WORKING PAPER · NO. 2022-130

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SEPTEMBER 2022

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We thank Yueran Ma for help with the Blue Chip Financial Forecasts data and Lars Hansen, Jean-Paul L'Huillier, Anil Kashyap, Aeimit Lakdawala, Yueran Ma, Ilaria Piatti (discussant), and Jeremy Stein and participants at various research seminars and conferences for valuable comments.

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JEL No. E03,E4,E42,E44,G12

ABSTRACT

We estimate perceptions about the Fed's monetary policy rule from micro data on professional forecasters. The perceived rule varies significantly over time, with important consequences for monetary policy and bond markets. Over the monetary policy cycle, easings are perceived to be quick and surprising, while tightenings are perceived to be gradual and data-dependent. Consistent with the idea that forecasters learn about the policy rule from policy decisions, the perceived monetary policy rule responds to high-frequency monetary policy surprises. Variation in the perceived rule impacts financial markets, explaining changes in the sensitivity of interest rates to macroeconomic announcements and affecting risk premia on long-term Treasury bonds. It also helps explain forecast errors for the future federal funds rate. We interpret these findings through the lens of a model with forecaster heterogeneity and learning from observed policy decisions.

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1 Introduction

Increased transparency and improved communication with the public has been a focus of central bankers over the last 30 years. Since it began announcing meeting decisions in 1994, the Federal Reserve has made an ever-increasing volume of information available, including detailed economic and interest rate forecasts, meeting transcripts, and intermeeting speeches. The main rationale for these efforts is the idea that the public's perceptions of monetary policy—including its goals, framework, and future course—play a crucial role in determining policy effectiveness. As former Fed Chair Bernanke explained: "Clarity about the aims of future policy and about how the central bank likely would react under various economic circumstances reduces uncertainty and—by helping households and firms anticipate central bank actions—amplifies the effect of monetary policy on longer-term interest rates" (Bernanke, 2010). Indeed, theoretical work suggests that the public's perceptions about the conduct of monetary policy determine the trade-offs faced by policy-makers, the anchoring of long-run expectations, and the stability of macroeconomic equilibria (e.g., Clarida et al. (2000), Eggertsson and Woodford (2003), and Eusepi and Preston (2010)). These perceptions are also crucial for financial market reactions to monetary policy surprises and macroeconomic announcements.[1] In other words, the success of monetary policy depends not only on the actual framework used by policy makers, but also public perceptions of that framework.

Monetary policy rules offer a compact way to summarize the policy framework and have been used extensively in both positive and normative analyses of monetary policy since the seminal work of Taylor (1993). Empirical estimates of policy rules generally use macroeconomic time-series data, which has two drawbacks. First, such estimates only capture actual, historical policies, not perceptions about monetary policy. In the absence of full information rational expectations (FIRE), the public may well have different perceptions about monetary policy than historical rules would suggest, as evidenced by the large literature on imperfect information and nonrational expectations (e.g., Coibion and Gorodnichenko (2015) and Bordalo et al. (2020)). Second, time-series estimates of the monetary policy rule can only uncover low-frequency, decade-by-decade changes in the rule's parameters, while perceptions may shift at higher frequencies. As a result, there are important gaps in what we know about the public's perceptions of the Fed's monetary policy rule, and how these perceptions change in response to policy actions and over the business cycle.[2]

[1] See, e.g., Piazzesi (2001), Ang and Piazzesi (2003), Cieslak (2018), Bauer and Swanson (2021), Law et al. (2020), and Bianchi et al. (2022a).

[2] Previous work estimating low-frequency changes in the monetary policy rule using historical data include Clarida et al. (2000); Kim and Nelson (2006); Boivin (2006); Orphanides (2003a); Cogley and Sargent (2005);

We break this impasse with new estimates of the perceived monetary policy rule using individual macroeconomic forecasts from the Blue Chip Financial Forecasts (BCFF). We measure perceptions of professional forecasters rather than households, uncovering the monetary policy rule perceived by sophisticated economic agents. Using monthly forecast panels for the federal funds rate and macroeconomic fundamentals we can estimate the perceived monetary policy rule and detect parameter shifts at substantially higher frequencies than previous work.

In its simplest form, our estimation methodology boils down to relating fed funds rate forecasts to inflation forecasts and output gap forecasts in the manner of Taylor (1993) using a forecaster-by-horizon panel each month. We obtain similar results using panel regressions and a state-space model. In the first method, we separately estimate regressions for each monthly panel of survey forecasts, accounting for forecaster heterogeneity using fixed effects. These regressions utilize 30-50 forecasters and forecast horizons ranging from 0 through 5 quarters. In our second method, we estimate a state-space model (SSM), where the latent state variables are the policy rule coefficients and the perceived long-term nominal rate. The SSM estimates are similar to the regression estimates, but smoother and more precisely estimated because they combine information across surveys over time.

Our empirics focus on the perceived policy response to the output gap for two reasons related to our sample period. First, over our post-1985 sample, inflation has been relatively stable and close to the Fed's now-explicit two percent target. As noted by Clarida et al. (2000), estimation of the response coefficient on inflation requires a sample with sufficient variation in inflation. Otherwise "one might mistakenly conclude that the Fed is not aggressive in fighting inflation" (p. 143). Second, the Fed's output gap response may also be interpreted as a summary statistic for the Fed's response to expected inflation in an economy dominated by demand shocks, as was plausibly the case for most of our sample period.

We first examine how and why the perceived monetary policy rule varies over time. In Section 3, we document that the perceived policy rule varies substantially over the monetary policy cycle. In particular, the perceived coefficient on the output gap, $\hat{\gamma}_t$, is positively related to the slope of the yield curve. When the yield curve is flat or downward-sloping, $\hat{\gamma}_t$ is low, consistent with the view that easing cycles begin with rate cuts that are quick and unpredictable—the Fed tries to "get ahead of the curve" by aggressively easing, and as a result, the policy rate is viewed to be less dependent on the macroeconomic outlook going forward. Conversely, $\hat{\gamma}_t$ is high at the early stages of tightening cycles, when the yield curve

Coibion and Gorodnichenko (2011). Notable exceptions are Carvalho and Nechio (2014) who study whether household expectations and professional forecasts are directionally consistent with a Taylor-type rule, and Bianchi et al. (2022a) and Bianchi et al. (2022b) who estimate shifts in the perceived monetary policy rules from asset prices.

is steep and the Fed is acting in a highly data-dependent manner. The relationship between the perceived monetary policy output weight and the slope of the yield curve is robust to controlling for the unemployment rate and financial conditions. While the relationship between the perceived output gap weight $\hat{\gamma}_t$ and the unemployment rate is weak, there is a significant relationship with financial conditions. In particular, the Fed is perceived to be less responsive to economic conditions when financial conditions are stressed. Our estimates of $\hat{\gamma}_t$ during the first zero-lower-bound (ZLB) episode are intuitive. The perceived coefficient $\hat{\gamma}_t$ remained high for the first part of the first ZLB and fell to zero only in 2011, when the Fed essentially committed itself to near-zero policy rates despite improving economic conditions, in line with Swanson and Williams (2014)'s findings from long-term bond yields.

We next show in Section 4 that beliefs about the monetary policy rule respond to high-frequency monetary policy surprises, suggesting that forecasters have imperfect information about the policy rule and learn about it from policy decisions. The response of $\hat{\gamma}_t$ to monetary policy surprises is state-contingent. A positive surprise in a strong economy leads forecasters to update that the monetary policy rule puts more weight on the output gap than anticipated, while a positive monetary policy surprise in a weak economy leads them to update that the weight on the output gap is smaller than previously thought. The response of the perceived output gap weight tends to peak six to twelve months after the monetary policy surprise, suggesting that forecasters update their beliefs about the monetary policy rule gradually. We then compare estimates of the policy rule from Blue Chip forecasts to estimates from the Fed's own projections in the Summary of Economic Projections (SEP) during the period around the first liftoff from the ZLB. The estimates from Blue Chip follow a similar pattern to the estimates from the Fed's projections, but with a lag. This suggests that the true monetary policy rule may not be fully known even to sophisticated forecasters, who instead need to learn about it from policy decisions.

Having examined the drivers of variation in the perceived monetary policy rule, we investigate the impact of changes in the perceived rule on financial markets. In Section 5, we show that variation in the perceived rule explains changes in the sensitivity of interest rates to macroeconomic news. Similar to Swanson and Williams (2014), we use high-frequency event studies to document that the responsiveness of interest rates to macro news varies over time. However, while they interpret their evidence as a combination of monetary and fiscal policy, we explicitly tie this time variation to changes in the perceived monetary policy rule. Specifically, we show that interest rates respond more strongly to macroeconomic data surprises, such as non-farm payroll news, when $\hat{\gamma}_t$ is high. These results suggest that the perceived monetary policy rule estimated from surveys is consistent with the "market-perceived" monetary policy rule that determines financial market reactions to macroeconomic news. These high-frequency results also help validate our estimates of the perceived output gap response $\hat{\gamma}_t$ and go some way in addressing identification concerns.

Perceptions of monetary policy also matter for subjective risk premia in long-term Treasury bonds. In Section 6.1, we follow Piazzesi et al. (2015) and Nagel and Xu (2022) and measure subjective expected excess bond returns using survey forecasts. A higher perceived monetary policy output gap weight $\hat{\gamma}_t$ is associated with lower subjective expected excess returns on Treasury bonds. This relationship is consistent with basic asset pricing logic as discussed in Campbell et al. (2017) and Campbell et al. (2020). The higher is $\hat{\gamma}_t$, the more investors expect interest rates to fall and hence bond prices to rise in bad economic states. Thus, a higher $\hat{\gamma}_t$ means that investors perceive Treasury bonds to be better hedges, lowering the risk premium they demand. Quantitatively, the effect is large. A one-standard deviation increase in the perceived $\hat{\gamma}_t$ is associated with a -1.1 percentage point decline in the subjective risk premium on the 11-year Treasury bond.

This relationship with expected bond risk premia provides a possible explanation for conundrum periods such as the tightening cycle of 2004-2005, when the Fed raised its policy rate but long-term yields barely increased or even decreased (Backus and Wright, 2007). Monetary tightenings during an expansion tend to increase the public's perception of how sensitive the Fed is to economic activity, which may lower bond risk premia and therefore counteract some of the tightening effects on long-term bond yields.

Finally, in Section 6.2, we document that variation in the perceived policy rule is related to the predictability of fed funds rate forecast errors. While previous authors have argued that predictable policy rate forecast errors arise from misperceptions of the policy rule (Cieslak, 2018; Bauer and Swanson, 2021; Schmeling et al., 2022), we explicitly show that these expectational errors are more predictable when the perceived monetary policy responsiveness to the output gap has recently increased. By contrast, misperceptions and thus predictable forecast errors are less likely when perceived responsiveness has been stable.

Our empirical findings are consistent with a simple model with forecaster heterogeneity and imperfect information about the policy rule, as we discuss in Section 7. Forecasters are endowed with heterogeneous priors about the monetary policy output weight and receive different signals about the output gap. Under the assumptions of the model, regressions of policy rate forecasts onto output gap forecasts in a forecaster-horizon panel provide a consistent estimate of the perceived output gap coefficient in the policy rule. The model implies that forecasters update their perceived monetary policy output weight following monetary policy surprises in a state-contingent manner; that bond risk premia are inversely related to the perceived output weight; and that fed funds futures should respond more strongly to macro news when the perceived output weight is high. If we add overconfidence bias to the learning problem, the model implies that dynamic responses of $\hat{\gamma}_t$ to monetary policy surprises are not only state-dependent but also gradual, and that fed funds forecast errors are systematically predictable, in line with our empirical evidence.

In summary, using a novel methodology for estimating perceptions of the monetary policy rule, we establish three key results. First, the perceived monetary policy rule varies systematically over time. Second, despite the Fed's substantial communication efforts, forecasters' information about the policy rule remains imperfect. Third, variation in the perceived rule impacts in financial markets, explaining variation in the sensitivity of interest rates to macro news and the term premium on long-term bonds.

Our methodology for estimating monetary policy rules essentially takes the idea of using linear regressions for monetary policy rules—in the manner of Taylor (1999) and many others—and applies it in a setting with multidimensional panel data of individual survey forecasts. The advantages of this approach include its simplicity and the comparability to the prior literature. But it also inherits some of the literature's challenges. In particular, it is well known that policy rule regressions yield biased estimates because macroeconomic variables endogenously depend on all shocks in the economy, including the monetary policy shock. A simple bias adjustment building on Carvalho et al. (2021) suggests that this bias is unlikely to affect the time-series variation in $\hat{\gamma}_t$, and hence our main results. In addition, some of our evidence clearly favors an interpretation of $\hat{\gamma}_t$ as the perceived monetary policy rule, including its response to monetary policy surprises and its role in explaining high-frequency responses of interest rates to macro news. Nevertheless, an alternative, more general interpretation of our estimates is that they simply capture the perceived comovement between the short-term policy rate and macroeconomic variables, and not necessarily the causal response of monetary policy. With this broader interpretation, many of the take-aways from our empirical analysis would still remain valid. For example, our asset pricing results suggest that this perceived comovement is priced in financial markets and determines Treasury bond risk premia.

Our paper contributes to empirical work on monetary policy and interest rate expectations in macroeconomics and finance. A recent literature studies the Federal Reserve's communication after its switch to average inflation targeting in 2020 (Coibion et al., 2021; Jia and Wu, 2022). Our work is complementary in that we estimate perceived monetary policy rules over a longer sample and therefore can study business cycle variation. Sastry (2021) and Caballero and Simsek (2021) study disagreement between the public and the Federal Reserve but not within the cross-section of forecasters. Hamilton et al. (2011) directly estimate the market-perceived rule using high-frequency responses to macroeconomic news, but do not allow for time-varying rule parameters. Kim and Pruitt (2017) estimate the perceived policy rule using consensus survey forecasts, assuming constant parameters aside from a single break due to the ZLB. Andrade et al. (2016) and Carvalho and Nechio (2014) use individual survey forecasts to estimate monetary policy rules, but do not study time-variation in monetary policy perceptions. Stein and Sunderam (2018) examine strategic communication between the central bank and market participants.

We also speak to a growing asset pricing literature on learning and bond risk premia. Bianchi et al. (2022b) study FOMC announcements and perceptions of regime-switching monetary policy rules in a New Keynesian asset pricing model. While they analyze the links between perceptions about monetary policy and bond risk premia in a structural framework, we directly estimate the perceived monetary policy rule from panel data of individual survey forecasts and provide new empirical evidence of the link between monetary policy perceptions and required bond risk premia. Haddad et al. (2021) estimate the option-implied state-contingency of the Fed's corporate bond purchase promises during the pandemic. By focusing on a rule for the short-term policy rate and using surveys we cover a much longer sample period, which allows us to study updating in the perceived state-contingency of monetary policy, and link these perceptions to long-term Treasury bond risk premia. Our findings are also related to Giacoletti et al. (2021). Using an affine term structure model they argue that learning is relevant and correlated with disagreement about interest rate forecasts. We provide a specific economic mechanism and directly estimate the perceived monetary policy rule from the cross-section of forecasters, with implications for monetary policy and bond markets.

2 Data and estimation

We begin by describing the details of our survey data set, and then explain how we use it to estimate survey-implied monetary policy rules with two different econometric techniques.

2.1 Survey data

Our main data source is the Blue Chip Financial Forecasts (BCFF) survey, a monthly survey of professional forecasters going back to 1982. The survey mainly asks for forecasts of various interest rates, including the federal funds rate and Treasury yields of different maturities. In addition, participants are queried about their forecasts for a few macroeconomic variables, including real GDP growth and CPI inflation. These macroeconomic forecasts are labeled as the "key assumptions" underlying the interest rate forecasts. The fact that the macro forecasts are explicitly tied to the rate forecasts make them ideal for estimating the relationship between interest rate and macroeconomic forecasts in the form of a monetary policy rule. The number of participants each month varies over time, ranging from about 30 to 50 different institutions. A distinguishing feature of the BCFF survey is that the individual forecasts are all recorded in the data, including the names of the forecasting institution. This rich cross-sectional information allows for a detailed analysis of individual forecasts.

While the BCFF survey started in 1982, we begin our sample in January 1985, since the data quality is spotty in the first few years of the survey. Our survey data ends in January 2021 for a total of 433 monthly surveys. Every month, each forecaster provides forecasts for horizons from the current quarter out to five quarters ahead.[3] The deadline for the survey responses is the 26th of the previous month, with the exception of December, when the deadline is the 21st.

We focus our analysis on the federal funds rate as the relevant interest rate for monetary policy. The precise variable being forecast is the quarterly average of the daily effective Fed Funds rate, in annualized percent, as reported in the Federal Reserve's H.15 statistical release. We denote individual j's forecast made at t for the fed funds rate at $t + h$ by $E_t^{(j)} i_{t+h}$. Here and throughout the paper, time t is measured in months. The monthly horizon h depends on both the survey month and the quarterly forecast horizon. If, for example, we measure the one-quarter-ahead forecast in the January 2000 survey, $t+h$ would correspond to June 2000 and $h = 5$.

Macroeconomic forecasts for output growth and inflation are reported as quarter-over-quarter forecasts in annualized percent. We transform these variables, since empirical monetary policy rules are usually specified in terms of year-over-year inflation and activity gap measures, such as the output gap (see, e.g., Taylor, 1999). We use CPI inflation forecasts, and we calculate predicted year-over-year inflation. For forecasts with horizons of three to five quarters, we simply calculate annual inflation forecasts from the quarterly forecasts for the four longest horizons. For forecasts with horizons of less than three quarters, we combine the forecasts with actual CPI inflation over recent quarters. We denote resulting four-quarter CPI inflation forecasts as $E_t^{(j)} \pi_{t+h}$.

We derive output gap forecasts from the growth forecasts, which are for real GDP growth from 1992 onwards and for real GNP growth before. Conceptually, the calculation is straightforward: Using the current level of real output and the quarterly growth forecasts, we calculate the forecasted future level of real output, which we then combine with CBO projections of potential output to calculate the implied output gap forecasts. In practice, the calculations are slightly involved, since careful account needs to be taken of the timing of the surveys and the available real-time GDP data and potential output projections. First, we need real-time GDP for the quarter before the survey. We obtain real-time data vintages for

[3] Before 1997, the forecast horizon extends out only four quarters.

GDP from ALFRED, and use the most recently observed vintage before the deadline of each survey. Second, we calculate forecasts for the *level* of real GDP, denoted as $E_t^{(j)} Y_{t+h}$ using the level in the quarter before the survey and the growth rate forecasts. Third, we obtain real-time vintages for the CBO's projections of future potential GDP, also from ALFRED, and again use the most recent vintage that was available to survey participants at the time.[4] Fourth and finally, output gap forecasts are calculated as the percent deviation of the GDP forecasts from the potential GDP projections, that is,

$$E_t^{(j)} x_{t+h} = 100 \frac{E_t^{(j)} Y_{t+h} - E_t Y_{t+h}^*}{E_t^{(j)} Y_{t+h}^*},$$

where x_t is the output gap and Y_t^* is potential GDP in the quarter ending in t. It is worth emphasizing that our output gap projections assume that all forecasters share the same potential output forecasts, equal to the CBO projection.

Table 1: Summary statistics for survey forecasts

	Mean	SD	Skewness	Min	10%	90%	Max	N
Federal funds rate	3.6	2.7	0.3	-0.1	0.1	7.2	13.5	111,503
CPI inflation	2.6	1.1	0.1	-4.6	1.5	4.1	9.8	110,707
Output growth	2.6	1.8	-4.4	-49.2	1.5	3.9	55.0	110,892
Output gap	-1.4	2.7	-0.3	-17.0	-5.2	1.8	7.7	110,882

Note: Summary statistics for individual survey forecasts in the Blue Chip Financial Forecasts from January 1985 to January 2021 (433 monthly surveys). Horizons are from current quarter to five quarters ahead (before 1997, four quarters ahead). Number of forecasters in each survey is between 28 and 50. Interest rate forecasts are in percentage points. CPI inflation forecasts are for four-quarter inflation, calculated from the reported quarterly inflation rates and, for short horizons, past realized inflation, in percent. Output growth forecasts are for quarterly real GDP growth (before 1992, real GNP growth) in annualized percent. Output gap forecasts are calculated from growth forecasts, real-time output, and CBO potential output projections as described in the text, in percent.

In Table 1 we report summary statistics for survey data. Across surveys, horizons and forecasters, there are over 110,000 individual forecasts. Output gap forecasts are negative on average, in line with the fact that both real-time and revised estimates of the output gap were negative for the majority of the time over our sample period. Forecasted CPI inflation averages around 2.6% and the average fed funds rate forecast equals 3.6%, in line

[4]In some cases, we use vintages of real GDP or potential GDP released shortly after the survey deadline. We do this either to obtain real GDP in the quarter immediately before the survey (in case this was released after the deadline), or to obtain consistent units for actual and potential real GDP (in case the dollar base year changed for the actual GDP but not for the potential GDP numbers). Furthermore, since the real-time vintages start in 1991, we use the earliest vintages for the surveys before that time.

with realized inflation and interest rates over our sample. The standard deviations of output gap forecasts and CPI inflation forecasts reflect substantial within-month variation, with the average within-month standard deviation of CPI inflation forecasts equal to 0.56% and the average within-month standard deviation of output gap forecasts equal to 0.63%.

An important feature of our survey data is the cross-sectional dispersion of forecasts across horizons, that is, the term structure of disagreement. As shown in Appendix A.1, disagreement tends to decline with the horizon for GDP growth forecasts, the term structure of disagreement is upward-sloping for the forecasts of the fed funds rate, inflation, and the output gap. In contrast to Andrade et al. (2016), we specify the perceived monetary policy rule in terms of the output gap rather than GDP growth, which is consistent with traditional monetary policy rules and naturally matches interest rate disagreement across different forecast horizons.

