Perceptions about Monetary Policy*

Michael D. Bauer   Carolin E. Pflueger   Adi Sunderam

May 2, 2022

Abstract

We estimate time-varying perceptions about the Fed's monetary policy rule from cross-sectional survey data and document systematic shifts in the perceived rule that are relevant for monetary policy and asset pricing. First, the perceived reaction coefficient to the output gap varies over the monetary policy cycle, with a pattern of quick and surprising rate cuts but gradual and data-dependent tightening. Second, this variation in the perceived rule explains changes in the sensitivity of interest rates to macroeconomic announcements. Third, high-frequency monetary policy surprises lead to updates in beliefs about the policy rule that depend on the state of the economy in the direction that is consistent with rational learning. Fourth, when monetary policy is perceived to be more responsive to real activity, risk premia on long-term Treasury bonds are low, consistent with standard asset pricing logic. Our findings can help explain certain empirical puzzles, such as systematic forecast errors about short-term interest rates and the decoupling of long-term rates during conundrum episodes.

Keywords: FOMC, monetary policy rule, survey forecasts, beliefs
JEL Classifications: E43, E52, E58

*Bauer: Universität Hamburg, CEPR and CESifo; Pflueger: University of Chicago, Harris School of Public Policy and NBER; Sunderam: Harvard Business School and NBER. We thank Yueran Ma for help with the Blue Chip Financial Forecasts data and Lars Hansen, Anil Kashyap, Aeimit Lakdawala, Yueran Ma, and seminar participants at the CEPR New Member Seminar, the Federal Reserve Bank of Atlanta, the London School of Economics and the University of British Columbia for valuable comments.

1 Introduction

The success of monetary policy over the past two decades has been largely predicated on increased transparency and improved communication with the public. Since starting to announce 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 communication efforts is that the public's perceptions of monetary policy—including its goals, framework, and future course—play a crucial role in determining policy effectiveness.[1] This view is supported by much theoretical work showing that the public's knowledge and beliefs about the conduct of monetary policy determine the stability and uniqueness of macroeconomic equilibria, the anchoring of long-run expectations, and the trade-offs faced by policy-makers.[2] In other words, what matters for the success of monetary policy is not only the actual monetary policy framework used by policy makers, but also the understanding of that framework by the public.

Since the seminal work of Taylor (1993), monetary policy rules have been used extensively in both positive and normative analysis of monetary policy. Policy rules play a central role not only in monetary economics, but also in asset pricing and macro-finance, as they provide a crucial link between macroeconomic fundamentals and the yield curve (e.g. Piazzesi, 2001; Ang and Piazzesi, 2003; Bianchi et al., 2022). Since empirical estimates of policy rules generally use observed macroeconomic time series data, they can yield insights into the actual historical conduct of monetary policy, but they do not reveal perceptions about monetary policy. While the two would coincide under full information rational expectations (FIRE), a large literature has documented the empirical importance of imperfect information and nonrational expectations.[3] Thus, the public may well have different perceptions about monetary policy than historical rules would suggest. In addition, traditional estimation techniques relying on time series data can only uncover low-frequency, decade-by-decade changes in monetary policy rules (Clarida et al., 2000; Boivin, 2006; Orphanides, 2003a; Cogley and Sargent, 2005; Coibion and Gorodnichenko, 2011; Hamilton et al., 2011), while perceptions may shift at higher frequencies. As a result, little is known about the public's perceptions

[1] In 2010 Chair Bernanke noted that "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). The Federal Reserve History website summarizes this argument as follows: "Fundamentally, a central bank defines the monetary regime through the way in which it conditions markets to anticipate how its instrument [. . .] will change in response to incoming information about the economy" (https://www.federalreservehistory.org/essays/treas-fed-accord-to-mid1960s).

[2] See, for example, Clarida et al. (2000), Eggertsson and Woodford (2003), Eusepi and Preston (2010).

[3] See Coibion and Gorodnichenko (2015) and Bordalo et al. (2020), among many others.

of the Fed's monetary policy rule, and how these perceptions change in response to policy actions and over the business cycle.[4]

We break this impasse by developing new techniques to estimate perceived monetary policy rules from panel data on macroeconomic forecasts.[5] Our policy rules link forecasts of the policy instrument, typically the federal funds rate, to forecasts of macroeconomic fundamentals, relying on variation across forecasters and forecast horizons to identify the rule's parameters. We use the Blue Chip Financial Forecasts (BCFF), which are compiled every month. Thus, we can measure shifts in monetary policy perceptions at substantially higher frequencies than can previous work on time-varying monetary policy rules. We use these new estimates to show that the variation in the perceived monetary policy rule matters for the conduct of monetary policy and risk premia in long-term Treasury bonds.

We estimate perceived monetary policy rules from individual macroeconomic forecasts using two different methods that produce similar results. In both cases, the policy rule includes inflation expectations and (implied) output gap forecasts. In the first method, we separately estimate panel regressions for each monthly survey. These regressions utilize 30-50 forecasters and forecast horizons ranging from 0 through 5 quarters. In our preferred specification, we include forecaster fixed effects to account for unobserved forecaster-specific determinants of interest rate forecasts, such as heterogeneous beliefs about the long-term real interest rate. In our second method, we estimate a state-space model (SSM), where the latent state variables are the perceived inflation and output gap coefficients and the perceived long-term nominal rate. The SSM estimates are similar to (pooled OLS) panel 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, the beginning of our sample period in 1992 is more than a decade after the "Volcker disinflation" in the early 1980s.[6] The previous macro-finance literature has documented substantial shifts in the Fed's responsiveness to inflation during the early 1980s, but much less variation since then (Clarida et al., 2000; Kim and Nelson,

[4] A notable exception is Carvalho and Nechio (2014) who study whether household expectations and professional forecasts are directionally consistent with a Taylor-type monetary policy rule.

[5] 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).

[6] Our sample starts in 1992 because that is when the Blue Chip Financial Forecasts started including real GDP growth forecasts.

2006). Second, over our post-1992 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). For this reason, our estimates of the perceived policy response to inflation are more erratic and somewhat difficult to interpret, and we focus on the response to the output gap. 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 during our sample period.[7]

Our analysis then investigates when and why there are shifts in the perceived monetary policy rule, and what the implications of these shifts are for monetary policy and asset pricing. First, we document and explain cyclical variation in the perceived rule. In particular, the perceived output gap weight, $\hat{\gamma}_t$, exhibits substantial variation over the monetary policy cycle. The coefficient increases with the level of short-term interest rates and the slope of the yield curve, and decreases with unemployment. These results are consistent with a monetary policy cycle in which the Federal Reserve tries to "get ahead of the curve" at the beginning of recessions by aggressively cutting rates. As a result, policy is viewed to be less dependent on the macroeconomic outlook, and the perceived rule coefficient $\hat{\gamma}_t$ falls at the same time that short rates are low, the yield curve is shallow, and unemployment is high. As the economy recovers and the Fed prepares to tighten, forecasters expect policy rate hikes to be gradual and data-dependent, with rising perceived responsiveness $\hat{\gamma}_t$. As a result $\hat{\gamma}_t$ rises when short rates are rising, the yield curve is steep (anticipating future rate hikes), and unemployment is low. Our estimates also capture forward guidance by the Fed, such as the calendar-based forward guidance during the (first) zero lower bound episode, when the Fed essentially committed itself to near-zero policy rates despite improving economic conditions.

Second, we explain the sensitivity of interest rates to macroeconomic news with the perceived responsiveness of monetary policy using high-frequency event studies. Similar to Swanson and Williams (2014), we document that the responsiveness of interest rates to macro news varies over time, but in contrast to their work, 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.[8] These high-frequency results provide

[7]For example, the tightening of monetary policy from 2015 to 2019 was partly driven by concerns about potential *future* inflation pressures due to an overheating economy.

[8]Hamilton et al. (2011) directly estimate the market-perceived rule using high-frequency responses to

some validation of our estimates of the perceived output gap response $\hat{\gamma}_t$, and go some way in addressing possible concerns about identification and exogeneity of our policy rule estimates. In addition, this evidence provides a policy-based explanation of changes in the financial market reaction to new macroeconomic information.

Third, beliefs about the monetary policy rule respond to high-frequency monetary policy surprises in a direction consistent with rational learning. As one might expect in a simple model of rational learning, we find that the perceived output gap coefficient increases following an identified high-frequency monetary policy tightening surprise, provided that the economy is in an expansion. Conversely, the perceived output gap coefficient decreases after a surprise monetary policy tightening that occurs during a recession. Peak responses occur six to twelve months after the shock, suggesting that forecasters update the perceived output gap coefficient only gradually in response to monetary policy surprises.

A comparison of the Blue Chip estimates to the Fed's own projections yields further insights about how the public updates its policy rule perceptions. We apply our estimation methodology to individual forecasts underlying the Summary of Economic Projections (SEP), which are available for the period from 2012–2016.[9] We find that the coefficients on the output gap estimated from the Blue Chip data and the SEP exhibit a similar pattern, but the Blue Chip-based estimates seem to react more slowly and lag the Fed's own policy rule coefficient. Of course, the SEP estimates are only available for a short period, and they should therefore be viewed as a case study. In any event, they are consistent with the view that the public updates its beliefs about monetary policy in the right direction, but somewhat sluggishly, in response to changes in the Fed's true monetary policy rule.

In line with these results about updating of policy rule perceptions, we find that variation in $\hat{\gamma}_t$ is related to the predictability of fed funds rate forecast errors using measures of current economic conditions. We thereby speak to the well-known finding that forecasts for the federal funds rate contain systematic, predictable expectational errors (Cieslak, 2018; Bauer and Swanson, 2021; Schmeling et al., 2022). While previous authors have argued that policy rate forecast errors arise from misperceptions of the policy rule, our evidence suggests that misperceptions primarily arise when monetary policy is thought to be highly responsive to output gap data, i.e., when $\hat{\gamma}_t$ is high. By contrast, misperceptions and thus systematic federal funds rate surprises are less likely when perceived responsiveness is low. An extreme example of this pattern is the period from 2012-2014 during the first zero-lower-bound period.

Our findings about the updating process for monetary policy perceptions have implica-

macroeconomic news, but do not allow for time-varying rule parameters.

[9] Similarly to the professional forecasters, the language in the Survey of Economic Projections (SEP) is frequently suggestive of a perceived rule, e.g. "To appropriately reflect lower longer-run GDP growth, I marked down my estimate of the longer-run federal funds rate. (...)" (SEP, September 16-17, 2015).

tions for the communication of monetary policy. In particular, they suggest that the public does not have an inherently biased picture of the monetary policy rule. Instead, the public (a) reacts to monetary policy actions and new information in a systematic way, and in the direction predicted by rational learning, and (b) only gradually updates its beliefs in response to changes in the conduct of monetary policy.

Fourth, perceptions of the monetary policy rule matter for term premia in long-term bond yields. We show that changes in $\hat{\gamma}_t$ predict excess returns on Treasury bonds, controlling for other known predictors such as the shape of the yield curve and economic activity. Periods with high $\hat{\gamma}_t$ are followed by low excess bond returns, and the predictive power is statistically and economically significant. A one-standard deviation increase in the SSM estimate of $\hat{\gamma}_t$ predicts a 1.5 percentage point decrease in 5-year Treasury bond excess returns over the next 12 months, and a nearly five percentage point decrease over the next 24 months. The negative correlation with bond risk premia is consistent with the basic asset pricing logic that investors should require a lower risk premium for assets that provide a hedge by paying off in bad economic states, as discussed in Campbell et al. (2017) and Campbell et al. (2020). A higher monetary policy coefficient raises the perceived comovement between interest rates and the economy, driving down the correlation between bond returns and the economy and increasing the hedging value of bonds.

This bond return predictability suggests a possible explanation for conundrum periods, when the Fed raised its policy rate but long-term yields barely increased or even decreased, as during the tightening cycle in 2004-2005. The tightening of monetary policy during an expansion tends to shifts the public's beliefs towards higher responsiveness to economic activity. In turn, perceptions of a more responsive Fed lower risk premia in long-term bonds, lowering long-term yields all else equal. A simple back-of-the-envelope calculation illustrates the quantitative importance of this channel: a 10 bps surprise increase in the monetary policy rate tends to lower the 5-year term premium by approximately 5 bps six to twelve months after the shock, provided that the economy is in an expansion. This decline in the term premium may well undo the increase in the expectations component of long-term yields due to tightening monetary policy. Thus, shifting perceptions of the policy rule can help explain why during some Fed tightening episodes the term premium appears to have decreased, and long-term yields have not increased as expected (Backus and Wright, 2007).

Our methodology for estimating monetary policy rules essentially takes the ideas of time-series regressions in the manner of Taylor (1999) and many others and transfers them to a setting with panel data on survey forecasts. This approach has the advantage of being transparent and comparable to the prior literature, but it also inherits some of the literature's challenges. In particular, it is well known that such regression estimates likely yield biased estimates of the parameters in the policy rule because macroeconomic variables endogenously depend on all shocks in the economy, including the monetary policy shock (Clarida et al., 2000; Carvalho et al., 2021). In other words, the equilibrium relation between the output gap and the policy rate depends both on how policy responds to the output gap and how the output gap responds to the policy rate.[10]

To address these concerns, we use a simple New Keynesian model to show theoretically that our estimates are econometrically identified and that the bias in them is likely small. The model is based on a simple, standard three-equation New Keynesian model consisting of an Euler equation, the Phillips curve, and a monetary policy rule. We consider the polar case of perfectly sticky prices, so that we can focus on the role of economic activity for monetary policy, as we do in the data. There are two main results. First, similarly to Carvalho et al. (2021), we obtain an expression for the bias in our estimates that depends on the ratio of the variance of monetary policy shocks relative to the variance of the output gap. Second, under the assumption that macroeconomic announcements provide information only about the output gap, and not about monetary policy shocks, the perceived rule, or the long-term real rate, we show that high-frequency regressions of interest rates on macroeconomic news surprises are also informative about the bias in our estimates. Taking both of these two separate results to the data, we find that endogeneity may bias our estimates of $\hat{\gamma}_t$ downwards, but is unlikely to affect its time-variation, which is our main focus. Combined with anecdotal evidence that forecasts are formed based on perceived monetary policy rules, this leads us to favor our preferred interpretation of $\hat{\gamma}_t$ as a policy rule coefficient.

An alternative, more general interpretation of our estimates is that they simply capture the perceived comovement between interest rates and macroeconomic variables, and not necessarily the causal response of monetary policy. With this interpretation most of the take-aways from our empirical analysis still remain valid. For example, our findings about updating of beliefs would then be interpreted as showing that forecasters update their beliefs about the comovement between interest rates and the output gap in the direction predicted by rational learning. Similarly, our asset pricing results indicate 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

[10] Another challenge is posed by Cochrane (2011), who argues that under certain conditions monetary policy rules cannot be econometrically identified from observed data, due to the endogenous response of long-run inflation to long-run nominal rates. However, Sims (2008) shows that the identification problem only arises in the special case when the central bank is able to exactly track the natural rate of interest.

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. Stein and Sunderam (2018) study strategic communication between the central bank and market participants. Several recent studies have used individual survey forecast data from the BCFF, such as Bordalo et al. (2020) and Giacoletti et al. (2021), who relate cross-sectional disagreement in interest rate forecasts to bond risk premia. Our study is most closely related to two recent papers that have estimated monetary policy rules using panel data of individual macroeconomic forecasts: Andrade et al. (2016) calibrate a monetary policy rule using the BCFF data to match the evidence on survey disagreement, and Carvalho and Nechio (2014) use individual responses from the Michigan survey of household expectations, as well as the Survey of Professional forecasters, to study whether household expectations and professional forecasts are directionally consistent with a Taylor-type monetary policy rule. However, these papers only consider policy rules with constant parameters, and do not study time-variation in monetary policy perceptions, which is a central focus of our analysis.

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. 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.

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 provides an ideal setting to estimate 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 forecast behavior. While the BCFF survey started in 1982, our sample begins in 1992, when forecasts of GDP were first included growth.[11] Our BCFF data ends in January 2021 for a total of 349 monthly surveys. Every month, each forecaster provides estimates for interest rates, inflation, and GDP growth at various forecast horizons. Forecasts are recorded for the current quarter and up to five quarters ahead.[12] 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 target 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.[13]

In addition, the real GDP growth and CPI inflation forecasts are key to our analysis. These macro forecasts are reported as quarter-over-quarter forecasts in annualized percent. In order to estimate monetary policy rules, we need to transform these variables. 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).[14] We calculate individual forecasts for year-over-year CPI inflation by cumulating the predicted quarterly inflation rates. For forecasts with horizons of less than three months, we combine the quarterly inflation forecasts with actual CPI inflation over the most recent quarters. We denote resulting CPI inflation forecasts as $E_t^{(j)} \pi_{t+h}$.

The calculation of output gap forecasts is conceptually straightforward: Using the current level of (real) GDP and the quarterly growth forecasts, we calculate the forecasted future level of GDP, which we then divide by CBO projections of potential GDP to calculate the implied forecast for the output gap. 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 GDP from ALFRED, and use the

[11] From 1984 to 1992, the survey included forecasts for real GNP growth. We could start our sample in 1984 if we ignored this change of the output variable definition. But there are other reasons for beginning our empirical analysis in the 1990s, including the availability of high-frequency monetary policy surprise measures for FOMC announcements.

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

[13] 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 $h=5$.

