Bond Market Views of the Fed*

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Abstract

This paper uses high-frequency data to detect shifts in financial markets' perception of the Federal Reserve's stance on inflation. We construct daily revisions to expectations of future nominal interest rates and inflation that are priced into nominal and inflation-protected bonds, and find that the relation between these two variables—positive and stable for over twenty years—weakened substantially over the 2020-2022 period. In the context of canonical monetary reaction functions considered in the literature, these results are indicative of a monetary authority that places less weight on inflation stabilization. We augment a standard New Keynesian model with regime shifts in the monetary policy rule, calibrate it to match our findings, and use it as a laboratory to understand the drivers of U.S. inflation post 2020. We find that the shift in the monetary policy stance accounts for 41% of inflation's excess over the 2% target in 2022:Q1.

Keywords: High-frequency identification, estimation of monetary rules, inflation

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1 Introduction

The surge in inflation following the pandemic stands out as one of the most remarkable macroeconomic developments in recent years. Twelve-month CPI inflation reached 9% in 2022, at levels not seen since the 1980s. Economists have focused on several potential root causes, pointing out the concurrence of adverse supply shocks—such as the disruptions in the global supply chain and increases in energy prices—and higher demand during the economic recovery due to pent-up forces and expansionary fiscal policies. Considerably less attention, however, has been drawn to the role played by monetary policy. Indeed, the Federal Reserve, similarly to other central banks in advanced economies, did not increase interest rates throughout 2021 despite the observed large increases in inflation. Did this episode trigger a change in the private sector's views about how the Federal Reserve would tackle inflation going forward? To what extent did these changes exacerbate the inflationary effects of the demand and supply shocks that hit the U.S. economy?

In this paper, we address these questions in two steps. First, we develop a methodology that exploits high-frequency financial market data to detect shifts in financial markets' perception of the Fed reaction function. Using the term structure of interest rates for nominal and inflation-protected bonds, we show strong and robust evidence of a shift in the perceived monetary rule over the 2020-2022 period, with financial markets viewing the Fed as substantially more tolerant to short- and medium-term fluctuations in inflation. In the second step, we assess the macroeconomic effects of this shift in policy by combining this high-frequency measurement with a standard New Keynesian model with regime switches in the monetary policy rule. Through the lens of this model, we find that changes in monetary policy played a first-order role during the episode. In particular, we estimate that inflation would have been about 6% in 2022:Q1 if the Fed had followed its historical reaction function.

To fix ideas, let's assume for now that the Federal Reserve follows a simple Taylor rule

$$i_t = i^\star + \psi_\pi(\pi_t - \pi^\star) + \varepsilon_{m,t}, \tag{1}$$

where i_t is the Fed funds rate, π_t is inflation, $\pi^\star$ is the inflation target, $i^\star$ is the "natural" nominal interest rate, and $\varepsilon_{m,t}$ is a monetary shock capturing transitory deviations from the systematic component of policy.

Our objective is to test whether investors perceived a change in ψ_π after 2020 and how long they expected it to persist.[1] This hypothesis is difficult to test using short-term nom-

[1] In the baseline New Keynesian model, more persistent changes in the policy rule have larger effects on output and inflation.

inal interest rates and inflation data for two reasons. First, the policy rate remained at the zero lower bound until March 2022. Second, monetary policy shocks affect both nominal interest rates and inflation, confounding the systematic response of policy to inflation with deviations from the rule.

One key insight of our paper is that these challenges can be addressed using high-frequency bond market data. First-differencing the time-t expectations of the Taylor rule (1) for a future date $k > t$ gives

$$\Delta\mathbb{E}_t[i_k] = \psi_\pi \Delta\mathbb{E}_t[\pi_k] + \Delta\mathbb{E}_t[\varepsilon_{m,k}], \tag{2}$$

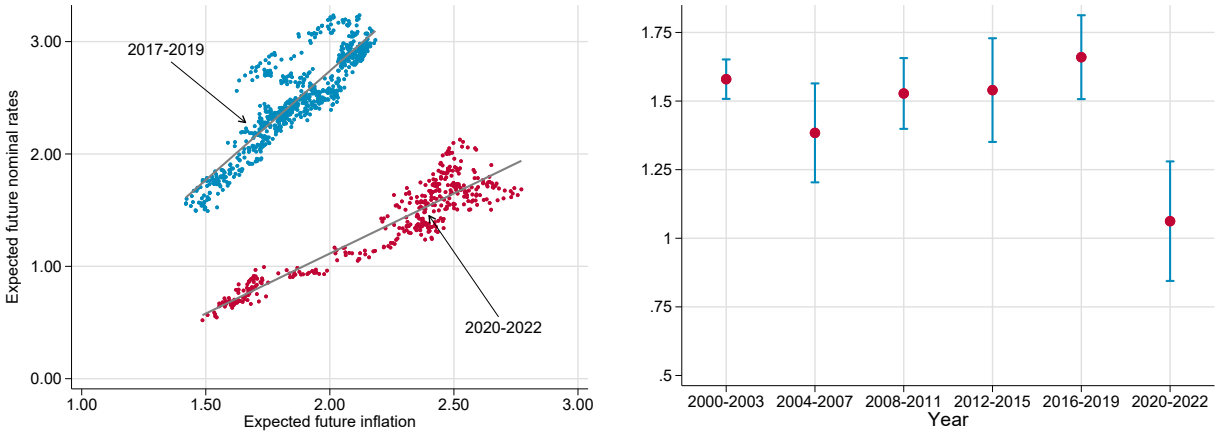
where $\Delta\mathbb{E}_t[x_k] \equiv \mathbb{E}_t[x_k] - \mathbb{E}_{t-1}[x_k]$ is the daily forecast revision of variable x at date k, and $\Delta\mathbb{E}_t[\varepsilon_{m,k}]$ captures news about future monetary policy shocks.

From the term structure of nominal and inflation-protected bonds, we can retrieve daily "risk-neutral" expectations of future nominal interest rates and inflation, whose daily changes provide proxies for $\Delta\mathbb{E}_t[i_k]$ and $\Delta\mathbb{E}_t[\pi_k]$. These data help address both difficulties. First, expected future interest rates can respond to news even when the current policy rate is at the zero lower bound. Second, the high-frequency nature of the data allows us to condition the analysis on days in which the Fed does not take policy decisions or release information.[2] Our identifying assumption is that investors receive no news about future monetary policy shocks on these non-monetary-event days, that is, $\Delta\mathbb{E}_t[\varepsilon_{m,k}] = 0$.

To illustrate our approach with a simple example, consider what happens after the release of a CPI report. Following the news, investors may revise their forecasts of future inflation and their expectations of how the Fed will respond to it. If there is no monetary event that day, our assumption and equation (2) imply that the comovement between these revisions reflects the systematic response of policy to inflation—the coefficient ψ_π. Comparing this relationship over time allows us to test for shifts in the perceived reaction function, while comparing it across forecast horizons provides information about their expected duration.

We start our empirical analysis by studying the relationship between market-implied expectations of future nominal interest rates and inflation. As an initial illustration, panel (a) of Figure 1 plots the levels of these expectations for two subperiods. There is a strong linear relationship between the two variables, with a much flatter slope in 2020–2022 than in preceding years. Panel (b) reports the estimates of ψ_π using our approach for different subsamples. These estimates are remarkably stable before the pandemic, centered around 1.5 for almost twenty years, and declined substantially afterward. When varying the maturity

[2]Policy decisions and communications are referred to in the literature as "monetary events" and include FOMC announcements, press conferences, releases of FOMC minutes, and speeches by the Fed chair.



(a) $\mathbb{E}_t[\tilde{i}_{t,k}]$ vs $\mathbb{E}_t[\bar{\pi}_{t,k}]$ for different sub-samples

(b) Estimates of ψ_π over different sub-samples

Figure 1: Market-based expectations of nominal interest rates and inflation

Notes: Panel (a) shows a scatter plot of daily market-based expectations of average nominal interest rates and average inflation over a ten-year horizon for two sub-samples, Jan 2017- Dec 2019 (blue dots) and Aug 2020- Feb 2022 (red dots). The shaded areas show 95% confidence bands around the fitted regression lines. Panel (b) reports estimates of ψ_π in different sub-samples, together with 95% confidence intervals based on robust standard errors. See Section 2 for a description of the data and the estimation of ψ_π.

of bonds, we find that the decline is concentrated at forecast horizons of up to five years, while not finding significant differences in ψ_π over time when looking at longer forecasting horizons.

Through the lens of the Taylor rule in equation (1), these findings indicate that financial markets perceived the Fed after 2020 to be systematically less responsive to inflation over the short and medium term. However, there are other forces that could potentially explain a drop in the sensitivity of nominal interest rates to inflation and confound our measurement. We examine three plausible alternative explanations: expectations of a binding zero lower bound, misspecification of the monetary policy reaction function, and time-varying risk and liquidity premia. We address the first concern by explicitly correcting for the attenuation induced by the lower bound and by controlling for option-implied probabilities of a binding constraint. We address the second by allowing for movements in the natural interest rate and the inflation target, and by using survey forecasts to account for the policy response to economic activity. Finally, we repeat our analysis using expectations adjusted for risk and liquidity premia. Our main results survive all these checks.

In the last part of the paper, we study the macroeconomic implications of these perceived changes in the Fed reaction function by enriching a New Keynesian model with a monetary policy rule with two regimes that differ in the responsiveness of nominal interest rates to inflation. The two regimes are disciplined to fit the US historical evidence on nominal

interest rates, inflation and output as well as the shift identified in our empirical analysis. We then use the parametrized model to perform policy counterfactuals. In an event study, we find that inflation would have been substantially less responsive to the demand and supply shocks hitting the economy if the Fed had responded according to the historical Taylor rule: at the observed peak in 2022:Q1, annualized inflation would have reached 6% in this scenario instead of the observed 8.9%. So, the shift to a more accommodative policy stance accounts for 41% of the inflation excess over the 2% target observed at its peak in 2022:Q1.

We subject these findings to a battery of sensitivity checks. We consider a version of the model with cognitive discounting (Gabaix, 2020) in order to address the concern that inflation in the baseline model is too sensitive to future real interest rates, a feature related to the "forward guidance puzzle". We also consider alternative monetary policy rules and more conservative parametrizations. In all these robustness checks, the shift in the policy rule that we identified plays a key role in accounting for the observed inflation dynamics: inflation under the historical rule would have ranged between 4.5% and 7.1% in 2022:Q1. Thus, the shift in the policy rule accounts for between 26% and 63% of inflation's excess over the 2% target observed in this event.

Related literature. There are several recent papers studying the drivers of U.S. inflation post 2020. A series of papers have focused on the importance of sectoral shocks and capacity constraints, for instance the work of Bohr (2024), Comin, Johnson, and Jones (2023), Ferrante, Graves, and Iacoviello (2023) and Di Giovanni, Kalemli-Ozcan, Silva, and Yildirim (2022). These forces are isomorphic to endogenous cost-push shocks in the canonical one-sector model (Guerrieri, Lorenzoni, Straub, and Werning, 2021), which generate inflationary pressures. Another branch of the literature has focused on mechanisms that make the Phillips curve steeper, amplifying the pass-through of shocks onto prices. See for example Gagliardone and Gertler (2023) and Benigno and Eggertsson (2023). The contribution of our paper is to quantify the role of monetary policy. Specifically, we provide evidence of a sizable shift in investors' beliefs about the conduct of monetary policy during this episode. In addition, we show that these shifts in beliefs are quite consequential for inflation dynamics when fed through a benchmark New Keynesian model.[3] Our results are consistent with Gagliardone and Gertler (2023), Comin, Johnson, and Jones (2023) and Giannone and Primiceri (2024), who also document an important role for monetary policy.

[3] Doh and Yang (2023) study how different assumptions about a Taylor rule with average inflation targeting, for example a lengthening of the horizon of inflation targeting or a reduction in the inflation feedback parameter in the Taylor rule, can generate a larger response of inflation to shocks. Differently from them, our paper introduces a methodology to quantify these shifts in the rule and assess the impact of these changes on macroeconomic outcomes.

Our paper also contributes to the literature on the estimation of monetary policy rules. In a now classic paper, Clarida, Gali, and Gertler (2000) identify substantial differences in the monetary policy reaction function before and after Volcker's appointment as Fed Chairman and quantify the implication of these changes for macroeconomic volatility through the lens of a New Keynesian model. Our analysis shares a similar objective but introduces a different methodology. Specifically, because we are interested in testing a recent shift in policy, we cannot use realized retrospective data as in Clarida, Gali, and Gertler (2000); instead, we use real-time bond market data and estimate a shift in the Fed reaction function using expectations. Starting with Hamilton, Pruitt, and Borger (2011), recent literature has used expectations data—either market-based or surveys—to quantify aspects of the conduct of monetary policy. See for example King and Lu (2022), Mertens and Zhang (2023) and Campos, Fernández-Villaverde, Nuño, and Paz (2024).

The paper most closely related to our work is Bauer, Pflueger, and Sunderam (2022). These authors use cross-sectional variation in the forecast of future nominal interest rates, inflation, and output—up to five quarters ahead—by professional forecasters to estimate time-variation in the parameters of a Taylor rule. We view our approach as complementary, as it builds on different data and methodology to estimate a related object. First, we rely on a different variation in the data—the comovement of market-based forecast updates about nominal interest rates and inflation—to estimate the sensitivity of the former to the latter. Second, our approach focuses on the medium- to long-run forecast horizon, which is less affected by possible biases induced by the zero lower bound constraint. Third, by focusing on the entire term structure, we can assess the perceived persistence of a shift in the monetary policy regime. Aside from the methodological differences, the two papers differ in their objectives and scope: Bauer, Pflueger, and Sunderam (2022) focus on assessing the impact of these perceived shifts in the monetary policy rule on financial markets' outcomes while we incorporate this measurement in a baseline New Keynesian model to study their impact on macroeconomic variables such as inflation and the output gap.

In contemporaneous work, Cuciniello (2024) estimates rolling linear regressions of the level of nominal interest-rate expectations on expected inflation and other controls, finding substantial variation in the ECB's perceived response to inflation. Our approach instead exploits the comovement of daily forecast revisions in those variables on non-monetary-event days. Cuciniello (2024) focuses on measuring time-variation in the perceived policy rule, while we combine information from the term structure with a New Keynesian model to jointly discipline the magnitude and expected persistence of the policy shift and quantify its macroeconomic effects.[4]

[4]The most recent version of Cuciniello's paper, dated July 2025, extends the analysis to the United States, broadly confirming the findings in our paper.

Our approach builds on high-frequency monetary identification techniques (Kuttner, 2001; Nakamura and Steinsson, 2018; Bauer and Swanson, 2023). The main innovation in our approach is that we use the timing of monetary events to isolate forecast revisions on the remaining days and test for shifts in the *systematic* component of the Fed reaction function rather than to measure monetary shocks and their propagation through the economy. To the best of our knowledge, we are the first to use these techniques for this purpose.

Finally, there is a large literature studying the macroeconomic effects of shifts in the monetary policy rule. Examples include Bianchi (2013), Bianchi and Ilut (2017), Bianchi, Lettau, and Ludvigson (2022), Bianchi, Ludvigson, and Ma (2022), and Hack, Istrefi, and Meier (2023). Our finding that a sizable component of the increase in inflation in 2021-22 is attributable to a change in the policy rule is consistent with the findings in Bianchi, Faccini, and Melosi (2023). That paper links the perceived increase in the Fed's dovishness to an increase in the amount of unfunded fiscal spending during the pandemic. Relative to this work, our contribution is to provide direct evidence of the monetary policy shift using bond price data.

2 Bond market views of the Fed

We now describe our empirical approach to detect shifts in the monetary policy reaction function using bond prices, and apply our approach to US data. We document a substantial decline in the sensitivity of nominal interest rates to inflation during the 2020-2022 horizon, especially when using bonds with residual maturities of up to 5 years. Through the lens of a simple Taylor rule, this evidence points toward bond market investors expecting the Fed to respond less forcefully to inflationary shocks over the short- to medium-term horizon.

This section is divided into four parts. Section 2.1 describes the data used in the empirical analysis. Section 2.2 presents our approach to identifying shifts in the Federal Reserve's reaction function and reports the baseline results. Section 2.3 presents a sensitivity analysis of the results, while Section 2.4 discusses the interpretation of the main empirical findings.