2.2 Specification of the policy rule

We now turn to estimating the perceived policy rule from monthly forecaster-horizon panels of forecasts for the fed funds rate, inflation, and the output gap. Our starting point is that forecasters believe the Fed uses the following simple policy rule:

$$i_t = r_t^* + \pi_t^* + \beta_t(\pi_t - \pi_t^*) + \gamma_t x_t + u_t, \tag{1}$$

where π_t^* is the inflation target, r_t^* is the equilibrium real interest rate, and the equilibrium nominal short-term interest rate is $i_t^* = r_t^* + \pi_t^*$. The key parameters are β_t and γ_t, the coefficients on the inflation gap and the output gap. Finally, u_t is a monetary policy shock that is exogenous to the policy rule. This type of policy rule is consistent with the specifications used in a large literature in empirical macroeconomics (e.g. Taylor, 1999; Orphanides, 2003b; Taylor and Williams, 2010), but more general in that it allows for time-varying parameters.

Anecdotal evidence suggests that forecasters indeed calculate their projected federal funds rate according to a perceived rule. For instance, Blue Chip financial forecasters are explicitly asked to provide the GDP growth and inflation *assumptions* used to form interest rate forecasts. Commentary in Blue Chip financial forecasts further supports the idea that forecasters use a perceived monetary policy rule, e.g. "Real GDP growth is poised to rebound in the current quarter following the Q1 weakness (...) As a result, the consensus still expects the Fed to begin raising its overnight policy rate at the September meeting, likely lifting it to the vicinity of 1.5%-1.75%" (Blue Chip Financial Forecasts, June 1, 2015).

Our main object of interest is the time-series variation in the average monetary policy weights perceived by forecasters. Forecasters do not know the rule's parameters but form beliefs about them. To start, we assume that beliefs about the coefficients are identical across forecasters but vary over time, and we denote the perceived coefficients by $\hat{\beta}_t$ and $\hat{\gamma}_t$, though we consider heterogeneity across forecasters in the robustness Section 2.5 and in the learning model in Section 7. We use $E^{(j)}$ to denote forecaster j's expectation and $\bar{E}$ to denote the average expectation across forecasters. As usual for time-varying parameters, we assume that they are martingales and orthogonal to other shocks in the economy, thus $E_t^{(j)}\beta_{t+h} = \hat{\beta}_t$ and $E_t^{(j)}\beta_{t+h}z_{t+h} = \hat{\beta}_t E_t^{(j)} z_{t+h}$ for any macro variable z_t, and likewise for γ_t.

The long-run parameters π_t^* and r_t^* are also martingales, in line with previous work on macroeconomic trends (e.g. Del Negro et al., 2017; Bauer and Rudebusch, 2020a). For now, forecasters may disagree about them, so that $E_t^{(j)} r_{t+h}^* = E_t^{(j)} r_t^*$ and likewise for π_t^*. Our assumptions imply that forecasts made at time t are related as follows:

$$E_t^{(j)} i_{t+h} = \underbrace{E_t^{(j)} r_t^* + (1-\hat{\beta}_t) E_t^{(j)} \pi_t^*}_{c_t^{(j)}} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + e_{th}^{(j)}, \tag{2}$$

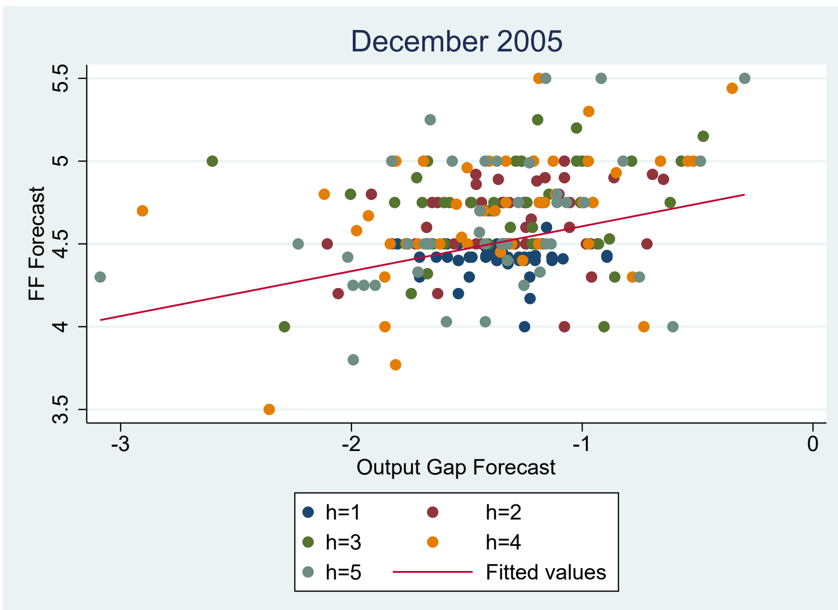
where $c_t^{(j)}$ denotes the part of the forecast that does not depend on horizon, and the error term $e_{th}^{(j)}$ contains the policy shock expected by forecaster j, $E_t^{(j)} u_{t+h}$, as well as possible measurement error. We will estimate equation (2) using two different methods, which we describe below. We use hats to denote the coefficients of the *perceived* monetary policy rule to distinguish them from the coefficients of the *true* monetary policy rule followed by the Federal Reserve.

Our monetary policy rule (1) does not include an inertial term loading on the lagged fed funds rate because the forecast horizon in the data is between one and five quarters and hence close to the monetary policy cycle. To the extent that the Fed is expected to enter a monetary policy tightening cycle, rate increases may be expected to be followed by further rate increases over our forecast horizon, even if monetary policy decisions are expected to mean-revert at longer horizons. To the extent that forecasters anchor their interest rate forecasts to the pre-existing interest rate this would further be absorbed by the time-specific fixed effect in our month-by-month panel regressions. We acknowledge, however, that due to the relatively short horizons in our forecast data, we cannot fully distinguish between variation in the perceived inflation and output gap coefficients and perceived monetary policy rule inertia, and our estimates may need to be interpreted more broadly as a combination of the perceived long-term weights and inertia.

2.3 Panel regression estimate

Our first method for estimating the perceived coefficients $\hat{\beta}_t$ and $\hat{\gamma}_t$ is to estimate separate panel regressions for each survey. We regress fed funds rate forecasts on inflation and output gap forecasts, consistent with equation (2). We estimate regressions either with Pooled OLS or with forecaster fixed effects (FE). OLS is consistent only if the forecaster specific intercept $c_t^{(j)}$ is uncorrelated with the macro forecasts for all h. By contrast, FE will also be consistent if $c_t^{(j)}$ is correlated with the macro forecasts, which arguably is the more relevant case.

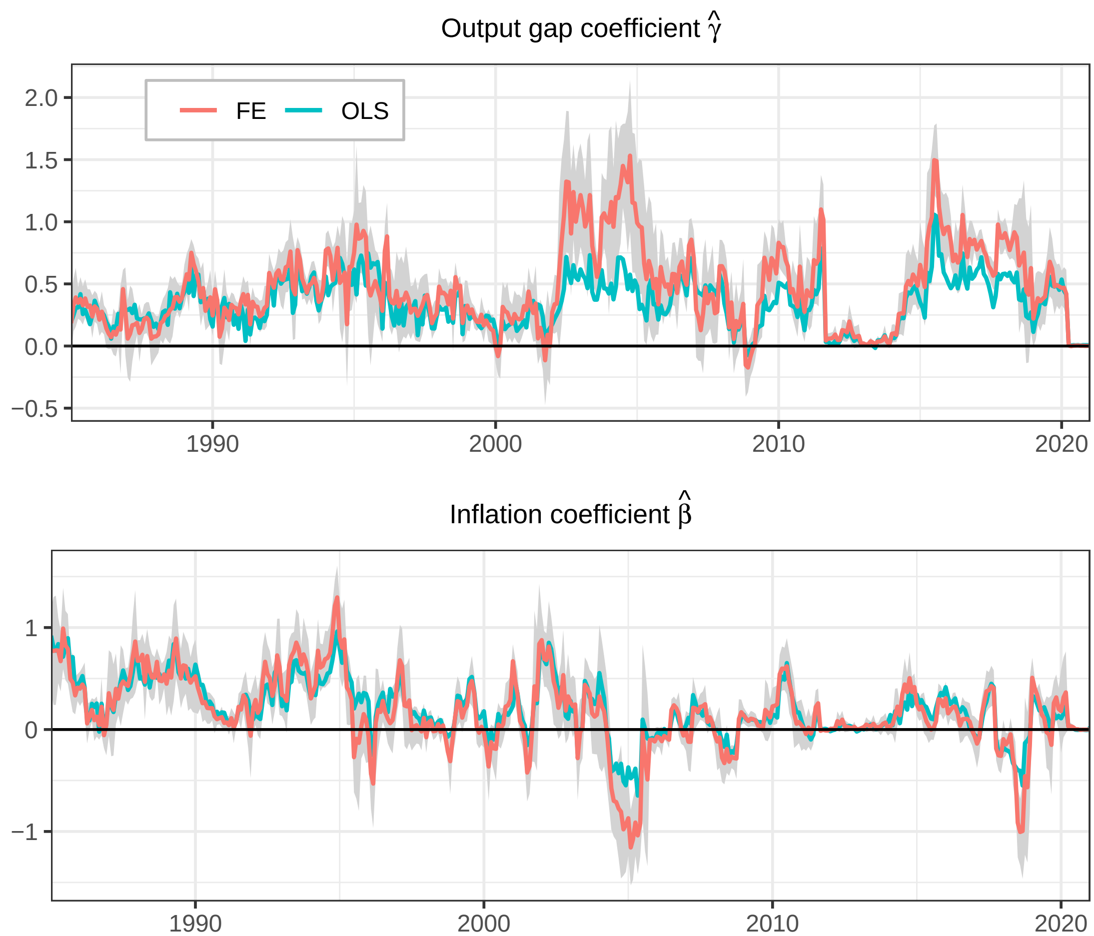
Figure 1: Federal funds rate and output gap forecasts in December 2005



Note: Output gap and federal funds rate forecasts used to estimate regression (2). Each dot corresponds to one forecaster-horizon pair (j, h) in the December 2005 survey. Horizons h are color-coded. Output gap forecasts are constructed from individual forecasters' real GDP growth forecasts and the real-time vintages for the CBO's projections of future potential GDP from ALFRED. For a detailed description of the data construction see Section 2.1.

Figure 1 illustrates the variation in the data driving our estimated perceived monetary policy rule for December 2005. At this time, economic uncertainty was dominated by a well-defined event: the recovery from Hurricane Katrina, which devastated New Orleans in August 2005. Thus, disagreement across forecasters about future output gaps and fed funds rates was likely driven by disagreement about the short-term recovery, as opposed to confounding factors like long-term growth expectations or financial conditions. Each dot shows the output gap forecast on the x-axis and the federal funds rate forecast on the y-axis for a specific forecaster at a specific forecast horizon. Different colors are used to denote different forecast horizons of one through five quarters. There is significant variation in the output gap at all forecast horizons, and we see a clear relationship between output gap forecasts and fed funds rate forecasts. The R^2 in an OLS regression of fed funds rate forecasts onto output gap and inflation forecasts in this survey equals 20%. The perceived output gap coefficient from the December 2005 survey was close to average, with a FE estimate of $\hat{\gamma}_t = 0.53$. While this is only a specific month, it is representative of the sample overall. For an average month in our sample the R^2 for a regression of fed funds rate forecasts onto output gap and inflation forecasts equals 33%, indicating that a simple linear perceived monetary policy rule explains a substantial portion of the variation in policy rate forecasts.

Figure 2: Panel regression estimates of perceived policy rule coefficients



Note: Estimated policy-rule parameters $\hat{\gamma}_t$ and $\hat{\beta}_t$ from month-by-month panel regressions (2), using Pooled OLS (OLS) and forecaster Fixed Effects (FE). FE estimates include 95% confidence intervals based on standard errors with two-way clustering (by forecasters and horizon). The sample consists of monthly Blue Chip Financial Forecast surveys from January 1985 to January 2021.

Using the panel regression approach, Figure 2 shows the full time-series of estimated output gap coefficients $\hat{\gamma}_t$ in the top panel and estimated inflation coefficients $\hat{\beta}_t$ in the bottom panel. The differences between the OLS and FE estimates are generally moderate. However, during the expansionary periods of 2003–2005 and 2015–2018 the FE estimates of $\hat{\gamma}_t$ are noticeably above the OLS estimate. These differences suggest that it is important to account for forecaster fixed effects in the estimation. The coefficients are generally estimated quite precisely. Figure 2 shows 95% confidence intervals for the FE estimates, based on standard errors with two-way clustering (by forecasters and horizon).

The most notable feature of the estimates of $\hat{\gamma}_t$ in Figure 2 is the significant amount of variation over time. For example, the FE estimate varies in a range from zero to about 1.5. As expected, the estimates of the output gap coefficient $\hat{\gamma}_t$ are generally positive, and usually statistically significant. The average level of the FE estimate is 0.5, which is roughly in line with the magnitudes found in the previous literature estimating the monetary policy rule. For example, the original Taylor (1993) rule used an output gap coefficient of $\gamma = 0.5$, while Clarida et al. (2000) estimate output gap coefficients of $\gamma = 0.3$ for the pre-Volcker period and $\gamma = 0.9$ for the post-Volcker period. Understanding the cyclical patterns in $\hat{\gamma}_t$ will be the focus of Section 3.

The estimates of the perceived inflation coefficient $\hat{\beta}_t$ are harder to interpret. The estimates are persistently positive only over the first few years of our sample, but fluctuate around zero from the late 1990s onward. The estimates of $\hat{\beta}_t$ almost never satisfy the "Taylor principle," according to which $\beta > 1$ and a positive real-rate response to inflation is needed for macroeconomic stability. What explains the low magnitudes and seemingly erratic movements in the estimated $\hat{\beta}_t$? The main reason is that neither actual nor expected inflation exhibited meaningful, persistent variation over our sample period. Both have generally fluctuated in the vicinity of the Fed's two-percent inflation target. In the absence of sufficient variation in inflation, the estimated coefficient in policy rules tends to be low, although the central bank has in fact been committed to stable inflation (Clarida et al., 2000). Another factor impacting the estimates of $\hat{\beta}_t$ is that the BCFF records forecasts of headline CPI inflation, which is much more volatile than alternative measures such as core CPI or core PCE. In additional, unreported analysis using the Survey of Professional Forecasters, we find that using core inflation forecasts leads to somewhat less erratic and more consistently positive estimates of $\hat{\beta}_t$. However, these forecasts are available only starting in 2007, and are thus not suitable for our main analysis. Going forward, we focus our analysis on the economically more interesting output gap coefficient, $\hat{\gamma}_t$.

2.4 State-space model estimate

So far, we have seen that we can use our rich panel data of survey forecasts to obtain precise and economically meaningful estimates of the link between forecasts for the federal funds rate and the output gap. To eliminate the higher-frequency movements due to month-to-month noise and improve the precision of our estimates, we now estimate a state-space model that links information in surveys in adjacent months over time. While the panel estimates treat the information available each month as completely separate information, a state-space model (SSM) stipulates a time-series model for the perceived coefficients $\hat{\beta}_t$, $\hat{\gamma}_t$ and the long-term nominal short rate i_t^*.

In order to keep the SSM estimation simple, we make some additional assumptions about π_t^* and i_t^*. First, we assume that perceptions about long-run inflation are homogenous and constant, i.e., $E_t^{(j)}\pi_{t+h} = \pi^*$. A constant perceived long-run inflation prevents the state-space model from becoming nonlinear and therefore substantially simplifies the estimation. In our view, this is a reasonable approximation for beliefs over our sample period, as most survey forecasts suggest a broad consensus for long-run inflation expectations around 2%.[5] Second, we also assume that there is no disagreement about the long-run nominal short rate, i.e., $E_t^{(j)}i_{t+h}^* = i_t^*$. Homogeneous beliefs about i_t^* avoid the complexity of having to model and keep track of each forecasters long-run expectations for the policy rate. This rules out any variation in $c_t^{(j)}$ across forecasters, in line with the assumption underlying pooled OLS estimation of our panel regressions. An implication is that beliefs about the equilibrium real rate, r_t^*, are also assumed to be homogeneous. It should be noted that π^* and i_t^* denote (common) beliefs by the forecasters and do not necessarily need to correspond to their "true" value. Overall, the assumptions for our SSM estimation are necessarily somewhat more restrictive, a price we pay for incorporating the time-series dimension into our estimates while keeping the estimation manageable.

Under these additional assumptions, equation (2) becomes

$$E_t^{(j)}i_{t+h} = i_t^* + \hat{\beta}_t(E_t^{(j)}\pi_{t+h} - \pi^*) + \hat{\gamma}_t E_t^{(j)}x_{t+h} + e_{th}^{(j)}. \quad (3)$$

The three state variables are i_t^*, $\hat{\beta}_t$ and $\hat{\gamma}_t$, which we model as independent random walks:

$$i_t^* = i_{t-1}^* + \xi_{1t}, \quad \hat{\beta}_t = \hat{\beta}_{t-1} + \xi_{2t}, \quad \hat{\gamma}_t = \hat{\gamma}_{t-1} + \xi_{3t}, \quad (4)$$

where the innovations are *iid* normal, have variances σ_1^2, σ_2^2 and σ_3^2, and are mutually un-

[5] Consistent with these subjective estimates, econometric estimates of long-run inflation have also been steady and close to 2% since the 1990s (e.g. Bauer and Rudebusch, 2020b).

correlated. The state vector is $x_t = (i_t^*, \hat{\beta}_t, \hat{\gamma}_t)'$ and the observation equation is

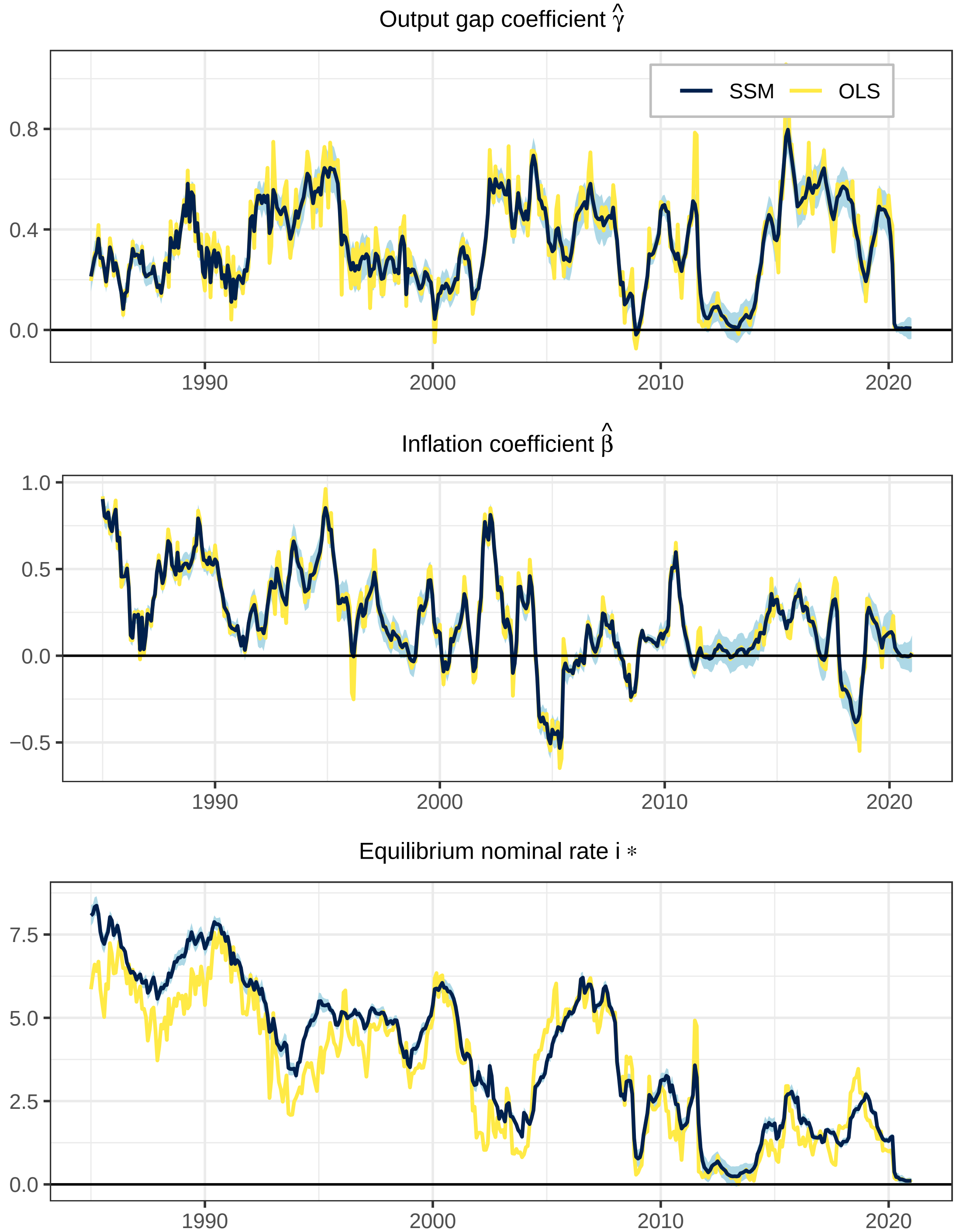
$$y_t = Z_t x_t + u_t,$$

where the n-vector y_t contains all rate forecasts made at time t (stacked for all forecasters and horizons), Z_t is a $n \times 3$ coefficient matrix with ones in the first column, the inflation gap forecasts in the second column, and the output gap forecasts in the third. Depending on how many forecasters participated in the survey at time t, a number of elements in y_t and corresponding rows in Z_t may be missing, which can be handled easily by the Kalman filter. The measurement error vector u_t is taken to be *iid* normal, with elements that are uncorrelated across forecasters and horizons, so that $Cov(u_t) = \sigma_e^2 I_n$. Many extensions of this model are possible, including different measurement error specifications, serially correlated policy shocks, and heterogeneous beliefs about r_t^*. The advantage of this simple specification of the state-space model is that it corresponds to the assumptions under which the pooled OLS regressions would be both consistent and efficient, since we rule out both fixed effects and random effects. We use Bayesian methods to estimate the state-space model, and Appendix A.2 describes the details.

