sources.”
Table 2: Sentiment, beliefs, and surprises around two FOMC meetings.

<table>
<thead>
<tr>
<th></th>
<th>January 2001</th>
<th>May 2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate change</td>
<td>-0.5</td>
<td>-0.5</td>
</tr>
<tr>
<td>Last Month’s Change in Sentiment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Michigan Unemp.</td>
<td>-13%</td>
<td>-3%</td>
</tr>
<tr>
<td>NFIB Sales</td>
<td>-3%</td>
<td>-3%</td>
</tr>
<tr>
<td>Fed minus Blue Chip Beliefs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP: 1Q</td>
<td>-1.2</td>
<td>-0.8</td>
</tr>
<tr>
<td>GDP: 4Q</td>
<td>0.1</td>
<td>-0.2</td>
</tr>
<tr>
<td>PCE: 1Q</td>
<td>-1.0</td>
<td>-0.8</td>
</tr>
<tr>
<td>PCE: 4Q</td>
<td>-1.7</td>
<td>-1.6</td>
</tr>
<tr>
<td>Futures Surprise</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FFR: this meeting</td>
<td>0.04</td>
<td>-0.10</td>
</tr>
<tr>
<td>Eurodollar: 4Q</td>
<td>-0.04</td>
<td>-0.15</td>
</tr>
<tr>
<td>Policy news factor</td>
<td>0.00</td>
<td>-0.09</td>
</tr>
</tbody>
</table>

mentions, as a contrast to these negative anecdotes, that the Blue Chip survey of professional forecasters remains relatively optimistic about growth prospects. While he does not “take that forecast literally” in levels, given its generally slow and “stodgy” adjustment, he is concerned by its negative trend of revisions.

The first column of Table 2 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, revised downward their expectations of future rates.

May. Four months later, a more substantial disagreement had opened up about the state of the economy. At the center of the disparity is, again, confidence. Research and Statistics Division leader David Stockton clarifies that his personal pessimism, over and above what model simulation suggest, is related to the “the real risk that confidence could deteriorate.” He clarifies 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.

While published confidence survey data from Michigan are not as dire as January’s, multiple regional presidents remark on depressed confidence in their own survey data. Ultimately, the
Fed adopts a reasonably pessimistic stance that surprises markets, as alluded to by Column 2 of Table 2.

5.2 Sentiment predicts rate changes

Does this concern about consumer sentiment — in excess even of other macro indicators — show up systematically in policy decisions? As a simple test for this for this hypothesis, I check in the data from 1995 to 2008 (the beginning of an extensive period at the zero lower bound) whether lagged sentiment variables predict changes in the Federal Funds Rate at scheduled announcement dates. Let $t$ be the date of a scheduled FOMC meeting and $\ell_{k(t)}$ index the $k$th most recent scheduled meeting. I regress $\bar{R}_t$, the Federal Funds target after the date $t$ meeting, on the most recent release of a given sentiment variable ($\text{Sentiment}_{t}$) controlling for the target from the past three meetings and other recent macro indicators in the vector $X_t$. The exact regression is

$$
\bar{R}_t = \beta \cdot \text{Sentiment}_t + \sum_{k=1}^{3} \gamma_k \cdot \bar{R}_{\ell_{k(t)}} + \gamma' X_t + \epsilon_t
$$

(5.1)

The additional controls help determine if the effect of sentiment is subsumed by other measurements of macro and financial conditions, or instead an independent signal.

I run this regression for three measures of economic sentiment: the sentiment indices for unemployment and interest rates and Michigan’s reported Consumer Expectations Index. Table 3 shows that each measure is a significant predictor of policy change. This is attenuated but not removed if one includes the positive and negative components of excess stock returns between leaders:

I think attitudes and confidence, especially among our business contacts, are significantly weaker. A couple of months ago people thought: Yes, there’s a big slowdown and it’s going to take a couple of months to get out of it, but by the time we get to the second half of the year things are going to be moving up. We don’t hear that view much anymore.
meetings ("Fed put controls"), as emphasized by Cieslak and Vissing-Jorgensen (2018) as an important “high-frequency” predictor of Fed actions. It is not surprising that the effects would be partially related — the stock market plausibly both reflects and determines how consumers feel the economy will do in the near future.

The result survives, but is attenuated by, controlling for four more “usual” suspects that could enter a Taylor rule: recent (month $t - 4$ to $t - 1$) growth in industrial production and the PCE price level; the unemployment rate in the previous month; and the previous month’s average excess bond premium of Gilchrist and Zakrajšek (2012), a measure of credit market distress.

**Asymmetry in signs.** In Table A7, I re-run the first three panels of Table 3 splitting up the regressor when it is above and below its median value in the sample of FOMC meetings. Much of the effect comes from the Fed lowering rates in response to low sentiment. This echoes the much-discussed “Fed put” strategy of the 1990s and 2000s (recently discussed by Cieslak and Vissing-Jorgensen, 2018), involving insurance against downside risks. This consideration came up in the FOMC case studies and, fixing investor inattention to the same information, is broadly consistent with the observed greater surprise predictability for policy loosening.20

**Are macro beliefs the “mechanism?”** The general story running through the anecdotal evidence is that sentiment data affect Fed decisions via macro beliefs. In Appendix C.1, I re-run the main specification in column 1 of Table 4 with controls for the Greenbook output point estimate forecast at various horizons (Table A6). This is roughly like checking whether an exercise like Romer and Romer’s (2004) would capture the considerations identified here. The higher-frequency forecasts, in particular, soak up much but not all of the variation that Michigan variables are explaining. There is a good reason to believe, based on the anecdotes and also the previous evidence on sign asymmetry, that whatever variation remains might be spanned by effects on “tail risk scenarios” that are difficult to measure in data on mean beliefs.

5.3 Sentiment predicts disagreement with the public

A point raised in the January 2001 minutes is that the survey (and anecdotal) evidence closely watched by the Fed may less quickly be integrated into private-sector beliefs. An ideal test to connect back with the monetary surprises evidence would be to check whether sentiment data predicts the gap in macro beliefs between the Fed and futures market investors. An implementable alternative, with directly measurable macro beliefs, is to do the same with the gap between the Fed’s beliefs and professional forecasters’ from the Blue Chip Economic Indicators survey. The Blue Chip survey is taken each month by more than 50 economists “employed by some of America’s

---

20The same is not true for the stock market “Fed put” pattern. In a regression of “policy news shock” surprises on the Michigan unemployment sentiment (from the most recent survey), the inter-meeting excess return, and negative inter-meeting excess returns, the latter two “Fed put” variables are insignificant (joint test p-value: 0.48).
Outcome: forecast gap for Real GDP

<table>
<thead>
<tr>
<th>horizon q =</th>
<th>1</th>
<th>3</th>
<th>1</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>MichUnempSent_{t-1}</td>
<td>3.232</td>
<td>2.714</td>
<td>1.884</td>
<td>2.133</td>
</tr>
<tr>
<td>Macro controls?</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>σ-on-σ</td>
<td>0.555</td>
<td>0.466</td>
<td>0.338</td>
<td>0.383</td>
</tr>
</tbody>
</table>

Table 4: Estimation of (5.2), the relationship between sentiment and forecast gaps.

largest and most respected manufacturers, banks, insurance companies, and brokerage firms,” so it is at least partially representative of “Wall Street” beliefs.\(^{21}\)

Governor Gramlich’s comment about the “stodgy” Blue Chip beliefs in January 2001 fore- shadows the coming result: that measured consumer sentiment persistently predicts the wedge between Fed and Blue Chip beliefs, in a way that suggests more inertial adjustment to the latter.

Let Gap\(_{t,q}\) be the Greenbook minus Blue Chip forecast gap for Real GDP, at meeting month \(t\) for \(q \) quarters ahead. I regress each gap for \(q \in \{1, 3\}\) on last month’s Michigan unemployment sentiment and, in a secondary specification, the same macro controls \(X_{t-1}\) from the Taylor rule estimation:

\[
\text{Gap}_{t,q} = \alpha_{y,q} + \beta \cdot \text{MichUnempSent}_{t-1} + \gamma' X_{t-1} + \varepsilon_{t,q}
\] (5.2)

Table 4 shows that each Michigan variable is a good predictor of the relevant survey gap, even at relatively long horizons. The second and fourth columns demonstrate that this prediction is stable to including macro controls, and that all the controls together add at best double the \(R^2\) of the univariate regression.

Perhaps most interesting is the magnitude. A one standard deviation difference in the sentiment variable explains between 1/3 and 1/2 of a standard deviation in this disagreement (the “σ-on-σ” row). In different units, the Fed predicts -0.43 percentage points lower annualized GDP growth than the professionals do at one quarter out when the public is “one-σ pessimistic,” and 0.39 percentage points higher when the public is “one-σ optimistic.”\(^{22}\)

\(^{21}\)https://lrus.wolterskluwer.com/store/blue-chip-publications/

\(^{22}\)A method to “clean” high-frequency monetary surprises, proposed in the literature, is orthogonalize the surprise from Greenbook-to-Blue-Chip forecast gaps for output and inflation (as in Gertler and Karadi, 2015; Ramey, 2016; Miranda-Agrippino and Ricco, 2015). A reasonable question, in light of this section’s results, is whether this subsumes all this paper’s results with sentiment. In Appendix C.2 I test this by regressing surprises on the sentiment variables as well as the gap between Greenbook and Blue Chip beliefs about GDP and prices. I find that sentiment variables boost fit even conditional on the controls. This could reflect the fact that sentiments are a better proxy for the gap between Fed and trader beliefs than the survey data gap or otherwise capture important higher-moments of the Fed’s beliefs (including, as discussed in the minutes, risk of crashes).
The last section’s anecdotal and quantitative evidence, taken together, suggested that (i) the Fed uses sentiment data to measure aggregate demand in real time and (ii) the public is often slower to do the same. I now show that this interpretation matches up with the macro data ex post.

I first calculate a predicted and unpredicted component of the monetary surprise based on the predictability regression (4.2). This regressed the “policy news” surprise on three months’ lags each of (i) unemployment beliefs in the Michigan survey and (ii) sales beliefs in the National Federation of Independent Businesses Survey. Moreover, all of the information that spans the predictable component of a time \( t \) monetary surprise is measurable in some individual’s information dated \( t − 1 \) and earlier. Let the predicted values and residuals (unpredicted values) be called \((\text{PrSurprise}_t, \text{UnprSurprise}_t)\), respectively.