2.1 The data

We use daily data on zero-coupon nominal and real bond (Treasury Inflation-Protected Securities, or "TIPS") yields for different maturities constructed by Gürkaynak, Sack, and Wright (2007, 2010). We denote by $i_t^{(k)}$ the zero-coupon yield on a nominal bond maturing k years from date t and by $r_t^{(k)}$ the zero-coupon yield on an inflation-protected bond maturing k years from date t. The difference between these two reflects the inflation compensation

required by investors for holding the inflation component in the nominal bond, which we denote by $IC_t^{(k)} \equiv i_t^{(k)} - r_t^{(k)}$.

Our sample runs from January 3rd, 2000, to December 31st, 2024. The start of the sample is restricted by the fact that TIPS were only issued starting in 1997 and that, initially, the market was quite small and illiquid with only a few outstanding securities (see Sack and Elsasser (2004), for example).

We can use these data to construct the expectation of the average short-term nominal interest rate and of the average inflation rate over the lifetime of the bonds. Specifically, from standard asset pricing relationships, we have

$$i_t^{(k)} = \mathbb{E}_t\left[\bar{i}_{t,k}\right] + \eta_{t,k} \tag{3}$$

$$IC_t^{(k)} = \mathbb{E}_t\left[\bar{\pi}_{t,k}\right] + \iota_{t,k}, \tag{4}$$

where $\bar{i}_{t,k}$ and $\bar{\pi}_{t,k}$ denote the average nominal interest rate and inflation rate over the next k years, and $\mathbb{E}_t\left[\cdot\right]$ denotes the expectation conditional on time t information.

Bond yields do not reflect exclusively physical expectations because of the presence of term and inflation risk premia.[5] In addition, nominal Treasuries are typically more liquid than inflation-protected bonds in the United States, and this liquidity advantage lowers their yields relative to otherwise comparable securities (Gürkaynak, Sack, and Wright, 2010; D'Amico, Kim, and Wei, 2018). Ceteris paribus, this differential liquidity premium reduces measured inflation compensation. We capture all these discrepancies by $\eta_{t,k}$ and $\iota_{t,k}$ in the equations above.

For our baseline results, we will assume that $\eta_{t,k}$ and $\iota_{t,k}$ are constant over time at the daily frequency. This assumption is quite restrictive, and in the sensitivity analysis of Section 2.3 we will relax it. In addition, we exclude from our sample historical episodes of heightened financial turmoil, specifically 2008 and the first half of 2020 (January 1 to July 31), periods in which liquidity premia were especially sizable and volatile.

[5] Several studies have documented that nominal bond yields and inflation compensation also reflect time-varying term and inflation risk premia; see, among many others, Kim and Wright (2005), Piazzesi and Swanson (2008), Adrian, Crump, and Moench (2013), Abrahams, Adrian, Crump, Moench, and Yu (2016), Cieslak and Povala (2015), D'Amico, Kim, and Wei (2018), Cieslak and McMahon (2023), and Kekre, Lenel, and Mainardi (2024).

2.2 Identifying shifts in the monetary policy rule

For our baseline analysis, we assume that bond market participants perceive that the conduct of monetary policy is described by the rule

$$i_\tau = \rho_i i_{\tau-1} + (1-\rho_i)\left[i^\star + \psi_\pi\left(\pi_\tau - \pi^\star\right)\right] + \varepsilon_{m,\tau}, \tag{5}$$

where i_τ is the nominal interest rate prevailing in year τ, $(\pi_\tau - \pi^\star)$ is the deviation of inflation from its target $\pi^\star$, $i^\star$ is a fixed "natural" nominal interest rate, and $\varepsilon_{m,\tau}$ is a monetary shock—a transitory deviation from the rule. In what follows, we discuss how we can use the data presented earlier to identify shifts in the Fed's perceived reaction function.

First, we take the k-years-ahead expectations of both sides of equation (5) at date t. For variable x, we denote this expectation by $\mathbb{E}_t[x_k]$. Next, we construct the *daily* forecast revisions of these variables by first-differencing them with respect to t, $\Delta\mathbb{E}_t[x_k] = \mathbb{E}_t[x_k] - \mathbb{E}_{t-1}[x_k]$. We can then rewrite equation (5) as

$$\Delta\mathbb{E}_t\left[i_k - \rho_i i_{k-1}\right] = (1-\rho_i)\psi_\pi \Delta\mathbb{E}_t\left[\pi_k\right] + \Delta\mathbb{E}_t\left[\varepsilon_{m,k}\right]. \tag{6}$$

The data described in Section 2.1 provide market-based measures of the forecast revisions of future short-term nominal rates and future inflation appearing in equation (6). Since equation (6) holds at every forecast horizon, we can combine these objects across maturities and, after accounting for the interest-rate smoothing term, use their comovement to estimate ψ_π.

There is, however, a well-known endogeneity problem when estimating monetary policy reaction functions due to the presence of $\varepsilon_{m,t}$. News about future monetary policy shocks can directly affect expected nominal interest rates and, at the same time, induce revisions in expected inflation. The resulting correlation between $\Delta\mathbb{E}_t[\varepsilon_{m,k}]$ and $\Delta\mathbb{E}_t[\pi_k]$ confounds the systematic response of policy to inflation, ψ_π, with revisions in the non-systematic component of the policy rule.

Importantly, the high-frequency nature of our data allows us to address this problem directly. Previous research has identified a set of "monetary events" (FOMC announcements, releases of FOMC minutes, and other communications by the Fed chair) during which investors receive direct news about the conduct of monetary policy. Our identifying assumption is that investors receive no direct news about future monetary policy shocks on the remaining days: that is, we assume that $\Delta\mathbb{E}_t[\varepsilon_{m,k}] = 0$ if t is not in the set of monetary events. Under this assumption and equation (6), movements in expected short-term interest rates reflect the *systematic* response of policy to revisions in expected inflation rather

than revisions in monetary shocks.

A simple example may help fix ideas. Following a CPI release, investors may learn something about the nature of the shocks hitting the economy and may end up revising their forecasts of future inflation. On the same day, they may also revise their forecasts of future nominal interest rates. Our identifying assumption is that, on those days, investors do not receive independent news about $\varepsilon_{m,k}$ if the Fed chair does not speak and the Fed does not take policy actions—that is, if t is not in the set of monetary events. Under this assumption, the resulting comovement between revisions in expected inflation and expected short-term interest rates around those days tells us something about the systematic component of the policy rule—the parameter ψ_π in equation (5).

Restricting attention to non-monetary-event days, and using the fact that equation (6) holds for every k, we obtain

$$\Delta\mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i \frac{k-1}{k}\bar{i}_{t,k-1}\right] = \psi_\pi \Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right], \tag{7}$$

where $\overline{x}_{t,k}$ is the average of variable x between now and k years ahead, and we use the fact that i_{t-1} is predetermined at t. By taking averages over different horizons, we can smooth out any idiosyncratic behavior of forward rates across the maturity structure and obtain estimates for ψ_π using the most liquid traded securities. Specifically, in our baseline analysis, we consider expectations constructed using nominal and inflation-protected bond yields with a residual maturity of ten years.

To estimate equation (7), we proxy for $\Delta\mathbb{E}_t\left[\bar{i}_{t,k}\right]$ and $\Delta\mathbb{E}_t\left[\overline{\pi}_{t,k}\right]$ using daily changes in nominal bond yields and inflation compensation for a bond with residual time to maturity of k years. To minimize the impact of outliers, we winsorize these variables at the 1st and 99th percentiles. Since equation (5) is specified at an annual frequency, we fix ρ_i to 0.8 following previous research and construct a time series for $\Delta\mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i\frac{k-1}{k}\bar{i}_{t,k-1}\right]$ and $\Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right]$.[6] We can then estimate ψ_π over different sub-samples.

We partition the sample 2000-2022 into 6 different sub-samples of approximately equal length (4 years), and estimate by ordinary least squares the relationship

$$\Delta\mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i \frac{k-1}{k}\bar{i}_{t,k-1}\right] = c + \sum_{s=1}^{6}\psi_{\pi,s}\left(D_{t,s}\times\Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right]\right) + e_t, \tag{8}$$

where $D_{t,s}$ takes a value of 1 if period t is in subsample s and zero otherwise.[7]

[6] As we discuss in Appendix B.2, our main results are robust to varying ρ_i in the empirically plausible range between 0.7 and 0.9.

[7] Results are very similar when we use sub-samples of 3 or 5 years.

Table 1: Estimates of equation (8)

	2000–2003	2004–2007	2008–2011	2012–2015	2016–2019	2020–2022
$\psi_{\pi,s}$	1.580^{***}	1.384^{***}	1.528^{***}	1.540^{***}	1.660^{***}	1.062^{***}
	(0.037)	(0.092)	(0.066)	(0.096)	(0.078)	(0.111)
$R^2 = 0.430$; Observations: 4,639						

Note: The table reports estimates of $\psi_{\pi,s}$ in equation (8) using expectations over the [0–10] year horizon. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 1 reports the estimates of these coefficients estimated using 10-year averages, which we also reported graphically in panel (b) of Figure 1. We observe a remarkable stability of $\psi_{\pi,s}$ over the twenty years preceding the pandemic. Even more remarkably, we observe a sizable fall in the coefficient post-2020, with a point estimate of 1.06.

Because the estimated coefficients in the pre-2020 period are close to each other for the forecast horizon that is mostly relevant for our analysis, we will consider from now on only two sub-samples—pre- and post-2020—and estimate the relation

$$\Delta\mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i\frac{k-1}{k}\bar{i}_{t,k-1}\right] = c + \psi_\pi\Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right] + d\left(D_t \times \Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right]\right) + e_t, \quad (9)$$

where D_t is a dummy equal to 1 if t is after 2020:M8 and zero otherwise. The coefficient d captures the difference in ψ_π across the two sub-periods, such that a negative estimate of d indicates a weaker relationship between nominal interest rates and inflation in the post-2020 period.

Figure 2 reports the point estimate of d in equation (9) along with a 95% confidence interval for the baseline specification ([0-10] years forward). The point estimate of d in the baseline is -0.48 with a tight confidence interval.

We also exploit the term structure of the data and estimate equation (9) using expectations constructed over a relatively medium-term horizon ([0–5] years forward) and a long-term horizon ([6–10] years forward).[8] Figure 2 reports the point estimates of d in those specifications. We can see that the largest deviations occur for short- to medium-term expectations (up to year five) while financial markets expected these deviations to

[8]We construct forward averages by subtracting the cumulative expectations over the excluded initial years from those over the full horizon. For years x through y, with $1 \leq x \leq y$, the nominal-rate measure is $[yi_t^{(y)} - (x-1)i_t^{(x-1)}]/(y-x+1)$; the inflation measure replaces $i_t^{(k)}$ with $IC_t^{(k)}$. The initial term is zero when $x = 1$. Thus, [3–10] denotes the eight years following the first two years, and the corresponding nominal-rate measure is $(10i_t^{(10)} - 2i_t^{(2)})/8$. The [0–2] horizon uses the two-year yields directly. We use daily changes in these measures and apply the interest-rate inertia adjustment in equation (7).

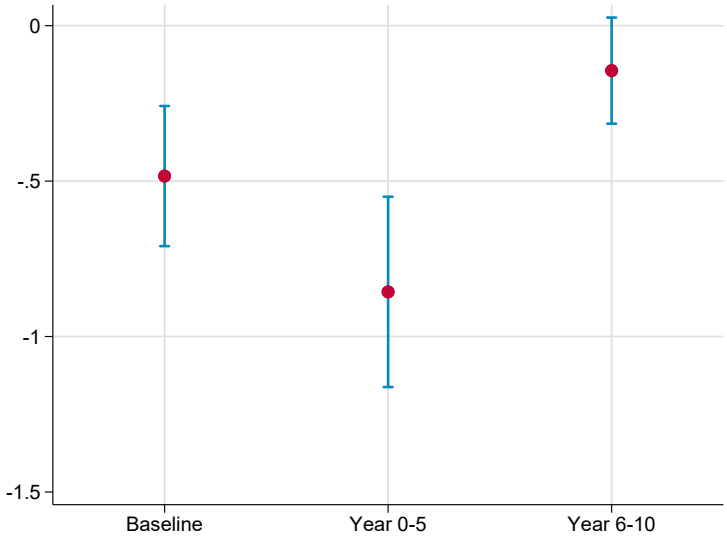


Figure 2: Medium-term vs. long-term expectations

Notes: The figure reports point estimates and 95% confidence intervals for the coefficient d in equation (9) estimated using: i) expectations of nominal interest rates and inflation averaged over the next ten years; ii) expectations of nominal interest rates and inflation averaged over the next five years; iii) expectations of nominal interest rates and inflation averaged over years six through ten. Confidence intervals are constructed based on robust standard errors.

eventually fade away over time. For expectations between years six and ten, the coefficient d is closer to zero, with a point estimate of -0.14, and not significantly different from it at the 5% significance level.

Discussion. The changes in sensitivity documented above should not, in general, be interpreted as direct estimates of changes in specific parameters of the monetary policy rule. Under the simple reaction function adopted in this section, the regression coefficient coincides with ψ_π. Even in this simple case, however, our derivation holds ψ_π fixed when taking expectations and constructing forecast revisions. If investors anticipate future changes in the rule, the regression coefficient need not equal ψ_π in any particular regime. Thus, under our maintained assumptions, the exercise is better interpreted as a test of the null hypothesis that ψ_π is constant rather than as an estimate of its change.

Under more realistic reaction functions, there will not be a simple mapping between the regression coefficient in our specification and ψ_π. For example, changes in interest-rate inertia can also affect the measured sensitivity, while omitting the output gap can introduce a bias, as we discuss in Section 2.3. Nevertheless, conditional on a specified reaction function and a model of its evolution, changes in sensitivity can be informative about its parameters. This is the approach we follow in Section 3, where we use the estimated changes

in sensitivity at different horizons as empirical targets for estimating shifts in the reaction function via indirect inference.

2.3 Sensitivity analysis

In the previous section, we have documented a weakening in the correlation between nominal bond yields and inflation compensation post-2020, especially when considering residual maturities up to 5 years. We have also argued that these facts are indicative of a shift in financial markets' perception of the Fed reaction function—specifically a more Dovish policy toward inflation over the medium term.

In this section, we put this interpretation under scrutiny. We discuss three plausible confounding factors that could also explain a reduced sensitivity of nominal interest rates to inflation even in the absence of a shift of the reaction function: the possibility of an occasionally binding zero lower bound constraint, a misspecification of the monetary policy reaction function, and time-varying risk/liquidity premia. We propose ways to control for these confounding factors and show that our main results—the decline in the sensitivity of nominal interest rates to inflation at short- to medium-term horizons—survive this sensitivity analysis.

Controlling for the zero lower bound constraint. The presence of the zero lower bound (ZLB) mechanically reduces the sensitivity of nominal interest rates to inflation when rates are expected to remain close to zero. Thus, the decline in sensitivity that we document after 2020 could reflect a higher probability of a binding lower bound rather than a change in the perceived policy rule. We address the issue using two complementary approaches. The first explicitly incorporates the ZLB into the policy rule and corrects for the resulting attenuation bias in the response of expected interest rates to inflation. The second uses option-implied probabilities to control directly for the lower-bound risk perceived by financial markets.

Our first approach assumes that the Taylor rule in equation (5) determines a shadow interest rate $\hat{i}_t$, while the observed interest rate satisfies

$$i_t = \max\left\{\hat{i}_t, 0\right\}.$$

When the expected shadow rate is close to zero, negative revisions are censored while positive revisions are not. As a result, changes in expected inflation generate smaller movements in expected observed rates than they would in the absence of the constraint. The size of this attenuation depends on the distance of expected rates from the lower bound and on the volatility of the shadow interest rate.

To derive a correction for this issue, we approximate the conditional distribution of the shadow interest rate at each horizon by a Gaussian distribution with mean $\mathbb{E}_t[\hat{i}_{t+k}]$ and standard deviation s, which we hold fixed. With zero conditional mean monetary policy shocks, the expected future short-term rate at horizon k is

$$\mathbb{E}_t[i_{t+k}] = \rho_i \mathbb{E}_t[i_{t+k-1}] + (1-\rho_i)\left\{i^\star + \psi_\pi \mathbb{E}_t[\pi_{t+k} - \pi^\star]\right\} + s f\left(\frac{\mathbb{E}_t[\hat{i}_{t+k}]}{s}\right), \tag{10}$$

where $f(x) = \varphi(x) - x[1-\Phi(x)]$, and $\varphi(\cdot)$ and $\Phi(\cdot)$ denote, respectively, the probability density function and cumulative distribution function of a standard normal random variable. The final term captures the effect of censoring negative realizations of the shadow rate.

