Perceptions about Monetary Policy *

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Abstract

We estimate perceptions about the Fed's monetary policy rule from panel data on professional forecasts of interest rates and macroeconomic conditions. The perceived dependence of the federal funds rate on economic conditions is time-varying and cyclical: high during tightening episodes but low during easings. Forecasters update their perceptions about the policy rule in response to monetary policy actions, measured by high-frequency interest rate surprises, suggesting that forecasters have imperfect information about the rule. The perceived rule impacts asset prices crucial for monetary policy transmission, driving how interest rates respond to macroeconomic news and explaining term premia in long-term interest rates.

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1 Introduction

Over the last 30 years, the Federal Reserve and other central banks have increasingly focused on communicating monetary policy strategy to the public. Underlying this trend are two propositions: First, monetary policy strategy is complex, depending on a wide range of considerations that vary across time and states of the world (Woodford, 2005). Second, the public's perceptions of monetary policy—including its goals, framework, and future course—play a crucial role in determining policy effectiveness (Bernanke, 2010).[1] But what monetary policy strategy does the public perceive? How do these perceptions vary over time? And how is the perceived strategy linked to actual decisions made by the Fed?

Empirical progress on these questions has been limited by the macroeconomic data typically used to characterize monetary policy frameworks. Since the seminal work of Taylor (1993), the monetary economics literature has commonly described monetary policy frameworks using simple monetary policy rules that link policy rates to macroeconomic conditions. This approach has been the foundation of extensive positive and normative analyses of monetary policy (e.g., Clarida et al., 2000; Smets and Wouters, 2007). However, the estimation of policy rules—and thus empirical descriptions of policy frameworks—is traditionally based on macroeconomic time series data. As a consequence, prior work could only capture low frequency variation in monetary policy strategy, but not the higher-frequency, cyclical variation that is regularly part of policy deliberations. Furthermore, such estimates cannot speak to the public's perceptions of monetary policy strategy.[2]

In this paper, we sidestep the constraints of traditional macroeconomic data by using rich survey data from the Blue Chip Financial Forecasts (BCFF) to estimate a perceived monetary policy rule *each month* from January 1985 until January 2021. We take two estimation approaches which both exploit variation across forecasters and forecast horizons to relate fed funds rate forecasts to inflation forecasts and output gap forecasts. In our first estimation methodology, each month we estimate a separate regression on that month's forecaster-by-horizon panel of forecasts, which consists of about 30-50 forecasters and horizons from zero

[1]The classic New Keynesian model of monetary policy suggests that the public's perceptions about the conduct of monetary policy determine the trade-offs faced by policy-makers, the anchoring of long-run expectations, and the stability of macroeconomic equilibria (e.g., Clarida et al. (2000), Orphanides and Williams (2005), Eggertsson and Woodford (2003), Cogley et al. (2015)). Perceptions of the monetary policy framework are also crucial for financial market reactions to monetary policy surprises and macroeconomic announcements (e.g., Piazzesi (2001), Ang and Piazzesi (2003), Cieslak (2018), Bauer and Swanson (2021), Law et al. (2020), and Bianchi et al. (2022a)).

[2]Studies estimating low-frequency changes in the monetary policy rule using historical data include Clarida et al. (2000); Kim and Nelson (2006); Boivin (2006); Orphanides (2003); Cogley and Sargent (2005). Notable exceptions to this approach are Bianchi et al. (2022a) and Bianchi et al. (2022b), who use models linking asset prices to the monetary policy rule.

to five quarters. In a second approach, we estimate a state-space model (SSM), where the latent state variables are the policy rule coefficients and the perceived natural rate. The SSM estimates are similar to the regression estimates, but smoother and more precisely estimated.

In our empirical analysis, the coefficient on the output gap in the perceived rule, $\hat{\gamma}_t$, summarizes the Fed's overall responsiveness to economic conditions for two reasons related to our sample period. First, inflation was relatively stable and close to the Fed's now-explicit two percent target, which renders the coefficient on inflation less meaningful.[3] Second, supply shocks were largely absent over this period. When demand shocks are the dominant drivers of economic fluctuations, the output gap also captures anticipated inflationary pressures, and thus serves as a summary statistic for both parts of the Fed's dual mandate.

Our first key finding is that the perceived monetary policy rule exhibits substantial variation over time. The Fed's perceived responsiveness, as measured by $\hat{\gamma}_t$, varies between about 0 and 1.5 when measured using our regression methodology, and between 0 and 0.8 using our SSM methodology. As shown in Section 2, our estimates are robust to various alternative specifications, including policy inertia, heterogeneous beliefs about the Fed's responsiveness, and inclusion of financial conditions.

In Section 3, we relate variation in the perceived policy rule to the monetary policy cycle. We show that $\hat{\gamma}_t$ is positively correlated with the slope of the yield curve. When the yield curve is flat or downward-sloping, $\hat{\gamma}_t$ tends to be low, consistent with the view that easing cycles begin with rate cuts that are quick and unpredictable—the Fed tries to "get ahead of the curve" or uses "insurance cuts"—and the policy rate is viewed to be less dependent on the macroeconomic outlook going forward as a result. The Fed's responsiveness is also perceived to be lower when economic or financial uncertainty is high, consistent with models of incomplete information that suggest optimal monetary policy is more cautious in the presence of higher uncertainty. Conversely, $\hat{\gamma}_t$ is high at the early stages of tightening cycles, when the yield curve is steep, indicating that the Fed is perceived to be highly data-dependent at these times. The perceived responsiveness $\hat{\gamma}_t$ does not drop immediately to zero during the first zero-lower-bound (ZLB) period, but instead falls to zero only in 2011, when the Fed essentially committed itself to near-zero policy rates despite improving economic conditions (see also Swanson and Williams (2014) and Campbell et al. (2019)).

We next show in Section 4 that beliefs about the monetary policy rule respond to high-frequency monetary policy surprises on Federal Open Market Committee (FOMC) announcement dates. This updating suggests that forecasters have imperfect information about the

[3]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).

policy rule prior to announcements of monetary policy decisions. In particular, we find that the responses of the perceived monetary policy output weight $\hat{\gamma}_t$ to high-frequency monetary policy surprises are state contingent, as one would expect if forecasters rationally update from observed monetary policy decisions. The magnitudes of the empirical responses suggest that monetary policy surprises on FOMC dates would be 50% less volatile if the monetary policy rule were fully known.

Having examined the drivers of variation in the perceived monetary policy rule, we next show that the perceived rule affects the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates. Section 5.1 documents that market interest rates react more strongly to macroeconomic news when the Fed's perceived responsiveness is high. These results link our survey-based estimates of the perceived policy rule to the high-frequency analysis of Swanson and Williams (2014), which documents changes in the market's sensitivity to macro news. Our high-frequency analysis also validates our estimates of $\hat{\gamma}_t$ using a data source that is completely different than our Blue Chip survey data. Economically, this finding shows that the perceived monetary policy rule can "do the central bank's work for it" (Woodford, 2005), moving the expected path of rates in response to economic developments before the Fed changes the actual policy rate.

Shifts in the perceived monetary policy rule also have a pronounced impact on long-term interest rates, as we document in Section 5.2. Long-term rates are particularly important for the transmission of monetary policy because they affect mortgages and other borrowing in the economy. We show that policy rule perceptions affect the term premium that investors require for holding long-term bonds, driving a wedge between long-term rates and the expected path of short-term policy rates. Classic finance theory suggests that the higher is $\hat{\gamma}_t$, the more investors expect interest rates to fall, and hence bond prices to rise, in bad economic states. Thus, a higher $\hat{\gamma}_t$ means that investors perceive Treasury bonds to be better hedges, lowering the risk premium they demand. We document precisely this pattern: Both subjective risk premia, calculated from survey expectations of future yields as in Piazzesi et al. (2015) and Nagel and Xu (2022), and statistical risk premia, based on predictive regressions, move inversely with $\hat{\gamma}_t$. In addition to substantiating the empirical and economic relevance of shifts in perceptions of the policy rule, this finding also provides a possible explanation for "conundrum periods", when short- and long-term interest rates appear to decouple, such as the tightening cycle of 2004-2005 (Backus and Wright, 2007). Our evidence suggests that term premia are not disconnected from monetary policy, but instead are linked to monetary policy through the perceived rule.

Finally, in Section 6 we present a simple model with forecaster heterogeneity and imperfect information about the policy rule that synthesizes our empirical findings. Forecasters are endowed with heterogeneous priors about the weight on the output gap in the monetary policy rule and receive different signals about the output gap. Under the assumptions of the model, regressions of policy rate forecasts onto output gap forecasts in a forecaster-horizon panel provide a consistent estimate of the coefficient on the output gap in the perceived policy rule. The model implies that forecasters update their perceived monetary policy output weight following monetary policy surprises in a state-contingent manner; that fed funds futures should respond more strongly to macro news when the perceived output weight is high; and that bond risk premia are inversely related to the perceived output weight.

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

Our methodology for estimating monetary policy rules takes the idea of using linear regressions for monetary policy rules—in the manner of Taylor (1999) and many others—and applies it in a setting with multidimensional panel data on survey forecasts. The advantages of this approach include its simplicity and comparability to the prior literature. But it also inherits some of the literature's challenges. In particular, it is well known that policy rule regressions can yield biased estimates because macroeconomic variables endogenously depend on all shocks in the economy, including the monetary policy shock. A simple bias adjustment building on Carvalho et al. (2021) suggests that this bias is unlikely to affect the time-series variation in $\hat{\gamma}_t$ and hence our main results. In addition, some of our evidence clearly favors an interpretation of our $\hat{\gamma}_t$ estimate as the perceived policy rule coefficient, including its response to monetary policy surprises and its role in explaining high-frequency responses of interest rates to macro news. Nevertheless, an alternative, more general interpretation of $\hat{\gamma}_t$ as simply the perceived comovement between the short-term policy rate and macroeconomic variables is possible. Under this broader interpretation, many of the take-aways from our empirical analysis remain valid. For example, we show that this perceived comovement is priced in financial markets and determines bond risk premia.

By providing estimates of the perceived monetary policy rule, our paper contributes to the growing literature on incomplete information and monetary policy (e.g., Primiceri, 2006; Coibion and Gorodnichenko, 2015; García-Schmidt and Woodford, 2019; Gabaix, 2020; Angeletos and Lian, 2022; Angeletos and Sastry, 2021; Afrouzi and Yang, 2021; Bordalo et al., 2020). We document that investors learn about the rule from policy decisions, and document that their perceptions of the rule are transmitted into financial market prices like short- and long-term interest rates. Cogley et al. (2015) and Orphanides and Williams (2005) argue that the real cost of a disinflation is substantially higher when agents learn about the monetary policy rule, as our empirical evidence suggests. Also closely related are Caballero and Simsek (2022), who study the implications for monetary policy of disagreement between the public and the Federal Reserve, and Stein and Sunderam (2018), who examine strategic communication between the central bank and market participants. In addition, our work connects to the debate on rules versus discretion in monetary policy going back to Kydland and Prescott (1977) and Taylor (1993). While our results do not speak directly to the optimal conduct of monetary policy, they suggest that in practice monetary policy strategy varies significantly over time, consistent with the arguments of advocates for discretion.

Our paper contributes to an evolving empirical literature on the estimation of monetary policy rules from financial and survey data. Hamilton et al. (2011) estimate a market-perceived rule using high-frequency responses to macroeconomic news; Kim and Pruitt (2017) estimate the perceived rule using consensus survey forecasts; Andrade et al. (2016) and Carvalho and Nechio (2014) use individual survey forecasts. These studies generally impose constant parameter in the policy rules, aside from at most a single parameter break, while we study time-variation in monetary policy perceptions.

Finally, we contribute to a large and growing macro-finance literature on the financial market impacts of monetary policy (e.g., Cochrane and Piazzesi, 2002; Gürkaynak et al., 2005; Hanson and Stein, 2015; Nakamura and Steinsson, 2018). Some recent studies connect this issue to perceptions about monetary policy, as we do: Bianchi et al. (2022b) study FOMC announcements and perceptions of regime-switching policy rules in a New Keynesian asset pricing model, and Haddad et al. (2021) estimate the option-implied state-contingency of the Fed's corporate bond purchases during the pandemic. Our empirical approach is different as we directly estimate policy rule perceptions from survey data. It has the added advantage of covering a long sample period, which allows us to study time-variation in the perceived monetary policy rule, and to show empirically how it is transmitted to financial markets.

2 Data and estimation

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

2.1 Survey data

Our main data source is the Blue Chip Financial Forecasts (BCFF) survey, a monthly survey of professional forecasters going back to 1982. The survey mainly asks for forecasts of various interest rates, including the federal funds rate and Treasury yields of different maturities. In addition, participants are queried about their forecasts for a few macroeconomic variables, including real GDP growth and CPI inflation. The number of participants each month varies over time, ranging from about 30 to 50 different institutions. A distinguishing feature of the BCFF survey is that the individual forecasts are all recorded in the data, including the names of the forecasting institution. This rich cross-sectional information allows for a detailed analysis of individual forecasts and enables us to recover the monetary policy perceptions of a relatively sophisticated set of agents in the economy.

While the BCFF survey started in 1982, our sample begins in January 1985 because the data's quality is poor in the first few years of the survey. Our survey data ends in January 2021 for a total of 433 monthly surveys. Every month, each forecaster provides forecasts for horizons from the current quarter out to five quarters ahead.[4] 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, the policy rate of the Federal Reserve. The precise variable being forecast is the quarterly average of the daily effective 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 funds rate at $t+h$ by $E_t^{(j)} i_{t+h}$. Throughout the paper, time t is measured in months, unless otherwise stated. The monthly horizon h depends on both the survey month and the quarterly forecast horizon. For example, for the one-quarter-ahead forecast in the January 2000 survey, $t+h$ corresponds to June 2000 and $h = 5$.

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

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

We derive output gap forecasts from real GDP growth forecasts from 1992 onwards and from real GNP growth forecasts before. Conceptually, the calculation is straightforward: Using the current level of real output and the quarterly growth forecasts, we calculate the forecasted future level of real output, which we then combine with CBO projections of potential output to calculate implied output gap forecasts. In practice, the calculations are slightly involved, since careful account needs to be taken of the timing of the surveys and the available real-time GDP data and potential output projections. First, we need real-time GDP for the quarter before the survey. We obtain real-time data vintages for GDP from ALFRED, and use the most recently observed vintage before the deadline of each survey. Second, we calculate forecasts for the *level* of real GDP, denoted as $E_t^{(j)} Y_{t+h}$ using the level in the quarter before the survey and the growth rate forecasts. Third, we obtain real-time vintages for the CBO's projections of future potential GDP, also from ALFRED, and again use the most recent vintage that was available to survey participants at the time.[5] Fourth and finally, output gap forecasts are calculated as the deviation of the GDP forecasts from the potential GDP projections in percentage points:

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

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.

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

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

Table 1: Summary statistics for survey forecasts

	N	Mean	Standard Deviations			
			SD	Within-Month	Within-Month-ID	Within-Month-Horizon
Fed funds rate	111,503	3.6	2.7	0.46	0.33	0.33
CPI inflation	110,707	2.6	1.1	0.56	0.43	0.39
Output growth	110,892	2.6	1.8	1.01	0.76	0.81
Output gap	110,882	-1.4	2.7	0.63	0.39	0.51

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

2.2 Specification of the policy rule

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

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

where π_t^* is the inflation target, r_t^* is the equilibrium real interest rate, and the equilibrium nominal short-term interest rate is $i_t^* = r_t^* + \pi_t^*$. The key parameters are β_t and γ_t, the coefficients on the inflation gap and the output gap. Finally, u_t is a monetary policy shock that is exogenous to the policy rule. This type of policy rule is consistent with the specifications used in a large literature in empirical macroeconomics (e.g., Taylor, 1999; Orphanides, 2003; Taylor and Williams, 2010), but more general in that it allows for time-varying parameters.[6]

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

[6] In contrast to Andrade et al. (2016), we specify the perceived monetary policy rule in terms of the output gap rather than GDP growth. This specification is consistent with the literature and matches variation in interest rate disagreement across different forecast horizons, see Appendix A.1.

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). Similarly to Caballero and Simsek (2022), we therefore assume that fundamental disagreement generates interest rate disagreement via the policy rule. Because our estimation relies on forward-looking data, the perceived rule will naturally be influenced by both data-dependent and unconditional forward guidance (Campbell et al., 2012).