Figure 3 shows the posterior means and 95% credible intervals for the output gap coefficient $\hat{\gamma}_t$, the inflation coefficient $\hat{\beta}_t$ and the long-run nominal interest rate i_t^* obtained from the SSM defined by equations (3) through (4). For comparison, we also include the OLS coefficients estimated month-month from Figure 2. The main takeaway is that the state-space model (SSM) output gap and inflation weights are economically similar to the panel OLS estimates. The SSM estimate of the long-run policy rate, i_t^*, exhibits a significant amount of cyclical variation, because this component subsumes any variation in interest rate forecasts unrelated to the forecasts of inflation and the output gap, including any effects due to interest-rate smoothing. However, the overall downward trend is consistent with previous empirical work on shifting endpoints in interest rates (Del Negro et al., 2017; Bauer and Rudebusch, 2020a).

The SSM estimates are different from the panel regression estimates in two important ways. They are even more precise, as evident from the very narrow credibility intervals. And they display less “noise” or month-to-month variation than the panel regression estimates. Both of these differences arise from the fact that the SSM estimates exploit information in the time-series dimension—linking surveys in months t and $t + 1$—which increases the effective amount of observations used in the estimation each month. This increased precision will provide useful in mitigating the attenuation bias in subsequent analysis of high-frequency federal funds rate responses to macroeconomic news. In subsequent sections we present

Figure 3: State-space model estimates of perceived policy rule coefficients



Note: Estimated policy-rule parameters $\hat{\gamma}_t$ and $\hat{\beta}_t$, and the perceived equilibrium nominal short rate i_t^*, from state-space model defined by equations (3) and (4); details of the Bayesian estimation are in Appendix A.2. Shaded areas are 95%-credibility intervals based on the posterior distributions. Also shown are the Pooled OLS estimates from Figure 2. The sample consists of monthly Blue Chip Financial Forecast surveys from January 1985 to January 2021.

results for the FE and SSM estimates of $\hat{\gamma}_t$. Since the OLS estimates are essentially a noisy version of the SSM estimates, we do not include results for these additional estimates.

2.5 Robustness of estimated perceived policy rules

We next show the robustness of our estimated perceived monetary policy output gap weight $\hat{\gamma}_t$ to different specifications, including controlling for expected financial conditions and allowing for forecaster heterogeneity. Appendix A.4 describes the details of the alternative estimates.

We estimate several multidimensional panel regressions of equation (2). That is, instead of estimating a separate forecaster-horizon (i, h) panel regression for each survey t, we estimate a single survey-forecaster-horizon (t, i, h) panel regression, and consider different fixed effects specifications. As a starting point, we use forecaster and time (survey) fixed effects. This estimation, which we call "Constant FE", differs from our baseline Panel FE estimate because it restricts forecaster fixed effects to be constant over time, meaning that each forecaster's perceptions of the natural rate and inflation target are assumed to be time-invariant. Table 2 shows that the resulting $\hat{\gamma}_t$ estimate has a very high correlation with our Pooled OLS and SSM estimates, suggesting that this version of fixed effects is unlikely to affect any of our results below.

Table 2: Robustness: Correlation of alternative $\hat{\gamma}_t$ estimates

	Pooled OLS	FE	SSM	Constant FE	Hetero-geneous	Terciles 1	Terciles 2	Terciles 3	Credit spreads	Bias adjusted
Pooled OLS	1	0.84	0.96	0.98	0.96	0.74	0.83	0.83	0.84	0.77
FE		1	0.84	0.87	0.88	0.71	0.77	0.73	0.94	0.91
SSM			1	0.95	0.94	0.74	0.82	0.81	0.83	0.78
Constant FE				1	0.99	0.76	0.84	0.84	0.86	0.81

Note: Correlations between different estimates for the perceived output gap weight in the policy rule, $\hat{\gamma}_t$. Sample period ends in January 2021, and starts in January 1985 for baseline estimates (*Pooled OLS, FE, SSM*), in January 1993 for *Heterogeneous* and *Tercile* estimates, and in January 2001 for *Credit spreads* estimate. For details on alternative estimates, see Appendix A.4.

We next show that the time-series of our baseline estimates is not affected by forecaster heterogeneity. The model in Section 7 lays out some simple assumptions under which our baseline estimates recover the cross-forecaster average of the perceived rule coefficient every month, even if forecasters have heterogeneous beliefs about the perceived monetary policy rule. In the model, Bayesian learning implies that forecasters update their beliefs about the monetary policy coefficient in lockstep and heterogeneity in the perceived monetary policy coefficient is fully captured by fixed differences across forecasters. If, as we assume in the model, output gap forecasts are further homoskedastic across forecasters, our baseline estimates recover the equal-weighted forecaster average of the perceived monetary policy rule coefficient every month. However, if this homoskedasticity assumption is violated, one might be concerned that our baseline estimation weights heterogeneous forecasters differently at different times, rather than capturing time-variation in the forecaster-average of the perceived monetary policy coefficients. To address this concern, we add forecaster fixed effect interactions with output gap and inflation forecasts to the multidimensional panel regression, meaning that we allow each forecaster to have different beliefs about the rule parameters but restrict the difference to be constant. The fourth column in Table 2 shows that the correlations of the resulting "Heterogeneous" estimate with the OLS, SSM, and Constant FE estimates is 0.96, 0.94, and 0.99 respectively. This exercise therefore suggests that our baseline estimates capture time-series variation in the consensus perceived monetary policy coefficient $\hat{\gamma}_t$ in the presence of fixed forecaster differences.

We next use a less parametric way of considering forecaster heterogeneity, splitting forecasters by characteristics and estimating different policy rules for each forecaster group. In particular, one might wonder whether periods of high $\hat{\gamma}_t$ reflect periods when some outliers of particularly inaccurate forecasters dominate the variation of output gap and inflation forecasts. We split forecasters into terciles by the full-sample mean-squared-error of their fed funds rate forecasts, with the first tercile representing the most accurate forecasters. We then estimate "Constant FE" regressions for each group of forecasters. The estimates of $\hat{\gamma}_t$ naturally become noisier due to the smaller sample sizes, but the correlations with our baseline estimates of $\hat{\gamma}_t$ remain high on the order of 80%. Reassuringly, the correlation between the SSM estimate of $\hat{\gamma}$ is highest for the middle tercile of forecasters by accuracy, supporting again the notion that we estimate an average or central tendency of $\hat{\gamma}_t$ across forecasters.

A separate concern about our estimates is that changes in $\hat{\gamma}_t$ might partly reflect the Fed's perceived concern with financial conditions.[6] We investigate this possibility by controlling in our Panel FE estimation for each forecaster's expectation of the spread between Baa corporate bond yields and the ten-year Treasury yield, as a proxy for expected financial conditions. Forecasts of the Baa yield are available in the Blue Chip data starting in 2001. Our estimates suggest an important role for expected credit spreads in the determination of the policy rate, with a coefficient that is often substantially negative and statistically significant (results omitted). However, as Table 2 shows, incorporating credit spread forecasts

[6] A number of empirical and theoretical studies suggest a role for financial conditions and risk in the determination of the policy rate by the Fed. Examples include Atkeson and Kehoe (2008), Woodford (2010) and Gilchrist and Zakrajšek (2012).

into the perceived policy rule has little effect on the estimated response to output gap forecasts. The correlation with the baseline Panel FE estimate is 94%, indicating that our baseline estimate for $\hat{\gamma}_t$ is barely affected by the Fed's response to financial conditions. This is consistent with the results in Table 3, where we find that the perceived $\hat{\gamma}_t$ becomes smaller when financial conditions are tight. If $\hat{\gamma}_t$ reflected the perceived response to financial conditions, one would have expected it to increase in times when financial conditions are a concern.

As an additional robustness check, we have also estimated perceived monetary policy rules using a completely different data set, namely the Philadelphia Fed's quarterly Survey of Professional Forecasters (SPF). Appendix A.5 shows that the resulting estimate of $\hat{\gamma}_t$, which is based on unemployment rate forecasts instead of output gap forecasts, exhibits very similar time-series variation as our baseline estimate using the BCFF data. In Appendix D.2 we correlate our baseline estimates of $\hat{\gamma}_t$ with the measures of forecaster interest rate disagreement from Giacoletti et al. (2021). As one might expect, we find that a higher perceived monetary policy output weight is positively correlated with forecaster disagreement over future interest rates. However, the correlations are small in magnitude, ranging from 0 to 0.27, so variation in the perceived monetary policy coefficient $\hat{\gamma}_t$ appears distinct from disagreement about interest rates.

Overall, we find that our various alternative estimates of $\hat{\gamma}_t$ are all highly correlated with our baseline OLS, Panel FE, and SSM estimates.

2.6 Endogeneity and estimation bias

A key concern with empirical monetary policy rules is that standard regression estimates might be inconsistent due to the endogeneity of the macroeconomic variables with respect to the monetary policy shock. That is, even in large samples an estimation bias results from the fact that inflation and output are endogenously determined by all structural shocks in the economy.[7] Recent work by Carvalho et al. (2021) analyzing different types of New Keynesian models suggests that OLS estimates of policy rules may not be affected much by such estimation bias. Nevertheless, one might worry that our estimates of $\hat{\gamma}_t$ might be biased by the *perceived* endogenous response of inflation and output to monetary policy, and that they do not capture the perceived response of monetary policy to changes in the output gap.

There are several arguments supporting the interpretation of $\hat{\gamma}_t$ as the coefficient in

[7] Cochrane (2011) shows that under certain conditions monetary policy rules cannot be identified at all from observed data, due to the endogenous response of long-run inflation to long-run nominal rates. Sims (2008), however, shows that the identification problem is less of a concern when the natural rate of interest is unknown.

a perceived monetary policy rule. First, the Blue Chip commentary suggests forecasters believe that monetary policy acts with "long and variable lags" as hypothesized by Milton Friedman. Because the forecast horizons are relatively short—up to five quarters—this implies that the survey forecasts are more conducive to estimating a perceived Taylor rule (the response of monetary policy to output) rather than a perceived Euler equation (the response of output to monetary policy). Second, the estimated $\hat{\gamma}_t$ is consistently positive as we would expect if forecasters have a perceived monetary policy rule in mind, rather than focusing on the endogenous economic response to interest rates. Third, in our subsequent analysis we document evidence that clearly supports the structural interpretation of $\hat{\gamma}_t$ as a policy rule coefficient. In particular, we find that $\hat{\gamma}_t$ responds to monetary policy surprises in a state-dependent, theory-consistent manner (Section 4.2), and that it explains interest rate responses to macroeconomic news (Section 5).

Finally, we conduct an explicit bias adjustment, accounting for the endogenous macroeconomic response to monetary policy by adapting the approach of Carvalho et al. (2021) to our cross-sectional setting. Appendix A.6 explains the details. As expected, we find that the endogeneity bias adjusted panel FE $\hat{\gamma}_t$ is somewhat higher than the baseline panel FE estimate, with a sample mean of 0.61 vs. 0.46 for our baseline estimate. However, the endogeneity bias adjustment leaves the time-series variation, our main object of interest, almost unchanged. The last column of Table 2 shows the correlation of this bias-adjusted version with our other estimates. The correlation of the panel FE estimates with and without endogeneity bias adjustment is 91%.

Overall, we favor a structural interpretation of our estimates as coefficients in a perceived policy rule. That said, an alternative interpretation of $\hat{\gamma}$ as simply the perceived comovement between the policy rate and the macroeconomy circumvents is possible, sidestepping the endogeneity concern. Under this interpretation, it is still interesting to understand how sophisticated observers learn about this comovement, and whether their perceptions are reflected in financial markets.

3 Cyclical shifts in monetary policy perceptions

We now discuss how monetary policy is perceived to vary over the monetary policy, business, and financial cycles. In Figures 2 and 3 the perceived output gap coefficient $\hat{\gamma}_t$ exhibits pronounced cyclical variation. The perceived output gap coefficient appears to be high just before and during monetary tightening cycles, but low after the end of tightening cycles and during monetary easing cycles. For instance, $\hat{\gamma}_t$ was elevated before and during the tightening cycle of 2004-2006 and during 2014, just prior to lift-off from the zero lower bound in December 2015. By contrast, it was low from 1998 to 2002 during the late stages of the dot-com bubble and the following bust, as well as during the period from 2007 to 2008 including the financial crisis. In addition, $\hat{\gamma}_t$ was near zero during ZLB episodes, provided that sufficiently strong forward guidance was in place, as from late 2011 to early 2014, and from April 2020 to the end of our sample.

Table 3 investigates more formally the relationship between $\hat{\gamma}_t$ and indicators of the monetary policy, business, and financial condition cycles, as measured by the slope of the yield curve, the unemployment rate, and the Chicago Fed's National Financial Conditions Index (NFCI). The first four columns use the panel FE estimate of $\hat{\gamma}_t$, while the last four columns use the SSM estimate. We use a one-month lead of $\hat{\gamma}_t$ in all regressions to account for publication lags. Taken together, we find a strong association between the perceived output gap coefficient $\hat{\gamma}_t$ with the slope of the yield curve and financial conditions, but only a weak relationship with the unemployment rate.[8]

Column (1) of Table 3 shows a strong positive association between the perceived output gap coefficient $\hat{\gamma}_t$ and the slope of the yield curve, measured as the second principal component of Gürkaynak et al. (2007) Treasury yields. In unreported results, we have found that slope has a significantly positive contemporaneous relationship with $\hat{\gamma}_t$, but an even stronger relationship with future values and we therefore lag the slope by 12 months in our regressions. The relationship is economically and statistically very significant, and suggests that an upward-sloping yield curve predicts high values of $\hat{\gamma}_t$. This relationship is intuitive in light of our previous discussion: An upward-sloping yield curve signals that the stance of monetary policy is accommodative and that, going forward, a monetary tightening cycle is about to unfold (Rudebusch and Wu, 2008). Thus, when interest rates are expected to rise, the federal funds rate is perceived to be more sensitive to the state of the economy. By contrast, the yield curve is flat or inverted and its slope low after a series of rate hikes, when there is little room to tighten further. Before and during the next easing cycle, $\hat{\gamma}_t$ is low and the fed funds rate perceived to be less sensitive to the state of the economy.

It is well-known that the slope of the yield curve predicts recessions, so it is important to control for the unemployment rate to disentangle variation in $\hat{\gamma}$ over the monetary policy cycle from business cycle variation. Regressions onto the unemployment rate yield a negative relationship, though this is insignificant for the Panel FE estimate of $\hat{\gamma}$, and the R^2 is generally much smaller than for regressions on the slope of the yield curve. In unreported results, we have also considered lead-lag relationships with the unemployment rate, as well

[8] In Table 3, we think of the slope of the yield curve as primarily capturing the expected path of future interest rates, even though it of course also incorporates bond risk premia (Campbell and Shiller, 1991). We investigate bond risk premia in detail in Section 6.1.

as various other business cycle indicators, and generally found only weak correlation with $\hat{\gamma}_t$. The negative sign is consistent with the view that monetary policy is perceived to be more sensitive to economic data during expansions, but overall these simple regressions suggest that the perceived monetary policy output coefficient $\hat{\gamma}$ is more closely related to the monetary policy cycle than the business cycle.

Table 3: Policy rule perceptions and the monetary policy cycle

	Panel FE $\hat{\gamma}$				SSM $\hat{\gamma}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Slope (12m lag)	0.12***			0.17***	0.05***			0.08***
	(0.03)			(0.04)	(0.02)			(0.02)
Unemployment rate		−0.03		−0.08***		−0.03**		−0.05***
		(0.02)		(0.03)		(0.01)		(0.01)
NFCI			−0.21***	−0.09**			−0.13***	−0.07***
			(0.05)	(0.05)			(0.03)	(0.03)
Constant	0.23***	0.66***	0.39***	0.58***	0.23***	0.50***	0.29***	0.45***
	(0.06)	(0.14)	(0.04)	(0.13)	(0.04)	(0.08)	(0.02)	(0.08)
R^2	0.15	0.03	0.10	0.33	0.11	0.07	0.14	0.36

Note: Regressions for $\hat{\gamma}_t$ in monthly data from January 1985 to January 2021 (432 observations). Columns (1) through (4) use the panel fixed effects (FE) estimate of $\hat{\gamma}_t$. Columns (5) through (8) repeat the same regressions for the state-space model (SSM) estimate of $\hat{\gamma}$. *Slope* is the second principal component of Treasury yields from Gürkaynak et al. (2007), which is lagged by twelve months. *Unemployment rate* is taken from FRED (series: UNRATE), and *NFCI* is the National Financial Conditions Index from the Chicago Fed. Regressions use a one-month lead of $\hat{\gamma}_t$ to account for the publication lag. Newey-West standard errors using 12 lags are in parentheses.

Column (3) of Table 3 considers a popular indicator of financial conditions, the Chicago Fed's National Financial Conditions Index (NFCI), and shows that it is negatively related with the perceived monetary policy output coefficient $\hat{\gamma}$. Since high values of this index indicate tight financial conditions, it appears that forecasts for the funds rate are less sensitive to the economic outlook during periods of financial stress. Of course, these are likely to be episodes when the Fed is easing the stance of monetary policy. But the multivariate regression in column (4) shows that even accounting for the state of the monetary policy and the business cycle NFCI maintains a strong negative association with $\hat{\gamma}_t$. One possible explanation for this finding is that the Fed is perceived to cut rates aggressively in the face of deteriorating financial conditions, leading it to put less weight on the economic outlook, consistent with a "Fed put" (Cieslak and Vissing-Jorgensen, 2021).

Our evidence supports the view that perceptions about monetary policy significantly differ during easing and tightening cycles, particularly during the early phases. During easing cycles, the public does not anticipate rate cuts that depend on economic activity, and the Fed typically cuts quickly and surprisingly. One interpretation is that the Fed "gets ahead of the curve" and the public rarely expects more rate cuts. By contrast, during tightening cycles, the Fed is perceived to raise the policy rate in a gradual and data-dependent manner. Anecdotal and narrative evidence is consistent with this view. For instance, the FOMC meeting minutes from January 29-30, 2001 described the sequence of large interest rate cuts in that month as "front-loaded easing policy", while the New York Times noted that "investors and analysts do not expect the Fed to be as fast in cutting rates in the months ahead". Similarly, the FOMC committee conference call on January 9, 2008 described interest rate cuts as "taking out insurance against (...) downside risks." On the other hand, rate increases are often publicly characterized as being gradual and data-dependent, including communication by all three recent Fed Chairs Bernanke, Yellen and Powell.

4 Updating about the perceived monetary policy rule

We now turn to the question of how private forecasters update their perceived $\hat{\gamma}_t$ to understand the Fed's communication of its monetary policy rule to financial markets participants. We start by comparing our estimates of $\hat{\gamma}_t$ to estimates of the monetary policy rule from the Fed's own forecasts. If communication is relatively frictionless, our estimates from professional forecasters should closely track the Fed's own rule. We then ask how policy rate decisions themselves shape perceptions of the monetary policy rule, studying how $\hat{\gamma}_t$ evolves following monetary policy surprises.

Forecasters could update about the monetary policy rule in several ways. First, if communication is highly effective, then the true monetary policy coefficient would effectively be known to the public with $\hat{\gamma}_t = \gamma_t$. This is the full information rational expectations (FIRE) case. Second, forecasters could be uncertain about the true rule but update in a rational manner from observing policy rate decisions. In this case, forecasters' perceived monetary policy coefficient might move more slowly than the true underlying monetary policy coefficient, but should respond instantaneously to interest rate decisions. Third, forecasters and financial markets might be subject to behavioral biases, leading to a further wedge between the actual and perceived monetary policy rule coefficients. In this section, we provide some descriptive empirical evidence that speaks to these questions. This evidence is complementary to the cyclical variation documented in Section 3, which could be driven by time-variation in either the true coefficient γ_t or the wedge between the perceived $\hat{\gamma}_t$ and the true γ_t.

Overall, the evidence in this section suggests that FIRE is violated and the true monetary policy rule is not known, but that forecasters consistently update in the same direction a rational Bayesian would. However, the perceived monetary policy output weight $\hat{\gamma}_t$ updates gradually over the six months following monetary policy surprises. While we cannot conclusively rule out fully rational updating, this slow reaction is suggestive of behavioral biases such as overconfidence. We flesh out this interpretation through the lens of the model in Section 7.

4.1 Comparison with the Fed's rule: A case study

We start by comparing our estimates of the perceived monetary policy rule from Blue Chip forecasts to direct estimates of the Fed's actual monetary policy rule, which we construct from the cross-section of Fed forecasts in the "Summary of Economic Projections" (SEP). This descriptive comparison suggests that the perceived rule roughly aligns with the actual rule, but also that there are important differences, i.e., that FIRE is violated.

