Public Sentiment and Monetary Surprises

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Abstract

Public sentiment predicts movements in interest rate futures around Federal Reserve policy announcements. 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 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 medium-run output contractions, stock market reversals, and negative professional forecast revisions. This requires no Fed persuasion about fundamentals, which the data only weakly support.

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1. INTRODUCTION

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

A classic perspective is that clear communication about future policy plans helps the Fed accomplish its goals by allowing markets to price in future loosening or tightening. To empirically support this claim, the literature has argued that changes in the prices of interest rate futures contracts around FOMC announcements (henceforth, “monetary surprises”) are an acceptable measure of the newly communicated information, and then documented that surprise tightening correlates with an increase in bond yields (Kuttner, 2001; Gürkaynak et al., 2005) and a decline in equity prices (Bernanke and Kuttner, 2005) on announcement day. But an opposite possibility is that the Fed’s outlook about economic fundamentals, whether explicitly described in statements or assumed to underlie their policy content, counter-productively spills over to the public. A newer literature substantiates this point by reporting a positive correlation between the same market-based surprise tightenings and positive revisions about growth and employment by professional forecasters in the following month (Campbell et al., 2012, 2016; Nakamura and Steinsson, 2018).

This paper provides a different interpretation of the Fed’s capacity to surprise and persuade. It is centered around a new fact that contradicts both previous narratives: that measurable public sentiment before FOMC meetings predicts what markets register as a monetary surprise. Consumer pessimism in survey data (respectively, optimism) precedes surprise loosening (respectively, tightening) as measured via interest rate futures. This market under-reaction to patterns in aggregate beliefs is pervasive throughout the sample but especially at the onset of recessions (e.g., 2001 and 2007). Evidence from FOMC minutes, target rate decisions, and macro beliefs (in the Greenbook) confirm the opposite side of the story — that the modern Fed closely monitors public beliefs and actively uses policy to “hedge” against swings in consumer sentiment.

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1For 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).

2An even newer literature focuses on the possibility of additional effects in this “positive” direction that are plausibly related to either conventional or leaked communication between meetings. See Cieslak et al. (2019), Neuhierl and Weber (2018); and Morse and Vissing-Jorgensen (2019) for more discussion.
This single empirical pattern ("sentiment predicts surprises") can unify many seemingly disparate findings. Waves of pessimism before FOMC announcements explain almost all the puzzlingly negative response of output and stock prices to surprise loosening at medium-run horizons. Negative professional forecast revisions are similarly spanned almost entirely by measurable pre-announcement pessimism. Moreover, the lag at which professionals assimilate this pessimism is almost completely unaffected by the presence of an FOMC meeting. This is more consistent with even policy-savvy onlookers "agreeing to disagree" with the Fed’s outlook than being persuaded to share it.

The following scenario illustrates the main points. The Fed cuts rates because it senses sluggish aggregate demand. Markets, not fully aware of the demand headwinds, are surprised about the extent of planned future accommodation. 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; output and consumption also eventually go down. This appears, in the time series, like an initial over-reaction followed by a "correction" that matches eventual dividend flows. Professional survey expectations measured multiple weeks later turn pessimistic, but with the same lag to consumer sentiment that they normally exhibit regardless of monetary decisions. Common causation — underlying sentiment induces immediate Fed action and, with some delay, market and forecaster revisions — masquerades as the Fed’s delivering bad news to the public. Events in early 2001, as the Fed cut rates in response to a slowly evolving downturn, anecdotally fit this pattern quite closely.

The main conclusions are threefold. First, the Fed’s persuasive ability is for better or worse mostly limited to the future policy path. Second, more methodologically, appeals to the informational efficiency of financial markets may be insufficient for identifying economic "shocks" in a world of heterogeneous and slowly moving beliefs.3 Finally, something that resembles a "demand shock" from standard macro theory can germinate in the public consciousness before it is fully recognized even by experts with money on the line. This brings to the forefront theories in which heterogeneous beliefs, and uncertainty about others’ beliefs, are a driving force in business cycle

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3 For 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.
dynamics (e.g., Lorenzoni, 2009; Angeletos and La’O, 2013; Benhabib et al., 2015).

**Detailed findings.** My main empirical result correlates the past several months’ sentiment about unemployment in the University of Michigan Survey of Consumers with a weighted average of monetary surprises from a 30-minute window around FOMC announcements since 1995, as constructed by Nakamura and Steinsson (2018) to capture information about short and long-run policy decisions (“policy news”). Three lags of the unemployment variable predict these “policy news” surprises with an $R^2$ of 15.2% and adding additional lags of different variables increases that number to 20.9%. 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).

I find that the same sentiment variables are reliable predictors of Fed target rate changes, even conditional on more traditional macro indicators (output and price growth, recent stock market performance, and credit spreads). Discussion about sentiment, particularly related to downside risks of pessimism, is widespread in FOMC transcripts. Sentiment is more quickly incorporated into internal Fed (Greenbook) forecasts than their private sector (Blue Chip) counterparts, suggesting that the Fed more closely measures the pulse of aggregate demand than private sector experts do.

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 transitory rate change that (very imprecisely) traces out the conventional negative output response.

On the announcement day, equities uniformly fall and bond yields uniformly rise in response to the two different “types” of monetary surprises. 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.

The correlation between monetary surprises and Blue Chip forecasters’ revisions about real GDP, taken as evidence of persuasion effects in the literature, is mostly driven by the predictable shocks. I find only limited evidence, at short horizons, that FOMC announcements increase the
pass-through of lagged sentiment to these updates. Put differently, professional expectations have essentially the same correlation with lagged sentiment regardless of whether the FOMC makes any announcement that could publicly broadcast the information.

**Interpretation and broader scope.** In the penultimate section of the paper, I contextualize this story in a very simple, closed-form model that is inspired by the policy considerations anecdotally mentioned in my case studies of FOMC meetings and the literature on “sentiment-driven business cycles” (e.g., Lorenzoni, 2009). This demonstrates more formally how this paper’s results (shock predictability, a lack of high-frequency persuasion about fundamentals, and delayed assimilation of information) could manifest in a world in which the public (i) has heterogeneous expectations of future income and (ii) “agrees to disagree” about these fundamentals. The first condition, which is natural if important information (about consumer demand, labor markets, etc.) is dispersed, generates predictability and the potential for learning.

The second ensures that the learning is not instantaneous and also has broader implications for deciding the appropriate model for policy announcements as public signals. Much of the literature has focused on the possibility that policy announcements, as public signals to listeners eager to coordinate with one another, can have outsize influence on equilibrium outcomes (e.g., Morris and Shin, 2002). But this may not be the right model for “regular” monetary policy communication, especially when there is scope for significant disagreement about its causes and consequences.

The very last section discusses how to apply the lessons of this paper to “empirical practice”: attempting to use monetary surprises as instruments for surprise policy actions. A broad takeaway is that neither Fed actions nor market forecast errors thereof 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. If these macro shocks have limited effects on high-frequency outcomes, and Fed persuasion is limited at short horizons (as suggested by my empirical evidence), then monetary surprises may allow approximately correct tests of how monetary policy affects asset markets in the very short run. But for estimating longer-horizon effects it may be necessary to explicitly model confounding demand shocks. This involves thinking carefully about which “control variables” soak up the predictable variation in market forecast errors — a task that, for better or worse, resembles (and potentially requires) specifying the monetary rule in the first place.
Related literature. My paper connects with the large literature on using forecast data to explore information rigidity and/or non-rational expectations in macroeconomics (e.g., Coibion and Gorodnichenko, 2012, 2015; Bordalo et al., 2018) and finance (e.g., Greenwood and Shleifer, 2014; Adam et al., 2017). Of particular relevance in this literature are studies about the sensitivity of those beliefs to macro shocks, information treatments, and policy communication (the last of which is summarized nicely by Blinder et al., 2008). My message also relates to Carroll (2003)’s study of information transmission across groups (e.g., consumers, “experts,” and markets). More narrowly, Lewis et al. (2019) and Coibion et al. (2019) share my interest of relating monetary announcements to consumer sentiment. But both use much higher-frequency data and focus on estimating causal effects instead of pre-trends.