To make it easier to interpret the scale of subsequent figures, I normalize each component separately by its sample standard deviation to generate new, unit-scale regressors identified with a “check” notation: \((\hat{\text{PrSurprise}}_t, \hat{\text{UnprSurprise}}_t)\). Keep in mind that the unpredictable variable has about twice the standard deviation and four times the variance as the predictable one, since the \( R^2 \) of the original regression was a little less than 20%.

Throughout this section, for various outcomes \( Y_t \), I will estimate projection regressions of each
shock component onto changes relative to a base period:

\[
Y_{t+h} - Y_{t+1} = \alpha_h^Y + \beta_{p,h}^Y \cdot \text{PrSurprise}_t + \beta_{u,h}^Y \cdot \text{UnprSurprise}_t + \epsilon_{t,h}
\] (6.1)

The coefficients trace out a sort of impulse response that does not control for lagged macro dynamics. For all the reasons discussed in the last section, neither the predicted impulse response \((\beta_{p,h}^Y)_{h \geq 0}\) nor its unpredicted counterpart \((\beta_{u,h}^Y)_{h \geq 0}\) may trace out a “true” impulse response to an identified structural shock. But they are simpler to interpret without further controls as raw correlations of a potentially unknown combination of macro shocks with macro outcomes.

6.1 Predictable variation dominates interest rate responses...

A first question is what realized policy correlates ex post with the initial news. Figure 3 estimates (6.1) for the monthly (average) Federal Funds rate and 1-year Treasury yield up to and including 2008 (i.e., before the ZLB).

The predictable shock strikingly dominates the long-run response of interest rates, despite constituting only a minority of the original surprise variable. A one standard deviation “predictable surprise” over this period correlates with about a 50 basis-point change in the Federal Funds rate after 24 months. This is economically quite large.

6.2 ...and looks like systematic response to demand shocks

I next estimate (6.1) for four important policy outcomes: output (here, proxied by Industrial Production), consumption (PCE), stock prices (total value of the S&P500), and goods prices (CPI), all in log units.\(^{23}\) The predicted surprise looks like a relatively large demand shock that fades away with time, with hump-shaped responses in all four quantities (Figure 4).\(^{24}\) Whether or not policy causes the eventual reversion to zero response is impossible to say with just this information, though the interest rate ramp-up in Figure 3 and the output decline in Figure 4 do line up.

The unpredicted component induces a small and imprecise reduction in IP, but not consumption. This is consistent with negative real effects of monetary policy concentrated in investment. The point estimate for the real effect of an unpredicted one-standard-deviation unpredicted shock is -0.001 at the 3-month horizon and -0.003 at the 12-month horizon in a log point scale (i.e., 0.01 = 1 percent = 100 basis points). This is unsurprisingly small given the size of observed shocks. When scaled back up to the “intended” normalization of a unit (100 basis point) impact on one-year Treasury yields on the day of announcement, these numbers jump to the economically quite

\(^{23}\)I again exclude surprises (regressors) from July 2008 to June 2009, but data from these periods are used as outcome variables.

\(^{24}\)This is similar to an observation made by Jarocinski and Karadi (2018) in their decomposition of high-frequency monetary shocks. But our interpretations are quite different — these authors think of the shock reflecting the Fed’s informational advantage over financial conditions, which is very different from consumer sentiment.
Figure 4: Response of output, consumption, stock prices, and goods prices on both components of the monetary surprise. Variables are in log point units and error bands are 95% bootstrap standard errors (including the generated regressor).

7. Asset Prices and Forecasts Adjust Slowly

A few months after a surprising FOMC meeting, there is a very obvious distinction between systematic policy changes and “trembles” that do not materialize into large policy. But the premise
of the original shock construction was that markets treated each event symmetrically on the day of the FOMC announcement. This is essentially by assumption for futures markets. For additional confirmation in bond markets, I run the following regression of announcement-day changes in (nominal) bond yields of maturity $m$, $y^m_t$, on each component of the monetary surprise:

$$y^m_t = a^m + \beta^m_p \cdot \text{PrSurprise}_t + \beta^m_u \cdot \text{UnprSurprise}_t + \epsilon^m_t$$

(7.1)

Note that I do not normalize the surprises by standard deviation here, to retain the original normalization to unit impact on market-based interest rate expectations. Figure 5 plots for different maturities the coefficients $(\beta^m_p, \beta^m_u)$, which in each case are very close to one another. If there is any difference it goes in the wrong direction, with unpredicted shocks being treated as the more persistent ones.

This section explores how the stories of short-term confusion and long-run divergence meet in the middle. At what point do markets realize that monetary response corresponds with a fundamental demand shock?

7.1 Asset prices diverge after announcements

Equities. I start with equity markets, which are the focus of Bernanke and Kuttner (2005) and a large follow-up literature on the real effects of Fed communication.

My estimating equation is a version of the projection regression (6.1), but with log cumulative
returns (value-weighted, dividend-excluding) of the S&P 500 on the left-hand-side:

\[
100 \cdot \sum_{i=0}^{h} \log R_{t+i} = \alpha_h^Y + \beta^h_P \cdot \text{PrSurprise}_t + \beta^h_u \cdot \text{UnprSurprise}_t + \epsilon_{t,h}
\]  

(7.2)

The horizons $h$ are measured in trading days (i.e., five per week) after the FOMC announcements.

The left panel of Figure 6 shows the impulse response of stock returns after $n$ trading days. The “day 0” response is a similar, though imprecisely estimated, negative response for each shock.

This is consistent with the story of financial market confusion about the reasons underlying the monetary surprise.

It contradicts a different hypothesis that Fed announcements clearly signal both policy and its justification (e.g., an announcement of the patterns in the Figure 4 IRF). Holding fixed the interest rate expectations in each case, the latter model would predict stock prices to differentially increase in response to the predictable shocks in anticipation of future dividends.

Over time, though, the responses diverge. Stocks predictably increase in the weeks after a predictable monetary tightening. This, plus the low-frequency stock market response (bottom left

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25Replicating the same regression with the “high-frequency” change in stock prices in a 30-minute window around the announcement tells the same story even more precisely. The point estimates are -0.0563 and -0.0534 on the unpredicted and predicted components of the surprise, respectively. These have (bootstrap) standard errors 0.016 and 0.038, respectively.
panel of Figure 4), resembles the dynamics reported in Bernanke and Kuttner (2005) and attributed either to behavioral over-reaction or changes in the appetite for risk. A natural interpretation for the same dynamics in this context, given the conditioning on sentiment, is a slowly evolving wave of exuberance and/or delayed learning about fundamentals.

**Nominal yields.** The second panel of Figure 6 estimates a similar specification (7.2) for changes in one-year Treasury yields $Y_t$:

$$Y_{t+h} - Y_{t-1} = \alpha^Y_h + \beta^h \cdot \text{PrSurprise}_t + \beta^h \cdot \text{UnprSurprise}_t + \varepsilon_{t,h}$$  \hspace{1cm} (7.3)

It tells a similar story more noisily over 6 weeks of trading. In the very short-run, and only the very short-run, markets over-respond to the unpredictable “tremble” and under-respond to the predictable demand shock.

**Aside: revisiting same-day stock response.** My results tell quite a different story than the findings of Jarocinski and Karadi (2018). These authors show that conditioning on the same-day response of stock markets can provide, in a structural VAR context, an interpretable decomposition of demand and monetary shocks. In my dataset, shock predictability has a weak relationship with the sign or magnitude of stock market response. In Appendix C.3, I show that the sentiment-based decomposition explains much more heterogeneity in long-run response than conditioning on same-day stock responses.

### 7.2 Forecast revisions follow sentiment, not surprises

To what extent do the market responses above truly reflect changes in expectations? To get some sense of this, at a lower frequency, I turn again to the Blue Chip Economic Indicators survey. I focus, for simplicity, on revisions to four expectations: annualized growth in real GDP and Personal Consumption Expenditures (PCE), in the next 1 or 3 quarters. Patterns with different indicators and different horizons are similar but omitted for brevity. I subset the sample to FOMC meetings occurring after the first Friday of the month, when survey submissions are likely to be due.

Let $Re_{t+1}^{Y,q}$ be the forecast revision for variable $Y$ and horizon $q$. I first estimate the following regression on the previous month’s surprise:

$$Re_{t+1}^{Y,q} = \alpha^{Y,q} + \beta^{Y,q} \cdot \text{Surprise}_t + \varepsilon^{Y,q}_{t+1}$$  \hspace{1cm} (7.4)

Note that the timing of this regression, which follows Campbell et al. (2012) and Nakamura and

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26The regression of predicted policy news shocks on the sign of stock market responses has an $R^2$ of 0.008. The regression with both predicted and unpredicted shocks, like the $t = 0$ regression in Figure 6, gives very similar point estimates for each component.
Steinsson (2018), allows for the monetary policy announcement to fall in-between the two Blue Chip surveys from which the revision $\text{Rev}_{t+1}^{Y,q}$ is calculated. Results, which essentially replicate the findings of Campbell et al. (2012) and Nakamura and Steinsson (2018), are reported in the odd columns of Table 5. Positive surprises correlate with positive revisions.

An obvious question in light of this paper’s previous results is whether this correlation mostly reflects an omitted variable, public sentiment. If the correlation between forecast revisions and policy surprises were explained entirely by something the public already knew on average, it would be much harder (though not impossible) to tell the story of Fed persuasion (“information effects”).

To this end, I estimate the following regression separately on the predicted and unpredicted components of the surprise:

$$\text{Rev}_{t+1}^{Y,q} = \alpha^{Y,q} + \beta^{Y,q,p} \cdot \text{PrSurprise}_{t} + \beta^{Y,q,u} \cdot \text{UnprSurprise}_{t} + \epsilon_{t+1}^{Y,q} \quad (7.5)$$

The coefficient $\beta^{Y,q,u}$, on the unpredicted surprise, is like an effect of the surprise holding fixed pre-meeting sentiment. The even numbered columns of Table 5 prints the results. Indeed, the majority of the correlation comes from the predictable component of monetary surprises and the unpredicted shocks, up to statistical precision, have zero effects.

In magnitudes, the effects of the predicted components are large in the present normalization (5% growth revisions for 100 basis point shocks) but small in terms of what size surprises we have observed in the data (one-standard-deviation = a 1.5 basis point predicted shock). The product of those two numbers, a 0.08 percentage point adjustment to the Blue Chip forecast, is about 1/4 of the “typical” ex ante disagreement between the Fed and professional forecasters described in Section 5.3.
In Appendix C.4 I verify a corollary result that predicted surprises (by extension, sentiment) continue to predict positive revisions in subsequent months. This is indicative of slower learning that may eventually close the beliefs gap, albeit somewhat late.