Our main object of interest is the time-series variation in the average monetary policy weights perceived by forecasters. Forecasters do not know the rule's parameters but form beliefs about them. To start, we assume that beliefs about the coefficients are identical across forecasters but vary over time, and we denote the perceived coefficients by $\hat{\beta}_t$ and $\hat{\gamma}_t$. We consider heterogeneity across forecasters in our robustness checks in Section 2.5 and in the learning model in Section 6. We use the operators $E^{(j)}$ for forecaster j's expectation and $\bar{E}$ for the average expectation across forecasters. Following common practice we assume that the time-varying parameters are martingales and orthogonal to other shocks, i.e., $E_t^{(j)}\beta_{t+h} = \hat{\beta}_t$ 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., Bauer and Rudebusch, 2020). Forecasters may disagree about them, so that $E_t^{(j)} r_{t+h}^* = E_t^{(j)} r_t^*$ and likewise for π_t^*. Our assumptions imply that forecasts made at time t are related as follows:

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

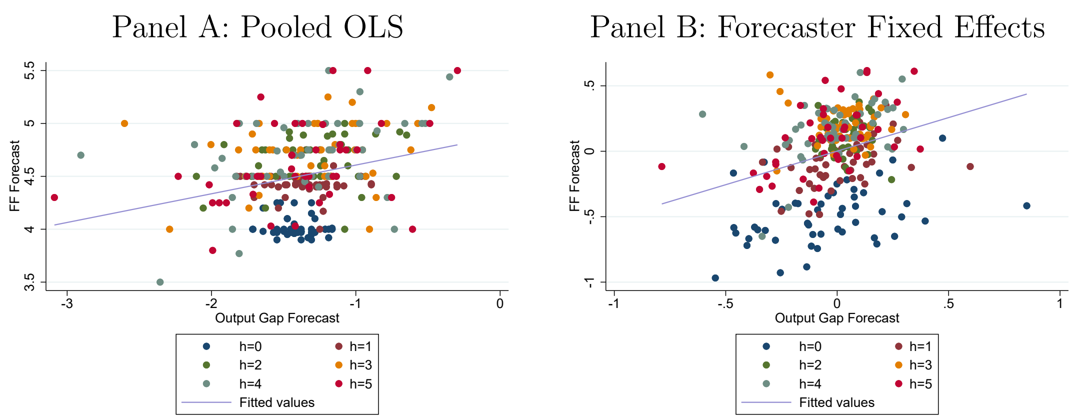
where $c_t^{(j)}$ denotes the part of the forecast that does not depend on horizon, and the error term $e_{th}^{(j)}$ contains the policy shock expected by forecaster j, $E_t^{(j)} u_{t+h}$, as well as possible measurement error. We will estimate equation (2) using two different methods described below.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

Our baseline monetary policy rule (1) does not include an inertial term on the lagged fed funds rate forecast because the regression intercept already absorbs the time t level of the policy rate. In Section 2.5 we show that the estimated parameters exhibit similar time-variation when the rule includes inertia, allowing the fed funds rate forecast to also depend on the funds rate forecasted for the preceding quarter.

2.3 Panel regression estimate

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

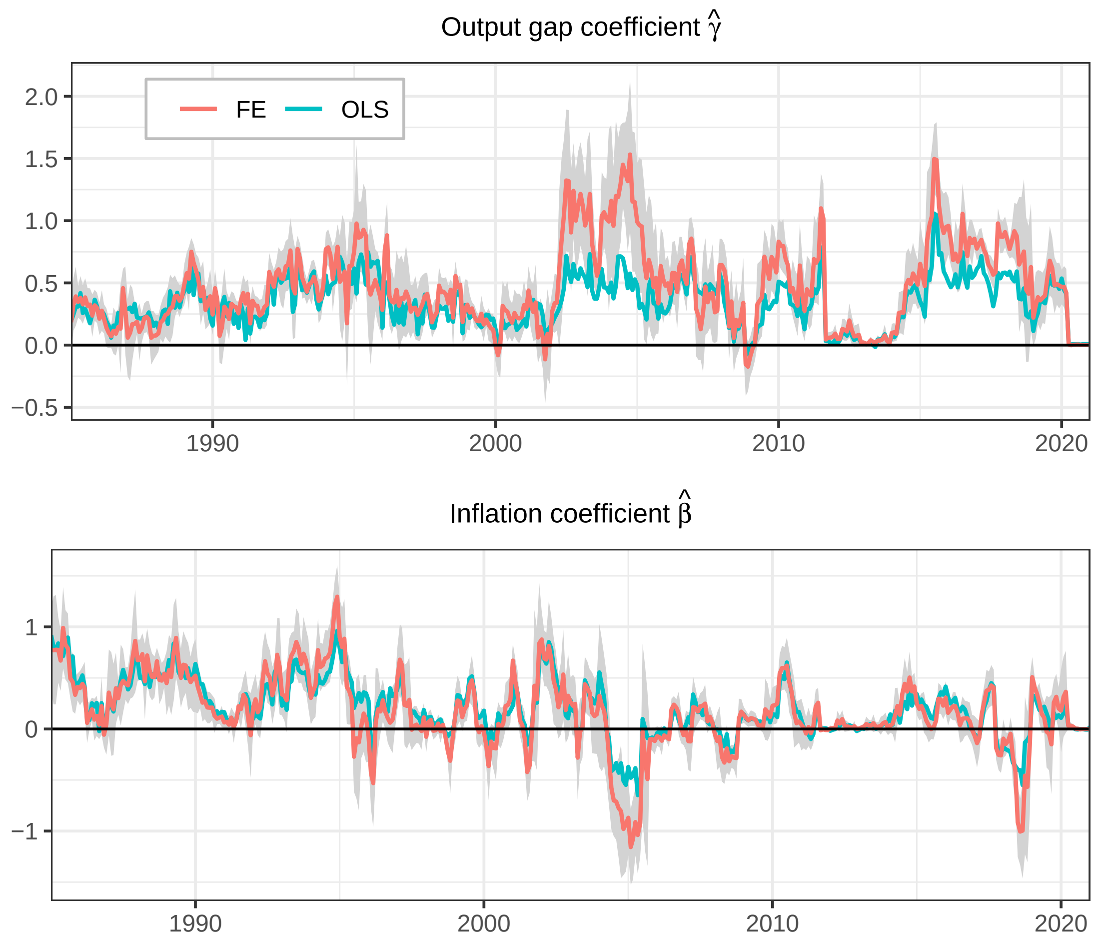
Figure 1: Federal funds rate and output gap forecasts in December 2005



Output gap and federal funds rate forecasts used to estimate regression (2) without (left) and with (right) residualizing with respect to forecaster fixed effects. Each dot corresponds to one forecaster-horizon pair (j, h) in the December 2005 survey. Forecast horizons (in quarters) h are color-coded. Output gap forecasts are constructed from individual forecasters' real GDP growth forecasts and the real-time vintages for the CBO's projections of future potential GDP from ALFRED. For a detailed description of the data construction see Section 2.1.

Figure 1 illustrates the variation in the data driving our estimated perceived monetary policy rule for December 2005. At this time, economic uncertainty was dominated by a well-defined event: the recovery from Hurricane Katrina, which devastated New Orleans in August 2005. Thus, disagreement across forecasters about future output gaps and fed funds rates was likely driven by disagreement about the short-term recovery, as opposed to confounding factors like long-term growth expectations or financial conditions. Each dot shows the output gap forecast on the x-axis and the federal funds rate forecast on the y-axis for a specific forecaster at a specific forecast horizon. Different colors are used to denote different forecast horizons of one through five quarters. There is significant variation in the output gap at all forecast horizons, and we see a clear relationship between output gap forecasts and fed funds rate forecasts. The slope in the left panel equals 0.27 and the slope in the right panel equals 0.51.[7] The R^2 in an OLS regression of fed funds rate forecasts onto output gap and inflation forecasts in this survey equals 20%. While this is only a specific month, it is representative of the sample overall. On average, the regression (2) without forecaster fixed effects has an R^2 of 33% and the regression with forecaster fixed effects has an R^2 of 70% (including forecaster dummies), indicating that a simple monetary policy rule fits the forecast data well.

Figure 2: Panel regression estimates of perceived policy rule coefficients



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

Figure 2 shows the estimated output gap coefficients $\hat{\gamma}_t$ in the top panel and estimated inflation coefficients $\hat{\beta}_t$ in the bottom panel. The differences between the OLS and FE

[7] These univariate slopes are almost identical to $\hat{\gamma}^{OLS}_{Dec2005} = 0.26$ and $\hat{\gamma}^{FE}_{Dec2005} = 0.53$, because the output gap and inflation forecasts on the right-hand-side of regression (2) are close to uncorrelated for this date.

estimates are generally moderate, but during the expansionary periods of 2003–2005 and 2015–2018, the FE estimates of $\hat{\gamma}_t$ are noticeably above the OLS estimate. These differences suggest that it is important to account for forecaster fixed effects in the estimation. The coefficients are generally estimated quite precisely, as indicated by the 95% confidence intervals that are shown for the FE estimates, based on standard errors with two-way clustering.

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

The perceived inflation coefficient $\hat{\beta}_t$ generally fluctuates around zero, and is persistently positive only over the first few years of our sample. This pattern contrasts with typical empirical and optimal policy rules, which feature an inflation coefficient exceeding unity in line with the "Taylor principle" (Taylor, 1993; Clarida et al., 2000). The reason is that our sample period (i) featured mostly low and stable inflation and (ii) was dominated by demand shocks. Under these conditions, the output gap is a sufficient statistic for inflationary pressures, and variation in the perceived output gap coefficient captures the Fed's perceived time-varying response to both economic and inflationary imbalances. After all, with overall low and stable inflation, absent any major supply shocks, forecasts mainly reflected expectations of demand-driven cyclical inflation. With a limited amount of variability in inflation, the estimated coefficient in policy rules should then expected to be low, even though the central bank has in fact been committed to stable inflation (Clarida et al., 2000).[8] For these reasons, we interpret the output gap coefficient $\hat{\gamma}_t$ as a summary statistic of the Fed's overall responsiveness to economic conditions in the remainder of our analysis.

2.4 State-space model estimate

Our rich panel data of survey forecasts yields precise and economically meaningful estimates of the link between policy rate forecasts and macroeconomic forecasts. But the regression estimates treat the monthly surveys as completely separate. In order to eliminate the higher-frequency movements due to month-to-month noise and further improve the precision of our estimates, we now estimate a state-space model (SSM) that links information in surveys in

[8] Nonetheless, we cannot rule out that the low perceived inflation coefficient at least partially reflected forecasters' beliefs that the Fed would only react with a substantial lag to emerging inflation, as indeed appeared to be the case in 2021.

adjacent months over time, by specifying and incorporating the dynamic evolution of 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 homogeneous and constant, i.e., $E^{(j)}_t \pi_{t+h} = \pi^*$. A constant perceived long-run inflation keeps the state-space model linear 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%.[9] Second, we also assume that there is no disagreement about the long-run nominal short rate, i.e., $E^{(j)}_t i^*_{t+h} = i^*_t$. Homogeneous beliefs about i^*_t avoid the complexity of having to model and keep track of each forecasters long-run expectations for the policy rate. This rules out any variation in $c^{(j)}_t$ 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 homogeneous. It should be noted that π^* and i^*_t denote (common) beliefs by the forecasters and do not necessarily need to correspond to their "true" values.

Under these additional assumptions, equation (2) becomes

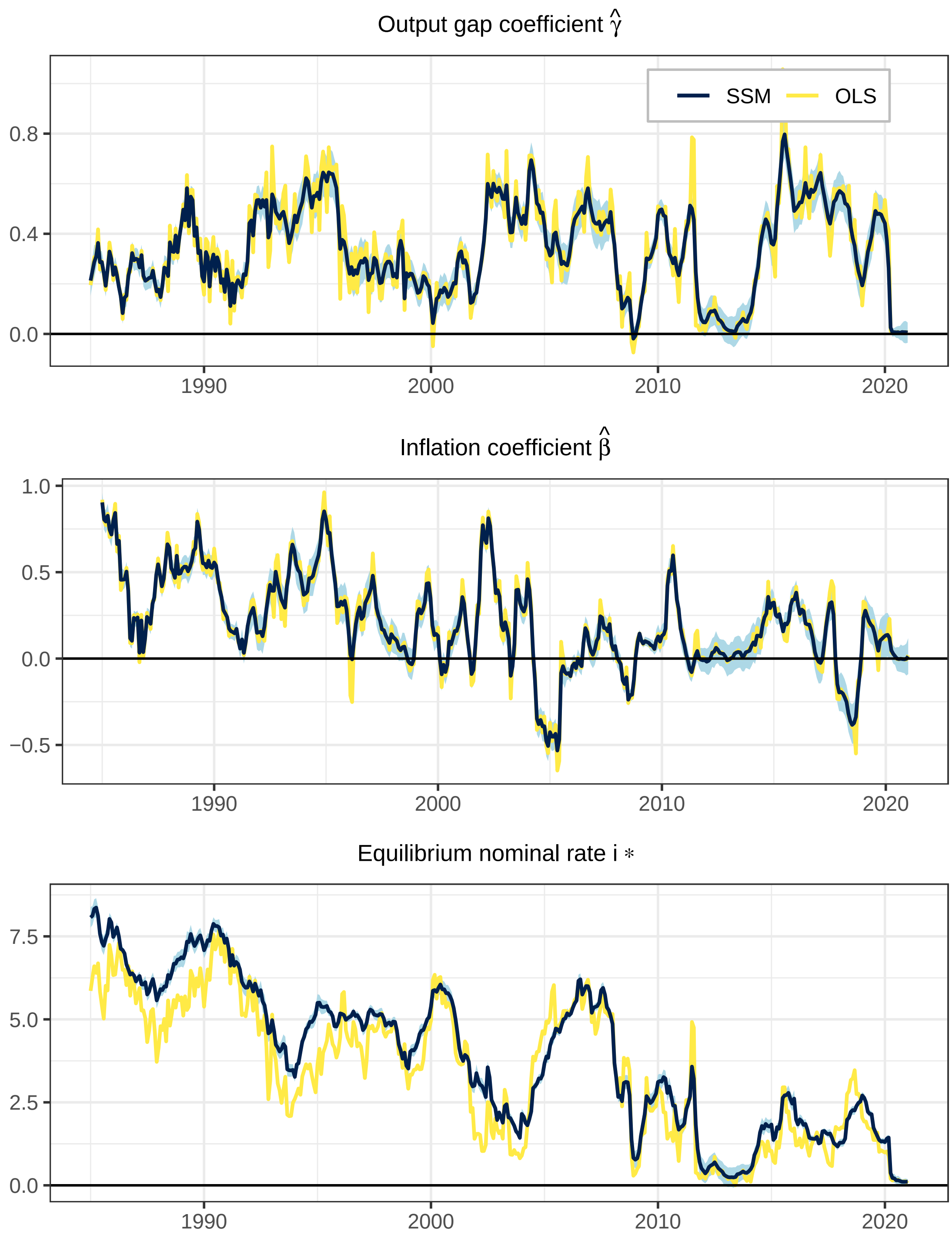
$$E^{(j)}_t i_{t+h} = i^*_t + \hat{\beta}_t (E^{(j)}_t \pi_{t+h} - \pi^*) + \hat{\gamma}_t E^{(j)}_t x_{t+h} + e^{(j)}_{th}. \tag{3}$$

The three state variables are i^*_t, $\hat{\beta}_t$ and $\hat{\gamma}_t$, which we model as independent random walks with *iid* Gaussian innovations that are mutually uncorrelated. The observation equation of the SSM is simply a matrix version of equation (3) that links the observed rate forecasts at time t, across all forecasters and horizons, to the state variables, with a coefficient matrix that includes the inflation gap and output gap forecasts. Missing forecasts are easily handled with the Kalman filter. We assume that the measurement errors in the observation equation, $e^{(j)}_{th}$, are uncorrelated across forecasters and horizons. This simple SSM specification imposes the assumptions under which the pooled OLS regressions would be both consistent and efficient, since it includes neither fixed nor random effects. Many extensions of this model are possible, including different measurement error specifications, serially correlated policy shocks, and heterogeneous beliefs about r^*_t. We use Bayesian methods to estimate the SSM, as detailed in Appendix A.2.

Figure 3 shows the resulting posterior means and 95%-credibility intervals for the output gap coefficient $\hat{\gamma}_t$, the inflation coefficient $\hat{\beta}_t$ and the long-run nominal interest rate i^*_t. For comparison, we also include the OLS coefficients estimated month-month from Figure 2. The main takeaway is that the state-space model (SSM) output gap and inflation weights

[9] 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, 2020).

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



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

are economically similar to the panel OLS estimates. The SSM estimate of the long-run policy rate, i_t^*, exhibits a significant amount of cyclical variation, because this component subsumes any variation in interest rate forecasts unrelated to the forecasts of inflation and the output gap, including any effects due to interest-rate smoothing. However, the overall downward trend is consistent with previous empirical work on shifting endpoints in interest rates (Bauer and Rudebusch, 2020).