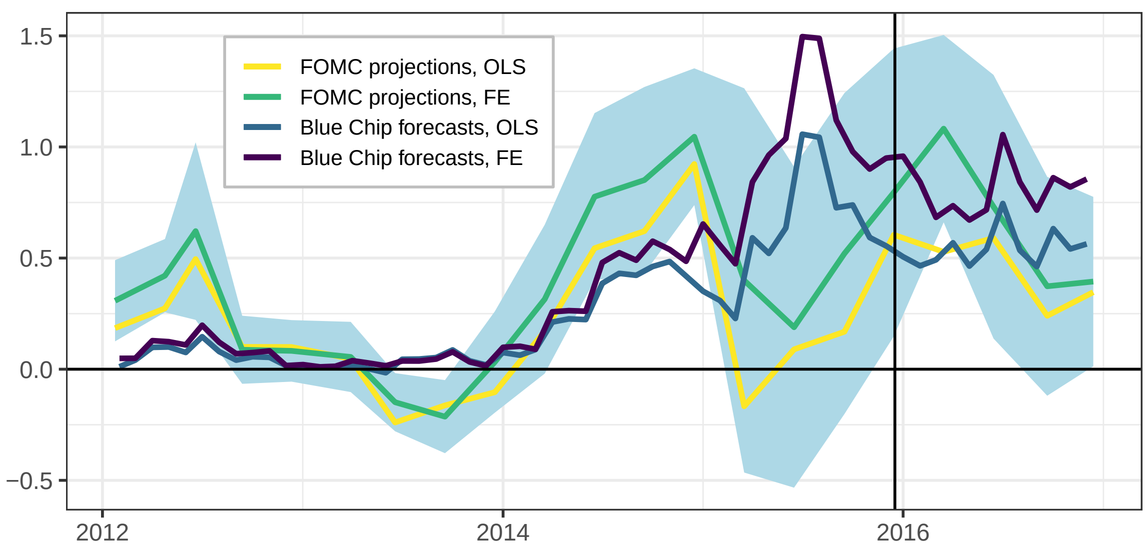
To obtain monetary policy coefficients from the Fed's own forecasts, we use the same panel regression approach as for the Blue Chip data, described in Section 2.3. We construct output gap projections by combining CBO projections for potential output with the those for the level of real GDP implied by the growth forecasts. While there are some differences in the forecast data—such as the sample period, the forecast horizons, and the inflation measure (PCE instead of CPI)—the estimation method remains the same, which allows for a meaningful comparison of the estimates. For comparability with the Blue Chip forecasts, we use only the forecasts for the current and next years. The macro forecasts pertain to the last quarter of each year, and for the inflation and real GDP growth rates are four-quarter percentage changes. For the fed funds rate, the projections are for the end of each year. Due to data availability, we study the years 2012-2016, a period covering the first liftoff from the ZLB and thus including rapid changes in the stance of monetary policy and a strong Fed focus on communicating those changes.[9] For each of 21 forecast releases over the period from 2012 to 2016, we have a panel of 16 to 19 Fed forecasters in the SEP.

As shown in Figure 2, there were significant fluctuations in the perceived output gap coefficient $\hat{\gamma}$ in the time period around the first ZLB. After both the funds rate and $\hat{\gamma}_t$ decreased to zero in 2008, the $\hat{\gamma}$ quickly rose again and remained at a high level until August 2011. During this period, forecasters generally expected the Fed to lift the policy rate off the ZLB within the next year or so, resulting in a high estimated perceived output gap

[9]Individual projections of each FOMC participant are made public with a publication lag of five years, and since 2012 these projections have include the forecasted path of the federal funds rate. Detailed information about FOMC meetings, including the staff ("Greenbook") forecasts, the transcripts of the meetings, and individual economic projections, are made public with a delay of five years and can be found at https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm. In these forecasts, each participant projects a corresponding path for the federal funds rate "under appropriate monetary policy". That is, the projections reflect what the participants think the policy rate *should* be, not what it is most likely to be. It is therefore natural to view these projections as reflecting each participant's implicit monetary policy rule.

weight $\hat{\gamma}$. On August 9, 2011, however, the Fed introduced calendar-based forward guidance, predicting a near-zero policy rate "at least through mid-2013." In response, the estimated $\hat{\gamma}$ dropped sharply and stayed near zero until lift-off started to come into view again in spring 2014, suggesting that our estimates pick up on "Odyssean" forward guidance where the Fed predicts and essentially commits to a certain path for the future policy rate (Campbell et al., 2012).[10]

Figure 4: Output gap policy rule coefficients implied by FOMC economic projections



Note: Estimated policy-rule parameters γ_t from repeated panel regressions (2), using Pooled OLS (OLS) and forecaster Fixed Effects (FE). FE estimates include 95% confidence intervals based on robust standard errors. Estimates for the FOMC are based on the individual projections of FOMC participants for the "Summary of Economic Projections" (SEP) between 2012 and 2016 (21 meetings, 16-19 individual projections, forecasts for the current year and the following year). Also shown are the OLS and FE estimates of the perceived coefficients from the Blue Chip Financial Forecasts. The vertical line indicates the Federal Reserve's actual liftoff date from the zero-lower-bound.

Figure 4 shows the OLS and FE estimates of γ_t obtained from the FOMC projections (SEP), together with 95% confidence intervals for the FE estimates. It also includes the estimates of the perceived coefficients $\hat{\gamma}_t$ based on the Blue Chip data for the time period where both are available. The date of actual liftoff is indicated with a vertical line. We see that the perceived output gap coefficient as estimated from Blue Chip forecasts captures well the change in the Fed's own monetary policy rule around liftoff. It rises from around zero to roughly 0.5 shortly before actual liftoff. The magnitude of the Blue Chip private forecaster

[10] An alternative way to estimate the perceived policy rule is to use forecasts for the two-year Treasury yield, which is more immune to concerns that the ZLB mechanically produces these results (Swanson and Williams, 2014; Hanson and Stein, 2015). Appendix A.3 shows that doing so generally leads to very similar results, although during the 2011-2014 period the estimate of $\hat{\gamma}_t$ remains slightly higher and increases earlier.

coefficient is similar to the Fed's, though the private forecaster coefficient appears to lag somewhat behind.Overall, the episode around the first lift-off from the ZLB suggests that private forecasters updated their perceived output gap coefficient $\hat{\gamma}_t$ in the right direction but more slowly than the true response coefficient γ_t. This suggests that the true monetary policy coefficient is unknown and must be estimated. We next study how forecasters learn about the monetary policy rule from interest rate decisions.

4.2 Responses to monetary policy surprises

We next show that the perceived monetary policy rule responds to monetary policy surprises in a manner consistent with imperfect information about the rule. If forecasters do not exactly know the Fed's monetary policy rule, beliefs about the rule's parameters should react to monetary policy surprises, and this response should depend on the state of the economy. Specifically, in an economic boom a tightening surprise suggests that the Fed is even more committed to reigning in an overheating economy than previously believed. Therefore, this kind of surprise should lead to an increase in $\hat{\gamma}_t$. By contrast, a tightening surprise during a period of a recession would signal less Fed concern with output stabilization, so forecasters would tend to revise downward $\hat{\gamma}_t$. This logic is formalized in our model in Section 7 below (see also Bauer and Swanson, 2021, 2022).

We empirically investigate updating of policy rule beliefs by studying the evolution of $\hat{\gamma}_t$ in response to monetary policy surprises calculated from high-frequency money market futures rate changes around FOMC announcements (following Gürkaynak et al., 2005; Nakamura and Steinsson, 2018, and many others). Interest rates before FOMC announcements reflect the market's expectations for the path of the policy rate based on current macroeconomic data. Under the commonly made assumption that changes in these market rates around FOMC announcements are mainly due to the monetary policy announcement itself, they reflect the surprise component of the monetary policy actions.

We estimate state-dependent impulse responses of $\hat{\gamma}_t$ to monetary policy surprises using local projections.[11] To capture episodes when the economy is growing slowly and economic slack is high, we define an indicator variable $weak_t$, which equals one when the output gap is below its median and is zero otherwise.[12] We follow Bauer and Swanson (2022) and measure the monetary policy surprise, mps_t, as the first principal component of 30-minute changes in several Eurodollar futures rates around the FOMC announcement. This measure, which

[11] Our estimation method for state-dependent local projections using identified shocks largely follows Ramey and Zubairy (2018).

[12] For this classification, we calculate the output gap using the real GDP data and CBO potential output estimates from FRED.

is available from 1988 to 2019, captures changes in policy rate expectations over a horizon of about a year, and thus includes changes in forward guidance. We normalize the surprise to have a unit effect on the four-quarter-ahead Eurodollar futures rate, measured in percentage points. We convert the announcement-frequency surprises to a monthly series by summing them if there is more than one announcement during a month, and setting $mps_t = 0$ if there are no announcements during month t, following Gertler and Karadi (2015) and many others. We estimate the following state-dependent local projection regressions:

$$\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}, \qquad (5)$$

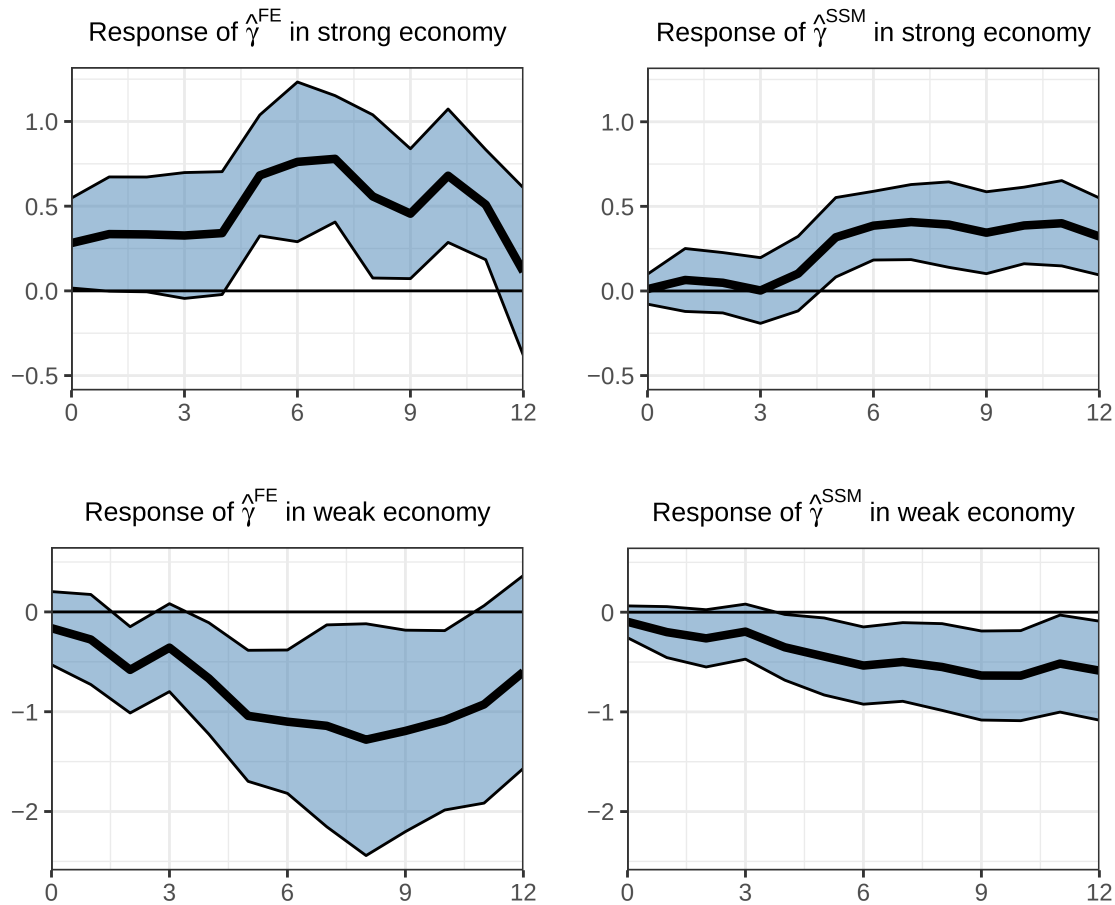
and to account for the residual autocorrelation we calculate Newey-West standard errors with $1.5h$ lags. The regressions include lagged $\hat{\gamma}_t$ as a control to account for the serial correlation in the perceived policy rule coefficient. We estimate these local projections for horizons h from zero to twelve months. The sample period is from January 1988 to December 2019.

The impulse responses of the perceived monetary policy coefficient are shown in Figure 5, and they strongly support the prediction of a state-dependent response of $\hat{\gamma}_t$ to monetary policy surprises. The left two panels show responses for the panel FE estimate of $\hat{\gamma}_t$, while the right two panels show them for the SSM estimate. The top panels plot estimates of $b_1^{(h)}$, and they show that there is a pronounced and persistent positive response of $\hat{\gamma}_t$ to monetary policy surprises during episodes when the economy is strong. The responses peak between six and nine months, and they are statistically significant for several horizons, judging by the 90%-confidence bands shown in the plots. In line with our hypothesis, the picture completely reverses in the bottom panels, which show persistently negative responses during times of a weak economy. These responses are roughly symmetric, though the responses in the bottom panels are somewhat larger. The responses for the SSM estimate are generally quite similar to those for the FE estimate, but somewhat smaller because this time-series is smoother and thus exhibits less pronounced responses to shocks. Consistent with the pronounced differences in the estimated responses in the top and bottom panels, Appendix C shows that the interaction effect $mps_t weak_t$ is statistically significant.

The magnitudes in Figure 5 are economically meaningful, in light of the sample standard deviations of 0.3 for the FE estimate of $\hat{\gamma}_t$ and 0.2 for the SSM estimate. In Section 7, we provide a simple back-of-the-envelope calculation that delivers another way of thinking about economic magnitudes. We show that the impulse responses can be used to compute the fraction of variation in monetary policy surprises driven by uncertainty about the policy rule and show that our estimates imply it is large, at roughly 50% of the total variation.

Overall, the estimates support the view that perceptions of the monetary policy rule

Figure 5: Response to high-frequency monetary policy surprise



Note: Monthly local projection estimates of the state-dependent response of $\hat{\gamma}_t$ to high-frequency monetary policy surprise of Nakamura and Steinsson (2018), mps_t. The estimated regression is $\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where $weak_t$ is an indicator for whether the output gap during month t was below the sample median. The top panels show estimates of $b_1^{(h)}$, and the bottom panels show estimates of $b_2^{(h)}$. Estimates in the left panels use the panel FE estimate of $\hat{\gamma}_t$, and the estimates in the right panels use the SSM estimate. Shaded areas are 90% confidence bands based on Newey-West standard errors with $1.5 \times h$ lags. Sample period: Jan-1985 to Jan-2021.

consistently update in the direction predicted by rational learning, and that the magnitudes of these updates are economically significant. In addition, updating appears to take place in a gradual manner, which is likely to lead to persistent gaps between the perceived and true policy rule coefficients.

5 Interest rate responses to macroeconomic news

Having examined variation in the perceived monetary policy rule, we next turn to the impact of the perceived rule on current and expected future interest rates. We start by examining high-frequency responses of interest rates to macroeconomic news. We show that the magnitude of these responses is closely connected to beliefs about the monetary policy rule, as theory would predict. In particular, we show that interest rates respond more strongly to macroeconomic news, such nonfarm payroll surprises, when the estimated $\hat{\gamma}_t$ is high. This analysis can also be viewed as a validation of our estimates of the perceived monetary policy rule using high-frequency financial data.

We estimate event-study regressions of the form

$$\Delta y_t = b_0 + b_1 \hat{\gamma}_t + b_2 Z_t + b_3 \hat{\gamma}_t Z_t + \varepsilon_t, \tag{6}$$

where Δy_t is change in yield y on announcement date t and Z_t is a macroeconomic news announcement relative to survey expectations of this specific macroeconomic aggregate on the day prior to the announcement. Macroeconomic announcement surprises have been used extensively in empirical work, and several studies have used them to identify the effects of monetary policy on financial markets, including Boyd et al. (2005), Law et al. (2020) and Swanson and Williams (2014).

Our regression specification in equation (6) is closely related to the empirical setup of Swanson and Williams (2014), who also document time variation in the high-frequency responses of financial market variables to macroeconomic news announcements. Like them, we rely on the identification assumption that the information released during narrow intervals around macroeconomic announcements is primarily about the macroeconomy, and that interest rates responses reflect the anticipated Fed response to this macroeconomic news. The key difference is that Swanson and Williams (2014) allow the magnitude of the response to vary over time in an unrestricted fashion, while we directly tie it to our estimate of perceived monetary policy rule. We use our econometric setup to investigate whether the output gap coefficient we estimate from surveys $\hat{\gamma}_t$ is consistent with time-variation in the strength of the high-frequency responses of interest rates to macroeconomic news. Specifically, a positive interaction coefficient b_3 would reveal that our estimates of $\hat{\gamma}_t$ are consistent with the perceived monetary policy rule in financial markets.

We study the response of four different interest rates: 3-month and 6-month federal funds futures rates, and 2-year and 10-year Treasury yields. Fed funds futures provide the closest match to the policy rate definition used in the estimation of $\hat{\gamma}_t$ from survey data, and we include results for medium-term and long-term Treasury bond yields for comparability with Swanson and Williams (2014) and previous studies. The left four columns in Table 4 use the single most influential macroeconomic announcement, non-farm payroll surprises, as Z_t. The right four columns use a linear combination of all macroeconomic surprises. Following Swanson and Williams (2014), this linear combination is simply the fitted value of the regression of the high-frequency interest rate change on all macroeconomic news. In Table 4, panel A reports results for the FE estimate of $\hat{\gamma}_t$, while panel B uses the SSM estimate.

Table 4 shows that the coefficient of interest, b_3, is uniformly estimated to be positive and highly statistically significant across all combinations of interest rates, macroeconomic news, and estimates of $\hat{\gamma}_t$. The only exception is the 3-month fed funds futures. The magnitudes are economically meaningful. For example, the second column in Panel A has an unconditional coefficient on the non-farm payroll surprise of $b_2 = 0.02$ and an interaction coefficient of the surprise with $\hat{\gamma}_t$ of $b_3 = 0.04$. The standard deviation of the panel FE estimate of $\hat{\gamma}_t$ is 0.3. Thus, a one-standard deviation increase in $\hat{\gamma}_t$ increases the response of the 6-month federal funds futures to nonfarm payroll surprises by more than 50%. The ratio of b_3/b_2 is even larger in Panel B, as would be expected if the SSM estimate of $\hat{\gamma}_t$ is less noisy and close to unbiased.

Overall, the evidence from high-frequency macroeconomic announcements supports the interpretation of the estimated $\hat{\gamma}_t$ as a perceived monetary policy rule coefficient. These results suggest that survey and financial markets expectations are consistent. In addition, they also partly address concerns that our estimates reflect the perceived impact of monetary policy shocks on output, rather than the perceived response of the policy rate to the output gap. Under the assumption that the announcements do not reveal news about policy shocks, market reactions only capture expectations about policy responses to the economy, and Table 4 shows that our estimated $\hat{\gamma}_t$ moves with those expectations. This suggests that a substantial part of the variation in $\hat{\gamma}_t$ reflects changes in the perceived monetary policy rule.

6 Predicting interest rates and expected bond returns

We next turn to the impact of the perceive monetary policy rule on the predictability of interest rates and variation in expected bond risk premia. We will show that $\hat{\gamma}_t$ is negatively related to subjective expected bond excess returns, as one would expect if a higher value of $\hat{\gamma}_t$ means that investors believe that the Fed is more responsive to the economy, making Treasury bonds better macroeconomic hedges. In addition, we will show that $\hat{\gamma}_t$ predicts forecast errors for the fed funds rate.

Table 4: Sensitivity of interest rates to macroeconomic news announcements

Panel A: Panel FE

	Z=Nonfarm Payroll				Z=All Announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
$\hat{\gamma}^{FE}$	0.6***	0.5***	0.07	-0.04	0.7***	0.6***	0.3	0.1
	(3.71)	(2.65)	(0.26)	(-0.11)	(3.99)	(3.04)	(1.17)	(0.33)
Z	0.03***	0.02***	0.03***	0.01	1.0***	0.7***	0.7***	0.7***
	(4.81)	(3.66)	(3.08)	(1.60)	(6.94)	(6.49)	(6.72)	(5.59)
$\hat{\gamma}^{FE} \times Z$	-0.0009	0.04***	0.05***	0.05***	-0.04	0.6***	0.6***	0.6**
	(-0.11)	(3.99)	(3.43)	(3.26)	(-0.20)	(3.64)	(3.54)	(2.55)
Const.	-0.4***	-0.3**	-0.3	-0.1	-0.3***	-0.3**	-0.2	-0.05
	(-3.51)	(-2.04)	(-1.54)	(-0.58)	(-3.10)	(-2.41)	(-0.92)	(-0.24)
N	3350	3350	3350	3350	3350	3350	3350	3350
R^2	0.06	0.07	0.08	0.04	0.10	0.13	0.14	0.09

Panel B: SSM estimate

	Z=Nonfarm Payroll				Z=All Announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
$\hat{\gamma}^{SSM}$	0.8**	0.5	-0.3	-0.5	1.0***	0.6	0.2	-0.2
	(2.36)	(1.20)	(-0.61)	(-0.83)	(3.00)	(1.55)	(0.37)	(-0.32)
Z	0.02**	0.008	0.02*	0.01	0.7***	0.5***	0.6***	0.7***
	(2.43)	(1.08)	(1.66)	(1.17)	(3.56)	(3.55)	(4.31)	(4.27)
$\hat{\gamma}^{SSM} \times Z$	0.03	0.09***	0.10***	0.07**	0.9*	1.6***	1.3***	0.9**
	(1.26)	(3.97)	(3.07)	(2.35)	(1.77)	(4.05)	(3.86)	(2.28)
Const.	-0.3***	-0.2	-0.1	0.05	-0.3***	-0.2	-0.06	0.08
	(-2.81)	(-1.09)	(-0.54)	(0.18)	(-2.86)	(-1.47)	(-0.28)	(0.30)
N	3350	3350	3350	3350	3350	3350	3350	3350
R^2	0.06	0.07	0.08	0.04	0.10	0.13	0.14	0.09

Note: This table reports the regression $\Delta y_t = b_0 + b_1\hat{\gamma}_t + b_2 Z_t + b_3\hat{\gamma}_t Z_t + \varepsilon_t$. The dependent variables are daily changes in yields on macroeconomic announcement dates, expressed in basis points. The independent variable Z is either the surprise in non-farm payrolls, normalized to have mean zero and standard deviation 1, or an aggregate variable that captures all surprises. We compute the aggregate variable as the fitted value of a regression of the change in yields on all announcements following Swanson and Williams (2014) normalized such that the coefficient of the change in yields onto Z without interaction terms equals 1. t-statistics are calculated using robust standard errors.