These results, all together, further cast doubt on the hypothesis of Fed persuasion about fundamentals. They are consistent with the stock price results if one thinks of a vertical slice of the IRF (left panel of Figure 6) after a few weeks as a differential response of expected future dividends (broadly, economic conditions) to each component of the monetary surprise.

But there remains the possibility, which would elude any of the tests done so far, that jointly (i) monetary surprises are accompanied by precise justifications and (ii) these take some time for the public to absorb. The upward swing in stock prices after 10 days in Figure 6 could reflect some moment at which markets achieve a consensus understanding about why the Fed acted, or received follow-up policy communication that clarified the message. In this case the announcement-day response of stock prices would not be informative of persuasion. Instead, the several-weeks out response of stock prices and the positive coefficient $\beta^{Y,q}$ from (7.5) would be an effect of Fed persuasion relative to a counterfactual in which the public had to figure out, without any policy assistance, how demand had shifted.

### 7.3 Announcements do not “re-affirm” sentiment

I now design an empirical test that compares FOMC and non-FOMC months to investigate this story more carefully. I construct “placebo” policy news shocks from the predictability regression in months without scheduled FOMC meetings. These identify events of similar sentiment dynamics but no FOMC meeting. If Fed signaling matters, it seems reasonable that this shock have a positive interaction effect with there being a scheduled FOMC meeting.

The exact regression equation is

$$\text{Rev}_{t+1}^{Y,q} = \alpha^{Y,q} + \text{FOMC}_t + \beta^{Y,q} \cdot \text{PrSurprise}_t + \lambda^{Y,q} \cdot (\text{PrSurprise}_t \times \text{FOMC}_t) + \epsilon_{t+1}$$  \hspace{1cm} (7.6)

now estimated on the entire sample, excluding months with an unscheduled FOMC meeting or FOMC meeting in the first week. The key coefficient is the interaction $\lambda^{Y,q}$, which measures how much more markets react to sentiment (summarized in the one-dimensional index PrSurprise$_t$) when the FOMC makes an announcement. If $\lambda^{Y,q}$ were large and $\beta^{Y,q}$ small, this would suggest that the informed public (i.e., Blue Chip forecasters) truly need the Fed either to describe sentiment data or provide the right macro interpretation thereof in order to update their own forecasts. My sample is all months from 1/1995 to 3/2014, again excluding the height of the Great Recession (7/2008 to 6/2009) and also months with unscheduled FOMC meetings.

The results (Table 6) suggest that there is not much support for the persuasion view: the interaction coefficients are uniformly insignificant. The delay with which the information in
sentiment passes through to forecasts, either because the actual data become public or the dispersed information percolates through to professional forecasters, is essentially unaffected by the Fed’s decisions.\textsuperscript{27}

### 8. An Organizing Model

I now try to write a simple model that can rationalize my empirical findings. The formalism is a dynamic Keynesian cross model in which agents have heterogeneous beliefs about income in the far future (a “sentiment shock”). The goal is to demonstrate that a combination of incomplete information with some form of belief dogmatism (“agreeing to disagree” with the Fed) can generate the previous empirical patterns.

#### 8.1 Setup

**Timing.** There are four relevant periods: \( t \in \{0, 0+, 1, 2\} \). At \( t = 0 \), financial and goods markets operate but monetary policy is fixed at some steady state level. At \( t = 0+ \), just an instant after \( t = 0 \), a monetary authority announces the interest rate \( r \) from \( t = 1 \) to \( t = 2 \), but no consumption takes place. At \( t = 1 \), financial and goods markets operate again. At \( t = 2 \), interest rates go back to a steady state. There is an infinite future of \( t \geq 3 \) which will also be in steady state and will not feature importantly in the analysis.\textsuperscript{28}

\textsuperscript{27}The interaction for three-quarter forecast of consumption (column 4) has a \( t \)-statistic of 1.45 (\( p \)-value \( \approx 0.15 \)) and at least has an economically significant magnitude. This rather weak signal is the main remaining evidence for a persuasion effect.

\textsuperscript{28}Why have an infinite future at all? This makes “permanent income” expressions for consumption and expected future income more familiar.
Main idea: Keynesian cross. In Appendix D, I solve (and log-linearize) a model populated by a continuum of consumers indexed by $i \in [0, 1]$ with (i) income proportional to aggregate output and (ii) log preferences. For simplicity, I assume that during this episode prices are perfectly rigid and an unmodeled supply block of the economy commits to meeting demand. This makes the model a pure “Keynesian cross” with only a demand equation and market clearing.

This assumption, of course, also be internalized as an interesting state-dependence to all the results being presented here. The anecdotal evidence from FOMC minutes mainly highlighted the importance of confidence in downturns. Insofar as these states of the world naturally have more price rigidity (e.g., because of asymmetric downward rigidity in wages), all lessons would apply more strongly conditional on low fundamentals.

Aggregate demand. Let $c_{it}$ be individual consumption in period $t$. In aggregate, the market clears so total consumption equals total income: $\int c_{it} \, di = Y_t$.

Let $\mathbb{E}_{i0}[\cdot]$ denote agent $i$’s beliefs about future prices and quantities and $r$ be the interest rate from $t = 1$ to $t = 2$. Agent $i$’s consumption function in log deviations has the following form, for a given discount rate $\beta \in [0, 1]$, at $t = 0$:

$$c_{i0} = -\beta^2 \mathbb{E}_{i0}[r] + (1 - \beta) \left( Y_0 + \beta \mathbb{E}_{i0}[Y_1] + \beta^2 \mathbb{E}_{i0}[Y_2] \right)$$

(8.1)

Note immediately that expectations of future income have the potential to be self-fulfilling for fixed (real) interest rates — this will be the driving force of fluctuations in the model.

Let $\overline{\mathbb{E}}_0[\cdot] := \int \mathbb{E}_{i0}[\cdot] \, di$ denote the average expectation across all agents. Aggregating and substituting in market clearing at $t = 0$, $C_0 = Y_0$, gives

$$Y_0 = -\beta^2 \overline{\mathbb{E}}_0[r] + (1 - \beta) \left( Y_0 + \beta \overline{\mathbb{E}}_0[Y_1] + \beta^2 \overline{\mathbb{E}}_0[Y_2] \right)$$

(8.2)

At $t = 1$ the interest rate is revealed and there is only one future period to forecast. The general-equilibrium Keynesian cross, analogous to the previous expression, is

$$Y_1 = -\beta r + (1 - \beta) \left( Y_1 + \beta \overline{\mathbb{E}}_0[Y_2] \right)$$

(8.3)

Actual outcomes at $Y_2$ will be irrelevant in this analysis. As a baseline case, it is fine to imagine that output goes back to steady-state ($Y_2 = 0$).

Asset prices. The agents $i \in [0, 1]$ also price an asset $p$ which pays dividend $Y_t$ at each date $t$ (extending also into the infinite future). I assume for now that this asset is in zero net supply, so it

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29Imagine that consumers elastically supply labor to firms that commit to meeting demand.
30See Benigno and Ricci (2011), Schmitt-Grohé and Uribe (2016), and Dupraz et al. (2019) for theoretical exploration; and Hazell and Taska (2018) and Grigsby et al. (2019) for direct empirical evidence.
can be meaningfully priced without actually affecting any equilibrium outcomes (like in a classic
“Lucas tree” model).

Each agent values the asset at as the present discounted value of future dividends at market
interest rates. I assume further that the market price of this asset equals the average belief of this
valuation at all horizons. Thus the asset prices for \( t \in \{0, 0+, 1\} \) are

\[
\begin{align*}
    p_0 &= (1 - \beta)(\bar{\mathbb{E}}_0[Y_1] + \beta \bar{\mathbb{E}}_0[Y_2]) - \beta \bar{\mathbb{E}}_0[r] \\
    p_{0+} &= (1 - \beta)(\bar{\mathbb{E}}_{0+}[Y_1] + \beta \bar{\mathbb{E}}_{0+}[Y_2]) - \beta r \\
    p_1 &= (1 - \beta)(\bar{\mathbb{E}}_1[Y_2] - r)
\end{align*}
\]  

(8.4)

Finally, in the background that there is also a “interest rate futures market” at \( t = 0 \) that prices
a contract paying out in proportion to policy rate \( r \) at \( 0+ \). I assume the price \( f \) is proportional to
the average expectation of policy:

\[
f = \bar{\mathbb{E}}_0[r]
\]

(8.5)

Note there is no discounting, because period \( 0+ \) is arbitrarily close to period 0.

**Demand shocks.** Let \( \varepsilon \sim \mathrm{Normal}(0, 1) \) be an aggregate variable and let \( \nu_i \sim \mathrm{Normal}(0, \sigma^2) \) be
idiosyncratic noise with known variance. Assume each individual agent, at \( t = 0 \) believes that \( Y_2 \)
will be \( \varepsilon_i := \varepsilon + \nu_i \).\(^{32}\) This means that the average expectation of future income is \( \varepsilon \):

\[
\bar{\mathbb{E}}_0[Y_2] = \varepsilon
\]

(8.6)

This is the main driving “demand shock.” Note that, in the model described here, no such boom
can actually materialize at \( t = 2 \).\(^{33}\) Nonetheless this optimism \( (\varepsilon > 0) \) or pessimism \( (\varepsilon < 0) \) will be
self-fulfilling in earlier periods because output is purely demand determined and expected future
income shifts demand.

**Policy.** Monetary policy takes place at \( t = 0 \). The Fed is concerned about a self-fulfilling wave of
optimism or pessimism at \( t = 1 \) and wants to counteract it via interest rates. It receives some signal
of the public’s average belief of the form \( \varepsilon + \nu \), where \( \nu \) is some error orthogonal to \( \varepsilon \) and unknown
to the public. The “information” could include both hard survey data and qualitative assessment
(e.g., from the Beige Book). So \( \nu \) is plausibly related both to survey error and some idiosyncratic
interpretation of the soft data.