To obtain a linear specification that can be analyzed using our previous approach, we take a first-order approximation of equation (10) around $\mathbb{E}_t[\pi_{t+k}] = \pi^\star$ and $\mathbb{E}_t[i_{t+k-1}] = i_{k-1}$. Defining

$$a_k = 1 + f'\left(\frac{\rho_i i_{k-1} + (1-\rho_i)\bar{i}^\star}{s}\right) = \Phi\left(\frac{\rho_i i_{k-1} + (1-\rho_i)\bar{i}^\star}{s}\right),$$

we can then write the first-order expansion of the right-hand side of equation (10) around this point as

$$\mathbb{E}_t[i_{t+k}] \approx A_k + a_k\Big[\rho_i \mathbb{E}_t[i_{t+k-1}] + (1-\rho_i)\psi_\pi \mathbb{E}_t[\pi_{t+k} - \pi^\star]\Big], \tag{11}$$

where A_k collects terms that are constant at the approximation point. Within each sub-sample, A_k disappears after taking first differences. The term a_k lies between zero and one and measures the probability that the shadow rate exceeds the lower bound at the approximation point. Equation (11) therefore provides a horizon-specific correction for the attenuation induced by the lower bound.

Importantly, a_k is known up to i_{k-1}, $\bar{i}^\star$ and s. Our approach consists of two steps. First, we use data to calibrate these three parameters in order to obtain numerical values for $\{a_k\}$ for each k for both sub-samples. In each sub-sample, we use the time average of the Laubach and Williams (2016) indicator of the natural real interest rate, add 2% inflation to obtain a value for $i^\star$, and use the time average of forward rates to set i_{k-1} at each maturity k. We set $s = 0.03$ and hold it fixed across horizons and sub-samples.[9] We use these values to compute $\{a_k\}$ for both sub-samples and use these coefficients along with equation (11)

[9] We use $\rho_i = 0.8$ both when calibrating a_k and in the regressions.

Table 2: Sensitivity analysis

	(1) Baseline	(2) ZLB structural	(3) ZLB reduced form	(4) Time-varying i^* and π^*	(5) Risk premia
d, [0–10] years	-0.48***	-0.24	-0.62*	-0.33***	-0.15
	(0.11)	(0.26)	(0.32)	(0.06)	(0.21)
d, [0–5] years	-0.86***	-1.09***	-1.11***	-0.57***	-0.89***
	(0.16)	(0.34)	(0.34)	(0.08)	(0.12)
d, [6–10] years	-0.14*	0.31*	0.02	-0.16***	0.14***
	(0.09)	(0.18)	(0.26)	(0.05)	(0.04)
N. obs.	4639	4639	3088	4639	4639

Note: The table reports estimates of d in equation (9) under different specifications. Column (1) restates the baseline. Column (2) applies the structural ZLB correction, and column (3) controls for option-implied lower-bound risk in reduced form. Column (4) allows i^* and π^* to vary over time, while column (5) uses expectations adjusted for the presence of time-varying risk and liquidity premia. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

to obtain an expression for the revision in expectations about the average of the short-term rate over the next k years

$$\Delta\mathbb{E}_t[\bar{i}_{t,k}] - \frac{1}{k}\sum_{j=1}^{k} a_j \rho_i \Delta\mathbb{E}_t[i_{t+j-1}] \approx \psi_\pi \frac{1}{k}\sum_{j=1}^{k} a_j (1-\rho_i)\Delta\mathbb{E}_t[\pi_{t+j}].$$

This expression is the first-order counterpart of equation (7) in the presence of the ZLB constraint, and we can use it to test for the stability of ψ_π in the sample.

Column (2) of Table 2 reports the estimates of d for this specification. We can see that the decline in sensitivity remains significant when we consider short- to medium-term expectations, with a point estimate of -1.09 for the [0–5]-year horizon.

Our second approach uses information from interest-rate options rather than imposing a parametric model for the risk of hitting the ZLB constraint. Specifically, we use the daily option-implied probabilities of a binding lower bound constructed by Mertens and Williams (2021).[10] We augment the baseline regression by allowing the sensitivity of

[10] Mertens and Williams (2021) compute daily estimates of risk-neutral distributions of short-term interest rates from caps and floors based on LIBOR from 2007 through 2021 and caps and floors based on SOFR starting in 2022. The distributions take the zero lower bound on interest rates into account and are available for 1 through 10 years ahead. Based on these distributions, it is possible to calculate an estimate of the

nominal yields to inflation compensation to vary with this probability.

For expositional clarity, define

$$x_{t,k} \equiv \Delta \mathbb{E}_t[(1-\rho_i)\overline{\pi}_{t,k}], \qquad y_{t,k} \equiv \Delta \mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i \frac{k-1}{k}\bar{i}_{t,k-1}\right].$$

We estimate

$$y_{t,k} = c + \beta x_{t,k} + \gamma x_{t,k} ZLB_{t,k} + d\, D_t x_{t,k} + d_2\, D_t x_{t,k} ZLB_{t,k} + e_{t,k}. \tag{12}$$

The interaction terms allow lower-bound risk to affect the relationship between nominal yields and inflation compensation in both subsamples. The pre-2020 sensitivity at a given level of lower-bound risk is $\beta + \gamma ZLB_{t,k}$, while the corresponding post-2020 sensitivity is $\beta + d + (\gamma + d_2)ZLB_{t,k}$. Thus, the post-2020 change in sensitivity at a given level of lower-bound risk is $d + d_2 ZLB_{t,k}$. Therefore, the parameter d measures the post-2020 change when the option-implied probability of a binding lower bound is zero. If the decline in sensitivity was entirely due to heightened lower-bound risk, allowing the sensitivity to vary with $ZLB_{t,k}$ should make d close to zero.

Column (3) in Table 2 reports the results. The estimate of d remains negative and economically meaningful for the [0–5]-year horizon.

Misspecification of the monetary policy reaction function. Our analysis thus far has been based on the Taylor rule in equation (5), with nominal interest rates responding only to deviations of inflation from its target. While this formulation makes the analysis transparent, it misses two empirically plausible aspects: time variation in the natural real interest rate $r^\star = i^\star - \pi^\star$ and in the inflation target $\pi^\star$, and the presence of an indicator of economic activity—such as the output or the unemployment gap. An important question is whether these omitted forces can spuriously induce the observed reduction in the sensitivity of nominal interest rates to inflation after 2020.

Let us start with time variation in the natural real interest rate and the inflation target. Consider the extension of equation (5)

$$i_\tau = \rho_i i_{\tau-1} + (1-\rho_i)\left[i^\star_\tau + \psi_\pi\left(\pi_\tau - \pi^\star_\tau\right)\right] + \varepsilon_{m,\tau}, \tag{13}$$

probability of a binding lower bound at each forward horizon. We thank the authors for sharing their data with us.

and suppose that both long-run objects follow random walks,

$$r^\star_\tau = i^\star_\tau - \pi^\star_\tau = r^\star_{\tau-1} + \nu^r_\tau, \qquad \pi^\star_\tau = \pi^\star_{\tau-1} + \nu^\pi_\tau. \tag{14}$$

Under this assumption, their time-t expected values are constant across forecast horizons: $\mathbb{E}_t[i^\star_{t+j}] = r^\star_t + \pi^\star_t$ and $\mathbb{E}_t[\pi^\star_{t+j}] = \pi^\star_t$ for every $j \geq 1$. Averaging equation (13) over the next k years and taking daily forecast revisions therefore gives

$$\Delta\mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i \frac{k-1}{k}\bar{i}_{t,k-1} - (1-\rho_i)i^\star_t\right] = \psi_\pi \Delta\mathbb{E}_t\left[(1-\rho_i)\left(\overline{\pi}_{t,k} - \pi^\star_t\right)\right]. \tag{15}$$

Under the assumption that bond market investors expect inflation to equal its target in the long run, we can use forward rates far in the future to proxy for $\{i^\star_t, \pi^\star_t\}$—that is, $i^{(k)}_t = i^\star_t$ and $IC^{(k)}_t = \pi^\star_t$ for k big enough—and substitute those values in equation (15) to test for time-variation in ψ_π. We use forward rates between years nineteen and twenty to construct proxies for the natural interest rate and the inflation target.

We reestimate equation (9) after replacing the left- and right-hand-side variables with their counterparts in equation (15). Column (4) of Table 2 reports the results. Allowing for time variation in $r^\star$ and $\pi^\star$ attenuates the estimated post-2020 change at short and medium horizons, but it does not eliminate it. The estimate of d is -0.33 for the [0–10]-year horizon, -0.57 for the [0–5]-year horizon, and -0.16 for the [6–10]-year horizon. All three estimates are statistically significant at the one-percent level. Hence, revisions to perceived long-run rates and inflation targets account for part of the baseline decline in the estimated inflation response, but the results are largely robust to these concerns.

Let us now turn to the second issue. To illustrate how the presence of the output gap can affect our empirical strategy, consider the following policy rule,

$$i_\tau = \rho_i i_{\tau-1} + (1-\rho_i)\left[i^\star + \psi_\pi\left(\pi_\tau - \pi^\star\right) + \psi_y \hat{y}_\tau\right] + \varepsilon_{m,\tau}, \tag{16}$$

where ψ_y measures the response of the policy rate to economic activity $\hat{y}_\tau$.

Applying the same steps discussed in Section 2.2, we obtain

$$\Delta\mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i \frac{k-1}{k}\bar{i}_{t,k-1}\right] = \psi_\pi \Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right] + \psi_y \Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\hat{y}}_{t,k}\right], \tag{17}$$

If we estimate equation (17) using only expected nominal interest rates and expected infla-

tion, as in our baseline analysis, the probability limit of the OLS estimator is

$$\widehat{\psi}_{\pi}^{\text{OLS}} \xrightarrow{p} \psi_{\pi} + \psi_{y} \frac{\text{Cov}\left(\Delta \mathbb{E}_t[\overline{\pi}_{t,k}], \Delta \mathbb{E}_t[\widehat{\tilde{y}}_{t,k}]\right)}{\text{Var}\left(\Delta \mathbb{E}_t[\overline{\pi}_{t,k}]\right)}. \tag{18}$$

Thus, omitting expected economic activity biases the estimated response to inflation as long as inflation and output are correlated. More importantly for our analysis, this bias can potentially vary across sub-samples if this correlation changes over time.

This possibility is particularly relevant for the post-2020 period. Supply shocks move inflation and output in opposite directions, while demand shocks move them in the same direction. A greater prevalence of supply shocks after 2020 could therefore reduce the covariance term in equation (18) and generate a decline in $\widehat{\psi}_{\pi}^{\text{OLS}}$ even if the underlying reaction function had not changed. The disruptions to global supply chains during the pandemic and the subsequent energy shocks make this a plausible alternative interpretation of our baseline results.

We address this concern using survey forecasts that allow us to include a direct measure of expected slack in the policy rule. Specifically, we combine data from the Survey of Professional Forecasters (SPF) and the Blue Chip Financial Forecaster survey. From the SPF, we obtain quarterly forecasts of the three-month Treasury bill rate, PCE inflation, and the unemployment rate at different forecasting horizons. Forecasts of the Treasury bill rate and unemployment are available up to three fiscal years ahead, while forecasts of PCE inflation are available up to two fiscal years ahead. The SPF also reports expectations of average PCE inflation over the next five and ten years, which we use to infer the average inflation rate expected between years six and ten and thus construct a proxy for the inflation target perceived by professional forecasters. Finally, the SPF provides forecasts of the natural rate of unemployment. From the Blue Chip survey, we obtain forecasts of the three-month Treasury bill rate six to ten years ahead, which we use as a proxy for the natural interest rate. Combining these data, we construct a quarterly dataset spanning 2009Q3–2022Q1.

For each survey date t and forecast horizon h, we use the survey forecasts to compute the short-term interest rate implied by a conventional Taylor rule. Let $i_{t,h}$, $\pi_{t,h}$, and $u_{t,h}$ denote, respectively, the short-term interest rate, inflation rate, and unemployment rate at horizon h. The Taylor-rule prescription is

$$\begin{aligned} i_{t,h}^{TR} = {} & \rho_i \mathbb{E}_t^{\text{survey}}\left[i_{t,h-1}\right] \\ & + (1-\rho_i)\left\{ i_t^{\star} + \psi_{\pi}\left(\mathbb{E}_t^{\text{survey}}[\pi_{t,h}] - \pi_t^{\star}\right) + \psi_{u}\left(\mathbb{E}_t^{\text{survey}}[u_{t,h}] - u_t^{\star}\right) \right\}, \end{aligned} \tag{19}$$

where $i_t^\star$ is the long-run nominal interest rate inferred from the Blue Chip forecasts, $\pi_t^\star$ is the inflation target proxied by the implied five-year, five-year-forward SPF inflation expectation, and $u_t^\star$ is the SPF forecast of the natural rate of unemployment. We set $\rho_i = 0.8$, as in our baseline analysis, and consider values of ψ_π between 1.5 and 3.0 and values of ψ_u between -1.5 and -0.5—broadly consistent with pre-pandemic estimates of this type of rule.[11]

We then compare the interest rate prescribed by equation (19) with the interest rate expected by professional forecasters. Specifically, we define the Taylor-rule residual as

$$\text{TR}_{t,h} \equiv i_{t,h}^{TR} - \mathbb{E}_t^{\text{survey}} \left[i_{t,h} \right]. \tag{20}$$

A positive value of $\text{TR}_{t,h}$ indicates that professional forecasters expected the Federal Reserve to set the short-term interest rate below the level prescribed by the historical Taylor rule, *conditional* on their own expectations of inflation and labor-market slack. We study whether the mean of this residual changes between the pre-pandemic sample, 2009Q3–2019Q4, and the post-2020 sample, 2020Q3–2022Q1.

Because SPF inflation forecasts extend only two fiscal years ahead, we conduct the exercise at the two-year horizon. Table 3 reports the difference between the average residual in the post-2020 and pre-pandemic subsamples for each combination of ψ_π and ψ_u. The numbers in parentheses are the p-values for a test of equality of the mean residual across the two subsamples.

Across all the parameterizations, the average residual is larger in the 2020–2022 subsample than in the pre-pandemic period. The increase ranges from 0.40 to 0.53 percentage points and is statistically significant at the 10 percent level in every specification. For example, when $\psi_\pi = 2$ and $\psi_u = -1$, the parameterization closest to the Taylor rule used in our quantitative analysis, the average residual increases by 0.45 percentage points, with a p-value of 0.04. This exercise confirms that professional forecasters expected the Fed to hold interest rates unusually far below historical norms *given* their own forecasts of inflation and unemployment—consistent with our interpretation of the results in Section 2.2.

Controlling for time-varying risk and liquidity premia. So far, we have assumed that daily changes in nominal bond yields and in inflation compensation are equivalent to forecast revisions about future nominal interest rates and future inflation. That is, we have assumed that risk and liquidity premia associated with nominal and inflation-protected se-

[11] For example, the unemployment-based specification in Table III of Clarida, Gali, and Gertler (2000) yields an inflation response of 2.01 and an unemployment-gap response of -0.56 for the Volcker–Greenspan period, after expressing their unemployment measure in our sign convention.

Table 3: Survey-based Taylor-rule residuals

$\psi_\pi \backslash \psi_u$	-0.5	-1.0	-1.5
1.5	0.40^{**} (0.03)	0.42^{**} (0.05)	0.45^{*} (0.08)
2.0	0.43^{**} (0.02)	0.45^{**} (0.04)	0.48^{*} (0.07)
2.5	0.46^{**} (0.02)	0.48^{**} (0.04)	0.51^{*} (0.06)
3.0	0.48^{**} (0.01)	0.51^{**} (0.03)	0.53^{*} (0.05)

Notes: Each entry reports the difference between the average Taylor-rule residual defined by equations (19) and (20) in 2020Q3–2022Q1 and its average in 2009Q3–2019Q4. The numbers in parentheses are p-values for a test of equality of the mean residual across the two subsamples. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

curities are constant over time. In what follows, we propose a way to relax this assumption, and document that our results still hold.