In monetary economics, in addition to the initially mentioned papers on shock measurement and monetary signaling, I relate to a newer literature proposing empirical methods to decompose “informational” and “non-informational” policy shocks (Andrade and Ferroni, 2016; Jarocinski and Karadi, 2018; Cieslak and Schrmpf, 2019; Miranda-Agrippino and Ricco, 2015; Miranda-Agrippino, 2015). The first three focus on ex-post financial responses, which my results suggest may not be particularly informative. The last two, which are most relevant to my paper, do recognize the connection between shock predictability and aggregate incomplete information. But each, in its main empirical application, focuses on professional beliefs which I find to be a sluggish indicator of demand. Neither emphasizes the role of consumer (or firm) beliefs and the connection with the Fed’s policy strategy.

Older related references in the same vein are Romer and Romer (2000)’s classic contribution on the Fed’s potential “informational advantage” and Faust et al. (2004)’s published comment about the previous. 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.

My results, from a different perspective, add direct evidence on the policy reaction to belief-

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4See also Coibion, Gorodnichenko and Kumar (2018a); Coibion, Gorodnichenko, Kumar and Ryngaert (2018c); Coibion, Gorodnichenko and Ropele (2018b) for more recent, and more direct, evidence.

5Curiously, my results are essentially opposite to Carroll (2003)’s 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 (2012) conclude from similar data that Michigan and professional inflation forecasts exhibit similar inertia in response to shocks.

6My contribution is closely related to papers highlighting the role of heterogeneous beliefs and heterogeneous interpretation of forward guidance (e.g., Andrade et al., 2019; Ehrmann et al., 2019). My paper shares the goal of digging deeper into different individuals’ or groups’ beliefs, but focuses on the coarser distinction between “experts” and the general public instead of more detailed comparisons among individual forecasters.
driven business cycles which are extensively modeled in the literature (Lorenzoni, 2009; Angeletos and La’O, 2013; Benhabib, Wang and Wen, 2015; Chahrour and Jurado, 2018). Finally, my model framework links to the theoretical literature on Central Bank communication and transparency.\footnote{Especially the related literature on how signaling potentially undermines intended direct effects (James and Lawler, 2011; Baeriswyl and Cornand, 2010) and on policy rules with dispersed information and/or bounded rationality (Angeletos and Pavan, 2009; Angeletos and Sastry, 2018).}

Roadmap. After a short discussion of measurement in Section 2, I present my main predictability result in Section 3. Section 4 provides direct evidence of the role sentiment data play in Fed decisionmaking. Section 5 demonstrates, \textit{ex post}, that sentiment-predicted monetary surprises look like demand shocks. I then dig deeper into responses of markets and professional forecasts in Section 6.

I organize my findings in a very simple model of monetary transmission in Section 7. Section 8 discusses more formally applications to shock identification questions in macro and finance. Finally, Section 9 concludes.

2. Data

2.1 Interest rate futures

My data on interest rate surprises come from Nakamura and Steinsson (2018), who themselves directly collected data from the CME Group.\footnote{A subset of these data were provided to Nakamura and Steinsson (2018) by Refet Gürkaynak in private communication.} 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 across days 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 (and, for day-to-day surprises, the realization of one overnight interest rate) provides the implied expected average interest rate for the remainder of the month (see Appendix A of Nakamura and Steinsson, 2018, for the details). 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 \textit{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 nth next contract to expire. 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 models that would naturally down-weight those observations.

**Policy news shock.** For most of the paper, I use Nakamura and Steinsson (2018)’s 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.”

### 2.2 Private sector 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 and sentiment. These data overlap completely with the monetary shocks.

In particular, I use the (survey-weighted) average response to certain questions about individual and aggregate outcomes. Appendix A.1 prints the exact questions and answers that I use in my analysis.

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 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

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10In February, the n = 1 contract expires on March 31, and the n = 2 contract expires on June 30.
3. Sentiment Predicts Surprises

I will first show results of the following form: a monetary surprise around an FOMC meeting in month $t$ positively correlates with the level of sentiment in the previous few months. I estimate the following regression for various sentiment measures at different horizons $j$ in the past and the future:

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

(3.1)

The full sequence coefficients for $J$ months prior to and $J$ months after the shock, $(\beta_j)_{j=-J}^J$, traces out the precise timing of the relationship between surprises and sentiment. In the main results, I measure the policy surprise using Nakamura and Steinsson (2018)'s policy news shock, a linear combination of surprises to current and future Fed Funds rates and future Eurodollar rates.

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\*This was confirmed from direct communication with the Michigan Survey Research Center.
3.1 Consumer sentiment

Figure 1 graphs the coefficients from a sequence of regressions (3.1) at different lags and leads with 95% confidence intervals for four Michigan consumer sentiment indicators from 1994 to 2014 (excluding the height of the financial crisis, July 2008 to June 2009). The two main indicators of general health (unemployment and business conditions sentiment), as well as Michigan’s constructed “expectations index,” spike the month before to the monetary shock.\(^{12}\) The first indicator, in particular, is generally elevated for several months prior to a positive monetary surprise. Interest rates are consistently higher than expected when survey respondents are optimistic about labor market conditions.

The bottom left panel is a particularly striking blow against the “monetary shock” interpretation: the public expects interest rates to go up in the months prior to a monetary “surprise.”\(^{13}\)

To provide a sense of scale, the regression coefficient of the monetary shock on the first lag of the unemployment sentiment has a standard-deviation-on-standard-deviation coefficient of 0.305. A one standard deviation elevation in the level of sentiment correlates with a 1.1 basis point policy news shock — obviously quite small, but not insignificant relative to the size of observed shocks (standard deviation: 3.6 basis points).

3.2 Alternative measures

I corroborate the previous story in three complementary sentiment data sources in Appendix B.1. First, I use the weekly survey of the American Association of Individual Investors about stock market bullishness to hone in on higher-frequency variation, at the cost of also shifting the focus away from macro variables (Figure A1). Here there is both significant predictability in levels and a trend that looks like smooth mean reversion leading up to the announcement.

Second, I use the monthly survey of the National Federation for Independent Businesses (Figure A2) to get a sense of small firm beliefs. Expectations of own-firm sales and assessment of whether it is a good time to expand (both seasonally adjusted) spike one month before the monetary surprise.

Third, I use the monthly consumer survey of the Conference Board (Figure A3). Responses

\(^{12}\)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) proportion of respondents who think interest rates will go up (over next 12 months) minus percentage who think down; (iv) Michigan consumer expectations index.

\(^{13}\)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 questions about future employment and business conditions have a similar correlation with shocks as in the Michigan data.

All of this suggests there is some independent “signal” in my results, evident in different measures of sentiment, instead of just Michigan-specific “noise.”

### 3.3 Extent of predictability

How much variation in the monetary surprise is spanned by these consumer sentiment variables? I regress different constructions of the shock on three lags of a subset of sentiment variables: Michigan unemployment sentiment, Michigan 12 month business condition sentiment, Michigan interest rate direction, and NFIB expected real sales. The estimated equation is

$$\text{Surprise}_t = \alpha + \sum_{x \in X} \sum_{t=1}^{3} \beta_{x,t} \cdot X_{t-t} + \varepsilon_t$$ (3.2)

The first row of Table 1 reports this model’s $R^2$ for the policy news shock, for which I have shown all results so far. The second column, which repeats the exercise with the sign of the surprise instead of the sign plus magnitude, suggests that a few outlier shocks are not completely driving the result. Numbers in parentheses are bootstrap standard errors from re-sampling all data points.
with replacement. These are all significantly different from 0. This contradicts the conventional model in which a representative investor prices risk-neutrally using all of their information, which would necessarily include average public beliefs.

**Different rates.** Rows 2-6 of Table 1 re-estimate the predictability exercise separately for different interest rate futures. Broadly, predictability is strongest for the longer maturity interest rates. These are the surprises that are most likely to correspond to 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 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).

**Financial interpretation.** It is helpful, perhaps, to put this puzzle in dollar terms. Consider a replicating portfolio that pays in proportion to the policy news shock across each announcement.\(^{14}\) The cost of this portfolio would be about 100 dollars each time, so payouts equal (percentage point unit) returns.\(^{15}\) Buying and holding this portfolio across all announcements in the sample would given an average return of essentially zero (0.129 basis points). Conditioning the decision to buy or sell on the prediction the prediction regression reported in Table 1 would produce an average return of 1.24 basis points, but with a standard deviation of 3.32 basis points.