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\[^{31}\]This can be formalized in the “standard” models of asset pricing with heterogeneous beliefs following Harrison and Kreps (1978) and a myriad related studies. The relevant assumption is that traders, while dogmatic in their belief
they may earn a positive expected return at the market price, are risk averse and thus take bounded positions.

\[^{32}\]This phrasing recalls heterogeneous priors but it is not substantially different to think of agents receiving heterogeneous Gaussian signals about a common Gaussian fundamental (e.g., TFP).

\[^{33}\]This particular point is not essential to any conclusions. It would be without loss of content, but only an increase in
complexity, to introduce some role for aggregate supply and allow \( \varepsilon \) to be “true” news about a TFP shock that manifests
at \( t = 2 \).
The monetary rule is simply a linear response to the signal with some slope $a$:

$$r = a(ε + ν)$$

(8.7)

Given the (eventually demonstrated) linearity of the model, this is isomorphic to the Fed’s responding to its beliefs about $Y_1$. The coefficient $a$ absorbs the Fed’s posterior updating about average beliefs, the conjecture about how output responds to beliefs, and decision about how aggressively to stabilize output in expectation.

### 8.2 Predictable surprises

**Beliefs of beliefs.** It is important in the model to know what other agents are thinking. Consumers want to know what the Fed is thinking to forecast interest rates, and what each other are thinking to forecast future income. The Fed wants to know what consumers are thinking to pick monetary policy from $t = 1$ to $t = 2$.

Let us assume that all agents internalize the previous stochastic structure and use Bayes’ rule to form these “beliefs of beliefs.” It is simple to show that, absent other information, consumers’ beliefs of other consumers’ beliefs are dampened by some parameter $λ = (1 + σ^2)^{-1} ∈ (0, 1)$:

$$\tilde{E}_0[\tilde{E}_0[Y_2]] = λε$$

(8.8)

A very optimistic agent ($ε_i > 0$), for example, is unsure whether her beliefs are representative of the public’s, and consequently has a more conservative estimate of others’ beliefs (i.e., pulled toward 0).

Second, consumers want to forecast monetary policy. This is in expectation the same as forecasting $ε$, since consumers have no relevant information about the idiosyncratic shifter $ν$:

$$\tilde{E}_0[ε + ν] = λε$$

(8.9)

**What’s news.** It is simple to calculate from the previous to calculate what should be the “monetary surprise,” or the difference between prior expected policy and realized policy:

**Proposition 1 (Demand shocks and monetary surprises)** The difference between the interest rate and the predicted interest rate (“monetary surprise”) is $Δ = a(1 - λ)ε + ν$.

This predictably depends on demand shocks. By implication, any pre-determined information that is informative about demand (like survey data that noisily measures $\tilde{E}_0[Y_2]$) will correlate with the monetary surprise in large enough samples. The mechanism is the difficulty agents have forecasting each others’ beliefs. Generically this will create some dependence of the surprise on $ε$. The linearity and the positive sign are direct results of the assumed Gaussianity.
It is necessary to have $\lambda < 1$, or some imperfect knowledge of the “public,” to get dependence on $\varepsilon$. Lower $\lambda$, or more disagreement, generates larger surprises. This matches the previously discussed evidence (printed in Appendix B.2) about high belief dispersion before announcements.\(^{34}\)

**Inference and information effects.** The monetary decision provides some information about the average belief $\varepsilon$. If agents were Bayesian, their average updated forecasts of the demand shock $\varepsilon$ would be a weighted average of the private signal and the interest rate.\(^{35}\) The Fed’s signal, in any natural calibration, is more informative than any one agent’s belief, so observing the interest rate should (in precision units) more than double the available information available for an individual. Moreover the information would have a disproportionate effect on the stock price at $0_+$ because it would be very easy for agents to form “forecasts of others’ forecasts.” This would illustrate the general lesson of Morris and Shin (2002) about the influence of public signals in environments of coordination.

To be perfectly clear, no regression in this paper perfectly isolates the high-frequency persuasion effect of monetary policy on beliefs on fundamentals. But the suggestive evidence from stock markets and professional forecasts casts doubt on the Bayesian benchmark.

I will thus explore the case of zero persuasion about fundamentals and endeavor to show it is fully consistent with the evidence (if not uniquely so). To generate this behavior, I will introduce here a behavioral assumption that each market participant treat the entire policy error as arising from an idiosyncratic Fed mistake:

**Assumption 1 (Full private-sector confidence)** Let $\Delta_t := r - \mathbb{E}_t[r]$ be an individual’s “monetary surprise.” Each agent $i$ believes, for $t \geq 0_+$, that $\nu = \frac{\Delta_t}{a}$ and maintains their priors that $\mathbb{E}_t[Y_2] = \varepsilon_i$ and $\mathbb{E}_t\mathbb{E}_{is}[Y_2] = \lambda \varepsilon_i$ for $t \geq 0_+$ and $s \geq t$.

As such, each agent maintains their $t = 0$ beliefs about fundamentals.

**Model uncertainty.** A closely related mechanism would be uncertainty about the Fed’s model of the economy. Say that the public did know that the Fed wanted to eliminate the output gap at $t = 1$ in expectation, and how precise was the Fed’s signal, but did not know how steep the Fed thought the Keynesian cross was. This would translate into uncertainty about coefficient $a$ in the Taylor rule. If agents on average under-forecasted $a$, monetary surprises would positively correlate with $\varepsilon$. And if uncertainty about $a$ were high, the monetary announcement may have very small effects

\[^{34}\text{It also roughly matches the direct evidence of Coibion et al. (2018b) on higher-order beliefs of economic actors in an advanced economy (firms in New Zealand). These authors find that second-order beliefs are more concentrated in the cross-section than first-order beliefs and also, at the individual level, correlated with first-order beliefs. Both properties are satisfied by this model with } \mathbb{E}_t[Y_2] = \varepsilon_i \text{ and } \mathbb{E}_t\mathbb{E}_i\mathbb{E}_s[Y_2] = \lambda \varepsilon_i.\]

\[^{35}\text{Precisely, if } \sigma^2_F \text{ is the variance of the Fed’s error } \nu,\]

\[\mathbb{E}_{0+r,\text{Bayes}}[\varepsilon] = \frac{\sigma^{-2}}{1 + \sigma^{-2} + \sigma_F^{-2}} \left( \sigma^{-2} \varepsilon_i + \sigma_F^{-2} \frac{r}{a} \right)\]
on fundamental beliefs, precisely because it would be difficult to “invert” policy and understand its justification.

This story captures the same spirit of “agreeing to disagree” with the Fed. This paper treats it as a complementary possibility that captures the same basic force: joint uncertainty about both what others think and why it matters.

8.3 Implications for monetary transmission and measurement

I now proceed to explore implications for aggregate outcomes and stock prices, to match the previously presented evidence.

It is simple to solve analytically for all quantities as linear functions of the underlying shocks. Consider first output at \( t = 1 \). Imposing the assumption that \( a < 1 - \beta \) is sufficient to allow the economy to respond positively to the sentiment shock:

\[
Y_1 = (1 - \beta - a)\epsilon - a\nu
\] (8.10)

Exuberance (or pessimism) today is partially self-fulfilling because there is a “Keynesian cross” feedback between current demand and current income. Note also that the extent of under-reaction is now irrelevant because income is perfectly observed. The tremble in interest rates, meanwhile, always has a negative effect.

At \( t = 0 \), operating under the same assumption on policy, there is also a boom based on expected future income at both \( t = 1 \) and \( t = 2 \):

\[
Y_0 = \left[ \beta(1 - \beta - \lambda a) + \lambda(1 - \beta - a) \right] \epsilon
\] (8.11)

Note that these consumers have dampened expectations of both \( Y_1 \) and the future monetary policy, which will generally reduce the effect of news.\(^{36}\)

Next, consider the stock market. At \( t = 0 \), the stock market price depends positively on expected future output at \( t = 1 \) and \( t = 2 \) and the expected interest rate.\(^{37}\) Across the monetary announcement, agents update their beliefs only about the interest rate. Thus the stock price will go down across the announcement in response to any positive monetary surprise. The proportionality, in this simple log preferences model, is exactly one-for-one:

**Proposition 2 (Stock market jump)** The jump in stock markets across the monetary announcement,

\(^{36}\)The only subtlety is its effect on expected future policy. But as long as \( 1 - \beta > a(1 + \beta) \), which is a slightly stronger condition on how small is the Fed’s reaction, more attention strictly increases the size of the boom.

\(^{37}\)The exact expression is

\[
p_0 = (\beta^2(1 - \lambda a) + \beta\lambda(1 - \beta - a))\epsilon
\]

which lists the terms mentioned in the main text in order.
$p_{0+} - p_0$, is linear in the monetary surprise and therefore decreases in both structural shocks:

$$p_{0+} - p_0 = -\Delta$$

Note that this slope (i.e., Bernanke and Kuttner (2005) regression coefficient) has no contamination from $\lambda$ or distinction between “good and bad” variation in $\Delta$. The sharpness of this result requires assuming zero persuasion about fundamentals at such a high frequency.

The stock price at $t = 1$ is not affected by the mis-forecasting because the $t = 1$ dividend, the only component that required reasoning about others’ beliefs, is now observed. A predictable forecast error for dividends generates predictable excess returns from 0+ to 1:

**Proposition 3 (Predictable stock returns)** The dividend-inclusive excess stock return from 0+ to 1 is

$$r_e := \beta Y_1 + (1 - \beta)Y_1 - p_{0+} = (1 - \beta)^2(1 - \lambda)\varepsilon$$

which increases in the belief shock $\varepsilon$.

To reiterate: when dividends (income) at $t = 1$ are observed, the inability to recover others’ beliefs ceases to matter. The stock gains (or losses) reflect this gap. This is a type of story in which the public learns over time about fundamentals without the Fed’s assistance.

### 8.4 Discussion: modeling “public signals”

Morris and Shin (2002), in their seminal paper about public information, model policy communication as a public signal about fundamentals. This can have an outsize influence on outcomes in a coordination-game environment. A large follow-up literature considers the additional possibility that policy actions implicitly signal intent, creating subtle trade-offs between more aggressive and more informative policies.\(^{38}\) In the more applied policy communication literature, Cieslak and Schrimpf (2019) and Jarocinski and Karadi (2018) use variations of the former announcement model to describe forward guidance information while Melosi (2016) explores the latter, though admittedly with less focus on the exact context of monetary policy since 1995.\(^{39}\)

My findings push against the independent-signals view, given the relatively uniform response of financial markets to ex post well-differentiated shocks. The signaling-through-actions view has some credence, but again is easily mid-identified by common causation that may masquerade as persuasion accompanying surprise policy changes.