[14] This is a key point where our estimation differs from Andrade et al. (2016), who instead assume a rule in terms of GDP growth.

most recently observed vintage before the deadline of each survey. If this vintage does not yet contain GDP for the quarter immediately preceding the survey, then we extrapolate this number from the latest available quarter using the most recent annual GDP growth rate. 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.[15] 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.

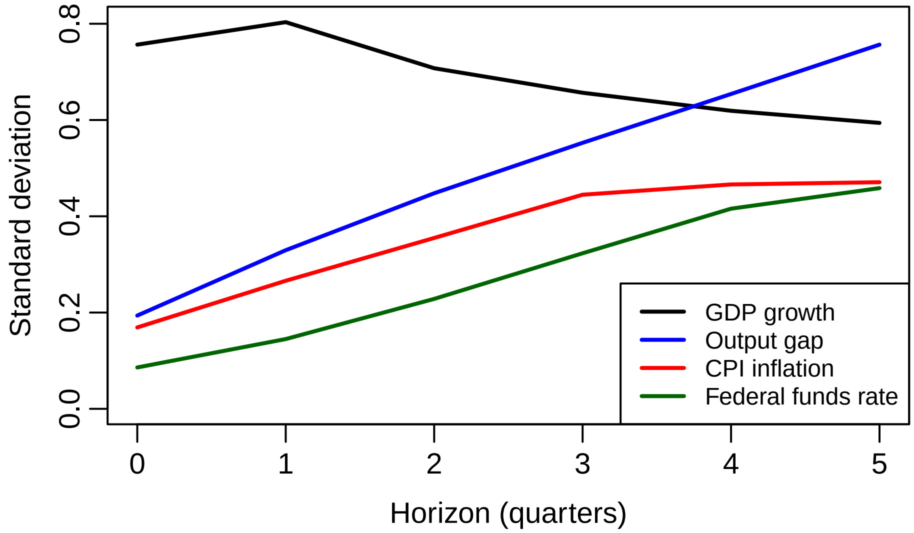
Before moving on, we show some simple summary statistics of individual survey forecasts. Figure 1 plots the term structure of disagreement, i.e., the average cross-sectional standard deviation across forecasters, for (i) forecasts of real GDP growth, (ii) implied forecasts for the output gap, $E_t^{(j)} x_{t+h}$, (iii) four-quarter CPI inflation forecasts, $E_t^{(j)} \pi_{t+h}$, and (iv) fed funds rate forecasts, $E_t^{(j)} i_{t+h}$. Only disagreement for GDP growth declines modestly with horizon. Disagreement about the output gap increases with forecast horizon because the output gap cumulates GDP growth forecasts. Similarly, the term structure of disagreement for inflation and the federal funds rate are strongly increasing, in line with our specification of a monetary policy rule in terms of the output gap rather than GDP growth. Because we specify the monetary policy rule in terms of the output gap rather than real GDP growth it does not seem necessary to generate additional disagreement for policy rate forecasts at longer horizons, using more complicated policy rule specifications as in Andrade et al. (2016).

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

[15] Occasionally, the units of real-time GDP and the CBO's potential GDP projections are not the same, because the dollar base year had changed for real GDP but not yet for potential GDP. In these cases, we use the next potential GDP vintage, even though it was not available in real time. For example, for the Feb-2019 survey, the most recent real GDP vintage, from 12/21/2018, is in billions of (chained) 2012 dollars, but the most recent potential GDP vintage, from 08/13/2018, is in billions of 2009 dollars, so we use the 01/28/2019 potential GDP vintage, even though it had not yet been released by the survey deadline on 01/26/2019.

Figure 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.

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.

Our policy rule does not explicitly include policy inertia, i.e., interest-rate smoothing. There would be little benefit in doing so, since our estimation exploits variation across forecasters at a given time t, taking the current (time-t) federal funds rate as given. To the extent that forecasters use an inertial rule, they would all anchor their forecasts at the same level, so that inertia should affect all forecasters equally and be absorbed by the regression intercept.[16] We therefore view the simple rule (1) as a natural starting point.

Forecasters do not know the rule's parameters but form beliefs about them. We assume

[16] Consistent with this argument, we have found in additional, unreported analysis that adding a partial adjustment term similar to Clarida et al. (2000) makes little difference to our estimated time series of $\hat{\gamma}_t$.

that beliefs about the coefficients are constant across forecasters, and we denote the perceived coefficients as $E_t^{(j)}\beta_t = \hat{\beta}_t$ and $E_t^{(j)}\gamma_t = \hat{\gamma}_t$, where j indexes expectations of individual forecasters. Of course, in reality forecasters may have heterogeneous beliefs about the policy rule. In this case, our estimates should be viewed as representing the average belief about the rule's parameters. 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:

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

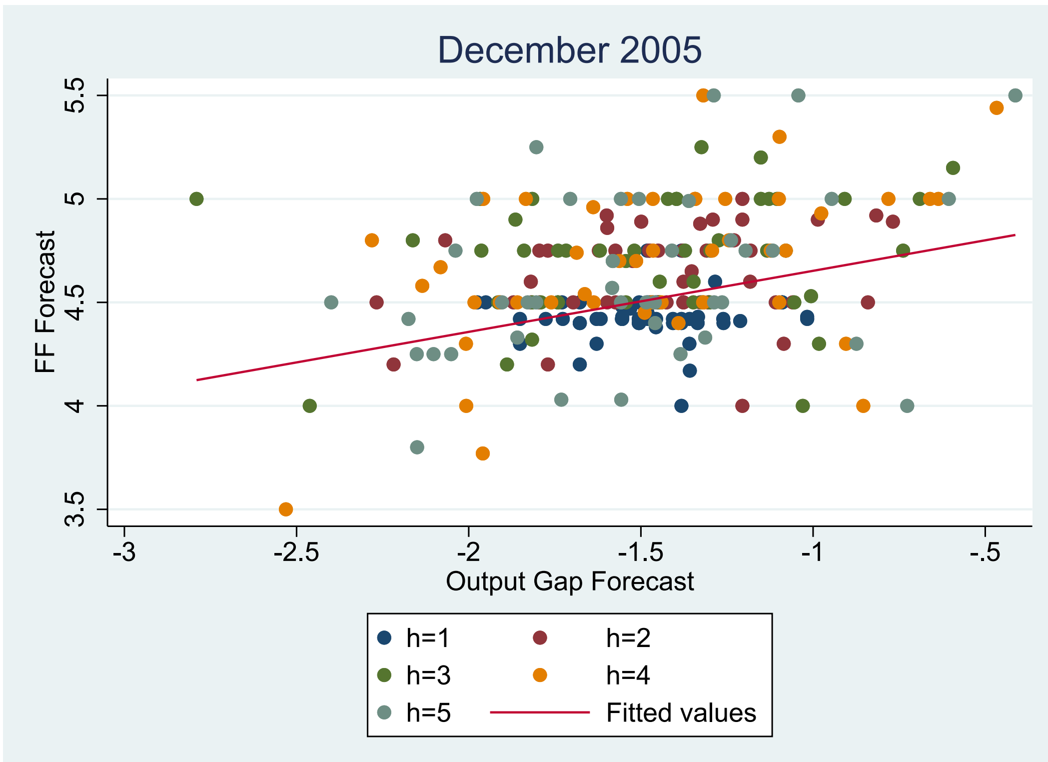
where $c_t^{(j)}$ denotes the part of the forecast that does not depend on horizon, and the error term $e_{th}^{(j)}$ contains the policy shock expected by forecaster j, $E_t^{(j)} u_{t+h}$, as well as possible measurement error. We will estimate equation (2) using two different methods, which we describe below.

2.3 Panel regressions

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 three different types of regressions that differ in their assumptions about $c_t^{(j)}$ and $e_{tj}^{(j)}$: Pooled OLS, Forecaster Random Effects (RE) and Forecaster Fixed Effects (FE). OLS and RE are consistent only if the forecaster specific intercept $c_t^{(j)}$ is uncorrelated with the macro forecasts for all h. In general, RE will be more efficient than OLS as it accounts for the variation in $c_t^{(j)}$, i.e., the disagreement about r_t^* and/or π_t^*. 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 2 illustrates the variation in the data driving our estimated perceived monetary policy rule for December 2005. The perceived output gap coefficient was estimated to be relatively high, with an FE estimate of $\hat{\gamma}_t = 0.48$. 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

Figure 2: Federal funds rate and output gap forecasts December 2005



Note: This figure shows scatter plots of output gap and federal funds rate forecasts used to estimate regression (2). We show output gap forecasts on the x-axis against federal funds rate forecasts on the y-axis for one example date, namely December 2005. The left plot uses data from the Blue Chip Financial forecasts as of $t = December 2005$. Each dot corresponds to one forecaster-horizon pair (j, h). Forecasts with a fixed horizon h are indicated with the same color. 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.

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. Reassuringly, there is significant variation in the output gap at all forecast horizons, driving the positive estimate for the perceived monetary policy coefficient.

Using the panel regression approach, Figure 3 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 three different 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 other estimates. These differences suggest that it is important to account for forecaster fixed effects in the estimation.

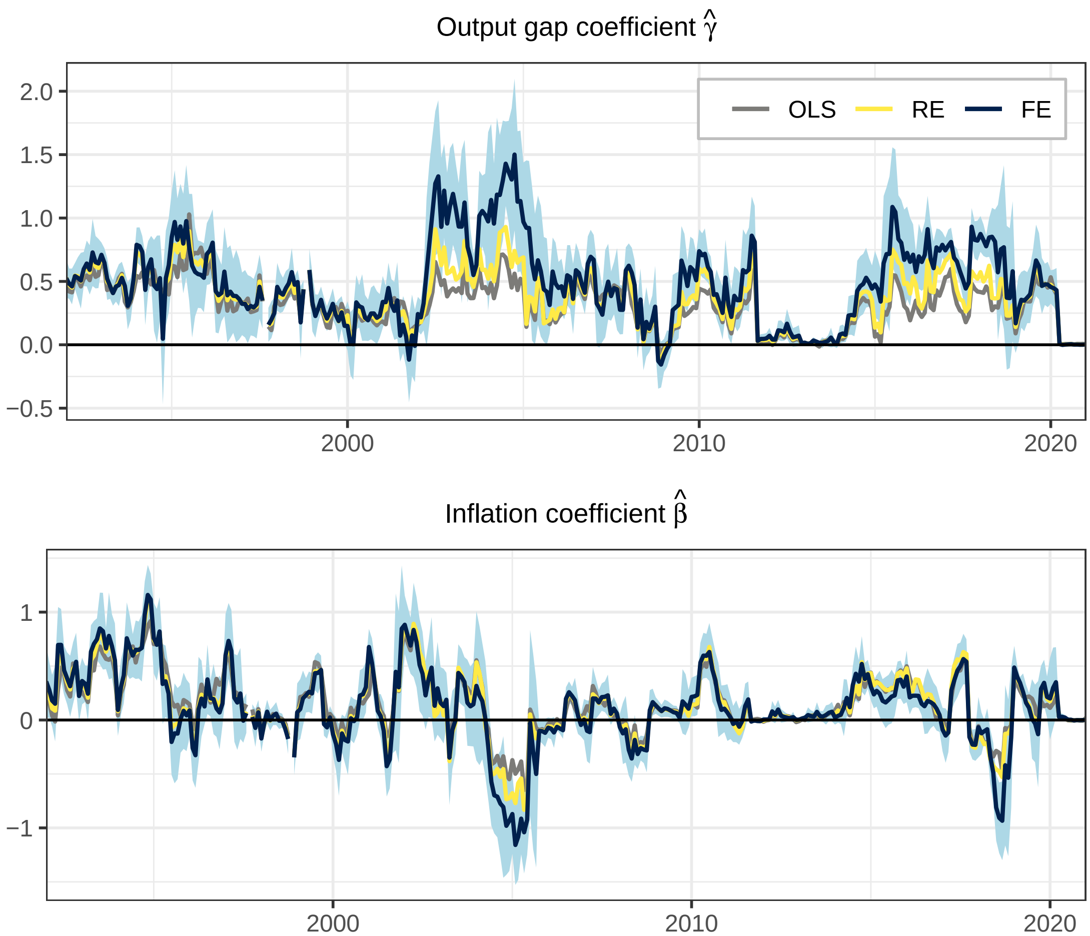
The coefficients are generally estimated quite precisely. Figure 3 shows 95% confidence intervals for the OLS estimates, based on standard errors with two-way clustering (by forecasters and horizon). Due to the fact that each month we bring to bear a sizeable amount of data to estimate the perceived policy rule—30-50 forecasts with horizons from zero to five quarters—these confidence intervals are quite narrow.

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. The most notable feature of the estimates of $\hat{\gamma}_t$ in Figure 3 is the significant amount of variation over time. For example, the FE estimate varies in a range from zero to about 1.5. Understanding these cyclical patterns in $\hat{\gamma}_t$ will be the focus of Section 2.5.

For the perceived inflation coefficient $\hat{\beta}_t$, 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 famous "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.[17] In the absence of sufficient variation in inflation, the

[17] This longer-run inflation target was implicit for most of our sample, but made explicit in January 2012 in the Fed's "statement of longer-run goals and policy strategy." The two-percent target applies to PCE

Figure 3: 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), forecaster Random Effects (RE) 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 1992 to January 2021.

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

So far, we have seen that we can using our rich panel data of survey forecasts to obtain relatively precise estimates and economically meaningful 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 generally 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., $E^{(j)}_t \pi_{t+h} = \pi^*$. 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%.[18] Second, we also assume that there is no disagreement about the long-run nominal short rate, i.e., $E^{(j)}_t i^*_{t+h} = i^*_t$. Homogenous 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 $c^{(j)}_t$ 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 homogenous. Overall, the assumptions for our SSM estimation are necessarily somewhat more restrictive, a price we pay for incorporating the

inflation, which translates into a slightly higher value for CPI inflation.

[18]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).

time series dimension into our estimates while keeping the estimation manageable.[19]

Under these additional assumptions, equation (2) becomes

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

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

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

where the innovations are *iid* normal, have variances σ_1^2, σ_2^2 and σ_3^2, and are mutually uncorrelated. The state vector is $x_t = (i_t^*, \hat{\beta}_t, \hat{\gamma}_t)'$ and the observation equation is

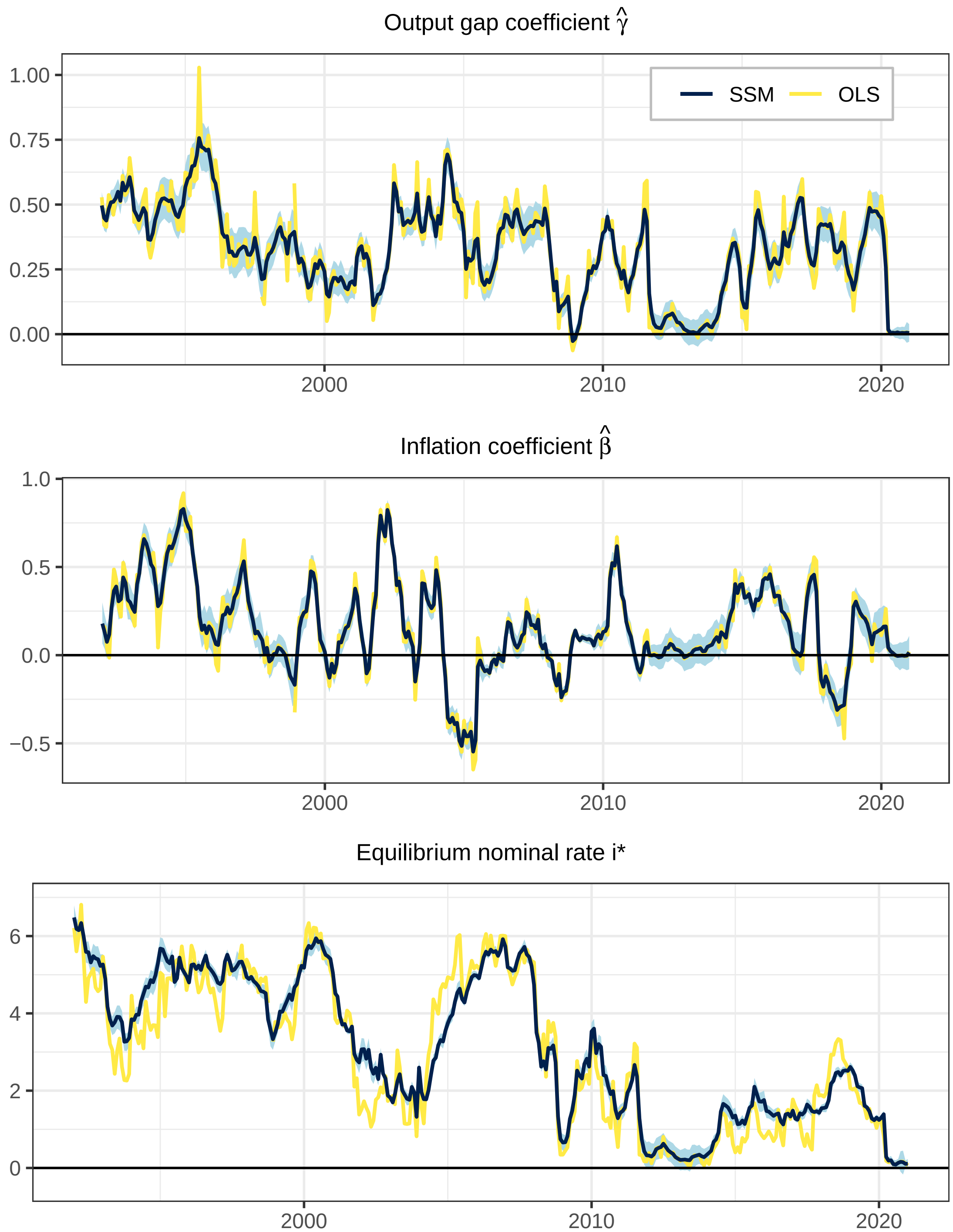
$$y_t = Z_t x_t + u_t,$$

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 B describes the details.