6.1 Expected bond excess returns

In this section, we show that the perceived policy rule coefficient $\hat{\gamma}_t$ is negatively related to expected excess returns on long-term Treasury bonds. This relationship affects the transmission of monetary policy because term premia are an important component of long-term bond yields and thus the cost of financing long-term real investments.

The intuition for why $\hat{\gamma}_t$ should be inversely related to expected bond excess comes from fundamental asset pricing logic: An asset that pays out in bad states of the world should command a higher price and require lower expected returns. A higher perceived monetary policy coefficient $\hat{\gamma}_t$ means that interest rates are expected to fall more – and bond prices are expected to rise more – during recessions. Thus, when $\hat{\gamma}_t$ is high, bonds are better hedges and should therefore have lower expected returns.[13]

We construct subjective expected 1-year excess returns on 6- and 11-year Treasury bonds similarly to Cieslak (2018), Piazzesi et al. (2015), and Nagel and Xu (2022).[14] We proxy for the expected 5-year Treasury bond par yield $\bar{E}_t y_{t+1}^{(5),par}$ using the average Blue Chip survey forecast of the 5-year Treasury bond yield at the 4-quarter forecast horizon. Because Blue Chip forecasters forecast par yields, we use the par yield on a 6-year Treasury bond from Gürkaynak et al. (2007), $y_t^{(6),par}$, to compute expected returns. Blue Chip forecasters are required to submit their responses at the end of the previous month, so to make sure the information sets are consistent we pair the March survey with the end-of-month par yield at the end of February. Letting $y_t^{(1)}$ denote the one-year zero-coupon yield, we then compute the 1-year expected excess return on the 6-year Treasury bond as

$$\bar{E}_t xr_{t+1}^{(6)} \quad = \quad Dur^{(6)} y_t^{(6),par} - (Dur^{(6)} - 1)\bar{E}_t y_{t+1}^{(5),par} - y_t^{(1)}. \tag{7}$$

The duration of the 6-year par bond, $Dur^{(6)}$, is estimated from bond yields, assuming that bonds sell at par following Campbell et al. (1998), p. 408. The expected 1-year excess return

[13] These predictions are worked out in detail in Campbell et al. (2017) and Campbell et al. (2020), for example. The link between $\hat{\gamma}_t$ and subjective bond risk premia does not crucially rely on the interpretation of $\hat{\gamma}_t$ as a perceived monetary policy rule coefficient, and remains valid if $\hat{\gamma}_t$ simply captures the perceived comovement of interest rates and the economy. The prediction for expected bond risk premia similarly remains valid, at least qualitatively, if our estimate of a higher perceived monetary policy output weight partially reflects greater inertia in the perceived monetary policy rule. Pflueger (2022) shows that Treasury bonds tend to have better hedging properties when the monetary policy rule is more inertial in a New Keynesian asset pricing model, though the composition of supply vs. demand shocks is also important.

[14] Our preferred measure of expected bond excess returns is the subjective expected excess return inferred from Blue Chip surveys, because realized returns are a noisy realization of expected returns and, in the presence of not fully rational expectations, may reflect both expected and unexpected returns due to systematic forecast errors. Forecasting regressions with realized rather than expected Treasury bond excess returns are shown in the Appendix and further support a negative relationship between $\hat{\gamma}_t$ and objective expected Treasury bond excess returns.

Table 5: Expected bond risk premia

	$\bar{E}_t xr^{(6)}_{t+1}$			$\bar{E}_t xr^{(11)}_{t+1}$		
$\hat{\gamma}^{FE}$	-0.70***	-0.78***	-0.81***	-1.12***	-1.26***	-1.18***
	(-4.41)	(-4.28)	(-7.87)	(-3.03)	(-3.15)	(-6.67)
TERM		0.33			0.54	
		(1.57)			(1.49)	
R^2	0.15	0.19	0.64	0.13	0.16	0.62
$\hat{\gamma}^{SSM}$	-0.44**	-0.46**	-0.68***	-0.75	-0.79	-1.02***
	(-1.98)	(-2.04)	(-5.99)	(-1.55)	(-1.60)	(-5.36)
TERM		0.21			0.35	
		(0.97)			(0.97)	
R^2	0.06	0.08	0.58	0.06	0.07	0.59
PCs	No	No	Yes	No	No	Yes

Note: Regressions for subjective expected log bond excess return on 6-year and 11-year nominal Treasury bonds over one-year holding periods on panel FE estimate (top panel) and SSM estimate (bottom panel) of $\hat{\gamma}_t$ and yield curve variables. $\hat{\gamma}_t$ is standardized to have unit standard deviation. Term spread $TERM_t$ is the difference between the 10-year and 1-year zero-coupon nominal Treasury yields from Gürkaynak et al. (2007). If indicated, regressions control for the first three principal components (PCs) of zero-coupon yields with maturities one, two, five, seven, ten, fifteen, and twenty years. Coefficients on the constant and the three principal components are omitted. Sample: 397 monthly observations from January 1988–January 2021. Newey-West t-statistics with automatic lag selection (between 19 and 28 months) in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

on a 11-year Treasury bond is computed analogously. We then run regressions of the form

$$\bar{E}_t xr^{(n)}_{t+1} = b_0 + b_1\hat{\gamma}_t + b_2 TERM_t + \varepsilon_t, \tag{8}$$

where the term spread $TERM_t$ is defined as the difference between 10-year and 1-year zero-coupon Treasury bond yields.

Table 5 reports the results. Starting with the first column in Panel A, we see that the coefficient on $\hat{\gamma}_t$ is indeed negative and highly statistically significant, as expected if higher values of $\hat{\gamma}_t$ mean that investors expect bonds to be better hedges. The magnitudes are economically meaningful. A one-standard deviation increase in $\hat{\gamma}_t$ is associated with a 0.7 percentage point decline in the expected excess return on a 6-year Treasury bond over the next year. The R^2 is substantial at 15 percent. This positive finding contrasts with the term spread in the second column, which does not enter significantly and does not increase the regression R^2, consistent with the findings in Nagel and Xu (2022). In the third column, we control for the first three principal components of the term structure, which increases the R^2

substantially but leaves the coefficient on $\hat{\gamma}_t$ unchanged. The right three columns in Panel A show analogous results for the expected 1-year returns on Treasury bonds with 11 years remaining to maturity, finding generally similar results with even larger point estimates. Panel B shows similar results when we use the state-space model estimate for $\hat{\gamma}_t$. In this case, the expected excess return for the 6-year Treasury bond always loads negatively and significantly on $\hat{\gamma}_t$, and the expected excess return for the 11-year Treasury bond loads always negatively but only sometimes statistically significantly. In Appendix D.2 we show that the relationship between expected bond excess returns and the perceived monetary policy output weight is unchanged when we control for Giacoletti et al. (2021)'s measure of interest rate disagreement across forecasters. Taken together, we find that the perceived monetary policy output weight $\hat{\gamma}_t$ is negatively related with expected bond excess returns.

These results provide a possible explanation for conundrum periods, when the Fed raised its policy rate but long-term yields barely increased or even decreased. When the Fed raises policy rates during an expansion, two consequences follow. First, as our results in Section 4.2 show, beliefs about the policy rule shift, with the public expecting monetary policy to be more responsive to economic activity going forward. The results in this section show that this shift in beliefs lowers the term premium. Consistent with this idea, Backus and Wright (2007) provide evidence that the decline in long-term yields during the most prominent example of a conundrum period—the "Greenspan conundrum" during the tightening cycle in 2004-2005—was largely due to a lower term premium

A simple back-of-the-envelope calculation illustrates the quantitative importance of this channel for the term premium in long-term yields. Conditional on being in a strong economy, the top-right panel in Figure 5 shows that a 10 bps positive monetary policy shock leads to an increase in the SSM estimate of $\hat{\gamma}_t$ of around 0.06—or 0.2 standard deviations—with a peak response at six months after the shock. The last column in Panel B of Table 5 shows that an increase in $\hat{\gamma}_t$ of this magnitude is associated with a $0.2 \times -0.68 = -0.136$ percentage point decrease in the subjective risk premium for a 6-year Treasury bond. A 10 bps surprise *increase* in the policy shock during good times could therefore lead to a comparably large *decrease* in the term premium of the 6-year Treasury bond. These magnitudes illustrate that this channel may be quantitatively important, and thus provide a new explanation for why long-term bond yields may appear decoupled from the short-term policy rate during some tightening cycles.

6.2 Fed funds forecast errors

Finally, we study survey forecast errors for the federal funds rate, following the literature that has used forecast errors and forecast revisions to test rationality (e.g. Coibion and Gorodnichenko, 2015; Bordalo et al., 2020). If forecasters are full information rational the difference between realized outcomes and fed funds forecast errors should be unpredictable. However, Cieslak (2018) has documented that in forecasting the federal funds rate professional forecasters make persistent errors, which are predictable with measures of past real activity. If forecasters are slow to update their estimates of γ_t, as suggested by the estimates shown in Figure 5, the gap between the actual and perceived monetary policy coefficient $\gamma_{t+h} - \hat{\gamma}_t$ would be higher when $\Delta\hat{\gamma}_t$ is high. In this case, forecasters would tend to be surprised by higher-than-expected fed funds rates when $\Delta\hat{\gamma}_t$ and the output gap are both high. Consistent with this intuition, we show that fed funds forecast errors load positively onto the change in the perceived monetary policy output weight interacted with a measure of expected economic activity.

Table 6: Predictability of forecast errors for the federal funds rate

			Panel FE $\hat{\gamma}$		SSM $\hat{\gamma}$	
	$q=2$	$q=4$	$q=2$	$q=4$	$q=2$	$q=4$
$CFNAI_t$	0.34***	0.72***	0.46***	0.92***	0.52***	0.93***
	(3.16)	(2.63)	(4.24)	(3.85)	(3.95)	(3.55)
i_t	-0.04	-0.08	-0.03	-0.07	-0.03	-0.07
	(-1.16)	(-1.46)	(-0.87)	(-1.16)	(-0.95)	(-1.19)
$\Delta\hat{\gamma}_t$			-0.03	-0.16*	-0.06	-0.16
			(-0.57)	(-1.66)	(-1.16)	(-1.47)
$\Delta\hat{\gamma}_t \times CFNAI_t$			0.17***	0.25***	0.17**	0.21**
			(2.64)	(2.82)	(2.28)	(2.40)
N	142	140	138	136	138	136
R^2	0.19	0.23	0.25	0.29	0.27	0.28

Note: This table estimates regressions for the q-quarter-ahead forecast error for the federal funds rate, using the mean BCFF forecast. CFNAI and $\Delta\hat{\gamma}_t = \hat{\gamma}_t - \hat{\gamma}_{t-4}$ are standardized to have a standard deviation of one and mean zero. The intercept b_0 is not reported. Data is quarterly and ranges from 1985.Q3 through 2019.Q4. Newey-West t-statistics with 6 lags are shown in parentheses.

Table 6 first replicates the well-known result that forecast errors for the federal funds rate are predictable from the Chicago Fed National Activity Index (CFNAI, CFNAIMA3) as a measure of economic activity (Cieslak (2018)). The left-hand-side variable in all regressions is the realized federal funds rate minus the mean BCFF q-quarter forecast q quarters prior.

We consider horizons of two and four quarters, and we use only the surveys in the third month of each quarter in order to ensure a constant forecast horizon, so that our sample is quarterly from 1992:Q1 to 2020:Q4. The first two columns confirm the finding from the prior literature that fed funds forecast errors are ex-post predictable from real economic activity, with an R^2 around 25%.

To test whether the perceived monetary policy rule plays a role in the predictability of federal funds rate forecast errors from economic activity, we next include the interaction terms between the CFNAI and the four-quarter change in the perceived monetary policy output gap weight $\Delta\hat{\gamma}_t = \hat{\gamma}_t - \hat{\gamma}_{t-4}$. The results show that this interaction term contains substantial additional predictive power. The bottom row in Table 6 shows that the interaction coefficient is positive and highly significant in all cases. The positive interaction coefficient means that the predictability is most pronounced when the perceived responsiveness of monetary policy to the output gap is high.[15] These findings suggest that the predictability of policy rate forecast errors from economic activity systematically varies over time, and that perceptions of the monetary policy rule are an important determinant of this time variation.[16]

7 Illustrative model with learning and heterogeneity

We now present a simple learning framework that delivers two key points. First, it characterizes the simplest conditions under which the cross-section of forecasts can be used to estimate the perceived monetary policy rule, i.e., the simplest conditions under which our estimation procedure is valid. Second, it rationalizes a number of our empirical results.

In our model, the policy rate is assumed to follow the simple rule

$$i_t = \gamma_t x_t + u_t, \tag{9}$$

where the output gap x_t is assumed to follow an exogenous AR(1) process

$$x_t = \rho x_{t-1} + \varepsilon_t. \tag{10}$$

[15]The change in the perceived output gap coefficient $\hat{\gamma}_t$ to close to zero at the beginning of the financial crisis is an important observation driving the coefficient on the interaction $\hat{\gamma}_t \times CFNAI_t$. When we exclude the period 2007Q3-2009Q4, our results for 2-quarter forecast errors are very similar, but the results for 4-quarter forecast errors lose significance.

[16]Consistent with these results, Wu (2022) argues that behavioral biases lead forecasters to generally underestimate cross-variable relationships on average, including the Phillips curve and the Taylor rule.

We assume that true process for γ_t is unobserved and follows a random walk:

$$\gamma_{t+1} \;=\; \gamma_t + \xi_{t+1}. \tag{11}$$

We follow Bauer and Swanson (2022) by using a monetary policy rule that only depends on the output gap. In contrast to their framework, we account for forecaster heterogeneity, and we do so by assuming that forecasters (i) have different priors about γ_t and (ii) receive different signals about the output gap. Forecasters differ in terms of their initial prior mean over the monetary policy rule parameter γ_t but share the same initial prior precision:

$$E^j\left(\gamma_1 \left| \mathcal{Y}_0\right.\right) \;=\; \hat{\gamma}_0^j, \tag{12}$$

$$Var^j\left(\gamma_1 \left| \mathcal{Y}_0\right.\right) \;=\; \sigma_0, \tag{13}$$

where $\mathcal{Y}_t$ denotes the filtration based on observing the output gap and interest rates up to and including time t. This assumption about cross-forecaster heterogeneity is in line with Patton and Timmermann (2010), who argue that differences in priors are a key source of forecaster disagreement. Throughout, we use the expectations operator $\bar{E}$ to denote average expectations across all forecasters j. We use $\hat{\gamma}_t$ to denote $\bar{E}\left(\gamma_{t+1} \left| \mathcal{Y}_t\right.\right)$ and $\hat{\gamma}_t^j = E^j\left(\gamma_{t+1} \left| \mathcal{Y}_t\right.\right)$.

In each period, forecasters first observe a noisy signal about the output gap:

$$\nu_t^j \;=\; x_t + \eta_t^j,\; \eta_t^j \sim N(0, \sigma_\eta^2), \tag{14}$$

where η_t^j has mean zero and is uncorrelated with forecasters' time-0 priors about the monetary policy rule parameter, $\hat{\gamma}_0^j$. Forecasters then make forecasts of future interest rates and output gaps, that is, $E^j\left(i_{t+h} \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right)$ and $E^j\left(x_{t+h} \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right)$. After making these forecasts, forecasters observe the period-t output gap. At that point, they only differ in their beliefs about γ_t. Finally, the Fed sets the policy rate i_t based on the policy rule, and forecasters update their beliefs. We interpret the instantaneous interval around observing the output gap as a macroeconomic announcement date, and the instantaneous interval around observing the policy rate as an FOMC announcement date.

Within-period timing:

			Period t					
Signal ν_t^j	$\Rightarrow$	Make forecasts	$\Rightarrow$	Observe x_t	$\Rightarrow$	Observe i_t	$\Rightarrow$	Update $\hat{\gamma}_t^j$

7.1 Rational learning

We now show that under rational learning, our model validates our estimation procedure and explains many of our empirical results. The monetary policy surprise due to an FOMC announcement is

$$mps_t \equiv i_t - \bar{E}\left(i_t \,|\mathcal{Y}_{t-1}, x_t\right) = u_t + (\gamma_t - \hat{\gamma}_t)x_t. \tag{15}$$

Surprises arise due to either monetary policy shocks u_t or forecasters' imperfect information about the policy rule. The following lemma describes how rational forecasters update policy rule beliefs in response to monetary policy surprises.

Lemma 1: If forecasters are rational, each forecaster j updates his perceived monetary policy coefficient as follows:

$$\hat{\gamma}_t^j - \hat{\gamma}_{t-1}^j = \hat{\gamma}_t - \hat{\gamma}_{t-1} = \omega_t \frac{mps_t}{x_t}, \qquad \omega_t \equiv \frac{\sigma_t^2}{\sigma_t^2 + \sigma_u^2/x_t^2}. \tag{16}$$

Belief uncertainty is the same for all forecasters:

$$Var^j\left(\gamma_{t+1} \,|\mathcal{Y}_t\right) \equiv \sigma_{t+1}^2 = \sigma_t^2(1-\omega_t) + \sigma_\xi^2. \tag{17}$$

The proof follows directly from the Kalman filter. Because all forecasters have the same prior dispersion, they update their perceived monetary policy coefficients in lockstep. Thus, forecaster j's perceived monetary policy rule coefficient can be expressed as the consensus coefficient plus a forecaster fixed effect:

$$\hat{\gamma}_t^j = \hat{\gamma}_t + \left(\hat{\gamma}_0^j - \hat{\gamma}_0\right). \tag{18}$$

We derive several corollaries from Lemma 1 in order to interpret our empirical results.

Corollary 1 (Cross-Forecaster Regression): We can recover the consensus perceived monetary policy coefficient $\hat{\gamma}_t$ at time t from the forecaster-horizon-time panel of forecasts as follows.

a. In a panel regression of policy rate forecasts on output gap forecasts:

$$E^j\left(i_{t+h} \,|\mathcal{Y}_{t-1}, \nu_t^j\right) = \alpha_j^0 + g_t E^j\left(x_{t+h} \,|\mathcal{Y}_{t-1}, \nu_t^j\right) + \varepsilon_{jht} \tag{19}$$

the estimated g_t is a consistent estimate of $\hat{\gamma}_t$.

b. In a panel regression of policy rate forecasts on output gap forecasts that allows for forecaster-specific coefficients on output gap forecasts:

$$E^j\left(i_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \alpha_j^0+\alpha_j^1 E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)+g_t E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)+\varepsilon_{jht} \quad (20)$$

the estimated g_t is a consistent estimate of $\hat{\gamma}_t$. Note that this regression corresponds exactly to the estimates labeled "Heterogeneous" in Table 2.

The implication of Corollary 1 is that our estimates in Section 2 recover the average perceived rule coefficient $\hat{\gamma}_t$ despite heterogeneity in forecaster perceptions of the policy rule. While the forecaster fixed effect, α_j^0, is zero under the assumptions of the model, a straightforward extension with disagreement about the natural rate would yield non-zero forecaster intercepts as in our empirical estimation.

Corollary 2 (Macro Surprises): The announcement of x_t corresponds to a macroeconomic surprise, $x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)$. This causes an update of the consensus interest rate forecasts, $\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},x_t\right.\right)-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)$, which can be measured using fed funds futures rates. High-frequency regressions of fed funds futures rates on macroeconomic news can be used to validate estimates of the perceived monetary policy rule $\hat{\gamma}_t$.

a. If we directly observe news about the output gap, then in a regression of the change in consensus interest rate forecasts on $\hat{\gamma}_t$, the news, and their interaction:

$$\begin{aligned}\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},x_t\right.\right)-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) &= b_0+b_1\hat{\gamma}_t+b_2\left(x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)\right)\\ &\quad +b_3\hat{\gamma}_t\left(x_t-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)\right)+\varepsilon_t \end{aligned} \quad (21)$$

the interaction coefficient equals $b_3=1$.

b. If instead we observe a macroeconomic surprise Z_t proportional to the output gap news

$$\alpha Z_t = x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) \quad (22)$$

where the constant α is scaled so that the univariate regression of fed funds futures surprises onto Z_t equals unity, then in the regression

$$\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},x_t\right.\right)-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = b_0+b_1\hat{\gamma}_t+b_2 Z_t+b_3\hat{\gamma}_t Z_t+\varepsilon_t \quad (23)$$

the estimate of the regression coefficient b_3 converges to $1/\bar{\hat{\gamma}}_t$, where $\bar{\hat{\gamma}}_t$ is the full-sample average of $\hat{\gamma}_t$.

Corollary 2 provides a model-based interpretation of the macro news results in Section 5. It says that the sensitivity of fed funds futures to macroeconomic news is larger when the perceived monetary policy coefficient $\hat{\gamma}_t$ is high. The model therefore predicts that a regression of fed funds futures changes onto the interaction of macro surprises with the perceived coefficient, $\hat{\gamma}_t Z_t$, should yield a positive coefficient, which is exactly what we find. The scale of this interaction coefficient depends on how much output gap forecasts move in response to a macroeconomic news surprise Z_t on average. When the news is scaled so that a univariate regression of fed funds futures changes onto Z_t equals unity as in Swanson and Williams (2014), the interaction coefficient is predicted to be $\frac{1}{\bar{\hat{\gamma}}}$.[17]

The predictions of Corollary 2 are borne out in our empirical regressions in Table 4, both qualitatively and quantitatively. Take the "All Announcement" columns in Panel B, which map most clearly into the model regressions.[18] The interaction coefficient in the "All Announcement" column for 6-month fed funds future changes in Panel B is statistically indistinguishable from $2 = \frac{1}{0.5}$. For comparison, the sample average of our panel FE estimate is roughly 0.5, which also happens to be value of in the classical Taylor (1993) rule.