### 3.4 Robustness and heterogeneity

**Statistical robustness.** Appendix B.2 describes an empirical Bayes approach that shrinks coefficients toward 0, which should naturally protect against over-fitting. This gives very similar results. Appendix B.3 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.

**Risk premia.** It is reasonable to wonder if my results simply reflect the fact that risk-neutrality is a poorly suited assumption in these markets. A reasonable corollary of this hypothesis is that the predictable components of the monetary surprise should not affect risk-neutral expectations of

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\(^{14}\)Because the policy news shock is a linear combination of interest rate futures shocks, this is feasible to construct.

\(^{15}\)Since futures pay out at $100 - r$ given an interest rate $r$. 
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) in Appendix B.4. I find essentially uniform correlations of the “unpredicted” and “predicted” components of surprises on these measures.

Other macro indicators. Is this a feature of sentiment in particular, or sentiment standing in for other correlated macro variables? I run a version of (3.2) 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 Gilchrist and Zakrajšek (2012)). The three lags of the unemployment sentiment variable are significant with a p-value of 0.0004, and increase the $R^2$ from 7.8% to 18.2%. IP growth also enters significantly at the 5% level in the combined regression, with an incremental $R^2$ of 2.01%. This makes sense since the Federal Reserve produces these data and may have advance knowledge of them. But this, too, is overshadowed in terms of $R^2$ by the sentiment variables.\footnote{To test a wider panel of possible macro correlates, and to compare with the predictability results of Miranda-Agrippino and Ricco (2015), I show in Appendix B.5 results controlling for the first several principal components of macro data (monthly frequency from 1992) from the 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 $R^2$.}

Subsamples and influential events. The regression of the 30-minute policy news shock on 3 lags of the Michigan unemployment sentiment variable has an $R^2$ of 15.2% in the whole sample and 20.3% in the sample post-2000 (the “main sample” of Nakamura and Steinsson (2018)). The fit is best from 2000 to 2005 ($R^2 = 36.49\%$), a period with significant rate changes (first down and then up). But it is still large from 1995 to 1999 ($R^2 = 11.3\%$) and 2006 onward ($R^2 = 13.0\%$).

Which individual observations matter? Figure 2 shows the scatter-plot for the regression of the policy news shock on the first lag of the sentiment variable. 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.6). 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.7 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...
the baby out with the bathwater.” Within the sample, 2001 is the most prevalent example of rate decreases and non-standard consumer sentiment dynamics. The case study of rate cuts in 2001 will come up in the next section.

4. Policy Tracks Sentiment

Previous authors (e.g., Nakamura and Steinsson, 2018) have claimed that high-frequency monetary surprises reflect, at least in part, the Federal Reserve’s superior ability to collect and interpret macroeconomic data. The notion of a Fed “informational advantage” traces back to Romer and Romer (2000). Here I argue that an important, and plausible, source of “systematic surprises” is the Fed’s rapid assimilation of data about aggregate beliefs, perhaps surprisingly large concern about how these beliefs will affect demand, and translation of this opinion into policy action.

(observations) reduces the coefficient from 0.083 to 0.055. This reduces the $p$-value from 0.001 to 0.026.
4.1 Case studies in 2001

A necessary condition for this hypothesis is that Fed is look at expectations data. Anecdotally, this is true. I focus on two example rate cuts from the 2001 recession, an influential period for the entire high-frequency shock literature.

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.¹⁸

   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.¹⁹ 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.

   Regional President Anthony Santomero, of the Philadelphia Fed, similarly remarks that, “given 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.” He mentions also a fairly optimistic, but downwardly revised, Blue Chip output forecast but claims not to “take that forecast literally.” The revision is still “remarkable,” he says, for such a “stodgy” indicator.

   The first column of Table 2 gives an ex-post report of the decision and its relation with beliefs. The confidence break, 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.

¹⁸Taken from the online archive of the Washington Post, accessible at https://www.washingtonpost.com/wp-srv/business/greenspan012501.htm.
¹⁹Mr. Slifman highlights, in response, 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.
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<th>January 2001</th>
<th>May 2001</th>
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<td>Rate change</td>
<td>-0.5</td>
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<td>Last Month’s Change in Sentiment</td>
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<tr>
<td>Mich. Unemp.</td>
<td>-13%</td>
<td>-3%</td>
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<tr>
<td>NFIB Sales</td>
<td>-3%</td>
<td>-3%</td>
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<td>GDP: 1Q</td>
<td>-1.2</td>
<td>-0.8</td>
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<tr>
<td>GDP: 4Q</td>
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<td>PCE: 1Q</td>
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<td>PCE: 4Q</td>
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<tr>
<td>Futures Surprise</td>
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</table>

Table 2: Sentiment, beliefs, and surprises around two FOMC meetings.

**May.** Four months later, a more substantial disagreement had opened up about the state of the economy. FOMC Adviser Donald Kohn remarked that

I think there has been an interesting disparity over the intermeeting period between the views of the markets and the views of economists. The markets seem to have become more optimistic about where the economy is going and its potential for recovery, whereas the economists — not just the economists in this building, but those on Wall Street as well — have become a little less optimistic.

At the center of the disparity is, again, confidence. Research and Statistics Division leader David Stockton clarifies that the pessimism of his qualitative outlook, over and above what model simulation suggest, is related to the “the real risk that confidence could deteriorate.” 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.\(^{20}\) Ultimately, the Fed adopts a reasonably pessimistic stance that surprises markets—as alluded to by Column 2 of Table 2 and the introduction to this paper.

\(^{20}\) Alford Broaddus, from the Richmond Fed, remarks that

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.
### 4.2 Sentiment predicts rate changes

Does this concern about sentiment show up in actual decisions? As a simple test 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 funds rate target after the date $t$ meeting, on the most recent release of a given sentiment variable ($\text{Sent}_t$) controlling for the target from the past three meetings and other recent macro indicators in the vector $X_t$. The exact regression is

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

(4.1)

With no additional controls $X_t$, this is a more flexible version of the regression run by Cieslak and Vissing-Jorgensen (2018) to determine whether the Fed systematically responds to the stock market. With additional controls, one can check if the effect of sentiment is subsumed by other macro and financial conditions.

I run this regression for three measures of economic sentiment — the sentiment indexes for unemployment and interest rates described above, plus the Consumer Sentiment 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 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 consumer sentiment.
Table 4: Estimation of (4.2), the relationship between sentiment and forecast gaps.

<table>
<thead>
<tr>
<th>Outcome: forecast gap for Real GDP</th>
<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></td>
<td>3.232</td>
<td>2.714</td>
<td>1.884</td>
<td>2.133</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.525)</td>
<td>(0.533)</td>
<td>(0.517)</td>
<td>(0.508)</td>
</tr>
<tr>
<td>Macro controls?</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>(\sigma)-on-(\sigma)</td>
<td></td>
<td>0.555</td>
<td>0.466</td>
<td>0.338</td>
<td>0.383</td>
</tr>
<tr>
<td>(N)</td>
<td></td>
<td>111</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R^2)</td>
<td></td>
<td>0.307</td>
<td>0.389</td>
<td>0.1142</td>
<td>0.2204</td>
</tr>
</tbody>
</table>

The result survives, but is further attenuated by, also 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. It is not surprising that many “real-time” economic indicators are close to collinear and difficult to tell apart in an estimated policy rule.

**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, as analyzed by Cieslak and Vissing-Jorgensen (2018): the key mechanism is insurance against the downside. The pattern is consistent with the asymmetric predictability result in Section 3.4 as well as the FOMC minutes evidence consistently emphasizing downside risk.\(^\text{21}\)

### 4.3 Internal forecasts

**Is the Central Bank responding more quickly to sentiment than professionals?** To more directly test the hypothesis that sentiment explains the difference between central bank and private-sector outlook, I check if it explains the reported gap in forecasts about important, policy-relevant variables. Let \(\text{Gap}_{t,q}\) 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

\(^{21}\) The 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).
sentiment and the same macro controls from the Taylor rule estimation:

$$\text{Gap}_{t,q} = \alpha_{y,q} + \beta \cdot \text{MichUnempSent}_{t-1} + \gamma'X_{t-1} + \varepsilon_{t,q}$$  \hspace{1cm} (4.2)$$

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. The standard deviation of the two forecast gaps in my sample, which runs from 1995 to 2009, are 0.740% and 0.707%, respectively, in units of annualized GDP growth. 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).