In order to understand how time variation in risk and liquidity premia affects our analysis, we can substitute equations (3) and (4) in equation (7), obtaining

$$\Delta \left[i_t^{(k)} - \rho_i \frac{k-1}{k} i_t^{(k-1)} \right] = \psi_\pi \Delta \left[(1-\rho_i) IC_t^{(k)} \right] + \varepsilon_t, \tag{21}$$

where ε_t is given by

$$\varepsilon_t = \Delta \left[\eta_{t,k} - \rho_i \frac{k-1}{k} \eta_{t,k-1} - (1-\rho_i)\psi_\pi \iota_{t,k} \right].$$

Similarly to what happens for the output gap, the presence of risk and liquidity premia in bond markets can bias the estimates of ψ_π, and time-variation in this bias can potentially account for the reduction in the measured sensitivity of nominal interest rates to inflation we have documented so far.

In what follows, we use methods developed in the literature to estimate movements in risk and liquidity premia, and use these estimates to back out from bond market data actual expectations of future nominal interest rates and inflation. We will then estimate equation (9) using these expectations measures.

In order to compute daily inflation expectations measures, we first obtain from the Survey of Professional Forecasters (SPF) the average expected inflation rate over the next five

and ten years at a quarterly frequency and interpret it to be a measure of the actual expectation of average inflation over that horizon, $\mathbb{E}_t[\overline{\pi}_{t,k}]$.

Most equilibrium asset pricing models imply that the risk and liquidity premia reflect the underlying factors that drive inflation and, therefore, also actual inflation expectations. That is, if inflation expectations are driven by a vector of factors X_t,

$$\mathbb{E}_t[\overline{\pi}_{t,k}] = f_{t,k}\left(X_t\right),$$

then the inflation compensation should also be a function of the same underlying factors, $IC_t^{(k)} = g_{t,k}\left(X_t\right)$.

Our approach to compute daily inflation expectations follows the insight of Aronovich and Meldrum (2021) and consists in approximating $f_{k,t}$ using local linear projections of survey expectations onto the observable inflation compensation measures and nominal yields. These regressions are estimated on a seven-year rolling sample in order to take into account the time-variation of f. We can then use the estimated parameters of this relation and our data on $IC_t^{(k)}$ and nominal bond yields to obtain *daily* measures of inflation expectations.[12] Appendix B.1 provides more details on this procedure and discusses the properties of the premium that we back out with this approach.

Unfortunately, the SPF does not ask similar questions for average expected nominal short rates over the time horizon we are interested in. So, in order to back out actual expectations about future nominal interest rates from our data, we subtract from nominal bond yields the estimates of nominal term premia from the Kim and Wright (2005) model, which are maintained at a daily frequency on the website of the Federal Reserve Board. We then use the resulting data to obtain a daily measure for $\mathbb{E}_t[\bar{i}_{t,k}]$.

Column (5) in Table 2 reports the estimates of d when using the risk and liquidity premia-adjusted expectation data. We continue to find a reduction in the sensitivity of expected future nominal interest rates to expected future inflation in the [0–5]-year horizon, with the coefficient being nearly identical to the one in the baseline specification.

2.4 Discussion

We conclude this section by discussing two issues. The first concerns how financial markets' perceptions of the policy rule evolved once the Federal Reserve began to raise interest rates

[12] The survey started to ask the question about the average expected inflation rate over the next five years only in 2005Q3. So, we estimate f starting from this date, but use the estimated coefficients and our data on the risk-neutral expectations to backcast what the actual inflation expectations would have been between 2000 and 2005Q3 using the first available set of regression coefficients.

in March 2022, and whether independent evidence supports interpreting our estimates as a shift in the perceived reaction function. The second relates to the underlying sources of the shift.

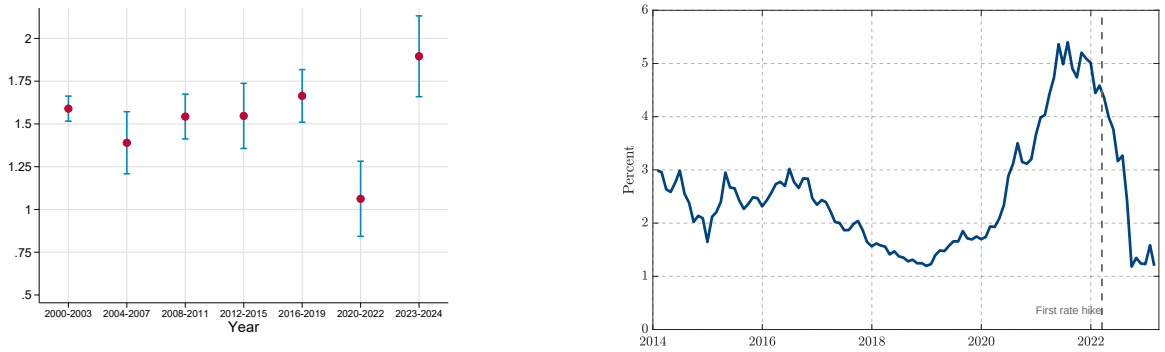
One may wonder whether the lift-off of interest rates in March 2022 affected investors' perceptions of the policy rule. To examine this question, we extend our sample through December 2024 and reestimate the benchmark specification allowing ψ_π to differ across the subperiods. As in our baseline analysis, we exclude monetary events from the estimation. This exercise allows us to study whether the perceived response to inflation remained low after 2022 or returned toward its historical level as the Federal Reserve tightened policy.

Panel (a) plots our previous results along with the estimates of ψ_π one obtains when estimating equation (7) for the 2023-2024 period. We can see that ψ_π increases sharply in the post-lift-off period, returning to values close to those observed in the pre-pandemic subsamples. Thus, the shift that we identify in the 2020-2022 period does not appear to be permanent: following the sequence of interest-rate increases that began in March 2022, financial markets again expected nominal interest rates to respond to inflation in a manner broadly consistent with the Federal Reserve's historical reaction function. These results confirm the findings of Bauer, Pflueger, and Sunderam (2024) and Kroner (2023) of an increase in the sensitivity of nominal interest rates to inflation after the lift-off of interest rates.

We can provide further evidence that these statistics indeed capture shifts in perceptions of the policy rule by studying the behavior of inflation uncertainty over the sample. A smaller value of ψ_π implies that a given inflationary disturbance is met with a smaller increase in real interest rates. Through the lens of a standard New Keynesian model, those shocks will then have larger effects on inflation. Hence, a decline in investors' perception of ψ_π should also be accompanied by an increase in their perceived volatility of inflation. Conversely, a stronger perceived response to inflation should make future inflation more stable. So, if our estimates capture changes in the perceived policy rule, we should observe a negative correlation between ψ_π and indicators of inflation volatility over the sample we are studying.

Panel (b) of Figure 3 plots the monthly option-implied volatility of inflation three years ahead.[13] Inflation volatility increased sharply during 2020–2022 and remained elevated before the first interest-rate increase in March 2022. It then declined substantially as the Federal Reserve tightened policy, eventually returning to levels below those observed be-

[13]The option-implied volatility of inflation is calculated based on quotes on inflation caps and floors. Mertens and Williams (2021) note that market trading of US inflation options had largely ceased by end-2016, but the options nevertheless continued to be quoted. Due to the illiquidity of the market, results should therefore be interpreted cautiously.



(a) Perceived response to inflation

(b) Option-implied inflation volatility

Figure 3: The perceived policy response and inflation uncertainty

Notes: Panel (a) reports point estimates of ψ_π and 95% confidence intervals for the indicated subsamples. The estimates are obtained from the benchmark specification. Panel (b) reports the monthly option-implied volatility of inflation three years ahead; see Appendix A for data definition and sources. The vertical dashed line marks the first increase in the federal funds target range in March 2022.

fore the pandemic. This is even more surprising since the beginning of 2022 was also marked by the Russian invasion of Ukraine, a major source of inflation uncertainty for the world economy. This timing closely mirrors the pattern in Panel (a): the recovery in the perceived response of nominal interest rates to inflation is accompanied by a marked decline in inflation uncertainty.

The second issue concerns the source of the perceived shift and its relevance for our counterfactual. Our methodology is designed to identify changes in financial markets' perceptions of the monetary policy reaction function, but it does not identify the underlying source of these changes. In the case of the United States, there are at least two plausible and related interpretations. One possibility is the adoption of the flexible average inflation targeting (FAIT) framework in August 2020, which may have led investors to expect greater tolerance for above-target inflation following a period in which inflation had been persistently below target. Another possibility is that investors inferred a change in the Federal Reserve's reaction function from the conduct and communication of policy during 2021. In particular, the fact that interest rates were kept near zero throughout 2021 despite inflation being well above target may have convinced investors about a more Dovish stance of the Fed toward inflation.[14] These interpretations are not mutually exclusive: the new framework may have influenced how investors interpreted the subsequent actions of the Federal Reserve.

The international evidence suggests that the shift cannot be attributed exclusively to the

[14]See Bocola, Dovis, Jørgensen, and Kirpalani (2025) for a model in which households and firms infer the central bank's "type" from its interest-rate decisions, so that policy actions affect expectations of future inflation and nominal interest rates.

formal adoption of FAIT. In Appendix B.2 we repeat our analysis for the euro area and the United Kingdom, and obtain a similar decline in the sensitivity of nominal interest rates to inflation in the 2020-2022 period. Neither central bank introduced a FAIT framework in this period, although both maintained an accommodative policy stance while inflation was rising above target. This evidence points more broadly to the conduct of monetary policy during the post-pandemic inflation episode, while not ruling out that the new framework played an important role in shaping investors' perceptions in the United States. More generally, the underlying reasons for the accommodative stance may have differed across countries, and our empirical analysis is not designed to distinguish among them.

Importantly, identifying the exact source of the perceived shift is not necessary for the counterfactual studied in our paper. Our empirical analysis measures how investors revised the expected path of nominal interest rates in response to inflation news, as well as how persistent they expected these changes to be. Together with the corresponding revisions in inflation expectations, these estimates discipline the change in the expected path of real interest rates induced by the perceived policy rule. The quantitative analysis of Section 3 will ask how inflation and output would have evolved if, conditional on the same shocks hitting the economy, monetary policy had instead followed its historical reaction function. The key input for this counterfactual experiment is the difference in the expected path of real interest rates generated by the two policy rules, not the underlying sources (adoption of a framework, prior policy commitment, etc.) leading to these differences.[15]

3 Quantitative analysis

In the previous section, we have presented evidence consistent with a perceived shift toward a more accommodative monetary policy stance during the pandemic. In this section, we use a standard New Keynesian model to quantify the macroeconomic implications of this shift. Section 3.1 presents the model, while Section 3.2 discusses the estimation of its parameters. Section 3.3 uses the estimated model to measure the drivers of inflation, output and nominal interest rates during the recovery phase after the pandemic. The model explains the dynamics of these variables via a combination of negative supply shocks, increasing demand, and a more accommodative monetary policy stance. In our main counterfactual we find that the behavior of the central bank accounts for a large share of the output/inflation dynamics: if the monetary authority had followed the historical reaction function, inflation would have been about 6% at the end of the event in 2022:Q1. Section

[15]See McKay and Wolf (2023) and Caravello, McKay, and Wolf (2024) for methods to evaluate counterfactual changes in monetary policy rules in dynamic stochastic general equilibrium models.

3.4 reports an extensive sensitivity analysis of our results: depending on alternative modeling assumptions, the shift to a more accommodative monetary policy regime accounts for between 26% and 63% of inflation's excess over the 2% target at the observed sample peak.

3.1 The model

Time is discrete and indexed by $t = 0, 1, \ldots$. The economy is populated by a continuum of identical and infinitely lived households, final good producers, intermediate good producers, and a monetary authority.

Preferences and technology. Households have preferences over consumption, c_t, and hours worked, l_t, given by

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \tilde{\theta}_{0,t} U(c_t - \alpha C_{t-1}, l_t) \right] \tag{22}$$

where C_{t-1} is the aggregate consumption in period $t-1$, $\alpha \in (0,1)$ is a parameter that measures the strength of external habits, U has standard properties, β is the discount factor, and $\tilde{\theta}_{0,t}$ is a preference shock, our "demand shock".[16]

The final good is produced by combining differentiated intermediate goods according to the CES technology

$$Y_t = \left(\int_0^1 y_{i,t}^{\frac{1}{\mu_t}} di \right)^{\mu_t} \tag{23}$$

where $\mu_t > 1$ is related to the constant elasticity of substitution across varieties, ϵ_t, by the following relation: $\mu_t = \epsilon_t / (\epsilon_t - 1)$. Time-variation in μ_t will generate shifts in the Phillips curve. So, we will equivalently refer to μ_t as the "supply shock".

The intermediate goods are produced using a linear technology,

$$y_{i,t} = n_{i,t} \tag{24}$$

where $n_{i,t}$ denotes the labor utilized in the production of good i. Feasibility requires that $\int n_{i,t} di = L_t$.

[16] As shown in Berger, Bocola, and Dovis (2023), for example, fiscal transfers to households with a high marginal propensity to consume—such as those observed in the US during the pandemic—are isomorphic to a discount factor shock in the baseline three-equation New Keynesian model.

Households. The stand-in household chooses consumption, leisure, and bond holdings to maximize (22) given the aggregate $\{C_t\}$ subject to its budget constraints

$$P_t c_t + b_t \leq W_t l_t + (1 + i_{t-1}) b_{t-1} + D_t$$

where P_t is the price level, W_t is the nominal wage rate, i_t is the nominal interest rate, and D_t denotes profits from the monopolistically competitive firms owned by the stand-in household.

Final good producers. The final good is produced by competitive firms who choose inputs $y_{i,t}$ to maximize

$$P_t Y_t - \int_0^1 P_{i,t} y_{i,t} di$$

where Y_t is given by (23) and $P_{i,t}$ is the price of intermediate good i. From this problem, we can derive the demand function for variety i

$$y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{\frac{\mu_t}{1-\mu_t}} Y_t \tag{25}$$

and the price index is given by

$$P_t = \left(\int_0^1 P_{i,t}^{\frac{1}{1-\mu_t}} di \right)^{1-\mu_t}. \tag{26}$$

Intermediate good producers. Each intermediate good is supplied by a monopolistically competitive firm that uses labor to operate the linear technology (24). The firm can reset its price in each period with a probability $1 - \zeta$. With complementary probability, the firm cannot adjust its price, and the old price is adjusted by past inflation, $P_{i,t} = (1 + \pi_{t-1})^{\gamma} P_{i,t-1}$, where $\gamma \in [0, 1]$. Intermediate goods firms are owned by the stand-in household and discount profits using the household's stochastic discount factor. A firm that has the opportunity to reset its price sets P_t^* to solve

$$\max_{P_t^*, y_{t+k}, n_{t+k}} \mathbb{E}_t \left[\sum_{k=0}^{\infty} Q_{t,t+k} \zeta^k \left(P_t^* \Pi_{t,k}^{\gamma} y_{t+k} - W_{t+k} n_{t+k} \right) \right] \tag{27}$$

subject to (24) and (25), where $Q_{t,t+k}$ is the nominal stochastic discount factor,

$$Q_{t,t+k} = \beta^k \frac{\tilde{\theta}_{t+k} U_{c,t+k} / P_{t+k}}{\tilde{\theta}_t U_{c,t} / P_t},$$

and $\Pi_{t,k}^{\gamma}$ is the price indexation rule. If $k = 0$ then $\Pi_{t,k} = 1$, while for $k \geq 1$ it is the cumulated realized inflation between t and $t+k-1$, $\Pi_{t,k} = P_{t+k-1}/P_{t-1}$.

Monetary policy. The monetary authority follows a Taylor rule with Markov switching regimes. There are two possible regimes $\xi \in \{H, D\}$. In particular, we have

$$1 + i_t = (1 + i_{t-1})^{\rho_i} \left[(1 + i^\star) \left(\frac{1 + \pi_t}{1 + \pi^\star} \right)^{\psi_\pi(\xi_t)} \left(\frac{y_t}{y^\star} \right)^{\psi_y} \right]^{1-\rho_i} \exp(\sigma_m \varepsilon_{m,t}) \tag{28}$$

where $i^\star$ is the steady-state interest rate, $\pi^\star$ is the inflation target, $y^\star$ is the steady-state output under flexible prices, and $\varepsilon_{m,t}$ is the monetary policy shock. The two regimes differ in the responsiveness of nominal rates to inflation, $\psi_\pi(\xi_t)$.

Equilibrium. Given an initial price distribution for intermediate good firms, the lagged nominal interest rate, aggregate consumption, and inflation, an equilibrium is a set of household allocations $\{C_t, L_t, B_{t+1}\}$, prices $\{P_t, P_t^*, W_t\}$, and policy $\{i_t\}$ such that i) the households' allocation solves the stand-in household's problem, ii) the reset price for the intermediate good firm solves (27), iii) the final good price satisfies (26), iv) the nominal interest rate satisfies the Taylor rule (28), v) labor and goods markets clear and $B_t = 0$ as nominal bonds are in zero-net supply.