Figure 4 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 3. 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

[19]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; we do not assume rational expectations. In other words, one should imagine hats on top of these variables as well.

Figure 4: State-space model estimates of perceived policy rule coefficients



Note: Estimated policy-rule parameters $\hat{\gamma}_t$ and $\hat{\beta}_t$, as well as equilibrium nominal short rate i_t^*, from state-space model defined by equations (3) and (4); details of the Bayesian estimation are in Appendix B. Shaded areas are 95%-credibility intervals based on the posterior distributions. Also shown are the Pooled OLS estimates from Figure 3. The sample consists of monthly Blue Chip Financial Forecast surveys from January 1992 to January 2021.

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

2.5 Cyclical shifts in the perceived monetary policy rule

We now characterize how monetary policy is perceived to vary over the business and monetary policy cycles. To this end, we regress the estimated output gap weight $\hat{\gamma}_t$ on key macroeconomic variables. The results show that there is strong cyclical variation. Economically, the estimates suggest interest rate cuts are quick and sudden, particularly early in monetary easing cycles, whereas rate increases tend to be gradual and data-dependent.

Our estimates in Figures 3 and 4 suggest that the perceived output gap coefficient $\hat{\gamma}_t$ is systematically related to the business cycle and the stance of monetary policy. The coefficient is typically high during monetary tightening cycles, especially at the early stages of a tightening. For instance, $\hat{\gamma}_t$ was estimated to be high during the tightening cycle of 2003-2005 and during the period from 2015 to 2018 after lift-off from the zero lower bound (ZLB). By contrast, $\hat{\gamma}_t$ was estimated to be low and close to zero at the end of tightening cycles—when market participants likely saw little room for the policy rate to rise further—and during monetary easing cycles. For instance, it was low from 1998 to 2002 during the late stages of the dot-com bubble and the following bust, the period from 2006 to 2008 before and during the financial crisis, and the two ZLB episodes.

Table 1 uses regressions to show how $\hat{\gamma}_t$ is related to the term structure of interest rates and economic conditions. We regress $\hat{\gamma}_t$ on the slope of the yield curve, the 1-year nominal yield, and the unemployment rate.

$$\hat{\gamma}_t = b_0 + b_1 Slope_t + b_2 y_{1,t} + b_3 Unemp_t + \varepsilon_t \tag{5}$$

The first three columns use the panel FE estimate of $\hat{\gamma}_t$, while the last three columns use the SSM estimate. Focusing on the first row, we see that the slope of the yield curve enters consistently positively for all specifications. The relationship between the slope of the yield curve and the perceived monetary policy weight is robust to controlling for the level of short-term interest rates, as proxied by the 1-year nominal yield, and the unemployment rate.

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). Our findings therefore suggest that the federal funds rate is indeed perceived to be more sensitive to the state of the economy when interest rates are expected to be on the rise, as they are during monetary tightening cycles.[20] By contrast, when the yield curve is flat or inverted, this suggests that the stance of monetary policy is relatively tight, as it is after a series of increases in the policy rate. Thus, our results suggest the fed funds rate is perceived to be less sensitive to the state of the economy when the Fed is ending a tightening cycle.

The regression coefficients for the one-year nominal yield and the unemployment rate further support the notion that monetary policy is perceived to be less sensitive to output following decisive rate cuts at the beginning of recession.[21] The one-year nominal yield enters somewhat inconsistently for the FE estimate of $\hat{\gamma}_t$ but is consistently positive for the less noisy SSM estimate. The unemployment rate enters consistently with a statistically significant negative coefficient, supporting the view that monetary policy is perceived to be more sensitive to economic data about the economy during economic expansions and monetary tightening.

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". Simi-

[20]In Table 1 we think of the slope of the term structure 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.

[21]Univariate regressions of $\hat{\gamma}_t$ on these variables yield coefficients of the same signs.

Table 1: Policy rule perceptions and the monetary policy cycle

	Panel FE $\hat{\gamma}$			SSM $\hat{\gamma}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Slope	0.08***	0.10***	0.16***	0.02	0.06***	0.08***
	(2.60)	(2.93)	(3.91)	(1.18)	(3.49)	(4.20)
1-Year Yield		0.07	-0.02		0.15***	0.12***
		(1.36)	(-0.39)		(5.16)	(3.95)
Unemployment			-0.17***			-0.05***
			(-4.47)			(-3.04)
Const.	0.47***	0.51***	0.45***	0.32***	0.41***	0.39***
	(14.44)	(14.03)	(11.91)	(16.43)	(17.32)	(14.66)
N	349	349	347	349	349	347
R^2	0.09	0.09	0.22	0.03	0.20	0.27

Note: This table estimates monthly regressions $\hat{\gamma}_t = b_0 + b_1 Slope_t + b_2 y_{1,t} + b_3 Unemp_t + \varepsilon_t$ using the sample from January 1992 to January 2021. Columns (1) through (3) use the panel fixed effects (FE) estimate of $\hat{\gamma}_t$. Columns (4) through (6) repeat the same regressions for the state-space model (SSM) estimate of $\hat{\gamma}$. *Slope* is the end-of-month 5-year zero-coupon nominal Treasury rate minus the 1-year zero-coupon nominal Treasury rate, and $y_{1,t}$ is the 1-year zero-coupon nominal Treasury rate from Gürkaynak et al. (2007). $Unemp_t$ is the unemployment rate from FRED (series UNRATE). All variables on the right-hand-side are normalized to have unit standard deviations. Newey-West t-statistics with 4 lags in parentheses.

larly, 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.[22]

The behavior of $\hat{\gamma}_t$ over the first ZLB period from 2008 to 2015 and its response to the Fed's forward guidance is particularly interesting. After both the funds rate and $\hat{\gamma}_t$ decreased to zero in 2008, the output gap coefficient 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; output gap and funds rate forecasts both pointed upwards, resulting in a high estimated coefficient. But then, on August 9, 2011, the

[22]One of numerous examples is a speech by Chair Yellen (2015) where she emphasized that "policy will depend on [. . .] incoming data."

Fed introduced calendar-based forward guidance, predicting a near-zero policy rate until "at least through mid-2013." In response, the estimated $\hat{\gamma}_t$ dropped sharply and stayed near zero until lift-off started to come into view again in spring 2014.[23] These patterns demonstrate 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).

3 New Keynesian model and estimation bias

We use a simple New Keynesian (NK) framework to aid in interpreting our results. One purpose of the framework is to specify the simplest set of assumptions under which our estimation yields valid estimates of the perceived monetary policy rule, and to quantify potential estimation bias from the endogenous response of the economy to monetary policy. We do not aim to provide an exhaustive list of conditions under which a monetary policy rule can be estimated via simple regression.[24] Instead, we show that both a simple bias adjustment and the macro news regressions below in Section 4 paint a remarkably consistent picture. 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.

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

$$x_t = E_t x_{t+1} - (i_t - E_t \pi_{t+1}) + v_t \tag{6}$$

$$\pi_t = E_t \pi_{t+1} + \kappa x_t \tag{7}$$

$$i_t = \beta \pi_t + \gamma x_t + u_t. \tag{8}$$

Our 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, (6), assumes log-utility and includes a reduced-form demand shock v_t.[25] Equation (7) is the Phillips curve. Our monetary policy rule, equation (8), includes a mone-

[23] An alternative way to estimate the perceived policy rule is to use forecasts for the two-year yield, which is more immune to ZLB concerns (Swanson and Williams, 2014; Hanson and Stein, 2015). Appendix A 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.

[24] Cochrane (2011) demonstrates that in certain cases a simple time-series regression does not reveal the monetary policy coefficients at all due to the endogenous inflation and output responses.

[25] Such a shock can arise from a variety of sources, such as time-preference shocks (Albuquerque et al. (2016)), shocks to risk or risk aversion (Christiano et al. (2014), Pflueger et al. (2020),Caballero and Simsek (2020)), or shocks to expected growth (Clarida et al. (2000), Caballero and Simsek (2021)). We do not take a stand on the precise source of demand shocks for our analysis.

tary 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 (6) through (8) 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, γ. 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 $\beta\pi_t$ drops out of the monetary policy rule. The solutions for x_t and i_t are straightforward to derive, as shown in Appendix C.

In our theoretical analysis of estimation bias, we use $\tilde{\gamma}$ to denote the statistically estimated monetary policy coefficient on the output gap, which may include statistical 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.

3.1 Time-series regressions

As a first step, it is helpful to derive the model's implications for time-series regression estimates of the policy rule, i.e., for regressions of the policy rate on the output gap under rational expectations. By its nature, such a time-series regression yields an estimate of the true coefficient γ, and not of the perceived coefficient $\hat{\gamma}$. Here we assume that v_t and u_t are each serially uncorrelated.

The estimated regression coefficient is

$$\tilde{\gamma}^{TS} = \frac{Cov\left(i_t, x_t\right)}{Var\left(x_t\right)} = \gamma - \frac{1}{1+\gamma}\frac{Var\left(u_t\right)}{Var\left(x_t\right)}. \tag{9}$$

Equation (9) shows that the time-series regression coefficient tends to be biased downwards relative to the true monetary policy coefficient γ.[26] The downward-bias is more significant if monetary policy shocks are volatile relative to the overall volatility of the output gap, and if the monetary policy coefficient γ is low. Intuitively, a hawkish monetary policy shock drives down the output gap and therefore drives down the correlation between the funds rate and the output gap. This endogeneity bias is weaker if the monetary policy rule counteracts movements in the output gap (if γ is large).

In her review chapter on the empirical evidence of monetary policy shocks, Ramey (2016) concludes that monetary policy shocks contribute between 0.5% and 7% of output fluctuations at a forecast horizon of 24 months (when the effect peaks). With $\frac{1}{1+\gamma}\frac{Var(u_t)}{Var(x_t)} \leq \frac{Var(u_t)}{Var(x_t)}$ this suggests that the bias of the time-series estimate should be no more than 0.07. To

[26] In Appendix C, we check that this expression for the time-series coefficient goes through in the presence of a non-zero long-run interest rate, which simply shifts the policy rate up by a constant.

put this number in perspective, the average value of our panel FE estimate for $\hat{\gamma}_t$ is 0.5, suggesting that the relative magnitude of the bias is small.

According to our model, the endogeneity bias in standard monetary policy rule regressions may be quite small. Carvalho et al. (2021) obtain similar results for a simple NK model. In addition, they use simulations to show that even in a quantitative, large-scale DSGE model, the estimation bias in such regressions is small.

3.2 Panel regressions

We now consider panel regressions using macroeconomic forecasts. Forecast-based regressions deliver estimates of the perceived policy rule coefficient $\hat{\gamma}_t$, but estimation bias may still be relevant if forecasters anticipate monetary policy shocks. Panel regressions use forecasts available at a fixed forecast date t, so in this subsection all estimates and moments have a time-t subscript.

For the sake of simplicity, and to focus on the cross-sectional regression of forecasted fed funds rates onto forecasted output gaps across forecasters, our baseline model assumes that forecasters disagree over future demand and monetary policy shocks but that they agree on the monetary policy rule.[27] 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 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 parameter $\hat{\gamma}_t$ and forecaster j's shock expectations into the model's rational expectations equilibrium given in Appendix C, and obtain forecaster j's conditional expectations for the policy rate and output gap at horizon $t + h$:

$$E_t^{(j)} x_{t+h} = \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}), \quad \text{and} \tag{10}$$

$$E_t^{(j)} i_{t+h} = \hat{\gamma}_t \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}) + E_t^{(j)} u_{t+h}. \tag{11}$$

We use the notation Cov_t and Var_t to denote covariances and variances of forecasts across forecast horizons and across forecasters at a given time t. The population coefficient

[27] In Appendix C, we consider an extension with disagreement over the monetary policy rule and show that in this case we estimate the forecaster-average of the perceived monetary policy rule.

for a pooled OLS panel regression of interest rate forecasts on output gap forecasts at time t equals

$$\tilde{\gamma}_t^{Panel} = \frac{Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)} \tag{12}$$

$$= \hat{\gamma}_t - \frac{1}{1+\tilde{\gamma}_t^{Panel}} \frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)}. \tag{13}$$

Comparing the panel regression coefficient (13) with the time-series regression coefficient (9) shows that the estimation bias takes a similar form, but it is relative to the *perceived* monetary policy coefficient. Since the panel regression coefficient relies only on forecast data available at time t and not on the time-series, it depends only on the perceived macroeconomic dynamics as opposed to realized dynamics. Another difference is that the bias is determined by relative variances *across forecasters and horizons*, i.e., the degree of disagreement and dispersion in the survey forecasts, rather than the relative variability of monetary policy shocks in the data.[28]

An issue with using equation (13) to estimate the statistical bias is that we do not know the variance of forecasters' expected monetary policy shocks. However, we can estimate forecaster j's expected monetary policy shock at horizon h using the residual from the panel regression. It turns out that substituting the variance of these residuals into (13) gives an estimate of the statistical bias that becomes accurate as the cross-sectional variance ratio $\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)}$ becomes small. We believe that this is a reasonable case to consider given the consensus in the empirical macroeconomic literature that the ratio of monetary policy shocks explaining realized output variance is small. We make the simplest distributional assumption: that shock expectations $E_t^{(j)} v_{t+h}$ and $E_t^{(j)} u_{t+h}$ are uncorrelated with each other and uncorrelated across forecasters and forecast horizons at a given point in time t. We can then derive the following approximate estimation bias. While these assumptions are strong, they lead to particularly tractable expressions for the estimation bias. Because we find little time-variation in the estimation bias, it is unlikely that more general assumptions would change this conclusion materially.

Proposition 1 *Let* $E_t^{(j)} \tilde{u}_{t+h} = E_t^{(j)} i_{t+h} - \tilde{\gamma}_t^{Panel} E_t^{(j)} x_{t+h}$ *denote the residual for forecaster* j

[28] We check in Appendix C that all expressions for the panel regression coefficient go through if we augment the model to include a non-zero long-run natural interest rate, over which forecasters may have differing beliefs. In that case, $\tilde{\gamma}^{Panel}$ simply needs to be defined as the regression coefficient of $E_t^{(j)} i_{t+h}$ onto $E_t^{(j)} x_{t+h}$ after projecting them onto forecaster fixed effects, i.e., the panel fixed effects estimate.

and forecast horizon $t+h$ from the panel regression of interest rate forecasts onto output gap forecasts at time t. Assuming that shock expectations $E_t^{(j)} v_{t+h}$ and $E^{(j)} u_{t+h}$ are uncorrelated with each other, and uncorrelated across forecasters and horizons at a given forecast date t, up to second-order terms in $\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t(x_{t+h})}$, the panel regression coefficient equals up to higher-order terms

$$\tilde{\gamma}_t^{Panel} = \hat{\gamma} - \frac{1}{1+\tilde{\gamma}^{Panel}} \frac{Var_t\left(E_t^{(j)} \tilde{u}_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)}. \tag{14}$$

This result, which is proved in Appendix C.2, shows that to first order the estimation bias depends on the ratio of the variance of monetary policy residuals to the variance of the output gap. While the panel coefficient (14) is for the pooled OLS regression, analogous expressions obtain if the panel regression is instead estimated with forecaster fixed effects. The only difference is that all variables need to be interpreted as residualized with respect to forecaster fixed effects first (see Appendix C.2). We solve for the bias exactly numerically, i.e. not dropping higher-order terms as in (14), and then compute the bias-adjusted perceived monetary policy coefficient. When we do this for our benchmark panel FE estimates $\tilde{\gamma}_t^{Panel}$, we find that the adjusted coefficient is higher on average by about 0.23, but has a similar volatility to our unadjusted estimates. Furthermore, the adjusted and unadjusted coefficients have a correlation of 0.97 in levels and 0.95 in monthly changes. These calculations suggest that while endogeneity bias may affect the average level of the estimated policy rule coefficient, it is unlikely to drive the time variation that is at the center of our analysis.

4 Policy perceptions and macroeconomic news

Next, we turn to high-frequency responses of interest rates to macroeconomic news, and 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 non-farm 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.

4.1 Event-study regressions around macroeconomic news

We estimate regressions of the form

$$\Delta y_t = b_0 + b_1\hat{\gamma}_t + b_2 Z_t + b_3\hat{\gamma}_t Z_t + \varepsilon_t, \tag{15}$$

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 (15) 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. 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 2 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 2, panel A reports results for the FE estimate of $\hat{\gamma}_t$, while panel B uses the SSM estimate.

