Perceptions about Monetary Policy *

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Abstract

We estimate perceptions about the Federal Reserve'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 varies substantially over time, in particular over the monetary policy cycle. Forecasters update their perceptions about the Fed's policy rule in response to monetary policy actions, measured by high-frequency interest rate surprises, suggesting that they have imperfect information about the rule. Monetary policy perceptions matter for monetary transmission, as they affect the sensitivity of interest rates to macroeconomic news, term premia in long-term bonds, and the response of the stock market to monetary policy surprises. A simple learning model with forecaster heterogeneity and incomplete information about the policy rule motivates and explains our empirical findings.

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1 Introduction

Over the past 30 years, the Federal Reserve and other central banks have increasingly focused on communicating monetary policy strategy to the public. Underlying this trend is the idea that public perceptions about the central bank's policy framework and strategy determine the macroeconomic effectiveness of monetary policy. Monetary transmission depends on expectations of future policy because expectations drive long-term interest rates and other asset prices.[1] But what monetary policy strategy does the public perceive? How do these perceptions vary over the cycle and in response to policy actions? And what role do they play in the transmission of monetary policy to financial markets?

Empirical progress on these questions requires a measure that captures the public's *forward-looking* perceptions of how the Fed will respond to future economic data at each point in time. Importantly, the perceived policy framework may differ from the Fed's historical behavior. Since Taylor (1993, 1999), however, empirical policy rules have typically been estimated in time series data by regressing the policy rate onto macroeconomic conditions.[2] Such estimates cannot speak to the role of public perceptions about the monetary policy framework because they are based on historical data and thus inherently backward-looking.

In this paper, we estimate perceived, forward-looking monetary policy rules *each month* using rich survey data from the Blue Chip Financial Forecasts (BCFF) spanning almost four decades of U.S. monetary policy. We characterize time variation in the estimated rules, their relationship to actual monetary policy decisions, and their influence on financial markets.

For each monthly survey from January 1985 to May 2023, we form a forecaster-by-horizon panel, which consists of forecasts for the federal funds rate, output gap, and inflation across 30–50 forecasters and horizons from zero to five quarters. We then estimate a perceived monetary policy rule that relates fed funds rate forecasts to macroeconomic forecasts in each month's panel. We also estimate an inertial perceived rule that includes lagged funds rate forecasts. All our subsequent analyses consider both types of rules, and we find broadly similar results.

Our estimation yields perceived response coefficients for the output gap, $\hat{\gamma}_t$, and inflation,

[1]Extensive theoretical and empirical research has documented the importance of monetary policy perceptions for macroeconomic stability and the effectiveness of monetary policy; see, for example, Clarida, Gali and Gertler (2000), Cukierman and Meltzer (1986), Orphanides and Williams (2004), Eusepi and Preston (2010), Cogley, Matthes and Sbordone (2015); Blinder et al. (2008) for a survey; and Bernanke (2010) for a central banker's perspective. These perceptions are also crucial for the financial market effects of monetary and macroeconomic news (Piazzesi, 2005; Cieslak, 2018; Bianchi, Lettau and Ludvigson, 2022; Bauer and Swanson, 2023*a*; Elenev et al., 2024).

[2]Studies estimating low-frequency changes in the monetary policy rule using historical data include Clarida, Gali and Gertler (2000); Kim and Nelson (2006); Boivin (2006); Orphanides (2003); Cogley and Sargent (2005).

$\hat{\beta}_t$. We focus our analysis on the perceived output gap coefficient, $\hat{\gamma}_t$, for two reasons. First, inflation was low and stable over our sample. Second, BCFF collects forecasts of headline CPI inflation, which reflect noisy short-term inflation fluctuations whereas monetary policy tends to focus on longer-term inflation pressures. We interpret the output gap coefficient $\hat{\gamma}_t$ as a measure of the Fed's perceived responsiveness to economic conditions.

Our first key finding is that the perceived monetary policy rule exhibits substantial variation over time. The Fed's perceived responsiveness to the output gap, $\hat{\gamma}_t$, varies between 0 and about 1.5. The perceived monetary policy rule often lines up with rolling estimates of the Fed's historical behavior from time series macroeconomic data. However, during several episodes, our forward-looking perceived rule diverges from the historical, backward-looking rule. This divergence is particularly pronounced during episodes with strong forward guidance, including zero lower bound (ZLB) and liftoff periods.

The perceived policy rule varies systematically over the monetary policy cycle and with uncertainty. The coefficient $\hat{\gamma}_t$ tends to be high in the early stages of monetary tightening cycles, when the slope of the yield curve is high, indicating that the Fed is perceived to be strongly data-dependent at these times. Conversely, $\hat{\gamma}_t$ tends to be low in monetary easing episodes and when uncertainty is high. At these times, the Fed is viewed to be less responsive to standard indicators of economic activity such as the output gap, perhaps because it is putting more weight on risks not captured by these indicators.

Section 3 shows that policy perceptions respond to high-frequency monetary policy surprises around Federal Open Market Committee (FOMC) announcements in a state-contingent manner. The way forecasters update their beliefs suggests that they have imperfect information about the policy rule and learn from observed policy decisions. Intuitively, a surprise tightening during an economic expansion signals to forecasters that the Fed's response to economic activity is stronger than expected, while a surprise tightening in a weak economy signals the opposite. We confirm this prediction in the data: $\hat{\gamma}_t$ increases following a positive high-frequency monetary policy surprise when the economy is strong, but declines following the same type of surprise when the economy is weak. The magnitude of the empirical response suggests that monetary policy surprises on FOMC dates would be 50% less volatile if the monetary policy rule were fully known.

Having characterized variation in the perceived monetary policy rule over time and in response to monetary policy decisions, we next show that these shifting perceptions matter for the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates, as well as stock prices.

Section 4.1 documents that market interest rates react more strongly to macroeconomic news when the Fed's perceived responsiveness $\hat{\gamma}_t$ is high. This high-frequency analysis validates our survey-based estimates of $\hat{\gamma}_t$ using financial market data, and suggests that they are consistent with the "market-perceived policy rule" of Hamilton, Pruitt and Borger (2011). It also connects our perceived policy rule to the results of Swanson and Williams (2014), who document changes in the market's sensitivity to macroeconomic news at the ZLB. Economically, our results show that monetary policy perceptions 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.[3]

Shifts in the perceived monetary policy rule also have a pronounced impact on long-term interest rates, which are particularly important for the transmission of monetary policy. Section 4.2 shows that policy rule perceptions affect the term premium in long-term bond yields, driving a wedge between long-term rates and expected short-term rates. Classic finance theory suggests that when $\hat{\gamma}_t$ is higher, investors expect interest rates to fall more, and hence bond prices to rise more, in bad economic states, i.e., when the output gap is low. Thus, they believe Treasury bonds are better hedges and require a lower term premium for holding them. We document precisely this pattern: both subjective term premia, calculated from survey expectations of future yields, and statistical term premia, estimated with predictive regressions, move inversely with $\hat{\gamma}_t$.

These results can help explain the reaction of long-term bond yields to monetary policy decisions (e.g., Hanson and Stein, 2015; Nakamura and Steinsson, 2018). Monetary policy has stronger effects on long-term yields if policy decisions affect perceptions of the monetary policy rule, which in turn impact term premia. Our mechanism predicts that the impact of policy surprises on term premia should be most pronounced when the economy is weak, i.e., the impact should be state-contingent. A surprise tightening in a weak economy leads investors to revise $\hat{\gamma}_t$ downwards, raising term premia. Thus, long-term yields should rise more than they would following the same surprise in a strong economy, when $\hat{\gamma}_t$ and term premia move in the other direction. In Section 4.3, we find strong evidence for such state-dependence, extending commonly used event-study regressions to document a stronger response of long-term rates to policy surprises in a weak economy than in a strong economy. These results provide additional evidence of updating about the perceived rule, and its effect on term premia, without relying on our survey-based estimate $\hat{\gamma}_t$.

We next show in Section 4.4 that the stock market's response to monetary policy also depends strongly on the perceived monetary policy rule. Using high-frequency regressions of stock returns on interest rate surprises around FOMC announcements (as in Bernanke and Kuttner, 2005), we document that the market response to a tightening surprise is significantly

[3]In a recent paper, Elenev et al. (2024) use our estimates of $\hat{\gamma}_t$ to show that the sensitivity of stock prices to macro news also depends on monetary policy perceptions.

more negative when $\hat{\gamma}_t$ is low. This result suggests that investors anticipate more pronounced economic consequences from a monetary policy shock when the Fed is perceived to be less responsive to economic conditions, consistent with standard New Keynesian theory.

In Section 5 we present a simple model with forecaster heterogeneity and imperfect information about the policy rule that motivates and explains our empirical findings. The true policy rule is time-varying and unobserved by forecasters, who learn about it from policy rate decisions. Forecasters receive different signals about the output gap and form policy rate forecasts according to their perceived rule. According to the model, regressions of policy rate forecasts on output gap forecasts in a forecaster-horizon panel recover the policy rule coefficient perceived by forecasters. The model predicts that forecasters update their perceived coefficient upwards following a surprise tightening in a strong economy, but update downwards following a surprise tightening in a weak economy. It also predicts that fed funds futures respond more strongly to macro news when the perceived coefficient is high, that term premia are inversely related to the perceived coefficient, and that long-term yields respond more strongly to monetary policy surprises when the economy is weak. All these predictions are confirmed in the data.

Finally, Section 6 shows that our estimates are robust to various changes in the policy rule specification, estimation method, and data sources. Linking policy rule beliefs over time using a state-space model or augmenting the perceived rule to include expected financial conditions has little effect on our estimates of $\hat{\gamma}_t$. We account for heterogeneity in beliefs about the policy rule across forecasters in several different ways. Accounting for heterogeneity does not significantly change the time series variation that is the focus of our paper. We also address the well-known concern that policy rule regressions can yield biased estimates because macroeconomic variables endogenously depend on all shocks in the economy, including the monetary policy shock. Building on Carvalho, Nechio and Tristao (2021), we use a model that captures this endogeneity bias and show that such bias is unlikely to affect the time-series variation in $\hat{\gamma}_t$ and hence our main results. In addition, our results in Sections 3 and 4 strongly support an interpretation of $\hat{\gamma}_t$ as a perceived policy rule coefficient. Nevertheless, many of the takeaways from our empirical analysis remain valid under a more general, non-causal interpretation of $\hat{\gamma}_t$ as the perceived endogenous comovement between the short-term policy rate and macroeconomic variables. For example, under this broader interpretation, our results show that perceived comovement is priced in financial markets and influences term premia.

In summary, using a novel methodology for estimating perceptions of the monetary policy rule from professional forecasts, we establish three key empirical results: First, the perceived monetary policy rule varies significantly and systematically over time. Second, the way forecasters update their beliefs suggests that they have incomplete information about the policy rule and learn about it from policy actions. Third, variation in the perceived rule impacts the transmission of monetary policy to financial markets, affecting the sensitivity of interest rates to macro news, the term premium in long-term bond yields, and the reactions of yields and stock prices to FOMC announcements.

By providing estimates of the perceived monetary policy rule, our paper contributes to the literature on incomplete information and monetary policy (Blinder et al., 2008; Eusepi and Preston, 2010; Taylor and Williams, 2010; Cogley, Matthes and Sbordone, 2015). We document that investors learn about the rule from policy decisions and that their perceptions are transmitted to financial markets. Our findings are complementary to Caballero and Simsek (2022), who study disagreement between the public and the Federal Reserve and its implications for monetary policy surprises, and Stein and Sunderam (2018), who examine strategic communication between the central bank and market participants. Our work also connects to the debate on rules versus discretion in monetary policy going back to Kydland and Prescott (1977) and Taylor (1993) because time variation in the perceived monetary policy rule is potentially consistent with the Fed exercising significant discretion.

Methodologically, our paper builds on previous work that estimates monetary policy rules from financial market and survey data. The main idea in this literature is to take the concept of an empirical monetary policy rule—in the manner of Taylor (1999)—and apply it to forward-looking data. Some papers have estimated perceived policy rules using consensus survey forecasts (e.g., Bundick, 2015; Kim and Pruitt, 2017; Jia, Shen and Zheng, 2023), while others have used individual forecasts to estimate constant-parameter rules, potentially allowing for a single parameter break (Carvalho and Nechio, 2014; Andrade et al., 2016, 2019). We make two related contributions to this literature: First, in contrast to prior work we estimate the perceived rule in each monthly survey, using variation across both forecasters and horizons to pin down the rule's parameters. Second, we relate month-to-month shifts in the perceived rule to monetary policy actions and the key asset prices responsible for monetary policy transmission. Our results suggest that the perceived monetary policy rule is an important determinant of risk premia and that FOMC announcements influence asset prices in part by changing perceptions of the policy rule.

Within the macro-finance literature on the financial market effects of monetary policy, our paper is closely related to recent work on incomplete information and policy perceptions. Bauer and Swanson (2023*a*,*b*) argue that high-frequency monetary policy surprises are predictable because investors do not know the Fed's monetary policy rule. Our results are consistent with this incomplete information view of monetary policy, and further show that forecasters update their perceived rule in response to Fed policy actions. Bianchi, Ludvigson and Ma (2023) study FOMC announcements and perceptions of regime-switching policy rules in a structural New Keynesian asset pricing model. While we model perceptions about monetary policy using continuously evolving parameters in the policy rule, our estimates could also be interpreted as reflecting shifting beliefs about the likelihood of future policy regimes. More generally, our empirical approach differs from earlier studies on monetary policy perceptions as we estimate policy rule perceptions from survey data, study time variation in the perceived monetary policy rule, and directly assess its transmission to financial markets.

2 The perceived monetary policy rule

In this section, we describe how the perceived monetary policy rule is estimated, and characterize its cyclical patterns.

2.1 Blue chip survey data

Blue Chip Financial Forecasts (BCFF) is a monthly survey of professional forecasters going back to 1982. The survey asks for forecasts of interest rates, including the federal funds rate, various Treasury yields, and corporate bond yields. In addition, forecasters are queried about the macroeconomic *assumptions* underlying their rate forecasts, specifically, their growth and inflation forecasts. The number of participating institutions, each identified by name, ranges between 30 and 50 across surveys. We start our sample in January 1985, because the quality of the data is poor in earlier years. Our sample ends in May 2023 for a total of 461 monthly surveys.

Forecasts are made for quarterly horizons from the current quarter out to five quarters ahead.[4] We denote the forecast of institution j made at t for a generic variable y by $E_t^{(j)} y_{t+h}$. We measure time t in months as the Blue Chip survey is monthly. Since forecasts are for end-of-quarter observations, the monthly horizon h depends on both the survey month and the forecast horizon. For example, for the one-quarter-ahead forecast in the January 2000 survey, $t+h$ corresponds to June 2000 and $h=5$.

We specify policy rules for the federal funds rate, the Fed's policy rate, denoted by i_t. Since empirical monetary policy rules are usually specified in terms of year-over-year inflation, π_t, and the output gap, x_t, we compute these measures from the macroeconomic forecasts in the BCFF. Year-over-year CPI inflation forecasts, denoted as $E_t^{(j)} \pi_{t+h}$, are calculated from quarterly forecasts and, for short horizons, observed CPI inflation. To calculate

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

output gap forecasts, $E_t^{(j)} x_{t+h}$, we impute forecasts for the level of real GDP from GDP growth forecasts, and take projections of potential GDP from the Congressional Budget Office (CBO), using real-time data at the time of the survey for most of our sample. These output gap projections assume that all forecasters share the same potential output forecast, equal to the CBO projection. Appendix B.4 shows that using unemployment rate projections in the Survey of Professional Forecasters (SPF) leads to similar results.

Across surveys, horizons, and institutions, our data contain about 120,000 individual forecasts. There is substantial variation across both forecasters and horizons. For detailed descriptions of the BCFF data, calculations, and summary statistics, see Appendix A.1.

2.2 Estimation of perceived rules from survey panels

We now describe how we estimate perceived monetary policy rules from survey data. The basic procedure is as follows: In each monthly BCFF survey, we regress forecasts for the federal funds rate on forecasts for the output gap and inflation. As we formalize in the model in Section 5, if survey respondents first form views on future output and inflation and then use a policy rule to translate these views into funds rate forecasts, this procedure recovers the perceived monetary policy rule.

In each month of the BCFF survey, there is variation across both forecasters and forecast horizons. In principle, either dimension of variation would be sufficient for our procedure. To see the intuition, suppose for simplicity that forecasters believe that the Fed follows a rule according to which it sets the federal funds rate to 0.5 times the output gap. Further suppose that two forecasters have one-year-ahead output gap forecasts of 2% and 4%. Then their one-year-ahead funds rate forecasts are 1% and 2% respectively, and a regression of funds rate forecasts on output gap forecasts correctly recovers a coefficient on the output gap of 0.5. Alternatively, suppose there is only one forecaster, who forecasts that the output gap will be 2% next year and 0% two years from now. Then her funds rate forecasts are 1% for next year and 0% for the year after that. Again, a regression of funds rate forecasts on output gap forecasts correctly recovers the perceived output gap coefficient. Our estimation procedure exploits variation across both forecasters and forecast horizons.

Our framework starts from the simple monetary policy rule

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

This type of policy rule has been standard in the macroeconomic literature since Taylor (1993, 1999). Crucially, we allow all parameters to vary over time. The inflation target π_t^* and the natural rate of interest r_t^* represent the expected long-run values for inflation and the real interest rate, once cyclical shocks have died out.[5] Our focus is on the coefficients capturing the monetary policy response to the inflation gap and the output gap, β_t and γ_t. The rule also includes an exogenous monetary policy shock, u_t.

To capture the perceptions of professional forecasters about the policy rule (1), we estimate the *perceived* coefficients $\hat{\gamma}_t$ and $\hat{\beta}_t$ by regressing federal funds rate forecasts on output gap and inflation forecasts. Specifically, for each Blue Chip survey at time t, we form a forecaster (j)-by-horizon (h) panel and estimate the regression

$$E_t^{(j)} i_{t+h} = a_t^{(j)} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + e_{th}^{(j)}. \tag{2}$$

The error term $e_{th}^{(j)}$ contains forecaster j's expectation of the future monetary policy shock at $t+h$, $E_t^{(j)} u_{t+h}$, as well as possible measurement and specification errors affecting the funds rate forecasts. Our estimation includes forecaster fixed effects $a_t^{(j)}$ to allow for the possibility that forecaster beliefs about π_t^* and r_t^* may be correlated with their inflation and output gap forecasts.

Four assumptions are sufficient for regression (2) to recover the perceived monetary policy rule. First, forecasters disagree about the economic outlook, meaning that there is some heterogeneity in $E_t^{(j)} x_{t+h}$ and $E_t^{(j)} \pi_{t+h}$ across forecasters j. This assumption builds on a large body of evidence for disagreement in economic expectations (e.g., Mankiw, Reis and Wolfers, 2003; Patton and Timmermann, 2010; Andrade et al., 2016). It is confirmed in our BCFF data, which contains substantial variation across both forecasters and horizons, as documented in Appendix Table A.1. Importantly, our estimation framework does not require that forecasts are rational, which would be at odds with a large literature documenting biases, overconfidence, strategic incentives, and other deviations from rational expectations in survey forecasts (Bordalo et al., 2020; Angeletos, Huo and Sastry, 2021).

The second assumption is that economic forecasts are determined independently of any expected future monetary policy shock, $E_t^{(j)} u_{t+h}$. This assumption is unlikely to hold exactly, and some endogeneity bias, arising from the perceived effects of monetary policy shocks on output, could affect our estimates. This problem afflicts most empirical work on monetary policy rules.[6] Endogeneity bias may be less severe in our context since the framing of the

[5] Similar policy rules with a time-varying long-run natural rate and/or inflation target have been used by Kim and Nelson (2006), Orphanides and Williams (2007), Ireland (2007). The Fed itself regularly uses such rules, with r_t^* described as "the level of the neutral real federal funds rate in the longer run" and π_t^* as its longer-run inflation target; see, for example, the "Monetary Policy Rules in the Current Environment" in Part 2 of the June 2023 Monetary Policy Report to Congress (Board of Governors, 2023). This long-run notion of r_t^* and π_t^* in empirical policy rules is distinct from the "stochastic intercept" of King (2000) and Cochrane (2011), or the short-run efficient real rate in New Keynesian models.

[6] While many studies following Clarida, Gali and Gertler (2000) use instrumental variables to estimate policy rules, Carvalho and Nechio (2014) argue that simple OLS estimates tend to be similarly accurate.

BCFF explicitly asks forecasters about the macroeconomic *assumptions* underlying their rate forecasts. Consistent with this view, the empirical results in Sections 3 and 4.1 suggest that our estimates indeed capture a perceived policy rule and that endogeneity bias is likely small or at least stable over time. To the extent that any bias is stable over time, it does not affect our main results, which concern time variation in the perceived rule. Section 6 shows that bias correction leads to very similar results.

