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Hawkish or Dovish Fed? Estimating a Time-Varying Reaction Function of the Federal Open Market Committee's Median Participant

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Abstract

This paper estimates a time-varying reaction function of the median participant of the Federal Open Market Committee, using a Taylor rule with time-varying coefficients estimated on one- to three-year ahead median forecasts of the federal funds rate, inflation, and the unemployment rate from the Summary of Economic Projections (SEP). We estimate the model with Bayesian methods, incorporating the effective lower bound on the median federal funds rate projections. The results indicate that the monetary policy rule has become significantly more persistent after the pandemic than in the years prior, and it currently reacts strongly to inflation, at more than twice the responsiveness estimated prior to 2020. Our proposed policy rule produces accurate predictions of the median federal funds rate projections in real time for given SEP forecasts of inflation and the unemployment rate, suggesting that the median participant's reaction function is well-represented by our assumed Taylor rule with time-varying coefficients. Our results show that the median participant's reaction function becomes less persistent and less responsive to inflation yet more responsive to the output gap in anticipation of tighter monetary policy conditions, measured by a steeper yield curve. We also find that labor market activity, inflation, and macroeconomic uncertainty correlate significantly with the evolution of the time-varying coefficients of the rule. Finally, we show that in times of a less persistent policy rule or more responsiveness to inflation, markets perceive nominal bonds as better macroeconomic hedges.

Keywords: Summary of Economic Projections, reaction function, Taylor rule, FOMC communications, time-varying coefficients, censored regression

JEL Classification Numbers: C32, C34, E52, E58

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*The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System.

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1 Introduction

How can the public infer in real time the strength of the response of the Federal Reserve (Fed) toward each of the goals of its dual mandate of low and stable inflation and maximum employment? For instance, could the Fed be reacting more strongly to inflation pressures and less to increases in the unemployment rate at a given point in time? In this paper, we assess changes in the Fed's policy responses to inflation and economic activity through a time-varying reaction function estimated with economic projections made by the participants of the Federal Open Market Committee (FOMC).

Bernanke (2016) and Faust (2016) advocate for the FOMC to make its monetary policy reaction function public to increase the transparency of Fed communications. In the spirit of offering clearer communications, the FOMC started releasing the Summary of Economic Projections (SEP) in which (since 2012) each participant projects a corresponding path for the federal funds rate "under appropriate monetary policy," in addition to other macroeconomic projections such as inflation and the unemployment rate consistent with that path. We use the information provided in the SEP to propose and estimate a monetary policy reaction function that private agents, especially firms and financial market participants, can use to gauge, for instance, the path of future interest rates.

We posit an inertial Taylor (1999) rule with time-varying coefficients as a reaction function of the FOMC. Some variants of this rule are a common way of modeling the Fed's reaction function (see Judd and Rudebusch, 1998, for example). In fact, the release of historical FOMC materials from 2017 shows that the Fed staff projection used an inertial Taylor (1999) rule as the interest-rate reaction function.[1] However, in contrast with several papers in the literature about Taylor rules with time-varying or Markov-switching coefficients (see Boivin, 2006; Kim and Nelson, 2006; Murray, Nikolsko-Rzhevskyy and Papell,

[1]See the "Monetary Policy" section of the "Key Background Factors" in the December 2017 Tealbook here: https://www.federalreserve.gov/monetarypolicy/files/FOMC20171213tealbooka20171201.pdf, and this memo from June 2016 to the FOMC: https://www.federalreserve.gov/monetarypolicy/files/FOMC20160603memo04.pdf.

2015; González-Astudillo, 2018, for example), we do not use historical/realized data on interest rates, inflation, and the output gap to estimate the rule.

Because we aim to measure how the median FOMC participant would respond to deviations of macroeconomic outcomes from the mandate of the Fed, we use the SEP forecasts of the federal funds rate, inflation, and the unemployment rate to estimate our Taylor rule with time-varying coefficients. These forecasts consider the end of the current year and the next two years (when the projections are made in March or June), or the end of the next three years (when they are made in October or December). In particular, we use the median SEP forecasts of these variables to inform the estimates of the persistence, inflation, and output gap coefficients of the monetary policy rule each period, with a sample from June 2012 to March 2023. Moreover, given that our sample covers two effective lower bound (ELB) episodes for the federal funds rate, we account for censoring in the monetary policy rule as otherwise the estimates of policy rule coefficients would be biased (see Kahn and Palmer, 2016; Morris, 2017; Arai, 2023, for censored estimations with SEP data).

Our state-space model (SSM) considers a Taylor rule equation across forecast horizons in which each time-varying coefficient is a latent variable that follows random walk dynamics and is the same across horizons. Because we consider three forecast horizons, our model has a factor structure in which the relationship among the median forecasts of the federal funds rate, inflation, and unemployment gaps over those horizons informs the evolution of the latent variables, i.e., the time-varying coefficients of the rule. Our Bayesian estimation results indicate that the persistence of the monetary policy rule has increased significantly since 2020 and the inflation coefficient has more than doubled compared with estimates obtained with information prior to the pandemic. These results suggest that the most recent monetary policy response of the median FOMC participant is to aggressively counteract inflation deviations from the Committee's target.

As a way to validate our proposed reaction function, we check if our monetary policy rule specification with time-varying coefficients is useful to predict the median SEP forecasts given inputs of the rule also taken from the SEP. We perform that prediction exercise in real time to find that our specification matches very well the federal funds rate median forecast at the three horizons and that it produces much smaller forecast errors than a monetary policy rule with constant coefficients. In particular, our specification is able to deliver median predictions at the ELB during the pandemic and is almost on point with the median SEP forecast in March 2023. These results indicate that the median FOMC participant's projections could be adequately estimated with a monetary policy rule whose coefficients magnitudes change over time. As a byproduct of our estimation technique that takes into account the ELB, we produce a shadow federal funds rate at the end of each year that reaches about -2% during each of the two ELB episodes in our sample.

We go one step further and examine what incoming macroeconomic data may be correlated with changes in the evolution of the time-varying policy rule coefficients, in an attempt to find determinants of variability in the conduct of monetary policy. The results suggest that the persistence of the rule and the reactions of the median participant of the FOMC to inflation and the output gap change during monetary policy tightening and easing cycles. In particular, at the onset of a tightening cycle or when tighter monetary conditions are expected in the future, the policy rule becomes less persistent and less responsive to inflation, but its responsiveness to the output gap increases, as this latter variable may be the focus of policy makers at this stage of the monetary policy cycle. Once in the tightening cycle, the rule increases its persistence and, as monetary policy eventually eases, the responsiveness to inflation and the output gap decline, perhaps indicating the inclination of the FOMC to have insurance cuts available. Moreover, if the federal funds rate ends up at the ELB, the rule becomes significantly more persistent as monetary policy could be operating under "Odyssean" forward guidance in these instances.

In addition, when the inflation rate increases, particularly above the 2% inflation target, the attention to inflation increases as well as the persistence of the reaction function. Also, weaker current labor market conditions make the policy rule more responsive to the output gap. However, a declining indicator of future labor market conditions leads the reaction function to become less sensitive to inflation and the output gap, signalling the ability to cut rates quickly in case of a downturn. Lastly, elevated macroeconomic uncertainty increases the responsiveness to inflation, possibly indicating a more hawkish stance of monetary policy to prevent losing control over inflation, perhaps through a reputation channel.

As a final exercise, we analyze if the evolution of the time-varying coefficients of the assumed monetary policy rule influence Treasury bond market returns in an attempt to justify our motivation that our estimation results can be useful to financial market participants. We find that when the reaction function of the median FOMC participant becomes less persistent or more focused on inflation, bond excess returns decline, indicating that Treasury bonds become better macroeconomic hedges. This feature is a reflection that when demand shocks hit the economy, the procyclicality of the federal funds rate (and countercyclicality of bond valuations) increases when policymakers pay more attention to inflation, or their policy prescriptions are less persistent.

2 Contacts With The Literature

Previous studies that estimated the FOMC's reaction function with SEP data did so in two ways: (i) with constant coefficients and (ii) with time-varying coefficients. Studies with constant coefficients often include a censored specification to take into account the ELB in the federal funds rate projections. To the best of our knowledge, there are no studies in the existing literature that estimate time-varying coefficients taking into account the censoring problem caused by the ELB.

Kahn and Palmer (2016) use, like us, median forecasts from the SEP at different horizons for the federal funds rate, headline and core inflation, and the unemployment rate to estimate a constant-coefficient reaction function akin to a Taylor (1993) rule with inflation and unemployment gaps, but without persistence in the interest rate projections. The estimation with data from January 2012 to March 2016 incorporates censoring in the reaction function and obtains a core inflation coefficient around 3.8 (1.6 with headline inflation) with an unemployment coefficient around -1.5 (-1.6 with headline). The results using headline inflation are relatively close to those obtained using real-time historical data from 1987:Q1 to 2007:Q4. Moreover, a counterfactual exercise that uses the coefficients of the reaction function estimated with SEP and real-time data on inflation and the unemployment rate shows that the projected federal funds rate closely mirrors the actual federal funds rate target from roughly 2001 to 2015.

Morris (2017) estimate a monetary policy rule à la Taylor with average SEP projections for the federal funds rate, inflation, and the unemployment rate from January 2012 to December 2016, incorporating censoring due to the ELB. The results show a headline inflation coefficient close to 3.1 and a coefficient on -2 times the unemployment gap (to mimic for the output gap, using Okun's law) of about 0.8. In addition, controlling for financial risk (measured by the 10-year versus 2-year Treasury yield spread) indicates that the federal funds rate reacts negatively to it and that the inflation coefficient is substantially lower, around 0.6. A consideration of breaks in the reaction function shows that there is statistical evidence of different coefficients before and after December 2014. In fact, rolling nine-meeting estimates show an inflation coefficient that declined steadily from about 1.5 in December 2014 to 0.5 two years later whereas the activity coefficient (that measures the reaction of the federal funds rate to the average of the output and unemployment gaps) is less noisy, but also declines from about 1 to about 0.2 in the same period. The author concludes that the change in policymaking over this period may be characterized as substituting responsiveness to financial risk for responsiveness to inflation.