The equilibrium dynamics can be summarized by an Euler equation

$$U_{ct} = \beta(1 + i_t)\mathbb{E}_t \left[\theta_{t+1} \frac{U_{c,t+1}}{1 + \pi_{t+1}} \right] \tag{29}$$

where U_{ct} is a shorthand for $U_c(C_t - \alpha C_{t-1}, L_t)$, $\theta_{t+1} = \tilde{\theta}_{t+1}/\tilde{\theta}_t$, a relation between the normalized reset price $p_t^* = P_t^*/P_t$ and inflation,

$$1 = (1 - \zeta)(p_t^*)^{1/(1-\mu_t)} + \zeta \left(\frac{1 + \pi_t}{(1 + \pi_{t-1})^\gamma} \right)^{1/(\mu_t - 1)} \int \left(\frac{P_{i,t-1}}{P_{t-1}} \right)^{1/(1-\mu_t)} di, \tag{30}$$

the optimality condition for the normalized reset price,

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} \zeta^k \beta^k \frac{\tilde{\theta}_{t+k} U_{c,t+k}}{\tilde{\theta}_t U_{c,t}} \frac{Y_{t+k}}{\mu_{t+k} - 1} \left(p_{t,t+k}^* \right)^{-\frac{\mu_{t+k}}{\mu_{t+k}-1}} \left(p_{t,t+k}^* - \mu_{t+k} w_{t+k} \right) \right] = 0 \tag{31}$$

where $w_{t+k} = -U_{L,t+k}/U_{C,t+k}$ is the real wage, $p_{t,t+k}^* = p_t^* \frac{\prod_{j=0}^{k-1}(1+\pi_{t+j})^\gamma}{\prod_{j=1}^{k}(1+\pi_{t+j})}$ is the relative price in period $t+k$ for a firm that set its price in t and does not have an opportunity to revise it

before $t+k$, and the resource constraint

$$C_t = Y_t = \frac{L_t}{\Delta_t} \tag{32}$$

where the cost of price dispersion $\Delta_t = \int \left(\frac{P_{i,t}}{P_t}\right)^{-\mu_t/(\mu_t-1)} di$ satisfies

$$\Delta_t = (1-\zeta)(p_t^*)^{-\mu_t/(\mu_t-1)} + \zeta \left(\frac{1+\pi_t}{(1+\pi_{t-1})^{\gamma}}\right)^{\mu_t/(\mu_t-1)} \int \left(\frac{P_{i,t-1}}{P_{t-1}}\right)^{-\frac{\mu_t}{\mu_t-1}} di \tag{33}$$

Thus, the equilibrium $\{C_t, L_t, Y_t, \pi_t, i_t, p_t^*, \Delta_t\}$ satisfies (28), (29), (30), (31), (32), and (33) together with the evolution of the price distribution, given the stochastic processes for the shocks in the economy and the initial conditions for i_{-1}, C_{-1}, π_{-1}, and an initial condition for the price distribution.

3.2 Estimation

Each period in the model corresponds to a quarter. We assume that households have a utility function

$$U\left(c_t - \alpha C_{t-1}, l_t\right) = \frac{\left(c_t - \alpha C_{t-1}\right)^{1-\sigma}}{1-\sigma} - \chi \frac{l_t^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}.$$

The exogenous state variables are $(\xi_t, \varepsilon_{m,t}, \mu_t, \theta_t)$. We assume that the policy regime ξ_t follows a two-state Markov chain with transition matrix $\mathbf{P}$ with representative element P_{ij} for row i column j. We assume that the demand and the supply shocks follow independent AR(1) processes. That is, letting $\hat{\theta}_t = \log(\theta_t)$ and $\hat{\mu}_t = \log(\mu_t) - \log(\bar{\mu})$,

$$\begin{aligned}
\hat{\theta}_t &= \rho_\theta \hat{\theta}_{t-1} + \sigma_\theta \varepsilon_{\theta,t} \\
\hat{\mu}_t &= \rho_\mu \hat{\mu}_{t-1} + \sigma_\mu \varepsilon_{\mu,t}
\end{aligned}$$

where $\varepsilon_{\theta,t}$ and $\varepsilon_{\mu,t}$ are standard normal random variables.

It is convenient to define κ to be the slope of the first-order approximation of the Phillips

curve around the deterministic steady state with full price indexation,[17]

$$\kappa = \frac{(1-\zeta)(1-\beta\zeta)}{\zeta(1+\beta)}\left(\frac{1}{\nu}+\frac{\sigma}{1-\alpha}\right).$$

We will estimate κ instead of ζ with the understanding that, given β, the coefficient κ is a strictly increasing function of the probability of price changes $1-\zeta$. The structural parameters are those governing preferences, technology and price rigidities, $[\sigma, \beta, \alpha, \nu, \chi, \kappa, \gamma, \overline{\mu}]$, policy, $[\pi^\star, \rho_i, \psi_y, \psi_\pi(H), \psi_\pi(D)]$, and the evolution of the shocks, $[\mathbf{P}, \sigma_m, \rho_\theta, \sigma_\theta, \rho_\mu, \sigma_\mu]$.

We fix a subset of the model parameters at conventional values. We set the intertemporal elasticity of substitution $1/\sigma$ and the Frisch elasticity of labor supply ν to 1, the average markup to 20%, and normalize the preference parameter χ so that consumption and output are equal to 1 in the deterministic steady state. We follow Christiano, Eichenbaum, and Evans (2005) and set the price-indexation parameter γ to 1.00, while we set the external habit parameter α to 0.75, in between the estimate of Smets and Wouters (2007) and the calibrated value in Bodenstein, Erceg, and Guerrieri (2011).[18] We set the inflation target to 2% annually, $\pi^\star = .005$, and $\beta = .9952$, so that the model roughly matches the average inflation and nominal interest rates in our sample. We interpret the H regime as encompassing the conduct of monetary policy in the US in the post-Volcker era, and, consistent with this interpretation, we set P_{HH} to 0.9937, to obtain an approximate duration of the H regime of 40 years.

For the remaining parameters, we proceed in two steps. In the first step, we discipline $\left[\kappa, \rho_i, \psi_\pi\left(H\right), \psi_y\right]$ along with the stochastic process for the shocks $\{\hat{\mu}_t, \hat{\theta}_t, \varepsilon_{m,t}\}$ by estimating a model with a single regime on the 1984:Q1-2019:Q4 time period, interpreting it as a period in which the H regime operated. The observables are the de-trended logarithm of employment, nominal interest rates, and CPI inflation.[19] We approximate the model's policy functions using a first-order perturbation around the deterministic steady state of the single-regime model and estimate the structural parameters with Bayesian methods (An

[17] With full indexation to lagged inflation, the linearized Phillips curve is

$$\hat{\pi}_t = \frac{1}{1+\beta}\hat{\pi}_{t-1} + \frac{\beta}{1+\beta}\mathbb{E}_t\hat{\pi}_{t+1} + \kappa\hat{y}_t + \frac{\kappa}{\frac{1}{\nu}+\frac{\sigma}{1-\alpha}}\left(\hat{\mu}_t - \frac{\sigma\alpha}{1-\alpha}\hat{y}_{t-1}\right).$$

[18] With full price indexation, $\gamma = 1$, the symmetric deterministic steady state has a normalized reset price equal to one. Thus, in a deterministic steady state, there is no price dispersion, $\Delta_t = 1$, and the effects of price dispersion on aggregates are second order.

[19] See Appendix A for data definitions and sources. In our model, there is an equivalence between output and hours worked. We use employment data in the analysis rather than direct measures of output, motivated by evidence on the usefulness of labor-market indicators for forecasting inflation. For example, Barnichon and Shapiro (2022) find that measures of labor-market tightness based on vacancies and worker flows outperform the output gap.

Table 4: Model parameters

Panel A: **Fixed parameters**		
	Value	Notes
σ	1.000	Intertemporal elasticity of substitution of 1
ν	1.000	Frisch elasticity of 1
χ	3.333	Normalize output to 1 in steady state
$\overline{\mu}$	1.200	20% markup in steady state
α	0.750	External habits of 0.75
γ	1.000	Full price indexation
$\pi^\star$	0.005	Inflation target of 2%
β	0.995	Annualized real interest rate of 2% in steady state
P_{HH}	0.994	40 years expected duration of H regime

Panel B: **Estimation of single-regime model**					
Parameter	Posterior mean	90% interval	Prior distribution	Prior mean	Prior st. dev.
κ	0.044	[0.020,0.067]	Normal	0.100	0.050
$\psi_\pi(H)$	2.048	[1.591,2.482]	Normal	1.500	0.500
ψ_y	0.234	[0.117,0.350]	Normal	0.500	0.500
ρ_i	0.919	[0.899,0.940]	Beta	0.500	0.289
ρ_θ	0.919	[0.887,0.950]	Beta	0.500	0.289
ρ_μ	0.034	[0.000,0.077]	Beta	0.500	0.289
$\sigma_\theta \times 100$	0.312	[0.233,0.389]	InvGamma	1.000	Inf
$\sigma_\mu \times 100$	41.938	[20.684,62.037]	InvGamma	1.000	Inf
$\sigma_m \times 100$	0.145	[0.130,0.161]	InvGamma	1.000	Inf

Panel C: **Parameters of Dovish rule**		
	Value	Notes
$\psi_\pi(D)$	0.967	Point estimates of d, 0–5 yrs. **Data: -0.856, Model: -0.856**
P_{DD}	0.950	Point estimates of d, 6–10 yrs. **Data: -0.145, Model: -0.145**

Note: The table reports the numerical values of the parameters that we use for the counterfactual exercise. A subset of parameters, reported in Panel A, is fixed to conventional values from the literature. The remaining parameters are estimated using a two-step procedure detailed in Appendix C.1. Panel B reports the posterior distribution of the parameters estimated in the first step by fitting the single-regime model to historical data on employment, inflation and nominal interest rates. Panel C reports the values of the parameters obtained in the second step.

and Schorfheide, 2007). We use the single-regime model in this step because it is easier to solve and estimate and still offers an accurate approximation of the policy functions of the model conditional on the H regime.[20] The resulting estimates are reported in panel B of

[20]This is the case in our application because—at any given point in time—the likelihood of transitioning from the H regime to the D regime is very close to zero.

Table 4, and they are broadly consistent with previous studies.

In the second step, we estimate the remaining parameters of the Dovish regime—$\psi_\pi(D)$ and P_{DD}—via indirect inference in order to match the evidence presented in Section 2. Specifically, we choose these parameters so that our model replicates the point estimates of the coefficient d in equation (9), which in our baseline specification is -0.86 for expectations over the [0–5] year horizon and -0.14 for expectations over the [6–10] year horizon.

We compute the model-implied counterparts of these two coefficients using the population moments of the first-order solution. For each candidate pair $\{\psi_\pi(D), P_{DD}\}$, we hold the parameters estimated in the first step at their posterior means and solve the two-regime model. We use this solution to compute the conditional expectations of inflation and the nominal interest rate over the [0–5] and [6–10] year horizons. For each horizon h, we construct

$$y^{\text{mod}}_{t,h} = \Delta \left[\frac{1}{20} \sum_{j \in \mathcal{J}_h} \mathbb{E}_t \left[i_{t+j} - \rho_i i_{t+j-1} \right] \right],$$

$$x^{\text{mod}}_{t,h} = (1-\rho_i)\Delta \left[\frac{1}{20} \sum_{j \in \mathcal{J}_h} \mathbb{E}_t \left[\pi_{t+j} \right] \right].$$

Here $\mathcal{J}_{[0\text{–}5]} = \{1, \ldots, 20\}$ and $\mathcal{J}_{[6\text{–}10]} = \{21, \ldots, 40\}$ index quarters ahead, ρ_i is the quarterly interest-rate smoothing parameter, and $\Delta X_t = X_t - X_{t-1}$ denotes a quarterly first difference. The forecast horizons are measured relative to each date, so these differences compare rolling averages of expected future interest rates and inflation. The model counterpart of our empirical specification is the population regression

$$y^{\text{mod}}_{t,h} = \alpha_h + \beta_h x^{\text{mod}}_{t,h} + d^{\text{mod}}_h \left(x^{\text{mod}}_{t,h} \times \mathbb{1}\{\xi_t = D\} \right) + u_{t,h}, \qquad h \in \{[0\text{–}5], [6\text{–}10]\}. \tag{34}$$

The coefficient β_h measures the model-implied sensitivity of expected nominal rates to expected inflation in the H regime, while $\beta_h + d^{\text{mod}}_h$ measures the corresponding sensitivity in the D regime. We compute these coefficients directly from the stationary variances and covariances implied by the model, as detailed in Appendix C.1. Motivated by our empirical restriction to non-monetary-event days, we set monetary policy innovations to zero when computing these moments, while allowing demand and supply shocks and the policy regime to vary according to their assumed processes. Finally, we choose $\psi_\pi(D)$ and P_{DD} to minimize the unweighted sum of squared differences between $\{d^{\text{mod}}_{[0\text{–}5]}, d^{\text{mod}}_{[6\text{–}10]}\}$ and their empirical targets. The first target is especially informative about the difference in the policy response across regimes, while the second helps discipline how quickly that difference fades at longer horizons and hence the perceived persistence of the D regime.

Panel C of Table 4 reports the numerical values of the parameters and an indicator

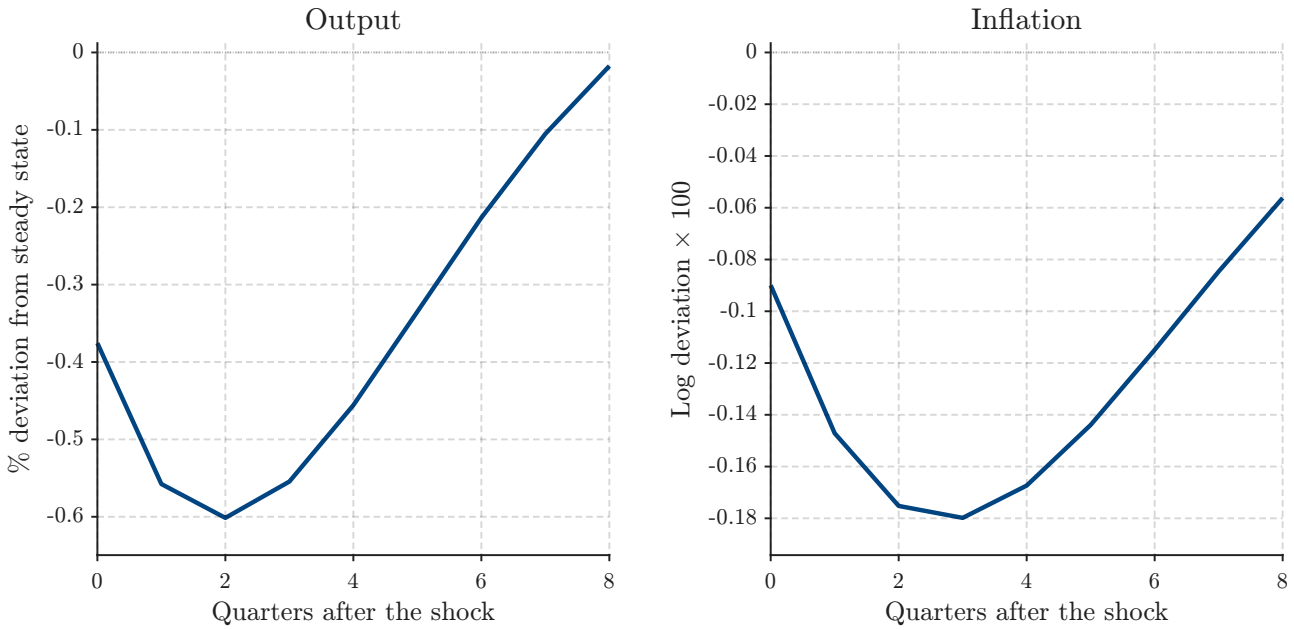


Figure 4: Responses to a 100-basis-point monetary policy shock

Notes: The figure reports impulse responses of output and inflation to a contractionary monetary policy shock that raises the annualized nominal interest rate by 100 basis points on impact. The responses are evaluated at the posterior mean of the estimated parameters, conditional on the economy being in the historical monetary policy regime, $\xi_t = H$. Output is reported in percent deviations from steady state; inflation is reported as 100 times the log deviation of gross quarterly inflation from steady state. The horizontal axis reports quarters after the shock.

of model fit. The model can replicate the large deviations observed in the sensitivity of expected future nominal interest rates to expected future inflation across the two regimes, with this gap narrowing at longer horizons. To achieve that, the model needs a substantially smaller value of ψ_π in the D regime, 0.97 versus 2.05, and a conditional probability of remaining in the D regime of about 95%.