**Is the Fed over-reacting?** As a rough test of whether the emphasis on consumer expectations in Fed decisionmaking is reasonable, I can check whether Michigan data has any effect on decisions except through its effect on forecasts. In particular, in Appendix C.1, I re-run the main specification in column 1 of Table 4 with controls for the Greenbook output forecast at various horizons (Table A6). The higher-frequency forecasts, in particular, seem to soak up much of the variation that Michigan variables are explaining. This suggests that sentiment matters through a conventional channel of affecting staff macro expectations, and not (mainly) through swaying the viewpoints of committee members of in excess of this.

**Does this entirely explain shock predictability?** Sentiment data may not be special in Fed decisionmaking. But it may be the specific component of the Fed’s informational advantage that markets cannot replicate. 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 suggests, practically, that existing empirical methods to “clean” monetary shocks with the forecast gap (as in Gertler and Karadi, 2015; Ramey, 2016; Miranda-Agrippino and Ricco, 2015) may be insufficient. This could reflect the fact that sentiments are a better proxy for the gap between Fed and trader beliefs than the survey data gap.
The anecdotal evidence from FOMC minutes suggested that the Fed uses sentiment as a real-time indicator of aggregate demand. I now bring this interpretation full-circle with the monetary surprises data by verifying that the sentiment-spanned component of monetary surprises has demand-like effects on aggregates.

I calculate a predicted and unpredicted component of the monetary surprise based on the predictability regression (3.2) of surprises on three months’ lags of several sentiment indicators. This regression produced the main “predictability $R^2$” reported in Table 1. Let these variables be called $(\text{PrSurprise}_t, \text{UnprSurprise}_t)$ for “predicted” and “unpredicted.” 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 about 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:

\[ Y_{t+h} - Y_{t+1} = \alpha^Y_h + \beta^Y_{p,h} \cdot \text{PrSurprise}_t + \beta^Y_{u,h} \cdot \text{UnprSurprise}_t + \varepsilon_{t,h} \] (5.1)

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 \((\beta^Y_{p,h})_{h\geq0}\) nor its unpredicted counterpart \((\beta^Y_{u,h})_{h\geq0}\) 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.

5.1 Interest rates

A first question to “validate” the response of long-term bonds and interest rate futures is to check the ex-post behavior of interest rates. Figure 3 estimates (5.1) for the monthly (average) Federal Funds rate and 1-year Treasury yield up to and including 2008 (i.e., before the ZLB).

Obviously the markets have something wrong — the predictable shock dominates the long-run response of interest rates, despite constituting only a minority (about 20%) of the original surprise variable. A one standard deviation “predictable surprise” over this period correlates with a 0.50% or 50 basis-point change in the Federal Funds rate after 24 months. This is economically quite large, though imprecisely estimated.

5.2 Output and prices

What is happening to the most relevant policy outcomes? I estimate (5.1) now for output (Industrial Production), prices (the PCE deflator), and consumption (PCE). The predicted shock looks like a relatively large demand shock that fades away with time. Whether or not policy is causes that reversion is impossible to say, though the timing of the interest rate ramp-up in Figure 3 with the output decline in Figure 4 lines 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 particularly for 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 -0.004 at the 12-month horizon — unsurprisingly small given

---

\(^{22}\)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.
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 serious -0.044 and -0.118. But the more “conventional” instrumental variables estimator that scales by the shock impact on the same-month average Fed Funds or 1-year Treasury would be extremely unstable, given the weak first-stage evident from Figure 3.

6. **Asset Prices and Forecasts**

The previous section showed that the predictable and unpredictable components of monetary surprises correlate with very different outcomes. The former looks like a slowly accelerating demand shock, while the latter is a transitory interest rate change with consistently negative (and quantitatively non-negligable) effects. A few months after the fact, given some basic macro data, the distinction is somewhat obvious.

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 (from the definition of the policy news shock as a linear combination of surprises). 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 shock:

$$y^m_t = \alpha^m + \beta^m_P \cdot \text{PrSurprise}_t + \beta^m_u \cdot \text{UnprSurprise}_t + \epsilon^m_t$$  \hspace{1cm} (6.1)

Note that I do not normalize the shocks 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 to short rates 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 learn the different “types” of interest rate shock?

### 6.1 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 (5.1), but with log cumulative
Figure 6: Regression of cumulative S&P 500 returns (left) and difference in 1-year Treasury yield (right) on each component of monetary surprise. Shaded areas are 95% bootstrapped confidence bands.

returns (value-weighted, dividend-excluding) of the S&P 500 on the left-hand-side:

\[
100 \cdot \sum_{i=0}^{i} \log R_{t+i} = \alpha_Y^h + \beta_P^h \cdot \text{PrSurprise}_t + \beta_u^h \cdot \text{UnprSurprise}_t + \varepsilon_{t,h} \tag{6.2}
\]

The horizons \(h\) are measured in trading days (i.e., five per week) from 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.\(^{23}\) This is consistent with the story of financial market confusion in bond and futures markets, and a further contradiction to the claim the Fed clearly signals the demand shock of Figure 4. If Fed announcements clearly signaled this future path of the economy, holding fixed the interest rate expectations in each case, one would expect stocks to differentially jump in response to the predictable shock component.

Over time, though, the responses diverge. The predictable increase in stocks after the monetary surprise is puzzling in its own right. It also curiously resembles the stock overreaction reported in

\[^{23}\text{Replicating the same regression with the “high-frequency” change in stock prices in a 30-minute window around the announcement tells the same story. The point estimates are -0.0607 and -0.0322 on the unpredicted and predicted components of the surprise, respectively. These have (bootstrap) standard errors 0.016 and 0.034, respectively.}\]
Bernanke and Kuttner (2005), but cast in a new light of misreading macro conditions.

The fact that markets do not immediately learn about positive demand conditions from the Fed ostensibly boosts monetary transmission to some extent, as long as relevant wealth effects for consumers “register” within relatively short horizons and/or the negative stock market performance itself dampens consumer or firm expectations.

### 6.2 Bond yields

The second panel of Figure 6 estimates a similar specification (6.2) for changes in one-year Treasury yields $Y_t$:

$$Y_{t+h} - Y_{t-1} = \alpha_h^Y + \beta_p^h \cdot \text{PrSurprise}_t + \beta_u^h \cdot \text{UnprSurprise}_t + \varepsilon_{t,h} \quad (6.3)$$

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.

Slow response of bond yields has the opposite implications as slow response of stocks for monetary transmission. In the unpredicted case, it is a boon for markets to assume a longer-term monetary shock than in reality. In the predicted case it delays market pass-through of short-rate tightening to more relevant longer-term rates.
6.3 Professional forecasts

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 to the Blue Chip Economic Indicators’ survey. The Blue Chip survey, according to its own website, is taken each month by more than 50 economists “employed by some of America’s largest and most respected manufacturers, banks, insurance companies, and brokerage firms.” The literature, notably including Nakamura and Steinsson (2018), has interpreted these expectations in single-agent models as jointly representative of financial market, firm, and consumer expectations. In light of all my previous results, it seems more realistic (and cautious) to assume they are very relevant for the first category, partially for the second, and potentially not at all for the third.

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). The specification for the odd columns of Table 5, given response forecast revision for variable $Y$ and horizon $q$, $\text{Rev}_{t+1}^{Y,q}$, is

$$\text{Rev}_{t+1}^{Y,q} = \alpha^{Y,q} + \beta^{Y,q} \cdot \text{Surprise}_t + \epsilon_{t+1}^{Y,q}$$

(6.4)

These columns largely replicate the findings of Campbell et al. (2012) and Nakamura and Steinsson (2018). But the even-numbered columns, which estimate the same specification separately on predicted and unpredicted components of the surprise,

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

(6.5)

reveal that the vast majority of these effects come from the predictable component of monetary surprises. Put differently, the effects of additional monetary surprise holding fixed the value of the relevant sentiment fundamentals are much smaller and equal to the coefficients on the unpredicted variable.