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 number 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 $\hat{\gamma}_t$. We do not include results for the OLS estimates since they are essentially a noisy version of the SSM estimates.

2.5 Robustness of estimated perceived policy rules

We next show the robustness of our key variable—the estimated perceived monetary policy output gap weight $\hat{\gamma}_t$—to variations in our baseline specification, including an inertial rule, controlling for expected financial conditions, and various approaches to address potential heterogeneity in the perceived rule across forecasters. Table 2 shows correlations with our baseline estimates and Appendix A.4 describes the details of the alternative estimates.

We first estimate a version of $\hat{\gamma}_t$ that gives each forecaster equal weight in the regressions, as one might be concerned that in our baseline estimation some forecasters might receive higher weight in some periods simply because they have more extreme output gap forecasts. Estimating a regression of the form (2) each month at the forecaster level (i.e., only utilizing the cross-horizon variation) and then taking an equal-weighted average across forecasters addresses this concern. The high correlation with our baseline FE estimates confirms that those estimates resemble closely the average perceived coefficient over time and are not driven by shifting weights of different forecasters in the estimation. Appendix A.4 characterizes the equal-weighted estimator as a multidimensional panel regression with appropriate fixed effects and interactions, and shows that this equal-weighted estimate has tight confidence intervals like our baseline FE estimate. This estimator also makes clear that variation of fed funds rate and macroeconomic forecasts across forecast horizons is important for our estimation. The cross-section matters because the regression for each individual forecaster is bound to be very noisy, but averaging slope coefficients across forecasters gives precise estimates that vary smoothly over time.

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

	FE	SSM	Equal Weighted	Hetero-geneous	Terciles 1	2	3	Credit spread	Inertial $\frac{\hat{\gamma}}{1-\hat{\rho}}$	Inertia $\hat{\rho}$	Bias adjust
Pooled OLS	0.84	0.96	0.60	0.96	0.77	0.73	0.64	0.84	0.54	-0.02	0.77
FE	1	0.84	0.83	0.88	0.83	0.86	0.86	0.94	0.72	0.14	0.92
SSM		1	0.64	0.94	0.78	0.74	0.65	0.83	0.58	-0.02	0.79

Correlations between different estimates for the perceived output gap weight in the policy rule, $\hat{\gamma}_t$. Sample period ends in January 2021, and starts in January 1985 for baseline, equal-weighted, and tercile 1, 2, 3 estimates (*Pooled OLS, FE, SSM, Equal-Weighted, Terciles*), in January 1993 for *Heterogeneous*, and in January 2001 for *Credit spread* estimates. *Terciles* split forecasters into terciles by the four-quarter horizon CPI inflation forecast residualized with respect to monthly fixed effects, and re-estimates the FE estimate of $\hat{\gamma}_t$ on these terciles. Inertial $\hat{\gamma}_t$ is from an estimation of the inertial rule $E_t^{(j)} i_{t+h} = \alpha_t^{(j)} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + \hat{\rho}_t E_t^{(j)} i_{t+h-3} + e_{th}^{(j)}$, where ρ is capped at 0.9. For details on alternative estimates, see Appendix A.4.

Next, we impose additional structure on forecaster heterogeneity motivated by our information model in Section 6. The "heterogeneous" estimate includes forecaster fixed effects interacted with the output gap and inflation, i.e., it estimates a multidimensional panel regression of the form

$$E_t^{(j)} i_{t+h} = a_t + \alpha_j + (b_j + \beta_t) E_t^{(j)} \pi_{t+h} + (g_j + \gamma_t) E_t^{(j)} x_{t+h} E_t^{(j)} \pi_{t+h} + \gamma_t E_t^{(j)} x_{t+h} + e_{t,j,h} \quad (4)$$

Note that this estimate does not contain forecaster-by-month fixed effects, so it should be expected to be closer to the "pooled OLS" estimate than the "FE" estimate, which is indeed what we see in Table 2.[10]

We next account for forecaster heterogeneity in a less parametric way, splitting forecasters by characteristics and estimating different policy rules for each forecaster group. In particular, one might wonder whether inflation hawks and doves perceive different monetary policy rules. We split forecasters into terciles by their four-quarter horizon CPI inflation forecast residualized with respect to monthly fixed effects. We then estimate "FE" regressions for each of the three terciles, with *Tercile 1* corresponding to the forecasters with low inflation expectations and *Tercile 3* corresponding to the forecasters with the highest inflation expectations. The estimates of $\hat{\gamma}_t$ naturally become noisier due to the smaller sample sizes, but

[10]Because forecaster ID's were reshuffled in 1993, this regression necessarily starts in January 1993.

the correlations with our baseline FE estimate of $\hat{\gamma}_t$ remain high, exceeding 80% for all three terciles. While hawks versus doves may therefore perceive different levels for the monetary policy output weight (the average $\hat{\gamma}_t$ equals 0.42 for the doves in *Tercile 1* vs. 0.52 for the hawks *Tercile 3*), the time-variation in $\hat{\gamma}_t$ is very similar. Splitting forecasters by inflation hence again confirms that our baseline estimator $\hat{\gamma}_t$ captures common time-variation in the perceived monetary policy rule shared by all forecasters.

A separate concern about our estimates is that a high value for $\hat{\gamma}_t$ might partly reflect the perceived monetary policy response to financial conditions, which are likely to be correlated with the economy. We investigate this possibility by including in our FE estimation each forecaster's expectation of the spread between Baa corporate bond yields and the ten-year Treasury yield, as a proxy for expected financial conditions. Forecasts of the Baa yield are available in the Blue Chip data starting in 2001. Our estimates suggest an important perceived role for financial conditions in determining the policy rate—expected credit spreads enter with a coefficient that is often substantially negative and statistically significant (results omitted). However, as Table 2 shows, incorporating credit spread forecasts into the perceived policy rule has little effect on the estimated response to output gap forecasts.

Finally, we ask whether our baseline estimate of the time-varying perceived output gap coefficient reflects variation in the perceived persistence of the monetary policy rule. To this end, we estimate a monetary policy rule that includes the forecast of the policy rate at horizon $t+h-3$ (i.e. one quarter prior) in addition to the output gap and inflation forecasts at horizon $t+h$. We denote the estimated parameter onto $E_t^{(j)} i_{t+h-3}$ by $\hat{\rho}$. We find that the perceived long-run response of monetary policy to the output gap, $\frac{\hat{\gamma}}{1-\hat{\rho}}$ with forecaster fixed effects is highly correlated with our baseline FE estimate of $\hat{\gamma}_t$. By contrast, the time-varying estimate of the inertia parameter $\hat{\rho}$, reported in the last column, is completely uncorrelated with our various estimates of $\hat{\gamma}_t$. We therefore conclude that our estimate of $\hat{\gamma}_t$ captures the time-varying perceived monetary policy weight on the economy, and not time-variation in the perceived inertia of the monetary policy rule. Additional robustness checks, including estimates using forecaster-level data from the Survey of Professional Forecasters (SPF) and the Fed' Survey of Economic Projections, are reported in the Appendix. In Appendix D.2 we show that our baseline estimates of $\hat{\gamma}_t$ are only slightly positively correlated with the measures of forecaster interest rate disagreement from Giacoletti et al. (2021), with univariate correlations ranging from 0 to 0.27, suggesting that the Fed's ability to eliminate disagreement about future policy rates is not driving our estimates.

Overall, we find that our various alternative estimates of $\hat{\gamma}_t$ are all highly correlated with our baseline OLS, FE, and SSM estimates, while the perceived inertia of the monetary policy rule is not.

2.6 Endogeneity and estimation bias

One concern with regression estimates of monetary policy rules is a potential bias arising from the endogeneity of the macroeconomic variables. After all, inflation and output are endogenously determined by all structural shocks in the economy, including the monetary policy shock.[11] Recent work by Carvalho et al. (2021) analyzing different types of New Keynesian models suggests that OLS estimates of policy rules may not be affected much by this bias. Nevertheless, one might worry that our estimates of $\hat{\gamma}_t$ might be biased by the *perceived* endogenous response of inflation and output to monetary policy, and therefore do not capture the perceived responsiveness of monetary policy to economic conditions.

One way to address this concern is to try to quantify the bias and adjust for it. We adapt the approach of Carvalho et al. (2021) to our cross-sectional setting to do this; Appendix A.6 shows the details. As expected, we find that the bias-adjusted FE $\hat{\gamma}_t$ is somewhat higher than the baseline FE estimate, with sample means of 0.61 vs. 0.46. This is consistent with the idea that forecasters expect exogenous monetary policy shocks to cause output to contract, biasing down $\hat{\gamma}_t$. However, the bias adjustment leaves the time-series variation in $\hat{\gamma}_t$, our main object of interest, largely unchanged. The last column of Table 2 shows the correlation of the bias-adjusted estimate with our other estimates. The correlation of the FE estimates with and without bias adjustment is 91%.

A structural interpretation of our estimates as coefficients in a perceived policy rule is also supported by our additional evidence, showing that $\hat{\gamma}_t$ responds to monetary policy surprises in a state-dependent, theory-consistent manner (Section 4), and that it explains interest rate responses during narrow intervals around macroeconomic news surprises (Section 5.1). That said, an alternative interpretation of $\hat{\gamma}_t$ as simply the perceived comovement between the policy rate and the macroeconomy is possible, sidestepping the endogeneity concern. Under this interpretation, our results help understand how forecasters learn about this comovement, and how their perceptions are reflected in financial markets.

3 Cyclical shifts in monetary policy perceptions

We now turn to the question of how the perceived monetary policy rule varies across the monetary policy and business cycles. In short, we find that the perceived monetary policy output gap coefficient is higher when the slope of the yield curve is high and during monetary tightening episodes. Conversely, the perceived monetary policy output gap coefficient is low

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

when financial and economic uncertainty are high; it is also weakly lower when the short-term rate is at the ZLB and when unemployment is high.

The cyclical variation in $\hat{\gamma}_t$ that is evident in Figures 2 and 3 suggests that this coefficient captures the data-dependence of monetary policy, which in turn depends on the monetary policy cycle. Fed Chairs and other FOMC members regularly describe monetary tightenings as "data-dependent".[12] By contrast, interest rate cuts are typically quick and unpredictable, as the Fed tries to "get ahead of the curve" or uses "insurance cuts" motivated by the risk management concerns rather than the expected central tendency of economic outcomes.[13] For these reasons, monetary policy may be less dependent on incoming data, and less strongly connected to macroeconomic forecasts, during monetary easing episodes. Anecdotal evidence therefore suggests that cyclical variation in the estimated perceived monetary policy rule is broadly reasonable and in line with actual variation in the Fed's monetary policy rule, even though the actual monetary policy rule may not be fully known.

The Fed's forward guidance naturally plays a key role in driving $\hat{\gamma}_t$ since the perceived rule is based on forward-looking information. The impact of forward guidance depends on the specific type of guidance. Forward guidance that publicly commits the Fed to a future policy action regardless of incoming economic data ("Odyssean" in the terminology of Campbell et al. (2012)) should lower $\hat{\gamma}_t$. By contrast forward guidance that forecasts future economic data and associated monetary policy actions ("Delphic"), should raise perceived data dependence and hence $\hat{\gamma}_t$. During the 2003-2006 tightening cycle, for instance, forward guidance was closely linked to economic fundamentals, which were described as requiring "some further (measured) policy firming" in 2005 and 2006. We accordingly estimated high values of $\hat{\gamma}_t$ during this period, as well as during the period surrounding liftoff from the ZLB in 2015.[14] By contrast, the FOMC's unconditional, calendar-based forward guidance during 2011-2012 led to a disconnect between the economic outlook and policy rate forecasts over

[12] Among many other examples, see, Janet Yellen's 12/2/2015 speech "The Economic Outlook and Monetary Policy".

[13] For example Reuters reported in 2019: "In July 1995, industrial production and job creation were slowing and new unemployment claims were rising. Though Fed policymakers at the time did not believe the data meant a recession was coming, they did not want to wait to find out. They cut rates three times." (Reuters, 8/1/2019, With Fed's 'insurance' cut, Powell takes cue from Greenspan). See also Bernanke (2022) for the historical role of "insurance cuts" since the mid-1990s.

[14] Our interpretation of the tightening cycle 2003-2006 differs from Lunsford (2020). While he interprets this as a period of relatively data-independent commitment to future interest rates, we estimate the perceived data dependency $\hat{\gamma}$ to be high. Our estimates are backed up by a strong response of interest rates to output gap relevant macroeconomic news during this period, noted at the time by then-Governor Ben Bernanke: "Because of the FOMC's communication strategy, which has linked future rate changes to the levels of inflation and resource utilization (...), markets have responded to recent data on payrolls, spending, and inflation by bringing forward a considerable amount of future policy tightening into current financial conditions." (May 20, 2004, Remarks by Governor Ben S. Bernanke).

the relevant horizons. This type of "Odyssean" forward guidance, also initiated in March 2020 in response to the COVID-19 pandemic, was accompanied by low estimates of $\hat{\gamma}_t$.

We now use regression analysis to better understand the cyclical behavior of $\hat{\gamma}_t$. We start in column (1) of Table 3 by regressing $\hat{\gamma}_t$ onto the slope slope of the yield curve, which we measure as the second principal component of Treasury yields. We use a one-month lead of $\hat{\gamma}_t$ to account for publication lags. We have found that lagged values of the slope are much more strongly correlated with $\hat{\gamma}_t$, so the slope is lagged by one year in these regressions. The relationship is economically and statistically very significant and indicates that $\hat{\gamma}_t$ is high during tightening cycles. An upward-sloping yield curve corresponds to an accommodative stance of monetary policy (Rudebusch and Wu, 2008) and signals expectations that short-term rates are going to rise in the future. Thus, going forward, a monetary tightening cycle is about to unfold, which are times when forecaster perceive policy rates to be closely related to the state of the economy, and $\hat{\gamma}_t$ is high. By contrast, the yield curve is flat or inverted and its slope low after a series of rate hikes, when there is little room to tighten further. Before and during the next easing cycle, $\hat{\gamma}_t$ is low and the fed funds rate perceived to be less sensitive to the state of the economy.[15]

We further drill into the relationship between $\hat{\gamma}_t$ and the monetary policy cycle in column (2), where we use indicator variables for episodes of monetary tightening and easing. We define these indicator variables as equal to one during months from the first to the last change in the fed funds rate of either tightening or easing cycles. The estimates in column (2) of Table 3 confirm that $\hat{\gamma}_t$ tends to be significantly elevated during tightening cycles. There is no additional explanatory power distinguishing easing cycles from periods when monetary policy is neither tightening nor easing.

It is well-known that the slope of the yield curve predicts economic activity, so it is important to control for the unemployment rate to disentangle variation in $\hat{\gamma}_t$ over the monetary policy cycle from business cycle variation. Column (3) of Table 3 shows that the unemployment rate has a negative relationship with $\hat{\gamma}_t$, consistent with the view that monetary policy is perceived to be more sensitive to economic data during expansions. However, this relationship is insignificant for the panel FE estimate, and the R^2 is generally much smaller than for regressions on the slope of the yield curve. In multivariate regressions, such as the one shown in column (7), the coefficient on the unemployment rate is weakly significant, while the coefficient on the lagged yield curve slope is very strongly statistically significant. Hence, while the perceived monetary policy rule is more data dependent in business cycle

[15]In Table 3, we think of the slope of the yield curve as primarily capturing the expected path of short-term rates, even though it also includes a risk premium (Campbell and Shiller, 1991). In unreported results, we find equally strong correlations with measures of the slope based on shorter-term rates, which are less strongly affected by risk premia. We investigate bond risk premia in detail in Section 5.2.