In a different attempt to determine if there have been changes in the reaction function of the FOMC over time, Knotek (2019) estimates a time-invariant monetary policy rule using rolling windows of the median SEP forecast of the federal funds rate, inflation, and the unemployment rate for the period December 2015 to March 2019. The findings suggest that the policy rule coefficients have changed, as the federal funds rate projections have become less responsive to the unemployment gap. Apart from Knotek's model having constant coefficients estimated on rolling windows of data and ours having truly time-varying ones, a key difference with respect to our approach is that his estimation is of a quarterly rule, using linearly interpolated missing quarterly forecasts from the SEP combined with nowcasts of the variables, whereas our rule is specified at an annual frequency in which no interpolation is needed (but still estimated with quarterly releases from the SEP). Additionally, the author does not include the ELB period from the Great Recession.

Kalfa and Marquez (2021) analyze the FOMC's projections, focusing on release dates, delays in release, the forecast process, and forecast assessment, using the median SEP. In the absence of an official reaction function, the authors estimate the coefficients of an inertial rule similar to Taylor's (specified at an annual frequency) that includes chairmanship dummies for Ben Bernanke and Janet Yellen, in the period 2012-2019, using quarterly SEP releases. The results of the final model specification show that (i) the estimated annual persistence of the median federal funds rate projection is 0.36 (0.77 if converted to quarterly frequency), (ii) a one-percentage-point increase in the median inflation projection increases the median federal funds rate projection by 0.45 pp, (iii) a one-percentage-point increase in the median unemployment rate forecast decreases the median interest rate projection by 0.42 pp, and (iv) the coefficient for Yellen's tenure is significantly negative, equivalent to an almost 0.7 pp lower federal funds rate projection, on average. Their paper does not take into account the ELB on the median federal funds rate projection during the Great Recession when estimating the model.

Lastly, among the studies with constant coefficients in the FOMC's reaction function using a censored specification, Arai (2023) estimates a Taylor rule that depends on the inflation and unemployment gaps but does not have persistence because of the difficulty to track past projections. This difficulty occurs because Arai uses individual participant's projections at different horizons instead of median or average statistics. The results with a sample from 2012 to 2017 (1471 individual projections) with core PCE inflation in the rule, including horizon dummies, yield an inflation coefficient around 1.3 and an unemployment gap coefficient around -0.6.

To the best of our knowledge, Bauer, Pflueger and Sunderam (2023) is the only study that considers time-varying coefficients in the perceived or assumed reaction function of the FOMC. The authors are interested in the perception of monetary policymaking because of its importance for policy effectiveness. They estimate a time-varying coefficient Taylor rule, relying on a forecaster-by-horizon monthly panel based on data from the Blue Chip Financial Forecasts. The authors use (pooled and fixed effects) panel regressions for each survey and estimate time series of the persistence, inflation, and output gap coefficients of the rule, assuming that each of the coefficients follows a martingale and, therefore, that they are uniform over forecast horizons (and forecasters). In an additional exercise, the authors estimate the same panel regressions with data from 16 to 19 FOMC participants in the period 2012-2016, using the SEP forecasts for the current and the following years.

The authors focus on the output gap coefficient throughout their discussion in the paper because they argue that an estimation of the inflation coefficient during periods of stable general price increases could lead to the mistaken conclusion that the Fed is not aggressively fighting inflation, as noted by Clarida, Gali and Gertler (2000). Although their estimated inflation coefficient increased significantly at the end of the sample (April 2023), the output gap coefficient would still be a summary statistic of the Fed's overall responsiveness to economic conditions as long as inflation is expected to move up and down a stable Phillips curve. Three distinctions are apparent with the approach in our paper. First, we use FOMC participants' information instead of private sector forecasters' projections. Because our intention is to gauge the FOMC reaction function through a Taylor rule with time-varying coefficients in real time yet the individual participants' forecasts are released with a delay of five years, we use the median SEP forecasts. Second, Bauer, Pflueger and Sunderam (2023) do not take into account the ELB when estimating their model. That omission could influence their results, especially those that indicate that the output gap coefficient was close to zero through 2014 when using the SEP data. Third, we obtain and discuss the evolution of the time-varying persistence, inflation, and unemployment (output) gaps coefficients of the rule, not only the last, so that we can shed more light on the monetary policy reaction function of the FOMC.

3 The Empirical Model

Assuming we have a sample of forecasts indexed by $t = 1, 2, \ldots, T$, the shadow interest rate projection for horizon h, where $h = 1, 2, 3$ years ahead (possibly including the current year as $h = 1$), is given by the following modified Taylor rule (the modification uses the unemployment gap to proxy for the output gap):

$$\boldsymbol{R}_h^* = \boldsymbol{\rho} \odot \boldsymbol{R}_{h-1}^* + (1-\boldsymbol{\rho}) \odot \left(\boldsymbol{R}^{LR} + \boldsymbol{\alpha}^{\pi} \odot (\boldsymbol{\pi}_h - 2) + \boldsymbol{\alpha}^{y} \odot 2(\boldsymbol{u}^{LR} - \boldsymbol{u}_h)\right) + \boldsymbol{\gamma}_h + \boldsymbol{\psi} + \boldsymbol{\varepsilon}_h, \quad (1)$$

where $\boldsymbol{\varepsilon}_h \sim N(0, \sigma_\varepsilon^2 I_T)$; and $\boldsymbol{R}_h^*$ is a $T \times 1$ vector with the shadow federal funds rate projection for horizon h, as we assume each element of the $T \times 1$ vector of actual federal funds rate projections, $\boldsymbol{R}$, is the maximum between an effective lower bound (ELB), $\underline{R}$, and the corresponding element of $\boldsymbol{R}_h^*$. In addition, $\boldsymbol{R}_{h-1}^*$ is a $T \times 1$ vector with the shadow rate projected for the previous horizon; $\boldsymbol{R}^{LR}$ is a $T \times 1$ vector with the long-run federal funds rate projection; $\boldsymbol{\pi}_h$ is a $T \times 1$ vector with the core inflation rate projection for horizon h (we assume the inflation target is 2 percent in our Taylor rule, as defined by the Statement on Longer-Run Goals and Monetary Policy Strategy of the FOMC);[2] $\boldsymbol{u}^{LR}$ is a $T \times 1$ vector with the long-run unemployment rate projection; and $\boldsymbol{u}_h$ is a $T \times 1$ vector with the unemployment rate projection for horizon h. Notice that $2(\boldsymbol{u}^{LR} - \boldsymbol{u}_h)$ proxies for a $T \times 1$ vector of projected output gaps in horizon h, where "2" is implied by usual estimates of Okun's law in the literature (see Ball, Leigh and Loungani, 2017, for instance). The coefficients of the rule

[2] See https://www.federalreserve.gov/monetarypolicy/files/FOMC_LongerRunGoals.pdf.

are time varying and, hence, $\boldsymbol{\rho}$, $\boldsymbol{\alpha}^{\pi}$, and $\boldsymbol{\alpha}^{y}$ are also $T \times 1$ vectors. Here, $\odot$ denotes the Hadamard or element-wise product. Because we allow the projections to have horizon-specific idiosyncratic components, we add a $T \times 1$ vector of constants, $\boldsymbol{\gamma}_h$.[3] In addition, we capture seasonality with a quarterly dummy variable, $\boldsymbol{\psi}$, also of dimension $T \times 1$ that we exclude in what follows to save on notation. Finally, $\boldsymbol{\varepsilon}_h$ is a $T \times 1$ vector of errors to the period h projection which should not be interpreted as a monetary policy shock, but as an error term reflecting that the modified Taylor rule (1) is an imperfect representation of the true reaction function of the median FOMC participant.

For a particular period t in which a projection h periods ahead is made, the Taylor rule for the expected shadow federal funds rate is as follows (here, E_t denotes the expectation conditional on the information available in period t, so that $E_t x_{t+h}$ is the h-period-ahead projection of variable x_t):

$$E_t R^*_{t+h} = \rho_t E_t R^*_{t+h-1} + (1-\rho_t)\left(E_t R^{LR}_t + \alpha^{\pi}_t (E_t \pi_{t+h} - 2) + \alpha^{y}_t 2(E_t u^{LR}_t - E_t u_{t+h})\right) + \gamma_h + \varepsilon_{t+h}, \quad (2)$$

with

$$\rho_t = \rho_{t-1} + \eta^{\rho}_t \ , \qquad \eta^{\rho}_t \sim \text{i.i.d. } N(0, \sigma^2_{\eta^{\rho}}) \ , \qquad \rho_0 \sim N(\mu_{\rho_0}, \sigma^2_{\rho_0}) \ , \quad (3)$$

$$\alpha^{\pi}_t = \alpha^{\pi}_{t-1} + \eta^{\alpha^{\pi}}_t, \qquad \eta^{\alpha^{\pi}}_t \sim \text{i.i.d. } N(0, \sigma^2_{\eta^{\alpha^{\pi}}}), \qquad \alpha^{\pi}_0 \sim N(\mu_{\alpha^{\pi}_0}, \sigma^2_{\alpha^{\pi}_0}), \quad (4)$$

$$\alpha^{y}_t = \alpha^{y}_{t-1} + \eta^{\alpha^{y}}_t, \qquad \eta^{\alpha^{y}}_t \sim \text{i.i.d. } N(0, \sigma^2_{\eta^{\alpha^{y}}}), \qquad \alpha^{y}_0 \sim N(\mu_{\alpha^{y}_0}, \sigma^2_{\alpha^{y}_0}). \quad (5)$$

In our setup, the frequency of the projections is quarterly, but the Taylor rule specification in equation (2) is at an annual frequency. That is, the lagged shadow rate for the projection in $t+h$ corresponds to the shadow rate projection one year prior. As a consequence, the size of the persistence coefficient, ρ_t, has to be interpreted accordingly.

[3] This idiosyncratic component plays the role of a fixed effect in a panel structure in which the cross section variability is given by the forecast horizons. We assume there are potentially unobserved components that may be correlated with the arguments of the Taylor rule in its right hand side, which gives rise to these fixed effects.