Response to a monetary shock. In our counterfactual analysis of Section 3.3, we will study how output and inflation in the US would have behaved under a different monetary policy stance. Because monetary policy affects these variables by changing the path of real interest rates, it is important that our model delivers empirically plausible macroeconomic effects of changes in interest rates: otherwise, even a correctly measured change in the policy rule could be mapped into misleading macroeconomic effects. McKay and Wolf (2023) and Caravello, McKay, and Wolf (2024) make this point precise by showing that, for a broad class of dynamic equilibrium models, the causal effects of contemporaneous and anticipated shocks to the prevailing policy rule are fundamental inputs for constructing counterfactuals under alternative policy rules.

To explore whether our model has reasonable predictions for the effects of interest rates

on output and inflation, we report in Figure 4 the response of these two variables to a contractionary monetary policy shock, normalized to increase the annualized nominal interest rate on impact by 100 basis points. The impulse response is constructed conditional on the economy being in the H regime—that is, under the reaction function prevailing in the pre-2020 period. We can see from the figure that output falls on impact by about 0.38%, reaches a trough of approximately 0.60% after two quarters, and then gradually returns toward its steady-state level. Quarterly inflation responds less on impact: it initially declines by about 0.09 percentage points, with the response building gradually to a trough of approximately -0.18 percentage points after three quarters before dissipating. Thus, both responses are hump-shaped, and the peak effect on inflation occurs later than the peak effect on output. External habits in consumption and price indexation are critical for generating this delayed propagation.

The magnitude and shape of these responses are broadly consistent with the evidence summarized by Ramey (2016). Among the contractionary estimates summarized in Table 1 of that review, shocks normalized to a peak increase of 100 basis points in the federal funds rate generate peak declines in economic activity ranging from about 0.6% to 5%, generally with a delayed trough and a subsequent gradual recovery. The response of output in our model lies at the lower end of this range. The relatively more delayed response of inflation is also consistent with Ramey's conclusion that price responses materialize with more lags relative to output responses. Quantitatively, the price level in our model falls by 1.2% at its trough, well within the range reported in Ramey (2016).

3.3 Monetary policy and the rise in inflation

We now combine our model with data to assess the role of monetary policy in the run-up of inflation observed during the recovery from the pandemic. We proceed in two steps. In the first step, we apply the particle filter to our model and estimate the paths of the structural shocks—$\hat{\theta}_t$, $\hat{\mu}_t$, and $\varepsilon_{m,t}$—as well as the monetary regime in place during the 2020:Q4–2022:Q1 period. In the second step, we use the model to construct counterfactual trajectories for inflation, the output gap, and nominal interest rates under the H monetary regime. We use these counterfactuals to isolate the role of the shift in the monetary policy rule in accounting for the dynamics observed during the event. See Appendix C.2 for a description of these two steps.

The first three panels in the top row of Figure 5 show that the model reproduces the sharp recovery in output, the rise in inflation, and the persistently low nominal interest rate observed during the event. The bottom panels report the filtered shocks and monetary

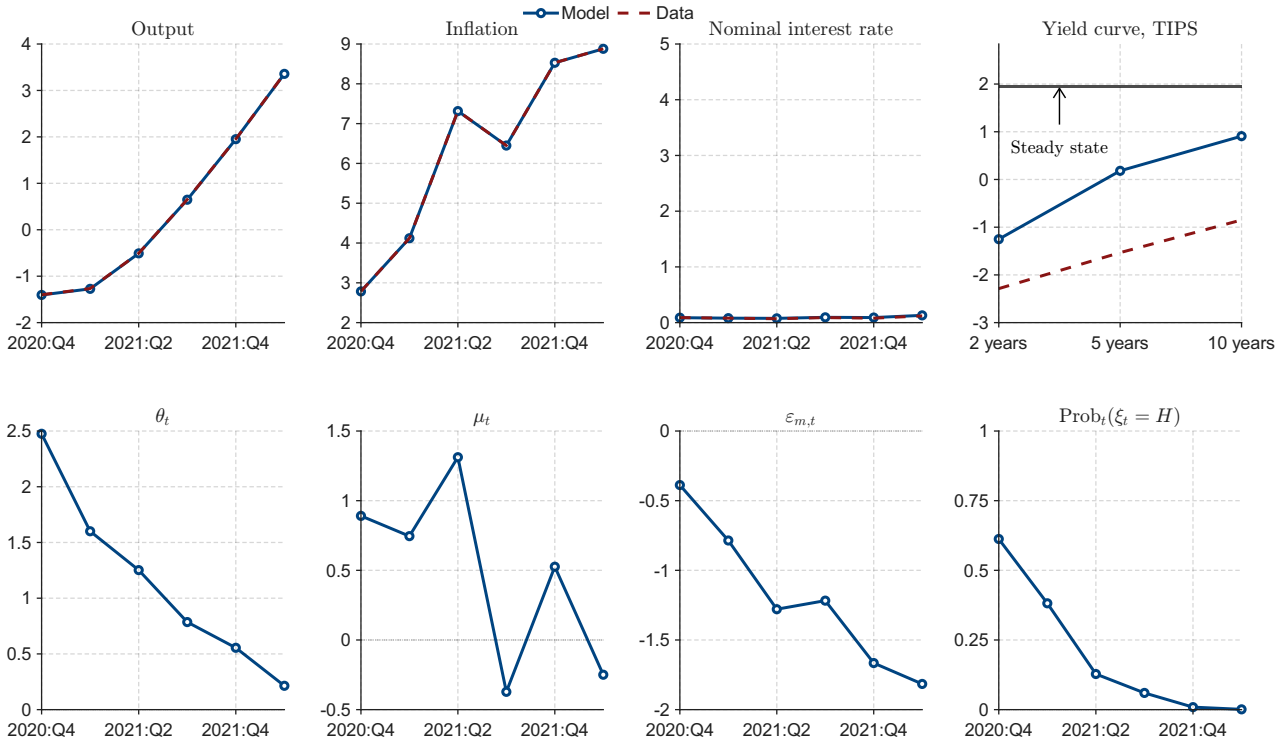


Figure 5: Event study, 2020:Q4–2022:Q1

Notes: In the first three panels of the top row, the dashed lines report the data used in the filtering exercise and the circled lines report the posterior mean of their model counterparts. The top-right panel compares yields on inflation-protected bonds with maturities of 2, 5, and 10 years, averaged over the event, with the corresponding model-implied real yields. These yields are not targeted by the filtering exercise. The bottom panels report the posterior mean of the filtered structural shocks, while the bottom-right panel reports the probability of being in the H regime. Inflation and interest rates are reported in annualized percentage points, and output is reported in percentage-point deviations from trend. The demand and markup shocks are reported in units of their unconditional standard deviations, and monetary innovations are reported in units of their standard deviation.

policy regime that rationalize these dynamics. The model requires a gradual recovery in household demand—represented by a declining path of $\hat{\theta}_t$ toward its steady-state level—and adverse supply shocks during the first half of 2021, as reflected in the path of the markup shock. The former contributes to the recovery in output, while the latter helps the model account for the rise in inflation.

The filter assigns increasing posterior probability to the D regime throughout the event. By 2021:Q2, output was around trend and inflation was five percentage points above the target: the historical rule would have prescribed a substantially higher nominal interest rate relative to the D regime in these circumstances. Since interest rates were kept at zero, the filter views this as evidence in favour of the D regime, with a posterior probability of approximately 87%. The filtered monetary innovations are also negative throughout the event, implying additional downward deviations of the policy rate from the systematic

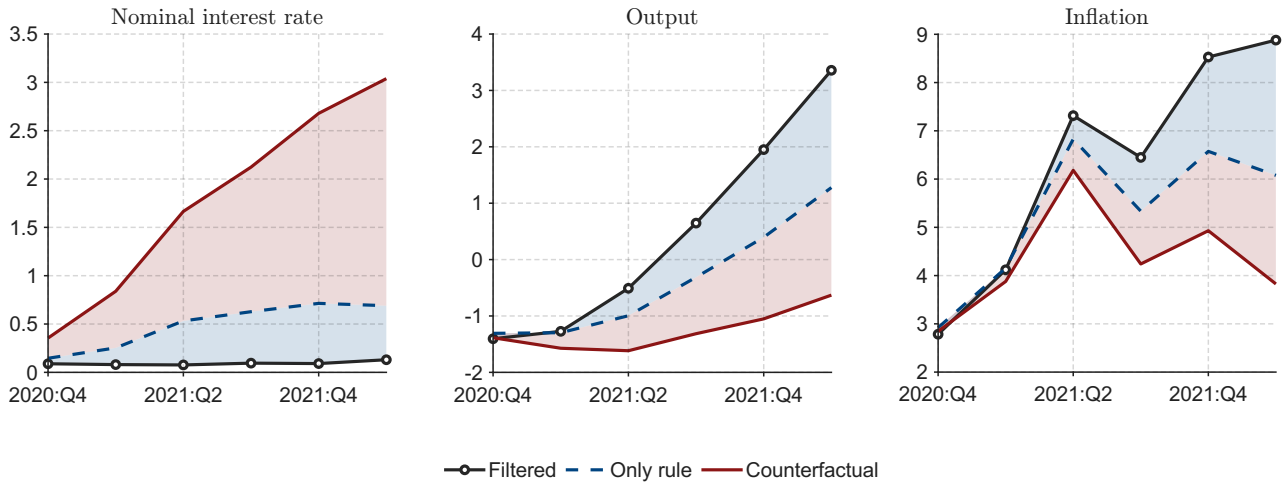


Figure 6: Counterfactual paths under the historical monetary policy rule

Notes: The circled lines report the filtered paths of output, inflation, and the nominal interest rate during the event. The dashed lines report a counterfactual that sets $\xi_t = H$ throughout the event while keeping all filtered structural shocks, including monetary policy innovations, unchanged. The solid lines additionally set monetary policy innovations to zero. Inflation and nominal interest rates are reported in annualized percentage points, and output is reported in percentage-point deviations from trend.

component of the D rule.

The top-right panel of Figure 5 reports yields on inflation-protected bonds with maturities of 2, 5, and 10 years, averaged over the event, together with their model-implied counterparts. These yields are not among the observables used to choose the filtered shocks, so comparing model and data provides an independent check regarding the model's ability to fit the term-structure of interest rates during this episode. In the data, real yields were exceptionally low by historical standards across all three maturities. The model captures the central feature of the evidence: the combination of inflationary shocks and the switch to the D regime generates real interest rates far below their 2% steady-state level across the maturity structure. Quantitatively, the model overpredicts real yields on average by 1.5 percentage points across the maturity structure. These are quantitatively meaningful discrepancies, but they are to be expected, since our model abstracts from factors that may have contributed to keeping interest rates low during the pandemic—such as heightened precautionary saving by households.

With the realized shock processes in hand, we can now use the model to perform a counterfactual analysis. We first consider the counterfactual reported by the solid lines in Figure 6. Specifically, we input the estimated shocks $\{\hat{\theta}_t, \hat{\mu}_t\}$ in the model, but impose the historical policy regime, $\xi_t = H$, and set $\varepsilon_{m,t} = 0$ in every period. This experiment asks how the economy would have evolved if the Federal Reserve had followed its historical rule without any additional deviations from it. The historical rule prescribes an immediate and

sustained increase in the nominal interest rate. As a result, output remains below trend for the entire event, while inflation is at 3.83% by 2022:Q1. In the data, inflation instead reaches 8.88% in 2022:Q1, its highest value within the event window.

The dashed lines implement a second counterfactual, aimed at isolating purely the macroeconomic effects of the shift in the systematic component of the monetary policy reaction function. We again impose $\xi_t = H$, but now keep monetary policy innovations at their filtered values along with the demand and supply shocks. The only difference between this counterfactual and the filtered history is therefore the systematic monetary policy rule. Accordingly, the gap between the circled and dashed lines isolates the effect of the shift from the H to the D regime, while the gap between the dashed and solid lines isolates the additional effect of setting the negative monetary policy innovations to zero.

The comparison shows that the shift in the rule has somewhat small effects on current interest rates—which increase by only 0.56 percentage points by the end of the event—but it is very consequential for output and inflation. By 2022:Q1, changing only the rule lowers output by roughly 2.08 percentage points and inflation by about 2.80 percentage points relative to the filtered history. These represent, respectively, 52.2 and 55.5% of the overall effects induced by monetary policy.

To understand why inflation and output are so sensitive to the shift in the policy rule, consider a simplified version of the model with no external habits, no price indexation, $\alpha = \gamma = 0$, and zero steady-state inflation. Iterating forward the linearized Euler equation (29) and the Phillips curve implied by (30)-(31) gives

$$\hat{y}_t = -\frac{1}{\sigma}\sum_{j=0}^{\infty}\mathbb{E}_t[\hat{r}_{t+j}] - \frac{1}{\sigma}\sum_{j=0}^{\infty}\mathbb{E}_t[\hat{\theta}_{t+1+j}], \tag{35}$$

$$\hat{\pi}_t = \kappa_0\sum_{j=0}^{\infty}\beta^j\mathbb{E}_t[\hat{y}_{t+j}] + \frac{\kappa_0}{(1/\nu+\sigma)}\sum_{j=0}^{\infty}\beta^j\mathbb{E}_t[\hat{\mu}_{t+j}] \tag{36}$$

where κ_0 is the slope of the Phillips curve in this version of the model, $\hat{r}_{t+j} = \hat{i}_{t+j} - \mathbb{E}_{t+j}[\hat{\pi}_{t+j+1}]$ is the real interest rate at time $t+j$. Substituting equation (35) into equation (36), and using the fact that the structural shocks are identical across the two paths, we can write the difference between inflation under the D and H regimes as

$$\begin{aligned}\hat{\pi}_t^D - \hat{\pi}_t^{\mathrm{H}} = & -\frac{\kappa_0}{\sigma}\Big\{\left(\hat{r}_t^D - \hat{r}_t^H\right) + (1+\beta)\left[\mathbb{E}_t(\hat{r}_{t+1}|\xi_t = D) - \mathbb{E}_t(\hat{r}_{t+1}|\xi_t = H)\right] \\ & + (1+\beta+\beta^2)\left[\mathbb{E}_t(\hat{r}_{t+2}|\xi_t = D) - \mathbb{E}_t(\hat{r}_{t+2}|\xi_t = H)\right] + \ldots\Big\},\end{aligned} \tag{37}$$

where $\mathbb{E}_t[.|\xi_t = x]$ is the conditional expectation at time t given that $\xi_t = x$.

Table 5: Sensitivity of the policy counterfactual

	(1) Baseline	(2) Forward guidance	(3) Conservative parametrization	(4) Movements in ρ_i	(5) Lower shock persistence
Panel A: Inflation reduction					
Rule change	2.80	2.06	1.76	4.34	2.73
Monetary shocks	2.25	1.66	2.63	1.56	2.54
Total	5.05	3.72	4.39	5.90	5.27
Panel B: Output decline					
Rule change	2.08	1.08	1.32	2.97	1.95
Monetary shocks	1.91	1.06	2.25	1.32	2.13
Total	3.99	2.13	3.57	4.29	4.08

Note: The table reports the results of the counterfactual of Section 3.3 in different versions of the model. Inflation reduction (Output decline) is filtered inflation (output) minus its value in the counterfactual in 2022:Q1. Both are measured in percentage points. "Rule change" reports the results of the counterfactual in which we set $\xi_t = H$ throughout the sample, while keeping all other structural shocks at their filtered values. "Monetary shocks" reports the additional effect of setting $\varepsilon_{m,t} = 0$ conditional on the historical rule. "Total" is the sum of these two effects. Column (1) reports these figures for the baseline. Column (2) reports the results in the model with cognitive discounting. Column (3) repeats the counterfactual under a more conservative calibration of $[\psi_\pi(D), P_{DD}]$. Column (4) allows the monetary policy regimes to differ in ρ_i rather than in ψ_π. Column (5) sets the persistence of demand shocks to $\rho_\theta = 0.8$, holding all other parameters at their baseline values.