A safer premise may be a heterogeneous priors environment in which statistically useful signals of where the economy is heading may not immediately change beliefs and/or resolve uncertainty.

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\(^{38}\)Including James and Lawler (2011); Baeriswyl and Cornand (2010); Kohlhas (2017).

\(^{39}\)And instead with more emphasis on monetary response to inflation in the 1970s and 1980s.
My analysis only scratches the surface of how this could inform realistic models of policy communication in various contexts (including setting “long-run anchors” or performing forward guidance in crises). I leave more investigation of this to future research.

9. Implications for Macro Identification

How do my findings relate with existing efforts to use high-frequency shocks to estimate the causal effect of monetary policy (e.g., Gertler and Karadi, 2015; Miranda-Agrippino and Ricco, 2015; Caldara and Herbst, 2019)? In Appendix E, I estimate a recursively-identified VAR system with the same full set of “macro data controls” (industrial production; PCE deflator; unemployment; the excess bond premium; Michigan unemployment sentiment; and the Federal Funds rate). I use monthly data from 1995 to 2014. This allows me to estimate, essentially, a version of the Taylor rule (5.1) with many more lags of controls, disciplined by informed priors. I find strong evidence (posterior probability > 99%) that sentiment enters with a positive sign in the monetary policy rule (Table A10). This could matter significantly for identification based an empirical Taylor rule, including but not limited to the recursive approach.

I also explore the implications for proxy SVAR techniques, which use the correlation between an excluded instrument and the reduced-form VAR residuals to identify shocks. Monetary surprises might work as instruments for monetary shocks conditional on the right controls, which project out information in lagged sentiment. But necessarily inference is fragile to choosing those controls. Ramey (2016) and Caldara and Herbst (2019) uncover a similar point.

In that sense the high-frequency approach is a “lateral shift” from carefully specifying zeros in the Taylor rule. It replaces a fully structural model of policymakers’ behavior with a structural model of how policymakers and markets differentially perceive shocks. This comes, too, at a significant cost in power given how small monetary surprises are.

The exclusion restriction at different horizons The implicit argument in the previous is that the high-frequency monetary instrument, in macro applications, does not satisfy the exclusion restriction: it is partially driven by demand shocks with large and confounding effects on the macroeconomy. In the language of Proposition 1, the monetary surprise \( \Delta \) may correlate with various future outcomes via the belief shock \( \varepsilon \) instead of the true monetary deviation \( v \).

On very short time scales the exclusion restriction may at least approximately hold, or one could use second-moment restrictions (as in Rigobon and Sack, 2004) to isolate the pure effect of news about future interest rates. Indeed, my general finding that Fed persuasion about fundamentals is not evident at high-frequencies makes this approach even safer. This was exact in the simple model from Proposition 2 about stock market jumps and their correlation with the monetary surprise.

Stepping back slightly, my analysis suggests a new reason why high-frequency identification
seems to “work” better at higher than lower frequencies. It is not an issue of precise measurement (“signal-to-noise”), but instead a clear failure of the exclusion restriction that may manifest more clearly at the long horizons. Figure 6, the daily IRF of stock prices and Treasury yields, gives a precise meaning to “long-enough” horizon in this context: more than about two weeks.

10. Conclusion

Market forecast revisions about monetary policy around FOMC announcements are predicted by pre-announcement consumer sentiment. The predictable component of these forecast errors drives most of the eventual dynamics in interest rates and beliefs and resembles a slowly evolving demand shock. Persuasion from the Fed about underlying demand shocks seems to play a limited role, if any at all, in modulating this shock’s effects.

The main conclusions are threefold. First, the Fed’s persuasive ability seems mostly limited to the future policy path. This could be for the better in the context of “regular” policy, for which persuasion about fundamentals is self-defeating, or for the worse insofar as the lesson extends to other cases in which Central Banks do want to manipulate beliefs about outcomes and/or fundamentals (e.g., for long-run inflation expectations).40

Second, appeals to the informational efficiency of financial markets may be insufficient for identifying economic “shocks” in a world of heterogeneous and slowly moving beliefs.

Finally, something that resembles a “demand shock” from standard macro theory can evidently catch hold in average sentiment before it manifests in financial markets. Understanding exactly why information aggregation across geography, economic sectors, and groups of individuals fails — and whether the scope for such failure is changing in an era of abundant and instantly accessible information — is a fascinating topic for follow-up research. In particular it may generate new hypotheses about when confidence breaks can lead to recessions and how they can be most effectively detected in the data.

References


Andrade, Philippe and Filippo Ferroni, “Delphic and Odyssean monetary policy shocks: Evidence from the euro-area,” School of Economics Discussion Papers 1216, School of Economics, University of Surrey October 2016.

40Unfortunately for policymakers, in the latter context too there is a growing body of evidence suggesting that policy communication fails to reach important audiences in the US and other advanced economies (Coibion et al., 2018a,b). More investigation into the extent of this phenomenon, and advice for designing policy in spite of it, seems justified.


_ _ _ _, Forward Guidance and Macroeconomic Outcomes Since the Financial Crisis, University of Chicago Press, October


A. RELEVANT SURVEY QUESTIONS

A.1 Michigan Survey of Consumers

All variables are aggregated using the survey weights provided by the Michigan survey in the micro-data. Everything is normalized so positive scores are “good.”

A.1.1 Unemployment forecast

**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)

A.1.2 Business conditions

**Question:** Now turning to business conditions in the country as a whole–do you think that during the next 12 months we’ll have good times financially, or bad times, or what?

**Answers:** 1. GOOD TIMES; 2. GOOD WITH QUALIFICATIONS; 3. PRO-CON; 4. BAD WITH QUALIFICATIONS; 5. BAD TIMES; 8. DON’T KNOW

**Coding:** (Share == 1) + (Share == 2) - (Share == 4) - (Share == 5)

A.1.3 Interest rate sentiment

**Question:** No one can say for sure, but what do you think will happen to interest rates for borrowing money during the next 12 months–will they go up, stay the same, or go down?

**Answers:** 1. GO UP; 3. STAY THE SAME; 5. GO DOWN; 8. DON’T KNOW

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

A.1.4 Real income sentiment

**Question:** During the next year or two, do you expect that your (family) income will go up more than prices will go up, about the same, or less than prices will go up?
**Answers:** 1. INCOME UP MORE THAN PRICES; 3. INCOME UP SAME AS PRICES; 5. INCOME UP LESS THAN PRICES; 8. DON’T KNOW

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

### A.2 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].”

### A.3 NFIB Survey

I take the NFIB data, aggregated and seasonally adjusted, straight from the website: [http://www.nfib-sbet.org/indicators/](http://www.nfib-sbet.org/indicators/).

#### A.3.1 Expansion plans

**Question:** Do you think the next three months will be a good time for small business to expand substantially?

**Answers:** 0. No reply; 1. Yes; 2. No; 3. Uncertain

**Coding:** “Percent of respondents who think the next three months will be a good time for small businesses to expand.”

#### A.3.2 Sales up

**Question:** Do you think the next three months will be a good time for small business to expand substantially?

**Answers:** 0. No reply; 1. Yes; 2. No; 3. Uncertain

**Coding:** “The percent of respondents who think sales will be "higher" minus those who think sales will be "lower" during the next three months.”

### A.4 Conference Board survey

I take the aggregated Conference Board data directly from the provider. Unfortunately the provided technical notes do not provide exact questions. The section of the survey that I use asks for respondents to report “expectations for six months hence.” For employment the three options
are: “more jobs,” “fewer jobs,” and “same.” For “business conditions” (described thusly) the three options are: “better,” “worse,” and “same.” In each case I calculate a diffusion index as the proportion with positive response minus the proportion with negative response (not using the proportion of neutral responses.)

B. Robustness of Predictability Result

B.1 Other data sources

Investor sentiment, at a higher frequency. For validation, and an opportunity to zoom in on sentiment at a higher frequency, I look also at the correlation between monetary surprises and sentiment of small-scale investors in the AAII survey. The questionnaire asks each respondent if he or she is “Bearish” (pessimistic), “Bullish” (optimistic), or neutral about the stock market in the next six months. The data are available at a weekly frequency over my entire sample.

Since only small-scale investors participate in the AAII, this survey measures “general public”. perceptions of financial conditions and not the sentiment of the modal, probably institutional investor. Nonetheless the metric has some traction in the financial press (it is a useful “barometer of American retail investor sentiment” according to the Wall Street Journal)\(^\text{41}\) and has empirical weight as a predictor for future excess returns (Greenwood and Shleifer, 2014).

Let \(X_t\) be the proportion of bullish or bearish agents, bounded in \([0,1]\), in week \(t\). I run

\(\text{Figure A1: Average investor sentiment before and after a policy news surprise. Points are regression coefficients from (B.1) and bands are 95% robust standard errors.}\)

\(^{41}\)Quoted from “Predicting the Next Bear Market in Six Charts,” published on November 5, 2018 (https://www.wsj.com/graphics/bear-market-signs/).
regressions of the form

\[ X_t = \alpha + \sum_{j=-5}^{-1} \beta_j \cdot \text{Surprise}_{t+j} + \sum_{j=1}^{5} \beta_j \cdot \text{Surprise}_{t+j} + \varepsilon_t \]  \hspace{1cm} (B.1)

where “surprises” are the policy news factor shock and indexed to given weeks. Surveys are indexed to the Friday of a given week, when final responses are collected, and surprises to the FOMC announcement day (usually in mid-week). Like previous regressions, this one uses the whole sample 1995 to 2014 excluding the height of the financial crisis. I do not estimate a coefficient for \( j = 0 \) because it is not clear if respondents fill out the survey before or after the FOMC announcement.

This sentiment measure also correlates strongly with monetary shocks (Figure A1). There is not only a clear pre-announcement pattern but also a high-frequency trend of mean reversion over the course of the announcement. A test of the difference across the announcement (from -3 to 3) are significant at the 5% level for the first measure and 10% for the second.

**Small firms.** The National Federation for Independent Businesses “Small Business Economic Trends,” administered monthly since 1986, asks small businesses various questions about their outlook for firm-level and aggregate variables. Results from the previous month’s survey are posted online on the second Tuesday of a given month. Appendix A.3 reviews the exact questions used in this paper, which span both firm-level and aggregate outcomes.

Figure A2 shows an estimation of regression equation (4.1) for measures of small business sentiment from the monthly National Federation for Independent Businesses (NFIB) survey. The pattern, as with consumers, is a spike the month before the monetary surprise.