The third assumption is that policy rate forecasts are made according to the policy rule in (1). Since Taylor (1993), extensive empirical evidence shows that this type of simple rule accurately captures the Fed's policy rate.[7] This assumption is supported by the fact that the simple policy rule fits the data well: The average R^2 of regression (2) across surveys is 70% with forecaster fixed effects and 33% without fixed effects. In Section 6 we consider the consequences of relaxing this assumption. First, the policy rule could depend on factors beyond the output gap and inflation. We show that including forecasts of credit spreads in the policy rule has little effect on the estimated output gap coefficients. Second, there is likely heterogeneity across forecasters in their beliefs about the policy rule. If forecasters have different coefficients $\hat{\gamma}_t^{(j)}$ and $\hat{\beta}_t^{(j)}$, our baseline estimation with common coefficients will recover the averages of the perceived monetary policy reaction coefficients across forecasters if disagreement about the policy rule is independent of disagreement in output gap and inflation forecasts. Section 6 also shows that accounting for belief heterogeneity in different ways leads to estimates with time-series variation that is similar to our baseline $\hat{\gamma}_t$.

Fourth, we assume that forecasters view the policy rule parameters as highly persistent. Formally, β_t, γ_t, π_t^* and r_t^* are assumed to follow martingales, so that their changes are unpredictable.[8] This martingale assumption is standard in time-varying parameter models (Primiceri, 2005). For π_t^* and r_t^*, the martingale property naturally follows from their definition as long-run macroeconomic trends (Laubach and Williams, 2003; Bauer and Rudebusch, 2020). As a result, the intercept in (2), $a_t^{(j)} = E_t^{(j)} r_t^* + (1-\hat{\beta}_t) E_t^{(j)} \pi_t^* = E_t^{(j)} r_{t+h}^* + (1-\hat{\beta}_t) E_t^{(j)} \pi_{t+h}^*$, differs across forecasters but not across horizons, and can be captured with forecaster fixed effects. It is important to account for this type of heterogeneity given the existing evidence for long-run disagreement (Patton and Timmermann, 2010; Andrade et al., 2016).

Much theoretical and empirical research has documented the relevance of interest-rate smoothing and policy gradualism (e.g. Woodford, 2003*b*; Bernanke, 2004; Taylor and Williams,

[7] In contrast to Andrade et al. (2016), we follow most of the monetary policy rule literature and specify the perceived rule in terms of the output gap rather than GDP growth. The patterns in forecaster disagreement about interest rates are more similar to disagreement about the output gap, rather than disagreement about GDP growth, supporting this choice (see Appendix A.2).

[8] We also assume that the innovations to $\hat{\beta}_t$ and $\hat{\gamma}_t$ are orthogonal to other shocks, that is, $E_t^{(j)} \beta_{t+h} = \hat{\beta}_t$ 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.

2010). We therefore also consider the possibility that policy follows an inertial rule:

$$i_t = \rho_t i_{t-3} + (1-\rho_t)(r_t^* + \pi_t^*) + \gamma_t x_t + \beta_t(\pi_t - \pi_t^*) + u_t, \tag{3}$$

where ρ_t is the time-varying "inertia parameter" that determines the extent to which last quarter's policy rate affects the current policy rate, and the coefficients β_t and γ_t are the short-run responses of monetary policy to inflation and the output gap. To estimate the perceived inertial rule we simply augment regression (2) with the funds rate forecast for the preceding quarter:

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

For $h = 0$ we use the actual fed funds rate that was observed in the previous quarter for $E_t^{(j)} i_{t+h-3}$. The forecaster fixed effect, $a_t^{(j)}$, again absorbs disagreement about long-run real rates and long-run inflation. The estimated coefficients in (4) capture the perceived short-run policy responses to inflation and the output gap, whereas the baseline estimates from (2) represent perceived medium-run reaction coefficients, in line with the BCFF forecast horizon of up five quarters.[9]

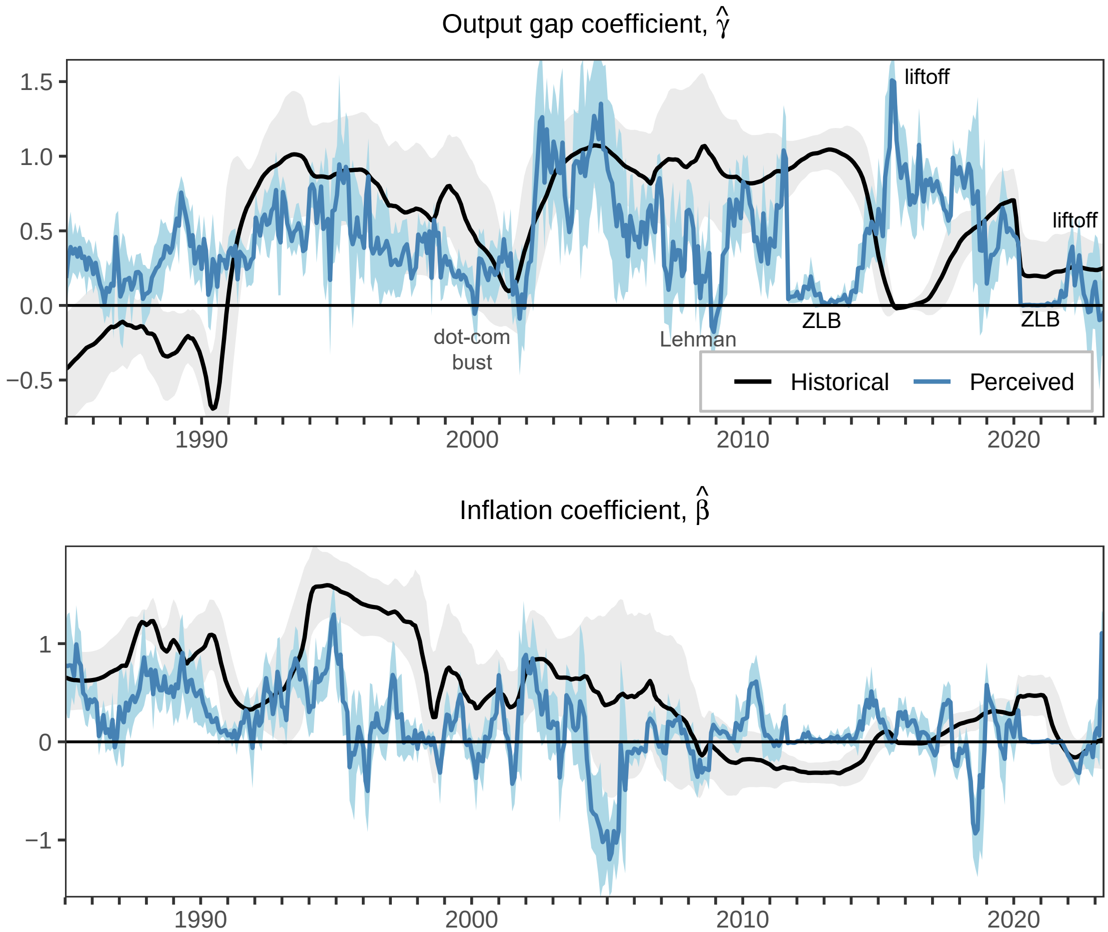
2.3 Perceived baseline policy rule

Figure 1 plots the time series of the estimated perceived policy rule from our baseline specification (2). The top panel shows the perceived output gap coefficient, $\hat{\gamma}_t$, which has a sample average around 0.5, in line with conventional empirical estimates of policy rules (Taylor, 1993; Clarida, Gali and Gertler, 2000). The estimated series exhibits a striking amount of variation, ranging between 0 and 1.5, that can be linked to the monetary policy cycle. The tight confidence intervals, based on standard errors that are clustered by both horizon and forecaster, show that the perceived parameters are estimated precisely, due to the large amount of information in each monthly panel of survey forecasts.

Before and during monetary tightenings—for instance, in the mid-1990s, between 2003 and 2005, and around liftoff from the ZLB in 2015 and in 2022—$\hat{\gamma}_t$ tends to be high, indicating that the rate outlook is perceived to be strongly related to the economic outlook. During these episodes the Fed is viewed as highly data-dependent, consistent with Fed communication at the time. Examples include speeches from all three recent Fed Chairs Bernanke,

[9] In principle, perceived long-run response coefficients could be calculated as $\hat{\beta}_t/(1-\hat{\rho}_t)$ and $\hat{\gamma}_t/(1-\hat{\rho}_t)$, provided that $|\hat{\rho}_t < 1|$. Because of the horizons available in the survey and the substantial noise in the estimated $\hat{\rho}_t$ (which sometimes exceeds one), these ratios are not meaningful and sometimes undefined. Appendix F.2 compares and derives expressions for the baseline and inertial estimates within our model.

Figure 1: Parameter estimates for baseline policy rule



Estimated policy-rule coefficients for the output gap, $\hat{\gamma}_t$, and inflation, $\hat{\beta}_t$. Blue lines show estimates of perceived policy rules from month-by-month panel regressions (2) with forecaster fixed effects, estimated from Blue Chip Financial Forecast surveys from January 1985 to May 2023. We base 95% confidence intervals (shaded) on standard errors with two-way clustering by forecasters and horizon. Black lines show estimated historical policy rules using a seven-year estimation window of monthly observations for the federal funds rate, the output gap, and four-quarter CPI inflation.

Yellen, and Powell, such as Yellen (2015)'s repeated emphasis that "policy will depend on [...] incoming data." The Fed also provided explicit forward guidance that led forecasters to expect rate hikes, for example in 2004 and before each liftoff.[10]

By contrast, before and during monetary easings, $\hat{\gamma}_t$ is typically low, as forecasters see little connection between the rate outlook and the economic outlook. These episodes are often marked by elevated financial stress, such as during the dot-com bust in 2001 and the failure of Lehman Brothers in 2008. At such times, the Fed likely pays attention to a broader set of indicators, including financial conditions, that are informative about economic risks in

[10]See Lunsford (2020) for an extensive discussion of forward guidance in the 2000s.

real time. As a result, the Fed's decisions may appear more discretionary and less rules-based during these periods. In addition, the Fed may take a "risk management approach," cutting rates before the economic outlook deteriorates too much.[11] Strong forward guidance at the ZLB, such as the announcement in September 2011 that the Fed would keep rates near zero "at least through mid-2013," led to a particularly sharp disconnect between expectations of rates and economic conditions, essentially pinning $\hat{\gamma}_t$ at zero.[12] Our results show that there is an asymmetry between easing and tightening episodes, consistent with financial market evidence that rate cuts are more often surprising than rate hikes (Cieslak, 2018; Schmeling, Schrimpf and Steffensen, 2022).

Figure 1 also compares the perceived rule to an estimate of the historical policy rule, obtained from rolling regressions of the fed funds rate on inflation (annual percent change in the CPI) and the output gap (percent deviation of real GDP from CBO potential output). We use a seven-year rolling window, long enough to allow for relatively precise estimates but short enough to uncover time variation in the rule's parameters.[13] Until 2008, the output gap coefficients in the perceived and historical rules exhibit broadly similar patterns, and their correlation is 0.5. But after 2008, the historical and perceived rules diverge, illustrating the value of our approach. For instance, the perceived coefficient, $\hat{\gamma}_t$ immediately captures the Fed's forward guidance in 2011 and plummets to zero, while the output gap coefficient in the historical policy rule barely budges. It only drops to zero several years later in 2015. However, by this time the Fed was already engaged in "data-dependent" tightening, as captured by the rise in $\hat{\gamma}_t$. These differences arise because the historical rule is necessarily backward-looking, while our survey-based perceived rule is forward-looking.

The perceived inflation coefficient $\hat{\beta}_t$, shown in the bottom panel of Figure 1, fluctuates around zero and is positive only over the first few years and at the very end of our sample. This pattern contrasts with typical empirical and optimal policy rules, which feature an inflation coefficient greater than one and satisfy the "Taylor principle". The reason is that over most of our sample period, inflation was low and stable, hovering near the Fed's inflation target. As noted by Clarida, Gali and Gertler (2000), with limited variability in inflation, the estimated policy rule coefficient may well be low and "one might mistakenly conclude that the Fed is not aggressive in fighting inflation" (p. 143) even if the central bank is in fact

[11] Anecdotal evidence includes FOMC meeting minutes from January 29-30, 2001, describing the sequence of large interest rate cuts in that month as "front-loaded easing policy," and an FOMC conference call on January 9, 2008, characterizing interest rate cuts as "taking out insurance against (...) downside risks."

[12] See Campbell et al. (2012) and Swanson and Williams (2014) for a discussion of this "Odyssean" forward guidance.

[13] Similarly to Bauer and Swanson (2023*b*), we find an upward-shift in the estimated historical output gap coefficient post-2000. We find a lower inflation coefficient than they do because our shorter rolling windows feature less variation in inflation.

committed to stable inflation. The low estimates of $\hat{\beta}_t$ also reflect the fact that BCFF collects forecasts for headline CPI inflation, which mostly capture short-run, transitory fluctuations in inflation that are of little relevance for monetary policy. This explains why the $\hat{\beta}_t$ estimates are volatile and even occasionally turn negative.[14]

We interpret $\hat{\gamma}_t$ as a summary measure of "perceived Fed responsiveness" and focus on this estimate in our subsequent analysis. This interpretation is supported by the fact that in the pre-COVID period—the first 35 years of our sample—the U.S. economy was affected mainly by demand shocks. As a result, the perceived output gap coefficient $\hat{\gamma}_t$ summarizes the Fed's overall responsiveness to economic conditions. Intuitively, the Fed is expected to react to changes in the output gap partly because it also summarizes demand-driven inflationary pressures.

We interpret variation in $\hat{\gamma}_t$ as changes in the beliefs about the Fed's policy rule. Because our estimates are forward-looking, an alternative interpretation is that these changes reflect shifting beliefs about future regime changes in monetary policy (Bianchi, 2013; Bianchi, Ludvigson and Ma, 2023). Both ways of modeling changes in monetary policy—time-varying parameters or discrete policy regimes—have long traditions. We assume continuously evolving parameters in the perceived policy rule because this is a simple and tractable way to capture changing perceptions about monetary policy, both in our empirical analysis and in our learning model in Section 5.

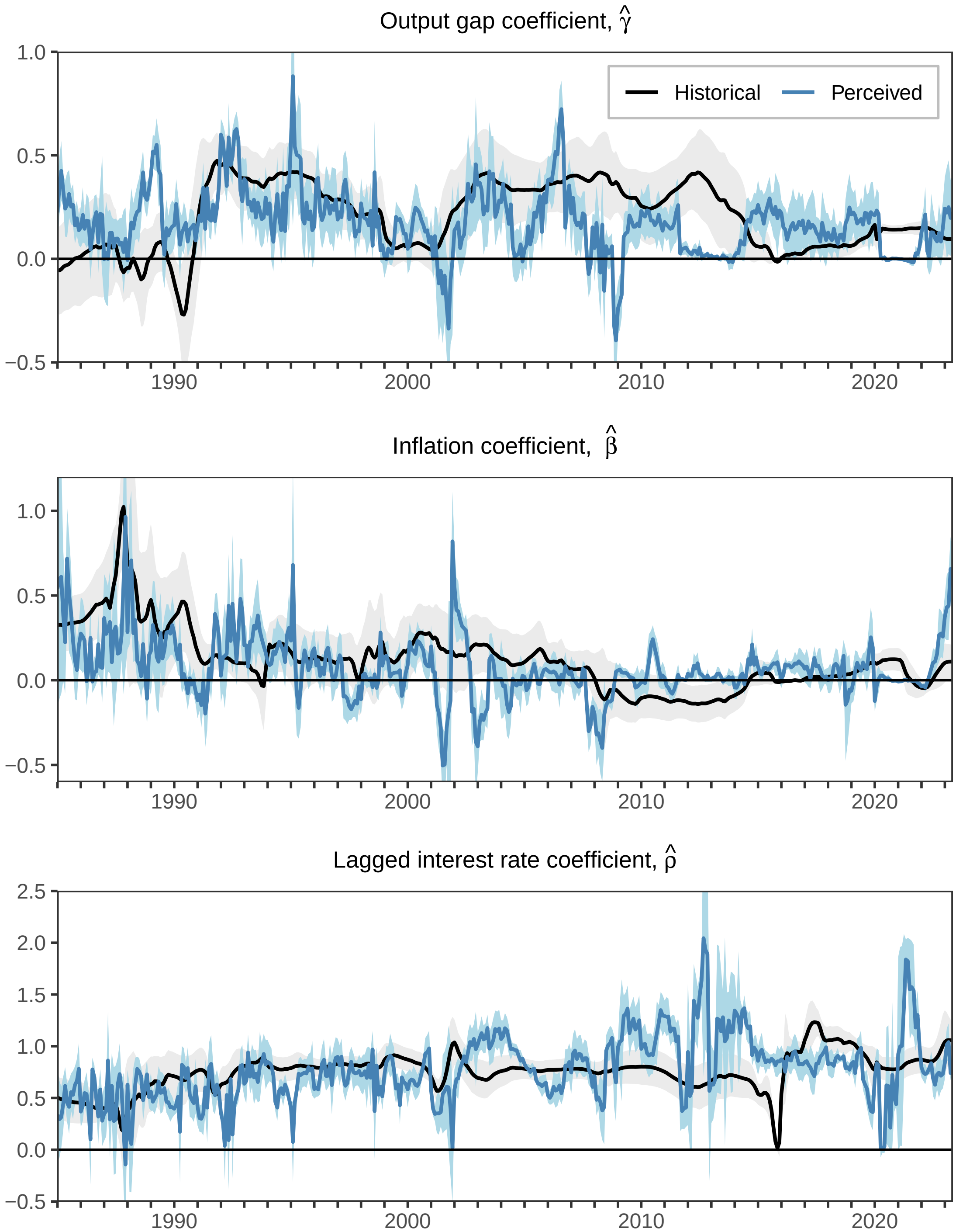
2.4 Perceived inertial policy rule

Figure 2 shows the estimated coefficients for the perceived inertial policy rule. We again superimpose historical policy rule coefficients from rolling-window regressions, in this case including a three-month lag of the funds rate as in equation (3).

The coefficients of the perceived inertial rule, shown in Figure 2, show broadly similar patterns as those for the baseline rule in Figure 1. The inertial rule coefficients are naturally smaller in magnitude because they capture the perceived short-run policy response, while the baseline rule captures the response over a medium-run horizon. Similar to our results above, there are substantial cyclical shifts in the perceived output gap coefficient $\hat{\gamma}_t$. These shifts are generally consistent with those in the historical policy rule before 2008, but differences arise thereafter due to the forward-looking nature of our survey-based estimates.

[14]The importance of transitory fluctuations is clearly evident for the February 2005 and August 2018 surveys, which yield negative estimates of $\hat{\beta}_t$. In both periods, inflation was expected to decline due to changes in energy prices, while the funds rate was expected to rise in response to strong economic conditions. We have found that core CPI forecasts from the Survey of Professional Forecasters yield estimates of $\hat{\beta}_t$ that generally remain positive. These forecasts are much less affected by transitory price fluctuations, but the data is not available before 2007.

Figure 2: Parameter estimates for inertial policy rule



Estimated policy-rule coefficients for the output gap, $\hat{\gamma}_t$, inflation, $\hat{\beta}_t$, and the one-quarter lagged interest rate, $\hat{\rho}_t$. Blue lines show estimates of perceived policy rules from month-by-month panel regressions (4) with forecaster fixed effects, estimated from Blue Chip Financial Forecast surveys from January 1985 to May 2023, with shaded areas for 95% confidence intervals based on standard errors with two-way clustering (by forecasters and horizon). Black lines show estimated historical policy rules using a seven-year estimation window of monthly observations for the federal funds rate, the output gap, and four-quarter CPI inflation.

The bottom panel of Figure 2 shows that $\hat{\rho}_t$ trends up over our sample period: the average is 0.6 prior to 2000 and 0.9 thereafter. This pattern is consistent with other evidence that the Fed has become more gradual and forward guidance more important (Coibion and Gorodnichenko, 2012; Pflueger, 2023; Bianchi, Ludvigson and Ma, 2023). At the same time, the inertial $\hat{\gamma}_t$ becomes more compressed relative to the baseline $\hat{\gamma}_t$, indicating that there is less variation in the perceived short-run responses of monetary policy than in the perceived medium-run responses in the second half of the sample. In light of this wedge, one might expect baseline $\hat{\gamma}_t$ to be more relevant for long-term asset prices.