Table 2 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

Table 2: 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
$\hat{\gamma}^{FE}$	0.5***	0.5**	0.03	-0.03	0.6***	0.6**	0.3	0.09
	(2.58)	(2.29)	(0.08)	(-0.09)	(2.93)	(2.54)	(0.91)	(0.24)
Z	0.02***	0.02***	0.02*	0.009	0.7***	0.7***	0.6***	0.7***
	(4.28)	(3.52)	(1.95)	(1.03)	(5.59)	(6.24)	(5.26)	(4.75)
$\hat{\gamma}^{FE} \times Z$	0.01*	0.04***	0.06***	0.06***	0.4*	0.7***	0.8***	0.6***
	(1.87)	(3.93)	(4.39)	(3.49)	(1.92)	(3.84)	(4.31)	(2.64)
Const.	-0.3**	-0.2*	-0.2	-0.10	-0.2**	-0.3*	-0.1	-0.02
	(-2.30)	(-1.69)	(-1.14)	(-0.45)	(-2.02)	(-1.94)	(-0.62)	(-0.10)
N	3155	3155	3155	3155	3155	3155	3155	3155
R-sq	0.04	0.07	0.07	0.04	0.07	0.12	0.13	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
$\hat{\gamma}^{SSM}$	0.07	0.1	-0.7	-0.7	0.3	0.2	-0.2	-0.4
	(0.18)	(0.20)	(-1.09)	(-1.02)	(0.91)	(0.37)	(-0.26)	(-0.62)
Z	0.004	0.003	0.008	0.01	0.2	0.3**	0.4***	0.6***
	(0.84)	(0.36)	(0.64)	(0.79)	(1.04)	(2.20)	(2.80)	(3.58)
$\hat{\gamma}^{SSM} \times Z$	0.06***	0.1***	0.1***	0.08**	1.9***	2.1***	1.7***	1.1**
	(3.05)	(4.76)	(3.39)	(2.09)	(3.89)	(5.49)	(4.70)	(2.38)
Const.	-0.04	-0.003	0.03	0.1	-0.07	-0.04	0.07	0.2
	(-0.34)	(-0.02)	(0.11)	(0.45)	(-0.59)	(-0.23)	(0.34)	(0.62)
N	3155	3155	3155	3155	3155	3155	3155	3155
R-sq	0.04	0.08	0.07	0.04	0.08	0.13	0.13	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.

news, and estimates of $\hat{\gamma}_t$. The magnitudes are economically meaningful. For example, the first column in Panel A has an unconditional coefficient onto the non-farm payroll surprise of $b_2 = 0.02$ and an interaction coefficient on to the same surprise multiplied with $\hat{\gamma}_t$ of $b_3 = 0.01$. For the panel FE estimate of $\hat{\gamma}_t$, the standard deviation is 0.4, which means that a one-standard deviation increase in $\hat{\gamma}_t$ increases the response of the three-month federal funds futures by roughly 25% relative to the unconditional response. The ratio of b_3/b_2 is even larger in Panel B, as would be expected if the noise-reduction in the SSM estimate of $\hat{\gamma}_t$ helps to address attenuation bias. It is intuitive that the effects are quantitatively largest for the three-month federal funds future contract, because our survey estimates are based also on forecasts of the federal funds rate.

Overall, the evidence from high-frequency macroeconomic announcements supports the interpretation of the estimated $\hat{\gamma}_t$ as a perceived monetary policy rule coefficient. First, it suggests that survey and financial markets expectations are consistent. In addition, the high-frequency regression results also partly address endogeneity issues. 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 2 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 response.

4.2 Model-based interpretation of macro news regressions

We now use the model introduced in Section 3 to help interpret the results of the macro news regressions. We show that these regressions provide a test of whether our estimate of perceived gamma is unbiased, i.e., whether $\tilde{\gamma}_t = \hat{\gamma}_t$. Because financial market regressions do not rely on cross-forecaster variation, we focus on the average or consensus expectations, which we denote $E_t(\cdot)$. All agents are assumed to perceive a monetary policy output weight $\hat{\gamma}_t$ and the long-run interest rate r_t^*.

Macroeconomic announcements provide new information to the public, which leads to an update of expectations. We denote by $E_{t-}(\cdot)$ the expectation based on information just prior to the announcement and by $E_t(\cdot)$ the expectation right after. Following Swanson and Williams (2014) and many other studies in this literature, we assume that during this narrow time interval from $t-$ to t, only information about the economic outlook is released, not new information about the monetary policy shock or the parameters of the monetary policy rule.

In the context of our simple model, we assume that macro data releases provide information about the output gap.[29] Specifically, we assume that the macroeconomic news surprise

[29] Our simple model assumes that inflation is constant, see Section 3.

Z_t is proportional to news about the future output gap,

$$Z_t \;=\; \alpha\,(E_t - E_{t-})\,x_{t+1}, \tag{16}$$

where the constant of proportionality α is chosen so that the univariate regression coefficient of interest rate surprises onto Z_t equals unity, corresponding to the scaling in Swanson and Williams (2014) and the "All Announcements" columns in our Table 2. Then we make the following predictions for a high frequency regression of the form

$$(E_t - E_{t-})\,i_{t+1} = b_0 + b_1\tilde{\gamma}_t + b_2 Z_t + b_3\tilde{\gamma}_t Z_t + \varepsilon_t. \tag{17}$$

Proposition 2 *Consider an estimate of the perceived output gap coefficient that includes both a constant bias and some estimation noise: $\tilde{\gamma}_t = \hat{\gamma}_t + \mu + e_t$. Assume that e_t is uncorrelated with $\hat{\gamma}_t$, so that it is classical measurement error. Let $\bar{\gamma}$ denote the time-series average of the perceived monetary policy coefficient $\hat{\gamma}_t$. Appendix C.5 shows that the regression coefficients in equation (17) are given by*

$$b_2 = -\frac{\mu}{\bar{\gamma}}\rho^2 + 1 - \rho^2 \quad \text{and} \quad b_3 = \frac{\rho^2}{\bar{\gamma}}, \tag{18}$$

where $\rho = Corr(\hat{\gamma}_t, \tilde{\gamma}_t)$ measures how precisely $\tilde{\gamma}_t$ is estimated.

Using Proposition 2, the high-frequency regressions in Table 2 shed light on whether our estimates of $\hat{\gamma}_t$ are biased and/or affected by estimation noise. One prediction is that in the absence of both bias and estimation error ($\mu = 0$ and $\rho = 1$), the coefficient on the interaction of $\tilde{\gamma}_t$ with macroeconomic news surprises equals the inverse of the average perceived monetary policy output gap coefficient, $b_3 = \frac{1}{\bar{\gamma}}$. This prediction is indeed borne out in our empirical regressions in Table 2 Panel B, as can be seen in the "All Announcements" columns using the 3-month fed funds futures, 6-month fed funds futures, or the 2-year Treasury rate as policy rate proxies. The interaction coefficients in these columns are statistically indistinguishable from $2 = \frac{1}{0.5}$. For comparison, the sample average of our panel FE estimate equals 0.5, which also happens to be value of γ in the classical Taylor (1993) rule.[30]

By contrast, the "All Announcements" regressions with the panel FE estimate in Panel A find smaller, but still positive and highly statistically significant estimates of the interaction coefficient b_3. The smaller magnitude suggests that $\rho^2 < 1$, consistent with attenuation bias due to the presence of noise in the panel FE estimates. This is unsurprising, as the month-

[30] Because non-farm payroll surprises are not scaled so that the univariate regression coefficient of interest rate surprises onto Z_t equals unity and 10-year Treasury bonds contain risk premia, we would not expect the prediction to bear out for Z=Nonfarm Payroll or changes in the 10y Treasury rate.

by-month panel regression estimates do not use information from previous surveys, and are therefore generally noisier than the state-space model estimates.

Furthermore, the "All Announcements" regressions in both panels generally find positive and mostly statistically significant coefficients b_2. Based on Proposition 2 and given that the empirical evidence is consistent with $\rho^2 \approx 1$, this suggests that there is a constant downward-bias in our SSM estimate (i.e., $\mu < 0$). In Panel A, the estimated coefficients for b_2 are also positive and generally larger than in Panel B. This makes sense, as Proposition 2 shows that as long as $\mu < -\bar{\gamma}$ (so that $\tilde{\gamma}_t$ has the correct sign on average), b_2 increases with classical measurement error ($\rho^2 < 1$). Given the presence of some measurement error for the panel FE estimate, the somewhat larger estimates for b_2 in Panel A are therefore exactly as expected. Overall, we conclude that our state-space model estimates of $\hat{\gamma}_t$ contain a slightly negative, but roughly time-invariant bias, while the panel FE estimates contain some additional classical measurement noise.

This model-based interpretation of our event-study regressions suggests that our survey-based estimates accurately capture variation in agents' perceived monetary policy rule coefficient $\hat{\gamma}_t$. In particular, while the panel FE estimate of $\hat{\gamma}_t$ may include some more estimation error, the SSM estimate of $\hat{\gamma}_t$ appears to be affected only by a constant downward bias. On the whole, the analysis here and in Section 3.2 substantiates the use of our estimates to understand time variation in perceptions about monetary policy rules.

5 Updating and rationality

We now turn to the question of how our estimates of private forecasters' perceived $\hat{\gamma}_t$ compare to the Fed's own monetary policy rule and how perceptions of the monetary policy rule are updated in the face of new information. This has implications for when the public is most likely to suffer predictable surprises from monetary policy actions.

Central bankers work hard to communicate their monetary policy framework, not only because policy is most effective when it is predictable and well-understood, but also to avoid sudden movements in financial markets such as the taper tantrum of 2013. However, given the practical difficulties of communicating monetary policy strategies, the public's perceived monetary policy rule is likely to differ from the actual rule followed by the Fed. If forecasters update in a Bayesian manner, they would update their perceived rule in the direction of the actual rule only after observing policy rate decisions generated from the actual rule. It might also be the case that certain monetary policy rules, such as a commitment to keep interest rates constant, are easier to communicate and commit to than others, such as state-contingent rules. Finally, forecasters and financial markets might be subject to behavioral biases driving a wedge between the actual and the perceived monetary policy rule. Our goal is not to conclusively distinguish between behavioral biases and rational beliefs about the policy rule. Instead, we simply some evidence on whether the variation in the perceived policy rule is consistent with Bayesian updating.

Recall that we denote the perceived monetary policy rule coefficient on the output gap by $\hat{\gamma}_t$ and the true monetary policy rule coefficient by γ_t. If observers have full information and rational expectations (FIRE), we would have $\hat{\gamma}_t = \gamma_t$, whereas imperfect information or non-rational expectations can drive a wedge between the two. Thus, the evidence on updating we present below is complementary to the cyclical variation documented in Section 2.5, which could be driven by time-variation in either the true coefficient γ_t or the wedge.

Our evidence supports the interpretation that the perceived $\hat{\gamma}_t$ moves in the direction predicted by rational updating but does so gradually, leading to persistent gaps relative to γ_t. First, we compare our perceived monetary policy output coefficient to the Federal Reserve's own policy rule coefficient, which we measure by applying our estimation techniques to individual FOMC members' forecasts. Because individual FOMC members' forecasts are only available for a short period, we are restricted to comparing the coefficients during the period around the first lift-off from the zero lower bound in December 2015. Second, we estimate impulse responses of perceived $\hat{\gamma}_t$ to high-frequency monetary policy shocks. The direction of the responses is consistent with rational updating, though the effects are gradual with a peak impact about six to twelve months after the shock. Third, we show that the predictability of federal funds rate forecast errors, documented by Cieslak (2018), is concentrated in periods when $\hat{\gamma}_t$ is high, which suggests that these are periods when the gaps between the actual and perceived monetary policy output coefficient is largest.

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

How does the monetary policy rule perceived by the public compare to the actual rule used by the Fed itself? We conduct a case study comparing the public's perceived rule to the Fed's actual rule during a period when changes in the monetary policy rule were particularly clear: the first liftoff from the ZLB in 2015. During this period, individual macroeconomic forecasts of FOMC participants make it possible to use the same empirical strategy on analogous data sets from private forecasters and Fed forecasters. 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. We therefore have a panel dataset of individual FOMC forecasts from 2012 to 2016, covering a total of 21 releases of the "Summary of Economic Projections" (SEP).[31]

These FOMC economic projections contain forecasts for headline and core PCE inflation, real GDP growth, and the unemployment rate. In addition, 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.

The forecast horizons are annual and include the current year and several future years, as well as a "longer-run" projection. For the sake of comparability with the Blue Chip forecasts, which are available out to a maximum forecast horizon of five quarters, we include only the projections for the current year and the following year.[32] For each SEP we have between 16 and 19 individual projections, depending on the exact number of participants at each FOMC meeting.

We use the same panel regression approach as for the Blue Chip data, described in Section 2.3. As before, 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.

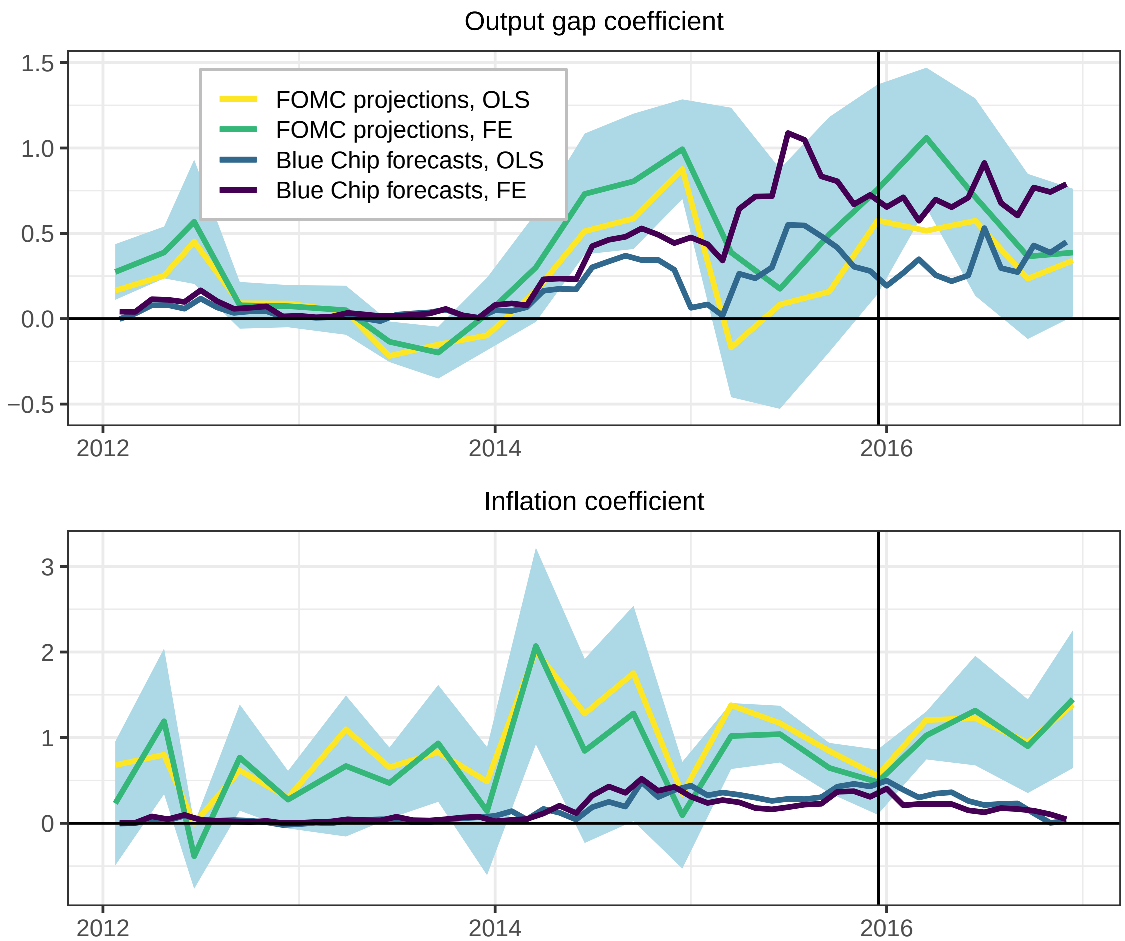
Figure 5 shows the OLS and FE estimates of γ_t and β_t obtained from the FOMC projections (SEP), together with 95% confidence intervals for the FE estimates. It also includes the estimates of the perceived coefficients $\hat{\gamma}_t$ and $\hat{\beta}_t$ based on the Blue Chip (BC) data for the time period where both are available. The date of actual liftoff is indicated with a vertical line.

The perceived output gap coefficient as estimated from the private forecasters' BC data 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 private forecaster coefficient is similar to the Fed's, though the private forecaster coefficient appears to lag somewhat behind the Fed's. This gradual and somewhat delayed updating is consistent with the idea that to convince the public the Fed has to communicate a change in its rule repeatedly and take actions in line with this change.

[31] 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.

[32] 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.

Figure 5: Policy rule coefficients implied by FOMC economic projections



Note: Estimated policy-rule parameters γ_t and β_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 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.

For the inflation coefficient, however, the picture looks quite different, with the Fed estimates being substantially higher than the private forecaster estimates. One possibility is that these differences reflect the different underlying inflation measures (CPI vs. core PCE), which could render the BC estimates noisy. We therefore focus on the policy rule coefficient on the output gap.

While our analysis here is limited to the episode from 2012 to 2016, this episode is particularly interesting because it included liftoff from the zero lower bound and the onset of the next monetary tightening cycle. During this episode, private forecasters appeared to update their perceived output gap coefficient $\hat{\gamma}_t$ in the right direction, but more slowly than the true response coefficient, γ_t revealed by the projections of FOMC participants.

5.2 Response to monetary policy surprises

How do forecasters learn about the monetary policy rule from actual policy decisions? To study this question, we study the evolution of $\hat{\gamma}_t$ following 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 prediction of the level and path of the policy rate based on current macroeconomic data. Under the commonly made assumption that changes in these market rates around the announcements are mainly due to the monetary policy announcement itself, they reflect the surprise component of the monetary policy actions.