**Conference Board consumer survey.** The Conference Board’s monthly consumer survey has been conducted by mail monthly since 1977 (bimonthly from 1967 to 1977). In February 2011, there was a discontinuity in survey design and aggregation as the Conference Board partnered with the Nielsen Company for operational support. Ignoring data after 2011 does not influence my main results.

In the Conference Board survey, I construct diffusion indices for the future health of labor markets and business conditions to match my constructions in the Michigan survey (see Appendix
Figure A2: Specification (4.1) estimated for four measures of small business sentiment in the National Federation for Independent Businesses survey: (i) difference in percent of respondents who think real sales in the next three months will be higher rather than lower; (ii) difference in percent of respondents who think it’s a good versus bad time for their business to expand in the next 3 months. Bands are 95% robust confidence intervals. See Appendix A.3 for details about survey questions.

Figure A3: Specification (4.1) estimated for two measures of consumer sentiment in the Conference Board survey. Units are percentage points. Bands are 95% robust confidence intervals. See Appendix A.4 for details about survey questions.

A.4. I estimate a version of (4.1), reprinted here:

\[ \text{Sentiment}_{t+j} = \alpha_j + \beta_j \cdot \text{Surprise}_t + \varepsilon_{t+j} \quad (B.2) \]

in Figure A3. The pattern is much the same, with a spike in the month before the surprise.
Figure A4: Estimation of (B.3) with 95% confidence intervals shaded.

**B.2 Disagreement**

Let the “source variable” for the unemployment variable, for respondee $i$ at time $t$, be $\text{MichUnemp}_{it} \in -1, 0, 1$, with the three values correspondingly referring to negative, neutral, and positive response about future labor market conditions (unemployment up, about the same, or down). The unemployment sentiment variable was constructed as the average over respondents $n \leq N$ of this coding, or the share positive minus the share negative:

$$\text{MichUnempSent}_i = \frac{1}{N} \sum_{n=1}^{N} \text{MichUnemp}_{it}$$

I now construct the cross-sectional dispersion based on the same coding as

$$\text{MichUnempDisp}_i = \frac{1}{N} \sum_{n=1}^{N} (\text{MichUnemp}_{it} - \text{MichUnempSent}_i)^2$$

and run a projection regression of this on the absolute value of the policy news shock:

$$\text{MichUnempDisp}_{t+j} = \alpha_j + \beta_j \cdot |\text{Surprise}_t| + \varepsilon_{t+j}$$  \hspace{1cm} (B.3)

The results in Figure A4 show (i) high predictability of large shocks and (ii) relatively flat responses.
Table A1: $R^2$ and $F$-stats from regressing monetary surprises on lags of macro aggregate factors and Michigan unemployment sentiment. $p$-values are in parenthesis.

B.3 Other macro controls

I generate control variables as the first $N$ principal components of the McCracken and Ng (2016) “FRED-MD” dataset of monthly macro-financial time series, subset from 1992:1 to the 2019:2. I use all data transformations suggested by those authors (e.g, log transformations, first differences, and second differences as appropriate).

This exercise is one way of reducing the dimension of macro “big data” to use in regressions. Conceptually, it involves picking the “synthetic” macro time series that explain the most variance in the panel. These are the most common macro shocks, but not mechanically the ones that are more relevant in the predictability regression. This is a feature, not a bug, in my case — my goal is to test whether “headline” macro news, which is at least imperfectly captured by these axes of greatest co-movement in macro time series, subsumes my result.

Table A1 suggests not. For brevity, I report only $F$ statistics and $R^2$ for a subset of the relevant predictability regressions. In general, the Michigan variables are more robustly significant across specifications and add quite a bit to the $R^2$.

B.4 Empirical Bayes estimation

Table A2 shows $R^2$ estimates an empirical Bayes model that shrinks coefficients toward 0. In particular, I assume that the prior distribution of $w = (w_i)_{i=1}^I$, the coefficients on each of the $I$ regressors, is an independent Gaussian $w_i \sim N(0, k_i \lambda_i)$, where $k_i = \delta^2 \lambda_i^2$ is a rescaling by the relative variance of the outcome and regressor and $\lambda_i$ is a prior hyperparameter distributed independently as Gamma($10^{-6}, 10^{-6}$) for all coefficients. The latter assumption allows each coefficient to be shrunk a different amount, which is an unstructured way to accommodate the reasonable prior belief that
<table>
<thead>
<tr>
<th>Measure</th>
<th>Surprise</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>1    Policy news factor (30 min.)</td>
<td>0.148</td>
<td>0.166</td>
</tr>
<tr>
<td>2    Fed Funds (this meeting)</td>
<td>0.023</td>
<td>0.008</td>
</tr>
<tr>
<td>3    Fed Funds (next meeting)</td>
<td>0.128</td>
<td>0.005</td>
</tr>
<tr>
<td>4    Eurodollar (2Q)</td>
<td>0.131</td>
<td>0.069</td>
</tr>
<tr>
<td>5    Eurodollar (3Q)</td>
<td>0.154</td>
<td>0.107</td>
</tr>
<tr>
<td>6    Eurodollar (4Q)</td>
<td>0.151</td>
<td>0.085</td>
</tr>
<tr>
<td>7    Orthogonal to FF</td>
<td>0.107</td>
<td>0.179</td>
</tr>
<tr>
<td>8    Policy news factor (1 day)</td>
<td>0.103</td>
<td>0.089</td>
</tr>
</tbody>
</table>

Table A2: \( R^2 \) estimates, mirroring Table 1, with an Empirical Bayes estimation strategy to shrink coefficients toward 0 with informative priors.

<table>
<thead>
<tr>
<th>Measure</th>
<th>( (\text{MichUmpSent}^{(t-j)}_{i\in{1,2}}) )</th>
<th>( (\Delta Y_{i_{h,gb}}^{(h)}_{k\in{0,4}}) )</th>
<th>( (F_{i_{h,gb}}^{(k)}_{k\in{1,2}}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1    Policy news factor (30 min.)</td>
<td>0.085</td>
<td>-0.035</td>
<td>-0.046</td>
</tr>
<tr>
<td>2    Fed Funds (this meeting)</td>
<td>-0.088</td>
<td>0.025</td>
<td>-0.119</td>
</tr>
<tr>
<td>3    Fed Funds (next meeting)</td>
<td>0.026</td>
<td>-0.035</td>
<td>-0.062</td>
</tr>
<tr>
<td>4    Eurodollar (2Q)</td>
<td>0.072</td>
<td>-0.015</td>
<td>-0.062</td>
</tr>
<tr>
<td>5    Eurodollar (3Q)</td>
<td>0.085</td>
<td>-0.002</td>
<td>-0.012</td>
</tr>
<tr>
<td>6    Eurodollar (4Q)</td>
<td>0.094</td>
<td>-0.002</td>
<td>-0.001</td>
</tr>
<tr>
<td>7    Orthogonal to FF</td>
<td>0.019</td>
<td>0.070</td>
<td>-0.084</td>
</tr>
<tr>
<td>8    Policy news factor (1 day)</td>
<td>0.019</td>
<td>0.086</td>
<td>0.015</td>
</tr>
</tbody>
</table>

Table A3: Pseudo-out-of-sample reduction in mean-squared-error, calculated as described in equation (B.4).

information in further lags matters less.\(^{42}\) I report the posterior mode \( R^2 \), which is relatively close to the OLS estimates.

### B.5 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 \( X \) be a vector of controls. 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 previous surprises (of a given type) on \( X \) 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

\(^{42}\)This is often formalized in a parametric “Minnesota prior” in Bayesian time series applications.
of an “approximate \( R^2 \),” I calculate reduction in MSE as

\[
\text{ReductionMSE} = 1 - \frac{MSE_{POOS}}{MSE_{naive}}
\]  

(B.4)

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.

Table A3 shows the result. These numbers are far less than the regression \( R^2 \) but, in most cases, still substantial with the Michigan variables. I similarly test two other predictors:

- The gap between Greenbook and Blue Chip survey expectations of Real GDP growth at 0 and 4 quarters (available, it should be noted, over about 2/3 the time period)
- Lagged values of the first two McCracken and Ng (2016) factors

and both do significantly worse than the sentiment measure.

### B.6 Risk-neutral expectations

It is reasonable to wonder if these results simply reflect the fact that risk-neutrality is a poorly suited assumption in these markets. A corollary of this hypothesis is that the predictable components of the monetary surprise should not affect risk-neutral expectations of interest rates. As a potential test for this, I follow Nakamura and Steinsson (2018) and check the correlation of the monetary surprise with risk-neutral changes in Treasury yields as derived by Abrahams et al. (2016).

Let \((\text{PrSurprise}_t, \text{UnprSurprise}_t)\) be the sentiment-predicted and sentiment-unpredicted components of the monetary surprise based on estimating (4.2). This is the same construction used in Section 6. Here I will estimate regressions of the form

\[
y^m_t = \alpha^m + \beta^m_p \cdot \text{PrSurprise}_t + \beta^m_u \cdot \text{UnprSurprise}_t + \epsilon^m_t
\]  

(B.5)

for different measures of changes in nominal bond yield \(y^m_t\) on announcement day. At horizons \(m = 1\) and \(m = 2\), I consider the (i) actual nominal bond yield, (ii) the risk-neutral yield estimated from the term structure model of Abrahams et al. (2016), and (iii) the difference between the two which is a crude and noisy measure of risk plus liquidity premia. Table A4 shows the results. In general, the predicted component of surprises moves 1 and 2-year yields less than the unpredicted component. But there is not clear evidence that it is acting primarily through the channel of risk premia as measured in this model.
Table A4: Estimation of (B.5) for (changes in) nominal Treasury yields, a model-implied risk neutral yield, and the difference thereof. Standard errors are bootstrapped to account for the generated regressor.