We postulate the following SSM to estimate the system in equations (2)-(5):

$$\begin{bmatrix} E_tR^*_{t+1} - E_tR^{LR}_t \\ E_tR^*_{t+2} - E_tR^{LR}_t \\ E_tR^*_{t+3} - E_tR^{LR}_t \end{bmatrix} = \begin{bmatrix} R^*_t - E_tR^{LR}_t & E_t\pi_{t+1} - 2 & 2(E_tu^{LR}_t - E_tu_{t+1}) \\ E_tR^*_{t+1} - E_tR^{LR}_t & E_t\pi_{t+2} - 2 & 2(E_tu^{LR}_t - E_tu_{t+2}) \\ E_tR^*_{t+2} - E_tR^{LR}_t & E_t\pi_{t+3} - 2 & 2(E_tu^{LR}_t - E_tu_{t+3}) \end{bmatrix} \begin{bmatrix} \rho_t \\ \tilde{\alpha}^\pi_t \\ \tilde{\alpha}^y_t \end{bmatrix} + \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_{t+1} \\ \varepsilon_{t+2} \\ \varepsilon_{t+3} \end{bmatrix},$$

$$\begin{bmatrix} \rho_t \\ \tilde{\alpha}^\pi_t \\ \tilde{\alpha}^y_t \end{bmatrix} = \begin{bmatrix} \rho_{t-1} \\ \tilde{\alpha}^\pi_{t-1} \\ \tilde{\alpha}^y_{t-1} \end{bmatrix} + \begin{bmatrix} \eta^\rho_t \\ \eta^{\tilde{\alpha}^\pi}_t \\ \eta^{\tilde{\alpha}^y}_t \end{bmatrix},$$

where $\rho_t \in [0, 1)$, $\tilde{\alpha}^\pi_t = \alpha^\pi_t (1 - \rho_t)$, $\tilde{\alpha}^y_t = \alpha^y_t (1 - \rho_t)$ $\forall t$, and

$$\left.\begin{bmatrix} \eta^\rho_t \\ \eta^{\tilde{\alpha}^\pi}_t \\ \eta^{\tilde{\alpha}^y}_t \end{bmatrix}\right| \mathfrak{F}_{t-1} \sim N \left(\mathbf{0}_{3\times1}, \begin{bmatrix} \sigma^2_{\eta^\rho} & -\alpha^\pi_{t-1}\sigma^2_{\eta^\rho} & -\alpha^y_{t-1}\sigma^2_{\eta^\rho} \\ -\alpha^\pi_{t-1}\sigma^2_{\eta^\rho} & \sigma^2_{t,\eta^{\tilde{\alpha}^\pi}} & \alpha^\pi_{t-1}\alpha^y_{t-1}\sigma^2_{\eta^\rho} \\ -\alpha^y_{t-1}\sigma^2_{\eta^\rho} & \alpha^\pi_{t-1}\alpha^y_{t-1}\sigma^2_{\eta^\rho} & \sigma^2_{t,\eta^{\tilde{\alpha}^y}} \end{bmatrix} \right),$$

$$\begin{aligned} \rho_0 &\sim N(\mu_{\rho_0}, \sigma^2_{\rho_0}), \\ \tilde{\alpha}^\pi_0 &\sim N\left((1 - \mu_{\rho_0})\mu_{\alpha^\pi_0}, \sigma^2_{\rho_0}\sigma^2_{\alpha^\pi_0}\right), \\ \tilde{\alpha}^y_0 &\sim N\left((1 - \mu_{\rho_0})\mu_{\alpha^y_0}, \sigma^2_{\rho_0}\sigma^2_{\alpha^y_0}\right), \end{aligned}$$

with $\sigma^2_{t,\eta^{\tilde{\alpha}^i}} = (1 - \rho_{t-1})^2 \sigma^2_{\eta^{\alpha^i}} + \alpha^{i2}_{t-1}\sigma^2_{\eta^\rho} + \sigma^2_{\eta^{\alpha^i}}\sigma^2_{\eta^\rho}$ for $i = \pi, y$, where $\mathfrak{F}_{t-1}$ is the σ-field with the information through period $t-1$. Notice that the error terms $\eta^{\tilde{\alpha}^i}_t = (1 - \rho_{t-1})\, \eta^{\alpha^i}_t - \alpha^i_{t-1}\eta^\rho_t - \eta^{\alpha^i}_t\eta^\rho_t$ for $i = \pi, y$ no longer have a conditional (on $\mathfrak{F}_{t-1}$) normal distribution. Nevertheless, we assume a misspecified model in which $\eta^{\tilde{\alpha}^i}_t$ is still normally distributed.[4]

4 The Data

This section describes the details of the data set we use to estimate the assumed monetary policy reaction function. Our data sources are the SEP releases from January 2012 through March 2023, which the Fed typically releases on a quarterly basis. It is a summary of FOMC

[4]The specification of the quarterly seasonal factors is such that $\psi_{1,t+1} = -\psi_{1,t} - \psi_{2,t} - \psi_{3,t} + \omega_t, \psi_{2,t+1} = \psi_{1,t}, \psi_{3,t+1} = \psi_{2,t}, \omega_t \sim$ i.i.d. $N(0, \sigma^2_\omega)$, as in Commandeur and Koopman (2007).

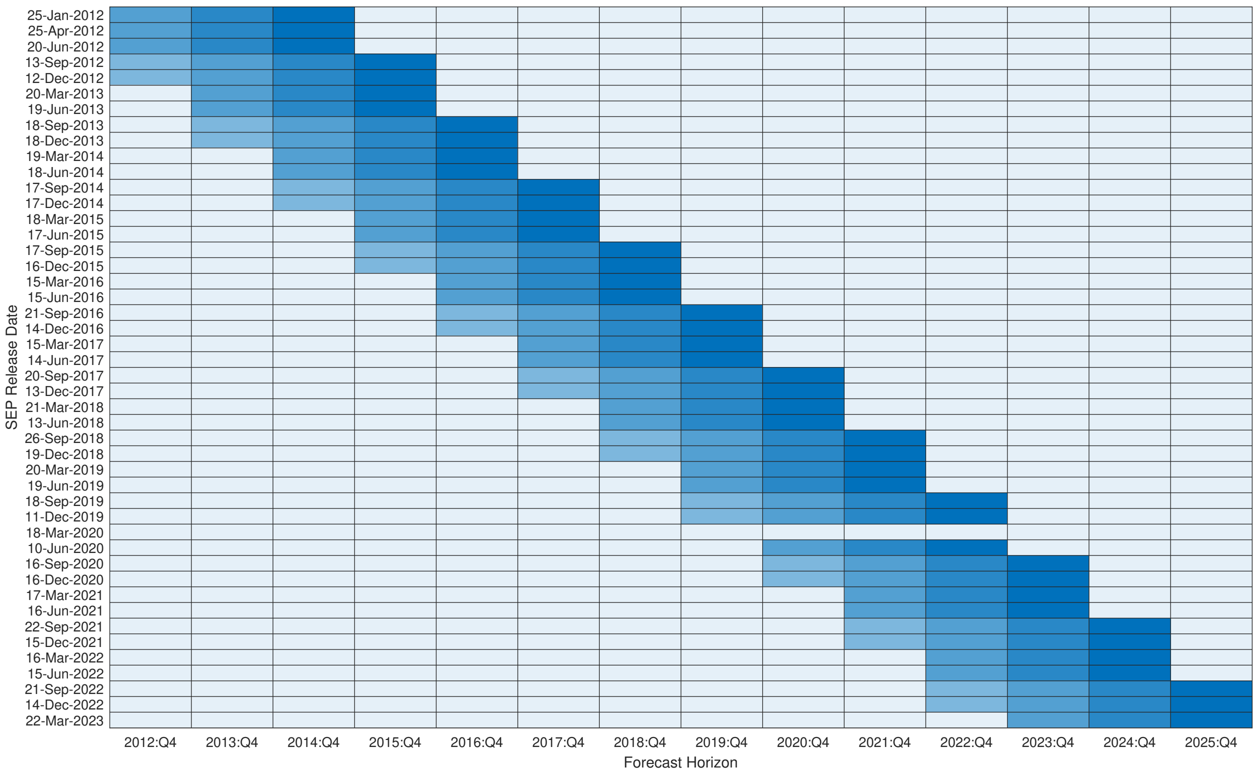
participants' economic projections. Each participant makes projections in the context of their individual view of appropriate monetary policy, which is the policy path that would deliver economic activity and inflation outcomes that best serve the dual mandate of maximum employment and price stability as interpreted by the individual participant.[5]

The SEP currently provides annual forecasts of the change in real gross domestic product (GDP), the unemployment rate, personal consumption expenditure (PCE) inflation, core PCE inflation, and the federal funds rate for each FOMC participant. We focus on the federal funds rate, core PCE inflation, and the unemployment rate. Our measure of the federal funds rate is the forecast of the midpoint of the appropriate target range or level at the end of the specified year. The unemployment rate is projected for the average civilian unemployment rate in the fourth quarter of the specified year. The projections for headline inflation are percent changes from the previous year's fourth quarter PCE price index to the fourth quarter of the specified year; and the core PCE price index excludes food and energy. The SEP also provides long-run projections for the federal funds, unemployment, and headline inflation rates, but not for core inflation, for which we use the 2 percent inflation target.

In addition to participants' projections of the change in real GDP, the unemployment rate, headline and core PCE inflation, projections for the appropriate interest rate were included in 2012, and the medians of the forecasts distributions of these variables have been reported since 2015. Figure 1 shows the date of the SEP release along the vertical dimension and the forecast horizon along the horizontal dimension. The cells shaded blue indicate that a forecast is made on the date in the vertical axis for the quarter in the horizontal axis. The darker the shading, the farther away the forecast is from the release date of the SEP.

[5]The FOMC consists of twelve members–the seven members of the Board of Governors of the Federal Reserve System; the president of the Federal Reserve Bank of New York; and four of the remaining eleven Reserve Bank presidents, who serve one-year terms on a rotating basis. The rotating seats are filled from the following four groups of Banks, one Bank president from each group: Boston, Philadelphia, and Richmond; Cleveland and Chicago; Atlanta, St. Louis, and Dallas; and Minneapolis, Kansas City, and San Francisco. Nonvoting Reserve Bank presidents attend the meetings of the Committee, participate in the discussions, and contribute to the Committee's assessment of the economy and policy options. See "About the FOMC" here: https://www.federalreserve.gov/monetarypolicy/fomc.htm

Figure 1: SEP Schematic



Note: The March 2020 SEP release did not happen because of the pandemic.

Two situations are noticeable: First, prior to June 2012, the SEP was not released quarterly. Second, the SEP that would have been released on March 18, 2020 was not because of the pandemic.