Table 3: Explaining changes in policy rule perceptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: FE $\hat{\gamma}$							
Slope (12m lag)	0.12***						0.17***
	(0.03)						(0.04)
Tightening		0.24***					
		(0.08)					
Easing		0.01					
		(0.08)					
Unemployment rate			−0.03				−0.07**
			(0.02)				(0.03)
ZLB				−0.11			−0.04
				(0.11)			(0.13)
VIX					−0.01***		−0.01
					(0.005)		(0.004)
Macro uncertainty						−1.53***	
						(0.53)	
Constant	0.23***	0.39***	0.66***	0.49***	0.71***	1.84***	0.70***
	(0.06)	(0.06)	(0.14)	(0.05)	(0.10)	(0.50)	(0.16)
R^2	0.15	0.10	0.03	0.02	0.10	0.06	0.34
Panel B: SSM $\hat{\gamma}$							
Slope (12m lag)	0.05***						0.08***
	(0.02)						(0.02)
Tightening		0.11**					
		(0.04)					
Easing		−0.04					
		(0.04)					
Unemployment rate			−0.03**				−0.03*
			(0.01)				(0.02)
ZLB				−0.11*			−0.09
				(0.07)			(0.08)
VIX					−0.01***		−0.01***
					(0.002)		(0.002)
Macro uncertainty						−1.10***	
						(0.35)	
Constant	0.23***	0.32***	0.50***	0.36***	0.51***	1.32***	0.52***
	(0.04)	(0.03)	(0.08)	(0.02)	(0.05)	(0.33)	(0.09)
R^2	0.11	0.11	0.07	0.07	0.17	0.11	0.41
N	432	432	432	432	420	432	420

Regressions for $\hat{\gamma}_t$ in monthly data from January 1985 to January 2021. Top panel shows results for the panel fixed effects (FE) estimate of $\hat{\gamma}_t$, bottom panel for the state-space model (SSM) estimate of $\hat{\gamma}_t$. *Slope*: slope of the yield curve measured as the second principal component of Treasury yields from Gürkaynak et al. (2007), lagged by twelve months; *Tightening* and *Easing*: indicator variables for the months from the first to the last change in the fed funds rate of monetary tightening or easing cycles; *Unemployment rate*: civilian unemployment rate from FRED; *ZLB* is an indicator variable for zero lower bound periods; *VIX*: CBOE S&P 100 Volatility Index; *Macro uncertainty*: 12-month-ahead macro uncertainty from Jurado et al. (2015). Regressions use a one-month lead of $\hat{\gamma}_t$ to account for the publication lag. Newey-West standard errors using 12 lags in parentheses.

expansions than contractions, the monetary policy cycle appears to be more important.

One reason that the perceived monetary policy rule might decouple from the business cycle is the ZLB. Column (4) shows that during periods when the Fed's policy rate is at the ZLB, estimates of $\hat{\gamma}_t$ tend to be somewhat lower than average. The association is rather weak because it mixes two types of ZLB periods. During periods when there is strong, unconditional forward guidance, such as during 2011–2013 and in 2020, $\hat{\gamma}_t$ drops to zero because the Fed essentially commits to severing the link between the policy rate and economic conditions. During ZLB periods without such forward guidance, however, such as 2009–2010, $\hat{\gamma}_t$ is quite elevated, as the Fed is expected to lift off from the ZLB soon.[16]

Finally, we include indicators of economic and financial uncertainty to account for the possibility that the Federal Reserve pays attention to the full distribution of potential economic and financial outcomes, which may weaken their response to the most likely path of events. Indeed there exists long literature arguing that the optimal monetary policy response to economic indicators should depend on economic uncertainty and to some extent on credit conditions (e.g., Sack, 2000; Aoki, 2003; Svensson and Woodford, 2003; Gertler and Karadi, 2011). In a related paper, Cieslak et al. (2022) study how policymakers' uncertainty impacts the level of the policy rate, whereas our analysis suggests that greater economic and financial uncertainty can also impact how the policy rate responds to the output gap. Columns (5) and (6) of Table 3 show that the perceived monetary policy output gap coefficient $\hat{\gamma}_t$ is lower when financial uncertainty and economic uncertainty are high, with economically meaningful R^2s.[17] Of course, these are likely to be episodes when the Fed is easing the stance of monetary policy, so this provides additional color on the relationship between the perceived monetary policy output coefficient and the monetary policy cycle. In the multivariate regression in column (8), the slope of the yield curve remains economically and statistically significant, while the VIX also retains some significance. One explanation for this finding is that the Fed is perceived to cut rates aggressively in the face of deteriorating financial conditions, causing it to put less weight on the economic outlook, consistent with a "Fed put" (Cieslak and Vissing-Jorgensen, 2021).[18]

[16] If we estimate the perceived policy rule using the 2-year nominal Treasury rate rather than the fed funds rate, the perceived coefficient looks very similar and only drops in 2011. See Appendix A.3.

[17] We use the CBOE S&P 100 Volatility Index (series VXOCLS on FRED) because a longer time series is available. We have found similar results using other measures like the VIX. We use the macro uncertainty measure from Jurado et al. (2015), but we have found similar results for many other measures.

[18] Our results in Table 2 show that including forecasters' expectations of financial conditions in our FE estimation procedure does not qualitatively change our estimates of $\hat{\gamma}_t$, while our results here show that the estimated $\hat{\gamma}_t$ itself tends to vary with realized financial conditions.

4 Belief updates and monetary policy actions

What drives changes over time in the perceived monetary policy rule? We next show that the perceived rule responds to high-frequency monetary policy surprises on FOMC announcement dates, consistent with the idea that forecasters have imperfect information and update their views based on policy decisions. Under the typical assumption that changes in market rates around FOMC announcements are mainly due to the monetary policy announcement itself, they reflect the surprise component of the monetary policy actions. This surprise component combines pure monetary policy shocks and—to the extent that the markets do not have full information about the monetary policy rule—news about the Fed's response to economic data (see also Bauer and Swanson, 2021, 2022).

The idea that economic agents do not have full information about the Fed's monetary policy rule has testable implications. In particular, the perceived rule should be expected to update in a state-contingent manner after monetary policy surprises. Intuitively, a tightening surprise in an economic boom suggests that the Fed is even more committed to reigning in an overheating economy than previously believed. Therefore, this kind of surprise should lead to an increase in $\hat{\gamma}_t$. By contrast, a tightening surprise during a recession would signal less Fed concern with output stabilization, so forecasters would tend to revise downward $\hat{\gamma}_t$. This logic is formalized in our model in Section 6 below.

We empirically investigate belief updating by studying the evolution of $\hat{\gamma}_t$ in response to monetary policy surprises, calculated from changes in high-frequency money market futures rates around FOMC announcements (following Gürkaynak et al., 2005; Nakamura and Steinsson, 2018, and many others). We follow Bauer and Swanson (2022) and measure the monetary policy surprise, mps_t, as the first principal component of 30-minute changes in several Eurodollar futures rates around the FOMC announcement. This measure, which is available from 1988 to 2019, captures changes in policy rate expectations over a horizon of about a year, and thus includes changes in forward guidance. We normalize the surprise to have a unit effect on the four-quarter-ahead Eurodollar futures rate, measured in percentage points. We convert the announcement-frequency surprises to a monthly series by summing them if there is more than one announcement during a month, and setting $mps_t = 0$ if there are no announcements during month t, following Gertler and Karadi (2015) and others.

We estimate the following state-dependent local projection regressions:

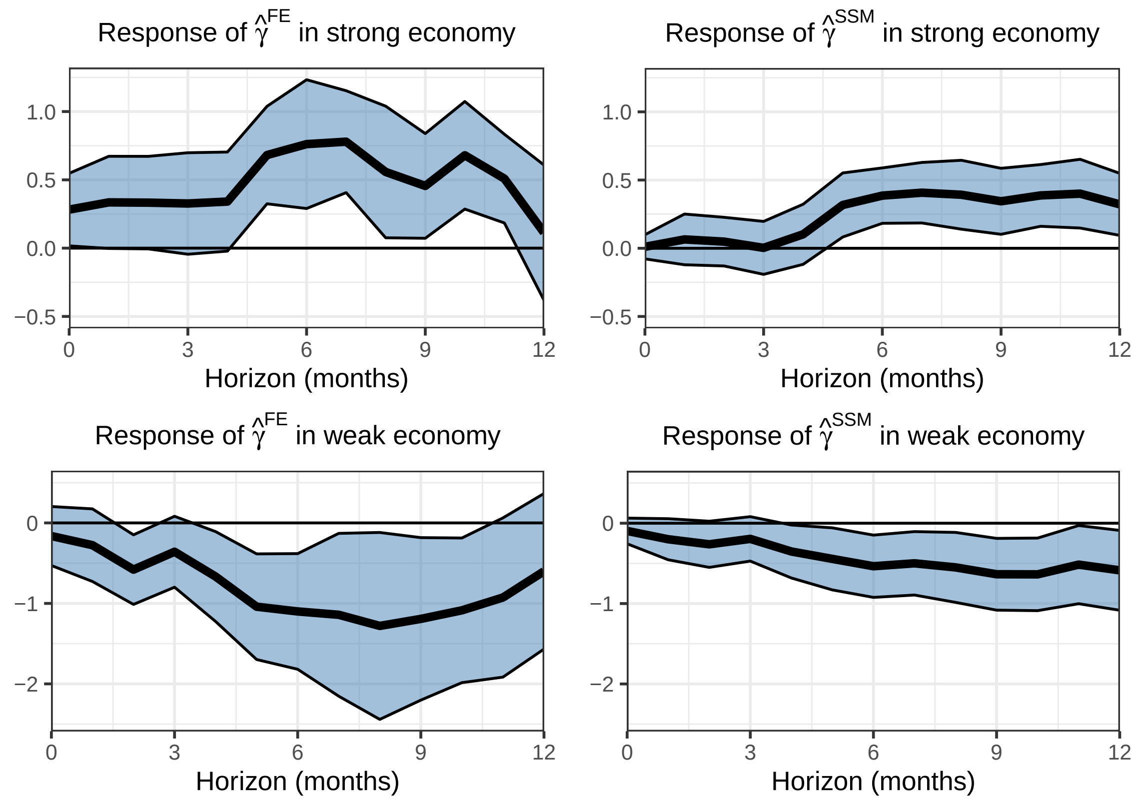
$$\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}, \qquad (5)$$

and calculate Newey-West standard errors with $1.5h$ lags.[19] To capture episodes when the

[19]Our estimation method for state-dependent local projections using identified shocks largely follows

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 zero otherwise.[20] The regressions control for lagged $\hat{\gamma}_t$ to account for serial correlation in the perceived policy rule coefficient. We estimate these local projections for horizons h from zero to twelve months. The sample period is from January 1988 to December 2019.

Figure 4: Response to high-frequency monetary policy surprise



State-dependent local projections for $\hat{\gamma}_t$, using regressions $\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)} \hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where mps_t is the monetary policy surprise, and $weak_t$ 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 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: monthly data January 1988-December 2019.

The impulse responses of the perceived monetary policy coefficient are shown in Figure 4, 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 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

Ramey and Zubairy (2018).

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

show that there is a pronounced and persistent positive response of $\hat{\gamma}_t$ to monetary policy surprises 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 reverses in the bottom panels, which show persistently negative responses when the economy is weak. These responses are roughly symmetric. 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. The magnitudes in Figure 4 are economically meaningful relative to the standard deviation of $\hat{\gamma}_t$ ($SD(\hat{\gamma}^{FE}) = 0.3$ and $SD(\hat{\gamma}_t^{SSM}) = 0.2$). Consistent with the pronounced differences in the estimated responses in the top and bottom panels, Appendix C shows that the interaction effect $mps_t \times weak_t$ is statistically significant.

Overall, the evidence in this section suggests that even a relatively sophisticated set of forecasters do not know the monetary policy rule, and update their beliefs about the rule after monetary policy surprises. Their updating about the monetary policy rule depends on the state of the economy, as would be expected if monetary policy surprises are informative about the Fed's response to economic data. In addition, it is worth noting that the perceived responsiveness $\hat{\gamma}_t$ updates gradually over the six months following monetary policy surprises.[21] We further explore this gradual updating in the model in Section 6.

5 Transmission to financial markets

Having examined the drivers of variation in the perceived monetary policy rule, we next show that the perceived monetary policy rule affects the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates.

5.1 Interest rate sensitivity to macroeconomics news

We start by examining high-frequency responses of interest rates to macroeconomic news. In particular, we show that interest rates respond more strongly to macroeconomic news, such nonfarm payroll surprises, when the estimated $\hat{\gamma}_t$ is high.

We estimate event-study regressions of the form

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

where Δy_t is change in yield y on announcement date t and Z_t is a macroeconomic an-

[21] We similarly find that the perceived monetary policy rule follows the Fed's own perceived rule, estimated analogously from the cross-section of the Survey of Economic Projections, with a lag. See Appendix A.8.

nouncement surprise (i.e., the realized announcement value relative to survey expectations of the announcement the day before). 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 Hamilton et al. (2011), Law et al. (2020) and Swanson and Williams (2014).

Our regression specification in equation (6) is closely related to the empirical setup of Swanson and Williams (2014), who also document time variation in the high-frequency responses of financial market variables to macroeconomic news announcements. Like them, we rely on the identification assumption that the information released during narrow intervals around macroeconomic announcements is primarily about the macroeconomy, and that interest rates responses reflect the anticipated Fed response to this macroeconomic news. The key difference is that Swanson and Williams (2014) allow the magnitude of the response to vary over time in an unrestricted fashion, while we directly tie it to our estimate of the perceived monetary policy rule. Specifically, a positive interaction coefficient b_3 reveals 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 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). The left four columns in Table 4 use the single most influential macroeconomic announcement, nonfarm payroll surprises, as Z_t. The right four columns use a linear combination of all macroeconomic surprises. Following Swanson and Williams (2014), this linear combination is simply the fitted value of the regression of the high-frequency interest rate change on all macroeconomic news. In Table 4, panel A reports results for the FE estimate of $\hat{\gamma}_t$, while panel B uses the SSM estimate.

Table 4 shows that our coefficient of interest, b_3, is uniformly estimated to be positive and highly statistically significant across all combinations of interest rates, macroeconomic news, and estimates of $\hat{\gamma}_t$.[22] The magnitudes are economically meaningful. In particular, the coefficient b_3 in the bottom-right panel for the 6-month fed funds futures rate is statistically indistinguishable from 2. This is exactly the expected magnitude because Z_t is the fitted value of interest rate surprises onto macroeconomic news, implying that a regression of Δy_t onto Z_t alone would yield a coefficient of one, and because $\hat{\gamma}_t \approx 0.5$ on average.[23]

[22]The only exception is the 3-month fed funds futures, potentially because a 3 month forecast horizon is substantially shorter than the Blue Chip forecast horizons.

[23]The coefficient b_2 is estimated to be positive. Such a positive coefficient would be expected if $\hat{\gamma}^{SSM}$ has a negative, but roughly time-invariant, bias (see Section 2.6). Because we mainly focus on time variation in $\hat{\gamma}_t$, this constant bias is unlikely to affect our main findings.

Table 4: Sensitivity of interest rates to macroeconomic news announcements

Panel A: FE

	Z=Nonfarm Payroll				Z=All Announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
$\hat{\gamma}^{FE}$	0.6***	0.5***	0.07	-0.04	0.7***	0.6***	0.3	0.1
	(0.17)	(0.20)	(0.28)	(0.33)	(0.17)	(0.20)	(0.29)	(0.33)
Z	0.03***	0.02***	0.03***	0.01	1.0***	0.7***	0.7***	0.7***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.15)	(0.11)	(0.10)	(0.13)
$\hat{\gamma}^{FE} \times Z$	-0.0009	0.04***	0.05***	0.05***	-0.04	0.6***	0.6***	0.6**
	(0.008)	(0.010)	(0.015)	(0.015)	(0.20)	(0.18)	(0.18)	(0.22)
Const.	-0.4***	-0.3**	-0.3	-0.1	-0.3***	-0.3**	-0.2	-0.05
	(0.11)	(0.13)	(0.17)	(0.20)	(0.11)	(0.13)	(0.17)	(0.20)
N	3350	3350	3350	3350	3350	3350	3350	3350
R^2	0.06	0.07	0.08	0.04	0.10	0.13	0.14	0.09

Panel B: SSM estimate

	Z=Nonfarm Payroll				Z=All Announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
$\hat{\gamma}^{SSM}$	0.8**	0.5	-0.3	-0.5	1.0***	0.6	0.2	-0.2
	(0.33)	(0.43)	(0.54)	(0.61)	(0.33)	(0.42)	(0.53)	(0.61)
Z	0.02**	0.008	0.02*	0.01	0.7***	0.5***	0.6***	0.7***
	(0.009)	(0.008)	(0.012)	(0.012)	(0.19)	(0.13)	(0.13)	(0.16)
$\hat{\gamma}^{SSM} \times Z$	0.03	0.09***	0.10***	0.07**	0.9*	1.6***	1.3***	0.9**
	(0.022)	(0.024)	(0.032)	(0.031)	(0.51)	(0.39)	(0.34)	(0.41)
Const.	-0.3***	-0.2	-0.1	0.05	-0.3***	-0.2	-0.06	0.08
	(0.12)	(0.16)	(0.21)	(0.25)	(0.12)	(0.15)	(0.21)	(0.25)
N	3350	3350	3350	3350	3350	3350	3350	3350
R^2	0.06	0.07	0.08	0.04	0.10	0.13	0.14	0.09

Estimates of 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 nonfarm 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. Robust standard errors are reported in parentheses.