Surprises can arise due to either monetary policy shocks or imperfect information about the monetary policy rule. If, for example, the Fed responds more strongly to the economy during an expansion than the public expects based on its perceptions of the monetary policy rule, then the public will be surprised by the degree of tightening. It should then update its beliefs and the perceived policy rule coefficient should rise. More generally, the perceived $\hat{\gamma}_t$ should respond differently to a monetary policy surprise depending on the state of the economy. For example, during a period of strong growth and high resource utilization, a tightening surprise suggests that the Fed may be 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 low growth and high unemployment/economic slack would signal less Fed concern with output stabilization, so forecasters would tend to revise downward $\hat{\gamma}_t$. Bauer and Swanson (2021) formalize these arguments in a simple theoretical model.

Historical episodes provide clear anecdotal evidence of this kind of updating. For example, the interest rate hikes of 1994 and 1995 took place in a strong economy and were intended to address above-average economic growth and resource utilization. We would expect perceptions of $\hat{\gamma}_t$ to rise during such an episode, which is indeed what we see in our estimated series (see Figure 3).

To systematically test the hypothesis that the response of beliefs about the policy rule to monetary policy surprises depends on the business cycle, we estimate state-dependent impulse responses using local projections.[33] 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. We follow Nakamura and Steinsson (2018) and measure the monetary policy surprise, mps_t, as the first principal component of 30-minute changes in fed funds and Eurodollar futures rates around the FOMC announcement. We normalize the surprise to have a unit effect on the four-quarter-ahead Eurodollar futures rate, measured in percentage points. This measure has the advantage of being meaningful throughout the zero-lower bound period, as it measures not only surprise changes in the target federal funds rate but also changes in forward guidance. 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:

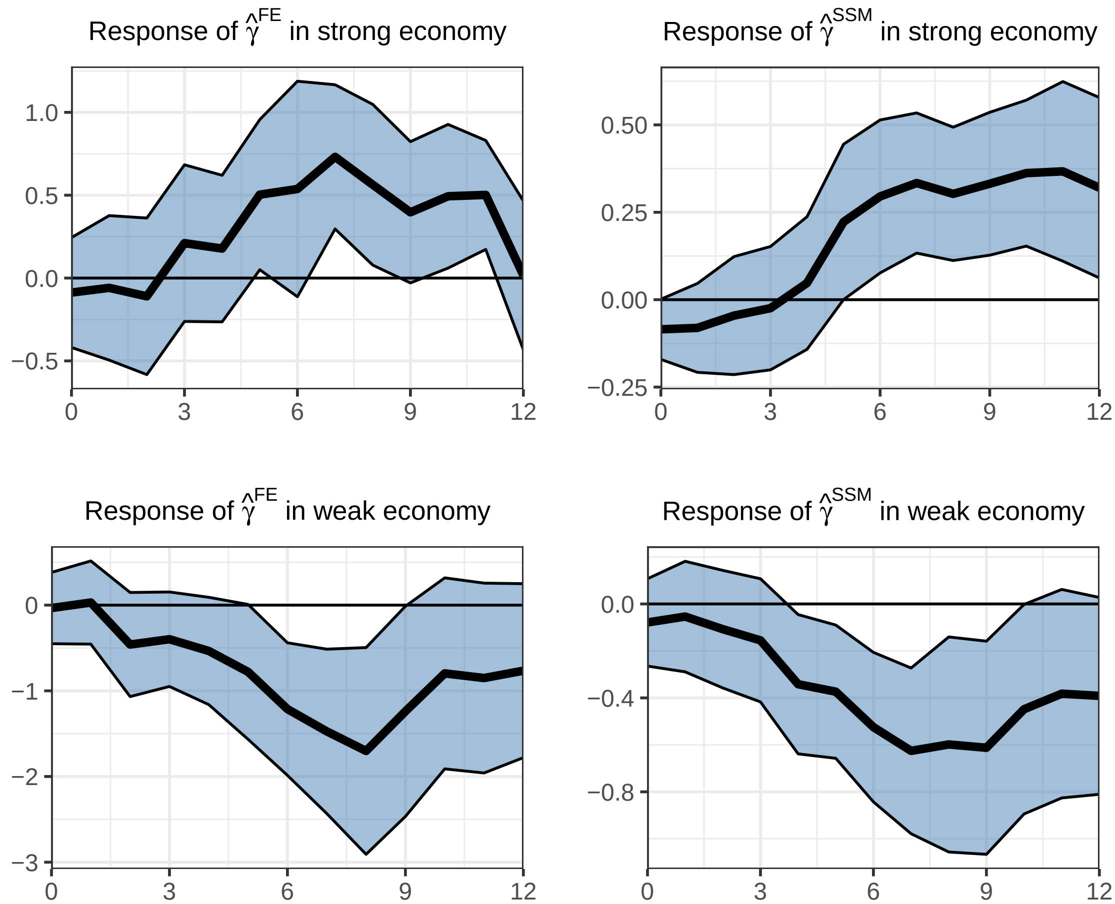
$$\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}, \qquad (19)$$

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 1992 to January 2021.

The impulse responses of the perceived monetary policy coefficient are shown in Figure 6, 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

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

Figure 6: Perceived output weight 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-1992 to Jan-2021.

a weak economy. These responses are quite a bit larger in absolute magnitude than the positive responses in the top panel, in particular for the panel FE estimate of $\hat{\gamma}_t$.

The magnitudes in Figure 6 are economically meaningful. During good times, a one percentage point monetary policy surprise increases $\hat{\gamma}$ by around 0.3-0.6. During bad times, a similar surprise decreases $\hat{\gamma}_t$ by around 0.6–1.8. For comparison, the FE estimate of $\hat{\gamma}_t$ has a standard deviation of around 0.4, while the SSM estimate has a standard deviation of around 0.2. 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 shown in the top and bottom panels, regressions that include mps_t and an interaction effect $mps_t weak_t$ provide evidence that the state dependence is statistically significant.[34]

Overall, the estimates support the view that perceptions of the monetary policy rule update sensibly following monetary policy surprises, and that 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.

5.3 Fed funds forecast errors

We next study the properties of 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 perfectly rational and have full information, 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.

We start with a simple decomposition to guide the empirical analysis. Using a simplified version of the policy rule (1) without intercepts and inflation, $i_t = \gamma_t x_t + u_t$, expectations of the future policy rate are given by:

$$E_t i_{t+h} = \hat{\gamma}_t E_t x_{t+h} + E_t u_{t+h}, \tag{20}$$

since we assume that $\hat{\gamma}_t$ is a martingale and its innovations are uncorrelated with macro shocks. Subtracting this expression from i_{t+h}, which follows the actual monetary policy rule,

[34] See Appendix D.1.

Table 3: Predictability of forecast errors for the federal funds rate

			Panel FE $\hat{\gamma}$		SSM $\hat{\gamma}$	
	$q = 2$	$q = 4$	$q = 2$	$q = 4$	$q = 2$	$q = 4$
$CFNAI_t$	0.32***	0.66**	0.57***	1.12***	0.70***	1.26***
	(2.90)	(2.31)	(5.45)	(5.15)	(6.39)	(5.87)
i_t	-0.10***	-0.17**	-0.10***	-0.17**	-0.11***	-0.18**
	(-3.08)	(-2.20)	(-3.49)	(-2.39)	(-3.49)	(-2.37)
$\hat{\gamma}_t$			-0.05	-0.11	-0.06	-0.08
			(-1.28)	(-1.55)	(-1.14)	(-0.67)
$\hat{\gamma}_t \times CFNAI_t$			0.25***	0.48***	0.33***	0.60***
			(4.46)	(5.33)	(5.88)	(5.20)
N	114	112	114	112	114	112
R^2	0.26	0.24	0.37	0.35	0.46	0.39

Note: This table estimates regressions for the q-quarter-ahead forecast error for the federal funds rate, using the mean BCFF forecast. CFNAI and $\hat{\gamma}_t$ 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 1992Q1 through 2020Q4. Newey-West t-statistics with 6 lags are shown in parentheses.

we obtain after some rearranging:

$$i_{t+h} - E_t i_{t+h} = (\gamma_{t+h} - \hat{\gamma}_t)x_{t+h} + \hat{\gamma}_t(x_{t+h} - E_t x_{t+h}) + u_{t+h} - E_t u_{t+h}. \tag{21}$$

This decomposition illustrates that forecast errors for the policy rate can arise from three sources: First, the actual policy rule may deviate from the perceived rule. Second, macroeconomic variables such as the output gap x_{t+h} may not evolve as expected. Third, there may be (unexpected) monetary policy shocks. Both the first and the second terms in the decomposition (21) depend on the interaction of monetary policy rule coefficients and economic activity. This suggests that the interaction between $\hat{\gamma}$ and measures of economic activity should help explain fed funds forecast errors. Because we do not have an estimate of the true policy coefficient, γ_{t+h}, we cannot carry out an exact decomposition as in equation (21). Instead, we first show that the interaction of $\hat{\gamma}$ with economic activity is indeed quite important in predictive regressions for fed funds forecast errors. We then provide some additional evidence suggesting that the first component in equation (21) is responsible for this predictability.

Table 3 starts from the well-known result that forecast errors for the federal funds rate are predictable. 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 in Cieslak (2018) that fed funds forecast errors are ex-post predictable from real economic activity, as measured by the Chicago Fed National Activity Index (CFNAI), with an R^2 around 25%.[35]

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 $\hat{\gamma}_t$. The results show that this interaction term contains substantial additional predictive power. The bottom row in Table 3 shows that the interaction coefficient is positive and highly significant in all cases. In some specifications, it nearly doubles the R^2 to almost 50%. The results in Table 3 therefore indicate that the predictability of forecast errors from economic activity varies through the monetary policy cycle. The positive interaction coefficient means that the predictability is most pronounced when the perceived responsiveness of monetary policy to the output gap is high.

An open question is which of the first two components in equation (21) drives this result. We provide two pieces of evidence that support the view that the first component, misperceptions about monetary policy, are most important. First, we show how CFNAI relates to the future output gap and output gap forecast errors. In Table 4, we report estimates of simple univariate predictive regressions. The CFNAI is well-known to be a good forward-looking economic indicator, and the first two columns of Table 4 confirm that CFNAI is indeed an informative predictor of the future output gap. By contrast, the CFNAI has essentially no predictive power for output gap forecast errors.[36] The fact that CFNAI correlates with the future output gap but not with output gap forecast errors indicates that the first term in (21), i.e., misperceptions about the monetary policy rule, is key for understanding the source of federal funds rate forecast errors.

In the Appendix, we also consider separate predictive regressions for the two components of the left-hand-side variable in equation (21): the future fed funds rate and forecasts for the fed funds rate. If indeed the first term in equation (21) is the dominant driver of the

[35] We use the 3-month moving average CFNAI from FRED (series CFNAIMA3). Table D.2 shows analogous regressions with 12-month employment growth rather than the CFNAI. We prefer the CFNAI because its univariate ability to predict federal funds forecast errors is stronger than that of 12-month employment growth over our sample.

[36] The absence of predictive power for forecast errors is consistent with rational forecasts, since all data used to construct the CFNAI is public. It also alleviates concerns about hindsight bias in the construction of the CFNAI and validates its value as a forward-looking measure.

Table 4: Predictability of output gap and output gap forecast errors

	Future output gap		Output gap forecast error	
	$q = 2$	$q = 4$	$q = 2$	$q = 4$
$CFNAI_t$	1.06***	1.34***	-0.09	0.00
	(6.19)	(6.15)	(-0.54)	(0.02)
N	114	112	114	112
R^2	0.26	0.30	0.00	0.00

Note: This table estimates regressions for the q-quarter-ahead output gap and output gap forecast error, using the mean BCFF forecast. The predictor CFNAI is standardized to have a standard deviation of one and mean zero. The intercept is not reported. Data is quarterly and ranges from 1992Q1 through 2020Q4. Newey-West t-statistics with 6 lags are shown in parentheses.

time-varying relationship between economic activity and forecast errors in the fed funds rate, this has implications for these separate predictive regressions: Taking the $CFNAI$ as a good proxy for the future output gap, it should be the case that $\hat{\gamma} \times CFNAI$ is positively related to the realized future fed funds rate (which is driven by the actual rule, $\gamma_{t+h}x_{t+h}$) as well as to the forecasts of the fed funds rate (which is driven by the perceived rule, $\hat{\gamma}_t x_{t+h}$), and that it predicts the former with a larger positive coefficient than the latter. Table D.5, discussed in Appendix D.4, reports estimates of regressions for i_{t+h} and for $E_t i_{t+h}$, and confirms that this is indeed the case.

The key result of this subsection is the finding 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. During episodes of high $\hat{\gamma}_t$, the predictability of forecast errors is stronger than during episodes of low $\hat{\gamma}_t$. Because $\hat{\gamma}_t$ tends to increase in economic expansions, this helps to explain the fact that forecast errors are less pronounced during recessions but tend to increase during expansions. Our estimate of $\hat{\gamma}_t$ also helps explain why forecast errors collapsed to zero during the period 2012-2015, as monetary policy was perceived to be almost constant during this period.[37] Overall, our results are in line with the view that forecasters update the perceived monetary policy rule in the same direction as the actual rule, that fed funds forecast errors

[37] 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.

arise because the monetary policy rule is not fully known, and that these forecast errors are (ex-post) more predictable during periods when the monetary policy rule is perceived to be state-dependent.

6 Bond Return Predictability

In this last part of our empirical analysis, we apply our new estimates of $\hat{\gamma}_t$ to predict excess returns on Treasury bonds. Long-term bond yields matter for monetary policy if policy makers intend to move long-term bond yields and thus the cost of financing long-term real investments, or if they look to long-term rates to understand markets' expectations of future short-term policy rates. 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, 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.

The intuition of why $\hat{\gamma}_t$ should predict bond excess returns with a negative sign 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 $\hat{\gamma}_t$ bonds are a better hedge and should therefore have lower expected returns. These predictions are worked out in detail in Campbell et al. (2017) and Campbell et al. (2020), for example. They do not crucially rely on the interpretation of $\hat{\gamma}_t$ as a perceived monetary policy rule coefficient, and remain valid if $\hat{\gamma}_t$ simply captures the perceived comovement of interest rates and the economy.

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

$$xr^{(n)}_{t\to t+h} = b_0 + b_1\hat{\gamma}_t + b_2 CFNAI_t + b_3\hat{\gamma}_t CFNAI_t + \delta' X_t + \varepsilon_{t+h}, \tag{22}$$

where $xr^{(n)}_{t\to t+h}$ is the log excess return on an 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.[38] In the main text, we report results for the five-year bond, and in Appendix D.3 we show results for other maturities, which exhibit the same basic patterns. We estimate equation (22) using both the panel FE estimate and

[38]As usual, we compute the h-month excess return on a zero-coupon bond with n years to maturity as $rx^{(n)}_{t+h} = ny^{(n)}_t - \left(n - \frac{h}{12}\right) y^{\left(n-\frac{h}{12}\right)}_{t+h} - \frac{h}{12} y^{(n)}_t$, where $y^{(n)}_t$ is the zero-coupon yield with maturity n years.

the SSM estimate of $\hat{\gamma}_t$, and we consider holding periods of both $h = 12$ and $h = 24$ months.[39]

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. The first column in Panel A shows that a one-standard deviation increase in perceived $\hat{\gamma}_t$ forecasts a one percentage point decrease in 5-year Treasury excess returns over the next twelve months, and a one-and-a-half percentage point decrease over the next 24 months. The ability of $\hat{\gamma}$ to predict bond excess returns does not diminish over the forecast horizon, consistent with monetary policy rules varying at business cycle.

To allow for the possibility that bond return predictability may arise from policy rate forecast errors, we also control for the lagged CFNAI and its interaction with the perceived output gap coefficient $\hat{\gamma}_t$.[40] If a higher value of the CFNAI predicts that forecasters and markets will be surprised by higher-than-expected interest rates, then this should predict that bond prices will be lower than expected. Since we have already seen that the predictability of fed funds forecast errors from the CFNAI is strongest when $\hat{\gamma}_t$ is high, we would expect the interaction term between $\hat{\gamma}_t$ and $CFNAI_t$ to predict bond excess returns with a negative sign. We confirm these predictions in Table 5. Further, controlling for the CFNAI and its interaction with $\hat{\gamma}_t$ leaves the coefficient on $\hat{\gamma}_t$ unchanged.[41]

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 5.2, 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 6 shows that a 10 bps positive monetary policy shock leads to

[39] 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.

[40] Joslin et al. (2014) showed that excess returns on Treasury bonds are predictable using CFNAI. Note that the signs on $CFNAI$ and $\hat{\gamma} \times CFNAI$ are reversed in Table 5 compared to 3 because bond returns are inversely related to interest rates.

[41] Interestingly, the interaction $\hat{\gamma}_t CFNAI_t$ enters only significantly at the 12-month holding period horizon, indicating that misperceptions about the monetary policy rule may converge over longer horizons.

an increase in the SSM estimate of $\hat{\gamma}_t$ of around 0.03—or 0.15 standard deviations—with a peak response at six to twelve 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 $0.15 \times -1.51 = -0.23$ percentage point decrease in the 24-month excess return for a 5-year Treasury bond. The yield on a bond is equal to its annualized return over the lifetime of the bond, so we need to make an assumption about returns after the 24 month forecasting horizon in order to estimate the effect on bond yields. Making the conservative assumption that bond excess returns after the 24 month horizon are unaffected by $\hat{\gamma}$, the implied change in the 5-year bond yield equals $-0.23/5 = -0.05$ percentage points. A 10 bps surprise *increase* in the policy shock during good times could therefore lead to a 5 bps *decrease* in the term premium of the 5-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.