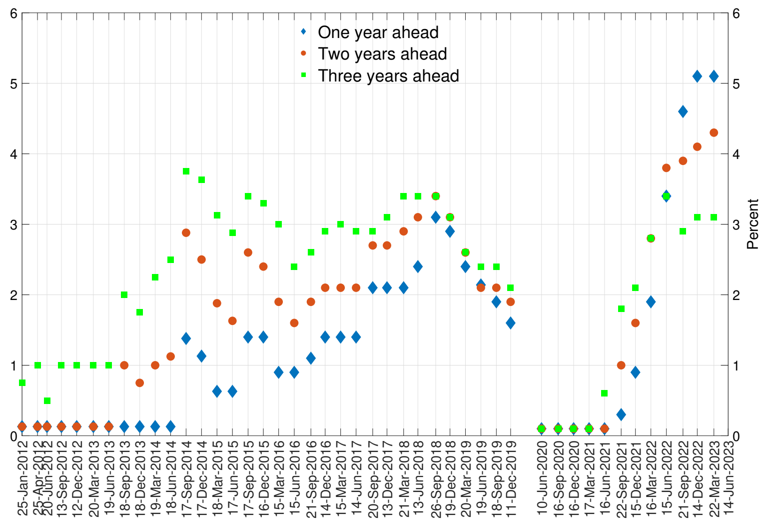
The SEP provides three or four annual projections and a long-run projection of the value to which each economic variable would converge given appropriate monetary policy, without further economic shocks. In general, the March and June releases have forecasts for the end of the current and the next two years, whereas the September and December releases have forecasts for the current year and the subsequent three years. We consider three forecast horizons from each SEP release as follows: In any given year, we take the one-, two-, and three-year ahead forecasts made in September and December of each year (that do not include the current year) in addition to the one-, two-, and three-year ahead forecasts made in March and June of the following year as the forecasts one, two, and three years ahead for the given year. This choice of a structure is relevant to determine what we should use as the lagged federal funds rate in the Taylor rule.

The lagged value of the September and December federal funds rate projections one year ahead is taken to be the projection provided in the December SEP for the current year and, because the one-year ahead forecast horizons are the same for the subsequent March and June releases, the September-December-March-June window shares the same previously mentioned lagged value for the forecast one year ahead. In fact, this window of releases also shares the same lagged value for the federal funds rate forecast two and three years ahead. In these cases, the lagged values correspond to the one- and two-year ahead projections, respectively, made at the time of the two- and three-year ahead federal funds rate projections.

Regarding the information provided by the SEP for each variable, we use the median forecasts as opposed to the individual projections. Faust (2016) reflects that the median SEP might be very far from unanimously supported monetary policy because of the disagreement among policymakers about how the economy is working. In order to incorporate the forecasters' disagreement mentioned by Faust, we believe the optimal data setup to estimate our model would have been a panel of forecasts of the federal funds, unemployment, and inflation rates in which the cross-sectional dimension is indexed by each FOMC participant. Bauer, Pflueger and Sunderam (2023) follow this approach with data on 16-19 Fed forecasters over 21 SEP releases from 2012 to 2016 to estimate the time-varying coefficients of a Taylor rule similar to ours. Unfortunately, because individual projections are published with a lag of five years, this approach is not useful to gauge the monetary policy reaction function in real time, which is the main focus of our paper.

Kalfa and Marquez (2021) show that, despite the dispersion of participants' views on the appropriate policy rate, the current-year SEP median tends to be close to the actual rate. Moreover, they find that there exists at least one econometric model that predicts well the FOMC forecasts for the current and the following years which would diminish Faust (2016)'s

Figure 2: SEP Median federal funds rate forecasts



critique. Hence, because of the timely information provided by the median SEP and the evidence that it may well represent unanimously supported policy, we resort to this statistic as our data choice. As indicated by Bauer, Pflueger and Sunderam (2023), the SEP forecasts reflect what the participants think the policy rate should be, not what it is most likely to be, for which we believe the median SEP forecast still provides information in line with our intended use of this database to estimate the time-varying coefficients of the monetary policy rule.

In our model setup in equations (2)-(5), we have three shadow rate equations for each period t, one for each forecast horizon, $h = 1, 2, 3$. Hence, we use the SEP data in a panel manner to inform, in each period, the common factor structure of the time-varying coefficients across the three equations. To the best of our knowledge, the use we give to this data structure in the SEP is the first in the literature. Figure 2 shows the federal funds rate forecasts in the SEP for the three forecast horizons.

Two things stand out from that figure. First, the period June 2020 to March 2021 is the only one in which the forecasts of the federal funds rate at all horizons were at the ELB. During the previous ELB episode, at least one forecast horizon had the median forecast above the bound. Second, since September 2022, there is an inversion of the "yield curve" associated with the federal funds rate in which the rate projected three years ahead is below the two-year ahead forecast and, in turn, the latter is below the one-year ahead projection. All in all, we use a sample that spans SEP releases between June 2012 and March 2023.[6]

5 Estimation

We estimate the model with Bayesian methods, using the Gibbs sampler to alternate sampling between coefficients and latent states.[7] For the latter, we use the Durbin and Koopman (2002) simulation smoother. To obtain the shadow federal funds rate that allows us to keep the state-space model linear (conditional on the lagged values of the time-varying coefficients), we embed data augmentation in the Gibbs sampler, as in Chib (1992), which is included to deal with the censored specification of the Taylor rule. This is the approach followed by González-Astudillo and Laforte (2020) to estimate the natural rate of interest when the Taylor rule is subject to censoring. However, we need to make a modification to that approach because our data set starts during the ELB period that prevailed in the Great Recession, with no history of projected rates above the bound, as we describe below.

Because the Taylor rule is specified at an annual frequency, we need a lagged shadow federal funds rate to estimate the rule at any point in time when the federal funds rate was at the ELB the prior year. For instance, for the projections made in the first half of 2012, which correspond to December of that year, we need a shadow rate prevailing in December 2011, but our data set starts in 2012. We treat that value as a parameter sampled with a Metropolis-Hastings step within the Gibbs sampler in which the proposal density is centered at the value obtained by Wu and Xia (2016) for December of 2011 and published by the Federal Reserve Bank of Atlanta.[8] Then, for the projections made past the first half of 2012, we take two approaches. In the first one, we assume that the shadow federal

[6] In the estimations, we linearly interpolate the data on the federal funds rate, inflation, and the unemployment rate for 18-March-2020 using the SEP releases of 11-Dec-2019 and 10-Jun-2020.

[7] For details on the sampler, see Appendix A.

[8] See https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate.

funds rate prevailing in December of a year when the ELB was binding—i.e., the lagged shadow interest rate for the projection of December of the following year—is the shadow rate projection made in June of the year when the ELB was binding in December. This projection is obtained with the data augmentation step we previously mentioned. This is our baseline approach. In the second approach, we employ the Wu and Xia values for each of the years when the ELB was binding in December to center a proposal density used by the Metropolis-Hastings steps within the Gibbs sampler in order to obtain the lagged shadow federal funds rate that will enter the Taylor rule specification. This second approach yields results similar to those from our baseline, but we prefer said baseline because of the internal consistency of the forecasts.

The prior distributions of the coefficients of the model follow an independent normal inverse-gamma scheme and appear in the second column of table 1. The horizon-specific fixed effects, γ_1, γ_2, and γ_3, are centered at zero with relatively large uncertainties. We choose prior means of the initial values of the parameters, μ_{ρ_0}, $\mu_{\alpha_0^\pi}$, and $\mu_{\alpha_0^y}$, in accordance with the values of an inertial Taylor rule, such as those found in Board of Governors of the Federal Reserve System (2018) and Bernanke (2015), with relatively low uncertainties. We center the prior distribution of the variance of the error of the policy rule, σ_ε^2, at 0.25 following the results in Kahn and Palmer (2016) with very large uncertainty. Regarding the time-varying coefficients, their shock variances, $\sigma_{\eta^\rho}^2$, $\sigma_{\eta^{\alpha^\pi}}^2$, and $\sigma_{\eta^{\alpha^y}}^2$ have prior means with masses close to zero and low uncertainty, implying that our prior beliefs are that the coefficients are nearly constant over time, as we do not expect the FOMC to make large changes every time there is an SEP release.[9]

[9] We also center the prior distribution of the variance of the quarterly seasonal effects, σ_ω^2, at 1 with very large uncertainty around.

6 Results

We estimate the posterior moments of the parameters and states of the model with 6,000 draws from the posterior distribution, after 50,000 burn-in draws and thinning every 50th draw out of a total of 350,000. The results appear in the third and fourth columns of table 1. The posterior medians of the fixed effect coefficients, γ_h, indicate that the interest rate projection tends to be upward sloping beyond what is implied by the inputs of the Taylor rule; on average, the federal funds rate projected three years ahead is 22 bps higher than that projected one year ahead. The posterior medians of the initial values of the time-varying policy rule coefficients are what would be expected, at 0.48 (0.83 in the usual quarterly frequency) for ρ_t, 1.61 for α_t^{π}, and 0.88 for α_t^{y}. The posterior median of the variance of the error to the policy rule is much lower than its prior mean. Despite the low uncertainty around the prior variances of the shocks to the time-varying coefficients, the posterior median of the variance of the shock to the inflation coefficient is significantly higher than its respective prior mean. Finally, the value of the shadow rate in December of 2011 has a posterior median equal to -2.5%.[10]

Figure 3 shows the estimated time-varying Taylor rule coefficients plotted against the date of the SEP release dates. Figure 3a plots the persistence coefficient and indicates that the half-life of a shock to the federal funds rate, keeping the inputs of the rule constant, is about one year during the first ELB period and thereafter through the end of 2016. This estimated persistence coefficient between 0.8 and 0.85 is very close to those seen in the practitioners' literature (see Brayton et al., 2014; Board of Governors of the Federal Reserve System, 2018). The coefficient begins to increases beyond this range with the advent of the monetary tightening cycle at the end of 2016. Its value reaches 0.89 in 2018, 0.91 in 2019, and 0.93 in 2020, during the pandemic ELB period. The coefficient peaks in early 2021 and declines thereafter, reaching 0.89 at the end of the sample, as the most recent

[10]The posterior mean of σ_{ω}^2 is estimated to be 0.09 with a 68% credible set between 0.07 and 0.12.

Table 1: Estimates of the model coefficients

	Prior Distribution	Posterior Median	68% Credible Set
γ_1	$N(0{,}2)$	-0.35	$[-0.44,-0.26]$
γ_2	$N(0{,}2)$	-0.25	$[-0.33,-0.18]$
γ_3	$N(0{,}2)$	-0.13	$[-0.19,-0.07]$
ρ_0	$N(0.5{,}0.2)$	0.48	[0.42,0.53]
α_0^π	$N(1.5{,}0.5)$	1.61	[1.31,1.92]
α_0^y	$N(1{,}0.5)$	0.88	[0.78,0.98]
σ_ε^2	$IG(0.5^2,\infty)$	0.24^2	$[0.21^2,0.28^2]$
$\sigma_{\eta^\rho}^2$	$IG(0.01^2,0.005)$	0.02^2	$[0.02^2,0.03^2]$
$\sigma_{\eta^{\alpha^\pi}}^2$	$IG(0.01^2,0.005)$	0.14^2	$[0.09^2,0.22^2]$
$\sigma_{\eta^{\alpha^y}}^2$	$IG(0.01^2,0.005)$	0.02^2	$[0.01^2,0.05^2]$
$R^*_{2011:12}$	$N(-1.47{,}1.1)$	-2.50	$[-4.73,-0.69]$

Note: "N" stands for normal distribution and "IG" stands for inverse gamma distribution. In both distributions, the first parameter is the mean and the second is the standard deviation. For the shadow interest rate in December of 2011, we report the proposal distribution under the prior distribution column.

monetary policy tightening cycle took place. All in all, the results evidence that the conduct of monetary policy has become significantly more persistent in the past three years than in the years prior.