Equation (37) shows that the regime change affects current inflation through the entire expected path of real interest rates. A difference in the current real rate receives weight κ_0/σ. A difference one period ahead receives weight $(1+\beta)\kappa_0/\sigma$, and a difference two periods ahead receives weight $(1+\beta+\beta^2)\kappa_0/\sigma$. These weights increase with the horizon and converge to $\kappa_0/[\sigma(1-\beta)]$. A shift in the policy rule affects not only current interest rates, but also the expected path of future interest rates, explaining why inflation and output are so responsive to it in our model.

3.4 Sensitivity analysis

We conclude this section with a sensitivity analysis of our results. We consider four exercises that modify, respectively, the propagation of future real interest rates in the model, the empirical targets used to estimate the parameters of the D regime, the specification of the monetary policy rule and the persistence of the structural shocks. Table 5 summarizes the implications of these exercises for our policy counterfactual.

Forward guidance puzzle. In the previous subsection, we showed that the shift in the policy rule has large effects on inflation for two reasons. First, a change in the policy rule affects the entire term structure of real interest rates, not only short-term rates. Second, as equation (37) makes clear, inflation in the baseline New Keynesian model is particularly sensitive to movements in real interest rates at longer horizons.

This sensitivity reflects two properties of the model. First, the output gap responds one for one to changes in future real interest rates—a feature commonly referred to as the "forward guidance puzzle" (Del Negro, Giannoni, Patterson et al., 2012). Second, because the New Keynesian Phillips curve is forward-looking, changes in current *and* expected future output gaps affect inflation today. Both of these properties have recently come under scrutiny (McKay, Nakamura, and Steinsson, 2016; Angeletos and Lian, 2018; Gabaix, 2020).

To assess the sensitivity of our results to these features of the model, we follow Gabaix (2020) and introduce cognitive discounting in the decisions of households and firms, summarized by the parameter $\overline{m}$. Cognitive discounting attenuates the weight on future marginal utility in the model's Euler equation by the factor $M = \overline{m}$, and the weight on expected future deviations from the price-indexation benchmark in the firms' pricing equation by the factor

$$M^f = \overline{m}\left[\zeta + (1-\zeta)\frac{1-\beta\zeta}{1-\beta\zeta\overline{m}}\right],$$

where ζ is the Calvo price-survival probability. The baseline rational-expectations model corresponds to $\overline{m} = 1$, which implies $M = M^f = 1$. We calibrate the cognitive parameter to $\overline{m} = 0.8$, as in Gabaix (2020). Given the other structural parameters, this calibration implies $M = 0.80$ and $M^f = 0.74$. Thus, agents place less weight on future outcomes, reducing both the response of current output to real interest rates far in the future and the response of current inflation to future output gaps.

We then recalibrate $\psi_\pi(D)$ and P_{DD} using the same indirect inference procedure and the same empirical targets as in our baseline specification. All remaining parameters are held at their benchmark values. The resulting values are $\psi_\pi(D) = 1.32$ and $P_{DD} = 0.97$. The model-implied changes in interest-rate sensitivity are $d_{0\text{–}5} = -0.40$ and $d_{6\text{–}10} = -0.07$, compared with empirical targets of -0.86 and -0.14, respectively. Thus, this specification reproduces about half the magnitude of the decline in sensitivity at each horizon. After recalibrating the model, we repeat the filtering exercise and the full policy counterfactual.

Column (2) of Table 5 reports the results of this experiment. As expected, cognitive discounting dampens the impact of shifts in the rule on the macroeconomy: imposing the historical rule lowers inflation by 2.06 percentage points and output by 1.08 percentage points, compared with 2.80 and 2.08 percentage points in the baseline model. Nevertheless,

the estimated monetary-policy contribution remains sizable, as the shift in the reaction function still accounts for 30% of inflation's excess over the 2% target by the end of the event.

Conservative parametrization. In our analysis we have selected $[\psi_\pi(D), P_{DD}]$ so that the model reproduces, using its population moments, the change in the sensitivity of nominal interest rates to inflation at the [0–5]- and [6–10]-year horizons reported in column (1) of Table 2, our baseline empirical specification.

We now re-estimate these parameters by targeting the point estimates of d reported in column (4) of Table 2. This specification allows the long-run nominal interest rate, $i_t^\star$, and the inflation target, $\pi_t^\star$, to vary over time. It provides a more conservative parametrization because the coefficient d is substantially closer to zero at short and medium horizons. Targeting these estimates therefore leads to a smaller difference between the H and the D regimes and dampens the macroeconomic effects of the policy shift.[21]

Column (3) of Table 5 reports the results of our main counterfactual. Under the conservative parametrization, a shift to the H regime would have led to a reduction in inflation by 1.76 percentage points and a decline in output by 1.32 percentage points. Thus, allowing the long-run nominal interest rate and the inflation target to vary over time attenuates the quantitative effects of monetary policy, but the effects remain sizable: the pure shift of the policy rule is still responsible for 26% of the inflation excess over the 2% target in 2022:Q1.

Movements in ρ_i rather than ψ_π. In our model, the two regimes differ in the responsiveness of the nominal rates to current inflation—the parameter ψ_π. However, other changes in the reaction function could also generate the decline in the sensitivity of nominal interest rates to inflation that we observe in the data. In particular, a more inertial policy rule could also produce a weaker response of nominal rates at short and medium horizons even if ψ_π remained unchanged.

To examine whether our results are robust to this alternative interpretation, we consider a specification of the Taylor rule in which the regimes differ in the interest-rate smoothing parameter, ρ_i, rather than in the inflation coefficient, ψ_π. Specifically, the monetary policy rule is

$$1 + i_t = (1 + i_{t-1})^{\rho_i(\xi_t)} \times \left\{ (1 + i^\star) \left[\frac{1 + \pi_t}{1 + \pi^\star} \right]^{\psi_\pi} \left(\frac{y_t}{y^\star} \right)^{\psi_y} \right\}^{1-\rho_i(\xi_t)} \times \exp\{\sigma_m \varepsilon_{m,t}\}. \quad (38)$$

[21] The recalibration gives $\psi_\pi(D) = 1.35$ and $P_{DD} = 0.96$, matching exactly the empirical targets.

Thus, both regimes have the same long-run inflation-feedback coefficient, ψ_π, but differ in interest-rate smoothing.

We fix $\rho_i(H)$ at its posterior mean of 0.92, estimated using pre-pandemic data, and keep the remaining parameters of the H regime at their benchmark values. We then estimate $\rho_i(D)$ and P_{DD} using the same indirect-inference procedure as in the baseline model.[22] Finally, we repeat the counterfactual exercise under this alternative specification.

Column (4) of Table 5 reports the results. Under this alternative interpretation, the switch to the H regime would have reduced inflation by 4.34 percentage points, and output by 2.97 percentage points, which are larger macroeconomic effects than what we obtain in the baseline. Thus, the conclusion that the change in the systematic conduct of monetary policy had sizable effects on output and inflation does not depend on interpreting the decline in interest-rate sensitivity as a change in ψ_π rather than as a change in ρ_i.

Shock persistence. In our baseline analysis, we use pre-2020 data to estimate a subset of the structural parameters, including the persistence of the demand and supply shocks. The implicit assumption is that these parameters did not experience a structural break during the pandemic. This assumption may be particularly restrictive for the persistence of the shock processes, as the pandemic recession was initially expected to be shorter-lived than a typical economic downturn.

To assess the importance of this assumption, we repeat the filtering and counterfactual exercises after setting demand-shock persistence to $\rho_\theta = 0.8$, compared with its posterior mean of 0.919. We keep all other parameters, including $\psi_\pi(D)$ and P_{DD}, at their baseline values.

Column (5) of Table 5 reports the results of this counterfactual. With lower demand-shock persistence, the shift to the H regime would have reduced inflation by 2.73 percentage points and output by 1.95 percentage points. These numbers are smaller than those in the baseline, but still imply sizable macroeconomic effects of the shift in the policy rule.

4 Conclusion

This paper introduces a novel method to measure shifts in the systematic conduct of monetary policy using bond market data. Our method exploits the high-frequency nature of the data to isolate market expectations about the reaction of nominal interest rates to future movements in inflation, thereby providing a real-time assessment of financial markets'

[22] The recalibration gives $\rho_i(D) = 0.96$ and $P_{DD} = 0.91$.

views on the monetary stance on inflation. Applying this methodology to U.S. data, we find that financial markets maintained remarkably stable expectations about the Federal Reserve's behavior over the 2000-2020 period, but significantly revised them in 2020.

We have used these estimates to quantify the size and duration of these shifts in the monetary policy rule and assess their macroeconomic effects. Through the lens of a baseline New Keynesian model, we find that the shifts in the policy rule accounted for 41% of the inflation excess over the 2% target observed at its peak in 2022:Q1. This figure varies between 26% and 63% in alternative specifications of the model or under more conservative calibrations. So, our overall conclusion is that private sector expectations of a more accommodative monetary policy stance going forward were a key driving force of the inflation dynamics observed in the US during this event.

Going forward, it would be interesting to apply our framework to analyze how different countries adjusted their monetary policies in response to the pandemic. Many other central banks in advanced economies did not initially respond to rising inflationary pressures in 2021, which may have influenced private sector views on their resolve to control inflation. In contrast, central banks in several emerging economies reacted more swiftly and experienced milder increases in inflation relative to their historical experience. An in-depth analysis of these differing responses could provide valuable insights into how reputation and credibility considerations shape monetary policy in the face of large shocks, such as those observed during the pandemic. We pursue this analysis in our companion paper Bocola et al. (2025).

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Appendix

A Data

Nominal Treasury Yields, Percent, Not Seasonally Adjusted, daily values. Maturities between 1 and 10 years, accessed at https://www.federalreserve.gov/data/nominal-yield-curve.htm.

Inflation Compensation, Percent, Not Seasonally Adjusted, daily values. Maturities between 2 and 10 years, accessed at https://www.federalreserve.gov/data/tips-yield-curve-and-inflation-compensation.htm.

Inflation expectations, Percent, Not Seasonally Adjusted, Quarterly values. The Survey of Professional Forecasters asks for inflation expectations one and two years ahead. It also asks for average expected inflation over the next five and ten years. Data can be accessed here: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters

Short-rate Expectations. Percent, Not Seasonally Adjusted, daily values. The expectations measure the average expected short-rates over a given horizon, based on Kim and Wright (2005), with horizons of 1 through 10 years available from https://www.federalreserve.gov/data/three-factor-nominal-term-structure-model.htm.

T-Bill rate expectations, Percent, Not Seasonally Adjusted, Quarterly values. The Survey of Professional Forecasters asks for 3-month T-Bill rate expectations one, two, and three years ahead. Data can be accessed here: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters

Long-horizon T-Bill rate expectations, Percent, Not Seasonally Adjusted, Semi-annual values. The Blue Chip Financial Forecasts survey asks for 3-month T-Bill rate expectations in the long-run, about 6-to-11-years ahead. We assume these expectations have not changed relative to the previous survey in quarters where no information is available. Data source is Wolters Kluwer Legal and Regulatory Solutions U.S. Blue Chip Financial Forecasts.

Unemployment rate expectations, Percent, Not Seasonally Adjusted, Quarterly values. The Survey of Professional Forecasters asks for unemployment-rate expectations one, two, and three years ahead. It also asks for the expected natural rate of unemployment. Data can be accessed here: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters

Option-implied probability of a binding ZLB, Percent, Not Seasonally Adjusted, Daily values. Horizons between 1 and 10 years ahead. Data are based on Mertens and Williams (2021) and can be accessed here: https://www.frbsf.org/research-and-insights/data-and-indicators/zero-lower-bound-probabilities-at-different-time-horizons/

Option-implied inflation volatility, Percent, Not Seasonally Adjusted, daily values. The option-implied distributions are based on inflation caps and floors. Data source is Bloomberg.

Euro area Overnight Index Swap (OIS) rates, Percent, Not Seasonally Adjusted, daily values. Maturities between 1 and 10 years. The swap contracts are tied to EONIA until August 2021 and €STR thereafter. Data source is Bloomberg.

Euro area Inflation-linked Swap (ILS) rates, Percent, Not Seasonally Adjusted, daily values. Maturities between 1 and 10 years. The swap contracts are tied to euro area HICP excluding tobacco. Data source is Bloomberg.

UK nominal sovereign yields, Percent, Not Seasonally Adjusted, daily values. Maturities between 1 and 10 years. The data can be accessed here: https://www.bankofengland.co.uk/statistics/yield-curves

UK inflation compensation, Percent, Not Seasonally Adjusted, daily values. Maturities between 2 and 10 years. The data can be accessed here: https://www.bankofengland.co.uk/statistics/yield-curves

Employment Level [CE16OV], Thousands of Persons, Seasonally Adjusted. We de-trend this series by estimating the following regression with ordinary least squares

$$\log(y_t) = a_0 + a_1 t + a_2 t^2 + \varepsilon_{y,t},$$

where $\log(y_t)$ is the logarithm of the employment level and t is calendar time. The residual of this regression, $\hat{\varepsilon}_{y,t}$, is the de-trended employment level series that we use in the application. Data source is FRED.

Federal Funds Effective Rate [FEDFUNDS], Percent, Not Seasonally Adjusted, quarterly averages of monthly figures. Data source is FRED.

Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL], Index 1982-1984=100, Seasonally Adjusted. Quarterly data are constructed by averaging monthly values. We take the percent change from the previous quarter. Data source is FRED.

B Sensitivity analysis

B.1 Actual expectations of inflation and interest rates

In this section we provide some details on how we estimate actual expectations of inflation and nominal interest rates, used in the sensitivity analysis of Section 2.3.

Inflation expectations. The Survey of Professional Forecasters (SPF) asks respondents about their expectation of average inflation over the next five and ten years. Such survey-based measures of inflation expectations should, in contrast to those obtained from asset pricing, be free of inflation risk premiums. We can therefore use the survey responses as a measure of actual, P-measure, expectations. Unfortunately, these surveys are conducted at a quarterly frequency, while our approach relies on high frequency variation in the data. We follow the insight of Aronovich and Meldrum (2021) and use the observed data from the SPF to estimate the functional relation between actual and risk-neutral expectations of future inflation—discussed in Section 2.3—and subsequently use the daily data on inflation compensation to obtain a high-frequency measure of actual expectations. Specifically, we estimate the following relation

$$SPF_t^{(n)} = \beta_{n,0} + \beta_{n,1} IC_t^{(2y)} + \beta_{n,2} IC_t^{(5y)} + \beta_{n,3} IC_t^{(10y)} + \beta_{n,4} i_t^{(2y)} + u_t^{(n)}, \tag{A.1}$$

for $n = 5y, 10y$.

The SPF provides historical response deadlines and we line up the survey responses with the average nominal yield and inflation compensation data from the business week prior to the deadline. The regressions are estimated on a 7 year rolling sample to take into account any structural instability or potential non-linearity. Using the resulting regression coefficients and the daily inflation compensation data, we can calculate fitted values on a daily basis.[23]

Figure A-1 plots the resulting regression fit in the two top panels. The fitted values track the broad movements in the survey-implied expectations quite well, and the implied R^2 is around 70 and 80 percent for the 5-year and 10-year horizons, respectively. Those values are only quarterly, when the survey is conducted. But the right-hand side variables are available at daily frequency, so we can use equation (A.1) to interpolate the surveys to daily values. The lower-left panel of Figure A-1 plots the implied daily values for the

[23]The question about the average expected inflation rate over the next five years was only included in 2005Q3, but our approach allows us to backcast what the financial data suggest that those expectations would have been between 2000 and 2005Q3 using the first available set of regression coefficients.