Corollary 3 (Responses to Monetary Policy Surprises): Monetary policy surprises lead to changes in policy rule beliefs, and the sign of the update depends on the output gap.

a. If the output gap is above zero ($x_t > 0$), a positive monetary policy surprise leads to an upward-revision in the consensus perceived monetary policy coefficient $\hat{\gamma}_t$.

b. If the output gap is below zero ($x_t < 0$), a positive monetary policy surprise leads to a downward-revision in the consensus perceived monetary policy coefficient $\hat{\gamma}_t$.

c. In both cases, the revision is permanent and impulse responses of $\hat{\gamma}_t$ to a monetary policy surprise are flat.

Corollary 3 and the related evidence in Section 4.2 are key to understanding how perceptions of the monetary policy rule evolve. Intuitively, in our model a tightening surprise when the economy is strong suggests that the Fed is more responsive to the output gap than forecasters believed, while a tightening surprise in a weak economy suggests the opposite. This state-dependent response of policy rule beliefs is consistent with the estimates shown in Figure 5, where we showed that the perceived $\hat{\gamma}_t$ increases following a positive monetary policy surprise

[17]Formally, Corollary 2b. assumes that the perceived monetary policy coefficient $\hat{\gamma}_t$ is stationary so its time-series average exists. While stationarity is at odds with the random walk assumption (11), all results continue to hold if the actual process for γ_t follows an arbitrarily persistent but not quite unit root process and forecasters update as if γ_t follows a random walk.

[18]The panel FE estimates in Panel A likely contain more measurement error, and the "Nonfarm Payroll" announcements in the left set of columns are scaled differently.

if the economy is strong, but $\hat{\gamma}_t$ decreases following a positive monetary policy surprise if the economy is weak. However, the model also predicts that these impulse responses should be instantaneous and permanent, in contrast to the gradual empirical responses in the data.

The empirical evidence in Section 4.2 sheds light on the forecasters' understanding of the policy rule. It helps rule out two alternative scenarios, under which Corollary 3 would no longer hold: (i) the full-information case in which forecasters observe γ_t at the beginning of each period (i.e., FIRE); and (ii) the case in which the volatility of the monetary policy shock is very large relative to the uncertainty about the monetary policy coefficient (i.e., $\sigma_u^2 \to \infty$). In both cases, monetary policy surprises are uninformative about γ_t beyond what forecasters already know, and therefore forecasters do not update at all in responses to them.

Furthermore, the model implies a simple back-of-the-envelope calculation, which suggests that the fraction of variation in monetary policy surprises driven by uncertainty about the policy rule is large. Equation (16) shows that the amount forecasters update their perceived rule $\hat{\gamma}_t$ following a surprise depends on their uncertainty about the rule (σ_t^2), the volatility of the policy shock (σ_u^2), and the output gap. In the top-left-panel of Figure 5, the peak response of $\hat{\gamma}_t$ to a policy surprise is around 0.7. The output gap is on average 1.4 percentage points above its median during the strong economic times. Substituting $\hat{\gamma}_t - \hat{\gamma}_{t-1} \approx 0.7$ and $x_t \approx 1.4$ into equation (16) and solving for ω_t suggests that forecasters attribute roughly 50% of the variation in monetary policy surprises to uncertainty about the policy rule.

Corollary 4 (Bond Risk Premia): Assuming a log stochastic discount factor $m_{t+1} = -i_t - \psi\varepsilon_t - \frac{1}{2}\psi^2\sigma_\varepsilon^2$, the model implies that expected excess bond returns depend negatively on the perceived monetary policy coefficient $\hat{\gamma}_t$.

Corollary 4 assumes a simple stochastic discount factor that is consistent with interest rate dynamics and captures the notion that recessions are states of high marginal utility, as in much of the consumption-based asset pricing literature. The only priced shock is the shock to the output gap, ε_{t+1}, and the parameter ψ captures investors' risk aversion. For simplicity, we abstract from inflation so the real and nominal stochastic discount factors are the same.

The model then predicts that expected bond risk premia move inversely with perceived $\hat{\gamma}_t$, consistent with the findings in Table 5. The intuition is that $\hat{\gamma}_t$ governs how much forecasters believe interest rates will fall when the output gap falls. Since bond prices are inversely related to interest rates, $\hat{\gamma}_t$ governs how much forecasters believe how much bond prices will rise in the bad, low marginal utility states of the world. The higher is the perceived $\hat{\gamma}_t$, the better the hedging properties of Treasuries, and the lower their risk premium.

Corollary 5 (Forecast Errors): The consensus federal funds forecast error $i_{t+h} - \bar{E}(i_{t+h} \mid \mathcal{Y}_t)$ is not predictable from any variables in the filtration $\mathcal{Y}_t$, including $\hat{\gamma}_t$, x_t or any functions of these variables and their lags.

In sum, under rational learning, our model with heterogeneous priors and signals about the output gap rationalizes our estimation strategy in Section 2 and is consistent with the majority of our empirical findings. Only two of our empirical results are not explained by the fully rational framework: First, Figure 5 documents that the impulse responses of $\hat{\gamma}_t$ following monetary policy surprises are gradual, rather than immediate and flat as predicted by Corollary 3.c. Second, we find strong predictability of fed funds forecast errors in Table 6, in contrast to Corollary 5.

7.2 Nonrational learning

We now show that adding a single behavioral bias—overconfidence—can help the model to explain both the gradual updating of $\hat{\gamma}_t$ in Figure 5 and the predictability results in Table 6. A large literature in behavioral economics provides empirical support for overconfidence and slow information diffusion.[19] Of course, we cannot rule out alternative explanations such as slow updating due to agency frictions, or rational updating with a more complicated data generating process.

Instead of rational updating, we now assume that forecasters update their perceived monetary policy coefficient $\hat{\gamma}_t^j - \hat{\gamma}_t^j$ using a forecast uncertainty $Var^j(\gamma_t | \mathcal{Y}_{t-1}) = \kappa \sigma_t$ for some constant $0 < \kappa < 1$, where σ_t denotes the forecast uncertainty of a rational Bayesian forecaster. In other words, overconfident forecasters over-estimate the precision of their own estimate of the policy rule $\hat{\gamma}_{t-1}$. Under this behavioral assumption, forecasters continue to update according to equation (16) but with a different ω_t. All model results with the exceptions of Corollaries 3.c and 5 therefore continue to hold with this particular form of nonrational learning.

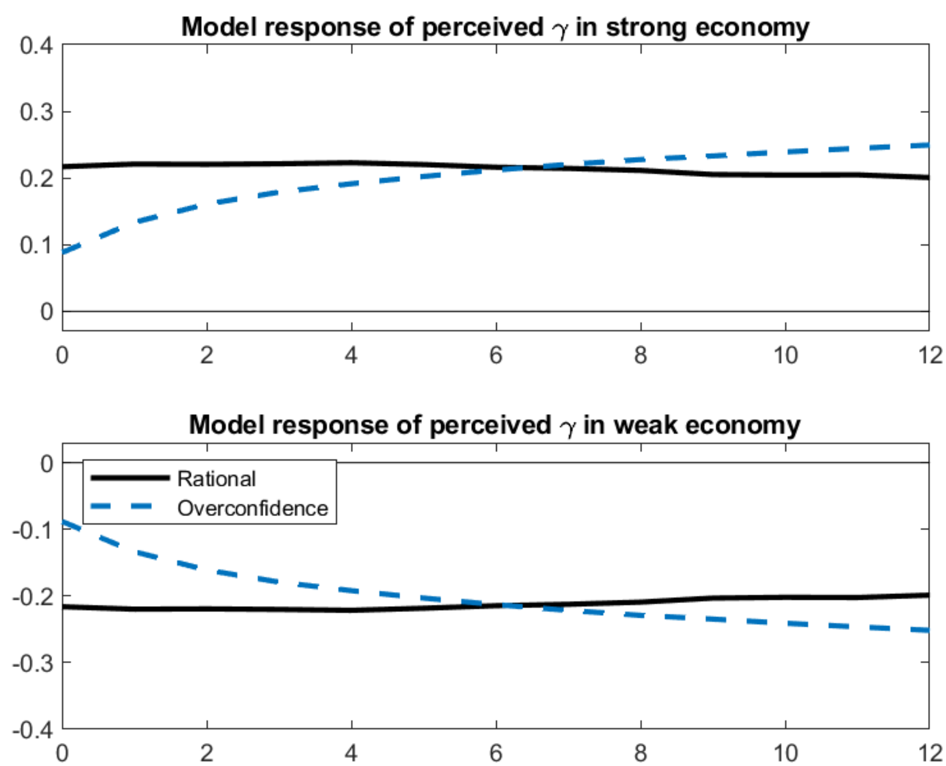
Figure 6 shows the model-simulated state-contingent response of $\hat{\gamma}_t$ to monetary policy surprises with nonrational learning. Parameter values are listed in Appendix Table B.1. To understand the intuition, we start with the black solid line where forecasters update rationally, corresponding to our baseline model described above in Section 7.1. As described in Corollary 3, the impulse responses are immediate and permanent since γ_t follows a random walk and fully rational forecasters understand this. When the output gap is above average, the perceived monetary policy coefficient $\hat{\gamma}_t$ jumps up following a positive monetary policy

[19] See, e.g., Barberis and Thaler (2003), Coibion and Gorodnichenko (2015), and Angeletos et al. (2021).

surprise (top panel). When the output gap is below average, $\hat{\gamma}_t$ jumps down following a positive monetary policy surprise (bottom panel).

In contrast, the blue dashed line in Figure 6 illustrates the impulse responses when forecasters are overconfident. The resulting impulse responses have the same signs as before, but they now capture the gradual response of $\hat{\gamma}_t$ we find in Figure 5 Intuitively, forecasters over-estimate the precision of their beliefs about of γ_t and thus initially underweight the new information in a monetary policy surprise. They are then predictably surprised by future policy decisions, leading to gradual updating.[20]

Figure 6: Model perceived output weight response to monetary policy surprise



Note: We run the following regression on model-simulated data: $\hat{\gamma}_{t+h|t+h-1} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where $weak_t$ is an indicator for whether the output gap during period t was negative. We report the average across 2000 simulations of length 3000.

Overconfidence, and the resulting slow response in the perceived monetary policy coefficient, can also explain why fed funds forecast errors are more predictable from economic

[20]As Figure 6, these predictable surprise can actually lead the perceived $\hat{\gamma}_t$ to overshoots as forecaster perceive a string of monetary policy surprises before converging to the rational response.

activity when the perceived monetary policy output coefficient has recently increased, as we find in the data in Table 6. Using model-simulated data, we run the same regression as in column (4) of Table 6 using the four-quarter consensus forecast for the output gap as the model-analogue for the CFNAI in the data. The regression coefficient on the interaction effect $\Delta\hat{\gamma}_t \times \bar{E}_t x_{t+4}$ equals 0.08 in the simulated data compared to 0.25 in the actual data. Intuitively, an increase in the perceived monetary policy output weight $\hat{\gamma}_t$ tends to accompany an under-estimation of the true output weight γ_t. When the perceived monetary policy output weight has recently increased and the output gap is above average, forecasters are therefore repeatedly surprised the tightness of monetary policy, leading to positive fed funds forecast errors.

In sum, our simple model with heterogeneous macro signals and heterogeneous policy rule priors can explain all empirical findings in our paper. With rational learning the model is consistent with most of our empirical results, but overconfidence is needed to account for the gradual responses of $\hat{\gamma}_t$ to monetary policy surprises and the predictability of fed funds forecast errors.

8 Conclusion

This paper presents new time-varying estimates of the publicly perceived monetary policy rule of the Federal Reserve. In contrast to prior work, we estimate the perceived monetary policy rule using rich monthly panel data for survey forecasts of interest rates and macro variables. We present two types of estimates—based on repeated panel regressions and on a state-space model—and find that they are mutually consistent.

Using our new estimates of the perceived monetary policy rule, we document a number of new facts that are relevant for monetary policy and asset pricing. First, the perceived weight on output drops towards the end of tightening cycles and monetary easing cycles, but rises before and at the beginning of tightening cycles. The Fed is hence perceived to get ahead of the curve at the beginning of easing cycles, but to tighten in a gradual and data-dependent manner. Second, forecasters appear to update their estimates of the perceived monetary policy output gap weight following macroeconomic data in the direction predicted by rational learning, but in a gradual or even sluggish manner. Third, shifts in the perceived rule explain time-varying financial market responses to macroeconomic news releases. This high-frequency evidence provides a validation of our survey-based estimates, showing that they are consistent with the market-perceived monetary policy rule. Fourth, predictable forecast errors for the federal funds rate are more likely to arise when the perceived policy output gap coefficient has increased, indicating that forecasters underestimate the Fed's response to news especially prior to tightening cycles. Finally, regressions of subjective expected excess returns on long-term Treasury bonds suggest that the perceived output gap coefficient is negatively related to subjective bond risk premia, consistent with investors requiring lower bond excess returns when monetary policy is perceived to improve bonds' hedging properties against macroeconomic risk. Taken together, our evidence suggests changing beliefs about the monetary policy rule as a new explanation for decoupling of long-term bond yields from changes in the policy rate, as during the conundrum period of 2004-2005. Our results illustrates the promise of further research into the role of perceptions and learning by the public for the effectiveness of monetary policy and the importance for central bank communication.

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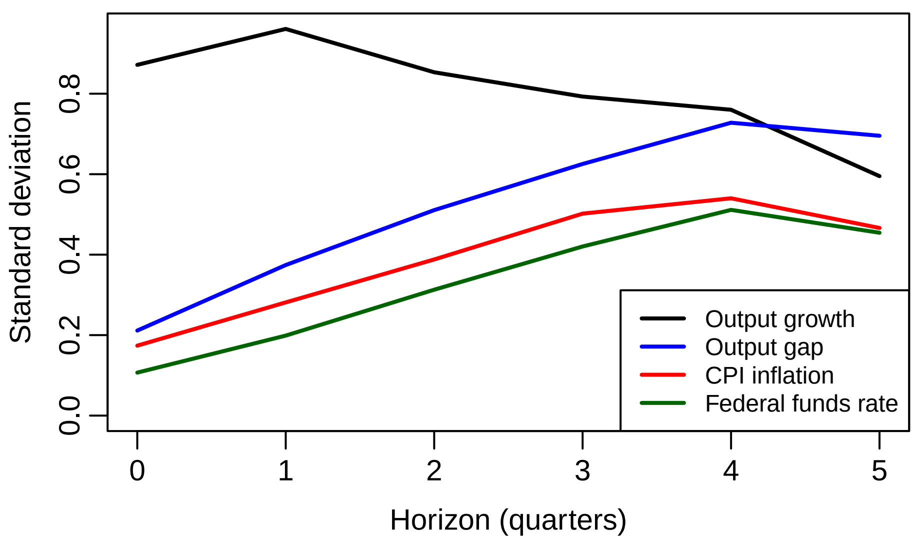
Appendix

A Details and additional results for Section 2

A.1 Term structure of disagreement

Figure A.1 plots the term structure of disagreement, i.e., the average cross-sectional standard deviation across forecasters, for (i) forecasts of output growth, (ii) implied forecasts for the output gap, $E_t^{(j)} x_{t+h}$, (iii) four-quarter CPI inflation forecasts, $E_t^{(j)} \pi_{t+h}$, and (iv) fed funds rate forecasts, $E_t^{(j)} i_{t+h}$. Cross-sectional disagreement for output growth declines with horizon. By contrast, disagreement in fed funds rate forecasts, inflation forecasts, and output gap forecasts increases with the forecast horizon. Intuitively, cross-sectional dispersion in output gap forecasts increases with forecast horizon because the output gap cumulates output growth forecasts.

Figure A.1: Term structure of disagreement



Note: Sample average of cross-sectional standard deviation in the BCFF survey for each forecast horizon for quarter-over-quarter real GDP growth, implied output gap projections, the four-quarter CPI inflation rate, and the federal funds rate. Sample: monthly surveys from Jan-1992 to Jan-2021.

These consistent patterns in the term structure of disagreement support our specification of policy rules for the fed funds rate forecasts in terms of inflation forecasts and output gap forecasts. By contrast, Andrade et al. (2016) estimate a model that specifies a policy rule with output growth, which makes it necessary to generate additional disagreement for policy rate forecasts at longer horizons using, for example, policy inertia in the interest rate rule.

A.2 Estimation details for state-space model

We use Bayesian estimation for the parameters and state variables, in order to correctly account for uncertainty over both. The parameters to be estimated are π^*, the variances of the shocks to the state variables, σ_1^2, σ_2^2 and σ_3^2, and the measurement error variance σ_e^2. The prior for π^* is taken to be Gaussian with a mean of 2% and a variance of 1%. The priors for the variance parameters are inverse-gamma distributions, but the hyperparameters matter little for the estimation results. There is a vast amount of information in the data, so the likelihood overwhelms the information in the priors.[21] We use the following Markov chain Monte Carlo (MCMC) algorithm to estimate the model:

1. Initialize the parameters using draws from the prior distributions.
2. Sample π^* using a random walk Metropolis-Hastings step with the states integrated out (i.e., using the Kalman filter to calculate the likelihood).
3. Sample the state variables, conditional on the parameters, using the simulation smoother of Durbin and Koopman (2002).
4. Sample the variance parameters from their conditional posterior distributions using four separate Gibbs steps.
5. Repeat steps (2)–(4) 1,500 times and discard the first 500 draws as a burn-in sample.

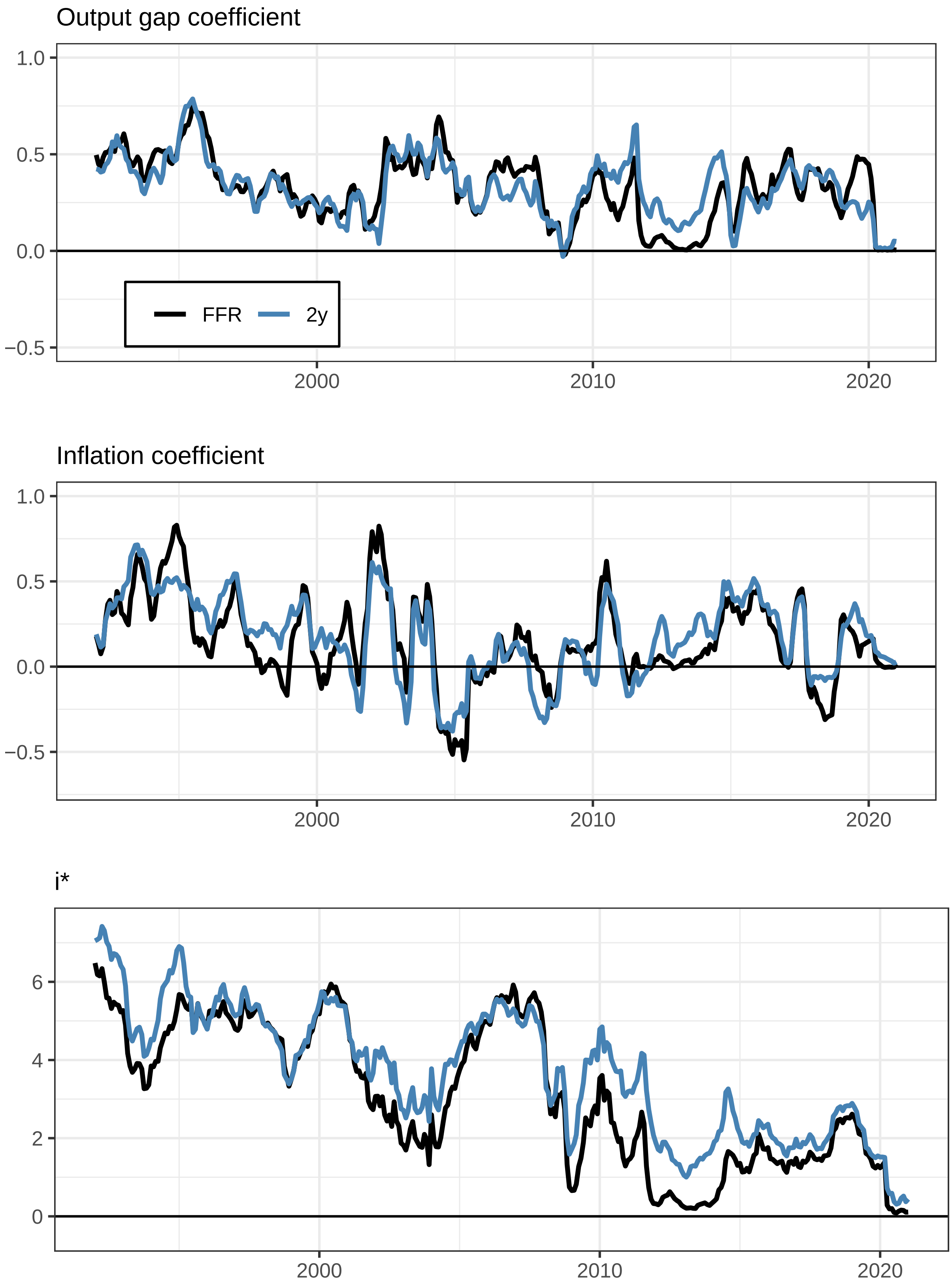
This MCMC sampler is fast and efficient, meaning that there is only modest serial correlation in the sampled chain, and different diagnostic checks indicate that the sampled chain appears to have converged.