Figure 3b plots the inflation reaction coefficient of the rule. As could have been inferred from the size of the estimated variance of its shock, $\sigma^2_{\eta^{\alpha^\pi}}$, in table 1, this coefficient shows substantially more variability than that associated with the persistence of the rule. It starts around 1.6 and ends around 3.6. Uncertainty around the estimate increases at the end of the first ELB period, peaking during the post-pandemic ELB episode and subsiding thereafter. One possibility for the increase in the uncertainty around the second ELB period is the difficulty of the model to identify time-varying coefficients when the dependent variable (the federal funds rate projections, in this case) is censored, as shown by González-Astudillo (2018). Summarizing, the increase in the inflation reaction coefficient would be an indication of the strong response of the FOMC to fight inflation in the recent past.

Finally, figure 3c shows the evolution of the output gap coefficient of the rule. This coefficient is estimated to be much more stable and less uncertain than that of inflation.

After starting around 0.88, it consistently stays between 0.8 and 1 through the end of the sample. These values are also mostly consistent with those found in the literature. We point out, however, that our estimate of the output gap is significantly more stable than that found by Bauer, Pflueger and Sunderam (2023) for the period 2012-2016. Possible reasons for the difference are that we incorporate the ELB explicitly in our estimation technique whereas they did not and that we use the median SEP whereas they use individual participant data.

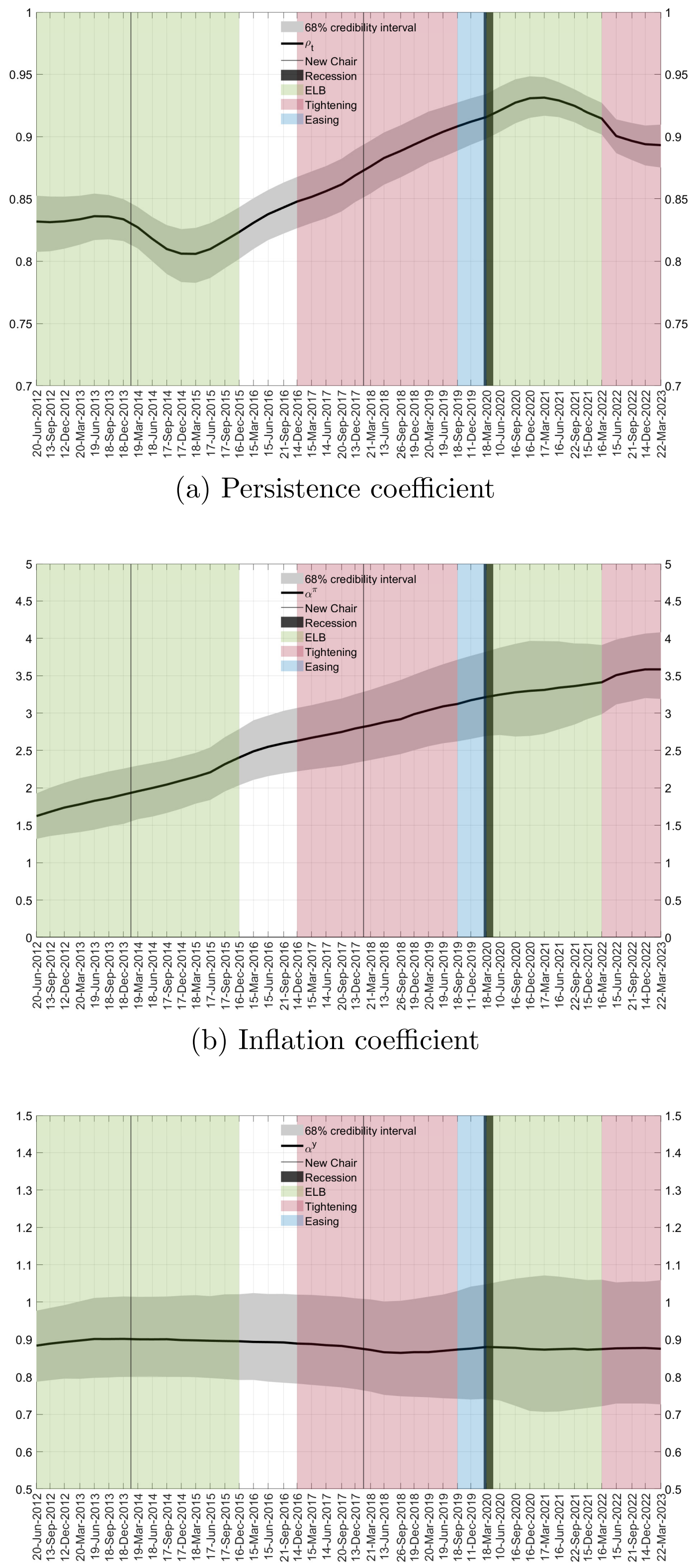
A byproduct of our estimation technique is the generation of a shadow rate. As we mentioned before, the shadow rate prevailing in December of every year when the ELB is binding is taken to be the rate forecast one year ahead in June of the ELB year. Figure 4 shows this SEP forecast when it is not at the ELB and the estimated shadow rate during the ELB periods for December of each year in the sample. As can be seen, the shadow federal funds rate reached about -2% during each ELB period. This value is very close to that estimated by Wu and Xia (2016) for 2013, but much lower than their estimate (at -0.29%) for 2020; for 2021, our estimate is very close to theirs.

6.1 Is the Taylor rule with time-varying coefficients adequate to model the forecasts of the median FOMC participant?

Both Bernanke (2016) and Faust (2016) argue that it would be convenient and pertinent for the public to understand monetary policy if the central bank made its reaction function known. In this paper, we have argued that a Taylor rule with time-varying coefficients (and forecast horizon-specific fixed effects) could help gauge the monetary policy reaction function through the values its reaction coefficients take over time. One way to determine if what is behind the monetary policy determination of the median FOMC participant is a reaction function such as the one we propose is to evaluate how well this rule fits the released forecasts in real time, given SEP forecasts of the arguments of the rule (interest and unemployment rates in the longer run, and inflation and the unemployment rate in the medium term).

To that end, we estimate the model in equations (2)-(5) sequentially, starting with data

Figure 3: Time-varying Coefficient Estimates

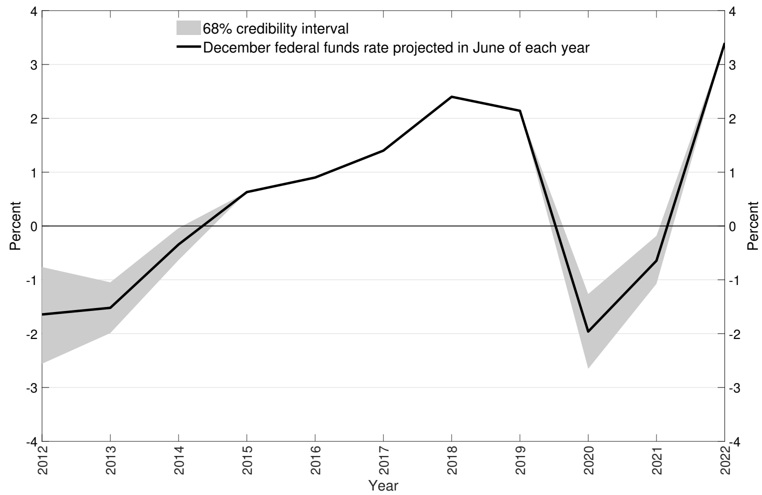


(a) Persistence coefficient

(b) Inflation coefficient

(c) Output gap coefficient

Figure 4: SEP and shadow federal funds rate forecast

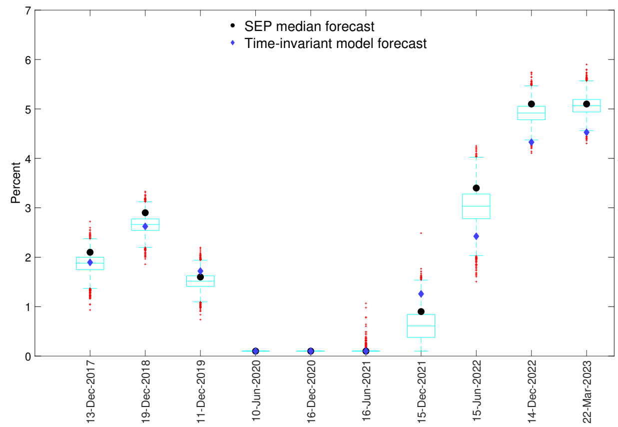


from June 2012 to December 2017. We produce an estimate of $E_t R^*_{t+h}$, for $h = 1, 2, 3$, using arguments of the rule released in the SEP for each horizon and our Taylor rule specification with time-varying coefficients. We do the same for each December from 2017 to 2019, adding information one year at a time. Starting in June 2020, we follow this procedure every six months through December 2022. Finally, we add the March 2023 release. Our sequential Bayesian estimation produces federal funds rate predictions from their posterior distributions, which are depicted in figure 5. The panels show the distribution of model predictions for each horizon (cyan box plots) in conjunction with the SEP forecasts (black dots).

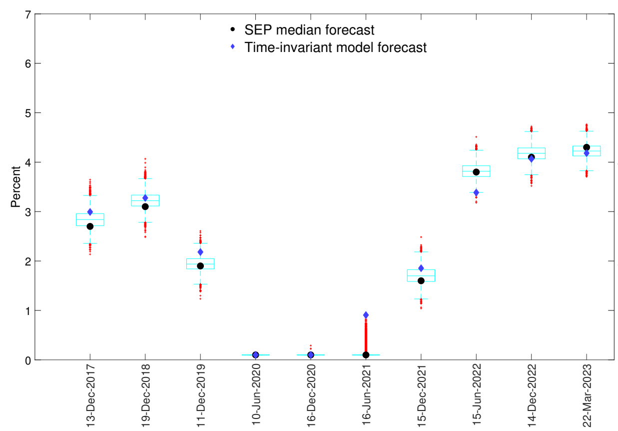
As can be seen from the three panels, the inter-quartile ranges of the model predictions capture well the actual SEP forecasts, and, when they are captured, the median predictions are very close to the actual forecasts, in particular for the two-year ahead horizon (figure 5b). Of note are the median predictions when the SEP forecasts are at the ELB: our model predicts very well those instances in real time, especially one and two years ahead (figures 5a and 5b, respectively). For March 2023, the median predictions from our model are almost on point with the actual SEP forecasts (that was also the case in December 2022).