7 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 at the beginning of recessions after quick interest rate cuts, but rises as the economy recovers and interest rates are expected to rise. The Fed is hence perceived to get ahead of the curve at the beginning of recessions, but to tighten in a gradual and data-dependent manner. Second, 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. Third, 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. Fourth, predictable forecast errors for the federal funds rate are more likely to arise when the perceived policy output gap coefficient is high, indicating that forecasters underestimate the Fed's response to news especially when the perceived monetary policy coefficient is high. In other words, there is less room for monetary rule misperceptions and predictable forecast errors when the Fed is believed to respond little to economic conditions than when monetary policy is perceived to be data-dependent. Finally, predictive regressions for excess returns on long-term Treasury bonds suggest that the perceived output gap coefficient is negatively related to bond risk premia, consistent with basic asset pricing logic. 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. Finally, a simple New Keynesian model bounds the bias in our estimates due to the endogenous response of output to monetary policy. 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.

Table 5: Predictability of excess bond returns

Panel A: Panel FE $\hat{\gamma}$						
	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
$\hat{\gamma}$	-1.02***	-0.86***	-0.87***	-1.55***	-1.24***	-1.24***
	(-3.64)	(-3.14)	(-3.47)	(-4.95)	(-4.57)	(-4.77)
$CFNAI$		-0.79	-2.08***		-1.56*	-2.60***
		(-0.99)	(-2.86)		(-1.94)	(-3.07)
$\hat{\gamma} \times CFNAI$			-1.38***			-1.09
			(-3.24)			(-1.61)
Const.	2.93***	2.96***	3.16***	3.96***	4.01***	4.17***
	(3.92)	(4.18)	(4.61)	(4.18)	(4.85)	(4.87)
N	337	337	337	325	325	325
R^2	0.18	0.19	0.22	0.19	0.23	0.26
Panel B: SSM $\hat{\gamma}$						
	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
$\hat{\gamma}$	-0.84*	-0.66	-0.84*	-1.69***	-1.35**	-1.51***
	(-1.84)	(-1.38)	(-1.94)	(-3.17)	(-2.58)	(-3.19)
$CFNAI$		-0.99	-2.58***		-1.65*	-3.26***
		(-1.16)	(-2.82)		(-1.93)	(-3.43)
$\hat{\gamma} \times CFNAI$			-1.61***			-1.59***
			(-2.94)			(-2.73)
Const.	3.17***	3.15***	3.55***	4.48***	4.43***	4.81***
	(4.22)	(4.45)	(5.42)	(5.01)	(5.97)	(6.57)
N	337	337	337	325	325	325
R^2	0.15	0.17	0.21	0.18	0.23	0.28

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. All right-hand-side variables are standardized to have unit standard deviations. One-year forecasting regressions run from $t =$January 1992 through $t =$March 2020. Two-year forecasting regressions run from $t =$January 1992 through $t =$March 2019. Newey-West t-statistics with 1.5 times lag length in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Appendix

A 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.1 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.

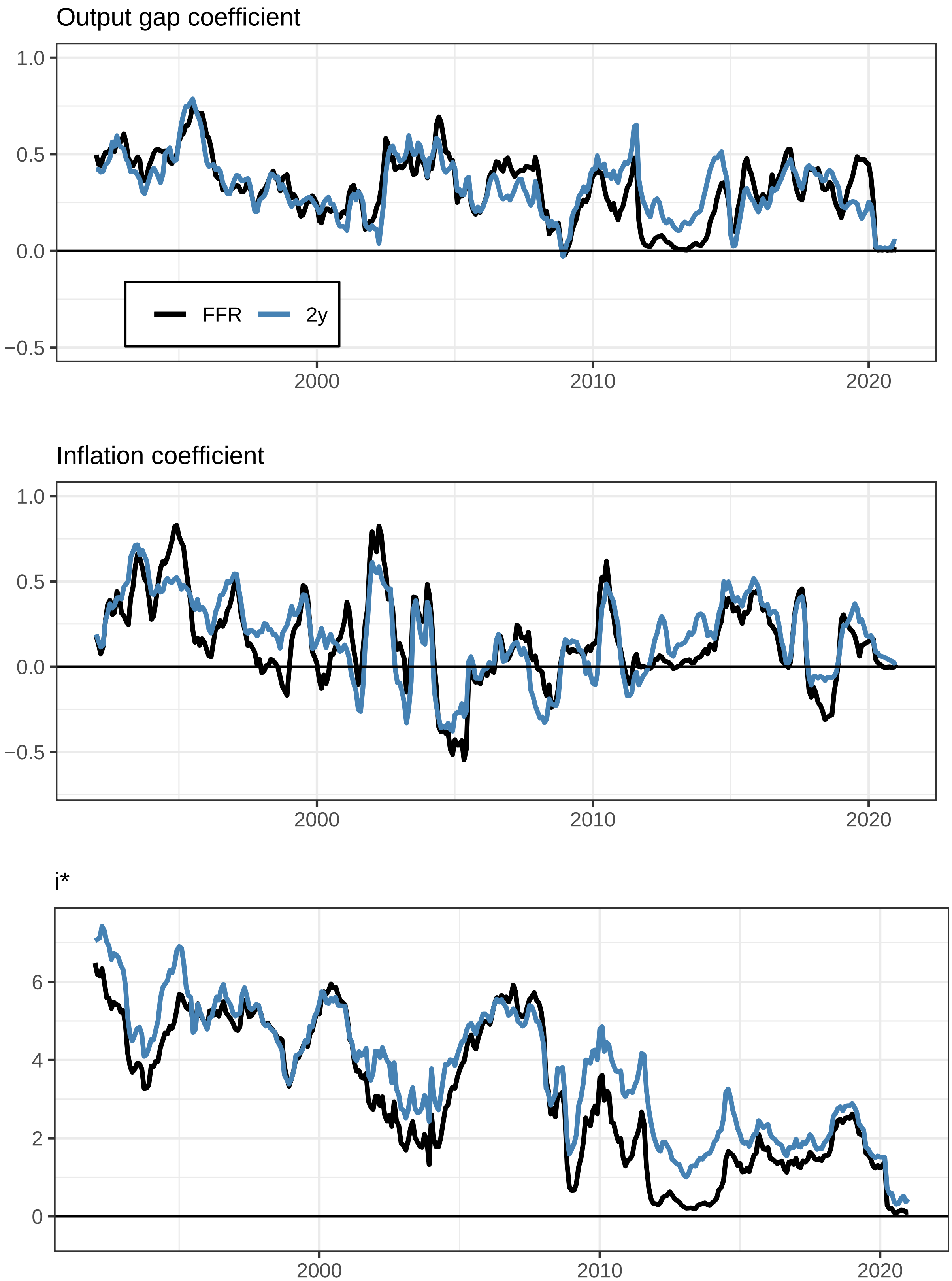
B Estimation details for state-space model

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.[42] 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.

[42]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.1: SSM estimates of rule parameters: fed funds rate vs. 2y yield



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.

C Details for New Keynesian model

We first solve for the rational expectations equilibrium, assuming that all agents in the economy share the same rational expectations of future shocks $E_t u_{t+h}$ and $E_t v_{t+h}$. Substituting the monetary policy rule (8) into the Euler equation (6) yields

$$(1+\gamma)x_t \quad = \quad E_t x_{t+1} - u_t + v_t. \tag{C.1}$$

Iterating forward and imposing that expectations for shocks $E_t v_{t+\tau}$ and $E_t u_{t+\tau}$ are bounded as $\tau \to \infty$ yields

$$x_t \quad = \quad \sum_{\tau=0}^{\infty} (1+\gamma)^{-(\tau+1)} E_t \left(v_{t+\tau} - u_{t+\tau} \right) \tag{C.2}$$

Substituting back into the monetary policy rule yields

$$i_t \quad = \quad \gamma \sum_{\tau=0}^{\infty} (1+\gamma)^{-(\tau+1)} E_t \left(v_{t+\tau} - u_{t+\tau} \right) + u_t \tag{C.3}$$

C.1 Time-series regressions

For the time-series regressions, we assume for simplicity that $\hat{\gamma} = \gamma$, i.e., that agents in the economy have full information about the monetary policy parameter. From equations (C.2) and (C.3) it then follows that

$$x_t \quad = \quad E_t x_{t+1} - i_t + v_t, \tag{C.4}$$
$$i_t \quad = \quad \gamma x_t + u_t, \tag{C.5}$$

where v_t, u_t are the realized actual shocks, and γ is the true monetary policy coefficient. This implies

$$x_t \quad = \quad \frac{v_t - u_t + E_t x_{t+1}}{1+\gamma}, \tag{C.6}$$
$$= \quad \frac{v_t - u_t}{1+\gamma} + \frac{E_t \left(v_{t+1} - u_{t+1} \right) + E_t x_{t+2}}{(1+\gamma)^2}, \tag{C.7}$$
$$= \quad \frac{v_t - u_t}{1+\gamma} + \sum_{\tau=1}^{\infty} \left(\frac{1}{1+\gamma} \right)^{\tau+1} E_t \left(v_{t+\tau} - u_{t+\tau} \right) \tag{C.8}$$

Assuming that shocks are serially uncorrelated over time, the time-series time-series covariance between the output gap and the policy rate equals

$$Cov(i_t, x_t) = \gamma Var(x_t) - \frac{1}{1+\gamma} Var(u_t). \tag{C.9}$$

Dividing by $Var(x_t)$ yields

$$\tilde{\gamma}^{TS} = \gamma - \frac{1}{1+\gamma} \frac{Var(u_t)}{Var(x_t)}. \tag{C.10}$$

C.2 Panel regressions

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

$$\begin{aligned} Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) &= Cov_t\left(\hat{\gamma} E_t^{(j)} x_{t+h} + E_t^{(j)} u_{t+h}, E_t^{(j)} x_{t+h}\right), & \text{(C.11)} \\ &= \hat{\gamma}_t Var_t\left(E_t^{(j)} x_{t+h}\right) - \frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{1+\hat{\gamma}_t}. & \text{(C.12)} \end{aligned}$$

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

$$\tilde{\gamma}_t^{Panel} = \hat{\gamma}_t - \frac{1}{1+\hat{\gamma}_t} \frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)} \tag{C.13}$$

If we knew $\hat{\gamma}_t$, which of course we do not, obtaining the ratio $\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)}$ would be simple because:

$$\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)} = \frac{Var_t\left(E_t^{(j)} i_{t+h} - \hat{\gamma}_t E_t^{(j)} x_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)} \tag{C.14}$$

We do not know $\hat{\gamma}_t$, but we can nonetheless solve for the ratio $\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)}$ either exactly or approximately. 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.

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:

$$\tilde{\gamma}_t^{Panel} = Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) \tag{C.15}$$

$$= \hat{\gamma}_t - (1+\hat{\gamma}_t)^{-1} Var_t\left(E_t^{(j)} u_{t+h}\right), \tag{C.16}$$

$$Var_t\left(E_t^{(j)} i_{t+h}\right) = \hat{\gamma}_t^2 + 2\hat{\gamma}_t Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) + Var_t\left(E_t^{(j)} u_{t+h}\right) \tag{C.17}$$

These are two nonlinear equations with two unknowns, so one can solve for the bias $\tilde{\gamma}^{Panel} - \hat{\gamma}$ and $Var_t\left(E_t^{(j)} u_{t+h}\right)$. We could solve this pretty easily numerically.

We can however also solve these equations analytically to first order. We expand the solution for the bias $\tilde{\gamma}_t^{Panel} - \hat{\gamma}_t$ up to first-order in the monetary policy shock variance $Var_t\left(E_t^{(j)} u_{t+h}\right)$. That is, we use an expansion that is valid when the bias $\tilde{\gamma}_t^{Panel} - \hat{\gamma}_t$ and the variance of perceived monetary policy shocks are small relative to the variance of perceived output gap. Then

$$\tilde{\gamma}_t^{Panel} - \hat{\gamma}_t = -\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{1+\hat{\gamma}_t}, \tag{C.18}$$

$$= -\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{1+\tilde{\gamma}_t^{Panel} + (\hat{\gamma}_t - \tilde{\gamma}_t^{Panel})}, \tag{C.19}$$

$$\approx -\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{1+\tilde{\gamma}_t^{Panel}} + \left(\frac{1}{1+\tilde{\gamma}_t^{Panel}}\right)^2 (\hat{\gamma}_t - \tilde{\gamma}_t^{Panel}) Var_t\left(E_t^{(j)} u_{t+h}\right),$$

$$\approx -\frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{1+\tilde{\gamma}_t^{Panel}} \tag{C.20}$$

We dropped the second term in the Taylor expansion because the interaction of the bias $\tilde{\gamma}^{Panel} - \hat{\gamma}_t$ and the monetary policy shock variance $Var_t\left(E_t^{(j)} u_{t+h}\right)$ is $\mathcal{O}\left(\left(Var_t\left(E_t^{(j)} u_{t+h}\right)\right)^2\right)$.

Using the notation $E_t^{(j)} \tilde{u}_{t+h} = E_t^{(j)} i_{t+h} - \tilde{\gamma}_t^{Panel} E_t^{(j)} x_{t+h}$ for forecaster j's horizon $t+h$ estimated monetary policy residual:

$$\begin{aligned}
Var_t\left(E_t^{(j)} u_{t+h}\right) &= Var_t\left(E_t^{(j)} i_{t+h} - \tilde{\gamma}_t^{Panel} E_t^{(j)} x_{t+h} - (\hat{\gamma}_t - \tilde{\gamma}_t^{Panel}) E_t^{(j)} x_{t+h}\right), \\
&= Var_t\left(E_t^{(j)} \tilde{u}_{t+h}\right) + (\hat{\gamma}_t - \tilde{\gamma}_t^{Panel})^2 \\
&\quad -2(\hat{\gamma}_t - \tilde{\gamma}_t^{Panel}) Cov_t\left(E_t^{(j)} \tilde{u}_{t+h}, E_t^{(j)} x_{t+h}\right), \\
&= Var_t\left(E_t^{(j)} \tilde{u}_{t+h}\right) + (\hat{\gamma}_t - \tilde{\gamma}_t^{Panel})^2, && \text{(C.21)} \\
&\approx Var^t\left(E_t^{(j)} \tilde{u}_{t+h}\right). && \text{(C.22)}
\end{aligned}$$

Here, we used that the covariance between the predicted output gap and the estimated monetary policy residual is zero by definition, and the that squared bias is $\mathcal{O}\left(\left(Var_t\left(E_t^{(j)}u_{t+h}\right)\right)^2\right)$ from equation (C.20). Putting together equations (C.20) and (C.22) it then follows that

$$\tilde{\gamma}_t^{Panel} - \hat{\gamma}_t \;=\; -\frac{Var_t\left(E_t^{(j)}\tilde{u}_{t+h}\right)}{1+\tilde{\gamma}_t^{Panel}} + \mathcal{O}\left(\left(Var_t\left(E_t^{(j)}u_{t+h}\right)\right)^2\right). \tag{C.23}$$

This completes the proof of Proposition 1.

C.3 Robustness to Policy Rule Intercept and Fixed Effects

It is straightforward to see that the expressions for the time-series regression extends to a regression with intercept and the panel regression coefficients extend to a model with forecaster fixed effects. Consider the NK model with the long-run natural rate r^*

$$x_t \;=\; E_t x_{t+1} - (i_t - r^*) + v_t, \tag{C.24}$$

$$i_t \;=\; r^* + \gamma x_t + u_t \tag{C.25}$$

As before, we have the Phillips curve slope set to zero and inflation switched off. The rational expectations equilibrium for the output gap (C.2) then is unchanged and the rational expectations equilibrium for the policy rate (C.3) is shifted up by a constant:

$$i_t \;=\; r^* + \gamma \sum_{\tau=0}^{\infty} (1+\gamma)^{-(\tau+1)} E_t\left(v_{t+\tau} - u_{t+\tau}\right) + u_t. \tag{C.26}$$

To understand how the time-series regression goes through, define $x_t^{\perp}$ and $i_t^{\perp}$ to be the de-meaned output gap (which also equals the output gap itself in equilibrium) and the demeaned policy rate. If we run a time-series regression

$$i_t \;=\; \alpha + \tilde{\gamma}^{TS} x_t + \varepsilon_t, \tag{C.27}$$

the estimated time-series slope coefficient equals

$$\tilde{\gamma}^{TS} \;=\; \frac{Cov\left(i_t^{\perp}, x_t^{\perp}\right)}{Var\left(x_t^{\perp}\right)}, \tag{C.28}$$

$$\;=\; \gamma - \frac{1}{1+\gamma}\frac{Var(u_t)}{Var(x_t)}, \tag{C.29}$$

as before.

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 $E_t^{(j)} r_t^*$. Forecasters do not learn from each other and expect this natural rate to be constant going forward. The equilibrium for the output gap (10) then is unchanged, and the equilibrium for the policy rate 11 is shifted up by a constant $E_t^{(j)} r_t^*$. After projecting onto forecaster-level fixed effects, the expression for $\tilde{\gamma}_t^{Panel}$ 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. We also need to replace $E_t^{(j)}x_t$ $E_t^{(j)}i_t$ by the corresponding residuals after regressing the time t forecasts onto forecaster fixed effects in expressions (C.16) and (C.17) and in Proposition 1.