A.3 Policy rule for two-year yield

Over the course of our sample, the policy rate of the Fed was stuck at the zero lower bound for extended periods of time, and the question arises how sensitive our policy rule estimates are to the presence of the ZLB. In particular, the values of the policy rule coefficients might be artificially low during parts of the ZLB episodes, even if the Fed was actually quite responsive to the economic downturn in terms of other monetary policy actions such as forward guidance. Motivated by the finding of Swanson and Williams (2014) that the two-year Treasury yield was not constrained by the ZLB, we re-estimated our policy rule models using the two-year yield as the dependent variable. Figure A.2 compares the estimates for the state-space model using survey forecasts of either the fed funds rate or the two-year Treasury yield in the perceived monetary policy rule. Overall, the differences between the estimates are quite modest. During the episode from late 2011 to early 2014, when the estimated γ coefficient was close to zero for the rule with the fed funds rate, the estimate for the 2y yield was only modestly above zero, around 0.1–0.2. In additional, unreported analysis we have found that our other estimates in the paper are not meaningfully affected by using the estimates from a rule for the two-year yield instead of our baseline estimates from a rule for the fed funds rate.

[21] For the four variance parameters, changing either the prior mean or the prior variance by an order of magnitude leaves our results almost unchanged.

Figure A.2: SSM estimates of rule parameters: fed funds rate vs. 2y yield



A.4 Robustness: alternative estimates using multidimensional panel

Here we provide details for the alternative estimates discussed in Section 2.5.

We stack all our observations in a survey-forecaster-horizon panel, so each observation is identified by (t, j, h). In this panel, we first estimate the following regression:

$$E_t^{(j)} i_{t+h} \quad = \quad a_t + \beta_t E_t^{(j)} \pi_{t+h} + \gamma_t E_t^{(j)} x_{t+h} + e_{t,j,h}. \tag{A.1}$$

That is, we include time fixed effects and, of course, allow for the coefficients on the macro forecasts to vary over time. The estimates of γ_t and β_t from regression (A.1) exactly replicate the OLS estimates from the separate survey panel regressions described in Section 2.3.

We next add time-invariant forecaster fixed effects:

$$E_t^{(j)} i_{t+h} \quad = \quad a_t + \alpha_j + \beta_t E_t^{(j)} \pi_{t+h} + \gamma_t E_t^{(j)} x_{t+h} + e_{t,j,h}. \tag{A.2}$$

This estimation is different from our baseline Panel FE estimates of γ_t and β_t because it forces the forecaster fixed effects to be constant over time, rather than being reestimated every month. The estimates of γ_t and β_t from regression (A.2) are denoted "Constant FE".

To explore heterogeneity, we allow for forecaster fixed effects in the time-varying perceived monetary policy coefficients. That is, we estimate the regression

$$E_t^{(j)} i_{t+h} \quad = \quad a_t + \alpha_j + b_j E_t^{(j)} \pi_{t+h} + g_j E_t^{(j)} x_{t+h} + \beta_t E_t^{(j)} \pi_{t+h} + \gamma_t E_t^{(j)} x_{t+h} + e_{t,j,h}. \tag{A.3}$$

We denote the estimates of γ_t and β_t from this regression, which represent the forecaster-average time-t perceived monetary policy coefficients, as "Heterogeneous". The estimates of b_j and g_j represent the forecaster-specific time-invariant shifters to these perceived monetary policy coefficients, and we do not report them.

Because the naming scheme for the forecasters changed fundamentally in 1993, and our forecaster IDs are thus effectively reassigned at that time, we estimate regressions A.2 and A.3 in a sample that starts in January 1993.

Finally, we split forecasters by their forecast accuracy and estimate the perceived monetary policy coefficients separately for different groups of forecasters. We do a very simple split, computing the average mean-squared error for the fed funds forecast of each forecaster:

$$MSE_j \quad = \quad \frac{1}{N_j} \sum_t \sum_h \left(i_{t+h} - E_t^{(j)} i_{t+h} \right)^2, \tag{A.4}$$

where N_j is the total number of fed funds forecasts available for forecaster j. We then compute terciles for MSE_j using our full panel (i.e., forecasters with more observations get counted multiple times). We then estimate regression (A.2) separately using only the observations with MSE_j in the bottom tercile (denoted "Tercile 1"), using only observations with MSE_j in the middle tercile (denoted "Tercile 2"), and finally observations with MSE_j in the top tercile (denoted "Tercile 3").

Figure A.3 plots the series underlying the correlations in Table 2. The level of the "Heterogeneous" estimate is different because of the forecaster fixed effect, so we plot it on a second axis for comparability. Because the "Credit Spreads" estimate is estimated with forecaster fixed effects that are allowed to vary over time, we plot it jointly with the FE estimate, which has the same fixed effects. Because the "Heterogeneous" estimate has forecaster fixed effects that are held constant over time, we plot it against the Constant FE estimate, which share this fixed effects specification. Overall, all versions of $\hat{\gamma}$ are highly correlated and usually between the FE or SSM estimates, justifying our focus on the SSM and FE estimates throughout the paper.

A.5 Robustness: Survey of Professional Forecasters

The Philadelphia Fed's quarterly Survey of Professional Forecasters includes individual forecasts of various macroeconomic variables and interest rates. We estimate a policy rule for the three-month T-bill rate, the interest rate with the shortest maturity, which is highly correlated with the federal funds rate. For inflation we use the CPI forecasts, as before. As a measure of economic activity we use the unemployment rate forecasts, since we are mainly interested how the use of a different variable than the output gap affects our estimates. The SPF includes forecasts for the current quarter and the next four quarters. The data starts in 1981:Q3, and each quarter there are generally around 30-35 individual forecasters.

We estimate Panel FE regressions for each quarterly SPF forecaster panel. The estimated coefficient on the unemployment rate forecasts has a correlation of -0.77 with the $\hat{\gamma}_t$ estimates from the BCFF over the period where they are both available. The former is generally about -2 times as large as the latter, consistent with Okun's law. Figure A.5 shows a visual comparison of the two estimates. For the BCFF, it shows the panel FE point estimates and 95% confidence intervals, as in the top panel of Figure 2. For the SPF, it shows the fitted values from a regression of the BCFF on the SPF estimate, in order to rescale the latter and make the two series comparable. While there is more volatility in the month-to-month BCFF estimates, the cyclical patterns of the two series are generally very similar.

A.6 Endogeneity bias adjustment in New Keynesian model

We use a simple New Keynesian (NK) framework to quantify potential estimation bias from the endogenous response of the economy to monetary policy. Our analysis suggests that our estimates of $\hat{\gamma}_t$ may contain a modest downward bias relative to the true perceived monetary policy coefficient $\hat{\gamma}_t$, but that this estimation bias appears to be constant over time. Thus, our primary object of interest, time-series variation in our estimated $\hat{\gamma}_t$, is unaffected.

In our theoretical analysis of estimation bias, we use $\tilde{\gamma}$ to denote the estimated perceived monetary policy coefficient on the output gap, which may include a bias. We contrast this with forecasters' perceived coefficient $\hat{\gamma}$. Recall that the perceived coefficient $\hat{\gamma}$ need not be equal to the true monetary policy coefficient γ.

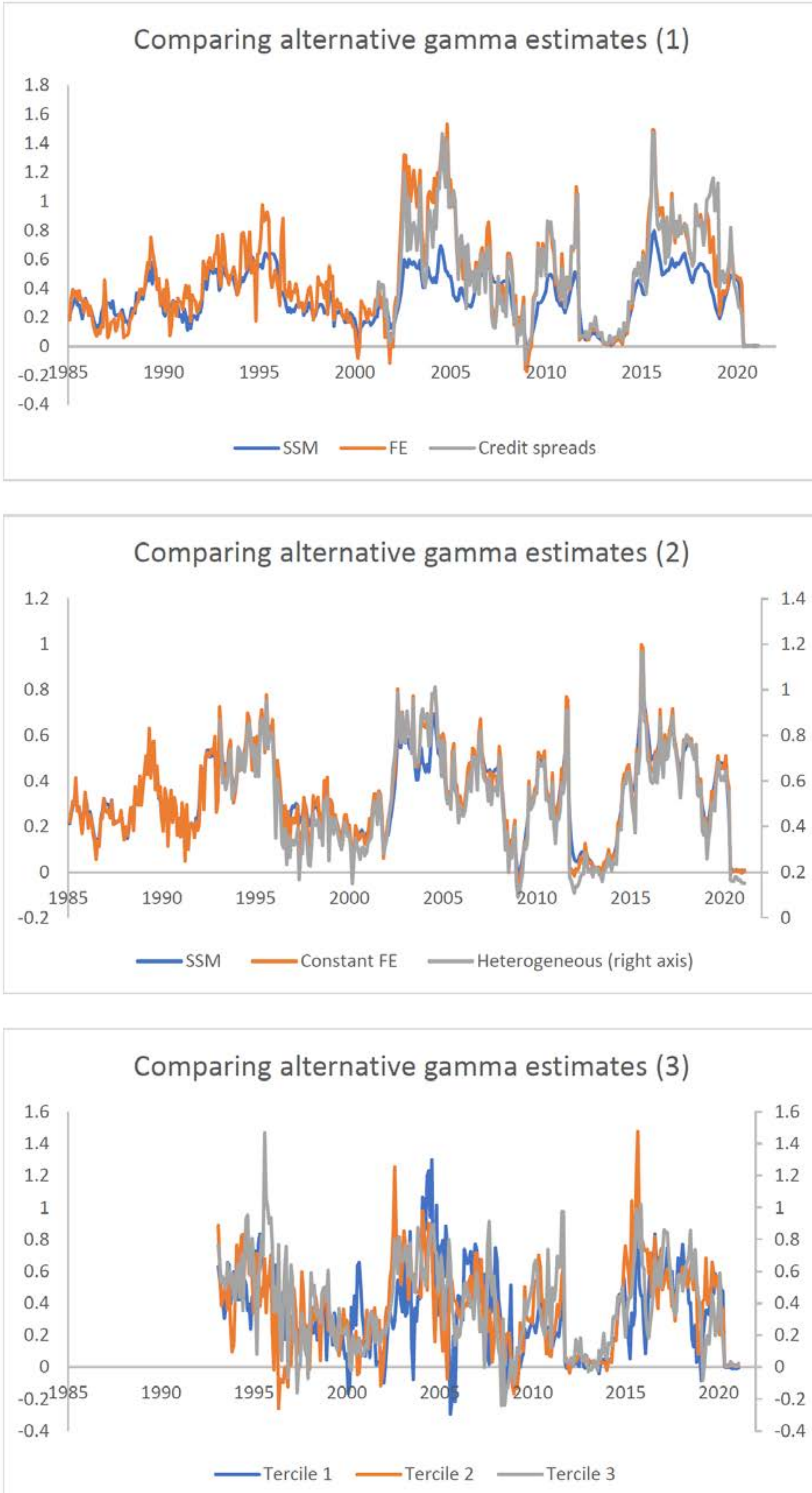
We use the following version of the canonical three-equation NK model:

$$x_t = E_t x_{t+1} - (i_t - E_t \pi_{t+1}) + v_t \tag{A.5}$$

$$\pi_t = E_t \pi_{t+1} + \kappa x_t \tag{A.6}$$

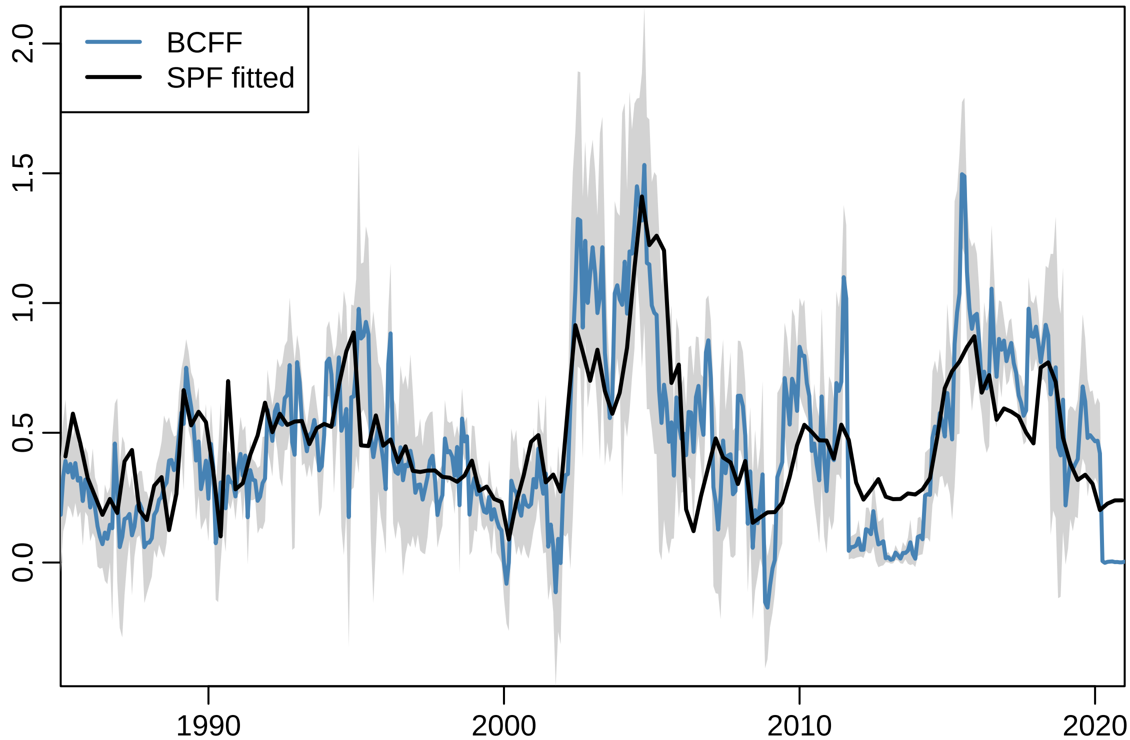
$$i_t = \hat{\beta} \pi_t + \hat{\gamma} x_t + u_t. \tag{A.7}$$

Figure A.3: Robustness: Alternative $\hat{\gamma}$ estimates



Note: This figure plots the time-series of the alternative estimates of $\hat{\gamma}_t$ used in the main paper in Table 2.

Figure A.4: Comparison with estimates for Survey of Professional Forecasters



Note: Comparison of perceived policy rule coefficients for real activity in Blue Chip Financial Forecasts (BCFF) and Survey of Professional Forecasters (SPF). Estimation method is Panel FE in both cases, as described in 2.3. Estimate for BCFF corresponds to the output gap forecasts, while the estimate for SPF corresponds to unemployment rate forecasts. SPF estimate is scaled using a regression of BCFF on SPF estimates, taking the fitted values. Sample is quarterly from 1985:Q1 to 2020:Q4.

This model is completely standard; details and derivations can be found in textbook treatments such as Galí (2015). For simplicity we take the rate of time preference to be zero. The Euler equation, (A.5), assumes log-utility and includes a reduced-form demand shock v_t. Equation (A.6) is the Phillips curve. Our monetary policy rule, equation (A.7), includes a monetary policy shock u_t that is uncorrelated with v_t. The rule has constant parameters, and we will analyze shifts using comparative statics. We abstract from the intercepts in equations (A.5) through (A.7) since they do not affect the second moments that we are interested in.

As in our empirical analysis, the focus is on the monetary policy rule's coefficient on the output gap, $\hat{\gamma}$. We can therefore shut down any effects from inflation by setting $\kappa = 0$ so that prices are fixed, following Caballero and Simsek (2021). That is, inflation is zero in equilibrium and $\hat{\beta}\pi_t$ drops out of the monetary policy rule.

For the sake of simplicity, and to focus on the cross-sectional regression of forecasted fed funds rates onto forecasted output gaps across forecasters, we assume in this analysis that forecasters disagree over future demand and monetary policy shocks but that they agree on the monetary policy rule. In addition, we assume that forecaster j believes that his perceived monetary policy rule parameter $\hat{\gamma}_t$ is the true rule followed by the Fed, that he does not expect this rule to change in the future, and that all agents in the economy share his beliefs about demand and monetary policy shocks $E_t^{(j)} v_{t+h}$ and $E_t^{(j)} u_{t+h}$ at all forecast horizons h. We further impose that expectations for shocks $E_t^{(j)} v_{t+h}$ and $E_t^{(j)} u_{t+h}$ are bounded as $h \to \infty$. We do not take a stand on where differences in expectations about demand shocks and monetary policy shocks come from.

With these assumptions, we can simply substitute the perceived monetary policy rule (A.7) into the Euler equation (A.5) and iterate forward to obtain forecaster j's conditional expectations for the equilibrium policy rate and output gap at horizon $t+h$ as:

$$E_t^{(j)} x_{t+h} = \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}), \quad \text{and} \tag{A.8}$$

$$E_t^{(j)} i_{t+h} = \hat{\gamma}_t \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}) + E_t^{(j)} u_{t+h}. \tag{A.9}$$

We use the notation Cov_t and Var_t to denote covariances and variances of forecasts across forecasters and forecast horizons at a given time t. In order to say something about these cross-forecaster covariances and variances, we need to make further assumptions about the distribution of expected shocks across forecasters. Since demand and monetary policy shocks are thought to reflect structural shocks, we assume that expected demand shocks $E_t^{(j)} v_{t+h_1}$ are orthogonal to expected monetary policy shocks $E_t^{(j)} u_{t+h_2}$ at all forecast horizons h_1 and h_2. For simplicity, we assume that $E_t^{(j)}(v_{t+h})$ and $E_t^{(j)}(u_{t+h})$ are perceived to be serially uncorrelated over forecast horizons. Even if these perceived serial correlations across forecast horizons may not be truly zero in the BCFF data, the inclusion of forecaster fixed effects in our estimation absorbs much of the correlation across forecast horizons within each forecaster. Finally, we assume that the sample means, variances and autocovariances of $E_t^{(j)}(v_{t+h})$ and $E_t^{(j)}(u_{t+h})$ converge to their population moments as the number of forecasters becomes large, i.e. that a law of large numbers holds.

We can then derive the time-t panel regression coefficient of interest rate forecasts onto output gap forecasts:

$$\begin{aligned} Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) &= Cov_t\left(\hat{\gamma} E_t^{(j)} x_{t+h} + E_t^{(j)} u_{t+h}, E_t^{(j)} x_{t+h}\right), \\ &= \hat{\gamma}_t Var_t\left(E_t^{(j)} x_{t+h}\right) - Var_t\left(E_t^{(j)} u_{t+h}\right). \end{aligned} \tag{A.10}$$

The panel regression uses only time t expectations as input, which is why the perceived output gap coefficient at time t, $\hat{\gamma}_t$, enters. The simple regression coefficient from regressing interest rate forecasts onto output gap forecasts in the forecaster-horizon panel then equals

$$\tilde{\gamma}_t = \hat{\gamma}_t - (1+\hat{\gamma}_t)^{-1} \frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)}$$

The term $-(1+\hat{\gamma}_t)^{-1} \frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)}$ reflects the estimation bias due to the endogenous macroeconomic response to monetary policy, which we want to correct.

From now on we make the normalization $Var_t\left(E_t^{(j)} x_{t+h}\right) = 1$ to save on notation. This is without loss of generality as long as all other variances and covariances are interpreted as relative to the variance of output forecasts. Then the perceived monetary policy coefficient $\hat{\gamma}_t$ and the cross-forecaster and cross-horizon variance of monetary policy shocks $Var_t\left(E_t^{(j)} u_{t+h}\right)$ can be solved for exactly as two unknowns from the following two nonlinear equations:

$$\tilde{\gamma}_t = Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) \tag{A.11}$$

$$= \hat{\gamma}_t - (1+\hat{\gamma}_t)^{-1} Var_t\left(E_t^{(j)} u_{t+h}\right), \tag{A.12}$$

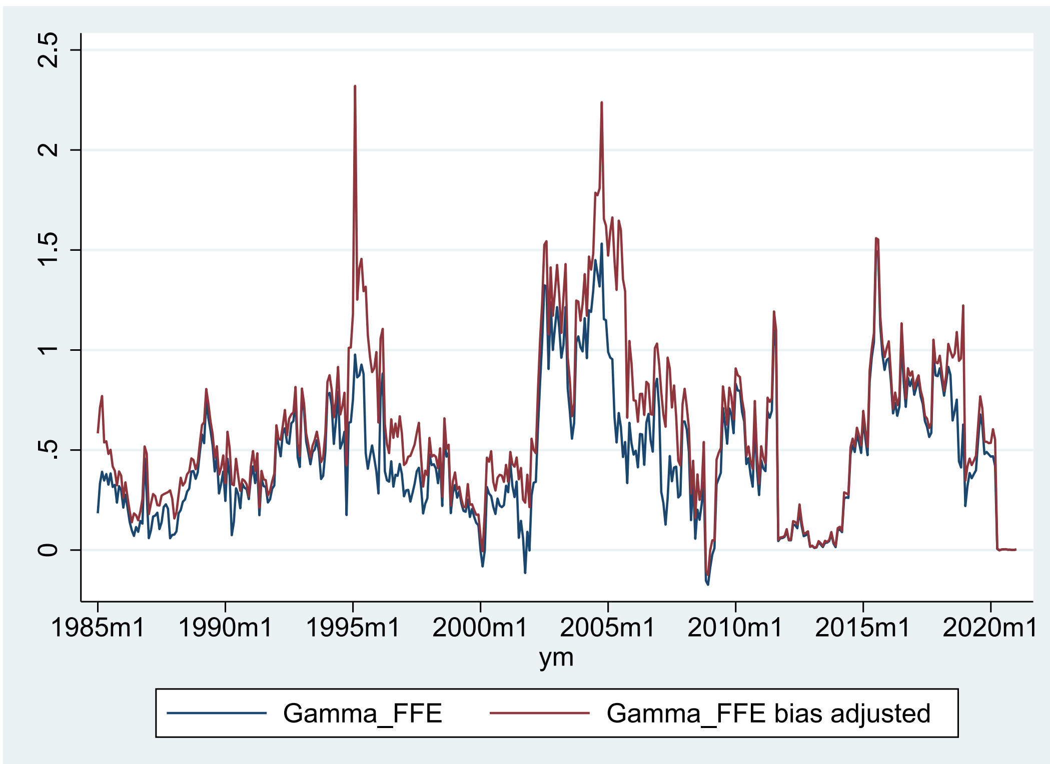
$$Var_t\left(E_t^{(j)} i_{t+h}\right) = \hat{\gamma}_t^2 + 2\hat{\gamma}_t Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) + Var_t\left(E_t^{(j)} u_{t+h}\right) \tag{A.13}$$

We use these two equations solve for $\hat{\gamma}_t$ and $Var_t\left(E_t^{(j)} u_{t+h}\right)$, where $Var_t\left(E_t^{(j)} i_{t+h}\right)$ and $Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right)$ are estimated from the data.