We perform an additional exercise to determine if our assumed time variation is a better representation of the median FOMC participant's reaction function compared with an alter-

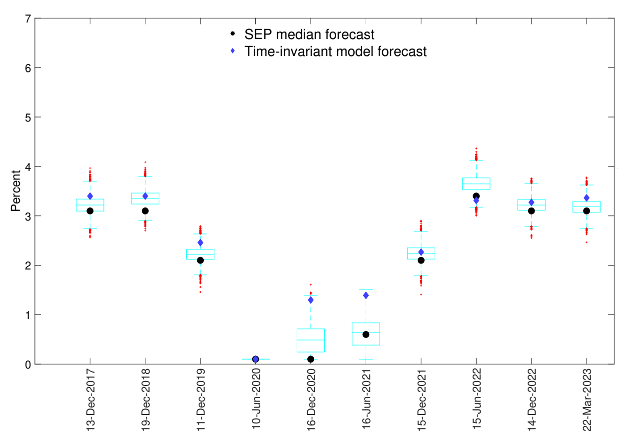
Figure 5: Federal Funds Rate Real-time Model Prediction versus SEP Median Forecast



(a) Interest rate forecast one year ahead



(b) Interest rate forecast two years ahead



(c) Interest rate forecast three years ahead

Note: The box plot shows in cyan the median, the inter-quartile range, and the range of the model prediction distributions. The red dots are considered outliers, defined as those points outside the (roughly) middle 99.3% of the distribution. The black dots are the SEP forecasts, and the blue diamonds are the median forecasts of the model with time-invariant coefficients.

native with constant coefficients. Figure 5 also shows in each panel the real-time forecast of the same model we consider in this paper but with constant coefficients (blue diamonds). Two features are worse in this case. First, the predictions one year ahead at the end of the sample are off, being significantly lower than the SEP forecasts, as seen in figure 5a. Second, the constant-coefficient model predicts rates above the ELB when the forecasts were at the lower bound in the two- and three-year-ahead forecasts, as shown in figures 5b and 5c.[11] These results suggest that our proposal of a Taylor rule with time-varying coefficients is a good approximation to the reaction function of the median SEP participant of the FOMC.

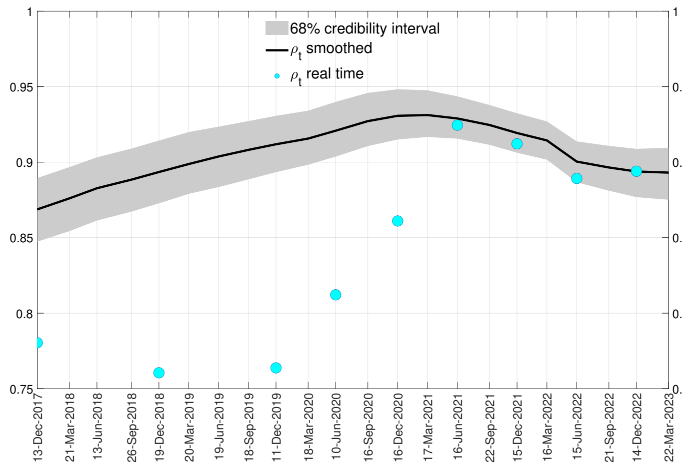
6.2 Real-time gauging of the monetary policy reaction function

The values of the estimated coefficients shown in figure 3 correspond to their smoothed counterparts. As a result of the backward induction in those estimates, it is not possible to assess in real time what the monetary policy reaction function was at a given point in time. If our proposed setup is meant to be useful to provide information about how strongly the FOMC is responding to inflation, for instance, we should look at how it performed in the past regarding the estimated policy rule coefficients in real time. Figure 6 contrasts the smoothed estimates of the policy rule coefficients with those obtained following the same sequential estimation procedure described in section 6.1, which are in fact the one-sided or filtered estimates (as opposed to the two-sided or smoothed estimates).

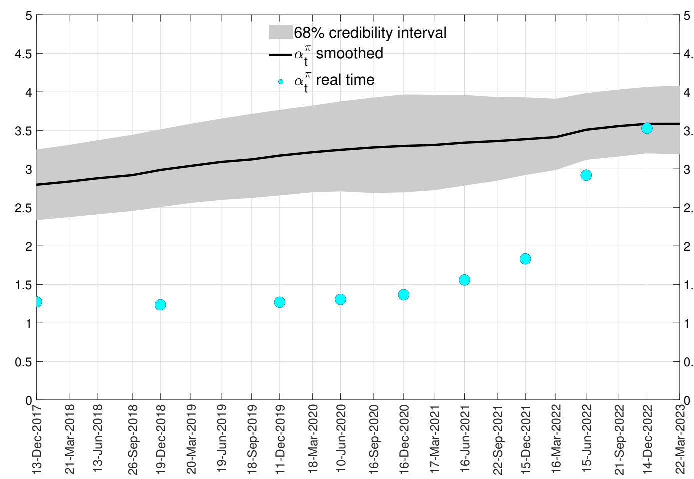
The results in figure 6a indicate that the persistence coefficient was estimated between 0.75 and 0.8 through the end of 2019, started to increase in mid-2020, reached 0.9 by mid-2021, and remained around there since then. The smoothed estimate tries to iron out the sudden increase in the real-time estimate during 2020, hence the significant discrepancy between the two estimates from late 2017 to late 2020. All in all, at least since mid-2021,

[11] The root-mean-squared forecast error (RMSFE) of the model with time-varying coefficients for these 10 predictions is 0.19 pp, 0.08 pp, and 0.19 pp for the one-, two-, and three-years ahead forecasts, respectively, compared with 0.46 pp, 0.33 pp, and 0.50 pp for the model with constant coefficients. We do not perform a Diebold and Mariano (2002) test of forecast accuracy because of the very low number of forecasts for each model-horizon.

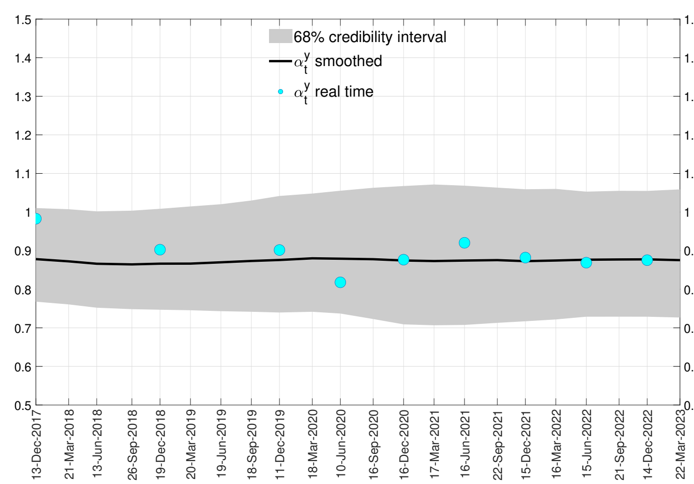
Figure 6: Real-time Time-varying Coefficient Estimates



(a) Real-time persistence coefficient



(b) Real-time inflation coefficient



(c) Real-time output gap coefficient

the results indicate that the median FOMC participant would prescribe significantly more persistent monetary policy.

As can be seen in figure 6b, the inflation reaction coefficient also shows relatively large differences between the real-time and smoothed estimates: most of the former falls below the credible set around the latter. After evolving just below the typical value of 1.5 from the end of 2017 until mid-2021, the coefficient begins to rise rapidly, reaching almost 2 by the end of 2021, just below 3 by mid-2022, and about 3.5 by the end of the sample in March 2023. Hence, at least since late 2021, one could conclude that the median FOMC participant would have been prescribing monetary policy to more actively fight inflation than before. As a side note, it is once again evident how the two-sided estimate smooths out the variation in the real-time one.

Finally, the output gap coefficient does not show significant differences between its smoothed and real-time counterparts, suggesting that the median FOMC participant has not changed the weight put on output (or unemployment) deviations from target in the past five years.

7 Explaining Changes in the Monetary Policy Reaction Function

In this section, we seek to obtain some of the variables that correlate with the changes in the evolution of the time-varying coefficients characterizing our assumed policy rule. We intend to shed light on the macroeconomic indicators that may influence the decision making of the median FOMC participant.

Bauer, Pflueger and Sunderam (2023) perform a similar analysis of cyclical shifts for the perceived monetary policy output gap coefficient estimated with Blue Chip data, arguing that anecdotal evidence suggests that the Fed's monetary policy rule experiences cyclical variation. They indicate that monetary policy tightening is usually characterized as data-dependent whereas monetary policy easing tends to be quick and unpredictable, as the Fed uses "insurance" cuts to manage the risk concerns of economic outcomes.[12] For these reasons, monetary policy may be less dependent on incoming data, and less strongly connected to macroeconomic forecasts, during monetary easing episodes. While Bauer et al. focus only on the output gap coefficient to understand this perceived monetary policy cyclical variation, we analyze the persistence, inflation, and output gap coefficients, offering a more exhaustive view on such variation for actual monetary policymaking (because our estimates are obtained from SEP rather than Blue Chip data).

Our regression analysis relies on monthly observations of macroeconomic variables available at the time of the SEP release to explain time-variation in the coefficients of the estimated monetary policy rule.[13] Table 2 shows that the expectation of a monetary policy tightening cycle arising or strengthening (measured by the spread between the 10-year Treasury yield and the 3-month Treasury rate, which also contains a term premium) affects all the coefficients of the Taylor rule, making it less persistent and less responsive to inflation but more sensitive to the output gap. More specifically, the rule becomes more persistent mainly when the economy is at the ELB, and it reacts more strongly to inflation when the labor market gains momentum, macroeconomic uncertainty increases, monetary policy is not currently easing, or inflation is high, especially above the 2% target. Also, the rule's responsiveness to the output gap increases when current labor market conditions worsen, but decreases when monetary policy is easing or the labor market loses momentum.