Overall, the evidence in Table 4 suggests that the perceived monetary policy rule is priced in financial markets. Changes in the perceived rule help explain the strength of interest rate responses to macroeconomic news, consistent with the idea that a well-communicated rule can "do the central bank's work for it" (Woodford, 2005), moving the expected path of rates in response to economic developments before the Fed changes the actual policy rate.

It seems plausible that there is no information about monetary policy shocks in narrow time intervals around nonfarm payroll and other macroeconomic news announcements. If one were concerned that our estimated $\hat{\gamma}_t$ primarily captures the perceived endogenous economic response to monetary policy shocks, interest rate movements during these narrow intervals should therefore be unrelated to $\hat{\gamma}_t$. By contrast, in the data high-frequency interest rate responses to macroeconomic news scale up with $\hat{\gamma}_t$. These high-frequency responses therefore help address endogeneity concerns and support the interpretation of $\hat{\gamma}_t$ as predominantly reflecting changes in the monetary policy rule.

5.2 Term premia in long-term interest rates

In this section, we show that term premia in long-term bonds vary with perceptions about the monetary policy rule. Concretely, we find that $\hat{\gamma}_t$ is negatively related to subjective expected bond excess returns, as one would expect if a higher value of $\hat{\gamma}_t$ means that investors believe that the Fed is more responsive to the economy, making Treasury bonds better macroeconomic hedges. Term premia are a key component of monetary policy transmission because they drive a wedge between the expected path of short-term policy rates and long-term rates, which matter for much of the borrowing in the economy. Whereas term premia are often viewed as outside the reach of traditional monetary policy, our evidence suggests that they are linked to monetary policy through perceptions of the policy rule, in line with the more structural analysis of Bianchi et al. (2022a).

The intuition that $\hat{\gamma}_t$ should be inversely related to expected bond excess comes from basic asset pricing logic: Assets that pay out in bad states of the world should require lower expected returns. A higher perceived monetary policy coefficient $\hat{\gamma}_t$ means that interest rates are expected to fall more—and bond prices are expected to rise more—during recessions. Thus, when $\hat{\gamma}_t$ is high, bonds are better hedges and should have lower expected returns.[24]

We construct subjective expected one-year excess returns on 6- and 11-year Treasury bonds similarly to Cieslak (2018), Piazzesi et al. (2015), and Nagel and Xu (2022).[25] We

[24]These predictions are worked out in detail in Campbell et al. (2017), Campbell et al. (2020), and Pflueger (2022), for example. The link between $\hat{\gamma}_t$ and subjective bond risk premia does not rely on the interpretation of $\hat{\gamma}_t$ as a perceived monetary policy rule coefficient, and remains valid if $\hat{\gamma}_t$ simply captures the perceived comovement of interest rates and the economy.

[25]Our preferred measure of expected bond excess returns is the subjective expected excess return inferred from Blue Chip surveys because realized returns are a noisy realization of expected returns. Forecasting regressions with realized rather than expected Treasury bond excess returns are reported in the Appendix

Table 5: Expected bond risk premia

	$\bar{E}_t xr^{(6)}_{t+12}$			$\bar{E}_t xr^{(11)}_{t+12}$		
$\hat{\gamma}^{FE}$	-0.70***	-0.78***	-0.81***	-1.12***	-1.26***	-1.18***
	(0.16)	(0.18)	(0.10)	(0.37)	0.40)	(0.18)
TERM		0.33			0.54	
		(0.21)			(0.36)	
R^2	0.15	0.19	0.64	0.13	0.16	0.62
$\hat{\gamma}^{SSM}$	-0.44**	-0.46**	-0.68***	-0.75	-0.79	-1.02***
	(0.22)	(0.23)	(0.11)	(0.49)	(0.49)	(0.19)
TERM		0.21			0.35	
		(0.22)			(0.36)	
R^2	0.06	0.08	0.58	0.06	0.07	0.59
PCs	No	No	Yes	No	No	Yes

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

proxy for the expected 5-year Treasury bond par yield $\bar{E}_t y^{(5),par}_{t+12}$ using the average Blue Chip survey forecast of the 5-year Treasury bond yield at the 4-quarter forecast horizon. Because Blue Chip forecasters forecast par yields, we use the par yield on a 6-year Treasury bond from Gürkaynak et al. (2007), $y^{(6),par}_t$, to compute expected returns. Blue Chip forecasters are required to submit their responses at the end of the previous month, so to make sure the information sets are consistent we pair the March survey with the end-of-month par yield at the end of February. Letting $y^{(1)}_t$ denote the one-year zero-coupon yield, we then compute the one-year expected excess return on the 6-year Treasury bond as

$$\bar{E}_t xr^{(6)}_{t+12} \quad = \quad Dur^{(6)} y^{(6),par}_t - (Dur^{(6)} - 1)\bar{E}_t y^{(5),par}_{t+12} - y^{(1)}_t. \tag{7}$$

The duration of the 6-year par bond, $Dur^{(6)}$, is estimated from bond yields, assuming that bonds sell at par (Campbell et al., 1996, p. 408). The expected one-year excess return on a

and further support a negative relationship between $\hat{\gamma}_t$ and objective expected Treasury bond excess returns.

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

$$\bar{E}_t xr_{t+12}^{(n)} = b_0 + b_1\hat{\gamma}_t + b_2 TERM_t + \varepsilon_t, \tag{8}$$

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

Table 5 reports the results. Starting with the first column in panel A, we see that the coefficient on $\hat{\gamma}_t$ is indeed negative and statistically significant, as would be expected if higher values of $\hat{\gamma}_t$ mean that investors expect bonds to be better hedges. The magnitudes are economically meaningful. A one-standard deviation increase in $\hat{\gamma}_t$ is associated with a 0.7 percentage point decline in the expected excess return on a six-year Treasury bond over the next year. The term spread in the second column, by contrast, does not enter significantly, consistent with the findings in Nagel and Xu (2022). In the third column, we control for the first three principal components of the term structure, which increases the R^2 substantially but leaves the coefficient on $\hat{\gamma}_t$ unchanged. The right three columns in panel A show analogous results for the expected one-year returns on 11-year Treasuries, finding similar results with even larger point estimates. Panel B shows similar results when we use the state-space model estimate for $\hat{\gamma}_t$. In this case, the expected excess return for the 6-year Treasury always loads negatively and significantly on $\hat{\gamma}_t$, and the expected excess return for the 11-year Treasury loads always negatively but only sometimes statistically significantly.[26]

We have analyzed *subjective* bond risk premia because the focus of our paper is on perceptions and the expectations of professional forecasters. But there is a long tradition of estimating *objective* (or statistical) risk premia using predictive regressions for excess bond returns (e.g., Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005). The results in Appendix D.1 show that the Fed's perceived responsiveness, $\hat{\gamma}_t$, predicts excess returns with a negative sign, controlling for the usual predictors including the slope of the yield curve. In sum, our evidence shows that the perceived policy rule is related to both subjective and objective bond risk premia in a way consistent with standard finance theory.

A simple back-of-the-envelope calculation illustrates the quantitative importance of this channel for long-term yields. Conditional on a strong economy, the top-right panel in Figure 4 shows that a 10 bps positive monetary policy shock leads to an increase in the SSM estimate of $\hat{\gamma}_t$ of 0.04—or 0.2 standard deviations—with a peak response six months after the shock. The last column in panel B of Table 5 shows that an increase in $\hat{\gamma}_t$ of this magnitude is associated with a $0.2 \times -0.68 = -0.136$ percentage point decrease in the subjective risk premium for a 6-year Treasury. A 10 bps surprise *increase* in the policy shock during good

[26]Appendix D.2 shows that the relationship between expected bond excess returns and $\hat{\gamma}_t$ is unchanged when we control for interest rate disagreement following Giacoletti et al. (2021).

times could therefore lead to a comparably large *decrease* in the term premium of the 6-year Treasury. Thus, this channel suggests a new explanation for why long-term bond yields may decouple from the short-term policy rate during some tightening cycles.

6 Illustrative model with learning and heterogeneity

We now present a simple model featuring heterogeneity across forecasters and learning that delivers three key points. First, it characterizes the simplest conditions under which the cross-section of forecasts can be used to estimate the perceived monetary policy rule, i.e., our estimation procedure is valid. Second, it rationalizes a number of our empirical results. Third, it provides a way to quantitatively assess the importance of uncertainty about the monetary policy rule in explaining high-frequency monetary policy surprises.

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

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

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

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

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

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

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

$$E^j\left(\gamma_1 \left| \mathcal{Y}_0 \right.\right) \;=\; \hat{\gamma}_0^j,\; Var^j\left(\gamma_1 \left| \mathcal{Y}_0 \right.\right) = \sigma_0, \tag{12}$$

where $\mathcal{Y}_t$ denotes the filtration based on observing the output gap and interest rates up to and including time t. Throughout, we use the operator $\bar{E}$ to denote average expectations across all forecasters j. We use $\hat{\gamma}_t$ to denote $\bar{E}\left(\gamma_{t+1} \left| \mathcal{Y}_t \right.\right)$ and $\hat{\gamma}_t^j = E^j\left(\gamma_{t+1} \left| \mathcal{Y}_t \right.\right)$.

In each period, forecasters first observe a noisy signal about the output gap $\nu_t^j = x_t + \eta_t^j$, where $\eta_t^j \sim N(0, \sigma_\eta^2)$ is uncorrelated with forecasters' time-0 priors about the monetary policy rule parameter, $\hat{\gamma}_0^j$. Forecasters then make forecasts of future interest rates and output gaps. After making these forecasts, forecasters observe the period-t output gap. Finally, the Fed sets the policy rate i_t based on the policy rule, and forecasters update their beliefs about γ_t. We interpret the instantaneous interval around observing the output gap as a macroeconomic announcement date, and the instantaneous interval around observing the policy rate as an FOMC announcement date.

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

$$mps_t \equiv i_t - \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, x_t\right.\right) = u_t + (\gamma_t - \hat{\gamma}_t)x_t. \tag{13}$$

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

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

$$\hat{\gamma}_t^j - \hat{\gamma}_{t-1}^j = \hat{\gamma}_t - \hat{\gamma}_{t-1} = \omega_t \frac{mps_t}{x_t}, \qquad \omega_t \equiv \frac{\sigma_t^2}{\sigma_t^2 + \sigma_u^2/x_t^2}. \tag{14}$$

Belief uncertainty is the same for all forecasters:

$$Var^j\left(\gamma_{t+1} \left| \mathcal{Y}_t\right.\right) \equiv \sigma_{t+1}^2 = \sigma_t^2(1-\omega_t) + \sigma_\xi^2. \tag{15}$$

The proof follows directly from the Kalman filter. Because all forecasters have the same prior dispersion, they update their perceived monetary policy coefficients in lockstep. Thus, forecaster j's perceived monetary policy rule coefficient can be expressed as the consensus coefficient plus a forecaster fixed effect. We derive several corollaries from Lemma 1 in order to interpret our empirical results.

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

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

$$E^j\left(i_{t+h} \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) = \alpha_j^0 + g_t E^j\left(x_{t+h} \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right) + \varepsilon_{jht} \tag{16}$$

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

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

$$E^j\left(i_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) = \alpha_j^0+\alpha_j^1 E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)+g_t E^j\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)+\varepsilon_{jht} \quad (17)$$

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

The implication of Corollary 1 is that our estimates in Section 2 recover the average perceived rule coefficient $\hat{\gamma}_t$ despite heterogeneity in forecaster perceptions of the policy rule.

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

a. If we directly observe news about the output gap, then the interaction coefficient in the following regression is predicted to equal $b_3 = 1$:

$$\Delta i_t = b_0 + b_1\hat{\gamma}_t + b_2\Delta x_t + b_3\hat{\gamma}_t\Delta x_t + \varepsilon_t. \quad (18)$$

b. Assume instead that we observe a macroeconomic surprise Z_t proportional to the output gap news $\alpha Z_t = \Delta x_t$, where the constant α is scaled so that the univariate regression of fed funds futures surprises onto Z_t equals unity. In the regression

$$\Delta i_t = b_0 + b_1\hat{\gamma}_t + b_2 Z_t + b_3\hat{\gamma}_t Z_t + \varepsilon_t \quad (19)$$

the interaction coefficient is predicted to converge to $b_3 = 1/\bar{\hat{\gamma}}_t$, where $\bar{\hat{\gamma}}_t$ is the full-sample average of $\hat{\gamma}_t$

Corollary 2 provides a model-based interpretation of the macro news results in Section 5.1. It says that the sensitivity of fed funds futures to macroeconomic news should be larger when the perceived monetary policy coefficient $\hat{\gamma}_t$ is high. The scale of this interaction coefficient depends on how much output gap forecasts move in response to a macroeconomic news surprise Z_t. When the news is scaled so that a univariate regression of fed funds futures changes onto Z_t equals unity as in Swanson and Williams (2014), the interaction coefficient is predicted to be $1/\bar{\hat{\gamma}}_t$.[27] The predictions of Corollary 2 are borne out in our empirical regressions in Table 4, both qualitatively and quantitatively. For example, the "All Announcement" columns in panel B, which map most clearly into the model regressions, shows an interaction coefficient b_3 that is statistically indistinguishable from 2.[28] For comparison, the sample average of our FE estimate is about 0.5.

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

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

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

c. In both cases, the revision is immediate and permanent.

Corollary 3 and the related evidence in Section 4 are key to understanding how perceptions of the monetary policy rule evolve. Intuitively, in our model a tightening surprise when the economy is strong suggests that the Fed is more responsive to the output gap than forecasters believed, while a tightening surprise in a weak economy suggests the opposite. This state-dependent response of policy rule beliefs is exactly what we find in Figure 4. However, the model also predicts that these impulse responses should be instantaneous and permanent, in contrast to the gradual empirical responses in the data.

The empirical evidence in Section 4 sheds light on the forecasters' understanding of the policy rule. It helps rule out two alternative scenarios, under which Corollary 3 would no longer hold: (i) an alternative full-information model where forecasters observe γ_t at the beginning of each period; and (ii) the limiting case in which the volatility of the monetary policy shock is very large relative to the uncertainty about the monetary policy coefficient (i.e., $\sigma_u^2 \to \infty$). In both cases, monetary policy surprises are uninformative about γ_t beyond what forecasters already know, and therefore forecasters do not update at all in response.

Furthermore, the model suggests a simple back-of-the-envelope calculation, which implies that the fraction of variation in monetary policy surprises driven by uncertainty about the

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

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

policy rule is large. Equation (14) shows that the amount forecasters update their perceived rule $\hat{\gamma}_t$ following a surprise depends on their uncertainty about the rule (σ_t^2), the volatility of the policy shock (σ_u^2), and the output gap. In the top-left-panel of Figure 4, the peak response of $\hat{\gamma}_t$ to a policy surprise is around 0.7. The output gap is on average 1.4 percentage points above its median during the strong economic times. Substituting $\hat{\gamma}_t - \hat{\gamma}_{t-1} \approx 0.7$ and $x_t \approx 1.4$ into equation (14) and solving for ω_t suggests that forecasters attribute about 50% of the variation in monetary policy surprises to uncertainty about the policy rule.

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

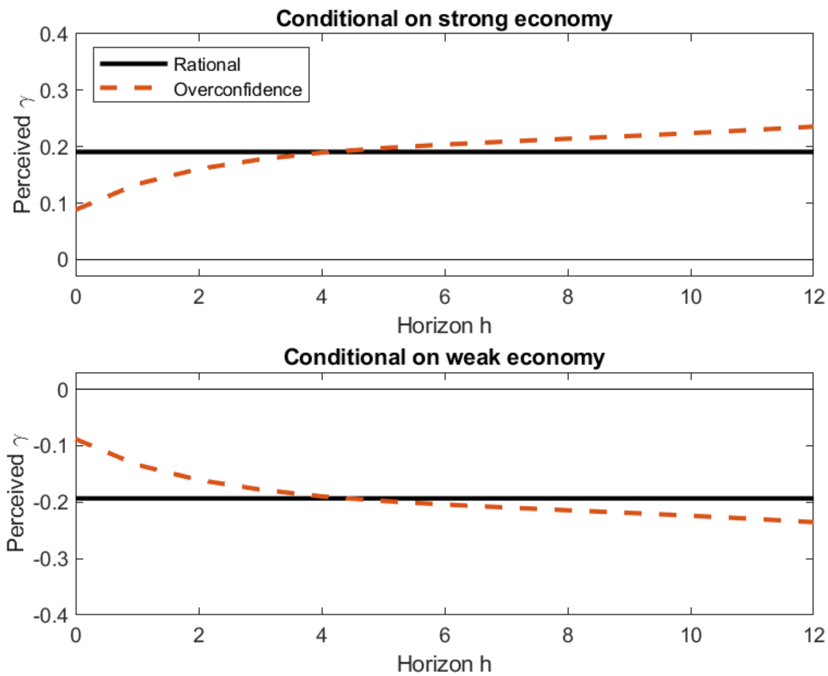
Corollary 4 assumes a simple stochastic discount factor that is consistent with interest rate dynamics and captures the notion that recessions are states of high marginal utility, as in much of the consumption-based asset pricing literature. The only priced shock is the shock to the output gap, ε_{t+1}, and the parameter ψ captures investors' risk aversion. For simplicity, we abstract from inflation so the real and nominal stochastic discount factors are the same. The model then predicts that bond risk premia move inversely with perceived $\hat{\gamma}_t$, consistent with the findings in Table 5.