In order to derive the panel regression coefficient on the panel of time t forecasts with fixed effects, we make the additional assumption that forecaster j believes that the long-run natural rate equals $E_t^{(j)} r_t^*$. The equilibrium for the output gap (A.8) then is unchanged, and the equilibrium for the policy rate A.9 is shifted up by a constant $E_t^{(j)} r_t^*$. After projecting onto forecaster-level fixed effects, the expression for $\tilde{\gamma}_t$ is therefore exactly as before and all derivations go through, provided that we replace the panel OLS coefficient with the panel regression coefficient with forecaster fixed effects.

The bias adjusted panel FE $\hat{\gamma}_t$ in Table 2 is obtained by solving the two equations (A.12) and (A.13) numerically for $\hat{\gamma}_t$ after residualizing everything with respect to forecaster fixed effects.

Figure A.5: Endogeneity bias adjusted panel FE $\hat{\gamma}_t$



Note: This figure plots the endogeneity bias adjusted panel FE estimate of $\hat{\gamma}_t$ versus the baseline panel FE estimate of $\hat{\gamma}_t$.

B Details for learning model

B.1 Proofs

Proof of Corollary 1: Forecaster j's optimal forecast of the time-t output gap after observing his signal is

$$E^j\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \rho x_{t-1}+\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\left(\varepsilon_t+\eta_t^j\right). \tag{B.1}$$

Because the monetary policy shock u_t is uncorrelated with ξ_t, ε_t and ν_t^j and all these shocks are independent of the filtration $\mathcal{Y}_{t-1}$, agent j's optimal forecast of the monetary policy rate at horizon h conditional on the macroeconomic signal equals

$$\begin{aligned} E^j\left(i_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) &= \hat{\gamma}_t^j E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right), && \text{(B.2)}\\ &= \left(\hat{\gamma}_t^j-\hat{\gamma}_t\right)E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)+\hat{\gamma}_t E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right), && \text{(B.3)}\\ &= \hat{\gamma}_t E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)+\left(\hat{\gamma}_0^j-\hat{\gamma}_0\right)E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) && \text{(B.4)}\end{aligned}$$

For the last equation we substituted in expression (18) for the coefficient dispersion across forecasters. Because $\left(\hat{\gamma}_0^j-\hat{\gamma}_0\right)$ is are assumed to be uncorrelated with η_t^j, ε_t, ξ_t and u_t for all $t>0$, it follows that $\left(\hat{\gamma}_0^j-\hat{\gamma}_0\right)E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)$ and $E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)$ are uncorrelated. Corollaries 1.a and 1.b then follow.

Proof of Corollary 2: Taking the forecaster average of (B.1) shows that the consensus forecast after observing the signals equals

$$\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \rho x_{t-1}+\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\varepsilon_t. \tag{B.5}$$

The revision in the consensus output gap forecast around the macroeconomic announcement therefore equals

$$x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \frac{\sigma_\eta^2}{\sigma_\varepsilon^2+\sigma_\eta^2}\varepsilon_t \tag{B.6}$$

Because the macroeconomic announcement leads to no updating about the perceived monetary policy coefficient, the change in the expected fed funds rate around the macroeconomic announcement equals

$$\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},x_t\right.\right)-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \hat{\gamma}_t\left(x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)\right). \tag{B.7}$$

Corollary 2.a follows immediately from (B.7).

Next, if we observe a surprise Z_t proportional to $(x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)$, i.e.

$$Z_t = \frac{1}{\alpha}\left(\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1}\right.\right)\right), \tag{B.8}$$

for some constant α, we assume that Z_t is scaled such that the univariate coefficient of $\bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) - \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}\right.\right)$ onto Z_t equals unity.

To derive α we look at the univariate regression

$$\bar{E}\left(i_t \left| \mathcal{Y}_t\right.\right) - \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) = a_0 + a_1 Z_t + \epsilon_t \tag{B.9}$$

With the additional assumption that $\hat{\gamma}_t$ is stationary and recalling that $\hat{\gamma}_t$ is defined to be conditional on the filtration $\mathcal{Y}_{t-1}$ the regression coefficient a_1 converges to

$$\begin{aligned} a_1 &= \alpha \frac{1}{\sigma_\varepsilon^2} Cov\left(\hat{\gamma}_t \varepsilon_t, \varepsilon_t\right), &\text{(B.10)}\\ &= \alpha \frac{1}{\sigma_\varepsilon^2} E\left(\hat{\gamma}_t \varepsilon_t^2\right), &\text{(B.11)}\\ &= \alpha \frac{1}{\sigma_\varepsilon^2} E\left(E\left(\hat{\gamma}_t \varepsilon_t^2 \left| \mathcal{Y}_{t-1}\right.\right)\right), &\text{(B.12)}\\ &= \alpha E \hat{\gamma}_t &\text{(B.13)} \end{aligned}$$

It therefore follows that if we choose the scaling factor α such that $a_1 = 1$ then α must converge to $\alpha = E\hat{\gamma}_t$ and therefore

$$\bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) - \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}\right.\right) = \frac{\hat{\gamma}_t}{E\hat{\gamma}_t} Z_t, \tag{B.14}$$

proving Corollary 2.b.

Proof of Corollary 3: This is a direct implication of Lemma 1 and the Kalman filter.

Proof of Corollary 4: Let $B_{n,t}$ denote the end-of-period t price of a bond with n periods remaining to maturity. Here, we use the subscript t to denote an expectation conditional on the filtration $\mathcal{Y}_t$. The two-period bond price is given by

$$\begin{aligned} B_{2,t} &= exp(-i_t) E_t \left[exp\left(-\psi \varepsilon_{t+1} - \frac{1}{2}\psi^2 \sigma_\varepsilon^2 - i_{t+1}\right)\right], &\text{(B.15)}\\ &= exp(-i_t) E_t \left[exp\left(-\psi \varepsilon_{t+1} - \frac{1}{2}\psi^2 \sigma_\varepsilon^2 - \gamma_{t+1}\left(\left(\rho x_t + \varepsilon_{t+1}\right)\right) - u_{t+1}\right)\right], &\text{(B.16)}\\ &= exp\left(-i_t - E_t i_{t+1} + \psi \hat{\gamma}_{t+1} \sigma_\varepsilon^2 + \frac{1}{2}\hat{\gamma}_{t+1}^2 \sigma_\varepsilon^2 + \frac{1}{2}\sigma_{t+1}^2 \left(\rho x_t\right)^2 + \frac{1}{2}\sigma_u^2\right) &\text{(B.17)} \end{aligned}$$

The expected log excess return on a two-period bond adjusted for a Jensen's inequality term then equals

$$\begin{aligned} E_t xr_{2,t+1} + \frac{1}{2} Var_t xr_{2,t+1} &= E_t\left(b_{1,t+1} - b_{2,t} - b_{1,t}\right) + Var_t\left(b_{1,t+1}\right), &\text{(B.18)}\\ &= -\psi \hat{\gamma}_{t+1} \sigma_\varepsilon^2. &\text{(B.19)} \end{aligned}$$

Equation (B.19) shows that the expected excess return on a long-term bond decreases with the perceived monetary policy coefficient $\hat{\gamma}_{t+1}$.

Proof of Corollary 5: The federal funds forecast error is given by

$$i_t - \bar{E}\left(i_t \mid \mathcal{Y}_{t-1}\right) \;=\; i_t - \hat{\gamma}_t \rho x_{t-1}. \tag{B.20}$$

Because forecasts are formed optimally based on the filtration $\mathcal{Y}_{t-1}$ they are not predictable by any variables in $\mathcal{Y}_{t-1}$, including $\hat{\gamma}_t$ or x_{t-1}.

B.2 Numerical simulation details

Table B.1 provides the numerical values used in the model simulations in Section 7.2.

Table B.1: Simulation Parameter Values

Persistence output gap	ρ	0.95
Std. output gap shock	σ_ε	1.2
Std. MP shock	σ_u	0.05
Std. MP rule innovations	σ_ξ	0.1
Overconfidence	κ	0.1
Overextrapolation	b	0.95

Note: This table lists the parameter values for the numerical model analysis.

C Additional results for local projections (Section 4.2)

Here we report regression estimates for the local projections shown in Figure 5 and discussed in Section 4.2. The regressors include mps_t instead of $mps_t(1-weak_t)$ so that the coefficient on the interaction term $mps_t weak_t$ measures the difference between the two state-dependent impulse responses, and we can easily report the test statistic for the null hypothesis that there is no state dependence. That is, we estimate the regression

$$\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t + \tilde{b}^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h},$$

where all variables are as defined in 4.2. Note that the impulse responses shown in the top panels of Figure 5 correspond to estimates of $b_1^{(h)}$, and the responses shown in the bottom panels correspond to $b_1^{(h)} + \tilde{b}^{(h)}$.

Table C.1 shows the estimation results for horizons of three, six, nine and twelve months. Most importantly, the interaction coefficient on is consistently negative and often highly statistically significant. This evidence confirms the visual impression from Figure 5 that $\hat{\gamma}$ responds positively to a hawkish policy surprise when the economy is strong, but negatively when the economy is weak.

Table C.1: Local Projection Regressions

	Panel FE $\hat{\gamma}_{t+h}$				SSM $\hat{\gamma}_{t+h}$			
Horizon:	$h=3$	$h=6$	$h=9$	$h=12$	$h=3$	$h=6$	$h=9$	$h=12$
mps_t	0.26	0.73**	0.39**	-0.02	-0.07	0.30**	0.30***	0.27**
	(1.00)	(2.28)	(2.03)	(-0.06)	(-0.56)	(2.51)	(2.70)	(2.02)
$mps_t \times weak_t$	-0.45	-1.63***	-1.33**	-0.36	-0.05	-0.75***	-0.86***	-0.78**
	(-1.17)	(-2.79)	(-1.98)	(-0.57)	(-0.25)	(-2.71)	(-2.75)	(-2.30)
$weak_t$	0.06	0.12*	0.18**	0.22***	0.03	0.06*	0.09**	0.11**
	(1.46)	(1.88)	(2.37)	(2.63)	(1.62)	(1.89)	(2.10)	(2.19)
$\hat{\gamma}_{t-1}$	0.67***	0.52***	0.40***	0.33***	0.78***	0.61***	0.49***	0.40***
	(10.18)	(5.65)	(3.80)	(3.01)	(15.14)	(7.22)	(4.71)	(3.53)
Constant	0.14***	0.18***	0.21***	0.23***	0.06***	0.11***	0.14***	0.16***
	(4.12)	(3.97)	(4.17)	(3.83)	(2.96)	(3.06)	(3.23)	(3.49)
N	356	353	350	347	356	353	350	347
R^2	0.46	0.32	0.25	0.22	0.61	0.4	0.31	0.26

Note: Local projection estimates of the state-dependent response of $\hat{\gamma}_t$—measured as the panel FE estimate of $\hat{\gamma}_t$ in the first four columns and as the SSM estimate in the last four columns—to high-frequency monetary surprises of Nakamura and Steinsson (2018), mps_t. The estimated regression is $\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t + \tilde{b}^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where $weak_t$ is an indicator for whether the output gap during month t was below the sample median. Newey-West t-statistics, using $1.5\times h$ lags, are reported in parentheses. Sample period: Jan-1992 to Jan-2021.

D Robustness expected bond excess returns

D.1 Objective bond excess returns

Here we report results on the predictability of excess returns on long-term Treasury bonds, which complement the regressions in Section 6.1 for survey-based/subjective expected excess bond returns. We expect bond excess returns to be predictable for two reasons. First, positive surprises in the federal funds rate should translate into negative excess bond returns through the expectations hypothesis and expectations errors, as in Cieslak (2018). Second, the coefficient $\hat{\gamma}_t$ captures the perceived comovement between interest rates and the state of the economy and should therefore carry a risk premium, just like in subjective bond risk premia.

Using Treasury yield data from Gürkaynak et al. (2007), we estimate the following predictive regressions:

$$xr^{(n)}_{t\to t+h} = b_0 + b_1\hat{\gamma}_t + b_2 CFNAI_t + b_3\hat{\gamma}_t CFNAI_t + \delta' X_t + \varepsilon_{t+h}, \tag{D.1}$$

where $xr^{(n)}_{t\to t+h}$ is the log excess return on a zero-coupon n-year nominal Treasury bond from month t to month $t+h$, and X_t contains the first three principal components of yields with maturities one, two, five, seven, ten, fifteen, and twenty years. We compute the h-month excess return on a zero-coupon bond with n years to maturity as $rx_{t+h}^{(n)} = ny_t^{(n)} - \left(n - \frac{h}{12}\right) y_{t+h}^{\left(n-\frac{h}{12}\right)} - \frac{h}{12} y_t^{(n)}$, where $y_t^{(n)}$ is the zero-coupon yield with maturity n years. We estimate equation (D.1) using both the panel FE estimate and the SSM estimate of $\hat{\gamma}_t$, and we consider holding periods of both $h = 12$ and $h = 24$ months. We focus on nominal Treasury bond excess returns as opposed to inflation-indexed (Treasury Inflation Protected Securities, TIPS) because of the longer time-series in nominal Treasury bonds and liquidity concerns in TIPS during the financial crisis of 2008-2009. For comparability, we use the same start date as for subjective expected returns in Table 5 in the main paper.

Table D.1 shows that $\hat{\gamma}_t$ predicts objective bond excess returns negatively and significantly with magnitudes that are similar to those for subjective expected excess returns in Table 5 in the main paper. The magnitude and significance of $\hat{\gamma}_t$ as a predictor of future bond excess returns increases further over longer return forecasting horizons, which were not available for subjective expected excess returns. In addition, the interaction $\hat{\gamma}_t \times CFNAI$ predicts bond excess returns negatively at the 1-year horizon. Bond prices are inversely related to interest rates, so the sign on $\hat{\gamma}_t \times CFNAI$ is exactly as expected from the fed funds forecast error regressions in the Table 6 in the main paper.

D.2 Robustness: Controlling for interest rate disagreement

We next compare our estimates of $\hat{\gamma}_t$ to the measures of forecaster disagreement from Giacoletti et al. (2021). Giacoletti et al. (2021) use the difference between the 90th and 10th percentiles of four-quarter interest rate forecasts across BCFF forecasters each month. They use the 90-10 spread for the 2-year and 10-year Treasury forecasts and show that these measures of forecaster disagreement predict future bond excess returns. One might naturally expect that the 90-10 spread in policy rate forecasts should be correlated with our measures of $\hat{\gamma}$, because a high perceived $\hat{\gamma}_t$ mechanically leads to a larger spread in policy rate forecasts, holding constant disagreement about the future output gap and disagreement about future monetary policy shocks. However, we find that the perceived monetary policy output weight $\hat{\gamma}_t$ shows distinct time-series variation from interest rate disagreement in the data. We replicate the measures of interest rate disagreement by Giacoletti et al. (2021). In addition, we consider the 90-10 forecaster spread for the 4-quarter fed funds rate forecast. We consider this measure of fed funds rate disagreement because this matches most closely our estimation of the perceived monetary policy rule and therefore might be expected to be more strongly correlated with $\hat{\gamma}_t$ than the other measures of interest rate disagreement.

Table D.2 shows correlations of our benchmark estimate of $\hat{\gamma}_t$ with these three measures of interest rate disagreement. As expected, the correlations between interest rate disagreement and $\hat{\gamma}_t$ are positive, but they are not large in magnitude, ranging from -0.05 to 0.27. These results therefore underscore that the perceived monetary policy response to the output gap is correlated with, but distinct from, disagreement about future interest rates across forecasters.

We can also control for these three measures of interest rate disagreement in our regressions of subjective bond risk premia onto $\hat{\gamma}_t$. Table D.3 estimates regressions analogous to those in Table 5, including $\hat{\gamma}_t$ as well as the level, slope and curvature of the yield curve. Adding different measures of cross-sectional interest disagreement does not materially affect the coefficient on $\hat{\gamma}_t$, which remains highly statistically significant. This evidence confirms

Table D.1: Predictability of excess bond returns

Panel A: Panel FE $\hat{\gamma}$						
	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
$\hat{\gamma}$	-0.79***	-0.74**	-0.73***	-1.42***	-1.06***	-1.10***
	(-2.76)	(-2.55)	(-3.01)	(-4.37)	(-3.87)	(-4.36)
$CFNAI$		-0.19	-1.60***		-1.99**	-2.80***
		(-0.49)	(-3.01)		(-2.44)	(-4.22)
$\hat{\gamma}\times CFNAI$			-1.25***			-1.11*
			(-3.56)			(-1.75)
N	390	390	390	378	378	378
R^2	0.17	0.17	0.21	0.20	0.28	0.30

Panel B: SSM $\hat{\gamma}$						
	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
$\hat{\gamma}$	-0.66*	-0.59	-0.65*	-1.43***	-1.06**	-1.17**
	(-1.72)	(-1.53)	(-1.69)	(-2.87)	(-2.18)	(-2.53)
$CFNAI$		-0.23	-1.91**		-1.99**	-2.99***
		(-0.56)	(-2.36)		(-2.40)	(-3.51)
$\hat{\gamma}\times CFNAI$			-1.17**			-1.11
			(-2.48)			(-1.61)
N	390	390	390	378	378	378
R^2	0.16	0.16	0.20	0.20	0.28	0.30

Note: This table uses the panel regression coefficient with fixed effects (Panel A) and the time-series model coefficient (Panel B) to predict log excess return on 5-year nominal Treasury bonds over 1- and 2-year return horizons: $xr^{(n)}_{t\to t+h} = b_0 + b_1\hat{\gamma}_t + b_2 CFNAI_t + b_3\hat{\gamma}_t CFNAI_t + \varepsilon_{t+h},$. All regressions control for the first three principal components of the yield curve. the regression coefficients on the three principal components and the constant are suppressed. All right-hand-side variables are standardized to have unit standard deviations. One-year forecasting regressions run from t =March 1985 through t =January 2020. Two-year forecasting regressions run from t =January 1988 through t =June 2020. Newey-West t-statistics with 1.5 times lag length in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

that the perceived monetary policy rule plays a role for bond risk premia that is distinct from forecaster disagreement about interest rates.

Table D.2: Robustness: Correlation with interest rate disagreement

	Disagreement		
	FFR	2y	10y
OLS	0.14	0.26	-0.05
FE	0.13	0.27	0.13
SSE	0.14	0.26	0.12

Note: Correlations between different estimates for the perceived output gap weight in the policy rule, $\hat{\gamma}_t$ with measures of interest rate disagreement in the cross-section of forecasters. Disagreement is measured as the difference between the 90th and 10th percentiles of 4-quarter horizon forecasts across forecasters for the fed funds rate (FFR), 2-year Treasury rate, and 10-year Treasury rate. Sample period ends in January 2021, and starts in January 1985 for fed funds rate disagreement. The sample period starts in January 1988 for 2-year Treasury rate and 10-year Treasury rate disagreement.

Table D.3: Subjective bond risk premia: controlling for forecaster interest rate disagreement

	Panel A: Panel FE $\hat{\gamma}$					
		$\bar{E}_t xr_{t+1}^{(6)}$			$\bar{E}_t xr_{t+1}^{(11)}$	
$\hat{\gamma}$	-0.72***	-0.74***	-0.81***	-1.05***	-1.04***	-1.16***
	(-6.06)	(-6.66)	(-7.87)	(-4.31)	(-4.43)	(-5.66)
FFR disagreement	-3.12***			-4.24*		
	(-3.52)			(-1.75)		
2y Disagreement		-1.07***			-1.93***	
		(-3.70)			(-2.72)	
10y Disagreement			-0.74*			-2.03**
			(-1.72)			(-2.40)
N	397	396	397	397	396	397
R^2	0.66	0.67	0.65	0.63	0.66	0.65
	Panel B: SSM $\hat{\gamma}$					
		$\bar{E}_t xr_{t+1}^{(6)}$			$\bar{E}_t xr_{t+1}^{(11)}$	
$\hat{\gamma}$	-0.57***	-0.58***	-0.66***	-0.88***	-0.85***	-0.96***
	(-4.63)	(-5.33)	(-5.34)	(-3.44)	(-3.42)	(-4.27)
FFR disagreement	-3.20***			-4.14		
	(-3.24)			(-1.63)		
2y disagreement		-1.03***			-1.83**	
		(-2.96)			(-2.50)	
10y disagreement			-0.46			-1.62*
			(-0.96)			(-1.65)
N	397	396	397	397	396	397
R^2	0.61	0.61	0.59	0.61	0.62	0.61

Note: This table uses the panel regression coefficient with fixed effects (Panel A) and the time-series model coefficient (Panel B) to explain subjective expected log bond excess returns on 6-year and 11-year Treasury bonds over $h = 1$ year forecast horizons while controlling for interest rate disagreement. All regressions also include a constant and the first three principal components of Treasury bond yields. The sample is the same as in Table 5. Newey-West t-statistics with automatic lag selection in parentheses. * p <0.10, ** p <0.05, *** p <0.01.