24https://lrus.wolterskluwer.com/store/blue-chip-publications/
Table 6: Placebo regressions for predictable monetary surprises. Standard errors are bootstrapped (including the generated regressor).

### 6.4 The importance of horizon

The following simple calculation sheds more light on these mechanisms. 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

\[
\text{Rev}_{t+1}^Y = \alpha_t + \beta_{Y,t} \cdot \text{PrSurprise}_t + \gamma_{Y,t} \cdot (\text{PrSurprise}_t \cdot \text{FOMC}_t) + \epsilon_{t+1}
\]  

now estimated on the entire sample, excluding months with an unscheduled FOMC meeting or FOMC meeting on the 7th or before. The key coefficient is the interaction \(\gamma_{Y,t}\), which measures how much more markets react to sentiment (summarized in the one-dimensional index \(\text{PrSurprise}_t\)) when the FOMC makes an announcement. 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, at longer horizons, there is something to this story — particularly for consumption, the variable about which sentiment likely contains the most information. These patterns are consistent with my previous finding of greater predictability for longer-horizon futures.

A plausible story is that markets are particularly underinformed about, and reliant on policy
communication to clarify, whether economic headwinds will have long-run effects. Interestingly, this was exactly the issue at hand in the January and May 2001 FOMC meetings highlighted above — in Chairman Greenspan’s words, would “something happen” to tip the economy into a protracted recession.

6.5 Revisiting same-day stock response

My results tell quite a different story than Jarocinski and Karadi (2018), who 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.25

In Appendix C.3, I show that conditioning on stock market response captures some of the asymmetry in professional belief responses that I highlight. Most of this difference seems spanned by the decomposition into predicted an unpredicted shocks. Additionally, given this paper’s premise that consumer (and investor) sentiment is endogenously low before “surprise” rate cuts, it is hard to interpret any conditioning on ex post financial variables as clearly identifying a different causal effect.

7. 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.

7.1 Setup

There is a continuum of agents \( i \in [0, 1] \) Let \( c_i \) be individual consumption. In aggregate, the market clears so total consumption equals total income: \( \int c_i \, di = Y \).

Timing. I assume 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

\[25\text{The regression of predicted policy news shocks on the sign of stock market responses has an } R^2 \text{ of 0.008. The regression with both predicted and unpredicted shocks, like the } t = 0 \text{ regression in Figure 6, gives very similar point estimates for each component.}\]
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 \( t = 2 \), which represents a sort of “infinite future,” interest rates go back to the steady state.

**Demand.** Each individual agent \( i \) has a permanent-income consumption function. In Appendix D, I solve (and log-linearize) a model in which consumers have (i) income proportional to aggregate output and (ii) log preferences, while prices are perfectly rigid and thus output is purely demand-determined. Let \( \mathbb{E}_{i0}[\cdot] \) denote agent \( i \)'s at this point entirely arbitrary beliefs about future interest rates and income. Their consumption function in log deviations has the following form, for a given discount rate \( \beta \in [0, 1] \):

\[
c_{i0} = -\beta^2 \mathbb{E}_{i0}[r] + (1 - \beta) \left( Y_0 + \beta \mathbb{E}_{i0}[Y_1] + \beta^2 \mathbb{E}_{i0}[Y_2] \right) \tag{7.1}
\]

Let \( \mathbb{E}_0[\cdot] \) denote the average subjective expectation across all agents. Substituting in market clearing at \( t = 0 \), \( C_0 = Y_0 \), gives

\[
Y_0 = -\beta^2 \mathbb{E}_0[r] + (1 - \beta) \left( Y_0 + \beta \mathbb{E}_0[Y_1] + \beta^2 \mathbb{E}_0[Y_2] \right) \tag{7.2}
\]

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

\[
Y_1 = -\beta r + (1 - \beta) \left( Y_1 + \beta \mathbb{E}_0[Y_2] \right) \tag{7.3}
\]

**Asset prices.** The agents \( i \in [0, 1] \) also price an asset \( p \) which pays dividend \( Y_1 \) at \( t = 1 \) and \( Y_2 \) at \( t = 2 \). I assume for now that this asset is in zero net supply, so it can be meaningfully priced without actually affecting any equilibrium outcomes (like in a classic “Lucas tree” model).

I assume that 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, or

\[
p_0 = \beta \mathbb{E}[Y_1] + \beta^2 \mathbb{E}[Y_2] - \beta^2 \mathbb{E}[r] \tag{7.4}
\]

where \( \mathbb{E}[\cdot] \) denotes the average expectation of the market. Similarly, at \( t = 0_+ \), the same expression holds but with updated information.
At $t = 1$ the price reflects the remaining dividend:

$$p_1 = \beta \bar{E}[Y_2] - \beta r$$  \hspace{1cm} (7.5)

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 $f$ proportional to the average expectation of policy:

$$f = \bar{E}[r]$$  \hspace{1cm} (7.6)

Note there is no discounting because period $0_+$ is arbitrarily close to period 0.

There are two relevant simplifications here. The first is that markets price at average beliefs in the presence of heterogeneity. This can be formalized in the “standard” models of asset pricing with heterogeneous beliefs and speculation, in the tradition of Harrison and Kreps (1978) and a myriad related studies. The assumption in these applications 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. All I will need in my setting, essentially, is for the price to reflect some central tendency of heterogeneous beliefs. This can be micro-founded in a risk-neutral setting, as well, as long as there exist some limits to excessively large positions.

The second simplification is that a first-order approximation, which captures dividends and risk-free rates but not risk premia, is a meaningful exercise in the first place for equities. I will not dispute this point more generally but instead endeavor to show that the “first-order considerations” are enough to get correctly-signed predictions from the model in this context. In that sense I will broadly follow in the tradition of Shiller (1981) in focusing on mis-specified beliefs as a key source of asset-pricing anamolies.

Policy. Monetary policy takes place at $t = 0$. The monetary authority can respond to a survey of consumer expectations about far future income, $\bar{E}_0[Y_2]$. It is also subject to a random perturbation $\nu$, which can be thought of as a shock to the central bank’s beliefs. I assume the rule is linear with parameter $a$ controlling the slope with respect to beliefs:

$$r = a \bar{E}_0[Y_2] + \nu$$  \hspace{1cm} (7.7)

Of course it would make sense for policy to respond to economic activity and/or asset prices at $t = 1$. But it will turn out, in the solution (and regardless of theses assumptions on the monetary
rule), the approaches will yield the same results.

7.2 A heterogeneous-priors story

The following specific case of the previous model is consistent with the empirical facts.

Beliefs. Let $\varepsilon \sim \text{Normal}(0, 1)$ be an aggregate variable and let $\eta_i \sim \text{Normal}(0, \sigma^2)$ be idiosyncratic noise with some variance $\sigma^2 > 0$. Assume each individual agent has the dogmatic belief that $Y_2$ will be $\varepsilon_i$. This means that, at all time periods, the average expectation of future income is $\varepsilon$:

$$\bar{E}_t[Y_2] = \varepsilon, \ t \in \{0, 0+, 1\}$$ (7.8)

Note that, in the model described here, no such boom can actually materialize at $t = 2$. Nonetheless this optimism ($\varepsilon > 0$) or pessimism ($\varepsilon < 0$) will be self-fulfilling in earlier periods. It is also the data that the Fed will use in making its interest rate decision.

In the same framework, it is also reasonable to think about the extra monetary rule shock $\nu$ as Fed policymakers’ average realization of the belief shifter $\eta_i$. Because the monetary decision involves finite individuals, this will not average to zero.

Assume further that each agent recognizes the previous stochastic structure when trying to forecast each other’s beliefs. It is simple to show that second-order beliefs, or beliefs about others’ beliefs, are multiplied by a parameter $\lambda := (1 + \sigma^2)^{-1} \in (0, 1)$:

$$\bar{E}_t[\bar{E}_s[Y_2]] = \lambda \varepsilon, \ t \in \{0, 0+, 1\}, s > t$$ (7.9)

This follows from the fact that a very optimistic agent ($\varepsilon_i > 0$) 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).