The inflation coefficient $\hat{\beta}_t$ again varies mostly around zero, with an important exception: Over the last year of our sample, $\hat{\beta}_t$ rose sharply, due to the surge in inflation and the corresponding monetary policy response. This pattern is more evident in the inertial than the baseline estimates because in 2023 inflation was expected to gradually decline.

2.5 Cyclical variation

To document systematic variation in the Fed's perceived responsiveness, Table 1 reports univariate regressions of $\hat{\gamma}_t$ on cyclical variables. Results for the baseline rule are in the top panel, and results for the inertial rule are in the bottom panel. While these regressions do not speak to causality, they suggest which factors could drive variation in the perceived rule.

The first two columns show that $\hat{\gamma}_t$ tends to be high during the tightening portion of a monetary policy cycle. The slope of the yield curve reflects the expected path of future policy rates, and a positive slope anticipates monetary tightening, while a flat or inverted yield curve predicts monetary easing and typically a recession.[15] We find a strong positive correlation between $\hat{\gamma}_t$ and the slope. The correlation is even stronger for the lagged slope—which is intuitive since the yield curve is often upward-sloping well before the onset of the tightening cycle—thus the slope is lagged by one year in the regression in Table 1. The second column uses a dummy variable for monetary tightening cycles, which is equal to one from the first to the last month with an increase in the fed funds rate during the cycle. Although the coefficient is statistically significant only for the baseline rule, the estimates generally confirm that $\hat{\gamma}_t$ tends to be elevated during tightening cycles.

While the perceived policy rule shifts with monetary policy, it has no clear relationship with the business cycle. Table 1 shows that $\hat{\gamma}_t$ is unrelated to the unemployment rate, and we have found similar results for various other indicators of economic activity, including NBER recession dummies.

[15] See Rudebusch and Wu (2008) on the slope as a measure of the monetary policy stance, and Bauer and Mertens (2018) on its predictive power for recessions.

Table 1: Cyclical variables and the perceived monetary policy rule

	Slope (12m lag)	Tightening dummy	Unemployment rate	ZLB dummy	VIX
Panel A: Baseline $\hat{\gamma}_t$					
Cofficient	0.12***	0.14*	-0.02	-0.12	-0.01***
	(0.03)	(0.08)	(0.02)	(0.11)	(0.00)
Intercept	0.20***	0.39***	0.54***	0.46***	0.72***
	(0.06)	(0.05)	(0.14)	(0.05)	(0.09)
R^2	0.18	0.04	0.01	0.03	0.12
Panel B: Inertial $\hat{\gamma}_t$					
Cofficient	0.04**	0.05	-0.01	-0.10***	-0.01***
	(0.01)	(0.04)	(0.01)	(0.03)	(0.00)
Intercept	0.10***	0.16***	0.20***	0.20***	0.32***
	(0.03)	(0.02)	(0.05)	(0.02)	(0.05)
R^2	0.07	0.02	0.00	0.08	0.14
N	460	460	460	460	448

Regressions of $\hat{\gamma}_t$ on cyclical variables in monthly data from January 1985 to May 2023. The top panel shows results for the baseline rule (2), and the bottom panel for the inertial rule (4). Regressors are the slope of the yield curve measured as the second principal component of Treasury yields from Gürkaynak, Sack and Wright (2007), lagged by 12 months; a tightening dummy for the months from the first to the last change in the fed funds rate of monetary tightening cycles; the unemployment rate; a ZLB dummy for zero lower bound periods; and the VIX, i.e., CBOE Volatility Index from 1990 onwards and S&P 100 Volatility Index 1986–1989. 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, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

The fourth column shows that the Fed is perceived to be somewhat less responsive to economic conditions during ZLB periods than non-ZLB periods, though only the negative coefficient on inertial $\hat{\gamma}_t$ is statistically significant. ZLB periods mix two kinds of episodes: When the Fed gave strong forward guidance for continued near-zero policy rates, as it did from September 2011 until 2013, funds rate forecasts are close to zero for all horizons in the BCFF data, so $\hat{\gamma}_t$ is essentially zero as well. But before liftoff from the ZLB—and also between 2009 and September 2011 when the Fed was mistakenly expected to lift off soon—$\hat{\gamma}_t$ is elevated.[16]

The last column of Table 1 shows that the Fed's perceived responsiveness to economic data tends to be lower when financial market uncertainty, here measured by the VIX, is high. In additional analysis we find similar patterns for various other measures of financial and macroeconomic uncertainty, including the uncertainty measures of Jurado, Ludvigson and Ng (2015). These findings suggest that the Fed is viewed as less data-dependent during

[16] Swanson and Williams (2014) also find that long-term rates remained sensitive to macro news until 2011.

easing episodes because elevated uncertainty and financial stress render standard economic data less informative about the true state of the economy.[17]

One might be concerned that misspecification of the policy rule is driving some of the time variation we document. Perhaps a more comprehensive perceived rule—including many more factors potentially important to Fed decisions—would lead to more stable perceived coefficients. But the empirical policy rules prominent in the literature tend to be simple and parsimonious. They provide a natural benchmark for our estimation of forward-looking rules and to assess how monetary policy perceptions vary over time. For robustness, we analyze both our baseline and inertial rule estimates throughout the paper. In Section 6 we consider alternative specifications, for example including credit spread forecasts.

In sum, perceptions about monetary policy exhibit substantial time variation related to easing and tightening cycles, forward guidance, and economic and financial uncertainty. But while the cyclical variables in Table 1 jointly explain a meaningful fraction of the variation in $\hat{\gamma}_t$, a large share of this variation remains unexplained. We next turn to understanding changes in the perceived monetary policy rule in response to new information.

3 The perceived rule and monetary policy surprises

Do forecasters revise their perceived monetary policy rule in response to actual Fed decisions? The analysis in this section shows that they do. Perceptions respond to monetary policy surprises in a manner consistent with the idea that forecasters have imperfect information about the policy rule and learn from observed policy decisions.

Following common practice, we measure monetary policy surprises as high-frequency rate changes around FOMC announcements, based on the assumption that these rate changes are mainly due to the announcement itself (e.g. Gürkaynak, Sack and Swanson, 2005; Nakamura and Steinsson, 2018). If market participants do not have full information about the policy rule, these surprises can arise not only from monetary policy shocks, but also from differences between the perceived and actual Fed response to macroeconomic data (Bauer and Swanson, 2023*a*,*b*).[18] In this case, beliefs about the policy rule should respond to surprises in a state-contingent manner: A tightening surprise in an economic boom suggests that the Fed cares even more about output than previously believed, so this kind of surprise should lead to an

[17]This interpretation is consistent with theories showing that the optimal monetary policy response to economic indicators should depend on economic uncertainty and financial conditions (e.g., Sack, 2000; Aoki, 2003; Svensson and Woodford, 2003).

[18]High-frequency monetary policy surprises could also contain Fed information effects (Nakamura and Steinsson, 2018; Bauer and Swanson, 2023*a*). However, information effects would be unlikely to move $\hat{\gamma}_t$, which has little correlation with standard business cycle variables (see Section 2.5).

increase in $\hat{\gamma}_t$. By contrast, a tightening surprise during a recession would signal less Fed concern with output stabilization, so forecasters should tend to revise downward $\hat{\gamma}_t$. This logic is formalized in our model in Section 5 below.

We empirically investigate belief updating by estimating the dynamic response of $\hat{\gamma}_t$ to monetary policy surprises using state-dependent local projections (Jordà and Taylor, 2016; Ramey and Zubairy, 2018). We use the high-frequency surprise measure of Bauer and Swanson (2023*b*), the first principal component of 30-minute changes in Eurodollar futures rates around FOMC announcements, which captures changes in policy rate expectations, and thus forward guidance, over a horizon of about a year. The surprise is normalized to have a unit effect on the four-quarter-ahead Eurodollar futures rate, measured in percentage points. The monthly monetary policy surprise, mps_t, sums up announcement surprises and equals zero in months without announcements. We estimate local projections

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

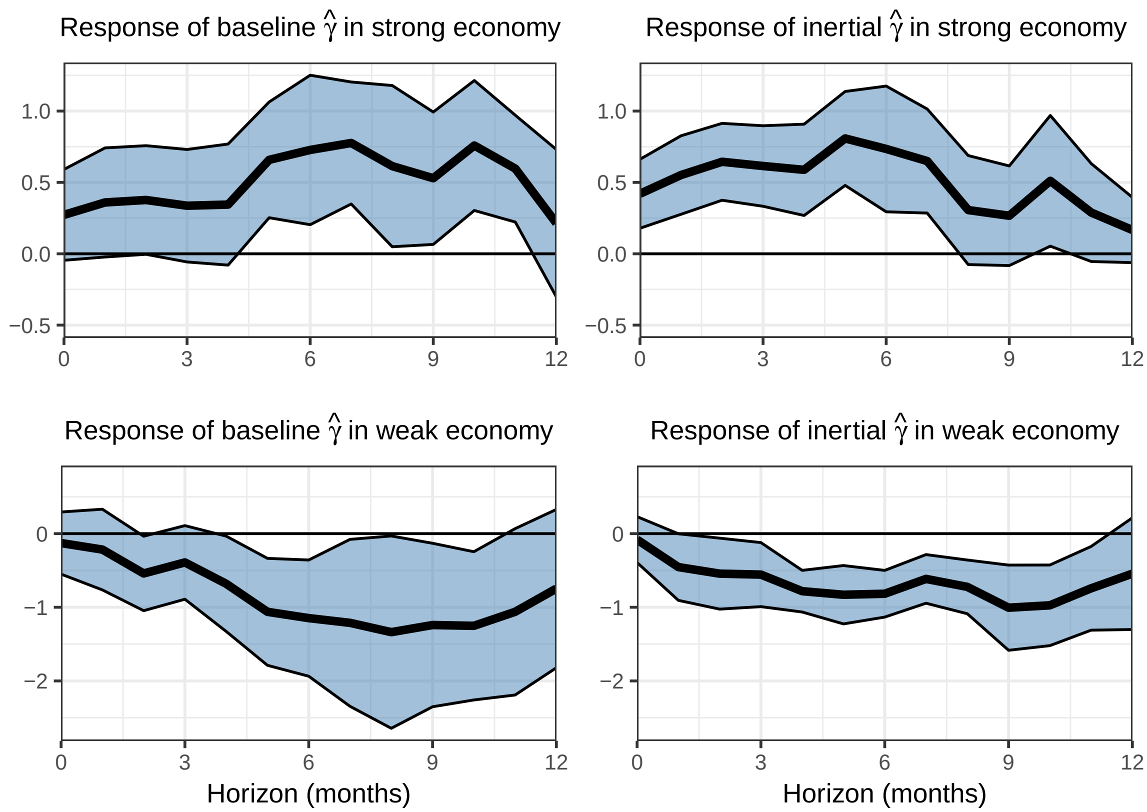
where the indicator variable $weak_t$ equals one when the output gap is below its median and zero otherwise, capturing episodes when the economy is growing slowly and resource slack is high. The regressions control for lagged $\hat{\gamma}_t$ to account for serial correlation in the perceived policy rule coefficient. We estimate equation (5) over the entire sample for $\hat{\gamma}_t$, from January 1985 to May 2023. There are 323 announcement surprises from February 1988 to December 2019, and we set mps_t to zero when no policy surprises are available.

The impulse responses in Figure 3 show that $\hat{\gamma}_t$ responds to monetary policy surprises in a state-contingent manner, consistent with the idea that forecasters learn about the monetary policy rule from actual Fed decisions. The top panels plot estimates of $b_1^{(h)}$ against h and document 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 are statistically significant for several horizons, judging by the 95%-confidence bands. In line with our hypothesis, the picture reverses in the bottom panels, which show persistently negative responses when the economy is weak. The responses for the inertial rule parameter, shown in the top right and bottom right panels, are similar and estimated somewhat more precisely.[19]

The magnitudes in Figure 3 are economically meaningful relative to the standard deviations of baseline $\hat{\gamma}_t$ (0.3) and inertial $\hat{\gamma}_t$ (0.15). A one percentage point monetary policy surprise leads to an increase in $\hat{\gamma}_t$ of roughly 0.7 in a strong economy. The same monetary policy surprise is estimated to lead to a somewhat larger decline in $\hat{\gamma}_t$ in a weak economy.

[19] Appendix D shows that the differences between the estimated responses in the top and bottom panels of Figure 3 are statistically significant.

Figure 3: 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 baseline estimate of $\hat{\gamma}_t$, and the estimates in the right panels use the inertial rule estimate. Shaded areas are 95% confidence bands based on Newey-West standard errors with $1.5 \times h$ lags. Sample: monthly data from January 1985 to May 2023.

A simple back-of-the-envelope calculation in Section 5, based on the model presented there and the magnitudes of these impulse responses, suggests that about 50% of the variation in monetary policy surprises is due to incomplete information about the policy rule.

The evidence in this section is closely related to recent work by Bauer and Swanson (2023*a*,*b*), who argue that market participants have incomplete information about the monetary policy rule and that misperceptions about the rule can explain the predictability of high-frequency monetary policy surprises. Our evidence is consistent with this view, but goes further by showing how professional forecasters update their beliefs in response to FOMC actions. In other words, Bauer and Swanson emphasize that the gap between γ_t and $\hat{\gamma}_t$ is an important driver of monetary policy surprises, while we provide evidence that these surprises lead to *changes in beliefs*, captured by $\hat{\gamma}_t$.

The evidence in Figure 3 for a state-dependent response of $\hat{\gamma}$ to monetary policy surprises is consistent with learning about the policy rule. As our model in Section 5 shows, the direction of the belief update depends on the sign of the output gap: After a hawkish policy surprise, $\hat{\gamma}_t$ increases in a strong economy and decreases in a weak economy. Under rational learning, the updating should be immediate. The gradual responses as in Figure 3 may emerge if forecasters are overconfident about their own signal about $\hat{\gamma}_t$ and hence underreact to information contained in monetary policy surprises. Overall, our evidence supports the view that the Fed's true monetary policy rule is at least partly unknown and the public learns about the rule from the FOMC's actions.

4 Transmission to financial markets

Having characterized time variation in the perceived monetary policy rule, we next show that it affects the key asset prices that transmit monetary policy to the real economy: short- and long-term interest rates, as well as stock prices.

4.1 Interest rate responses to macroeconomic news surprises

This section examines the sensitivity of interest rates to macroeconomic news. Event studies using narrow windows around macroeconomic announcements have previously been used to identify the effects of monetary policy on financial markets by Hamilton, Pruitt and Borger (2011) and Swanson and Williams (2014), among others. Our contribution is to document a connection between the sensitivity of financial markets to macroeconomic news and the perceived monetary policy rule, as captured by $\hat{\gamma}_t$.

To investigate this connection, we estimate event-study regressions

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

where Δy_t is the change in an interest rate on announcement date t and Z_t is a macroeconomic announcement surprise, that is, the value of the macroeconomic data release minus the consensus expectations for this data release before the day of the announcement. A positive interaction coefficient b_3 indicates that interest rates are more sensitive to macro news at times when the Fed is perceived to be more responsive to economic conditions.

Regression (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 in a narrow interval around a macro announcement is primarily about the macroeconomy, and that the interest rate response reflects the anticipated monetary policy reaction. Swanson and Williams (2014) allow the magnitude of the response to vary over time in an unrestricted fashion, investigating shifts during the ZLB period. By contrast, we directly tie variation in the sensitivity of interest rates to news to our estimates of the perceived monetary policy rule with the interaction effect $\hat{\gamma}_t \times Z_t$. In this way, we assess whether our survey-based estimates of the perceived policy rule, $\hat{\gamma}_t$, are consistent with changes in the sensitivity of financial market prices to macroeconomic news.

Table 2 reports estimates of equation (6) for four different interest rates: Three-month and six-month federal funds futures rates and two-year and ten-year Treasury yields. Fed funds futures measure policy rate expectations over the near term, and Treasury yields capture longer-term expectations. The left four columns in Table 2 use the single most influential macroeconomic announcement, nonfarm payrolls surprises, as Z_t. The right four columns use a linear combination of all macroeconomic surprises used by Swanson and Williams (2014), the fitted values from a regression of high-frequency interest rate changes on all these macro news. In Table 2, Panel A reports results for the baseline estimate of $\hat{\gamma}_t$, while Panel B uses the inertial estimate. The sample starts in 1990, when our macro news data begins, and ends in May 2023.[20]

The results in Table 2 show that our coefficient of interest, b_3, is uniformly positive and statistically significant across almost all combinations of interest rates, macroeconomic news, and estimates of $\hat{\gamma}_t$. That is, interest rates respond more strongly to macroeconomic news when the Fed is perceived to be more responsive to macro data. This result conforms with intuition: the same news about output leads markets to expect a larger change in future policy rates when the Fed is perceived to be more sensitive to output. The model in Section 5 formalizes this argument.[21]

The magnitudes of the interaction effects are also economically significant. Note that the 95th percentile of baseline $\hat{\gamma}_t$ is about one, and the 95th percentile of inertial $\hat{\gamma}_t$ is about 0.5; the 5th percentiles of both series are about zero. The estimates in Table 2 suggest that interest rates do not respond to nonfarm payrolls surprises when $\hat{\gamma}_t$ is zero, and respond strongly when $\hat{\gamma}_t$ is positive. Panel A shows that when baseline $\hat{\gamma}_t$ equals one, a one-standard deviation nonfarm payrolls surprise raises interest rates by 20 to 45 basis

[20] In Table 2 and other regressions in Section 4 where $\hat{\gamma}_t$ is an independent variable, the standard errors are not adjusted for the fact it is a generated regressor. Since $\hat{\gamma}_t$ is very precisely estimated, any such correction is likely to be small. Furthermore, the null hypothesis that the coefficient on $\hat{\gamma}$ is zero can be tested without any adjustment for the fact the regressor is generated (Pagan, 1984).

[21] The finding that changes in the shortest-term fed funds futures are more significantly related to the interaction with the inertial $\hat{\gamma}_t$ (Panel B) than the interaction with the baseline $\hat{\gamma}_t$ (Panel A) is also intuitive: Inertial $\hat{\gamma}_t$ captures the short-run response of monetary policy, and thus should determine the response of short-term interest rates to macro news surprises. In contrast, baseline $\hat{\gamma}_t$ captures the perceived medium-term response of monetary policy, and therefore should be more relevant for longer-term interest rates. Appendix F.1 makes this point explicit in the context of our model.

Table 2: Sensitivity of interest rates to macroeconomic news

	News: Nonfarm payrolls				News: All announcements			
	3m FF	6m FF	2y Tsy	10y Tsy	3m FF	6m FF	2y Tsy	10y Tsy
Panel A: Baseline $\hat{\gamma}_t$								
$\hat{\gamma}$	0.003	0.004*	0.002	0.000	0.003	0.004	0.003	0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Z	0.001	0.001	0.001	0.004***	0.84***	0.84***	0.76***	0.79***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.21)	(0.17)	(0.13)	(0.15)
$\hat{\gamma} \times Z$	0.21***	0.35***	0.45***	0.33***	0.46	0.48	0.69***	0.58**
	(0.03)	(0.04)	(0.05)	(0.05)	(0.39)	(0.32)	(0.25)	(0.27)
Intercept	-0.001	-0.001	-0.003	-0.002	-0.001	-0.002	-0.001	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
R^2	0.03	0.05	0.06	0.03	0.03	0.04	0.05	0.03
Panel B: Inertial $\hat{\gamma}_t$								
$\hat{\gamma}$	0.007	0.004	0.001	0.000	0.006	0.002	0.003	0.002
	(0.004)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.008)
Z	-0.002	-0.003	-0.002	0.002	0.58***	0.61***	0.65***	0.72***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.19)	(0.13)	(0.12)	(0.14)
$\hat{\gamma} \times Z$	0.48***	0.72***	0.85***	0.58***	2.89***	2.85***	2.61***	2.03***
	(0.08)	(0.08)	(0.09)	(0.10)	(0.91)	(0.78)	(0.54)	(0.65)
Intercept	-0.001	0.000	-0.002	-0.002	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.03	0.05	0.05	0.02	0.03	0.05	0.05	0.03

Estimates of the regression $\Delta y_t = b_0 + b_1\hat{\gamma}_t + b_2 Z_t + b_3\hat{\gamma}_t Z_t + \varepsilon_t$, where Δy_t is the interest rate change on days with macroeconomic announcements, expressed in percentage points, and Z_t is either the (standardized) surprise in nonfarm payrolls or a macro news aggregate that captures all announcements. Following Swanson and Williams (2014), we compute the news aggregate as the fitted value of a regression of the interest rate change on all macro news. Robust standard errors are reported in parentheses. The sample consists of all 3984 days with macro announcements between January 1990 and April 2023.

points. The estimates for all macroeconomic announcements show that the sensitivity of interest rates to macro news doubles and sometimes triples as $\hat{\gamma}_t$ changes from its 5th to 95th percentiles.