Putting the results together, one can see that the monetary policy cycle is related to changes in the reaction function of the median participant of the FOMC. When a tightening

[12]See also the Transcript from Chair Powell's Press Conference May 3, 2023 here: `https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20230503.pdf`.

[13]In this and the following sections, we use the filtered estimates of the time-varying coefficients obtained with the Kalman filter, in which the SSM matrices are constructed with the median posterior estimates of the parameters of the model shown in table 1. Appendix B shows the evolution of the filtered time-varying coefficients used in these regressions. We use the filtered estimates instead of the smoothed ones because we are interested in evaluating the real-time response of the median participant of the FOMC to changes in their information set (in this section) and how changes in the monetary policy reaction function in real time affect bond valuations (in the next section).

Table 2: Determinants of time-varying coefficient estimates

	$100 \times \rho_t$		α_t^{π}		α_t^{y}	
	(1)	(2)	(1)	(2)	(1)	(2)
Labor Level	0.39	0.27	0.14	0.14	-0.04^{**}	-0.04^{**}
Labor Momentum	0.21^{*}	0.24^{*}	0.08^{***}	0.08^{***}	0.01^{***}	0.01^{***}
Macro Uncertainty	-0.04	0.19	0.30^{***}	0.29^{***}	0.02	0.02
Financial Uncertainty	0.64	0.63^{*}	0.01	0.01	-0.01	-0.01
ELB	3.07^{***}	3.56^{***}	-0.08	-0.09	-0.02	-0.02
Tightening	1.09^{*}	1.55^{**}	-0.15	-0.16	-0.01	-0.02
Easing	0.40	0.17	-0.64^{***}	-0.63^{**}	-0.11^{***}	-0.11^{***}
Slope	-3.17^{***}	-3.16^{***}	-0.24^{***}	-0.24^{***}	0.04^{***}	0.04^{***}
Inflation	1.37^{***}		0.27^{***}		0.01	
Below Target		3.06^{**}		0.21		0.01
Above Target		1.09^{***}		0.28^{***}		0.01
Adjusted R^2	0.89	0.89	0.92	0.92	0.73	0.72
N	44					

Note: All regressions include a constant term that has been omitted in the table and have been checked for the existence of at least one cointegrating relationship. HAC standard errors are used to calculate statistical significance. Labor Level and Momentum are the labor market conditions indices produced by the Kansas City Fed. ELB is a dummy variable that takes the value of one during effective lower bound periods; Tightening is a dummy variable that takes the value of one during periods of increasing target federal funds rate; and Easing is a dummy variable that takes the value of one during periods of declining target federal funds rate. Slope is the spread between the 10-year Treasury yield and the 3-month Treasury rate, lagged 12 months. Macro Uncertainty is the Jurado, Ludvigson and Ng (2015) index of macroeconomic uncertainty 12 months ahead (standardized); and Financial Uncertainty is the VIX (standardized). Inflation is the 3-month average of the annual core CPI inflation rate; Below Target is the inflation rate minus 2.3; and Above Target is the inflation rate minus 2.3. All the variables are lagged to account for publication lags. Sample: 2012:Q2-2023:Q1.

* denotes a p-value<0.1, ** denotes a p-value<0.05, and *** denotes a p-value<0.01.

cycle is expected to start or to strengthen—so that current monetary policy conditions are looser than in the future and the slope of the yield curve increases—the policy rule becomes less persistent and less sensitive to inflation, but its responsiveness to the output gap increases as this latter variable may be the focus of policy makers at this stage of the monetary policy cycle. Once embarked in the tightening cycle, the rule increases its persistence and, as monetary policy eventually eases, the responsiveness to inflation and the output gap decline, making the rule less dependent on macroeconomic forecasts and more prone to insurance cuts. Moreover, if the economy ends up at the ELB, monetary policy would become significantly more persistent as it could be more calendar-based in these instances, or "Odyssean" in the terminology of Campbell et al. (2012).

The level of the observed inflation rate may also play a role in shaping the conduct of monetary policy by the median participant of the FOMC. The results indicate that when the inflation rate increases, particularly above the 2% inflation target, the attention to inflation also increases, perhaps indicating the concern of the median FOMC participant that inflation may enter an upward spiral in both actual and expected inflation rates. We also see that the persistence of the reaction function increases with higher inflation rates, signalling that the more hawkish stance of monetary policy may last longer.

Similarly, the state of the labor market could be related to the features of the reaction function over time. On the one hand, the results suggest that when the labor market activity level—which is the current-state indicator of the two labor market conditions indicators constructed by the Kansas City Fed—weakens, the rule becomes more responsive to output gap projections, implying that an overall weak current labor market leads to greater concern about economic activity.[14] On the other hand, when labor market momentum—which indicates the trajectory of future labor market conditions—declines, the median participant's reaction function becomes less persistent and, in general, less reactive to macroeconomic forecasts, signalling the ability to cut rates quickly if necessary. In fact, Chung et al. (2019)

[14]For more information on the Labor Market Conditions indicator, see https://www.kansascityfed.org/data-and-trends/labor-market-conditions-indicators/.

mention that an asymmetric policy rule with less inertia in bad times is more consistent with the speed at which the FOMC has cut its main policy rate in past economic downturns than the usual inertial Taylor rule.

Finally, indicators of macroeconomic and financial uncertainty could explain how the optimal response of monetary policy changes with respect to the incoming macroeconomic data because the Fed may consider the full distribution of macroeconomic and financial outcomes to make decisions. Our results show that when the Jurado, Ludvigson and Ng (2015) (JLN hereafter) macroeconomic uncertainty index 12 months ahead increases, the reaction function's sensitivity to inflation goes up. Cieslak et al. (2021) point out that higher policymakers' perceived inflation uncertainty predicts a more hawkish policy stance—a higher inflation coefficient in our setup—because an important driver of the FOMC's decisions is to maintain credibility for inflation control. Even though we do not have a measure of inflation uncertainty exclusively, the JLN macroeconomic uncertainty index does contain it, implying that our results point in the direction of Cieslak et al.'s. That is, higher macroeconomic uncertainty would lead to a more hawkish stance of monetary policy because of the median FOMC participant's desire to maintain credibility in inflation control.

All in all, we show macroeconomic factors that correlate with changes in the time-varying coefficients of the monetary policy rule we assume for the median FOMC participant, indicating that these factors could influence FOMC policymaking. In the next section, we examine if bond markets perceive changes in the reaction function of the median participant and how they price in those changes.

8 Predictability of Bond Excess Returns

This section examines if and how nominal bond excess returns respond to changes in the monetary policy reaction function of the median participant of the FOMC as measured by the evolution of the time-varying coefficients of the monetary policy rule. As we motivated in the introduction, firms and financial market participants may find useful the information about the degree of persistence of monetary policy decisions and the median FOMC participant's responsiveness to inflation and the output gap when trying to infer the path of future interest rates. For example, Bauer, Pflueger and Sunderam (2023) indicate that the time-varying output gap coefficient of a Taylor rule should be inversely related to bond excess returns because a higher perceived output gap coefficient means that interest rates are expected to fall more—and bond prices are expected to rise more—during recessions, which is what they find in their results using Blue Chip data. They also find that neither the inflation nor the persistence coefficients affect bond excess returns once the regression controls for the principal components of the yields. However, our findings suggest that a more inertial or less inflation-focused monetary policy predicts higher bond excess returns, and that no effect is expected from variations in the output gap coefficient. In other words, a less persistent or more hawkish monetary policy stance implies that bonds become better macroeconomic hedges.

We define bond excess returns one year ahead, $rx_{t+1}^{(n)}$, as the difference between (i) the return from holding an n-year bond at time t and selling it as an $n-1$ year bond at time $t+1$ (one year later) and (ii) the yield of a one-year bond at time t, as follows:

$$rx_{t+1}^{(n)} = ny_t^{(n)} - (n-1)y_{t+1}^{(n-1)} - y_t^{(1)}, \tag{6}$$

where $y_t^{(n)} = -\frac{1}{n}\ln P_t^{(n)}$ and $P_t^{(n)}$ is the price of a bond with maturity n years in period t. We use Treasury bond yield data from Gürkaynak, Sack and Wright (2007) to construct the bond excess returns in (6). Then, we regress the excess returns for $n = 2, \ldots, 10$ on their respective lags, the (standardized) estimated time-varying coefficients (ρ_t, α_t^{π}, and α_t^{y}), and the first three principal components of the yields used to construct the bond excess returns.

Table 3 shows the results. As mentioned before, a decrease in the persistence of the monetary policy rule (ρ_t) or an increase in its reaction to inflation (α_t^{π}) lower bond excess returns, on average, making them less risky than otherwise; we find no significant effect from changes to the output gap coefficient (α_t^y). Our results point to markets perceiving the median FOMC participant reacting mostly to demand shocks (as opposed to supply shocks) in their policymaking during the period 2012:Q3 to 2022:Q1 (effectively, we use data through 2023:Q1 to construct the bond excess returns one year ahead). The reason is as follows: When demand shocks hit the economy, output and inflation tend to move in the same direction, and the Taylor rule implies that the federal funds rate will be procyclical, making bond valuations countercyclical and, hence, good macroeconomic hedges. As the rule reacts more to inflation, the federal funds rate becomes even more procyclical and bonds become even better hedges, implying a likely negative covariance between movements in the inflation coefficient and bond excess returns. In contrast, when the rule becomes more persistent, the federal funds rate becomes less procyclical than otherwise, making bonds not as good hedges as before which implies a likely positive covariance between movements in the persistence coefficient and bond excess returns. Our results point in these directions. Additionally, like the effects of a higher inflation coefficient, if the rule becomes more sensitive to the output gap, a negative covariance between the output gap coefficient and bond excess returns would be expected. We do not find this channel to be significant in our results.[15]

[15]A similar analysis in the case of cost-push shocks would indicate the following: As output and inflation move in opposite directions, and depending on the size of these movements and the coefficients of the Taylor rule, the federal funds rate likely becomes countercyclical (following inflation), making bonds bad macroeconomic hedges. As the inflation coefficient increases, the federal funds rate becomes even more countercyclical, making bonds even riskier than before, and a positive covariance between movements in the inflation coefficient and bond excess returns is expected. If the output gap or persistence coefficients increase, the federal funds rate becomes less countercyclical, diminishing the riskiness of bonds and, therefore, negative or zero covariances between these coefficients and the bond excess returns are expected. In fact, Pflueger (2023) finds in a counterfactual exercise in which the economy is subject to volatile cost-push shocks that "nominal bond betas remain negative, even in the presence of shock volatility similar to the 1980s, provided that the monetary policy framework is more output-focused, less inflation focused and more inertial than during the 1980s."