The upshot of this, practically, is that individuals will doubt the extent to which optimism will affect aggregate outcomes and policy, both of which are functions of aggregate beliefs. The Gaussianity was necessary to ensure a clear link between belief dispersion and the correct “inertia” in second-order beliefs. This will be necessary in the present context to match inertial investor behavior in response to sentiment shocks. It is also to first approximation consistent with the direct

\[\text{26This particular point is not essential to any conclusions. It would be without loss of content, but only an increase in complexity, to introduce some role for aggregate supply and allow } \varepsilon \text{ to be “true” news about a TFP shock that manifests at } t = 2.\]
empirical evidence of Coibion et al. (2018c) on higher-order beliefs of economic actors (firms) and broader empirical evidence on aggregate belief inertia in the macroeconomy even for sophisticated professional forecasters (e.g., Coibion and Gorodnichenko, 2015; Bordalo et al., 2018).27

Finally, I assume that agents do not update these higher-order beliefs when they observe the monetary announcement. This could be formalized via Bayesian updating if the variance in the disagreement term $\eta_i$ (and, hence, $\nu$) was very large, or alternatively agents had a difficult time ascertaining the reaction function slope $a$. Concretely that means it is hard for observers to tell whether Fed policy reflects average beliefs, which everyone recognizes as important for outcomes, or an idiosyncratic feeling of Fed policymakers, which matters only through policy. Completely shutting down this updating, as an extreme case, makes the math easier without sacrificing much with respect to the evidence.

To close the model, I assume otherwise agents are rational and use equations (7.2), (7.3) and (7.7) to form expectations about endogenous objects. This puts some natural structure on how mistaken expectations matter — they affect the extent to which an individual thinks the macroeconomy will move in response to the belief shock.

**The real economy.** 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:

$$Y_1 = (1 - \beta - a)\epsilon - \nu$$

(7.10)

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 $t = 2$:

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

(7.11)

27The former reference, in particular, finds 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 $E_i[Y_2] = \epsilon$ and $E_i\bar{E}[Y_2] = \lambda \epsilon$. 

31
Note that these consumers have dampened expectations of both $Y_1$ and the future monetary policy, which will generally reduce the effect of news.\footnote{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.}

**Asset prices.** Consider now the “futures market,” which is easiest to analyze. Markets on average expect the policymaker to respond to demand shock $\lambda \epsilon$ instead of shock $\epsilon$. It is simple to compute the *ex-post* monetary surprise $\Delta := r - f = r - \mathbb{E}_0[r]$ and note that it depends positively on both shocks:

**Proposition 1 (Monetary surprise)** *The difference between the interest rate and the predicted interest rate ("monetary surprise") is $\Delta = (1 - \lambda)a \epsilon + \nu$, which depends positively on both demand shocks and monetary “trembles.”*

Note that the extent of this effect scales with both the level of inattention and the degree of monetary response. A similar result would also arise if monetary policy also responded to expected output in period 1, which is a rescaling of the same shock.

Next, consider the stock market. At $t = 0$, the stock market price depends positively on expected future output at $t = 2$, the same at $t = 1$, and the expected interest rate.\footnote{The exact expression is $p_0 = (p^2(1 - \lambda a) + \beta \lambda (1 - \beta - a))\epsilon$ which lists the terms mentioned in the main text in order.} Across the monetary announcement, agents update their beliefs only about the actual interest rate for discounting and computing output at $t = 1$. Thus the stock price generically will go down across the announcement in response to a shock to either $\epsilon$ or $\nu$:

**Proposition 2 (Stock market jump)** *The jump in stock markets across the monetary announcement, $p_{0+} - p_0$, is linear in the monetary surprise and therefore decreases in both structural shocks:*

$$p_{0+} - p_0 = -\beta(1 + \beta)\Delta$$

This combines an update about higher discount rates with an update about lower dividends, because of monetary policy’s real effects. In that sense monetary announcements are news about both discount rates and dividends even in this simple model. Additionally, the regression of this jump on the monetary surprise identifies a coefficient of interest — a combination of the effect of rates on discounting and on future output — without any contamination from $\lambda$ or distinction between “good and bad” variation in $\Delta$. 
The stock price at $t = 1$ is unaffected by both the mis-forecasting in rates and under-estimation of how the shock affects output in equilibrium: $p_1 = \beta \epsilon - r$. Moreover, there is a sense in which there are “predictable gains” from $0_+$ to $1$ based on the revelation of output at $t = 1$. Precisely, the dividend-inclusive and discounting-adjusted return $p_1 + Y_1 - \beta^{-1}p_{0+}$ increases in $\epsilon$:

**Proposition 3 (Predictable stock returns)** *The dividend-inclusive, discounting-adjusted stock gain from $0_+$ to $1$ is*

$$g := p_1 + Y_1 - \beta^{-1}p_{0+} = (1 - \beta)(1 - \lambda)\epsilon$$

*which increases in the belief shock $\epsilon$.*

When dividends (income) at $Y = 1$ are observed, the inability to recover others’ beliefs ceases to matter. The stock gains (or losses) reflect this gap.

### 7.3 Further discussion

**Modern monetary policy has a limited signaling role.** Morris and Shin (2002), in their seminal paper about public information, model policy communication as a public signal about fundamentals that may have outsize influence on equilibrium actions in a coordination game. A large follow-up literature considers the additional possibility that policy actions by themselves implicitly signal intent, creating subtle trade-offs between more aggressive and more informative policies.\(^{30}\)

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.\(^{31}\)

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. My basic model suggests that the model with no signaling at all may do a fine job explaining the data since 1995.

**Explaining public non-reaction** Why might it make sense for policy messages to have limited impact on consumer and market beliefs about fundamentals? For consumers, some (rational) inattention is not implausible. Even the sum total of macro considerations contains relatively

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\(^{30}\) Including James and Lawler (2011); Baeriswyl and Cornand (2010); Kohlhas (2017).

\(^{31}\) And instead with more emphasis on monetary response to inflation in the 1970s and 1980s.
little information about individual income (see, e.g., Pischke, 1995). Monetary announcements are a small percentage of even that and might be safely ignored by attention-constrained agents.\footnote{A similar point about rationally ignoring aggregate considerations from monetary policy for firms is made by Mackowiak and Wiederholt (2009)} Empirically it accords with an new literature about the ineffectiveness of traditional policy communication for “lay audiences” (Coibion et al., 2018a,c,b).

For markets, it is impossible to imagine that policy communication is unimportant or unobserved. But it is not impossible that participants simply “agree to disagree” with the Fed’s assessment of the economy. This sort of behavior breaks no axioms in a world of heterogeneous priors but changes the appropriate interpretation of monetary communication. While clear communication of the reasoning behind policy decisions may in the long run build credibility (which is far outside the scope of this model), the actual information may have very little persuasive effect on markets.

**The special case of recessions.** Policymakers’ anecdotal focus on confidence as an asymmetrically important issue in downturns is at odds with the simple linear model. But it is consistent with the sense that the entire model, with rigid prices and demand-determined output, would apply more closely in recessions (for instance, because of asymmetric downward wage rigidity). Hence the translation of confidence into economic activity is naturally higher on the downside and in down states of the economy.

8. **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; 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 (4.1) 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 A9). This could matter significantly for identification based on zeros in the Taylor rule, including but not limited to the recursive approach.

I also explore the implications of including various macro controls on the inference obtained.
by “proxy SVAR” techniques, which use the correlation between an excluded instrument and the reduced-form VAR residuals to identify the correct monetary shock. Monetary surprises might “work” as instruments conditional on the right controls, which orthogonalize out information in lagged sentiment. But necessarily inference is fragile to choice of controls. Ramey (2016) and Caldara and Herbst (2019) uncover a similar point with different conditioning variables.

In that sense the high-frequency approach is a “horizontal shift” from carefully specifying zeros in the Taylor rule. It replaces a full specification of policymakers’ behavior with a full specification of what markets perceive differently from policymakers. This comes, too, at a significant cost in power, since monetary surprises explain only a tiny fraction of all interest rate variation.

**What about high-frequency regressions?** 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. It is certainly possible, however, that on different time scales the exclusion restriction at least approximately holds, 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.