Overall, Table 2 documents the connection between $\hat{\gamma}_t$ and the sensitivity of interest rates to macro news, showing that our survey-based perceived policy rule is consistent with the "market-perceived monetary policy rule" (Hamilton, Pruitt and Borger, 2011). This evidence also alleviates endogeneity concerns that our estimates of $\hat{\gamma}_t$ might be influenced by the perceived endogenous response of output to monetary policy shocks. If changes in $\hat{\gamma}_t$ were primarily driven by this endogenous response, the sensitivity of interest rates to macro news should be unrelated to $\hat{\gamma}_t$ because macroeconomic data cannot respond to policy rates within narrow announcement windows. That the impact of macro news on interest rates scales up with $\hat{\gamma}_t$ suggests that we are indeed capturing the perceived monetary policy rule.

4.2 Term premia in long-term interest rates

In this section, we show that term premia in long-term bonds vary with monetary policy perceptions. This finding has important implications for monetary policy transmission because longer-term interest rates significantly influence aggregate spending and output. Term premia are often viewed as independent of conventional monetary policy, but recent work in macro-finance has questioned this view (e.g., Hanson and Stein, 2015; Song, 2017; Drechsler, Savov and Schnabl, 2018). Our evidence supports a direct link between term premia and the perceived monetary policy rule.

Standard asset pricing logic suggests that $\hat{\gamma}_t$ should be inversely related to term premia in long-term bonds. Assets that have higher payoffs in bad states of the world—when agents have higher marginal utility—should be more valuable and therefore command lower expected returns. With a higher perceived monetary policy coefficient $\hat{\gamma}_t$, interest rates are expected to fall more during a recession, and bond prices are expected to rise more. Thus, when $\hat{\gamma}_t$ is high, bonds are perceived to be better hedges and should have lower expected returns and term premia.[22] The model in Section 5 formalizes this prediction.

To investigate this prediction, we use survey expectations of future interest rates to construct subjective expected excess returns on long-term bonds. We prefer this measure over realized bond excess returns for two reasons: First, realized returns are a noisy realization of expected returns. Second, because our focus is on subjective perceptions we want to allow for discrepancies between full information rational expectations and subjective expectations, which recent work has documented to be empirically important for bond returns.[23]

We construct subjective expected one-year excess returns for par Treasury bonds following Piazzesi, Salomao and Schneider (2015). The expected twelve-month-ahead par yield on an n-year Treasury bond, $\bar{E}_t y_{t+12}^{(n),par}$, is approximated using the consensus BCFF forecast at

[22] These predictions are worked out in detail in Campbell, Pflueger and Viceira (2020) and Pflueger (2023), for example. The link between $\hat{\gamma}_t$ and subjective term 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.

[23] See Piazzesi, Salomao and Schneider (2015), Cieslak (2018), and Nagel and Xu (2023), among others. Consistent with this prior literature, our analysis studies subjective expectations of returns on *nominal* bonds. The difference between nominal and real term premia should be small in our sample period, which was largely characterized by low and stable inflation.

the 4-quarter forecast horizon. The log excess return on a par bond is:

$$\bar{E}_t xr_{t+12}^{(n+1)} = Dur_t^{(n+1)} y_t^{(n+1),par} - (Dur_t^{(n+1)} - 1)\bar{E}_t y_{t+12}^{(n),par} - y_t^{(1)}, \tag{7}$$

where $y_t^{(1)}$ denotes the one-year zero-coupon yield and $Dur_t^{(n+1)}$ is the duration of a par bond with maturity $n+1$ years (Campbell, 2017, pp. 236–237). Since we have forecasts for five- and ten-year yields, we calculate expected one-year returns for bond maturities of 6 and 11 years. Blue Chip forecasters are required to submit their responses at the end of the previous month, so for consistency we use observed yields from the last trading day of that month. We regress these subjective risk premia on contemporaneous $\hat{\gamma}_t$ and controls, for example,

$$\bar{E}_t xr_{t+12}^{(n+1)} = b_0 + b_1\hat{\gamma}_t + b_2 TERM_t + \varepsilon_t, \tag{8}$$

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

Table 3: Term premia

	$\bar{E}_t xr_{t+12}^{(6)}$			$\bar{E}_t xr_{t+12}^{(11)}$		
Panel A: Baseline $\hat{\gamma}_t$						
$\hat{\gamma}$	-1.93***	-2.24***	-2.61***	-3.02**	-3.49***	-3.79***
	(0.55)	(0.61)	(0.37)	(1.24)	(1.31)	(0.55)
TERM		0.32*			0.51	
		(0.19)			(0.34)	
R^2	0.12	0.16	0.61	0.09	0.12	0.61
Panel B: Inertial $\hat{\gamma}_t$						
$\hat{\gamma}$	1.06	1.10	-2.49***	1.69	1.76	-4.64***
	(1.24)	(1.14)	(0.74)	(2.37)	(2.21)	(1.50)
TERM		0.18			0.28	
		(0.19)			(0.33)	
R^2	0.01	0.02	0.46	0.01	0.02	0.52
PCs	No	No	Yes	No	No	Yes

Regressions of subjective expected log excess returns on six-year and 11-year nominal Treasury bonds over twelve-month holding periods on baseline $\hat{\gamma}_t$ (Panel A) and inertial $\hat{\gamma}_t$ (Panel B) and yield curve variables. $TERM$ is the spread between the ten-year and one-year zero-coupon nominal Treasury yields. If indicated, regressions control for the first three principal components (PCs) of Treasury yields. Coefficients on the constant and the three PCs are omitted. Sample: 425 monthly observations from December 1987 to May 2023. Newey-West standard errors with automatic lag selection (between 19 and 28 months) in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table 3 Panel A reports results for the baseline estimate of $\hat{\gamma}_t$. The first column shows a negative and statistically significant relationship with the subjective term premium on the six-year bond. The estimated coefficient is economically large: When baseline $\hat{\gamma}_t = 1$, the expected bond excess return is almost 2 percentage points lower than when $\hat{\gamma}_t = 0$.

Since the slope of the yield curve is correlated with $\hat{\gamma}_t$ (see Section 2.5), we control for information in the yield curve in columns (2) and (3). The term spread enters only marginally significantly in column (2), consistent with the findings in Nagel and Xu (2023). In the third column, we control for the first three principal components of Treasury yields with maturities one, two, five, seven, ten, fifteen, and twenty years. Naturally, including this yield curve information increases the R^2, but leaves the coefficient on $\hat{\gamma}_t$ largely unchanged. The remaining three columns in Panel A report similar results for the expected one-year excess returns on 11-year Treasuries.

Table 3 Panel B shows results for the inertial estimate of $\hat{\gamma}_t$. In the specifications that include the first three principal components of yields, the coefficient of interest is also negative and statistically significant at the one percent level, as in Panel A. For the other two specifications, however, the coefficient on $\hat{\gamma}_t$ is not statistically significant. This is consistent with the idea that the inertial $\hat{\gamma}_t$ captures the perceived *short-run* response of interest rates to the economy, whereas term premia depend on the longer-term behavior of interest rates, which is better captured by baseline $\hat{\gamma}_t$.[24]

While we focus on subjective term premia, there is a long tradition of estimating statistical term premia using predictive regressions for excess bond returns (e.g., Campbell and Shiller, 1991; Cochrane and Piazzesi, 2005; Bauer and Hamilton, 2018). Appendix E.1 shows that the perceived output gap coefficient, $\hat{\gamma}_t$, predicts realized bond excess returns with a negative sign, controlling for the usual predictors including the shape of the yield curve.

In sum, our evidence shows that the perceived policy rule is negatively related to both subjective and statistical bond term premia. The results are consistent with standard asset pricing logic: investors perceive bonds to be better hedges when they view the Fed as being more responsive to economic conditions. Our model in Section 5 formalizes this intuition and rationalizes these empirical results.

4.3 Bond market responses to monetary policy surprises

The link we document in Section 4.2 between the perceived monetary policy rule and term premia has additional implications when combined with our results on belief updating from

[24]In line with this intuition, Appendix Table E.4 shows that subjective term premia decline with perceived monetary policy inertia $\hat{\rho}_t$: holding fixed the perceived short-term monetary policy response, more policy inertia increases the perceived medium-term response and hence the effect on term premia.

monetary policy actions in Section 3: Monetary policy actions can affect term premia by changing beliefs about the policy rule.

The "Greenspan conundrum" is an illustrative example. During the monetary tightening of 2004–2005, the Fed raised the policy rate, but long-term yields stayed flat or even decreased. The Greenspan conundrum is often attributed to a decline in term premia (e.g., Backus and Wright, 2007), and our results suggest that shifting perceptions of the policy rule may have driven this decline. In particular, our results show that tightening episodes shift beliefs about the policy rule, raising the Fed's perceived responsiveness, $\hat{\gamma}_t$. As a consequence, term premia tend to fall, mitigating or even reversing the rise in long-term yields.

More broadly, since updating about the monetary policy rule from policy rates depends on the state of the economy, our results suggest that the response of long-term bond yields to FOMC announcements should too. Specifically, long-term bond yields should respond more strongly to monetary policy surprises around FOMC announcements when the economy is weak, since term premia move inversely with $\hat{\gamma}_t$. We test this hypothesis directly, using event-study regressions similar to Beechey and Wright (2009), Hanson and Stein (2015) and Nakamura and Steinsson (2018), who document that long-term nominal and real interest rates respond strongly to high-frequency monetary policy surprises.

We generalize the regression specification of Hanson and Stein (2015) as follows:

$$\Delta y_t = b_0 + b_1 \Delta y_t^{(2)} + b_2 weak_t + b_3 \Delta y_t^{(2)} weak_t + \varepsilon_t, \tag{9}$$

where each observation is an FOMC announcement. Following Hanson and Stein (2015), the monetary policy surprise proxy, $\Delta y_t^{(2)}$, is the two-day change in the two-year nominal Treasury yield. The dependent variable is the change in either nominal or real long-term Treasury yields or (instantaneous) forward rates, and the sample starts in 1999, when data on real interest rates becomes reliable. We add an interaction with the indicator variable $weak_t$, defined to equal one when the output gap is below its median as in Section 3. Our main interest is in b_3, the coefficient on the interaction $\Delta y_t^{(2)} \times weak_t$, which captures state-dependence and is predicted to be positive.

Table 4 shows our regression estimates, with results for five-year bonds in Panel A and ten-year bonds in Panel B. For each dependent variable, we present estimates of the univariate regression with only the policy surprise, for comparability with Hanson and Stein (2015), and for the multivariate regression (9). The first column of Panel A shows that the five-year nominal Treasury yield rises about one-for-one with the two-year yield around FOMC announcements, but the second column shows that this unconditional estimate masks pronounced state dependence. In a strong economy, a one percentage point tightening surprise

Table 4: Sensitivity of long-term rates to monetary policy surprises

	Nominal yield		Nominal forward		TIPS yield		TIPS forward	
Panel A: Five-year maturity								
$\Delta y_t^{(2)}$	1.07***	0.86***	0.92***	0.48***	0.85***	0.61***	0.89***	0.51***
	(0.06)	(0.04)	(0.12)	(0.09)	(0.10)	(0.08)	(0.15)	(0.08)
$weak_t$		0.00		0.01		-0.01		0.00
		(0.01)		(0.02)		(0.01)		(0.02)
$\Delta y_t^{(2)} \times weak_t$		0.52***		1.06***		0.60***		0.93***
		(0.12)		(0.24)		(0.22)		(0.29)
Intercept	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.00	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.74	0.79	0.32	0.42	0.33	0.37	0.25	0.31
Panel B: Ten-year maturity								
$\Delta y_t^{(2)}$	0.85***	0.56***	0.41***	0.14	0.71***	0.49***	0.33**	0.25**
	(0.09)	(0.07)	(0.11)	(0.11)	(0.09)	(0.07)	(0.14)	(0.10)
$weak_t$		0.01		0.02		0.00		0.01
		(0.01)		(0.02)		(0.01)		(0.02)
$\Delta y_t^{(2)} \times weak_t$		0.71***		0.65***		0.54***		0.19
		(0.16)		(0.19)		(0.19)		(0.34)
Intercept	0.00	-0.00	-0.00	-0.01	-0.00	-0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.43	0.50	0.09	0.14	0.32	0.37	0.07	0.07

Estimates of regressions $\Delta y_t = b_0 + b_1 \Delta y_t^{(2)} + b_2 weak_t + b_3 \Delta y_t^{(2)} weak_t + \varepsilon_t$, where the dependent variable is the two-day change in a nominal/TIPS yield or instantaneous forward rate with maturity five years (Panel A) or ten years (Panel B), $\Delta y_t^{(2)}$ is the two-day change in the two-year nominal Treasury yield, and $weak_t$ is an indicator of whether the output gap is below the median. The sample consists of 168 FOMC announcement dates between January 1999 and April 2023. Robust standard errors are reported in parentheses.

raises the five-year yield only 86 basis points, whereas in a weak economy, the effect rises to 138 basis points. That is, the effect is about 60 percent larger in a weak economy. The difference is even larger for the five-year forward rate, where the effect roughly triples (from 48 to 155 basis points). The stronger state dependence of forward rates is consistent with the idea that movements in term premia play an important role. The last four columns of Table 4 Panel A report results for five-year TIPS yields, where the effect of policy surprises on real rates doubles in a weak economy, and for five-year TIPS forward rates, where the effect roughly triples.

For ten-year bonds, the findings are similar, as shown in Panel B. The interaction coefficient is positive in all four multivariate regressions, and, with the exception of only the ten-year real forward rate, statistically significant at the one-percent level and large in magnitude. For both nominal and real ten-year yields, the effect of policy surprises on long-term rates more than doubles in a weak economy.

Our evidence clearly shows that a tightening monetary policy surprise increases long-term rates more in a weak economy than in a strong economy. These patterns can be explained by updating about the policy rule, coupled with a connection between the perceived policy rule and term premia. In a weak economy, a tightening surprise indicates to the public that the Fed is *less* sensitive to output than previously thought, making long-term bonds worse hedges. This in turn causes term premia to rise, which amplifies the response of long-term yields to the surprise. Conversely, in a strong economy, a tightening surprise decreases term premia because the public learns that the Fed is *more* sensitive to the economy than expected and that long-term bonds are better hedges, dampening the impact on long-term rates.

These results may help explain why long-term bond yields have responded only weakly to interest rate hikes during expansions (the Greenspan conundrum), while they have responded strongly on average over the post-1999 period (Hanson and Stein, 2015; Nakamura and Steinsson, 2018; Hanson, Lucca and Wright, 2021), which has been dominated by economic weakness and severe recessions. On the whole, our evidence supports the conclusion that perceptions about monetary policy influence term premia in long-term interest rates.

4.4 Stock market responses to monetary policy surprises

Finally, the perceived monetary policy rule should impact how stock prices respond to monetary policy surprises around FOMC announcements. If the Fed is perceived to better stabilize the output gap—and hence corporate profits and dividends—then stocks should respond less to any well-identified shock, including a high-frequency monetary policy surprise.

Bernanke and Kuttner (2005) documented that monetary tightening surprises are associated with large declines in the aggregate stock market, while easing surprises lead to sizable increases. To examine how this relationship varies with the perceived policy rule we estimate event-study regressions

$$R_t^M = b_0 + b_1\hat{\gamma}_t + b_2 mps_t + b_3\hat{\gamma}_t mps_t + \varepsilon_t, \tag{10}$$

where mps_t is the monetary policy surprise of Bauer and Swanson (2023*b*), as in Section 3. We estimate (10) with the stock returns R_t^M measured as either the CRSP value-weighted market return on the day of an FOMC announcement, or the intraday return on S&P500 futures from 10 minutes before to 20 minutes after the announcement. The sample starts in

February 1988 and ends in December 2019.[25]

Table 5 shows the results. In the first three columns, the dependent variable is the CRSP value-weighted return on the day of the announcement. The first column reports the benchmark result without interaction effect: stock returns are strongly negatively related to monetary policy surprises around FOMC announcements. The magnitudes are similar to those reported by Bernanke and Kuttner (2005), with a monetary policy surprise of 100 basis points causing a decline in the aggregate stock market index of seven percentage points.

Table 5: Stock market responses to monetary policy surprises

	CRSP Daily			S&P500 30-min		
	Benchmark	Baseline $\hat{\gamma}$	Inertial $\hat{\gamma}$	Benchmark	Baseline $\hat{\gamma}$	Inertial $\hat{\gamma}$
mps_t	-6.90***	-11.1***	-8.76***	-3.92***	-6.17***	-5.45***
	(1.47)	(2.48)	(1.62)	(0.89)	(1.21)	(1.00)
$\hat{\gamma}_t$		-0.072	-0.24		-0.0029	0.24
		(0.25)	(0.51)		(0.12)	(0.37)
$mps_t \times \hat{\gamma}_t$		10.1**	13.5***		5.41***	9.96***
		(4.78)	(5.05)		(1.74)	(3.01)
Intercept	0.20***	0.23*	0.24*	-0.018	-0.019	-0.072
	(0.060)	(0.14)	(0.14)	(0.031)	(0.076)	(0.095)
R^2	0.13	0.15	0.15	0.14	0.16	0.17

Regressions of stock market returns on monetary policy surprises, mps_t, the estimated output gap coefficient in the perceived policy rule, $\hat{\gamma}_t$, and the interaction of the two. In the first three columns, the dependent variable is the daily return on the CRSP value-weighted index. In the last three columns, the dependent variable is the return on S&P500 futures in the 30-minute window around the monetary policy announcement. The sample includes 316 FOMC announcements between February 1988 and December 2019. Robust standard errors in parentheses, * p <0.10, ** p <0.05, *** p <0.01.

The next two columns of Table 5 report estimates of regression (10) for the baseline estimate of $\hat{\gamma}_t$ and the inertial rule $\hat{\gamma}_t$, respectively. In both regressions, the coefficient on the interaction effect is statistically significant at least at the five percent level. The positive coefficient indicates that at times with high values for $\hat{\gamma}_t$, when the Fed is perceived to be highly responsive to economic conditions, the stock market reaction to policy surprises is less pronounced or even absent. To get a sense of the magnitudes, note that when baseline $\hat{\gamma}_t$ is one the implied response coefficient $b_2 + b_3\hat{\gamma}_t$ would be near zero, meaning that the

[25] In the case of intraday stock returns, t indexes FOMC announcements, of which there are 323 in the announcement data of Bauer and Swanson (2023*b*). With daily stock returns, t indexes days with FOMC announcements, of which there are 316 in the sample, since there are seven days with two announcements. Note that in equation (10), mps_t denotes the surprise around announcement (day) t, whereas in equation (5) it denotes the surprise in month t.

stock market does not respond to policy surprises at all. In other words, the negative market response to policy surprises is driven by times when the Fed's responsiveness to output is perceived to be low. The last three columns show similar, but more precisely estimated, coefficients for the return on S&P500 futures in a 30-minute window around the announcement as the dependent variable, following Gürkaynak, Sack and Swanson (2005) and Bauer and Swanson (2023*b*).

These results are consistent with the standard New Keynesian model, where a more responsive monetary policy rule dampens the volatility of the output gap in response to shocks (Clarida, Gali and Gertler, 2000). Intuitively, following a tightening surprise or contractionary monetary policy shock, the market anticipates that output and corporate profits will fall, driving down stock prices. If $\hat{\gamma}_t$ is high, markets perceive the Fed to be more sensitive to output and thus believe that the Fed will lower interest rates relatively sooner to undo the negative effects on the output gap. In this case, a tightening surprise is perceived to have smaller effects on future output, and the impact on stock prices today is less severe. On the other hand, when the Fed is perceived to be less sensitive to output and $\hat{\gamma}_t$ is low, the same tightening surprise is expected to last longer, leading to more severe macroeconomic consequences and more negative stock response.

The stock market's response to FOMC announcements is often interpreted as high-frequency evidence of the real effects of monetary policy, given that stock prices reflect macroeconomic expectations (Bernanke and Kuttner, 2005). Our results suggest that shifting perceptions about the monetary policy rule also matter for real economic outcomes. In particular, investors expect monetary policy shocks to more strongly affect economic outcomes at times when the Fed is perceived to be less responsive to the economy.[26]

5 A simple model with learning and heterogeneity

We now present a simple model that rationalizes our estimation of the perceived monetary policy rule and explains our empirical findings. The model features incomplete information about both the state of the economy (as in noisy information models, e.g., Woodford, 2003*a*) and about the Fed's policy rule (similar to Eusepi and Preston, 2010; Cogley, Matthes and Sbordone, 2015; Bauer and Swanson, 2023*a*,*b*). Forecasters receive idiosyncratic signals

[26] While we focus on the potential for cash flow effects to explain the results in Table 5, risk-bearing capacity and risk appetite may change as well (Bauer, Bernanke and Milstein, 2023). In the model of Pflueger and Rinaldi (2022), risk premia amplify the news about cash flows generated by monetary policy shocks. Thus, the stock response remains connected to the macroeconomic response even in the presence of volatile risk premia. We have also found that our results are robust to controlling for the change in the 10-year Treasury rate around FOMC announcements. This suggests that the results in Table 5 are not driven solely by changes in term premia in long-term bonds.

about the economy that lead to forecast disagreement. The Fed's interest rate decisions provide information about its policy rule and cause changes in the perceived rule. The model characterizes the relationship between interest rate and output gap forecasts, the belief updating in response to monetary policy surprises, the response of interest rates to macroeconomic news, and the properties of term premia in long-term bonds. It also allows us to quantify the importance of uncertainty about the monetary policy rule for high-frequency monetary policy surprises. All proofs are given in Appendix F.1.