Only one of our empirical results is not explained by this fully rational framework: the gradual pattern in the response of $\hat{\gamma}_t$ to monetary policy surprises in Section 4. Figure 5 shows that adding a common behavioral bias, overconfidence, can help better fit the data.[29] The black line shows that the immediate, state-contingent responses for $\hat{\gamma}_t$ with rational learning predicted by Corollary 3. The blue dashed line shows that with overconfidence the impulse responses are similar in sign and magnitude, but emerge more gradually. Overconfidence also predicts that policy rate forecast errors, i.e. the realized fed funds rate minus its consensus forecast, should be predictable from past changes in $\hat{\gamma}_t$ interacted with the output gap. We verify this prediction in the data in Appendix B.3.

In sum, our simple model with heterogeneous signals about the output gap and heterogeneous priors about the policy rule explains the key empirical findings in our paper.

[29] A large literature in behavioral economics provides empirical support for overconfidence and slow information diffusion. See, for example, Barberis and Thaler (2003), Coibion and Gorodnichenko (2015), and Angeletos et al. (2021). Formally, we assume that when updating their perceived monetary policy coefficient $\hat{\gamma}_t^j - \hat{\gamma}_t^j$ forecasters overestimate the precision of their estimate $Var^j(\gamma_t | \mathcal{Y}_{t-1}) = \kappa\sigma_t$ for some constant $0 < \kappa < 1$, where σ_t denotes the forecast uncertainty of a rational Bayesian forecaster.

Figure 5: Model impulse responses of perceived monetary policy coefficient



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

7 Conclusion

This paper presents new time-varying estimates of the monetary policy rule perceived by professional forecasters, using the rich panel data on forecasts available each month. With 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 responsiveness of monetary policy to the economy is high during monetary tightening cycles, but low during easing cycles and times of elevated economic and financial uncertainty. Intuitively, the Fed is perceived to be more data-dependent when it is raising the policy rate. Second, following high-frequency monetary policy surprises on FOMC announcement dates forecasters update their estimates of the monetary policy rule, indicating that they perceive monetary policy surprises to be informative in this regard. The way forecasters update depends on the state of the economy, as the same surprise tightening indicates higher responsiveness to the economy in a strong economy and weaker responsiveness in a weak economy. Third, the perceived monetary policy rule affects the transmission of monetary policy to financial markets, explaining the sensitivity of interest rates to macroeconomic news as well as variation in subjective and statistical term premia in long-term interest rates.

Taken together, our evidence suggests that forecasters perceive a highly time-varying monetary policy rule that reflects the Fed's shifting concerns about current economic data versus financial and other risks. Even a relatively sophisticated set of observers appears to learn about the monetary policy rule from observed interest rate decisions. Our results illustrate the promise of further research into how changes in the monetary policy framework affect beliefs about monetary policy and the macroeconomy.

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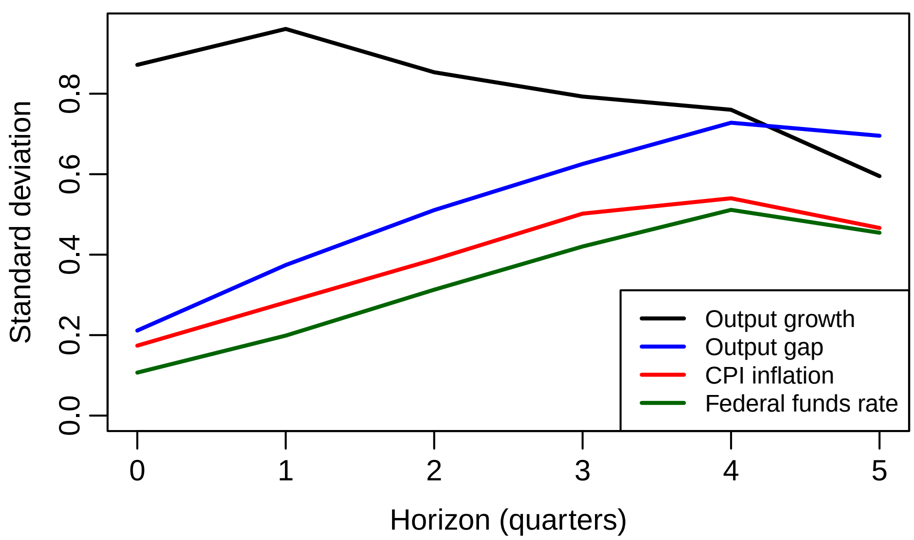
Appendix for Online Publication

A Details and additional results for Section 2

A.1 Term structure of disagreement

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

Figure A.1: Term structure of disagreement



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

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

A.2 Estimation details for state-space model

We use Bayesian estimation for the parameters and state variables, in order to correctly account for uncertainty over both. The parameters to be estimated are π^*, the variances of the state innovations, and the measurement error variance. 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.[30] We use the following Markov chain Monte Carlo (MCMC) algorithm to estimate the model:

1. Initialize the parameters using draws from the prior distributions.

2. Sample π^* using a random walk Metropolis-Hastings step with the states integrated out (i.e., using the Kalman filter to calculate the likelihood).

3. Sample the state variables, conditional on the parameters, using the simulation smoother of Durbin and Koopman (2002).

4. Sample the variance parameters from their conditional posterior distributions using four separate Gibbs steps.

5. Repeat steps (2)–(4) 1,500 times and discard the first 500 draws as a burn-in sample.

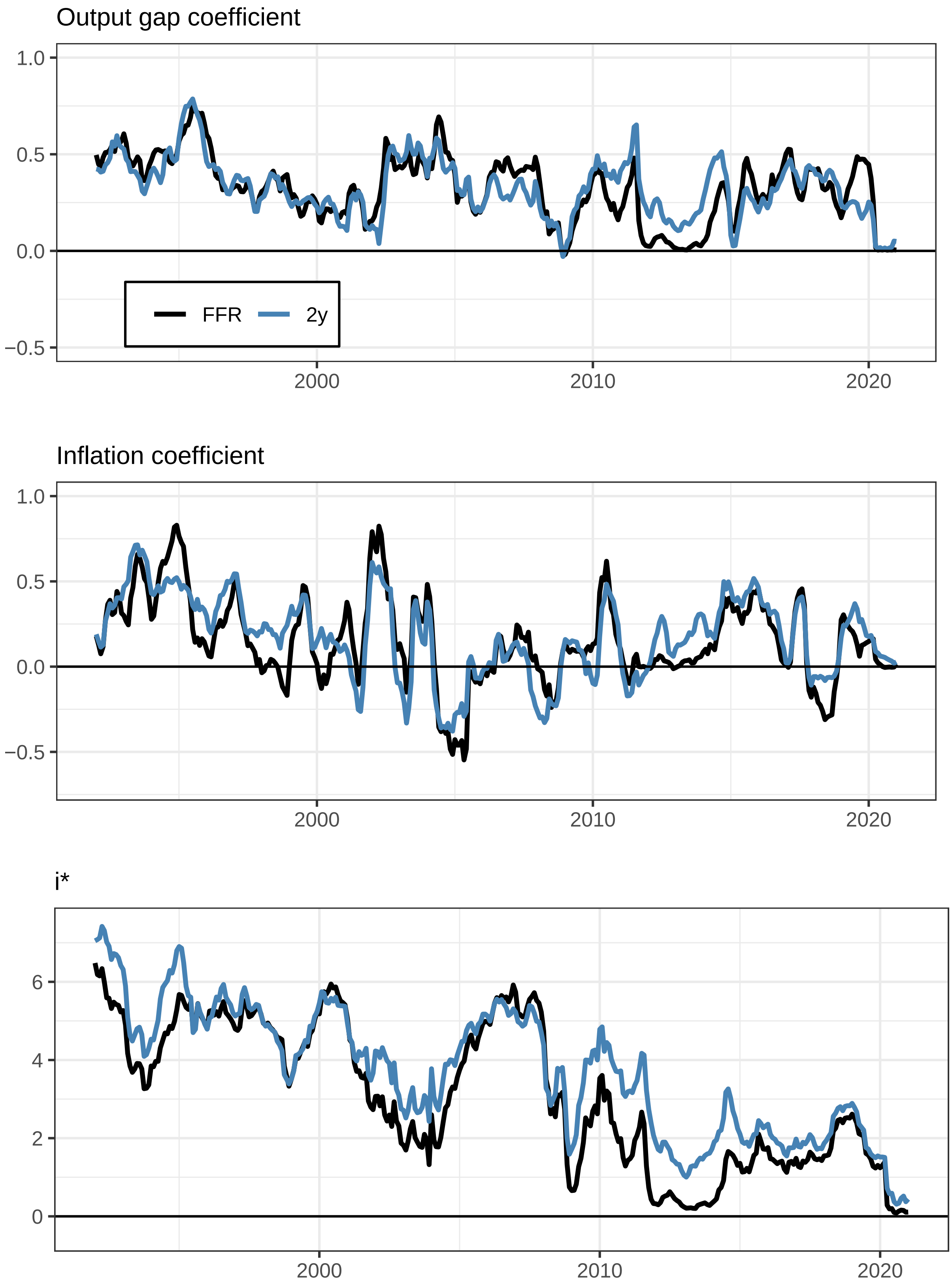
This MCMC sampler is fast and efficient, meaning that there is only modest serial correlation in the sampled chain, and different diagnostic checks indicate that the sampled chain appears to have converged.

A.3 Policy rule for two-year yield

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

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

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



A.4 Robustness: alternative estimates using multidimensional panel

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

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

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

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

The "equal-weighted" estimator is obtained by running

$$E_t^{(j)} i_{t+h} \;\; = \;\; = a_{j,t} + \beta_{j,t} E_t^{(j)} \pi_{t+h} + \gamma_{t,j} E_t^{(j)} x_{t+h} + e_{t,j,h} \tag{A.2}$$

And taking the average of $\gamma_{t,j}$ over j. Figure A.3 reports the estimated equal-weighted average of $\hat{\gamma}_{t,j}$ with confidence intervals based on standard errors clustered by forecaster and month.

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

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

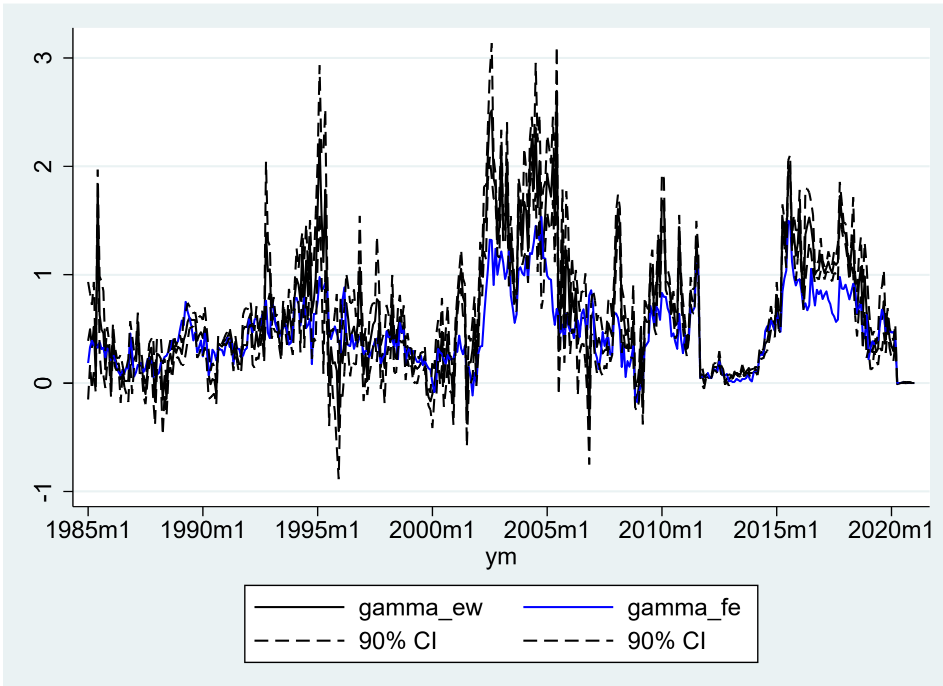
We denote the estimates of γ_t and β_t from this regression, which represent the forecaster-average time-t perceived monetary policy coefficients, as "Heterogeneous". The estimates of b_j and g_j represent the forecaster-specific time-invariant shifters to these perceived monetary policy coefficients, and we do not report them. Note that this estimate does not contain forecaster-by-month fixed effects, so it should be expected to be closer to the Pooled OLS estimate than the baseline FE estimate, which is indeed what we see in Table 2. Because forecaster ID's were reshuffled in 1993, this regression necessarily starts in January 1993.

Next, we split forecasters by the level of their inflation forecast. One might think that hawks vs. doves might perceive different monetary policy rules. The level of the inflation forecast might therefore serve as a signal of whether a particular forecaster or forecasting institution is a hawk or dove, where hawks would typically be expected to be more pessimistic on inflation. We do a very simple split based on forecasters' four-quarter CPI inflation forecast. We first de-mean the inflation forecast every month to make sure that our split captures forecasters who are relatively more hawkish than their peers in a way that is not sensitive to forecasters dropping in and out of the sample. We then compute terciles for this demeaned inflation forecast. Each month, each forecaster is sorted into a tercile depending on his de-meaned four quarter horizon CPI inflation forecast. We then run the estimation with forecaster FE on each of the terciles separately. Because we include the same fixed effects as the baseline FE estimator, only using a different sample, estimates to be most closely correlated with the FE estimate, which is indeed what we see in Table 2.

Finally, we estimate (2) while controlling for forecaster j's period $t+h$ forecast of the Baa-Treasury credit spread, $E_t^{(j)} credit_{t+h}$ in a regression that also includes forecaster fixed effects.

Figure A.4 plots the "Heterogeneity", "Credit Spread", and "Tercile" series underlying the correlations in Table 2. The level of the "Heterogeneous" estimate is different because of the forecaster fixed effect, so we plot it on a second axis for comparability.

Figure A.3: Robustness: Equal-weighted $\hat{\gamma}$ estimates



Alternative estimate of $\hat{\gamma}_t$ that weights forecasters equally ("equal-weighted") used in Table 2. 90% confidence interval based on double-clustered standard errors by forecaster and month for the equal-weighted estimator are shown. We show the baseline FE estimate for comparison.