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.

9. Conclusion

Market forecast revisions about monetary policy are predicted by past consumer sentiment. The predictable component of these forecast errors drives most of the eventual dynamics in interest rates and beliefs. The Fed ostensibly has some ability to “beat the market” in aggregating dispersed information about demand. But it is not hugely influential in persuading markets to share its macro outlook. 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 manipulating beliefs about outcomes is a clear goal (e.g., for long-run inflation expectations).

The policy upshot is that clear communication about future policy is not particularly “self-
defeating” via a persuasion channel. Any (in this paper, unmodeled) benefits of building long-run credibility via thoroughly explaining decisions does not, at least with respect to the small policy deviations measured and studied here, come at great cost.

Additionally, the type of asset price rebounds that appear like over-reaction and correction may instead be attributed to delayed diffusion of sentiment. Anecdotally, concerns about asset market over-reaction have motivated policies of low transparency. But the Fed may not be directly “to blame” for these dynamics.

This paper, in the progress of reaching these main conclusions, offers suggestive evidence about where the major disagreement between the Fed and markets lies in this sample period: measuring and modeling aggregate demand. This is challenging enough with the benefit of hindsight and even harder in real time. FOMC Research and Statistics Division leader David Stockton admits as much during the May 2001 meeting, with particular emphasis on the difficulty of measuring confidence breaks:

[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.

Progress has obviously been made in the intervening years. But macroeconomics is far from achieving consensus on how to model and measure aggregate demand. Continuing to improve on this front, as well as allowing models to internalize even experts’ inability to forecast the future, remains an important research frontier.

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33 Alan Greenspan spoke in retrospect about how his “Fed-speak” style of unclear rhetoric was specifically designed to prevent public reaction:

As Fed chairman, every time I expressed a view, I added or subtracted 10 basis points from the credit market. That was not helpful. But I nonetheless had to testify before Congress. […] I would hypothetically think of a little plate in front of my eyes, which was the Washington Post, the following morning’s headline, and I would catch myself in the middle of a sentence. Then, instead of just stopping, I would continue on resolving the sentence in some obscure way which made it incomprehensible.

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Appendix
For Online Publication

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 AAI Survey

Historical AAI survey data are available at: 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/.

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)\(^\text{34}\) 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

\(^{34}\) 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

\[ X_t = \alpha + \sum_{j=-5}^{-1} \beta_j \cdot \text{Surprise}_{t+j} + \sum_{j=1}^{5} \beta_j \cdot \text{Surprise}_{t+j} + \epsilon_t \]  

(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. A complementary source of sentiment data is the National Federation for Independent Businesses “Small Business Economic Trends” survey. This has been administered monthly since 1986. 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 (3.1) 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 (3.1) 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 (3.1) 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 (3.1), reprinted here:

\[ \text{Sentiment}_{t+j} = \alpha_j + \beta_j \cdot \text{Surprise}_t + \epsilon_{t+j} \]  

in Figure A3. The pattern is much the same, with a spike in the month before the surprise.
Table A1: $R^2$ 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>Surprise</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Policy news factor (30 min.)</td>
<td>0.170</td>
<td>0.198</td>
</tr>
<tr>
<td>2 Fed Funds (this meeting)</td>
<td>0.023</td>
<td>0.027</td>
</tr>
<tr>
<td>3 Fed Funds (next meeting)</td>
<td>0.177</td>
<td>0.093</td>
</tr>
<tr>
<td>4 Eurodollar (2Q)</td>
<td>0.150</td>
<td>0.080</td>
</tr>
<tr>
<td>5 Eurodollar (3Q)</td>
<td>0.171</td>
<td>0.122</td>
</tr>
<tr>
<td>6 Eurodollar (4Q)</td>
<td>0.171</td>
<td>0.105</td>
</tr>
<tr>
<td>7 Orthogonal to FF</td>
<td>0.154</td>
<td>0.179</td>
</tr>
<tr>
<td>8 Policy news factor (1 day)</td>
<td>0.105</td>
<td>0.198</td>
</tr>
</tbody>
</table>

B.2 Empirical Bayes estimation

Table A1 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 $k_i = \hat{\sigma}_y^2 / \hat{\sigma}_i^2$ 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 information in further lags matters less.\textsuperscript{35} I report the posterior mode $R^2$, which is relatively close to the OLS estimates.

B.3 Pseudo-out-of-sample fit

In this section I measure whether observing certain variables would have aided in “real time” forecasting of high-frequency monetary shocks. Let $X$ 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 of an “approximate $R^2”, I calculate reduction in MSE as

$$\text{ReductionMSE} = 1 - \frac{\text{MSE}_{POOS}}{\text{MSE}_{naive}}$$ \hspace{1cm} (B.3)

\textsuperscript{35}This is often formalized in a parametric “Minnesota prior” in Bayesian time series applications.
\[
\text{(MichUmpSent}_{t-j}) \in \{1,2\} \quad \text{Sign} \quad (\Delta Y^\text{GB}_h)_{h \in \{0,4\}} \quad \text{Sign} \quad (F_t^{(k)})_{k \in \{1,2\}} \quad \text{Sign}
\]

<table>
<thead>
<tr>
<th>Measure</th>
<th>(MichUmpSent)_{t-j}</th>
<th>(\Delta Y^\text{GB})_h</th>
<th>(F_t^{(k)})_k</th>
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</thead>
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<tr>
<td>1 Policy news factor (30 min.)</td>
<td>0.085</td>
<td>-0.035</td>
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<td>2 Fed Funds (this meeting)</td>
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<td>-0.119</td>
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<td>3 Fed Funds (next meeting)</td>
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<td>6 Eurodollar (4Q)</td>
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<td>7 Orthogonal to FF</td>
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<td>8 Policy news factor (1 day)</td>
<td>0.019</td>
<td>0.015</td>
<td>0.029</td>
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Table A2: Pseudo-out-of-sample reduction in mean-squared-error, calculated as described in equation (B.3).

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 A2 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 across the board.

### B.4 Risk-neutral expectations

Let $(\text{PrSurprise}_t, \text{UnprSurprise}_t)$ be the sentiment-predicted and sentiment-unpredicted components of the monetary surprise based on estimating (3.2). This is the same construction used in Section 5. Here I will estimate regressions of the form

\[
y^m_t = \alpha^m + \beta^m_p \cdot \text{PrSurprise}_t + \beta^m_u \cdot \text{UnprSurprise}_t + \epsilon^m_t \quad (B.4)
\]

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 A3 shows the results. In general, the predicted component of surprises moves 1 and 2-year yields less than the unpredicted
<table>
<thead>
<tr>
<th>Maturity</th>
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<th>Risk-neutral</th>
<th>Difference (premium)</th>
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<tbody>
<tr>
<td></td>
<td>1Y</td>
<td>2Y</td>
<td>1Y</td>
</tr>
<tr>
<td>PrSurprise&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.977</td>
<td>0.751</td>
<td>0.713</td>
</tr>
<tr>
<td></td>
<td>(0.223)</td>
<td>(0.287)</td>
<td>(0.308)</td>
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<tr>
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<td>1.175</td>
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<tr>
<td></td>
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<td>(0.173)</td>
<td>(0.238)</td>
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<td>N</td>
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</table>

Table A3: Estimation of (B.4) 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></th>
<th>Policy news</th>
<th>FFR, next meeting</th>
<th>Eurodollars, 4Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.138</td>
<td>0.240</td>
<td>0.190</td>
</tr>
<tr>
<td>3 lags each of 4 factors</td>
<td>1.73 (0.07)</td>
<td>1.91 (0.04)</td>
<td>1.57 (0.11)</td>
</tr>
<tr>
<td>3 lags of Unemp. sentiment</td>
<td>6.32 (0.00)</td>
<td>3.81 (0.01)</td>
<td>6.12 (0.00)</td>
</tr>
<tr>
<td>N</td>
<td>142</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table A4: R<sup>2</sup> and F-stats from regressing monetary surprises on lags of macro aggregate factors and Michigan unemployment sentiment. p-values are in parenthesis.

component. But there is not clear evidence that it is acting primarily through the channel of risk premia as measured in this model.