The policy rate is described by a simple monetary policy rule,

$$i_t \quad = \quad \gamma_t x_t + \rho i_{t-1} + u_t, \tag{11}$$

with *iid* monetary policy shocks $u_t \sim N(0, \sigma_u^2)$. The key parameter is the response to the output gap, γ_t, which is known by the Fed but not the public. It is time-varying and follows a random walk,

$$\gamma_{t+1} \quad = \quad \gamma_t + \xi_{t+1}, \tag{12}$$

with *iid* innovations $\xi_t \sim N(0, \sigma_\xi^2)$. For simplicity, the degree of policy inertia ρ is known and constant. We abstract from the effects of monetary policy on the economy and let the output gap x_t follow an exogenous AR(1) process,

$$x_t \quad = \quad \phi x_{t-1} + v_t, \tag{13}$$

with *iid* innovations $v_t \sim N(0, \sigma_v^2)$. The shocks u_t, ξ_t and v_t are mutually uncorrelated.

In period 1, the prior belief of forecaster j about the monetary policy rule is given by

$$E\left(\gamma_1 \,|\mathcal{Y}_0\right) \quad = \quad \hat{\gamma}_1, \qquad Var\left(\gamma_1 \,|\mathcal{Y}_0\right) = \sigma_1^2, \tag{14}$$

where $\mathcal{Y}_t$ denotes the information set including past output gaps and interest rates up to and including time t. All forecasters have the same prior beliefs about the policy rule. We denote beliefs about the policy rule, based on information up to time t, by $\hat{\gamma}_{t+1} = E(\gamma_{t+1}|\mathcal{Y}_t)$.

At the beginning of each period, each forecaster observes 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 *iid* across t and j. The signals lead to disagreement in output gap forecasts $E^{(j)}\left(x_{t+h}|\mathcal{Y}_{t-1}, \nu_t^j\right)$. Forecasters then use the perceived policy rule to make interest rate forecasts, $E^{(j)}\left(i_{t+h}|\mathcal{Y}_{t-1}, \nu_t^j\right)$. In our model, output gap forecasts are rational, but similar results would obtain in the presence of under- or overreaction, strategic incentives, or other biases (Bordalo et al., 2020; Angeletos, Huo and Sastry, 2021), as long as forecasters form policy rate forecasts consistent with their perceived policy rule.

Next, all forecasters observe the output gap x_t, similar to a macroeconomic announcement in the data. At the end of period t, the Fed sets the policy rate i_t based on the policy rule, similar to an FOMC announcement. In response to the interest rate decision, forecasters update their beliefs about the policy rule, captured by $\hat{\gamma}_t$.

In our baseline specification, forecasters update about the policy rule parameter as rational Bayesians, but we can allow for non-rational updating due to overconfidence. Building on the model of belief misspecifications of Angeletos, Huo and Sastry (2021), we assume that forecasters perceive the variance of the monetary policy shock to be $\frac{\sigma_u^2}{\kappa}$ when it is actually σ_u^2. If $\kappa < 1$, forecasters are effectively overconfident, overweighting their own private prior relative to the public signal contained in the policy rate in the spirit of Bordalo et al. (2020).

Lemma 1 shows that the perceived monetary policy rule can be recovered from a forecaster-horizon panel.

Lemma 1 (Period-by-Period Panel Regression) *In the panel regression of time-t policy rate forecasts on time-t output gap forecasts with forecaster fixed effects*

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

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

Our empirical strategy in Section 2 builds on the insight from Lemma 1 that the perceived coefficient $\hat{\gamma}_t$ can be estimated with a panel regression using forecasts made at t.

Lemma 2 describes how forecasters update their perceptions of the monetary policy rule. We use $\bar{E}(\cdot)$ to denote average or "consensus" expectations across all forecasters j.

Lemma 2 (Policy Surprises and Belief Updating) *The monetary policy surprise is*

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

and forecasters update their policy rule belief $\hat{\gamma}_t$ according to

$$\hat{\gamma}_{t+1} - \hat{\gamma}_t = \omega_t \frac{mps_t}{x_t}, \qquad \omega_t \equiv \frac{\sigma_t^2 x_t^2}{\sigma_t^2 x_t^2 + \frac{\sigma_u^2}{\kappa}}, \qquad \sigma_{t+1}^2 = \sigma_t^2(1-\omega_t) + \sigma_\xi^2. \tag{16}$$

Lemma 2 shows how the monetary policy surprise, mps_t, conveys information about the actual rule γ_t. In the absence of monetary policy shocks, we would have $\gamma_t - \hat{\gamma}_t = \frac{mps_t}{x_t}$ and thus γ_t could be learned perfectly. With monetary policy shocks, forecasters update their prior $\hat{\gamma}_t$ depending on the signal-to-noise ratio ω_t. The model predicts no updating following monetary policy decisions in the limiting case with vanishingly small uncertainty about the monetary policy coefficient, captured by the prior variance σ_t^2. In this case, ω_t is zero because agents are confident that they know the policy rule.

The key testable implication of Lemma 2 is that the perceived policy rule $\hat{\gamma}_t$ should respond to monetary policy surprises in a state-contingent manner. A positive monetary policy surprise could arise either from a positive output gap and higher-than-expected monetary policy coefficient, or from a negative output gap and lower-than-expected γ_t. Thus, in response to such a positive surprise, forecasters revise $\hat{\gamma}_t$ up in a strong economy but revise it down in a weak economy. Our evidence in Section 3 confirms this prediction and supports the view that agents have incomplete information about the policy rule.

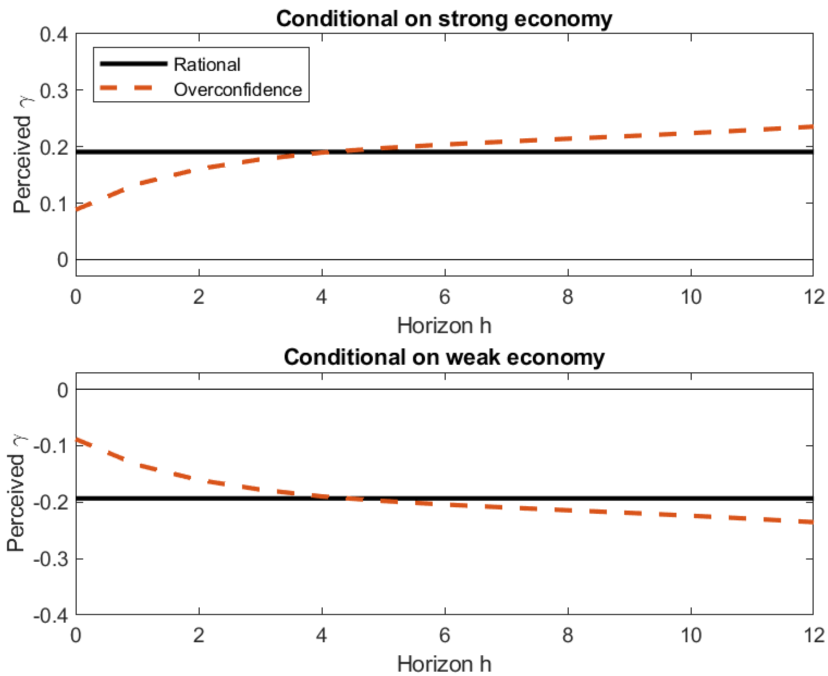
Figure 4 illustrates the model's implication that updating of beliefs about the policy rule is state-contingent. The speed at which forecasters update their beliefs $\hat{\gamma}_t$ differs depending on whether agents update rationally ($\kappa = 1$) or exhibit overconfidence ($\kappa < 1$). With rational updating, the perceived monetary policy coefficient responds immediately and permanently to the policy surprise (black lines). In the case of overconfidence, agents put too much weight on their priors about the policy rule, and thus respond more slowly (red lines). The gradual responses in this case match the empirical patterns in Figure 3. An additional implication of underreaction is that fed funds forecast errors should be predictable from the interaction of economic activity and the perceived monetary policy reaction coefficient $\hat{\gamma}_t$, a prediction that we verify in Appendix C.

Lemma 2 also allows us to roughly quantify the empirical relevance of incomplete information about the policy rule. The expression for ω_t in Lemma 1 provides a link between the magnitude of the response of $\hat{\gamma}_t$ to observations of $\frac{mps_t}{x_t}$ and the share of uncertainty about the monetary policy surprise that is due to uncertainty about the policy rule. We can use this link to conduct a simple back-of-the-envelope calculation: Comparing the peak response in the top-left-panel in Figure 3 of 0.7 with an average output gap of 1.4% percent suggests that about $0.7/1.4 = 50\%$ of the variation in monetary policy surprises are due to the uncertainty of forecasters about the policy rule.[27]

Incomplete information about the monetary policy rule can lead to macroeconomic instability through different channels (e.g., Eusepi and Preston, 2010; Cogley, Matthes and Sbordone, 2015). Our model illustrates one of these channels working through financial markets: The volatility of monetary policy surprises increases with uncertainty about the

[27]Equation (16) shows that the amount forecasters update their perceived rule $\hat{\gamma}_t$ following a surprise depends on their uncertainty about the rule (σ_t^2), the volatility of the policy shock (σ_u^2), and the output gap. The output gap is on average 1.4 percentage points above its median during the strong economic times. Substituting $\hat{\gamma}_{t+1} - \hat{\gamma}_t \approx 0.7$ and $x_t \approx 1.4$ into equation (16) and solving for ω_t suggests that forecasters attribute about 50% of the variation in monetary policy surprises to uncertainty about the policy rule.

Figure 4: Model impulse responses of perceived monetary policy coefficient



Regression on model-simulated data: $\hat{\gamma}_{t+h} = a^{(h)} + b_1^{(h)} mps_t(1 - weak_t) + b_2^{(h)} mps_t weak_t + c^{(h)} weak_t + d^{(h)}\hat{\gamma}_{t-1} + \varepsilon_{t+h}$, where $weak_t$ is an indicator for whether the output gap during period t was negative. We report the average across 2000 simulations of length 3000. The simulations us a persistence of the output gap of $\rho = 0.95$, and volatilities $\sigma_v = 1.2$, $\sigma_u = 0.05$, and $\sigma_\xi = 0.1$. "Rational" corresponds to $\kappa = 1$, and "Overconfidence" to $\kappa = 0.1$.

rule, because

$$Var\left(mps_t \left| \mathcal{Y}_{t-1}, x_t\right.\right) = Var\left(\gamma_t - \hat{\gamma}_t \left| \mathcal{Y}_{t-1}\right.\right) x_t^2 + \sigma_u^2.$$

That is, misperceptions about the monetary policy rule increase financial market volatility, which may translate to greater macroeconomic instability.

Lemma 3 states that the perceived monetary policy rule should also influence how strongly interest rates respond to macroeconomic news announcements.

Lemma 3 (Macroeconomic News) *Define a macroeconomic surprise as* $\Delta x_t = x_t - \bar{E}\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right)$ *and the contemporaneous change in interest rate forecasts as* $\Delta i_t = \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, x_t\right.\right) - \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, \nu_t^j\right.\right)$. *The interaction coefficient* b_3 *in the following regression is positive:*

$$\Delta i_t = b_0 + b_1\hat{\gamma}_t + b_2\Delta x_t + b_3\hat{\gamma}_t\Delta x_t + \varepsilon_t. \tag{17}$$

In Section 4.1, we confirm the prediction of Lemma 3 that the perceived monetary policy rule influences the sensitivity of interest rates to macroeconomic news.

Lemma 4 traces out the implications of the perceived monetary policy rule for term premia in long-term bonds, using the two-period bond as a stand-in. We assume a simple stochastic discount factor where marginal utility is inversely related to the output gap. One microfoundation for this assumption would be constant relative risk aversion (CRRA) utility over consumption with consumption equal to output and constant potential output. Similar assumptions for the stochastic discount factor are common in reduced form asset pricing models (e.g., Lettau and Wachter, 2007).

Lemma 4 (Bond Risk Premia) *Assuming a log stochastic discount factor* $m_{t+1} = -i_t - \psi v_{t+1} - \frac{1}{2}\psi^2\sigma_v^2$*, the expected excess return on a two-period bond declines with the perceived monetary policy coefficient* $\hat{\gamma}_t$*.*

Lemma 4 predicts that the perceived monetary policy rule should influence long-term interest rates beyond its impact on expected future policy rates, i.e., through term premia. When the perceived monetary policy coefficient, $\hat{\gamma}_t$, is high, interest rates are expected to fall and bond prices are expected to rise in recessions, which are states of high marginal utility. This perceived comovement makes long-term bonds desirable hedges, decreasing the term premia investors demand to hold them. We confirm these predictions for expected excess bond returns in Section 4.2.

Combining Lemmas 2 and 4 yields the following result for the responses of long-term bonds to monetary policy announcements:

Corollary 1 (State-Contingent Long-Term Bond Responses) *Denote the interest rate on a two-period bond by* $y_t^{(lt)}$ *and let* $weak_t$ *be an indicator variable equal to one when the output gap is negative, and zero otherwise. In the regression*

$$\Delta y_t^{(lt)} = b_0 + b_1 mps_t + b_2 weak_t + b_3 mps_t weak_t + \varepsilon_t, \tag{18}$$

the coefficient b_3 *is positive.*

Corollary 1 has further testable implications for the transmission of the perceived monetary policy rule to long-term interest rates. It uses a two-period bond to understand the behavior of long-term bond yields around monetary policy announcements, showing that long-term bond yields should display excess sensitivity to monetary policy surprises when the economy is weak, i.e., x_t is below average. Conversely, long-term bond rates should be relatively insensitive to monetary policy surprises if the economy is strong and x_t is above average. We confirm this prediction in Section 4.3.

6 Robustness of estimated perceived policy rules

This section demonstrates the robustness of our estimates of the perceived output gap coefficient $\hat{\gamma}_t$ to alternative specifications of the policy rule and different estimation methods. Overall, we find that are estimates are very robust: All of the alternative estimates of $\hat{\gamma}_t$ are highly correlated with our baseline estimates, with correlation coefficients above 0.8.

We first consider an estimate of the baseline rule (2) that does not include forecaster fixed effects. This simple pooled OLS estimate of $\hat{\gamma}_t$ has a correlation of 0.84 with our estimate including forecaster fixed effects. Appendix Figure B.1 plots both estimates. Because of the less restrictive assumptions required for the estimates with forecaster fixed effects, we focus on these throughout the paper.

While our panel regression estimates treat each Blue Chip survey as separate, we can link the surveys over time using state-space models. Appendix B.1 estimates two such models, corresponding to panel regressions with and without forecaster fixed effects. The resulting estimates of $\hat{\gamma}_t$ and $\hat{\beta}_t$ are somewhat smoother month-to-month, but overall exhibit very similar patterns to our panel regression estimates. For the estimate of $\hat{\gamma}_t$ with forecaster fixed effects, the correlation with the corresponding state-space model estimate is 0.99.

Our estimation assumed that forecasters share a common belief about the rule's parameters. What if there is heterogeneity in the perceived rule? Under certain conditions that are stated in Appendix B.2, heterogeneity is orthogonal to our estimates in the sense that we capture the average belief across forecasters. This is the case, for example, if heterogeneity in macroeconomic forecasts is uncorrelated with heterogeneity in the perceived rule parameters. To relax this assumption, we consider three alternative estimates of the perceived monetary policy rule that account for heterogeneity (details and plots are in Appendix B.2). First, we estimate a regression of the form (2) for each forecaster, only utilizing the cross-horizon variation, and then average the estimates across forecasters. The resulting series has a correlation of 0.81 with our baseline $\hat{\gamma}_t$. Second, we estimate a multidimensional panel regression (across i, j, and h) that includes forecaster fixed effects interacted with the output gap and inflation forecasts, thus allowing individual forecasters to persistently perceive the Fed to be more or less responsive to output and inflation than the average forecaster. In this case, the correlation with our baseline $\hat{\gamma}_t$ estimate is 0.88. A third way to address heterogeneity is to consider subsets of forecasters. We split forecasters into three groups based on their inflation forecasts, addressing the concern that inflation hawks (forecasters that expect high inflation) and doves might perceive different monetary policy rules. The resulting estimates of $\hat{\gamma}_t$ have a correlation with our baseline estimate of $\hat{\gamma}_t$ that is above 0.8 for all three groups. Taken together, these results suggest that the time variation evident in our perceived policy rule is common to the monetary policy beliefs across all forecasters, and that accounting for belief heterogeneity does not materially impact the time series patterns that are the main focus of our paper.[28]

We next address concerns about omitted variables in the perceived policy rule. In particular, there is extensive evidence that financial market conditions affect the Fed's monetary policy.[29] If forecasts for financial conditions and economic conditions are correlated, then a high value for $\hat{\gamma}_t$ could partly reflect the perceived monetary policy response to financial conditions. We investigate this possibility by including forecasts of future credit spreads—the difference between forecasts for Baa corporate bond yields and the ten-year Treasury yield—as a proxy for expected financial conditions.[30] These estimates indeed confirm an important perceived role for financial conditions in determining the policy rate, as the coefficient on the expected credit spread is often substantially negative and statistically significant (results omitted). But incorporating credit spread forecasts into the perceived policy rule has little effect on the perceived response to output gap forecasts. The correlation between our baseline estimates of $\hat{\gamma}_t$ and those including expected credit spreads is 0.94.

Another possible concern about our estimates is the reliance on output gap forecasts that are imputed from GDP growth forecasts. We address this concern by estimating perceived policy rules using the Survey of Professional Forecasters, which contains forecasts for the unemployment rate as an alternative measure of expected economic activity. Appendix B.4 shows that the resulting $\hat{\gamma}_t$ look very similar to those for the BCFF.

Finally, we address the concern that our estimates of monetary policy rules might be potentially biased due to 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. Recent work by Carvalho, Nechio and Tristao (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. To deal with this issue, we quantify the bias and adjust for it, adapting the model-based approach of Carvalho, Nechio and Tristao (2021) to our cross-sectional setting

[28] Relatedly, in Appendix E.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, Laursen and Singleton (2021). This finding suggests that the Fed's ability to eliminate disagreement about future policy rates is not driving our estimates.

[29] For example, Caldara and Herbst (2019) show that U.S. monetary policy reacts to changes in corporate credit spreads, and Cieslak and Vissing-Jorgensen (2021) document evidence for a Fed put, i.e., that policy reacts to stock market downturns.

[30] Forecasts of the Baa yield are available in the BCFF data starting in 2001.

as detailed in Appendix B.3. As expected, we find that the bias-adjusted $\hat{\gamma}_t$ is somewhat higher than the baseline estimate, with a sample mean of 0.57 versus 0.43. This difference 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, as evident from the high correlation between baseline and bias-adjusted estimates of 0.92.

A structural interpretation of our estimates as coefficients in a perceived policy rule is also supported by our empirical results, which show that $\hat{\gamma}_t$ responds to monetary policy surprises in a state-dependent, theory-consistent manner (Section 3) and that it explains interest rate responses during narrow intervals around macroeconomic news surprises (Section 4.1). That said, one could also simply interpret $\hat{\gamma}_t$ as the perceived endogenous comovement between the policy rate and the macroeconomy, sidestepping these causality concerns. Under this interpretation, our results help understand how forecasters learn about this comovement, and how their perceptions are reflected in financial markets.

7 Conclusion

This paper presents new time-varying estimates of the monetary policy rule perceived by professional forecasters, using rich panel data of monthly survey forecasts. With our 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 varies substantially over time, reflecting the Fed's shifting concerns about economic data versus financial and other risks. It tends to be high during monetary tightening cycles when Fed policy is perceived to be data-dependent, and low during easing cycles and times of elevated economic and financial uncertainty. 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 about the rule followed by the Fed. 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, the variation in term premia on long-term bonds both month-to-month and around monetary policy surprises, and time variation in the response of the stock market to FOMC announcements.