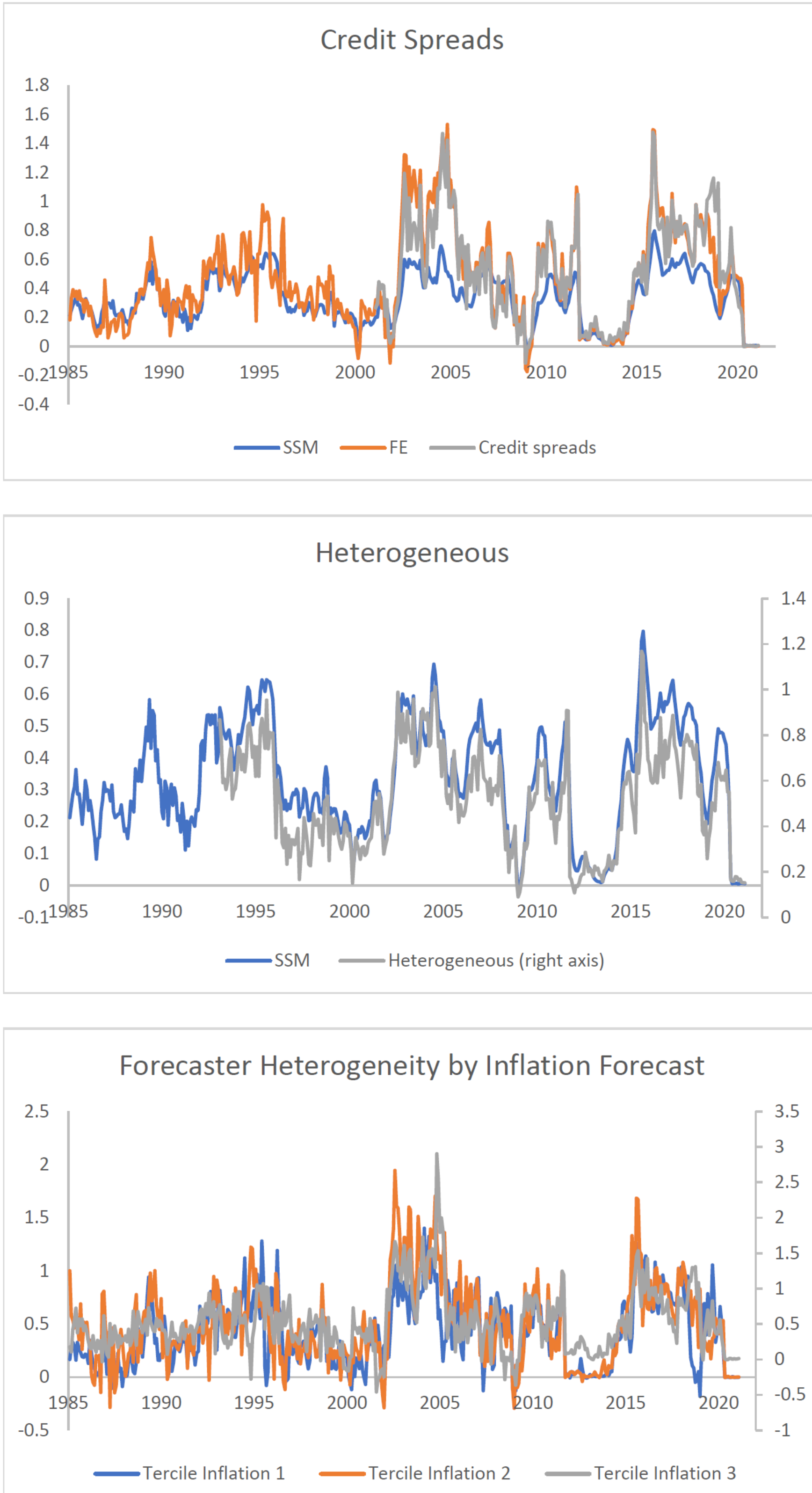
A.5 Inertial rule

To account for the possibility that lagged interest rates matter for the policy rule beyond their influence on output gap and inflation expectations, we estimate an inertial policy rule of the form

$$E_t^{(j)} i_{t+h} = \alpha_t^{(j)} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + \hat{\rho}_t E_t^{(j)} i_{t+h-3} + e_{th}^{(j)}. \tag{A.4}$$

Here, $E_t^{(j)} i_{t+h-3}$ denotes forecaster j's interest rate forecast three months (i.e. one quarter) prior. Figure A.5 plots the results against the FE estimate $\hat{\gamma}$ with the same fixed effects specification. With policy rule inertia, the long-run interest rate response to the output gap is $\frac{\hat{\gamma}}{1-\hat{\rho}}$, which we find 72% correlated with the baseline estimate of $\hat{\gamma}$ with a non-inertial rule. In order to make the ratio well-defined for the small number of observations where $\hat{\rho}$ spikes up, we cap $\hat{\rho}$ above at 0.9. By contrast, $\hat{\rho}$, which is shown in the bottom panel, is completely uncorrelated with our baseline estimate of $\hat{\gamma}$. The perceived inertia looks very intuitive, averaging around 0.6 prior 2000 and then shifting to a higher level of around 0.9 after 2000.

Figure A.4: Robustness: Alternative $\hat{\gamma}$ estimates



Alternative estimates of $\hat{\gamma}_t$ used in Table 2

These results therefore confirm that our baseline estimates reflect a time-varying perceived responsiveness to the output gap, rather than time-variation in the perceived monetary policy inertia.

A.6 Bias adjustment

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

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

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

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

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

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

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

As in our empirical analysis, the focus is on the monetary policy rule's coefficient on the output gap, $\hat{\gamma}$. We can therefore shut down any effects from inflation by setting $\kappa = 0$ so that prices are fixed, following Caballero and Simsek (2022). That is, inflation is zero in equilibrium and $\hat{\beta}\pi_t$ drops out of the monetary policy rule.

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

With these assumptions, we can simply substitute the perceived monetary policy rule

(A.7) into the Euler equation (A.5) and iterate forward to obtain forecaster j's conditional expectations for the equilibrium policy rate and output gap at horizon $t+h$ as:

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

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

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

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

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

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

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

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

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

$Var_t\left(E_t^{(j)}u_{t+h}\right)$ can be solved for exactly as two unknowns from the following two nonlinear equations:

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

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

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

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

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

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

A.7 Robustness: Survey of Professional Forecasters

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

We estimate FE regressions for each quarterly SPF forecaster panel. The estimated coefficient on the unemployment rate forecasts has a correlation of -0.77 with the $\hat{\gamma}_t$ estimates from the BCFF over the period where they are both available. The former is generally about -2 times as large as the latter, consistent with Okun's law. Figure A.7 shows a visual comparison of the two estimates. For the BCFF, it shows the FE point estimates and 95% confidence intervals, as in the top panel of Figure 2. For the SPF, it shows the fitted values from a regression of the BCFF on the SPF estimate, in order to rescale the latter and make the two series comparable. While there is more volatility in the month-to-month BCFF estimates, the cyclical patterns of the two series are generally very similar.

A.8 Comparison with the Fed's rule: A case study

In this section, we compare our estimates of the perceived monetary policy rule from Blue Chip forecasts to direct estimates of the Fed's actual monetary policy rule, which we construct from the cross-section of Fed forecasts in the "Summary of Economic Projections" (SEP). This descriptive comparison supports our findings elsewhere in the paper that the perceived rule behaves reasonably, but also that there are important differences, i.e., that FIRE is violated.

To obtain monetary policy coefficients from the Fed's own forecasts, we use the same panel regression approach as for the Blue Chip data, described in Section 2.3. We construct output gap projections by combining CBO projections for potential output with the those for the level of real GDP implied by the growth forecasts. While there are some differences in the forecast data—such as the sample period, the forecast horizons, and the inflation measure (PCE instead of CPI)—the estimation method remains the same, which allows for a meaningful comparison of the estimates. For comparability with the Blue Chip forecasts, we use only the forecasts for the current and next years. The macro forecasts pertain to the last quarter of each year, and for the inflation and real GDP growth rates are four-quarter percentage changes. For the fed funds rate, the projections are for the end of each year. Due to data availability, we study the years 2012-2016, a period covering the first liftoff from the ZLB and thus including rapid changes in the stance of monetary policy and a strong Fed focus on communicating those changes.[31] For each of 21 forecast releases over the period from 2012 to 2016, we have a panel of 16 to 19 Fed forecasters in the SEP.

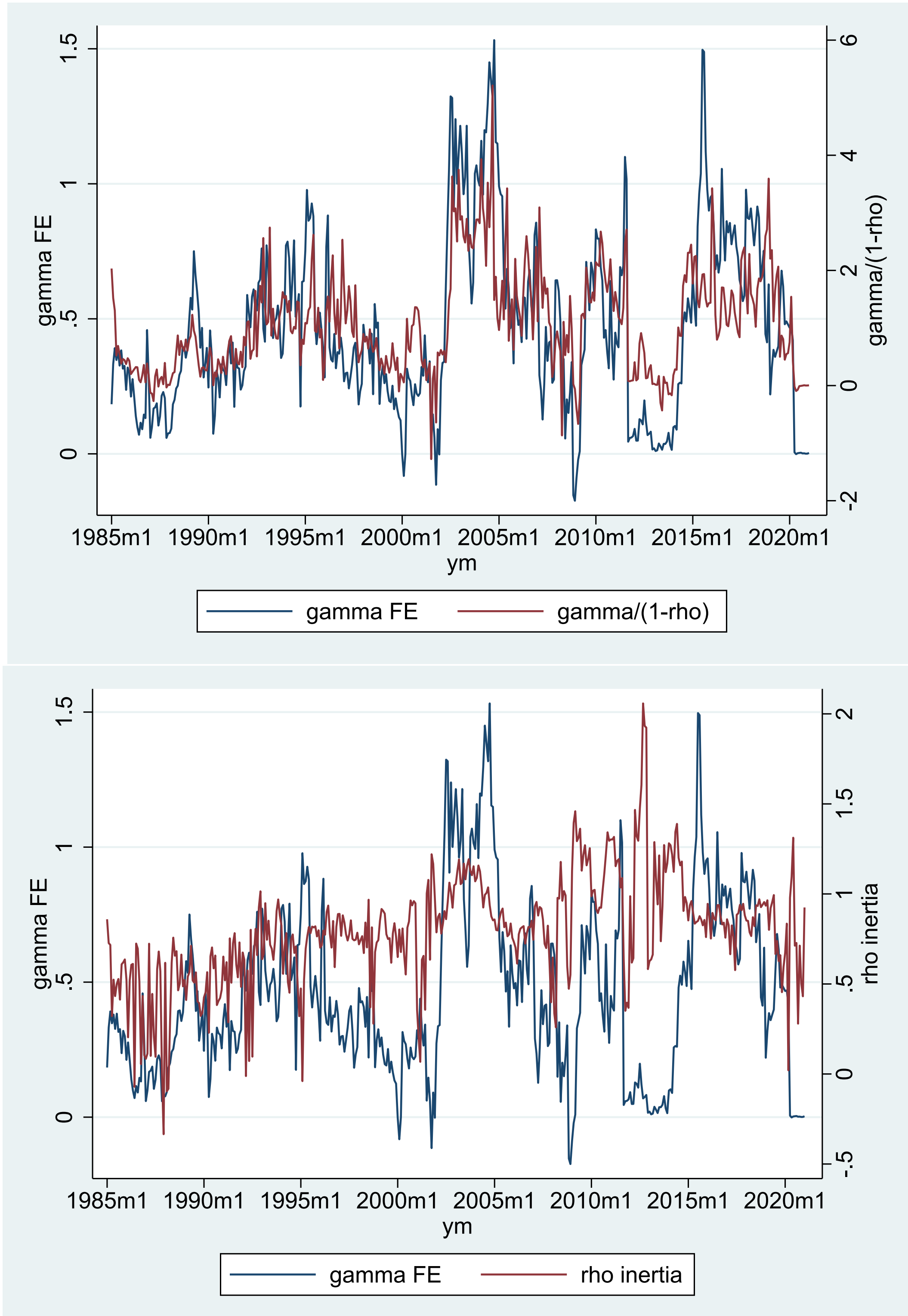
As shown in Figure 2, there were significant fluctuations in the perceived output gap coefficient $\hat{\gamma}$ in the time period around the first ZLB. After both the funds rate and $\hat{\gamma}_t$ decreased to zero in 2008, the $\hat{\gamma}$ quickly rose again and remained at a high level until August 2011. During this period, forecasters generally expected the Fed to lift the policy rate off the ZLB within the next year or so, resulting in a high estimated perceived output gap weight $\hat{\gamma}$. On August 9, 2011, however, the Fed introduced calendar-based forward guidance, predicting a near-zero policy rate "at least through mid-2013." In response, the estimated $\hat{\gamma}$ dropped sharply and stayed near zero until lift-off started to come into view again in spring 2014, suggesting that our estimates pick up on "Odyssean" forward guidance where the Fed predicts and essentially commits to a certain path for the future policy rate (Campbell et al., 2012).

Figure A.8 shows the OLS and FE estimates of γ_t obtained from the FOMC projections (SEP), together with 95% confidence intervals for the FE estimates. It also includes the estimates of the perceived coefficients $\hat{\gamma}_t$ based on the Blue Chip data for the time period where both are available. The date of actual liftoff is indicated with a vertical line. We see that the perceived output gap coefficient as estimated from Blue Chip forecasts captures well

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

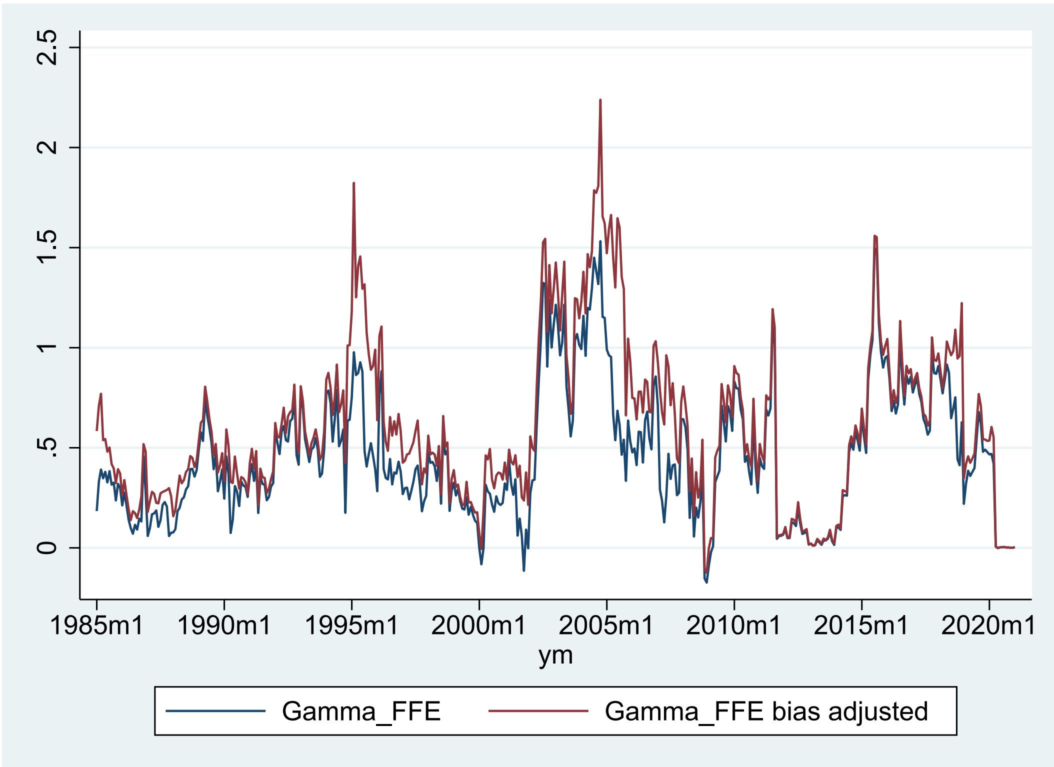
the change in the Fed's own monetary policy rule around liftoff. It rises from around zero to around 0.5 shortly before actual liftoff. The magnitude of the Blue Chip private forecaster coefficient is similar to the Fed's, though the private forecaster coefficient appears to lag somewhat behind. Overall, the episode around the first lift-off from the ZLB suggests that private forecasters updated their perceived output gap coefficient $\hat{\gamma}_t$ in the right direction but more slowly than the true response coefficient γ_t, consistent with the evidence of broadly rational but sluggish updating elsewhere in the paper.

Figure A.5: Inertial rule FE estimates



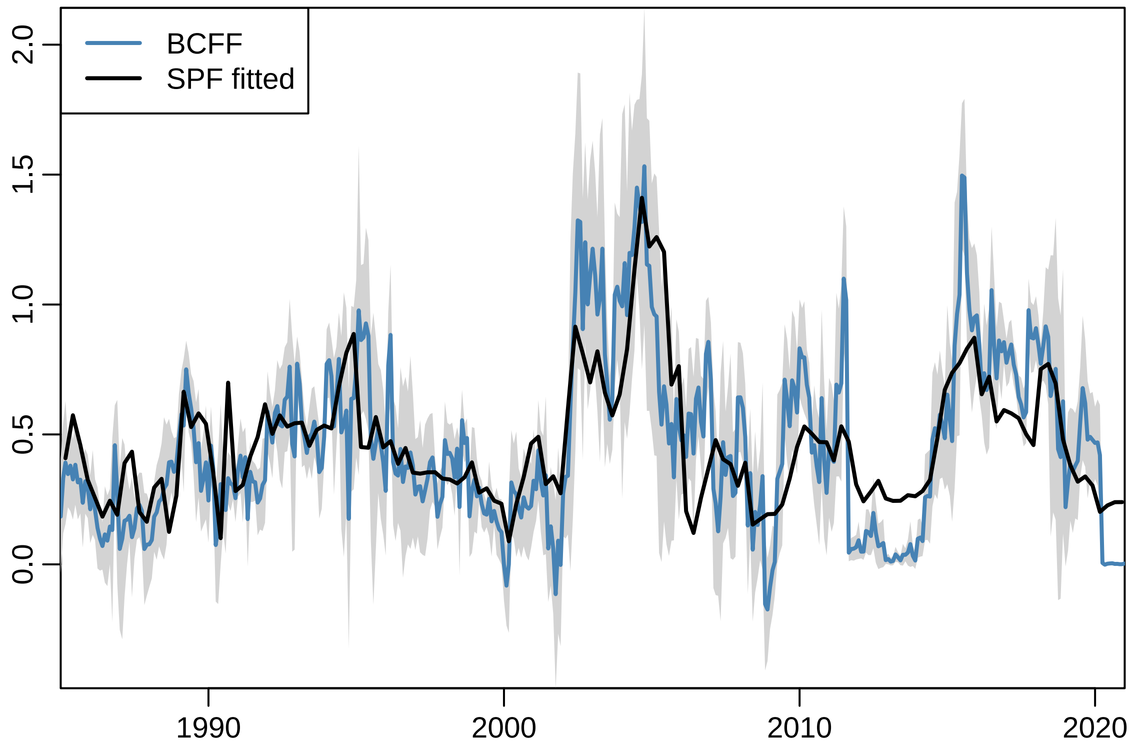
This figure shows estimates from the inertial perceived monetary policy rule regression (A.4). The top panel shows $\frac{\hat{\gamma}}{1-min(\hat{\rho},0.9)}$ and the bottom panel shows $\hat{\rho}$. The bottom panel is 72% correlated with the baseline FE estimate, and the bottom panel has a close to zero correlation with the baseline FE estimate.