### B.5 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 A4 suggests not. For brevity, I report only F statistics and R<sup>2</sup> 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.6 Different events

Of the 146 shocks in the main sample, 92 (or 63%) are positive — forecasts were revised upward. The first panel of Figure A4 shows coefficients from a regression like (3.1) with separate positive and negative shocks:

$$
\text{MichUnempSent}_{t+j} = \alpha_j + \beta^\text{Pos}_j \cdot \max(\text{RateSurprise}_{t}, 0) + \beta^\text{Neg}_j \cdot \min(\text{RateSurprise}_{t}, 0) + \varepsilon_{t+j}
$$

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

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

(B.6)

Shocks on FOMC meetings with rate changes have a significantly higher standard deviation (0.05 versus 0.02). The second panel Figure A4 shows the coefficients from a version of (3.1) with shocks split on this outcome. The story seems mainly about rate changes, which broadly suggests belief inertia and/or slow learning.\(^{36}\) These will be important themes in the remainder of the paper.

Finally, at the risk of reducing precision with a smaller sample, I subset among the rate change surprises to changes in the same direction as the policy news surprise and changes in the opposite direction. In the former case (31 “momentum” shocks), markets “undershoot” the rate change; in the latter (15 “non momentum” shocks), they undershoot. The final, bottom, panel of Figure A4 runs the following regression

\[
\text{MichUnempSent}_{t+j} = \alpha_j + \beta_j^{\text{Momentum}} \cdot (\text{RateSurprise}_t \cdot \text{Momentum}_t) \\
+ \beta_j^{\text{NoMomentum}} \cdot (\text{RateSurprise}_t \cdot \text{NoMomentum}_t) + \epsilon_{t+j}
\]  

(B.7)

and shows that there is weakly more evidence that the “momentum” shocks are predictable. There is possibly evidence of an opposite predictability pattern for reverses: in particular, if agents are pessimistic, they might expect rates to go down when in fact they go up. All of this provides additional suggestive evidence for a story based on belief inertia.

\section*{B.7 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

\(^{36}\)A predictability regression of the sort summarized in Table 1 gives an \( R^2 \) of 26.2\% for predicting whether or not rates will change.
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>

Table A6: Estimation of regression (4.1) with controls for Greenbook output forecasts.

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

Table A6: Estimation of regression (4.1) with controls for Greenbook output forecasts.

$N = 90$

$R^2 = 0.987$  $0.987$  $0.986$  $0.985$  $0.984$

C. ADDITIONAL TESTS: SENTIMENT AND POLICY

C.1 Additional tests of policy rules

Table A6 estimates regression (4.1) 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: Target rate

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Sent$_t^+$</td>
<td>0.586</td>
<td>0.330</td>
<td>0.152</td>
</tr>
<tr>
<td></td>
<td>(0.368)</td>
<td>(0.304)</td>
<td>(0.326)</td>
</tr>
<tr>
<td>Sent$_t^-$</td>
<td>0.747</td>
<td>0.590</td>
<td>0.421</td>
</tr>
<tr>
<td></td>
<td>(0.283)</td>
<td>(0.216)</td>
<td>(0.213)</td>
</tr>
<tr>
<td>Lag change controls?</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Fed Put controls?</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Macro data controls?</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.985</td>
<td>0.986</td>
<td>0.987</td>
</tr>
<tr>
<td>$N$</td>
<td>108</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table A7: Estimation of regression (4.1) from 1995 to 2008, for above and below median values of unemployment sentiment.

meeting’s (indexed by $p(t)$), and the last two lags of the Michigan measure:

$$\text{Surprise}_t = \alpha + \sum_{j=1}^{2} \gamma_j \cdot \text{MichUnempSent}_{t-j} + \sum_{x \in \{y, \pi\}} (\beta_{x,t} \cdot F_{x,0,t} + \beta_{x,p(t)} \cdot F_{x,0,p(t)}) \quad (C.1)$$

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

The first column of Table A8 runs this specific regression:

$$\text{AvgRevision}_{t+1} = \beta_{s} \cdot (\text{Surprise}_t \cdot \text{SameSign}_t) + \beta_{d} \cdot (\text{Surprise}_t \cdot \text{DiffSign}_t) + \gamma \cdot \text{SameSign}_t + \varepsilon_t$$
**Outcome: avg. GDP revision**

<table>
<thead>
<tr>
<th>Outcome</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surprise$_t \times$ DiffSign$_t$</td>
<td>0.622</td>
<td>3.753</td>
</tr>
<tr>
<td></td>
<td>(0.442)</td>
<td>(0.837)</td>
</tr>
<tr>
<td>Surprise$_t \times$ SameSign$_t$</td>
<td>1.685</td>
<td>2.363</td>
</tr>
<tr>
<td></td>
<td>(0.728)</td>
<td>(1.487)</td>
</tr>
<tr>
<td>PrSurprise$_t \times$ DiffSign$_t$</td>
<td>0.047</td>
<td>1.237</td>
</tr>
<tr>
<td></td>
<td>(0.402)</td>
<td>(1.026)</td>
</tr>
<tr>
<td>UnprSurprise$_t \times$ DiffSign$_t$</td>
<td>0.047</td>
<td>1.237</td>
</tr>
<tr>
<td></td>
<td>(0.402)</td>
<td>(1.026)</td>
</tr>
<tr>
<td>SameSign$_t$</td>
<td>✓</td>
<td>✓</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).

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:

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

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.

**D. Micro-founding 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 $(Y_{it})_{t\geq0}$, and zero other initial wealth. These incomes are known at time $t$.

The consumption policy function is

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

More generally, for any period $t$,

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

Let each consumer have income proportional to the aggregate: $Y_{it} \equiv Y_t, \forall i \in [0, 1]$. The market clears as $C_t = \int C_{it} \, di = Y_t$. 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):

$$c_{it} = (1 - \beta)y_{it} + \sum_{s>t} \beta^{s-t}E_{it}\left[(1 - \beta)y_{is} - r_s\right] \quad (D.2)$$

**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. SVAR Model**

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 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 $(A_j)^p_{j=1}$ and $n(n-1)$ covariance matrix parameters in $\Sigma$ to estimate. I specify a proper prior on these parameters along the lines of the one suggested by Sims and Zha (1998) (henceforth, SZ).

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, we 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 $\epsilon_t$:

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

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:

$$y_t = B_0 y_t + B(L)y_t + \epsilon_t$$

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 contemporaneously to the monetary shock. Table A9 shows the posterior probability that nonzero element of $B_0$, for these two equations, is greater than 0. There is overwhelming evidence that monetary policy responds to sentiment. Sentiment itself responds contemporaneous to news in credit markets, labor markets, and the price level.

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 economically sizable (i.e., the latter model is $\exp(6.79) \approx 880$ times more likely).
E.3 What do HF 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”). 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 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.
<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>-0.028</td>
<td>-0.006</td>
</tr>
<tr>
<td>P</td>
<td>-0.217</td>
<td>-0.036</td>
<td>0.038</td>
</tr>
<tr>
<td>U</td>
<td>0.097</td>
<td>0.112</td>
<td>0.078</td>
</tr>
<tr>
<td>EBP</td>
<td>0.818</td>
<td>0.836</td>
<td>0.553</td>
</tr>
<tr>
<td>MUS</td>
<td>-0.274</td>
<td>-0.423</td>
<td>-0.307</td>
</tr>
<tr>
<td>FFR</td>
<td>0.445</td>
<td>0.328</td>
<td>0.260</td>
</tr>
<tr>
<td><strong>prev. month</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IP</td>
<td>0.054</td>
<td>0.159</td>
<td></td>
</tr>
<tr>
<td>P</td>
<td>0.219</td>
<td>0.164</td>
<td></td>
</tr>
<tr>
<td>U</td>
<td>0.059</td>
<td>0.168</td>
<td></td>
</tr>
<tr>
<td>EBP</td>
<td>-0.190</td>
<td>-0.219</td>
<td></td>
</tr>
<tr>
<td>MUS</td>
<td>0.714</td>
<td>0.566</td>
<td></td>
</tr>
<tr>
<td>FFR</td>
<td>0.190</td>
<td>0.276</td>
<td></td>
</tr>
</tbody>
</table>

Table A10: 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.