These conclusions have broader implications for monetary economics and the practice of monetary policy. In particular, they imply that the impact of monetary policy on financial markets—the first stage of the monetary transmission mechanism—cannot be understood without taking into account that the public has incomplete information about the Fed's monetary policy strategy and learns about it over time. This opens the door for important additional research, addressing such questions as how central bank communication shapes perceptions about the monetary policy strategy and how optimal monetary policy should account for shifting perceptions in seeking to stabilize inflation and employment.

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Appendix for Online Publication

A Survey data and perceived policy rule

A.1 BCFF data and summary statistics

The professional forecasters are queried near the end of the month preceding the release of the survey. Specifically, the deadline for the survey responses is the 26th of the previous month, with the exception of December, when the deadline is the 21st.

The BCFF contains quarterly forecasts. For the federal funds rate, the forecast target is the quarterly average of the daily effective funds rate, in annualized percent, as reported in the Federal Reserve's H.15 statistical release. The macroeconomic forecasts for output growth and inflation are reported as quarter-over-quarter forecasts in annualized percent.

We calculate year-over-year inflation forecasts as follows: 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, observed CPI inflation over recent 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.[31] 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.

In Table A.1 we report summary statistics for our survey data. Across surveys, horizons,

[31] 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 A.1: Summary statistics for survey forecasts

	N	Mean	Standard Deviations			
			SD	Within-Month	Within-Month-ID	Within-Month-Horizon
Fed funds rate	120,152	3.5	2.6	0.46	0.33	0.33
CPI inflation	118,929	2.7	1.2	0.61	0.48	0.40
Output growth	119,317	2.6	1.8	1.04	0.80	0.83
Output gap	119,305	-1.4	2.6	0.65	0.40	0.52

Summary statistics for individual survey forecasts in the Blue Chip Financial Forecasts from January 1985 to May 2023 (461 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.

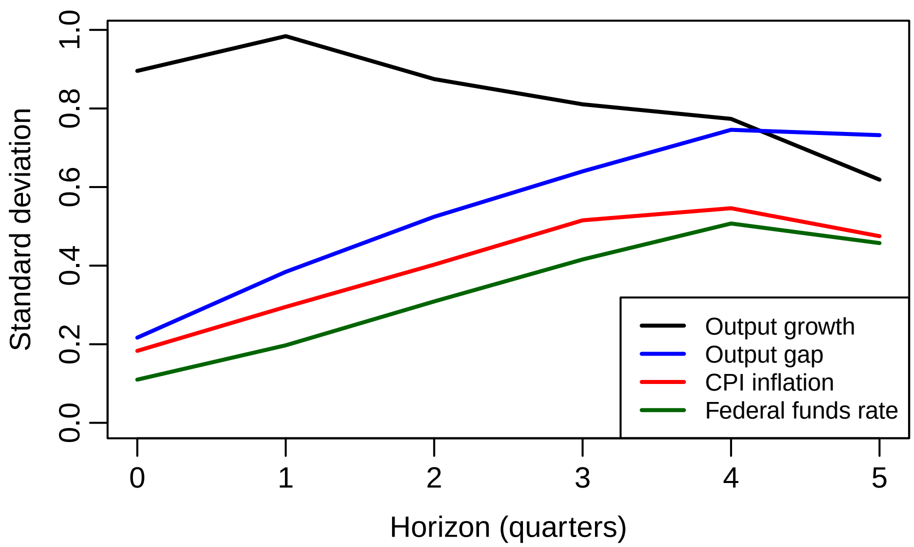
and forecasters, there are about 120,000 individual forecasts. Output gap forecasts are negative on average, in line with the fact that both real-time and revised estimates of the output gap were negative for the majority of our sample period. Forecasted CPI inflation averages around 2.7% and the average fed funds rate forecast equals 3.5%, 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.

A.2 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) 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, CPI 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.

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.

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.

B Robustness of policy rule estimates

B.1 State-space model: Linking coefficients over time

Our panel data regressions treat the monthly surveys as completely separate. An alternative approach that links the parameter estimates over time is a state-space model (SSM), with policy rule parameters as the state variables.

A simple SSM for perceived, survey-based policy rules has three state variables: a time-varying intercept $\hat{\alpha}_t$ and the inflation and output gap coefficients $\hat{\beta}_t$ and $\hat{\gamma}_t$. For each forecaster and horizon the observation equation is

$$E_t^{(j)} i_{t+h} = \alpha_t + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + e_{th}^{(j)}. \tag{B.1}$$

We assume that the Gaussian measurement errors $e_{th}^{(j)}$ have the same variance for all forecasters and horizons, and are uncorrelated across j, h, and t. The state variables are modeled as independent random walks, consistent with the martingale assumption from Section 2.2, with *iid* Gaussian innovations that are mutually uncorrelated. A necessary additional assumption for obtaining (B.1) is that perceptions about the long-run inflation and real interest rates are homogeneous, i.e., $E_t^{(j)} \pi_{t+h}^* = \pi_t^*$ and $E_t^{(j)} r_{t+h}^* = r_t^*$. The time-varying intercept is $\alpha_t = r_t^* + (1 - \hat{\beta}_t)\pi_t^*$. The observation equation of the SSM is simply a matrix version of (B.1), in which the coefficient matrix each period contains inflation gap and output gap forecasts across all forecasters and horizons. Missing forecasts are easily handled with the Kalman filter. The parameters to be estimated are the variances of the state innovations and the measurement error. We estimate the SSM using maximum likelihood and denote the resulting estimates as SSM OLS, as there are neither fixed nor random effects.

Earlier versions of the paper reported results for Bayesian estimation using MCMC. This has some advantages, including the ability to include prior information and to jointly account for filtering and estimation uncertainty. However, the results are virtually identical to simple MLE, because of the large amount of information in the forecast panel data about the latent state variables.

We also estimate an alternative SSM specification that imposes the within-transformation of the forecasts, corresponding to our regression estimates with forecaster fixed effects. The observation equation becomes

$$E_t^{(j)} i_{t+h} - \bar{E}_t i_{t+h} = \hat{\beta}_t (E_t^{(j)} \pi_{t+h} - \bar{E}_t \pi_{t+h}) + \hat{\gamma}_t (E_t^{(j)} x_{t+h} - \bar{E}_t x_{t+h}) + \ddot{e}_{th}^{(j)}. \tag{B.2}$$

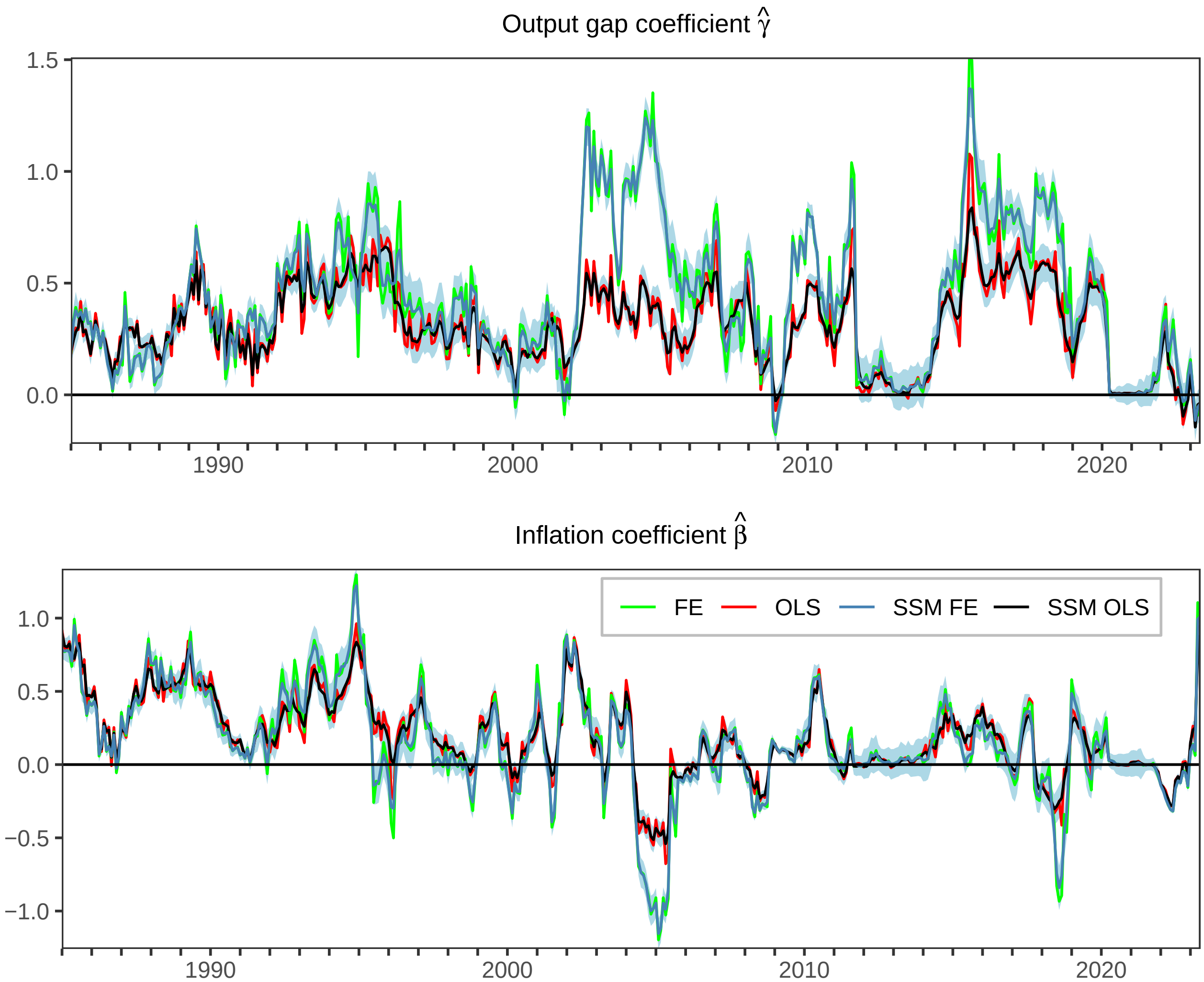
This specification, like our FE panel model, allows for heterogeneous beliefs about π_t^* and r_t^* that can be correlated with inflation and output gap forecasts. We denote the resulting estimates as SSM FE.

Figure B.1 shows the state-space estimates of the output gap coefficient $\hat{\gamma}_t$ and the inflation coefficient $\hat{\beta}_t$, obtained from the Kalman smoother, as well as 95%-confidence intervals based on the posterior variances. For comparison, we also include the OLS and FE panel estimates (the latter are also shown in Figure 1). The SSM estimates are generally very similar to the regression estimates. Some of the month-to-month movements are smoothed out by linking the coefficient estimates over time, but the general pattern of substantial variation at medium and high frequencies is preserved in the SSM. The reason is that each monthly survey contains many forecast observations and thus a lot of information about the policy rule parameters. This cross-sectional information dominates the time series information in the parameter estimates from adjacent months. The confidence intervals are slightly more narrow than for the regression estimates because of the additional time series information.

While our SSM estimates of the policy rule parameters are almost as volatile as the panel regression estimates, it is technically possible to obtain substantially smoother parameter estimates. One can either fix the variance of the measurement error at a higher value and the variances of the state variable innovations at lower values than their maximum likelihood estimates, or impose strong priors on these variances that accomplish a similar result in a Bayesian estimation. Such estimates may be helpful for certain applications, but they require a choice about the desired degree of smoothness.

The bottom line is that the SSM estimates are, for all practical purposes, similar to the corresponding panel regression estimates. Unsurprisingly, we have found that replacing the regression-based estimates with the SSM estimates has little effect on the results of our subsequent analysis of $\hat{\gamma}_t$.

Figure B.1: State-space model estimates of perceived policy rule coefficients



Estimated policy-rule parameters $\hat{\gamma}_t$ and $\hat{\beta}_t$ from the state-space models (SSM), and from FE and OLS panel regressions. The SSM estimates are the smoothed estimates of the state variables, and shaded areas are 95%-confidence intervals based on the posterior variances. Sample period: January 1985 to May 2023.

B.2 Forecaster heterogeneity

Forecasters may have different beliefs about the policy rule. Here we provide details on the consequences of such heterogeneity and some alternative estimates that account for it.

We first show under which conditions our baseline estimates correspond to the cross-sectional average of the perceived policy rule coefficients, meaning that heterogeneity is irrelevant for the time-series variation in the perceived policy rule that we are interested in. Allowing for heterogeneity in the perceived policy rule in equation (2) by introducting the heterogeneous coefficients $\hat{\gamma}_t^{(j)}$ and $\hat{\beta}_t^{(j)}$, and rewriting in terms of $\bar{\hat{\gamma}}_t$ and $\bar{\hat{\beta}}_t$, the cross-forecaster averages of these coefficients, yields

$$\begin{aligned} E_t^{(j)} i_{t+h} &= a_t^{(j)} + \hat{\gamma}_t^{(j)} E_t^{(j)} x_{t+h} + \hat{\beta}_t^{(j)} E_t^{(j)} \pi_{t+h} + e_{th}^{(j)}, && \text{(B.3)} \\ &= a_t^{(j)} + \bar{\hat{\gamma}}_t E_t^{(j)} x_{t+h} + \bar{\hat{\beta}}_t E_t^{(j)} \pi_{t+h} \\ &\quad \underbrace{+ \left(\hat{\gamma}_t^{(j)} - \bar{\hat{\gamma}}_t\right) E_t^{(j)} x_{t+h} + \left(\hat{\beta}_t^{(j)} - \bar{\hat{\beta}}_t\right) E_t^{(j)} \pi_{t+h} + e_{th}^{(j)}}_{\tilde{e}_{th}^{(j)}}, && \text{(B.4)} \end{aligned}$$

where we recall that $e_{th}^{(j)}$ is assumed to be an uncorrelated error. This expression shows that a simple fixed effects regression with homogeneous output gap and inflation coefficients recovers the forecaster averages $\bar{\hat{\gamma}}_t$ and $\bar{\hat{\beta}}_t$, if the error $\tilde{e}_{th}^{(j)}$ is uncorrelated with output gap and inflation forecasts, $E_t^{(j)} x_{t+h}$ and $E_t^{(j)} \pi_{t+h}$. A simple sufficient condition to ensure this is that $\hat{\gamma}_t^{(j)}$ and $\hat{\beta}_t^{(j)}$ are independent of $E_t^{(j)} x_{t+h}$ and $E_t^{(j)} \pi_{t+h}$. A weaker set of sufficient assumptions is that the four covariances all equal zero: $Corr\left(\hat{\gamma}_t^{(j)}, \left(E_t^{(j)} x_{t+h}\right)^2\right)$, $Corr\left(\hat{\gamma}_t^{(j)}, E_t^{(j)} x_{t+h} E_t^{(j)} \pi_{t+h}\right)$, $Corr\left(\hat{\beta}_t^{(j)}, \left(E_t^{(j)} \pi_{t+h}\right)^2\right)$, $Corr\left(\hat{\beta}_t^{(j)}, E_t^{(j)} x_{t+h} E_t^{(j)} \pi_{t+h}\right)$.

We can allow for belief heterogeneity in our estimation in different ways. First, we allow for arbitrary heterogeneity by estimating the regression

$$E_t^{(j)} i_{t+h} = a_j^{(j)} + \hat{\beta}_j^{(j)} E_t^{(j)} \pi_{t+h} + \hat{\gamma}_t^{(j)} E_t^{(j)} x_{t+h} + e_{th}^{(j)}$$

separately for each forecaster j, utilizing only the variation across forecast horizons h, and taking the average of $\hat{\gamma}_t^{(j)}$ across forecasters. These regressions use only cross-horizon variation in forecasts. These estimates are necessarily noisy, but an equal-weighted average provides consistent and more precise estimates of the forecaster averages $\bar{\hat{\beta}}_t$ and $\bar{\hat{\gamma}}_t$. Panel A of Figure B.2 shows the resulting estimate of $\bar{\hat{\gamma}}_t$.

Next, we explore heterogeneity in a more structured form. We allow for forecaster fixed effects in the time-varying perceived monetary policy coefficients. That is, we estimate the regression

$$E_t^{(j)} i_{t+h} = a_t + \alpha^{(j)} + b^{(j)} E_t^{(j)} \pi_{t+h} + g^{(j)} E_t^{(j)} x_{t+h} + \hat{\beta}_t E_t^{(j)} \pi_{t+h} + \hat{\gamma}_t E_t^{(j)} x_{t+h} + e_{tjh}. \quad \text{(B.5)}$$

We denote the estimates of $\hat{\gamma}_t$ and $\hat{\beta}_t$ from this regression, which represent the forecaster-average time-t perceived monetary policy coefficients, as "Interaction FE". The forecaster fixed effects are interacted with the macroeconomic forecasts—the estimates of $b^{(j)}$ and $g^{(j)}$

represent the forecaster-specific time-invariant coefficient shifters. Note that this estimate does not contain forecaster-by-month fixed effects, thus it is closer to the OLS estimate than our baseline FE estimate. Our estimation stars in January 1993, because Blue Chip forecaster IDs changed in 1993. Panel A of Figure B.2 also plots this estimate. Because the average level is different due to the forecaster fixed effect, we plot this estimate on a second axis for better comparability.

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, with hawks expecting higher 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, forecasters are sorted into a tercile depending on their de-meaned four quarter horizon CPI inflation forecast. We then estimate the perceived policy rule using FE regressions on each group of forecasters separately. Estimates of $\hat{\gamma}_t$ for all three groups are in Panel B of Figure B.2.

B.3 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 the following we use $\tilde{\gamma}$ to denote the estimated perceived monetary policy coefficient on the output gap, which may include a bias and thus can differ from 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:

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

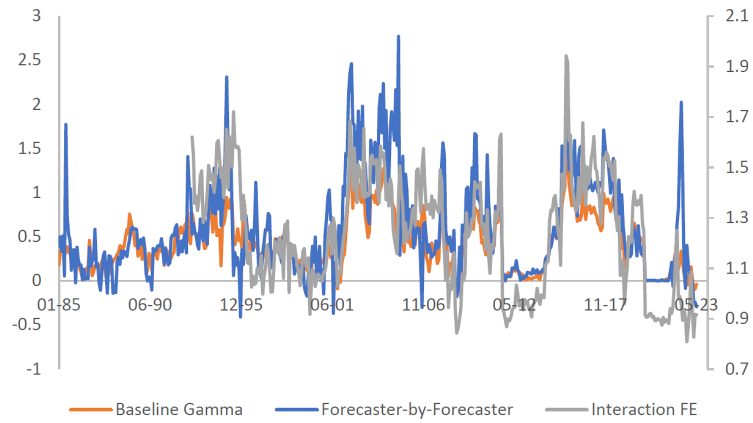
$$\pi_t = E_t \pi_{t+1} + \kappa x_t \tag{B.7}$$

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

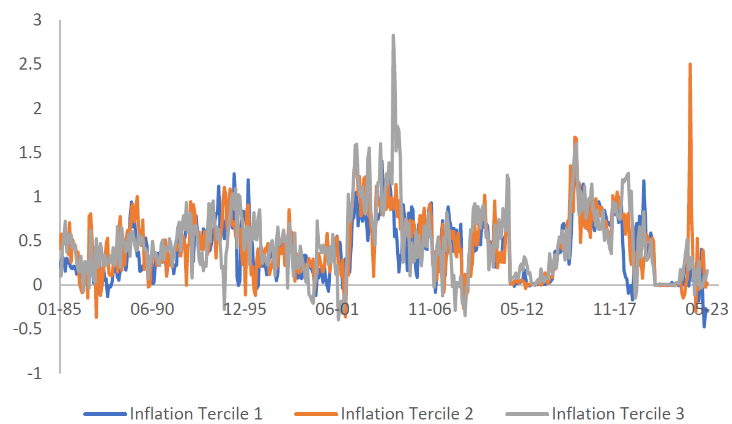
This model is completely standard; details and derivations can be found in textbook treatments such as Galí (2015). For simplicity we take the rate of time preference to be zero. The Euler equation, (B.6), assumes log-utility and includes a reduced-form demand shock v_t. Equation (B.7) is the Phillips curve. Our monetary policy rule, equation (B.8), 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 (B.6) through (B.8) since they do not affect the second moments that we are interested in.

Figure B.2: Accounting for forecaster heterogeneity in $\hat{\gamma}_t^{(j)}$

Panel A: Time-varying forecaster-average $\hat{\gamma}_t^{(j)}$



Panel B: Forecaster terciles



Alternative estimates of $\hat{\gamma}_t$ that account for heterogeneity. The estimate labeled "forecaster-by-forecaster" estimates the perceived rule separately for each forecaster using using cross-horizon variation, and reports the cross-forecaster average. The estimate labeled "Interaction FE" includes forecaster fixed effects interacted with output gap and inflation forecasts (B.5). Panel B estimates our baseline perceived monetary policy rule (2) on subsets of forecasters, where forecasters are split into terciles by their average inflation forecast.