<table>
<thead>
<tr>
<th>Maturity</th>
<th>Yield 1Y</th>
<th>Yield 2Y</th>
<th>Risk-neutral 1Y</th>
<th>Risk-neutral 2Y</th>
<th>Difference (premium) 1Y</th>
<th>Difference (premium) 2Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>PrSurprise$_t$</td>
<td>0.977</td>
<td>0.711</td>
<td>0.664</td>
<td>0.474</td>
<td>0.168</td>
<td>0.181</td>
</tr>
<tr>
<td></td>
<td>(0.224)</td>
<td>(0.284)</td>
<td>(0.323)</td>
<td>(0.376)</td>
<td>(0.157)</td>
<td>(0.236)</td>
</tr>
<tr>
<td>UnprSurprise$_t$</td>
<td>1.062</td>
<td>1.156</td>
<td>1.204</td>
<td>1.294</td>
<td>-0.189</td>
<td>-0.155</td>
</tr>
<tr>
<td></td>
<td>(0.127)</td>
<td>(0.160)</td>
<td>(0.214)</td>
<td>(0.246)</td>
<td>(0.082)</td>
<td>(0.112)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.472</td>
<td>0.392</td>
<td>0.381</td>
<td>0.335</td>
<td>0.077</td>
<td>0.023</td>
</tr>
<tr>
<td>$N$</td>
<td>146</td>
<td>114</td>
<td>114</td>
<td>114</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure A5: Heterogeneity in predictability by (left) sign of surprise and (right) whether the surprise coincided with a rate change.

B.7 Different events

Of the 146 shocks in the main sample, 92 (or 63%) are positive — forecasts were revised upward. The first panel of Figure A5 shows coefficients from a regression like (4.1) with separate positive and negative shocks:

$$\text{MichUnempSent}_{t+j} = \alpha_j + \beta_j^{\text{Pos}} \cdot \max (\text{RateSurprise}_t, 0) + \beta_j^{\text{Neg}} \cdot \min (\text{RateSurprise}_t, 0) + \epsilon_{t+j}$$  \hfill (B.6)

The latter are quite a bit more predictable.

For more clues, I can also sort the data by whether or not the Fed Funds target rate changed
Table A5: Influential observations in the regression of the (30-minute) policy news shock on one lag of the Michigan unemployment sentiment variable.

<table>
<thead>
<tr>
<th>Year</th>
<th>Month</th>
<th>PN Shock</th>
<th>DFBETA</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001</td>
<td>11</td>
<td>-0.106</td>
<td>0.539</td>
</tr>
<tr>
<td>2001</td>
<td>5</td>
<td>-0.094</td>
<td>0.409</td>
</tr>
<tr>
<td>2007</td>
<td>9</td>
<td>-0.131</td>
<td>0.345</td>
</tr>
<tr>
<td>2001</td>
<td>6</td>
<td>0.062</td>
<td>-0.340</td>
</tr>
<tr>
<td>2008</td>
<td>3</td>
<td>0.039</td>
<td>-0.281</td>
</tr>
<tr>
<td>2001</td>
<td>3</td>
<td>-0.069</td>
<td>0.255</td>
</tr>
<tr>
<td>2008</td>
<td>1</td>
<td>-0.072</td>
<td>0.237</td>
</tr>
<tr>
<td>2004</td>
<td>1</td>
<td>0.083</td>
<td>0.231</td>
</tr>
<tr>
<td>2002</td>
<td>11</td>
<td>-0.081</td>
<td>0.198</td>
</tr>
<tr>
<td>2003</td>
<td>6</td>
<td>0.101</td>
<td>0.168</td>
</tr>
</tbody>
</table>

(46 versus 100 observations, respectively) and estimate the following:

\[
\text{MichUnempSent}_{t+j} = \alpha_j + \beta_j^{\text{Change}} \cdot (\text{RateSurprise}_t \cdot \text{TargetChange}_t) + \beta_j^{\text{NoChange}} \cdot (\text{RateSurprise}_t \cdot \text{NoTargetChange}_t) + \epsilon_{t+j} \tag{B.7}
\]

Shocks on FOMC meetings with rate changes have a significantly higher standard deviation (0.05 versus 0.02). The second panel Figure A5 shows the coefficients from a version of (4.1) with shocks split on this outcome. The story seems mainly about rate changes, which broadly suggests belief inertia and/or slow learning. These will be important themes in the remainder of the paper.

### B.8 Sensitivity to individual observations

Consider the regression of the policy news shock on one lag of the Michigan unemployment sentiment variable (and a constant). Table A5 lists the 10 observations with the highest DFBETA, which scales the leave-one-out change in the regression coefficient by square root of the sample size. Most influential observations are biasing the coefficient up, and they are concentrated in the early 2000s recession. As stated in the main text, it is not obvious whether this is a “feature” or a “bug” of the results given that the early 2000s provide much of the variation in the instrument’s conventional applications.

\[^{43}\text{A predictability regression of the sort summarized in Table 1 gives an } R^2 \text{ of 26.2\% for predicting whether or not rates will change.}\]
Table A6: Estimation of regression (5.1) with controls for Greenbook output forecasts.

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Fed Funds target</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Sent}_t$</td>
<td>0.275  0.175  0.316  0.477  0.539</td>
</tr>
<tr>
<td></td>
<td>(0.228)  (0.219)  (0.227)  (0.243)  (0.248)</td>
</tr>
</tbody>
</table>

Controlling GB growth FC at $h = 0, 1, 2, 3, 4$

Lag change controls? ✓ ✓ ✓ ✓ ✓

$N$ 90
$R^2$ 0.987  0.987  0.986  0.985  0.984

Table A7: Estimation of regression (5.1) from 1995 to 2008, for above and below median values of unemployment sentiment.

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Target rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Sent}_t^+$</td>
<td>0.586  0.330  0.152</td>
</tr>
<tr>
<td></td>
<td>(0.368)  (0.304)  (0.326)</td>
</tr>
<tr>
<td>$\text{Sent}_t^-$</td>
<td>0.747  0.590  0.421</td>
</tr>
<tr>
<td></td>
<td>(0.283)  (0.216)  (0.213)</td>
</tr>
</tbody>
</table>

Lag change controls? ✓ ✓ ✓
Fed Put controls? ✓
Macro data controls? ✓

$R^2$ 0.985  0.986  0.987
$N$ 108

C. ADDITIONAL TESTS: SENTIMENT AND POLICY

C.1 Additional tests of policy rules

Table A6 estimates regression (5.1) with additional controls for the Greenbook forecast of real GDP at the specified horizon. The shorter-horizon forecasts are close to a sufficient statistic for the Fed’s use of sentiment information.

Table A7 replicates Table 3 with separate inclusion of positive and negative shocks. Across the board, negative shocks matter more.

C.2 Survey gaps and monetary surprises

I regress monetary surprises (policy news shocks) on the same month’s Greenbook-Blue Chip survey gap (for the nowcast; though results are robust to different horizons), the previous scheduled
Outcome: avg. GDP revision

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surprise$_t$ × DiffSign$_t$</td>
<td>0.622</td>
<td>(0.442)</td>
</tr>
<tr>
<td>Surprise$_t$ × SameSign$_t$</td>
<td>1.685</td>
<td>(0.728)</td>
</tr>
<tr>
<td>PrSurprise$_t$ × DiffSign$_t$</td>
<td>4.120</td>
<td>(1.014)</td>
</tr>
<tr>
<td>PrSurprise$_t$ × SameSign$_t$</td>
<td>1.766</td>
<td>(1.788)</td>
</tr>
<tr>
<td>UnprSurprise$_t$ × DiffSign$_t$</td>
<td>0.047</td>
<td>(0.395)</td>
</tr>
<tr>
<td>UnprSurprise$_t$ × SameSign$_t$</td>
<td>1.653</td>
<td>(0.880)</td>
</tr>
<tr>
<td>SameSign$_t$</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>$N$</td>
<td>129</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.064</td>
<td>0.194</td>
</tr>
</tbody>
</table>

Table A8: Regression of Blue Chip forecast revisions on monetary surprises, with stock-based and sentiment-based decompositions. Standard errors in parenthesis are robust (EHW).

The model fits with $R^2$ 20.39%. The two sentiment variables are jointly significant at the 5% level (p-value: 0.033); the four Greenbook gap variables are jointly significant at the 2% level (p-value: 0.011). When I add the same-month and previous-month levels of the Greenbook output forecast at 0 and 4 quarter horizons, as suggested by Ramey (2016), the $R^2$ increases to 25.6% but again the Michigan variables have p-value 0.029.

C.3 Stock market responses

To study the consistency of my results with the identification strategy of Jarocinski and Karadi (2018), I calculate SameSign$_t$ as an indicator for whether the stock market return in the 30-minute window around the announcement had the same sign as the policy news shock (DiffSign$_t$ as the opposite). I report regressions of Blue Chip GDP growth forecasts, averaged over quarters 1 to 3 for brevity of presentation, on the monetary surprise plus interactions with the same-sign variable. Like in the main text, I exclude months in which the FOMC meeting was before or on the 7th
Table A9: Equation (C.2) estimated for four different forecast revisions

<table>
<thead>
<tr>
<th>Outcome: Blue Chip revisions of . . .</th>
<th>GDP</th>
<th>PCE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$q = 1$</td>
<td>$q = 3$</td>
</tr>
<tr>
<td>-------------------------------------</td>
<td>-------</td>
<td>-------</td>
</tr>
<tr>
<td>$(1)$</td>
<td>$(2)$</td>
<td>$(3)$</td>
</tr>
<tr>
<td>PrSurprise$_t$</td>
<td>4.282</td>
<td>0.592</td>
</tr>
<tr>
<td></td>
<td>(2.110)</td>
<td>(0.790)</td>
</tr>
<tr>
<td>UnprSurprise$_t$</td>
<td>-0.920</td>
<td>-0.261</td>
</tr>
<tr>
<td></td>
<td>(0.533)</td>
<td>(0.235)</td>
</tr>
<tr>
<td>N</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.076</td>
<td>0.014</td>
</tr>
</tbody>
</table>

Table A9: Equation (C.2) estimated for four different forecast revisions

(before the Blue Chip survey may have been due).

The first column of Table A8 runs this specific regression:

$$\text{AvgRevision}_{t+1} = \beta_s \cdot (\text{Surprise}_t \times \text{SameSign}_t) + \beta_d \cdot (\text{Surprise}_t \times \text{DiffSign}_t) + \gamma \cdot \text{SameSign}_t + \epsilon_t$$

Having a same-sign stock market return has a fairly large, but imprecise, interaction coefficient.