Table 3: Bond Excess Returns Regressions

	$rx_{t+1}^{(2)}$	$rx_{t+1}^{(3)}$	$rx_{t+1}^{(4)}$	$rx_{t+1}^{(5)}$	$rx_{t+1}^{(6)}$	$rx_{t+1}^{(7)}$	$rx_{t+1}^{(8)}$	$rx_{t+1}^{(9)}$	$rx_{t+1}^{(10)}$
ρ_t					5.93^{***}				
α_t^{π}					-12.14^{***}				
α_t^{y}					0.13				
R^2	0.94	0.96	0.96	0.95	0.93	0.91	0.89	0.87	0.84

Note: The econometric model is a system of equations of demeaned excess Treasury bond returns, $rx_{t+1}^{(n)}$, for $n = 2, \ldots, 10$ years, estimated with weighted (nonlinear) least squares where the weight is at the equation level. Predictor variables are: the estimated time-varying coefficients of the Taylor rule (ρ_t, α_t^{π}, and α_t^{y}), the first three principal components of the yields, and the lagged excess returns (with equation-specific coefficients). All predictors, except the lagged excess returns, are standardized. Results show only the estimated (long-run) coefficients related to the time-varying Taylor rule coefficients. Sample: 351 observations from 2012:Q3-2022:Q1.
* denotes a p-value<0.1, ** denotes a p-value<0.05, and *** denotes a p-value<0.01.

9 Conclusion

This paper estimated time-varying coefficients of an inertial Taylor rule that we propose to model the median forecasts in the SEP to convey information about the monetary policy reaction function of the median FOMC participant in real time. After the pandemic, the median participant would be reacting more strongly to inflation than before in setting their federal funds rate, and rate settings would be more persistent. This information can be useful for the public to determine how strong the Fed's reaction to inflation is, so that private decisions can be made with that information in hand.

Additionally, we find evidence that changes in monetary policymaking, as measured by changes in the time-varying coefficients of the Taylor rule, are correlated with the evolution of macroeconomic variables such as the state of the labor market, inflation, macroeconomic uncertainty, and monetary policy cycles. We also find that bond excess returns are correlated with changes in the monetary policy reaction function.

Appendix

A Posterior Distribution Sampler

Our posterior distribution sampler works as follows:

1. For a given set of parameter values $\{\gamma_1, \gamma_2, \gamma_3, \rho_0, \alpha_0^\pi, \alpha_0^y, \sigma_\varepsilon^2, \sigma_{\eta^\rho}^2, \sigma_{\eta^{\alpha^\pi}}^2, \sigma_{\eta^{\alpha^y}}^2, R^*_{2011:12}\}$, sequences of lagged time-varying coefficients, $\{\rho_{t-1}\}_{t=1}^T$, $\{\alpha_{t-1}^\pi\}_{t=1}^T$, $\{\alpha_{t-1}^y\}_{t=1}^T$, and shadow federal funds rates, use the Metropolis-Hastings algorithm to sample $R^*_{2011:12}$ from the independent proposal density $N(-1.47, 1.1)$.

2. With the newly drawn $R^*_{2011:12}$, the initial set of parameters $\{\gamma_1, \gamma_2, \gamma_3, \rho_0, \alpha_0^\pi, \alpha_0^y, \sigma_\varepsilon^2, \sigma_{\eta^\rho}^2, \sigma_{\eta^{\alpha^\pi}}^2, \sigma_{\eta^{\alpha^y}}^2\}$, sequences of lagged time-varying coefficients, $\{\rho_{t-1}\}_{t=1}^T$, $\{\alpha_{t-1}^\pi\}_{t=1}^T$, $\{\alpha_{t-1}^y\}_{t=1}^T$, and shadow federal funds rates, use the Durbin and Koopman (2002) simulation smoother to draw the latent states $\rho_t, \tilde{\alpha}_t^\pi$, and $\tilde{\alpha}_t^y$. Obtain $\alpha_t^\pi = \frac{\tilde{\alpha}_t^\pi}{(1-\rho_t)}$ and $\alpha_t^y = \frac{\tilde{\alpha}_t^y}{(1-\rho_t)}$.

3. Conditional on the values of the other parameters and latent states in the model, obtain a draw of the initial value of the latent states, β_0, from $N\left(\bar{\mu}_{\beta_0}, \bar{\sigma}_{\beta_0}^2\right)$, where $\bar{\mu}_{\beta_0} = \bar{\sigma}_{\beta_0}^2 \left(\underline{\mu}_{\beta_0}/\underline{\sigma}_{\beta_0}^2 + \beta_1/\sigma_{\eta^\rho}^2\right)$ and $\bar{\sigma}_{\beta_0}^2 = 1/(1/\underline{\sigma}_{\beta_0}^2 + 1/\sigma_{\eta^\rho}^2)$, for $\beta = \rho, \alpha^\pi, \alpha^y$, where $\underline{\mu}_{\beta_0}$ and $\underline{\sigma}_{\beta_0}^2$ are the prior mean and variance of the initial value of each latent state, respectively.

4. Conditional on the values of the other parameters and latent states in the model, obtain a draw of the variance of the shock to each latent state, σ_β^2, from an inverse gamma distribution with shape parameter $\bar{a}_{\eta^\beta} = \underline{a}_{\eta^\beta} + 0.5T$ and scale parameter $\bar{b}_{\eta^\beta} = \underline{b}_{\eta^\beta} + 0.5\hat{\eta}^{\beta\prime}\hat{\eta}^\beta$, where each of the elements of $\hat{\eta}^\beta$ is $\hat{\eta}_t^\beta = \beta_t - \beta_{t-1}$, where $\underline{a}_{\eta^\beta}$ and $\underline{b}_{\eta^\beta}$ are the prior shape and scale parameters, respectively, for $\beta = \rho, \alpha^\pi, \alpha^y$.

5. Conditional on the values of the parameters and latent states in the model, sample shadow rates from a truncated (from above, at 0.13) normal distribution with mean

$\gamma_h + E_t R_t^{LR} + \rho_t \left(E_t R_{t+h-1}^{*} - E_t R_t^{LR} \right) + \tilde{\alpha}_t^{\pi} \left(E_t \pi_{t+h} - 2 \right) + 2 \tilde{\alpha}_t^{y} \left(E_t u_t^{LR} - E_t u_{t+h} \right)$ and variance σ_{ε}^2, for $h = 1, 2, 3$.

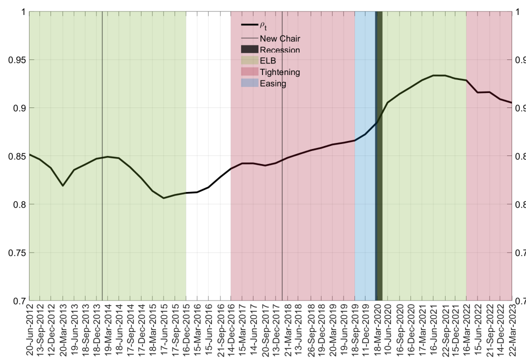
6. Conditional on the values of the parameters and latent states in the model, sample γ_h, for $h = 1, 2, 3$, from a normal distribution with mean $\bar{\sigma}_{\gamma_h}^2 \left(\underline{\mu}_{\gamma_h} / \underline{\sigma}_{\gamma_h}^2 + \sum_{t=1}^{T} y_{t,h} / \sigma_{\varepsilon}^2 \right)$ and variance $\bar{\sigma}_{\gamma_h}^2 = 1 / \left(1 / \underline{\sigma}_{\gamma_h}^2 + T / \sigma_{\varepsilon}^2 \right)$ where $\underline{\mu}_{\gamma_h}$ and $\underline{\sigma}_{\gamma_h}^2$ are the prior mean and variance, respectively, of γ_h, and $y_{t,h} = E_t R_{t+h}^{*} - E_t R_t^{LR} - \rho_t \left(E_t R_{t+h-1}^{*} - E_t R_t^{LR} \right) - \tilde{\alpha}_t^{\pi} \left(E_t \pi_{t+h} - 2 \right) - 2 \tilde{\alpha}_t^{y} \left(E_t u_{t+h} - E_t u_t^{LR} \right)$.

7. Conditional on the values of the parameters and latent states in the model, sample σ_{ε}^2 from an inverse-gamma distribution with shape parameter $\bar{a}_{\varepsilon} = \underline{a}_{\varepsilon} + 0.5 \times 3 \times T$ and scale parameter $\bar{b}_{\varepsilon} = \underline{b}_{\varepsilon} + 0.5 \hat{\varepsilon}' \hat{\varepsilon}$, where each of the elements of $\hat{\varepsilon}$ is $\hat{\varepsilon}_t = [y_{t,1} - \gamma_1, y_{t,2} - \gamma_2, y_{t,3} - \gamma_3]'$.

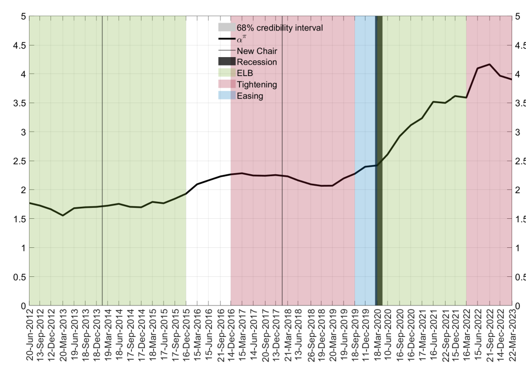
B Filtered Time-varying Coefficient Estimates

This section shows the time-varying coefficient estimates obtained with the Kalman filter, using the posterior median estimates as the parameters of the state-space model.

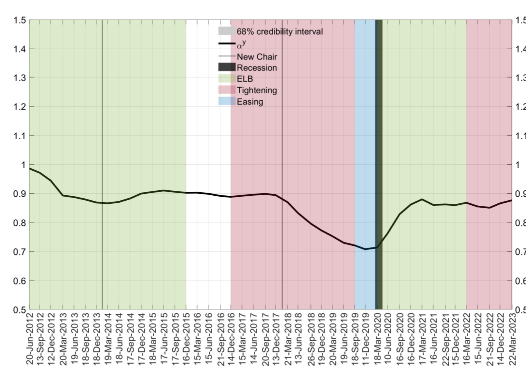
Figure B.1: Filtered Time-varying Coefficient Estimates



(a) Persistence coefficient



(b) Inflation coefficient



(c) Output gap coefficient

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