As in our empirical analysis, the focus is on the monetary policy rule's coefficient on the output gap, $\hat{\gamma}$, and we shut down any effects from inflation by setting $\kappa = 0$ so that prices are fixed, following Caballero and Simsek (2022). 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 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, which could be either rational or irrational.

With these assumptions, we can simply substitute the perceived monetary policy rule (B.8) into the Euler equation (B.6) and iterate forward to obtain forecaster j's conditional expectations for the equilibrium policy rate and output gap at horizon $t+h$ as:

$$E_t^{(j)} x_{t+h} = \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}), \quad \text{and} \tag{B.9}$$

$$E_t^{(j)} i_{t+h} = \hat{\gamma}_t \sum_{\tau=0}^{\infty} (1+\hat{\gamma}_t)^{-(\tau+1)} (E_t^{(j)} v_{t+\tau+h} - E_t^{(j)} u_{t+\tau+h}) + E_t^{(j)} u_{t+h}. \tag{B.10}$$

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 $E_t^{(j)} v_{t+h}$ are orthogonal to expected monetary policy shocks $E_t^{(j)} u_{t+h}$ at all horizons. 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:

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

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 downward 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:

$$
\begin{aligned}
Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) &= \hat{\gamma}_t - (1+\hat{\gamma}_t)^{-1} Var_t\left(E_t^{(j)} u_{t+h}\right) \\
Var_t\left(E_t^{(j)} i_{t+h}\right) &= \hat{\gamma}_t^2 + 2\hat{\gamma}_t Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right) + Var_t\left(E_t^{(j)} u_{t+h}\right)
\end{aligned}
$$

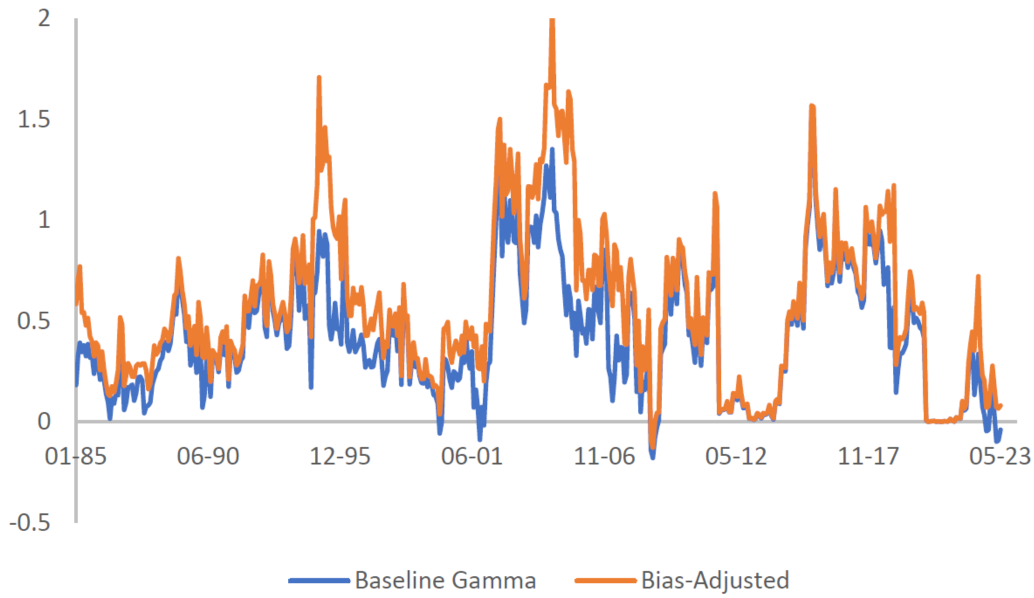
We use these two equations solve for $\hat{\gamma}_t$ and $Var_t\left(E_t^{(j)} u_{t+h}\right)$, where $Var_t\left(E_t^{(j)} i_{t+h}\right)$ and $Cov_t\left(E_t^{(j)} i_{t+h}, E_t^{(j)} x_{t+h}\right)$ are estimated from the data.

In order to derive the panel regression coefficient on the panel of time t forecasts with fixed effects, we need to allow for forecaster disagreement about the long-run real rate, which so far we have abstracted from ease of exposition. The equilibrium for the output gap (B.9) remains unchanged and the equilibrium for the policy rate (B.10) is shifted up by a constant $E_t^{(j)} i_t^*$. 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. In practice, we residualize all forecasts with respect to forecaster fixed effects, and then obtain the bias-adjusted estimate of $\hat{\gamma}_t$ by solving the two equations above. Figure B.3 plots the resulting estimate.

B.4 Survey of Professional Forecasters

The Philadelphia Fed's quarterly Survey of Professional Forecasters (SPF) includes individual forecasts of various macroeconomic variables and interest rates. We estimate a policy rule for the three-month T-bill rate, which is highly correlated with the federal funds rate. For inflation we use the CPI forecasts. The advantage of the SPF is that unemployment rate forecasts are a direct measure of expected resource slack, and no imputation is necessary as

Figure B.3: Estimated $\hat{\gamma}_t$ with New Keynesian Bias Adjustment



Baseline estimate of $\hat{\gamma}_t$ vs. estimate with bias adjustment for endogenous output gap response

for the output gap in our BCFF forecasts.

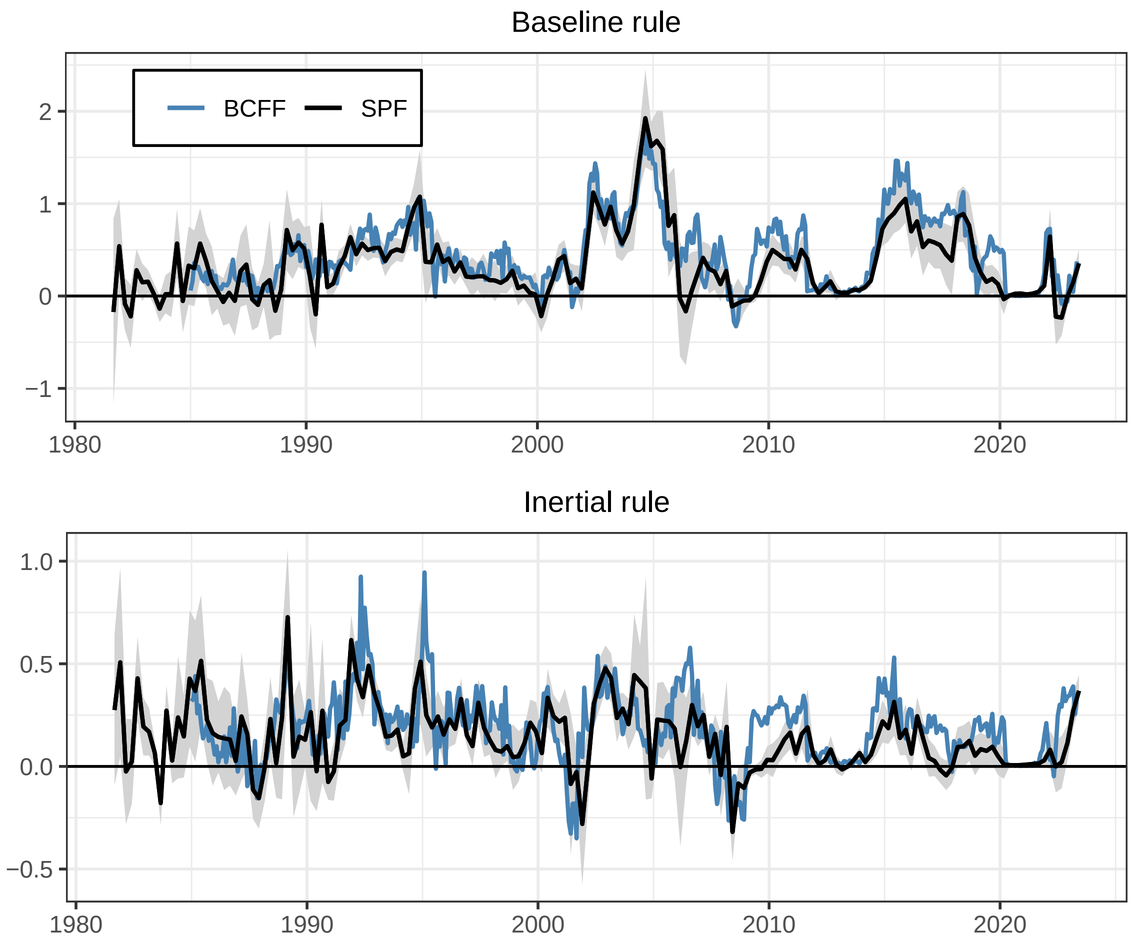
While we use unemployment rate forecasts, the unemployment *gap* would be the appropriate measure of resource slack and economic activity. Under the reasonable assumption that the natural rate of unemployment changes only slowly, these regressions pick up correlations of the forecasts for the T-bill rate with forecasts for economic slack, since heterogeneity about the natural rate is subsumed in the forecaster fixed effects.

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 both a simple baseline rule, similar to the specification in equation (2), as well as an inertial rule as in equation (4), in both cases using forecaster fixed effects.

For the baseline rule estimates the estimated coefficient on the unemployment rate forecasts has a correlation of -0.84 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. For the inertial rule estimates, the correlation is -0.60.

Figure B.4 provides a visual comparison. For the monthly BCFF, it plots the points estimates of $\hat{\gamma}_t$, and for the quarterly SPF, it shows the point estimates and 95% confidence intervals each multiplied by -1/2. The cyclical patterns of the SPF and BCFF series are strikingly similar, despite the different measures of economic slack being forecasted in each of these surveys. This similarity is comforting and suggests that the imputation of output gap forecasts does not introduce any spurious patterns into our policy rule estimates for the BCFF.

Figure B.4: 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 is the coefficient on output gap forecasts in the BCFF perceived rule, while the estimate for SPF corresponds to -1/2 times the coefficient on the unemployment rate forecasts in the SPF perceived rule. Top panel shows estimates for the baseline rule specification; bottom panel shows estimates for inertial rules that include the interest rate forecast for the preceding quarter. The sample for SPF is quarterly from 1981:Q3 to 2023:Q2; the sample for BCFF is monthly from 1985:01 to 2023:05.

C Fed funds forecast errors

In this section, we provide evidence on 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 rate forecasts 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. Relatedly, Bauer and Swanson (2023*a*) have argued that monetary policy surprises occur because markets are misinformed about the monetary policy rule, and in particular in the last few decades have *under*-estimated the Fed's response to economic conditions.

The relationship between fed funds forecast errors and $\hat{\gamma}_t$ can be understood by expressing the fed funds forecast error in our model in Section 5 as follows:

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

This expression shows that if forecasters have complete information about the policy rule ($\hat{\gamma}_t = \gamma_t$), the fed funds forecast error is equal to the idiosyncratic monetary policy shock, and hence unpredictable from information available at time $t-1$. Incomplete information, reflected in a deviation of $\hat{\gamma}_t$ from the true coefficient γ_t, is a possible source of predictability, at least when $\gamma_t - \hat{\gamma}_t$ is either systematically positive or negative, or if it is correlated with measurable variables. For example, if forecasters on average perceived γ_t to be lower than it actually was during our sample ($\gamma_t - \hat{\gamma}_t > 0$), this would lead to a positive coefficient of fed funds forecast errors onto economic activity. Indeed, (Cieslak, 2018) documents precisely such predictability of fed funds forecast errors from the lagged Chicago Fed National Activity Index (CFNAI). Table C.1 replicates this result.

In order to test the relationship (C.1) it would of course be ideal to have measures of the true rule parameter γ_t, the perceived rule parameter $\hat{\gamma}_t$, and a measure of economic activity. We do not have a direct measure of the true parameter γ_t, and rolling coefficients from historical data as in Figures 1 and 2 are necessarily much more slowly moving than our perceived monetary policy coefficient $\hat{\gamma}_t$. We therefore simply estimate a regression with the interaction of $\hat{\gamma}_t$ with the CFNAI as an additional predictor. A positive interaction coefficient would indicate that $\gamma_t - \hat{\gamma}_t$ is positively correlated with $\hat{\gamma}_t$, and that the true coefficient γ_t moves more than the perceived coefficient $\hat{\gamma}_t$. Conversely, finding a negative interaction coefficient would indicate that $\gamma_t - \hat{\gamma}_t$ is negatively correlated with $\hat{\gamma}_t$, and that the true coefficient γ_t moves less than the perceived coefficient $\hat{\gamma}_t$.

The results in Table C.1 show a significantly positive interaction coefficient, suggestive of underreaction in how forecasters update the perceived monetary policy coefficient $\hat{\gamma}_t$. This evidence for underreaction in the updating of $\hat{\gamma}_t$ by professional forecasters is consistent with the underreaction apparent in the somewhat more gradual empirical impulse responses in Figure 3.

Table C.1: Predictability of forecast errors for the federal funds rate

			Baseline $\hat{\gamma}$		Inertial $\hat{\gamma}$	
	$h=6$	$h=12$	$h=6$	$h=12$	$h=6$	$h=12$
$CFNAI_t$	0.18***	0.36***	0.095*	0.21**	0.17***	0.36***
	(0.056)	(0.11)	(0.052)	(0.095)	(0.055)	(0.11)
i_t	-0.040	-0.11	-0.045*	-0.12*	-0.043	-0.10
	(0.029)	(0.070)	(0.027)	(0.064)	(0.029)	(0.070)
$\hat{\gamma}_t$			-0.18	-0.54	0.17	-0.25
			(0.22)	(0.50)	(0.48)	(1.04)
$\hat{\gamma}_t \times CFNAI_t$			1.04***	2.02***	0.89**	1.84**
			(0.28)	(0.56)	(0.44)	(0.85)
N	461	456	461	456	461	456
R^2	0.07	0.11	0.15	0.21	0.09	0.14

Regressions for the h-month-ahead forecast error for the federal funds rate, using the mean BCFF forecast. CFNAI is standardized to have a standard deviation of one and mean zero. The regression intercept is omitted. The forecast error at horizon h is $i_{t+h} - \bar{E}_t i_{t+h}$, the realized federal funds rate minus the consensus forecast h months prior, where we approximate the 12-month forecast with the 4-quarter forecast and the 6-month forecast with the 2-quarter forecast. We use monthly CFNAIMA3 available from FRED. Data for the 6-month (12-month) forecast error ranges from December 1984 through April 2023 (November 2023). Newey-West standard errors with 18 lags ($h = 12$) and 9 lags ($h = 6$) are shown in parentheses.

D Additional results for local projections

Here we report additional regression estimates for the local projections shown in Figure 3 and discussed in Section 3. 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 Section 3. With this specification, the coefficients $\tilde{b}^{(h)}$ measure the difference between the two state-dependent impulse responses, and we can easily test the null hypothesis of no state dependence. Note that the impulse responses shown in the top panels of Figure 3 correspond to estimates of $b_1^{(h)}$, and the responses shown in the bottom panels correspond to $b_1^{(h)} + \tilde{b}^{(h)}$.

Table D.1 shows the estimation results for horizons of three, six, nine and twelve months. The interaction coefficient is consistently negative and, for horizons shorter than $h = 12$ months, strongly statistically significant. This evidence confirms that the response of $\hat{\gamma}_t$ to monetary policy surprises exhibits statistically significant state dependence.

Table D.1: Local Projection Regressions

	Baseline $\hat{\gamma}_{t+h}$				Inertial $\hat{\gamma}_{t+h}$			
Horizon:	$h=3$	$h=6$	$h=9$	$h=12$	$h=3$	$h=6$	$h=9$	$h=12$
mps_t	0.34*	0.73***	0.53**	0.21	0.61***	0.73***	0.27	0.17
	(1.67)	(2.72)	(2.24)	(0.81)	(4.27)	(3.27)	(1.50)	(1.43)
$mps_t \times weak_t$	-0.73**	-1.87***	-1.77***	-0.96*	-1.17***	-1.55***	-1.27***	-0.71*
	(-2.21)	(-3.72)	(-2.83)	(-1.68)	(-4.15)	(-5.39)	(-3.67)	(-1.81)
$weak_t$	0.03	0.07	0.12**	0.16**	-0.01	-0.01	0.00	0.02
	(0.94)	(1.46)	(2.06)	(2.47)	(-0.84)	(-0.20)	(0.06)	(0.46)
$\hat{\gamma}_{t-1}$	0.70***	0.56***	0.45***	0.39***	0.57***	0.42***	0.23***	0.12
	(13.31)	(7.66)	(5.21)	(4.32)	(8.76)	(5.52)	(3.82)	(1.60)
Constant	0.11***	0.15***	0.17***	0.18***	0.08***	0.10***	0.13***	0.14***
	(4.30)	(4.10)	(4.11)	(3.57)	(4.58)	(3.73)	(3.90)	(4.11)
N	457	454	451	448	457	454	451	448
R^2	0.48	0.33	0.25	0.21	0.36	0.22	0.10	0.03

Local projection estimates of the state-dependent response of $\hat{\gamma}_t$—measured using the baseline rule in the first four columns and using an inertial rule in the last four columns—to high-frequency monetary surprises of Bauer and Swanson (2023*b*), 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, * p <0.10, ** p <0.05, *** p <0.01. Sample period: January 1988–April 2023.

E Additional results for bond risk premia

E.1 Predictability of excess bond returns

Here we report results on the predictability of realized excess returns on long-term Treasury bonds, which complement the regressions in Section 4.2 for survey-based/subjective expected excess bond returns. We build on a large literature on predive regressions for excess returns in Treasury bonds, including Cochrane and Piazzesi (2005), Bauer and Hamilton (2018), and many others.

Using Treasury yield data from Gürkaynak, Sack and Wright (2007), we estimate the following predictive regressions:

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

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 $t+h$.[32] The controls X_t always include the first three principal components of Treasury yields with maturities one, two, five, seven, ten, fifteen, and twenty years. As additional controls, we include the Chicago Fed National Activity Index (CFNAI) and its

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

interaction with $\hat{\gamma}_t$, inspired by Cieslak (2018) and similar to our specification above for Table D.1.

We estimate equation (E.1) using both the baseline and the inertial rule estimate for $\hat{\gamma}_t$, and we consider holding periods of both $h = 12$ and $h = 24$ months. We end our estimation sample in February 2020 to avoid the noise from wild and unexpected swings in interest rates during the pandemic period. For comparability, we use the same start date as for subjective expected returns in Table 3 in the main paper, that is, December 1987. We report results only for the five-year bond for the sake of brevity, but other bond maturities yield qualitatively similar findings.

Table E.1: Predictability of excess bond returns

	$xr^{(5)}_{t\to t+12}$			$xr^{(5)}_{t\to t+24}$		
Panel A: Baseline $\hat{\gamma}_t$						
$\hat{\gamma}$	-2.76***	-2.25**	-2.47***	-4.81***	-3.67***	-3.12***
	(-2.92)	(-2.53)	(-2.98)	(-4.13)	(-3.91)	(-3.18)
$CFNAI$		-0.88	-1.58***		-1.96**	-1.99**
		(-1.28)	(-2.64)		(-2.49)	(-2.44)
$\hat{\gamma} \times CFNAI$			-1.09***			-3.51**
			(-2.66)			(-2.44)
R^2	0.20	0.21	0.24	0.22	0.30	0.32
Panel B: Inertial $\hat{\gamma}_t$						
$\hat{\gamma}$	-0.21	1.52	0.89	-5.28*	-2.20	-2.35
	(-0.10)	(0.75)	(0.39)	(-1.71)	(-0.72)	(-0.82)
$CFNAI$		-1.32*	-1.31**		-2.30***	-2.31***
		(-1.91)	(-2.09)		(-2.79)	(-2.78)
$\hat{\gamma} \times CFNAI$			-2.34			1.52
			(-0.99)			(0.58)
R^2	0.16	0.19	0.20	0.13	0.24	0.24
N	375	375	375	363	363	363

Predictive regressions for excess returns on five-year nominal Treasury bonds over one-year and two-year holding periods. The top panel uses the baseline estimate and the bottom panel uses the inertial estimate of $\hat{\gamma}_t$. All regressions control for the first three principal components of the yield curve. Coefficients on the three principal components and the constant are suppressed. CFNAI, the Chicago Fed National Activity Index, is standardized to have unit standard deviation. The estimation sample starts in December 1987 and ends in February 2019 for the one-year holding period ($h = 12$) and in February 2018 for the two-year holding period ($h = 24$). Newey-West t-statistics using $1.5h$ lags in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table E.1 shows that high values of $\hat{\gamma}_t$ predict low realized excess bond returns, similar to the results for subjective expected excess returns in Table 3. 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. This holds whether or not we control for the CFNAI. Similar to Table 3, the return predictability regressions are stronger for baseline $\hat{\gamma}_t$ than for inertial $\hat{\gamma}_t$, consistent with the interpretation of baseline $\hat{\gamma}_t$ as the perceived medium-run monetary policy response, and inertial $\hat{\gamma}_t$ as a perceived short-run response. We conclude that perceptions about monetary policy matter for both statistical and subjective bond risk premia.