C.4 Robustness to Disagreement over MP Rule

It is plausible to think that different forecasters have different monetary policy coefficients in mind. After all, each forecasting institution runs its own model. It would also be consistent with the message from Patton and Timmermann (2010). Here, we argue that if forecasters disagree our estimation will reveal the average perceived monetary policy coefficient, and that disagreement has at most a quantitatively small effect on the estimation bias.

Let's make the simplest distributional assumption possible, namely that each forecaster's perceived coefficient is given by

$$1+\hat{\gamma}_t^{(j)} = (1+\hat{\gamma}_t)exp\left(\varepsilon_t^{(j)}-\frac{1}{2}\sigma_\varepsilon^2\right), \tag{C.30}$$

where the random variable $\varepsilon_t^{(j)} \sim N\left(0,\sigma_\varepsilon^2\right)$ is assumed to be independent across forecasters and independent of the forecasted shocks $E_t^{(j)}v_{t+h}^x$ and $E_t^{(j)}u_{t+h}$. In line with our assumptions elsewhere, we assume that forecasters are not aware of disagreement and believe that all other agents in the economy share their beliefs $\hat{\gamma}^{(j)}$ and that they believe that $\hat{\gamma}^{(j)}$ will be constant going forward. Note that the assumption (C.30) implies that the cross-forecaster average equals $E_t\left(1+\hat{\gamma}_t^{(j)}\right) = 1+\hat{\gamma}_t$, so $\hat{\gamma}_t$ is indeed the cross-forecaster average of the perceived monetary policy coefficients at time t.

Given our other assumptions, forecaster j's equilibrium output gap and interest rate forecasts then equal:

$$E_t^{(j)}i_{t+h} = \hat{\gamma}_t^{(j)}\sum_{\tau=0}^{\infty}\left(1+\hat{\gamma}_t^{(j)}\right)^{-(\tau+1)}\left(E_t^{(j)}v_{t+\tau+h}-E_t^{(j)}u_{t+\tau+h}\right)+E_t^{(j)}u_{t+h}, \tag{C.31}$$

$$E_t^{(j)}x_{t+h} = \sum_{\tau=0}^{\infty}\left(1+\hat{\gamma}_t^{(j)}\right)^{-(\tau+1)}\left(E_t^{(j)}v_{t+\tau+h}-E_t^{(j)}u_{t+\tau+h}\right). \tag{C.32}$$

The panel regression coefficient $\tilde{\gamma}_t^{Panel}$ then is proportional to the covariance between interest rate and output gap forecasts, which we can decompose as follows:

$$\begin{aligned} Cov_t\left(E_t^{(j)}i_{t+h},E_t^{(j)}x_{t+h}\right) &= E_t\left(\hat{\gamma}_t^{(j)}E_t^{(j)}x_{t+h}\left(E_t^{(j)}x_{t+h}-E_tE_t^{(j)}x_{t+h}\right)\right) \\ &\quad +E_t\left(E_t^{(j)}u_{t+h}\left(E_t^{(j)}x_{t+h}-E_tE_t^{(j)}x_{t+h}\right)\right) \end{aligned} \tag{C.33}$$

We now apply the law of iterated expectations to taking the cross-forecaster cross-horizon average at time t $E_t(\cdot) = E_t\left(E_t\left(\cdot|\,\hat{\gamma}_t^{(j)}\right)\right)$ to give

$$\begin{aligned}
\tilde{\gamma}_t^{Panel} &= \frac{Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)} && \text{(C.34)} \\
&= \frac{E_t\left(\hat{\gamma}_t^{(j)} Var_t\left(E_t^{(j)} x_{t+h}\right) - \frac{1}{1+\hat{\gamma}_t^{(j)}} Var_t E_t^{(j)} u_{t+h}\right)}{Var_t^t\left(E_t^{(j)} x_{t+h}\right)} && \text{(C.35)} \\
&= \hat{\gamma}_t - \frac{exp\left(\sigma_\varepsilon^2\right)}{1+\hat{\gamma}_t} \frac{Var_t\left(E_t^{(j)} u_{t+h}\right)}{Var_t\left(E_t^{(j)} x_{t+h}\right)} && \text{(C.36)}
\end{aligned}$$

The panel regression coefficient hence reflects the average perceived monetary policy coefficient $\hat{\gamma}_t$ minus a bias:

$$\tilde{\gamma}_t^{Panel} - \hat{\gamma}_t = -\frac{exp\left(\sigma_\varepsilon^2\right)}{1+\hat{\gamma}_t} \frac{Var_t\left(E^{(j)} u_{t+h}\right)}{Var_t\left(E^{(j)} x_{t+h}\right)}. \tag{C.37}$$

Comparing to equation (21) in the main paper shows that the panel regression coefficient has a downward-bias that is amplified by a factor $exp(\sigma_\varepsilon^2)$. This downward-bias is increased in magnitude from forecaster disagreement about the monetary policy coefficient due to a Jensen's inequality term. Intuitively, the equilibrium covariance of expected interest rates and the expected output gap is convex in the perceived output gap coefficient $\hat{\gamma}_t$, so variation in $\hat{\gamma}_t^{(j)}$ across forecasters drives up the average covariance.

What is a reasonable magnitude for the standard deviation σ_ε? We cannot estimate separate regressions for each forecaster j and forecast date t because this would amount to trying to estimate a regression on only four or five observations (corresponding to the number of forecast horizons), which would be extremely noisy. Instead, we estimate a regression for each forecaster on a panel pooling all forecast dates t and forecast horizons h. For each forecaster j, we regress the interest rate forecasts onto output gap forecasts and inflation forecasts and time fixed effects. This gives us time-invariant forecaster-specific estimates $\hat{\gamma}^{(j)}$, that we use to assess the plausible magnitude of cross-forecaster variation in the perceived output gap coefficient. Having done this, we find that the standard deviation of $\log\left(1+\hat{\gamma}^{(j)}\right)$ is approximately 0.25, so less than the time-series standard deviation of our benchmark panel estimate $\hat{\gamma}_t$. Substituting in $\sigma_\varepsilon = 0.25$ into the heterogeneity-adjusted bias expression (C.37) suggests that disagreement about the perceived monetary policy coefficient scales the downward-bias by a factor that is quantitatively small at $exp(0.25^2) = 1.064$.

C.5 High-frequency regressions

From the solutions (11) and (10) and the informational assumptions in Section 4.2 we have that

$$\left(E_t - E_{t-}\right) i_{t+1} = \hat{\gamma}_t \left(E_t - E_{t-}\right) x_{t+1}. \tag{C.38}$$

With assumption (16) this means that

$$(E_t - E_{t-})\, i_{t+1} \;=\; \frac{\hat{\gamma}_t}{\alpha} Z_t. \tag{C.39}$$

We start by deriving the scaling parameter α in terms of $\bar{\gamma}$. Start with the univariate regression

$$(E_t - E_{t-})\, i_{t+1} \;=\; a_0 + a_1 Z_t + \varepsilon_t. \tag{C.40}$$

From the assumption that macroeconomic news events do not reveal information about the perceived monetary policy coefficient $\hat{\gamma}_t$, we can apply the law of total expectation to derive the estimated slope coefficient a_1:

$$\begin{aligned}
a_1 &= \frac{Cov\left(\left(E_t - E_{t-}\right) i_{t+1}, Z_t\right)}{Var Z_t}, && \text{(C.41)}\\
&= \frac{1}{\alpha}\frac{E\left(\hat{\gamma}_t Z_t^2\right)}{Var\left(Z_t\right)}, && \text{(C.42)}\\
&= \frac{1}{\alpha}\frac{E\left(\hat{\gamma}_t\right) Var\left(Z_t\right)}{Var\left(Z_t\right)} = \frac{\bar{\gamma}}{\alpha}. && \text{(C.43)}
\end{aligned}$$

Because macro news surprises Z_t are scaled so that $a_1 = 1$, it follows that

$$\alpha \;=\; \bar{\gamma}. \tag{C.44}$$

Proof of Proposition 2: Assume that

$$\tilde{\gamma}_t \;=\; \hat{\gamma}_t + \mu + e_t, \tag{C.45}$$

where e_t is mean-zero and uncorrelated with $\hat{\gamma}_t$ and Z_t. Then the regression coefficients are given by

$$\begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} \;=\; \left(E \begin{bmatrix} 1 \\ \tilde{\gamma}_t \\ Z_t \\ \tilde{\gamma}_t Z_t \end{bmatrix} \begin{bmatrix} 1 \\ \tilde{\gamma}_t \\ Z_t \\ \tilde{\gamma}_t Z_t \end{bmatrix}' \right)^{-1} \begin{bmatrix} E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t\right) \\ E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t \tilde{\gamma}_t\right) \\ E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t Z_t\right) \\ E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t \tilde{\gamma}_t Z_t\right) \end{bmatrix} \tag{C.46}$$

The matrix of second moments equals

$$\mathbb{V} \equiv E\begin{bmatrix} 1 \\ \tilde{\gamma}_t \\ Z_t \\ \tilde{\gamma}_t Z_t \end{bmatrix}\begin{bmatrix} 1 \\ \tilde{\gamma}_t \\ Z_t \\ \tilde{\gamma}_t Z_t \end{bmatrix}'$$

$$= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & Var(\tilde{\gamma}_t) + (\mu+\bar{\gamma})^2 & 0 & 0 \\ 0 & 0 & Var\,(Z_t) & (\bar{\gamma}+\mu)Var\,(Z_t) \\ 0 & 0 & (\bar{\gamma}+\mu)Var\,(Z_t) & \left(Var(\tilde{\gamma}_t) + (\mu+\bar{\gamma})^2\right) Var\,(Z_t) \end{bmatrix} \tag{C.47}$$

Its inverse equals

$$\mathbb{V}^{-1} = \begin{bmatrix} 1 & 0 & 0_{1\times 2} \\ 0 & \frac{1}{Var(\tilde{\gamma}_t)+(\mu+\bar{\gamma})^2} & 0_{1\times 2} \\ 0_{2\times 1} & 0_{2\times 1} & W \end{bmatrix}, \tag{C.48}$$

with the lower-right block matrix W given by

$$W = \frac{1}{Var Z_t Var(\tilde{\gamma}_t)} \begin{bmatrix} Var(\tilde{\gamma}_t) + (\mu+\bar{\gamma})^2 & -(\mu+\bar{\gamma}) \\ -(\mu+\bar{\gamma}) & 1 \end{bmatrix} \tag{C.49}$$

The vector equals

$$\begin{bmatrix} E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t\right) \\ E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t \tilde{\gamma}_t\right) \\ E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t Z_t\right) \\ E\left(\frac{\hat{\gamma}_t}{\bar{\gamma}} Z_t \tilde{\gamma}_t Z_t\right) \end{bmatrix} = \frac{Var Z_t}{\bar{\gamma}} \begin{bmatrix} 0 \\ 0 \\ \bar{\gamma} \\ \bar{\gamma}(\bar{\gamma}+\mu) + Cov(\hat{\gamma}_t, \tilde{\gamma}_t) \end{bmatrix} \tag{C.50}$$

It then follows immediately that $b_0 = b_1 = 0$. Further,

$$b_2 = \frac{1}{\bar{\gamma} Var \tilde{\gamma}_t} \left(\bar{\gamma} Var \tilde{\gamma}_t - (\mu+\bar{\gamma}) Cov(\hat{\gamma}_t, \tilde{\gamma}_t)\right), \tag{C.51}$$

$$= -\frac{\mu}{\bar{\gamma}}\rho^2 + \left(1-\rho^2\right) \tag{C.52}$$

and

$$b_3 = \frac{1}{\bar{\gamma}} \frac{Cov(\hat{\gamma}_t, \tilde{\gamma}_t)}{Var \tilde{\gamma}_t}, \tag{C.53}$$

$$= \frac{1}{\bar{\gamma}}\rho^2, \tag{C.54}$$

where $\rho = Corr(\hat{\gamma}_t, \tilde{\gamma}_t)$.

D Robustness and additional results

D.1 Local projections

Here we report regression estimates for the local projections shown in Figure 6 and discussed in Section 5.2. 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 5.2. Note that the impulse responses shown in the top panels of Figure 6 correspond to estimates of $b_1^{(h)}$, and the responses shown in the bottom panels correspond to $b_1^{(h)} + \tilde{b}^{(h)}$.

Table D.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 6 that $\hat{\gamma}$ responds positively to a hawkish policy surprise when the economy is strong, but negatively when the economy is weak.

Table D.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	0.25	0.55	0.40	-0.01	-0.00	0.30**	0.31**	0.31*
	(0.93)	(1.46)	(1.48)	(-0.02)	(-0.02)	(2.33)	(2.43)	(1.93)
$mps_t \times weak_t$	-0.65	-1.77***	-1.64*	-0.76	-0.15	-0.83***	-0.93***	-0.71***
	(-1.54)	(-2.77)	(-1.94)	(-1.25)	(-0.79)	(-3.63)	(-3.07)	(-2.69)
$weak_t$	0.01	0.06	0.12	0.15*	-0.01	0.00	0.02	0.03
	(0.23)	(1.13)	(1.63)	(1.71)	(-0.28)	(0.08)	(0.57)	(0.74)
$\hat{\gamma}_{t-1}$	0.70***	0.54***	0.41***	0.36***	0.73***	0.55***	0.45***	0.40***
	(10.98)	(5.61)	(3.54)	(2.92)	(11.59)	(5.56)	(3.79)	(3.08)
Constant	0.14***	0.18***	0.21***	0.23***	0.08***	0.14***	0.16***	0.17***
	(3.64)	(3.40)	(3.34)	(3.11)	(3.22)	(3.62)	(3.68)	(3.53)
N	343	340	337	334	343	340	337	334
R^2	0.47	0.29	0.2	0.16	0.52	0.29	0.2	0.16

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.2 Fed funds forecast errors

Here, we report the regressions in Table 3 using the 12-month past employment growth instead of the CFNAI. Recall that the coefficient of interest is the interaction of $\hat{\gamma}_t$ with the economic activity measure, $\hat{\gamma}_t \times \Delta EMP_t$ in this case. The results are similar to the results in the main paper, though the interaction $\hat{\gamma}_t \times \Delta EMP_t$ is only statistically significant for the state-space model estimate $\hat{\gamma}_t^{ssm}$, potentially due to the greater measurement noise in the panel fixed effects estimator $\hat{\gamma}^{fe}$.

D.3 Bond return predictability

Table 5 in the main paper shows that excess returns on 5-year Treasury bonds are predictable from the perceived monetary policy-output gap coefficient. However, this predictability is not specific to the 5-year bond maturity. Table D.3 shows the analogous regresssion for 2-year Treasury bonds and Table D.4 shows the analogous regressions for 10-year Treasury bonds. The 12-month excess returns on the 10-year Treasury bonds are only predictable from one version of gamma but not the other one, but everything else goes through perfectly. We therefore conclude that the bond excess return predictability results are robust to considering Treasury bonds of different maturities.

D.4 Actual vs. Perceived Monetary Policy Rule in the Time Series

Table D.5 reports estimates of regressions of the future fed funds rate (panel A) and the forecast for the fed funds rate (panel B). The predictive regressions for i_{t+q} in panel A show that $\hat{\gamma}_t \times CFNAI_t$ is significantly related to the future policy rate, conditional on other controls. To interpret this finding, remember that our previous evidence established that CFNAI strongly predicts the future output gap but is uncorrelated with output gap forecast errors, meaning that $CFNAI_t$ is associated with x_{t+h}. Therefore these regressions confirm that the actual rule $\gamma_{t+h}x_{t+h}$ varies with the perceived monetary policy coefficient $\hat{\gamma}_t$. The positive interaction coefficients on $\hat{\gamma} \times CFNAI$ in Panel A are good news, as we would expect this to be the case as long as forecasters are somewhat right about time-variation in the monetary policy rule.

The regressions in panel B of Table D.5 confirms that the perceived rule in the time series of the mean fed funds rate forecast is correlated with the perceived coefficient $\hat{\gamma}_t$ estimated from the panel of forecasters.

Importantly, comparing the magnitudes of the coefficients in panels A and B of Table D.5 shows that the realized federal funds rate varies substantially more with the interaction $\hat{\gamma} \times CFNAI$ than the forecasted federal funds rate. This suggests that forecasters tend to underpredict the future fed funds rate when $\hat{\gamma}$ and $CFNAI$ are both high.

Table D.2: Predicting Federal Funds Rate Surprises - Employment Growth

Panel A: Panel FE $\hat{\gamma}$

	$q=2$		$q=4$	
ΔEMP_t	0.21*	0.26**	0.65**	0.68**
	(1.82)	(2.05)	(2.31)	(2.45)
i_t	-0.10**	-0.10**	-0.21**	-0.21**
	(-2.27)	(-2.37)	(-2.17)	(-2.22)
$\hat{\gamma}_t$		0.08		0.12
		(1.28)		(1.16)
$\hat{\gamma}_t \times \Delta EMP_t$		0.11		0.17
		(1.42)		(1.45)
Const.	-0.03	-0.04	-0.10	-0.11
	(-0.30)	(-0.36)	(-0.47)	(-0.56)
N	114	114	112	112
R^2	0.11	0.16	0.19	0.23

Panel B: SSM $\hat{\gamma}$

	$h=2$		$h=4$	
ΔEMP_t	0.21*	0.32**	0.65**	0.77***
	(1.82)	(2.24)	(2.31)	(2.83)
i_t	-0.10**	-0.12**	-0.21**	-0.25**
	(-2.27)	(-2.35)	(-2.17)	(-2.26)
$\hat{\gamma}_t$		0.05		0.10
		(0.62)		(0.78)
$\hat{\gamma}_t \times \Delta EMP_t$		0.14*		0.30**
		(1.93)		(2.27)
Const.	-0.03	-0.00	-0.10	-0.05
	(-0.30)	(-0.02)	(-0.47)	(-0.20)
N	114	114	112	112
R^2	0.11	0.16	0.19	0.23

Note: This table runs regressions analogous to Table 3 in the main text, but using 12-month employment growth rather than the CFNAI as a predictor. Employment growth, ΔEMP_t, is constructed as the percent change in total nonfarm employees (series PAYEMS on FRED) from 12 months prior. Both $\hat{\gamma}_t$ and ΔEMP_t are standardized to have mean zero and unit standard deviation. We construct the federal funds rate forecast error using the median BCFF forecast for the federal funds rate q quarters in the future. Data is quarterly and ranges from 1992Q1 through 2020Q4. Newey-West t-statistics with 6 lags are shown in parentheses.