Figure A.6: Endogeneity bias adjusted FE $\hat{\gamma}_t$



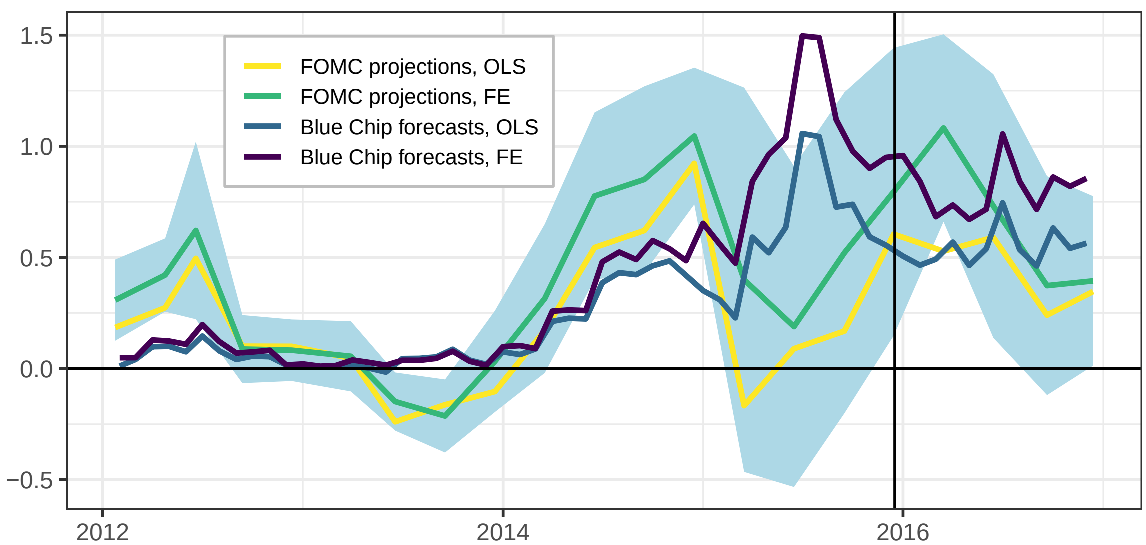
Endogeneity bias-adjusted FE estimate of $\hat{\gamma}_t$ versus the baseline FE estimate of $\hat{\gamma}_t$.

Figure A.7: Comparison with estimates for Survey of Professional Forecasters



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

Figure A.8: Output gap policy rule coefficients implied by FOMC economic projections



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

B Details for learning model

Within-period timing:

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

B.1 Proofs

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

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

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

$$E^j\left(i_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) = \hat{\gamma}_t^j E^j\left(x_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right), \tag{B.2}$$

$$= \left(\hat{\gamma}_t^j - \hat{\gamma}_t\right) E^j\left(x_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) + \hat{\gamma}_t E^j\left(x_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right), \tag{B.3}$$

$$= \hat{\gamma}_t E^j\left(x_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) + \left(\hat{\gamma}_0^j - \hat{\gamma}_0\right) E^j\left(x_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) \tag{B.4}$$

Note that Lemma 1 implies that forecaster j's perceived monetary policy rule coefficient can be expressed as the consensus coefficient plus a forecaster fixed effect:

$$\hat{\gamma}_t^j = \hat{\gamma}_t + \left(\hat{\gamma}_0^j - \hat{\gamma}_0\right). \tag{B.5}$$

For the last equation we substituted in expression (B.5) for the coefficient dispersion across forecasters. Because $\left(\hat{\gamma}_0^j - \hat{\gamma}_0\right)$ is are assumed to be uncorrelated with η_t^j, ε_t, ξ_t and u_t for all $t > 0$, it follows that $\left(\hat{\gamma}_0^j - \hat{\gamma}_0\right) E^j\left(x_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right)$ and $E^j\left(x_{t+h} \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right)$ are uncorrelated. Corollaries 1.a and 1.b then follow. While the forecaster fixed effect, α_j^0, is zero under the assumptions of the model, a straightforward extension with disagreement about the natural rate would yield non-zero forecaster intercepts as in our empirical estimation.

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

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

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

$$x_t - \bar{E}\left(x_t \left|\mathcal{Y}_{t-1}, \nu_t^j\right.\right) = \frac{\sigma_\eta^2}{\sigma_\varepsilon^2 + \sigma_\eta^2}\varepsilon_t \tag{B.7}$$

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

$$\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},x_t\right.\right)-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) \;=\; \hat{\gamma}_t\left(x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)\right). \tag{B.8}$$

Corollary 2.a follows immediately from (B.8).

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

$$Z_t \;=\; \frac{1}{\alpha}\left(\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1}\right.\right)\right), \tag{B.9}$$

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

To derive α we look at the univariate regression

$$\bar{E}\left(i_t\left|\mathcal{Y}_t\right.\right)-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) \;=\; a_0+a_1Z_t+\epsilon_t \tag{B.10}$$

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

$$\begin{aligned} a_1 &= \alpha\frac{1}{\sigma_\varepsilon^2}Cov\left(\hat{\gamma}_t\varepsilon_t,\varepsilon_t\right), && \text{(B.11)}\\ &= \alpha\frac{1}{\sigma_\varepsilon^2}E\left(\hat{\gamma}_t\varepsilon_t^2\right), && \text{(B.12)}\\ &= \alpha\frac{1}{\sigma_\varepsilon^2}E\left(E\left(\hat{\gamma}_t\varepsilon_t^2\left|\mathcal{Y}_{t-1}\right.\right)\right), && \text{(B.13)}\\ &= \alpha E\hat{\gamma}_t && \text{(B.14)} \end{aligned}$$

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

$$\bar{E}\left(i_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)-\bar{E}\left(i_t\left|\mathcal{Y}_{t-1}\right.\right) \;=\; \frac{\hat{\gamma}_t}{E\hat{\gamma}_t}Z_t, \tag{B.15}$$

proving Corollary 2.b.

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

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

$$\begin{aligned}
B_{2,t} &= exp(-i_t)E_t\left[exp\left(-\psi\varepsilon_{t+1}-\frac{1}{2}\psi^2\sigma_\varepsilon^2-i_{t+1}\right)\right], && \text{(B.16)}\\
&= exp(-i_t)E_t\left[exp\left(-\psi\varepsilon_{t+1}-\frac{1}{2}\psi^2\sigma_\varepsilon^2-\gamma_{t+1}\left((\rho x_t+\varepsilon_{t+1})\right)-u_{t+1}\right)\right], && \text{(B.17)}\\
&= exp\left(-i_t-E_t i_{t+1}+\psi\hat{\gamma}_{t+1}\sigma_\varepsilon^2+\frac{1}{2}\hat{\gamma}_{t+1}^2\sigma_\varepsilon^2+\frac{1}{2}\sigma_{t+1}^2\left(\rho x_t\right)^2+\frac{1}{2}\sigma_u^2\right) && \text{(B.18)}
\end{aligned}$$

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

$$\begin{aligned}
E_t xr_{2,t+1}+\frac{1}{2}Var_t xr_{2,t+1} &= E_t\left(b_{1,t+1}-b_{2,t}-b_{1,t}\right)+Var_t\left(b_{1,t+1}\right), && \text{(B.19)}\\
&= -\psi\hat{\gamma}_{t+1}\sigma_\varepsilon^2. && \text{(B.20)}
\end{aligned}$$

Equation (B.20) shows that the expected excess return on a long-term bond decreases with the perceived monetary policy coefficient $\hat{\gamma}_{t+1}$.

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

$$i_t-\bar{E}\left(i_t \mid \mathcal{Y}_{t-1}\right) = i_t-\hat{\gamma}_t\rho x_{t-1}. \qquad \text{(B.21)}$$

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

B.2 Numerical simulation details

Table B.1 provides the numerical values used in the model simulations in Section 6.

Table B.1: Simulation Parameter Values

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

B.3 Fed funds forecast errors

Finally, we study survey forecast errors for the federal funds rate, following the literature that has used forecast errors and forecast revisions to test rationality (e.g., Coibion and Gorodnichenko, 2015; Bordalo et al., 2020). If forecasters are full information rational the difference between realized outcomes and fed funds forecast errors should be unpredictable. However, Cieslak (2018) has documented that in forecasting the federal funds rate professional forecasters make persistent errors, which are predictable with measures of past real activity. If forecasters are slow to update their estimates of γ_t, as suggested by the estimates shown in Figure 4, the gap between the actual and perceived monetary policy coefficient $\gamma_{t+h} - \hat{\gamma}_t$ would be higher when $\Delta\hat{\gamma}_t$ is high. In this case, forecasters would tend to be surprised by higher-than-expected fed funds rates when $\Delta\hat{\gamma}_t$ and the output gap are both high. Consistent with this intuition, we show that fed funds forecast errors load positively onto the change in the perceived monetary policy output weight interacted with a measure of expected economic activity.

Table B.2: Predictability of forecast errors for the federal funds rate

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

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

Table B.2 first replicates the well-known result that forecast errors for the federal funds rate are predictable from the Chicago Fed National Activity Index (CFNAI, CFNAIMA3) as a measure of economic activity (Cieslak (2018)). The left-hand-side variable in all regressions is the realized federal funds rate minus the mean BCFF q-quarter forecast q quarters prior. We consider horizons of two and four quarters, and we use only the surveys in the third month of each quarter in order to ensure a constant forecast horizon, so that our sample is quarterly from 1992:Q1 to 2020:Q4. The first two columns confirm the finding from the prior literature that fed funds forecast errors are ex-post predictable from real economic activity, with an R^2 around 25%.

To test whether the perceived monetary policy rule plays a role in the predictability of federal funds rate forecast errors from economic activity, we next include the interaction terms between the CFNAI and the four-quarter change in the perceived monetary policy output gap weight $\Delta\hat{\gamma}_t = \hat{\gamma}_t - \hat{\gamma}_{t-4}$. The results show that this interaction term contains substantial additional predictive power. The bottom row in Table B.2 shows that the interaction coefficient is positive and highly significant in all cases. The positive interaction coefficient means that the predictability is most pronounced when the perceived responsiveness of monetary policy to the output gap is high.[32] These findings suggest that the predictability of policy rate forecast errors from economic activity systematically varies over time, and that perceptions of the monetary policy rule are an important determinant of this time variation.

C Additional results for local projections (Section 4)

Here we report regression estimates for the local projections shown in Figure 4 and discussed in Section 4. The regressors include mps_t instead of $mps_t(1 - weak_t)$ so that the coefficient on the interaction term $mps_t weak_t$ measures the difference between the two state-dependent impulse responses, and we can easily report the test statistic for the null hypothesis that there is no state dependence. That is, we estimate the regression

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

where all variables are as defined in 4. Note that the impulse responses shown in the top panels of Figure 4 correspond to estimates of $b_1^{(h)}$, and the responses shown in the bottom panels correspond to $b_1^{(h)} + \tilde{b}^{(h)}$.

Table C.1 shows the estimation results for horizons of three, six, nine and twelve months. Most importantly, the interaction coefficient on is consistently negative and often highly statistically significant. This evidence confirms the visual impression from Figure 4 that $\hat{\gamma}$ responds positively to a hawkish policy surprise when the economy is strong, but negatively when the economy is weak.

D Robustness expected bond excess returns

D.1 Objective bond excess returns

Here we report results on the predictability of excess returns on long-term Treasury bonds, which complement the regressions in Section 5.2 for survey-based/subjective expected excess bond returns. We expect bond excess returns to be predictable for two reasons. First, positive surprises in the federal funds rate should translate into negative excess bond returns through the expectations hypothesis and expectations errors, as in Cieslak (2018). Second, the coefficient $\hat{\gamma}_t$ captures the perceived comovement between interest rates and the state of the economy and should therefore carry a risk premium, just like in subjective bond risk premia.

[32] 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.

Table C.1: Local Projection Regressions

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

Local projection estimates of the state-dependent response of $\hat{\gamma}_t$—measured as the 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.

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

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

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

Table D.1 shows that $\hat{\gamma}_t$ predicts objective bond excess returns negatively and significantly with magnitudes that are similar to those for subjective expected excess returns in Table 5 in the main paper. The magnitude and significance of $\hat{\gamma}_t$ as a predictor of future bond excess returns increases further over longer return forecasting horizons, which were not available for subjective expected excess returns. In addition, the interaction $\hat{\gamma}_t \times CFNAI$ predicts bond excess returns negatively at the one-year horizon. Bond prices are inversely related to interest rates, so the sign on $\hat{\gamma}_t \times CFNAI$ is exactly as expected from the fed funds forecast error regressions in the Table B.2 in the main paper.

Table D.1: Predictability of excess bond returns

Panel A: FE $\hat{\gamma}$						
	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
$\hat{\gamma}^{FE}$	-0.79***	-0.74**	-0.73***	-1.42***	-1.06***	-1.10***
	(-2.76)	(-2.55)	(-3.01)	(-4.37)	(-3.87)	(-4.36)
$CFNAI$		-0.19	-1.60***		-1.99**	-2.80***
		(-0.49)	(-3.01)		(-2.44)	(-4.22)
$\hat{\gamma}^{FE} \times CFNAI$			-1.25***			-1.11*
			(-3.56)			(-1.75)
N	390	390	390	378	378	378
R^2	0.17	0.17	0.21	0.20	0.28	0.30
Panel B: SSM $\hat{\gamma}$						
	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
$\hat{\gamma}^{SSM}$	-0.66*	-0.59	-0.65*	-1.43***	-1.06**	-1.17**
	(-1.72)	(-1.53)	(-1.69)	(-2.87)	(-2.18)	(-2.53)
$CFNAI$		-0.23	-1.91**		-1.99**	-2.99***
		(-0.56)	(-2.36)		(-2.40)	(-3.51)
$\hat{\gamma}^{SSM} \times CFNAI$			-1.17**			-1.11
			(-2.48)			(-1.61)
N	390	390	390	378	378	378
R^2	0.16	0.16	0.20	0.20	0.28	0.30

Predictive regressions for excess returns on 5-year nominal Treasury bonds over one-year and two-year holding periods: $xr^{(n)}_{t\to t+h} = b_0 + b_1\hat{\gamma}_t + b_2 CFNAI_t + b_3\hat{\gamma}_t CFNAI_t + \varepsilon_{t+h},$. Top panel uses FE estimate and bottom panel uses SSM estimate of $\hat{\gamma}_t$. All regressions control for the first three principal components of the yield curve. the regression coefficients on the three principal components and the constant are suppressed. All right-hand-side variables are standardized to have unit standard deviations. One-year forecasting regressions run from t =March 1985 through t =January 2020. Two-year forecasting regressions run from t =January 1988 through t =June 2020. Newey-West t-statistics with 1.5 times lag length in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

D.2 Robustness: Controlling for interest rate disagreement

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

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

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

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

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

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

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

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

Regressions for subjective expected excess returns on six-year and 11-year Treasury bonds over one-year holding period, controlling for interest rate disagreement. All regressions also include a constant and the first three principal components of Treasury bond yields. The sample is the same as in Table 5. Newey-West t-statistics with automatic lag selection in parentheses. * p <0.10, ** p <0.05, *** p <0.01.