E.2 Interest rate disagreement

To investigate potential links with interest rate disagreement, we compare our estimates of $\hat{\gamma}_t$ to the measures of forecaster disagreement from Giacoletti, Laursen and Singleton (2021). We first establish that the relationship between expected bond excess returns and $\hat{\gamma}_t$ documented above is unchanged when we control for interest rate disagreement.

Giacoletti, Laursen and Singleton (2021) use the 90-10 spread for the two-year and ten-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, Laursen and Singleton (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 E.2 shows that correlations of these three interest rate disagreement measures with our estimates of $\hat{\gamma}_t$ are generally low. Our baseline estimate of $\hat{\gamma}_t$ is essentially uncorrelated with interest rate disagreement. For inertial $\hat{\gamma}_t$, the correlations are positive as expected, but they are not large in magnitude, ranging from 0.30 to 0.38. The Fed's perceived response to the output gap is correlated with, but distinct from, disagreement about future interest rates across forecasters.

We can also control for these three measures of interest rate disagreement in our regressions of subjective bond risk premia onto $\hat{\gamma}_t$. Table E.3 estimates regressions analogous to those in Table 3, 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 E.2: Robustness: Correlation with interest rate disagreement

	Disagreement		
	FFR	2y	10y
Baseline $\hat{\gamma}_t$	0.03	0.11	-0.05
Inertial $\hat{\gamma}_t$	0.31	0.38	0.30

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), two-year Treasury rate, and ten-year Treasury rate. Sample period ends in JMay 2023, and starts in January 1985 for fed funds rate disagreement. The sample period starts in January 1988 for two-year Treasury rate and ten-year Treasury rate disagreement.

E.3 Policy inertia

Table E.4 reports results from multivariate regressions of subjective expected excess bond returns on perceived $\hat{\gamma}_t$, $\hat{\beta}_t$ and $\hat{\rho}_t$ from the inertial rule. It shows that subjective bond risk premia decline with perceived inertia $\hat{\rho}_t$. Expected bond risk premia also weakly increase with the time-varying perceived inflation weight $\hat{\beta}_t$ in columns (1) and (2). To the extent that a higher weight on inflation fluctuations in the monetary policy rule is similar to a lower weight on output fluctuations, these signs are as expected by theory. The negative coefficient on the time-varying perceived inertia parameter in most of the columns indicates that fluctuations in the *long-term* perceived cyclicality of interest rates are priced in term premia of long-term bonds. This is in line with the model predictions in Appendix F.

Table E.3: Term premia controlling for forecaster interest rate disagreement

	Panel A: Baseline $\hat{\gamma}_t$					
		$\bar{E}_t xr^{(6)}_{t+1}$			$\bar{E}_t xr^{(11)}_{t+1}$	
$\hat{\gamma}$	-2.39***	-2.52***	-2.65***	-3.53***	-3.67***	-3.88***
	(-5.86)	(-6.60)	(-7.23)	(-5.02)	(-5.68)	(-6.63)
FFR disagreement	-0.72***			-0.88		
	(-3.10)			(-1.48)		
2y disagreement		-0.83***			-1.32*	
		(-2.86)			(-1.83)	
10y disagreement			-0.70**			-1.70**
			(-2.13)			(-2.31)
N	425	424	425	425	424	425
R^2	0.64	0.64	0.63	0.62	0.63	0.64
	Panel B: Inertial $\hat{\gamma}_t$					
		$\bar{E}_t xr^{(6)}_{t+1}$			$\bar{E}_t xr^{(11)}_{t+1}$	
$\hat{\gamma}$	-2.01***	-2.18***	-2.42***	-4.06**	-4.24***	-4.47***
	(-3.13)	(-3.46)	(-3.44)	(-2.54)	(-2.79)	(-3.04)
FFR disagreement	-1.02***			-1.25**		
	(-3.05)			(-1.96)		
2y disagreement		-0.94**			-1.41	
		(-2.24)			(-1.61)	
10y disagreement			-0.50			-1.37
			(-1.28)			(-1.57)
N	425	424	425	425	424	425
R^2	0.51	0.49	0.47	0.55	0.55	0.54

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 3. Newey-West t-statistics with automatic lag selection in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

Table E.4: Term premia onto components of perceived inertial rule

	$\bar{E}_t xr^{(6)}_{t+12}$			$\bar{E}_t xr^{(11)}_{t+12}$		
Inertial $\hat{\gamma}_t$	0.00	-0.02	-0.39***	-0.015	-0.043	-0.72***
	(0.15)	(0.13)	(0.12)	(0.29)	(0.25)	(0.22)
Inertial $\hat{\beta}_t$	0.25*	0.25*	0.10	0.25	0.26	0.068
	(0.14)	(0.14)	(0.13)	(0.22)	(0.23)	(0.25)
$\hat{\rho}_t$	-0.44**	-0.56***	-0.014	-0.92***	-1.12***	-0.20
	(0.22)	(0.21)	(0.12)	(0.33)	(0.33)	(0.17)
TERM		0.32**			0.55**	
		(0.15)			(0.27)	
N	425	425	425	425	425	425
R^2	0.09	0.13	0.46	0.09	0.13	0.53
PCs	No	No	Yes	No	No	Yes

This table is analogous to Panel B of Table 3 in the main paper, but controls for time-varying $\hat{\rho}_t$ and $\hat{\beta}_t$ estimated from the time-varying perceived rule with inertia. Sample: 425 monthly observations from February 1988–May 2023. Newey-West standard errors with automatic lag selection (between 19 and 28 months) in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

F Details for learning model

Within-period timing:

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

F.1 Proofs

Proof of Lemma 1

Forecaster j's optimal forecast of the time-t output gap after observing his signal $\nu_t^j = x_t + \eta_t^j = \phi x_{t-1} + v_t + \eta_t^j$ equals

$$E^{(j)}\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j \right.\right) = \phi x_{t-1} + \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\eta^2}\left(v_t + \eta_t^j\right). \tag{F.1}$$

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

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

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 implies non-zero forecaster intercepts.

Proof of Lemma 2

Since forecasters observe the output gap before the Fed's policy decision, they expect

$$E^{(j)}(i_t|\mathcal{Y}_{t-1}, x_t) = \hat{\gamma}_t x_t + \rho i_{t-1},$$

which equals the "consensus" expectation $\bar{E}(i_t|\mathcal{Y}_{t-1}, x_t)$. Subtracting this expression from i_t, given in equation (11), yields the result in equation (15).

The results for the updating follow directly from the Kalman filter. The observed signal can be written as $\frac{mps_t}{x_t} = (\gamma_t - \hat{\gamma}_t) + \frac{u_t}{x_t}$. If forecasters perceive the variance of the monetary policy surprise to be $\frac{\sigma_u^2}{\kappa}$ the signal-to-noise ratio can be calculated as $\omega_t = \frac{\sigma_t^2}{\sigma_t^2 + \frac{\sigma_u^2}{\kappa x_t^2}} = \frac{\sigma_t^2 x_t^2}{\sigma_t^2 x_t^2 + \frac{\sigma_u^2}{\kappa}}$. The case with $\kappa = 1$ is the rational Bayesian case.

Proof of Lemma 3

Taking the forecaster average of (F.1) shows that the consensus forecast after observing the signals but prior to observing the output gap equals

$$\bar{E}\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j \right.\right) = \phi x_{t-1} + \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\eta^2} v_t. \tag{F.3}$$

The macroeconomic news due to the output gap announcement therefore equals

$$x_t - \bar{E}\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j \right.\right) = \frac{\sigma_\eta^2}{\sigma_v^2 + \sigma_\eta^2} v_t \tag{F.4}$$

Because macroeconomic announcements do not lead to updating about $\hat{\gamma}_t$, the change in the expected fed funds rate around the macroeconomic announcement equals

$$\bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, x_t \right.\right) - \bar{E}\left(i_t \left| \mathcal{Y}_{t-1}, \nu_t^j \right.\right) = \hat{\gamma}_t \left(x_t - \bar{E}\left(x_t \left| \mathcal{Y}_{t-1}, \nu_t^j \right.\right)\right). \tag{F.5}$$

Proof of Lemma 4

We use the subscript t to denote an expectation conditional on the information set $\mathcal{Y}_t$. The two-period bond price at the end of period t is given by

$$\begin{aligned}
B_t^{(2)} &= exp(-i_t) E_t \left[exp\left(-\psi v_{t+1} - \frac{1}{2}\psi^2 \sigma_v^2 - i_{t+1} \right) \right], && \text{(F.6)} \\
&= exp(-i_t) E_t \left[exp\left(-\rho i_t - \psi v_{t+1} - \frac{1}{2}\psi^2 \sigma_v^2 - \gamma_{t+1}\left(\phi x_t + v_{t+1}\right) - u_{t+1} \right) \right], && \text{(F.7)} \\
&= exp\left(-i_t - E_t i_{t+1} + \psi \hat{\gamma}_{t+1} \sigma_v^2 + \frac{1}{2}\hat{\gamma}_{t+1}^2 \sigma_v^2 + \frac{1}{2}\sigma_{t+1}^2 \left(\phi x_t\right)^2 + \frac{1}{2}\sigma_u^2 \right) && \text{(F.8)}
\end{aligned}$$

The term $\psi \hat{\gamma}_{t+1} \sigma_v^2$ is the risk premium, $\frac{1}{2}\hat{\gamma}_{t+1}^2 \sigma_v^2$ is a standard Jensen's inequality adjustment, and $\frac{1}{2}\sigma_{t+1}^2 \left(\rho x_t\right)^2$ is a Jensen's inequality adjustment for uncertainty about the monetary policy rule.

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

$$\begin{aligned}
E_t xr_{t+1}^{(2)} + \frac{1}{2} Var_t xr_{t+1}^{(2)} &\equiv E_t \left(b_{t+1}^{(1)} - b_t^{(2)} - i_t \right) + \frac{1}{2} Var_t \left(b_{t+1}^{(1)} \right), && \text{(F.9)} \\
&= -\psi \hat{\gamma}_{t+1} \sigma_v^2. && \text{(F.10)}
\end{aligned}$$

Equation (F.10) shows that the expected excess return on a two-period bond decreases with the perceived monetary policy coefficient $\hat{\gamma}_{t+1}$. Since $\hat{\gamma}_{t+1}$ is the perceived monetary policy coefficient as of the end of period t conditional on the same information set $\mathcal{Y}_t$, the expected long-term bond excess return is hence inversely related to the contemporaneously perceived monetary policy output gap coefficient.

Proof of Corollary 1

Throughout this corollary we use the 2-period bond yield as a stand-in for long-term bond yields. In line with our interpretation of the FOMC announcement as the announcement of the policy rate at the end of period t, we compare the expectation of the end-of-period long-term bond yield immediately prior to this announcement to the end-of-period bond yield immediately after. The log yield on the 2-year nominal bond by definition equals $y_t^{(2)} = -\frac{1}{2}\log B_t^{(2)}$. The change in the two-year bond yield in response to the Fed's rate decision equals

$$\begin{aligned}\Delta y_t^{(2)} &\equiv y_t^{(2)} - E\left(y_t^{(2)} \left|\mathcal{Y}_{t-1}, x_t\right.\right) \qquad \text{(F.11)}\\ &= \frac{1}{2}\Bigg(mps_t + \left(E_t i_{t+1} - E\left(i_{t+1}\left|\mathcal{Y}_{t-1}, x_t\right.\right)\right) - \psi(\hat{\gamma}_{t+1} - \hat{\gamma}_t)\sigma_v^2 - \frac{1}{2}\left(\hat{\gamma}_{t+1}^2 - \hat{\gamma}_t^2\right)\sigma_v^2 \\ &\quad -\frac{1}{2}\left(\frac{\omega_t}{x_t}\right)^2\left(\sigma_t^2 x_t^2 + \sigma_u^2\right)\sigma_v^2\Bigg).\end{aligned}$$

The first two terms reflect agents' updating about the current and next-period policy rate around the FOMC announcement. The last three terms reflect the change in the risk premium and Jensen's inequality terms as agents update their perceived monetary policy rule after observing the FOMC announcement. The last term arises because we need to expand $-\frac{1}{2}E\left(\hat{\gamma}_{t+1}^2\left|\mathcal{Y}_{t-1}, x_t\right.\right)$. Because $\frac{1}{2}\sigma_{t+1}^2\left(\phi x_t\right)^2$ is known conditional on x_t, it drops out of the innovation. Substituting in for $\hat{\gamma}_{t+1} - \hat{\gamma}_t$ from Lemma 1 it then follows that

$$\begin{aligned}y_t^{(2)} - E\left(y_t^{(2)}\left|\mathcal{Y}_{t-1}, x_t\right.\right) &= \frac{1}{2}\Bigg(mps_t(1+\phi\omega_t) - \psi\sigma_v^2\omega_t\frac{mps_t}{x_t} - \frac{1}{2}\omega_t\frac{mps_t}{x_t}\left(\hat{\gamma}_{t+1} + \hat{\gamma}_t\right)\sigma_v^2 \\ &\quad -\frac{1}{2}\left(\frac{\omega_t}{x_t}\right)^2\left(\sigma_t^2 x_t^2 + \sigma_u^2\right)\sigma_v^2\Bigg), \\ &= \frac{1}{2}\Bigg(mps_t(1+\phi\bar{\omega}) + mps_t\phi\left(\omega_t - \bar{\omega}\right) - \psi\sigma_v^2\omega_t\frac{mps_t}{x_t} \\ &\quad -\frac{1}{2}\left(\omega_t\frac{mps_t}{x_t}\right)^2\sigma_v^2 - \omega_t\frac{mps_t}{x_t}\hat{\gamma}_t\sigma_v^2 - \frac{1}{2}\left(\frac{\omega_t}{x_t}\right)^2\left(\sigma_t^2 x_t^2 + \sigma_u^2\right)\sigma_v^2\Bigg),\end{aligned}$$

where $\bar{\omega}$ is the unconditional time-series average of the signal-to-noise ratio ω_t. Next, we note that only one term in this expression is correlated with $mps_t weak_t$, controlling for mps_t and $weak_t$, as $Cov(mps_t 1_{x_t<0}, -\psi\sigma_v^2\omega_t\frac{mps_t}{x_t}) > 0$. Further, $Cov\left(mps_t 1_{x_t<0}, mps_t\left(\omega_t - \bar{\omega}\right)\right) = 0$ because the signal-to-noise ratio ω_t is independent of the sign of x_t and mps_t. Moreover, $E\left(mps_t^3\left|\mathcal{Y}_{t-1}, x_t\right.\right) = 0$ implying that $Cov(mps_t 1_{x_t<0}, -\frac{1}{2}\left(\omega_t\frac{mps_t}{x_t}\right)^2\sigma_v^2) = 0$. Moreover, $\hat{\gamma}_t$ is mean zero and uncorrelated with the sign of x_t, so $Cov\left(mps_t 1_{x_t<0}, -\omega_t\frac{mps_t}{x_t}\hat{\gamma}_t\sigma_v^2\right) = 0$. Finally, x_t^2, ω_t^2 and σ_t^2 are uncorrelated with mps_t and the sign of x_t. This proves the corollary.

F.2 Baseline vs. inertial estimates in the model

In our model the policy rule is inertial, and Lemma 1 shows that an inertial policy rule regression of the form (4) correctly recovers the perceived short-run reaction to the output gap, $\hat{\gamma}_t$. What would the baseline regression (2) recover? Iterating on equation (F.2) and plugging in the perceived AR(1) process for the output gap, agent j's interest rate and output gap forecasts at forecast horizon h can be related as

$$E^{(j)}\left(i_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) \;=\; \hat{\gamma}_t\frac{1-(\rho/\phi)^{h+1}}{1-(\rho/\phi)}E^{(j)}\left(x_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right), \tag{F.12}$$

where $\hat{\gamma}_t$ is defined as before, i.e., it is the perceived short-run monetary policy response to the output gap. A univariate regression of interest rate forecasts onto output gap forecasts in the model hence has slope coefficient

$$\hat{\gamma}_t^{baseline} \;\equiv\; \hat{\gamma}_t\frac{1-(\rho/\phi)^{h+1}}{1-(\rho/\phi)}, \tag{F.13}$$

which is the model analogue of the baseline estimation in the data. This expression simplifies to $\hat{\gamma}_t^{baseline}=\frac{\hat{\gamma}_t}{1-\rho}$ in the special case when the output gap is a random walk ($\phi=1$) and the forecast horizon is long ($h\to\infty$). However, if h is finite and perceived monetary inertia is less than the perceived output gap persistence ($\rho<\phi$), then $\hat{\gamma}_t^{baseline}$ can be smaller or larger than $\frac{\hat{\gamma}_t}{1-\rho}$ and may be closer to $\hat{\gamma}_t$. In that sense, the estimated coefficient from our baseline regression should be viewed as a perceived medium-term monetary policy response to the output gap.

The model baseline regression coefficient can be linked to changes in long-term interest rates around macroeconomic announcement surprises. For simplicity we consider the consensus forecast for the future fed funds rate as a stand-in for a long-term bond yield. This forecast responds to the macroeconomic announcement according to

$$\begin{aligned}\bar{E}\left(i_{t+h}\left|\mathcal{Y}_{t-1},x_t\right.\right)-\bar{E}\left(i_{t+h}\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right) \;&=\; \hat{\gamma}_t\phi^h\frac{1-(\rho/\phi)^{h+1}}{1-(\rho/\phi)}\left(x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)\right)\\ &=\; \hat{\gamma}_t^{baseline}\phi^h\left(x_t-\bar{E}\left(x_t\left|\mathcal{Y}_{t-1},\nu_t^j\right.\right)\right).\end{aligned} \tag{F.14}$$

One interpretation of this result is that the sensitivity of long-term interest rates to macroeconomic surprises is therefore determined by $\hat{\gamma}_t^{baseline}$. By contrast, the sensitivity of short-term interest rates to macroeconomic surprises is determined by inertial $\hat{\gamma}_t$, as shown in Lemma 3. This is consistent with the empirical evidence in Table 2.

The model also suggests that $\hat{\gamma}_t^{baseline}$ should improve explanatory power for term premia, as we document in Table 3. For simplicity, we solve for the three-period bond price ignoring uncertainty in $\hat{\gamma}_t$. Formally, we assume that $\hat{\gamma}_t=\gamma$ is known and expected to be constant going forward (for this derivation only), so that the two-period bond price simplifies to

$$B_{2,t} \;=\; exp\left(-i_t(1+\rho)-\gamma\phi x_t+\psi\gamma\sigma_v^2+\frac{1}{2}\gamma^2\sigma_v^2+\frac{1}{2}\sigma_u^2\right). \tag{F.15}$$

The three-period bond price then equals

$$
\begin{aligned}
B_{3,t} &= exp(-i_t)E_t\left[exp\left(-\psi v_{t+1} - \frac{1}{2}\psi^2\sigma_v^2\right)B_{2,t+1}\right], &\text{(F.16)}\\
&= exp\left(-i_t - E_t\left(i_{t+1} + i_{t+2}\right)\right)\\
&\quad \times exp\left(\gamma\psi\sigma_v^2(2+\rho+\phi) + \frac{1}{2}\gamma^2\sigma_v^2\left(1+(1+\rho+\phi)^2\right) + \frac{1}{2}(1+\rho)^2\sigma_u^2 + \frac{1}{2}\sigma_u^2\right), &\text{(F.17)}
\end{aligned}
$$

and the expected log excess return on the three-period bond equals

$$
\begin{aligned}
E_t xr_{3,t+1} + \frac{1}{2}Var_t xr_{3,t+1} &\equiv E_t\left(b_{2,t+1} - b_{3,t} - i_t\right) + \frac{1}{2}Var_t\left(b_{2,t+1}\right), &\text{(F.18)}\\
&= -\psi\gamma\left(1+\rho+\phi\right)\sigma_v^2, &\text{(F.19)}
\end{aligned}
$$

Note that in the case with $h = 1$ and $\phi = 1$ the baseline coefficient collapses to

$$
\hat{\gamma}_t^{baseline} = \hat{\gamma}_t\left(1+\rho\right), \tag{F.20}
$$

so the expected bond excess return is related to the average of the inertial and baseline coefficients

$$
E_t xr_{3,t+1} + \frac{1}{2}Var_t xr_{3,t+1} = -2\psi\left(\gamma + \gamma^{baseline}\right)\sigma_v^2. \tag{F.21}
$$

More broadly, bonds of longer maturity would load even more on baseline $\gamma^{baseline}$.