Table D.3: Bond Excess Return Predictability 2-YR Treasury Bonds

Panel A: Panel FE $\hat{\gamma}$

	$xr^{(2)}_{t\to t+12}$		
$\hat{\gamma}$	-0.37***	-0.26***	-0.26***
	(-3.31)	(-2.78)	(-3.74)
$CFNAI$		-0.55*	-1.02***
		(-1.85)	(-4.37)
$\hat{\gamma} \times CFNAI$			-0.50***
			(-4.82)
Const.	0.83***	0.85***	0.92***
	(3.37)	(3.90)	(4.45)
N	337	337	337
R^2	0.18	0.25	0.31

Panel B: SSM $\hat{\gamma}$

	$xr^{(2)}_{t\to t+12}$		
$\tilde{\gamma}$	-0.31**	-0.20	-0.27**
	(-2.12)	(-1.49)	(-2.19)
$CFNAI$		-0.61**	-1.19***
		(-1.98)	(-4.48)
$\hat{\gamma} \times CFNAI$			-0.59***
			(-3.66)
Const.	0.92***	0.91***	1.05***
	(3.46)	(3.96)	(5.04)
N	337	337	337
R^2	0.14	0.23	0.30

Note: This table is analogous to Table 5 in the main paper but predicts excess returns on 2-year zero coupon Treasury bonds instead of 5-year zero coupon Treasury bonds. We do not show predictability regressions for the 24-month forecasting horizon in this table, because the 24-month excess returns on 2-year Treasury bonds are zero by definition. Newey-West t-statistics with 1.5 times lag length in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table D.4: Bond Excess Return Predictability - 10 YR Treasury Bonds

Panel A: Panel FE $\hat{\gamma}$

	$xr^{(10)}_{t\to t+12}$			$xr^{(10)}_{t\to t+24}$		
$\hat{\gamma}$	-1.08**	-1.16**	-1.16**	-1.87***	-1.60***	-1.59***
	(-2.46)	(-2.41)	(-2.20)	(-3.38)	(-2.82)	(-2.89)
$CFNAI$		0.40	-1.18		-1.41	-2.87*
		(0.37)	(-0.84)		(-1.04)	(-1.78)
$\hat{\gamma} \times CFNAI$			-1.69*			-1.55
			(-1.87)			(-1.22)
Const.	5.44***	5.42***	5.66***	8.33***	8.38***	8.61***
	(4.78)	(4.79)	(5.07)	(5.77)	(6.30)	(6.25)
N	337	337	337	325	325	325
R^2	0.18	0.18	0.20	0.15	0.16	0.17

Panel B: SSM $\hat{\gamma}$

	$xr^{(10)}_{t\to t+12}$			$xr^{(10)}_{t\to t+24}$		
$\hat{\gamma}$	-0.91	-0.94	-1.17	-1.87***	-1.60***	-1.59***
	(-1.17)	(-1.11)	(-1.46)	(-3.38)	(-2.82)	(-2.89)
$CFNAI$		0.17	-1.78		-1.41	-2.87*
		(0.15)	(-1.07)		(-1.04)	(-1.78)
$\hat{\gamma} \times CFNAI$			-1.96**			-1.55
			(-2.01)			(-1.22)
Const.	5.70***	5.71***	6.18***	8.33***	8.38***	8.61***
	(5.11)	(5.04)	(5.77)	(5.77)	(6.30)	(6.25)
N	337	337	337	325	325	325
R^2	0.17	0.17	0.19	0.15	0.16	0.18

Note: This table is analogous to Table 5 in the main paper but predicts excess returns on 10-year zero coupon Treasury bonds instead of 5-year zero coupon Treasury bonds. We do not show predictability regressions for the 24-month forecasting horizon in this table, because the 24-month excess returns on 2-year Treasury bonds are zero by definition. Newey-West t-statistics with 1.5 times lag length in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table D.5: Decomposing forecast errors for the federal funds rate

Panel A: *Dependent Variable* = Realized federal funds rate						
			Panel FE $\hat{\gamma}$		SSM $\hat{\gamma}$	
	$q = 2$	$q = 4$	$q = 2$	$q = 4$	$q = 2$	$q = 4$
$CFNAI_t$	0.39***	0.80**	0.71***	1.34***	0.90***	1.57***
	(2.62)	(2.27)	(4.69)	(5.31)	(6.05)	(6.62)
i_t	0.90***	0.74***	0.90***	0.76***	0.89***	0.72***
	(20.21)	(8.22)	(24.37)	(10.35)	(24.44)	(10.11)
$\hat{\gamma}_t$			0.01	0.09	-0.04	0.07
			(0.19)	(1.04)	(-0.63)	(0.61)
$\hat{\gamma}_t \times CFNAI_t$			0.35***	0.67***	0.45***	0.82***
			(5.61)	(6.08)	(6.56)	(6.48)
N	114	112	114	112	114	112
R-sq	0.91	0.74	0.93	0.81	0.94	0.82

Panel B: *Dependent Variable* = Forecasted federal funds rate						
			Panel FE $\hat{\gamma}$		SSM $\hat{\gamma}$	
	$q = 2$	$q = 4$	$q = 2$	$q = 4$	$q = 2$	$q = 4$
$CFNAI_t$	0.07	0.14*	0.14*	0.22***	0.19***	0.31***
	(1.59)	(1.77)	(1.90)	(3.54)	(2.65)	(4.38)
i_t	1.00***	0.92***	1.00***	0.93***	0.99***	0.89***
	(55.59)	(25.91)	(68.28)	(41.92)	(71.71)	(39.52)
$\hat{\gamma}_t$			0.06**	0.21***	0.02	0.15**
			(2.22)	(4.52)	(0.60)	(2.37)
$\hat{\gamma}_t \times CFNAI_t$			0.10**	0.19***	0.12***	0.23***
			(2.31)	(5.05)	(2.67)	(5.08)
N	114	112	114	112	114	112
R-sq	0.99	0.96	0.99	0.97	0.99	0.97

Note: This table estimates regressions for the q-quarter-ahead realized federal funds rate (Panel A) and the mean BCFF federal funds rate forecast for the matching forecast horizon. The federal funds rate forecast error in Table 3 equals the realized federal funds rate minus the forecasted federal funds rate. CFNAI and $\hat{\gamma}_t$ are standarized to have a standard deviation of one and mean zero. The intercept b_0 is not reported. Data is quarterly and ranges from 1992Q1 through 2020Q4. Newey-West t-statistics with 6 lags are shown in parentheses.

References

Albuquerque, Rui, Martin Eichenbaum, Victor Xi Luo, and Sergio Rebelo (2016) "Valuation risk and asset pricing," *Journal of Finance*, 71 (6), 2861–2904.

Andrade, Philippe, Richard K. Crump, Stefano Eusepi, and Emanuel Moench (2016) "Fundamental disagreement," *Journal of Monetary Economics*, 83, 106–128.

Ang, Andrew and Monika Piazzesi (2003) "A No-Arbitrage Vector Autoregression of Term Structure Dynamics with Macroeconomic and Latent Variables," *Journal of Monetary Economics*, 50 (4), 745–787.

Backus, David K and Jonathan H Wright (2007) "Cracking the Conundrum," *Brookings Papers on Economic Activity*, 2007 (1), 293–316.

Bauer, Michael D. and Glenn D. Rudebusch (2020a) "Interest Rates Under Falling Stars," *American Economic Review*, 110 (5), 1316–1354.

——— (2020b) "Interest Rates Under Falling Stars," *American Economic Review*, 110 (5), 1316–1354.

Bauer, Michael D. and Eric T. Swanson (2021) "An Alternative Explanation for the "Fed Information Effect"," Working Paper 2020-06, Federal Reserve Bank of San Francisco.

Bernanke, Ben (2010) "Central Bank Independence, Transparency, and Accountability," https://www.federalreserve.gov/newsevents/speech/bernanke20101015a.htm, speech at the Institute for Monetary and Economic Studies International Conference, Bank of Japan, Tokyo, Japan on May 25.

Bianchi, Francesco, Martin Lettau, and Sydney C. Ludvigson (2022) "Monetary Policy and Asset Valuation," *Journal of Finance*, forthcoming.

Boivin, Jean (2006) "Has US Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data," *Journal of Money, Credit and Banking*, 38 (5), 1149–1173.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer (2020) "Overreaction in macroeconomic expectations," *American Economic Review*, 110 (9), 2748–82.

Boyd, John H., Jian Hu, and Ravi Jagannathan (2005) "The stock market's reaction to unemployment news: Why bad news is usually good for stocks," *Journal of Finance*, 60 (2), 649–672.

Caballero, Ricardo J. and Alp Simsek (2020) "A risk-centric model of demand recessions and speculation," *Quarterly Journal of Economics*, 135 (3), 1493–1566.

——— (2021) "Monetary Policy with Opinionated Markets," Working Paper 27313, National Bureau of Economic Research.

Campbell, Jeffrey R., Charles L. Evans, Jonas D. M. Fisher, and Alejandro Justiniano (2012) "Macroeconomic Effects of Federal Reserve Forward Guidance," *Brookings Papers on Economic Activity*, 1–54.

Campbell, John Y., Carolin Pflueger, and Luis M. Viceira (2020) "Macroeconomic drivers of bond and equity risks," *Journal of Political Economy*, 128 (8), 3148–3185.

Campbell, John Y. and Robert J. Shiller (1991) "Yield spreads and interest rate movements: A bird's eye view," *Review of Economic Studies*, 58 (3), 495–514.

Campbell, John Y., Adi Sunderam, and Luis M. Viceira (2017) "Inflation Bets or Deflation Hedges? The Changing Risks of Nominal Bonds," *Critical Finance Review*, 6 (2), 263–301.

Carvalho, Carlos and Fernanda Nechio (2014) "Do people understand monetary policy?" *Journal of Monetary Economics*, 66, 108–123.

Carvalho, Carlos, Fernanda Nechio, and Tiago Tristao (2021) "Taylor rule estimation by OLS," *Journal of Monetary Economics*, 124, 140–154.

Christiano, Lawrence J, Roberto Motto, and Massimo Rostagno (2014) "Risk shocks," *American Economic Review*, 104 (1), 27–65.

Cieslak, Anna (2018) "Short-Rate Expectations and Unexpected Returns in Treasury Bonds," *Review of Financial Studies*, 31 (9), 3265–3306.

Clarida, Richard, Jordi Gali, and Mark Gertler (2000) "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115 (1), 147–180.

Cochrane, John H. (2011) "Determinacy and identification with Taylor rules," *Journal of Political Economy*, 119 (3), 565–615.

Cogley, Timothy and Thomas J. Sargent (2005) "Drifts and volatilities: monetary policies and outcomes in the post WWII US," *Review of Economic Dynamics*, 8 (2), 262–302.

Coibion, Olivier and Yuriy Gorodnichenko (2011) "Monetary policy, trend inflation, and the great moderation: An alternative interpretation," *American Economic Review*, 101 (1), 341–70.

——— (2015) "Information rigidity and the expectations formation process: A simple framework and new facts," *American Economic Review*, 105 (8), 2644–78.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber (2021) "Monetary policy communications and their effects on household inflation expectations," *Journal of Political Economy*, forthcoming.

Del Negro, Marco, Domenico Giannone, Marc P Giannoni, and Andrea Tambalotti (2017) "Safety, Liquidity, and the Natural Rate of Interest," *Brookings Papers on Economic Activity*, 2017 (1), 235–316.

Durbin, James and Siem Jan Koopman (2002) "A Simple and Efficient Simulation Smoother for State Space Time Series Analysis," *Biometrika*, 89 (3), 603–616.

Eggertsson, Gauti B. and Michael Woodford (2003) "Zero bound on interest rates and optimal monetary policy," *Brookings Papers on Economic Activity*, 2003 (1), 139–233.

Eusepi, Stefano and Bruce Preston (2010) "Central Bank Communication and Expectations Stabilization," *American Economic Journal: Macroeconomics*, 2 (3), 235–71.

Galí, Jordi (2015) *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*: Princeton University Press.

Gertler, Mark and Peter Karadi (2015) "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7 (1), 44–76.

Giacoletti, Marco, Kristoffer Laursen, and Kenneth Singleton (2021) "Learning From Disagreement in the U.S. Treasury Bond Market," *Journal of Finance*, 76 (1), 395–441.

Gürkaynak, Refet S., Brian P. Sack, and Eric T. Swanson (2005) "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1 (1), 55–93.

Gürkaynak, Refet S, Brian Sack, and Jonathan H Wright (2007) "The US Treasury yield curve: 1961 to the present," *Journal of Monetary Economics*, 54 (8), 2291–2304.

Hamilton, James D., Seth Pruitt, and Scott Borger (2011) "Estimating the market-perceived monetary policy rule," *American Economic Journal: Macroeconomics*, 3 (3), 1–28.

Hanson, Samuel G. and Jeremy C. Stein (2015) "Monetary policy and long-term real rates," *Journal of Financial Economics*, 115 (3), 429–448.

Jia, Chengcheng and Jing Cynthia Wu (2022) "Average Inflation Targeting: Time Inconsistency and Intentional Ambiguity," Working Paper 29673, National Bureau of Economic Research.

Joslin, Scott, Marcel Priebsch, and Kenneth J Singleton (2014) "Risk premiums in dynamic term structure models with unspanned macro risks," *The Journal of Finance*, 69 (3), 1197–1233.

Kim, Chang-Jin and Charles R. Nelson (2006) "Estimation of a forward-looking monetary policy rule: A time-varying parameter model using ex post data," *Journal of Monetary Economics*, 53 (8), 1949–1966.

Law, Tzuo Hann, Dongho Song, and Amir Yaron (2020) "Fearing the Fed: How wall street reads main street," Working Paper.

Nakamura, Emi and Jón Steinsson (2018) "High-frequency identification of monetary non-neutrality: the information effect," *Quarterly Journal of Economics*, 133 (3), 1283–1330.

Orphanides, Athanasios (2003a) “Historical monetary policy analysis and the Taylor rule,” *Journal of Monetary Economics*, 50 (5), 983–1022.

——— (2003b) “Historical monetary policy analysis and the Taylor rule,” *Journal of Monetary Economics*, 50 (5), 983–1022.

Patton, Andrew J. and Allan Timmermann (2010) “Why do forecasters disagree? Lessons from the term structure of cross-sectional dispersion,” *Journal of Monetary Economics*, 57 (7), 803–820.

Pflueger, Carolin, Emil Siriwardane, and Adi Sunderam (2020) “Financial Market Risk Perceptions and the Macroeconomy,” *Quarterly Journal of Economics*, 135 (3), 1443–1491.

Piazzesi, Monika (2001) “An Econometric Model of the Yield Curve with Macroeconomic Jump Effects,” Working Paper 8246, National Bureau of Economic Research.

Ramey, Valerie A. (2016) “Macroeconomic shocks and their propagation,” *Handbook of Macroeconomics*, 2, 71–162.

Ramey, Valerie A. and Sarah Zubairy (2018) “Government spending multipliers in good times and in bad: evidence from US historical data,” *Journal of Political Economy*, 126 (2), 850–901.

Rudebusch, Glenn D. and Tao Wu (2008) “A Macro-Finance Model of the Term Structure, Monetary Policy, and the Economy,” *Economic Journal*, 118 (530), 906–926.

Sastry, Karthik A. (2021) “Disagreement About Monetary Policy,” Working Paper.

Schmeling, Maik, Andreas Schrimpf, and Sigurd A. M. Steffensen (2022) “Monetary Policy Expectation Errors,” Working Paper 996, Bank for International Settlements.

Sims, Eric (2008) “Identification and estimation of interest rate rules in new keynesian models.”

Stein, Jeremy C. and Adi Sunderam (2018) “The fed, the bond market, and gradualism in monetary policy,” *Journal of Finance*, 73 (3), 1015–1060.

Swanson, Eric T. and John C. Williams (2014) “Measuring the effect of the zero lower bound on medium-and longer-term interest rates,” *American Economic Review*, 104 (10), 3154–85.

Taylor, John B. (1993) “Discretion Versus Policy Rules in Practice,” *Carnegie-Rochester Conference Series on Public Policy*, 39, 195–214.

——— (1999) “A historical analysis of monetary policy rules,” in *Monetary Policy Rules*, 319–348: University of Chicago Press.

Taylor, John B. and John C. Williams (2010) “Simple and robust rules for monetary policy,” in *Handbook of Monetary Economics*, 3, 829–859: Elsevier.

Yellen, Janet L. (2015) "The Economic Outlook and Monetary Policy," https://www.federalreserve.gov/newsevents/speech/yellen20151202a.htm, speech at the Economic Club of Washington, Washington, D.C., on December 2.