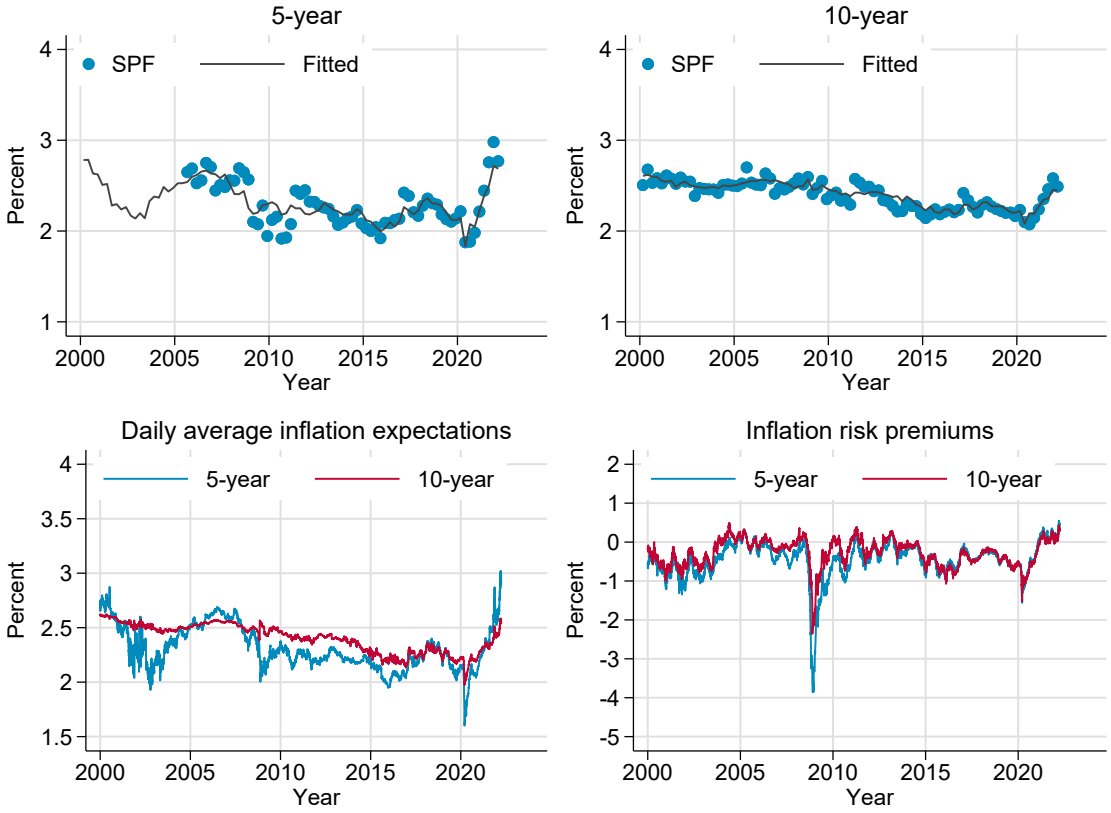

Figure A-1: Risk premia correction for inflation

5-year and 10-year average inflation expectations. The resulting daily series have some intuitive properties: the 5-year average expectations are more volatile than the 10-year average expectations and they both increased following the pandemic when realised inflation spiked.

Given the implied actual expectations, we can back out the implied inflation risk premium as $IRP_t^{(n)} = IC_t^{(n)} - \hat{SPF}_t^{(n)}$. In theory, the inflation risk premium should be positive if inflation increases in bad times (when the stochastic discount factor is high) and negative otherwise. Through the lens of a standard New Keynesian model, this implies that the inflation risk premium is positive if the economy is dominated by supply type shocks that move growth and inflation in opposite directions. That is because a negative supply shock increases inflation and devalues the real value of the fixed nominal payments of nominal bonds at the exact time where growth is low and the payments are valued the most. On the other hand, inflation risk premiums should be negative if the economy is dominated by demand type shocks. The lower-right panel of Figure A-1 plots our implied inflation risk premium estimates. The fact that this estimate of the inflation risk premium is mostly neg-

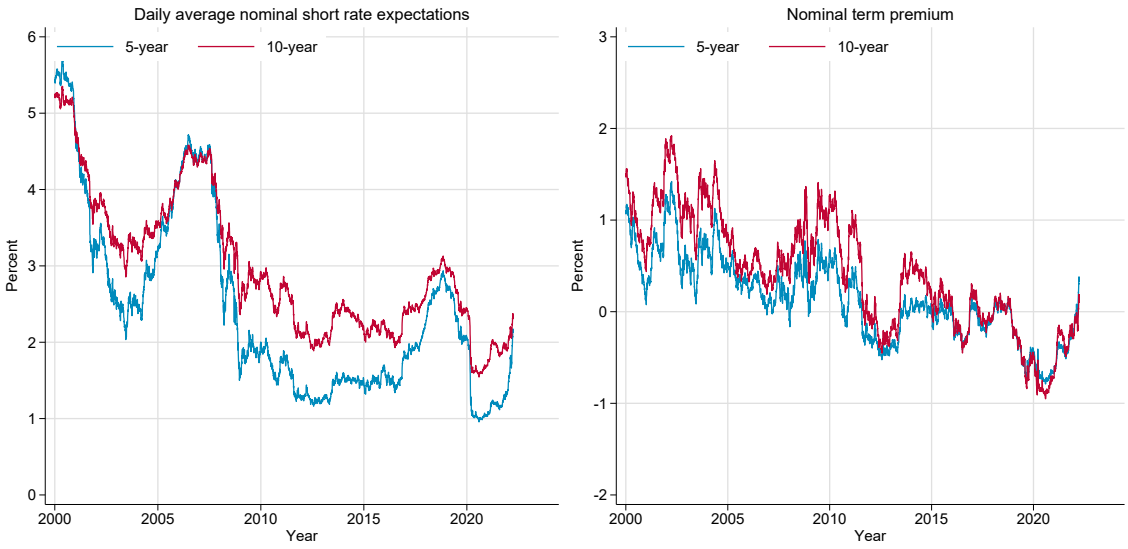

Figure A-2: Risk premia correction for nominal interest rates

ative over the sample indicates that the economy has been dominated by demand shocks over this period. This is consistent with Campbell, Pflueger, and Viceira (2020) and Song (2017), who argue that the stock-bond correlation changed sign around year 2000 as a result of demand type shocks becoming dominant relative to supply type shocks. In addition, we can see that the inflation risk premium increases sharply in the post pandemic recovery, turning positive in 2021-2022—lending support to the views that this period was characterized by large supply shocks.

Expectations of nominal interest rates. Unfortunately, the SPF does not ask similar questions for short-term nominal interest rates at these horizons. In order to obtain a measure of the actual expectations of future nominal interest rates, we use the model of Kim and Wright (2005) to estimate the nominal term premium. This is a standard affine term structure model and it is maintained by staff at the Federal Reserve Board, who make the estimates available at daily frequency on the Federal Reserve Board website. The left panel of Figure A-2 plots these estimates of daily values for the 5-year and 10-year average nominal short rate expectations, while the right panel of the figure plots the estimates of 5-year and 10-year nominal term premiums.

B.2 Additional sensitivity

In our baseline specification, we fixed $\rho_i = 0.8$ at an annual frequency. To verify that this choice is not critical, Table A-1 reports results for $\rho_i = 0.7$ and $\rho_i = 0.9$. The table also

Table A-1: Additional sensitivity

	(1) Baseline	(2) $\rho_i = 0.7$	(3) $\rho_i = 0.9$	(4) Euro area	(5) U.K.
d, [0–10] years	-0.48***	-0.45***	-0.59***	-0.61***	-0.91***
	(0.11)	(0.10)	(0.16)	(0.12)	(0.12)
d, [0–5] years	-0.86***	-0.71***	-1.29***	-0.48***	-1.19***
	(0.16)	(0.12)	(0.25)	(0.13)	(0.12)
d, [6–10] years	-0.14*	-0.15*	-0.11	-0.31**	-0.22*
	(0.09)	(0.08)	(0.13)	(0.15)	(0.11)
N. obs.	4639	4639	4639	3715	5198

Note: The table reports additional sensitivity analysis for the estimates of d in equation (9). Column (1) restates the U.S. baseline with $\rho_i = 0.8$; columns (2) and (3) instead set ρ_i to 0.7 and 0.9. Columns (4) and (5) apply the baseline specification to euro-area and U.K. data. Heteroskedasticity-robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

repeats the baseline specification using euro-area and U.K. bond data. The estimated post-2020 decline is robust to the alternative values of ρ_i and is also present in both international samples.

C Quantitative Analysis

In this Appendix we discuss details of the estimation of the New Keynesian model and of the main counterfactual reported in Section 3 of the paper.

C.1 Estimation of the New Keynesian model

We denote the state vector with $\mathbf{s}_t = (s_t, \hat{i}_{t-1}, \hat{y}_{t-1}, \pi_{t-1}) = (\xi_t, \varepsilon_{m,t}, \mu_t, \theta_t, \hat{i}_{t-1}, \hat{y}_{t-1}, \pi_{t-1})$ where Θ is the vector collecting all the structural parameters of the model. The structural parameters are those governing preferences and technology, $[\sigma, \alpha, \beta, \nu, \chi, \overline{\mu}, \gamma, \kappa]$, those governing policy, $[\pi^\star, \rho_i, \psi_y, \psi_\pi(H), \psi_\pi(D)]$ and those governing the evolution of the shocks, $[\mathbf{P}, \sigma_m, \rho_\theta, \sigma_\theta, \rho_\mu, \sigma_\mu]$. We consider the perturbation approach of Foerster, Rubio-Ramírez, Waggoner, and Zha (2016) to obtain a numerical solution of the two-regime New Keynesian model. This approach leads to the state space representation for control variables y_t

and state variables $\mathbf{s}_t$ given by:

$$\begin{aligned} y_t &= T_1(\xi_t;\Theta)\cdot \mathbf{s}_t \\ s_t &= T_2(\xi_t;\Theta)\cdot \mathbf{s}_{t-1} + R(\xi_t;\Theta)\cdot \varepsilon_t \end{aligned} \tag{A.2}$$

where $T_1(\cdot)$, $T_2(\cdot)$, and $R(\cdot)$ are perturbation matrices and ε_t collects the structural shocks, $\left[\varepsilon_{m,t}, \varepsilon_{\mu,t}, \varepsilon_{\theta,t}\right]$. Note that the perturbation matrices depend on the regime ξ_t, which itself follows a two-state Markov process with transition matrix $\mathbf{P}$.

As described in the main text, we fix a subset of model parameters, $[\sigma, \alpha, \beta, \nu, \chi, \overline{\mu}, \gamma]$ to conventional values, and fix $P_{H,D} = 0.0063$. The remaining parameters are estimated in two steps. In the first step, we estimate the model with just one monetary policy regime (the H regime) on the 1984:Q1-2019:Q4 sample.[24] This allows us to obtain estimates of the parameters governing the shock processes, the historical monetary policy rule and the degree of nominal rigidities. In the second step, we calibrate the parameters governing the monetary policy rule of the D regime—$\psi_\pi(D)$ and $P_{D,D}$—by fitting the high frequency evidence in Section 2 of the paper. We now give some more details on each of these steps.

Step 1. We approximate the policy functions using a first-order perturbation around the deterministic steady state and evaluate the likelihood function by applying the Kalman filter. Panel B of Table 4 reports the prior distribution for the model parameters and statistics for the posterior distribution. Draws from the posterior distribution are generated using the random walk Metropolis Hastings algorithm described in An and Schorfheide (2007). The proposal distribution is a multivariate normal, with variance-covariance matrix given by $c\Sigma$, where Σ is the negative of the inverse Hessian of the log-posterior evaluated at the posterior mode and c is a constant that we set to obtain roughly a 30% acceptance rate in each Markov chain. We generate two Markov chains of 500,000 draws each and discard the first half of the draws.

Step 2. In the second step we choose the remaining parameters, $\psi_\pi(D)$ and P_{DD}, so that the full model replicates the high-frequency evidence in Section 2. For that purpose, we fix the parameters estimated in step 1 at their posterior means and, for each candidate pair $\{\psi_\pi(D), P_{DD}\}$, solve the two-regime model using the perturbation approach of Foerster et al. (2016). We restrict attention to determinate solutions with stable first and second moments.

[24] The approach of estimating the single regime model is justified because its numerical solution is numerically very close to that of the two-regime model once we condition on $\xi_t = H$, due to the fact that the probability of shifting from the H to the D regime is close to zero.

The model-implied counterparts of the empirical coefficients are computed using the variables $x_{t,h}^{\text{mod}}$ and $y_{t,h}^{\text{mod}}$ defined in Section 3.2. These variables are quarterly changes in rolling expectations over the [0–5] and [6–10] year horizons, adjusted for interest-rate smoothing. For each horizon h and current regime $\xi \in \{H, D\}$, we compute the population regression slope

$$\beta_h(\xi) = \frac{\text{Cov}\left(x_{t,h}^{\text{mod}}, y_{t,h}^{\text{mod}} \mid \xi_t = \xi\right)}{\text{Var}\left(x_{t,h}^{\text{mod}} \mid \xi_t = \xi\right)}.$$

The first-order model implies zero conditional means for these changes, so the coefficients in equation (34) satisfy $\beta_h = \beta_h(H)$ and

$$d_h^{\text{mod}} = \beta_h(D) - \beta_h(H).$$

We obtain the required variances and covariances directly from the model solution. Specifically, we solve for the stationary covariance matrices conditional on each regime using the transition probabilities and the matrices governing the first-order dynamics. We then use these matrices to compute the covariances of first differences, accounting for transitions between regimes. Monetary policy innovations are set to zero in this calculation, while demand and supply innovations retain their estimated variances. Computing the population moments directly avoids simulation error in the evaluation of the model-implied coefficients.

Finally, we choose $\psi_\pi(D)$ and P_{DD} to minimize

$$\sum_{h \in \{[0\text{–}5],[6\text{–}10]\}} \left(d_h^{\text{mod}} - \widehat{d}_h\right)^2,$$

where $\widehat{d}_h$ is the empirical target at horizon h. The results are reported in Panel C of Table 4.

C.2 Counterfactual

We now detail the counterfactual exercise of Section 3.3. We first explain how we use the particle filter to obtain an estimate of the structural shocks. Next, we describe how we generate the counterfactual trajectories for output, inflation and nominal interest rates.

Denote by $y^T = [y_1, \ldots, y_T]$ the vector collecting observations on employment, inflation and nominal interest rates and by $p(s_t|y^t)$ the conditional distribution of the state vector at date t given observations up to period t. We set the structural parameters in step 1 at their

posterior mean, we numerically solve the model, and we apply the fully adapted particle filter to the regime-switching state space system in (A.2) to estimate the density of the state vector for each t.[25] The approximation is done via a set of pairs of particles and weights $\{s_t^i, \tilde{w}_t^i\}_{i=1}^N$ that satisfy:

$$\frac{1}{N}\sum_{i=1}^{N} f(s_t^i)\tilde{w}_t^i \rightarrow^{a.s.} \mathbb{E}[f(s_t)|y^t]$$

where each particle s_t^i contains the monetary regime, the structural shocks, and the interest rate, output and inflation needed to propagate the model, and $\tilde{w}_t^i$ is its weight. The algorithm consists of 3 steps.

Step 0: Initialization. Set $t = 1$ and initialize $\{s_0^i, \tilde{w}_0^i = 1\}_{i=1}^N$ with equal weights.

Step 1: Prediction. For each particle $i = 1, \ldots, N$ and regime $\xi \in \{H, D\}$, compute $q_t^i(\xi) = P_{\xi_{t-1}^i, \xi}\, p(y_t|s_{t-1}^i, \xi_t = \xi)$. The predictive density is Gaussian conditional on the previous state and the current regime.

Step 2: Resampling. Draw an ancestor a_t^i for each new particle, assigning ancestor j a probability proportional to $\tilde{w}_{t-1}^j \sum_\xi q_t^j(\xi)$. Conditional on this ancestor, draw ξ_t^i with probabilities proportional to $q_t^{a_t^i}(\xi)$.

Step 3: Filtering. Conditional on $s_{t-1}^{a_t^i}$, ξ_t^i and y_t, draw the structural innovations from their Gaussian conditional distribution and propagate the model to obtain s_t^i. Set $\tilde{w}_t^i = 1$. If $t < T$, set $t = t + 1$ and go to Step 1. If not, stop.

We set $N = 50000$. We apply the particle filter to our data for the 2020:Q4-2022:Q1 period and obtain an estimate for the probability density of the latent states. Figure 5 in the main text reports the time series for the observables and the average for the latent states, computed using $\{s_t^i, \tilde{w}_t^i\}_{i=1}^N$. For the lower-persistence exercise in column (5) of Table 5, we compute the filtering distribution exactly as a Gaussian mixture over the possible regime histories.

Once we have estimated the latent states, we can compute the counterfactual trajectories. Specifically, we feed the model with the realization of the markup shocks, monetary shocks and discount factor shocks estimated using the historical data, but set $\xi_t = H$ for the whole sample. This gives us the counterfactual path for output, inflation and nominal interest rates under the scenario in which the monetary authority kept operating using the

[25] In order to run the particle filter, we add iid Gaussian measurement errors to each variable in y_t. The variance of these measurement errors is set to 0.05% of the variance of the series in the 1984:Q1–2019:Q4 sample.

historical rule during the recovery from the pandemic. The results of this counterfactual are reported in Figure 6 in the main text.