In column 2, I run the same regression but split between unpredicted and predicted surprises:

$$\text{AvgRevision}_{t+1} = \beta_{ps} \cdot (\text{PrSurprise}_t \times \text{SameSign}_t) + \beta_{pd} \cdot (\text{PrSurprise}_t \times \text{DiffSign}_t) + \beta_{us} \cdot (\text{UnprSurprise}_t \times \text{SameSign}_t) + \beta_{ud} \cdot (\text{UnprSurprise}_t \times \text{DiffSign}_t) + \gamma \cdot \text{SameSign}_t + \epsilon_t$$

Column 2 demonstrates, consistently with this paper’s story, that this extra effect manifests almost entirely for the predictable component of the monetary surprise. From this perspective, the sign of same-day stock market returns seems a weakly less useful conditioning variable for “classifying” monetary surprises than lagged sentiment.

C.4 Revisions in subsequent months

I estimate the following regression, which is a version of (7.5) but two months after the FOMC announcement:

$$\text{Rev}_{t+2}^{Y,q} = \alpha^{Y,q} + \beta^{Y,q,p} \cdot \text{PrSurprise}_t + \beta^{Y,q,u} \cdot \text{UnprSurprise}_t + \epsilon_{t+1}^{Y,q}$$ (C.2)
I maintain the same restrictions on the sample (i.e., excluding FOMC meetings that occurred very early in the month). The results, in Table A9, confirm positive responses to the predicted component and also estimate, imprecisely, negative responses to the unpredicted component (in line with being a “true” monetary shock).

D. Micro-foundations for Model

There are a continuum of households \( i \in [0, 1] \), each with log preferences over consumption over the infinite future. The discount geometrically at rate \( \beta \). Their intertemporal preferences are represented by the following:

\[
\mathcal{U} = \sum_{t=0}^{\infty} \beta^t \log C_{it}
\]

They can borrow and lend at risk-free rate \( R_t \) between the periods, incomes \( (Y_{it})_{t \geq 0} \), and zero other initial wealth. These incomes are known at time \( t \).

The consumption policy function is

\[
C_{i0} = (1 - \beta) \mathbb{E}_{i0} \left[ \sum_{s=0}^{\infty} \frac{Y_{is}}{\prod_{j=0}^{s} R_j} \right]
\]

More generally, for any period \( t \),

\[
C_{it} = (1 - \beta) \mathbb{E}_{it} \left[ \sum_{s=t}^{\infty} \frac{Y_{is}}{\prod_{j=t}^{s} R_j} \right] \tag{D.1}
\]

Let each consumer have income proportional to the aggregate: \( Y_{it} \equiv Y_t, \forall i \in [0, 1] \). The market clears as \( C_t = \int_i C_{it} \, di = Y_t \). There is a supply block of the economy that is suppressed because output is demand determined — the agents commit to supply enough labor as necessary to meet demand. Let \( Y_t \equiv 1 \) be the “natural” rate of output that is produced when labor supply is optimal.

**Log-linearization.** The log-linearized consumption policy takes the following “permanent income” form (with lowercase letters standing for log-deviation quantities):

\[
c_{it} = (1 - \beta) y_{it} + \sum_{s > t} \beta^{s-t} \mathbb{E}_{it} \left[ (1 - \beta) y_{is} - r_s \right] \tag{D.2}
\]
Nesting in abstract model. The previous fits the abstract model after one ensures that expected income and interest rates are uniformly 0 (i.e., at steady state) for \( t \geq 3 \), and that the interest rate is at steady state in period 0.

A steeper Keynesian cross (and lower weight on intertemporal substitution effects) corresponds to longer periods, which comprise a larger fraction of lifetime income. The fraction of capitalized wealth determines whether the transmission is intermediated by asset prices or directly via agents’ expectations.

E. Recursive VAR

A different interpretation of all the previous facts is that there is plausibly two-way feedback between monetary policy and average beliefs even within a single months, which needs to be jointly modeled. A relevant test is whether the VAR-implied monetary reaction function (i.e., the monetary policy row of the SVAR’s structural form) predicts a non-zero coefficient for consumer sentiment. This is a “more structural” version of the previous monetary rule estimation, with a larger set of controls (e.g., lags of all relevant VAR variables) disciplined by an informed prior. This allows allows for interesting comparisons of identification methods in the multiple-equation literature.

I estimate a medium-size VAR using monthly data on the following six variables: log Industrial Production, the log consumer price level, unemployment, the Gilchrist and Zakrajšek (2012) excess bond premium, the Michigan “unemployment sentiment” variable, and the effective (monthly average) Federal Funds rate. I restrict the sample to 1994:5 to 2014:3 and estimate with 8 lags. Appendix E describes the details, including my Bayesian prior specification (which is a standard “Minnesota” prior). As a baseline, I identify structural shocks (and the monetary policy reaction function) by causally ordering the variables as listed. This allows, in particular, for the largest possible set of monetary policy reactions.

E.1 Priors and inference

Let \( n \) be the number of variables and \( p \) be the number of lags. My model has \( n \times n \times p \) reduced-form coefficient parameters in the \( (A_t)_{j=1}^{p} \) 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).
Reduced Form Coefficients $A_j$. As a minimal proper prior, I implement the “Minnesota prior”
dummy observations described explicitly in SZ. These implement independent Gaussian priors for
each coefficient, centered around 1 for own first lags and 0 for everything else, with prior precision
increasing (prior variance decreasing) for further lags. The economic interpretation of the prior
mean is an independent random walk for each variable. The “tightness” and “decay” for these
dummy observations are uniform across equations. I choose values of 3 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 1.

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

E.2 Monetary response function

Assume the VAR has the following structural form for data vector $y_t$, contemporaneous response
matrix $A_0$, positive lag polynomial $A(L)$, and structural shock $\varepsilon_t$:

$$A_0 y_t = A(L) y_t + \varepsilon_t$$

The matrix $A_0$ is lower-triangular by assumption (Cholesky causal ordering). A different form
of this equation takes, in equation row $n$, all variables except the $n$th to the right-hand-side and
normalizes:

$$y_t = B_0 y_t + B(L) y_t + \varepsilon_t$$  \hspace{1cm} (E.1)

The last row of this series of equations is like a “monetary policy rule,” writing the Federal Funds
rate as a function of current and past economic conditions and the monetary disturbance. The
penultimate row shows the response of sentiment, which is restricted not to respond contemporane-
ously to the monetary shock. Table A10 shows the posterior probability that nonzero element of
$B_0$, for these two equations, is greater than 0. There is overwhelming evidence that monetary pol-
Table A10: Posterior probabilities that entries in the matrix $A_0$ are greater than 0. Colors (red or green) denote 90% “posterior confidence” that a given entry is negative or positive, respectively.

<table>
<thead>
<tr>
<th>Shock is . . .</th>
<th>IP</th>
<th>P</th>
<th>U</th>
<th>EBP</th>
<th>MUS</th>
<th>FF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MUS</td>
<td>0.308</td>
<td>0.002</td>
<td>0.002</td>
<td>0.004</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>FF</td>
<td>0.163</td>
<td>0.931</td>
<td>0.977</td>
<td>0.078</td>
<td>0.993</td>
<td>—</td>
</tr>
</tbody>
</table>

Testing causal ordering. The true model of the world is likely not triangular. Nonetheless, it is instructive to check whether a model in which sentiment is ordered after the Federal Funds rate fits better — this is a test, among a constrained set of models, of whether it is better to allow monetary policy to follow sentiment or vice-versa at the monthly frequency. The data prefer the former model (monetary policy last) by a log posterior odds ratio of 6.79, which is sizable (i.e., the latter model is $\exp(6.79) \approx 880$ times more likely).

E.3 What do surprises correlate with?

A common strategy in the literature, which is particularly useful for “breaking” joint endogeneity problems for which short-run restrictions are not instructive, is to use an external instrument. The standard, frequentist method for estimating an external instrument “proxy SVAR” is to regress a noisy signal of the true structural shock on the VAR residuals to recover (one row of) the relationship $\tilde{\epsilon}_t = Q_t \epsilon_t$, where $\tilde{\epsilon}_t$ are the “true” structural shocks, $Q_t$ is an orthogonal (rotation) matrix, and $\epsilon_t$ are the Cholesky structural shocks.

As a rough approximation to this, without fully specifying a model for inference, I regress various plausible monetary instruments on present and past values of the normalized Cholesky residuals at the posterior mode (i.e., the “point estimate”).\(^4\) I use the time period 1995:1 to 2008:6, to avoid issues of fitting surprises at the zero lower bound, and I rescale everything to unit variance and then rescale the coefficient vector to have a norm of 1 (i.e., as a row of $Q$ should). I find, across measures, that running this regression without controlling for past residuals, as one may be tempted to given the story for exogeneity of monetary shocks, would introduce a negative (Cholesky) sentiment shock into the supposedly identified monetary shock. When I add controls for the previous months’ structural errors, there is also a correlation with a positive sentiment shock.

\(^4\)Caldara and Herbst (2019) describe how to do an exact Bayesian procedure that jointly estimates this regression with the VAR to do valid inference on all parameters jointly.
<table>
<thead>
<tr>
<th></th>
<th>Policy news</th>
<th>FFR, next meeting</th>
<th>FFR, this meeting</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>same month</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IP</td>
<td>0.028</td>
<td>0.034</td>
<td>-0.028</td>
</tr>
<tr>
<td>P</td>
<td>-0.217</td>
<td>-0.111</td>
<td>-0.036</td>
</tr>
<tr>
<td>U</td>
<td>0.097</td>
<td>0.061</td>
<td>0.112</td>
</tr>
<tr>
<td>EBP</td>
<td>0.818</td>
<td>0.479</td>
<td>0.836</td>
</tr>
<tr>
<td>MUS</td>
<td>-0.274</td>
<td>-0.181</td>
<td>-0.423</td>
</tr>
<tr>
<td>FFR</td>
<td>0.445</td>
<td>0.289</td>
<td>0.328</td>
</tr>
</tbody>
</table>

| **prev. month** |           |                   |                  |
| IP             | 0.054      | 0.159             | 0.081            |
| P              | 0.219      | 0.164             | 0.063            |
| U              | 0.059      | 0.168             | -0.098           |
| EBP            | -0.190     | -0.219            | -0.021           |
| MUS            | 0.714      | 0.566             | 0.323            |
| FFR            | 0.190      | 0.276             | 0.035            |

Table A11: Loadings of monetary instruments on own-period (and first lag) structural shocks in the Cholesky VAR. The largest two, in absolute value, are highlighted in green.

in the previous period — the exactly belief predictability identified in reduced form in previous exercises. The extent of this problem very roughly seems to decrease as the monetary instrument focuses on shorter-term rate changes. This is again roughly consistent with the reduced-form predictability results and the findings of Caldara and Herbst (2019).