Bond Market Views of the Fed*

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October 2024

Abstract

This paper uses high frequency data to detect shifts in financial markets' perception of the Federal Reserve 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—has 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 half of the observed increase in inflation.

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

*First draft: February 2024. The views and opinions in this paper are those of the authors and do not necessarily reflect those of the European Central Bank or its staff. We thank Davide De Bortoli, Luca Fornaro, Jordi Gali, Rohan Kekre, Juanpa Nicolini, Jón Steinsson, and seminar participants at Stanford, Duke, University of Pennsylvania, SED, BSE Summer Forum, University of Maryland, the Board of Governors, the Federal Reserve Banks of Minneapolis, Philadelphia, Saint Louis, and San Francisco for very useful comments. Tomas Tapak and Javier Tasso provided excellent research assistance. All errors are our own. Luigi Bocola thanks the National Science Foundation for generous funding.

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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. U.S. consumer prices rose by 10% in 2021, an inflation rate not seen since the 1970s. 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 during this episode. 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. These actions were consistent with the new monetary policy framework adopted by the Fed in August 2020 and centered on the concept of *flexible average inflation targeting*. 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 peaked at about 5% in 2021 if the Fed had followed its historical reaction function.

To illustrate our approach to detecting shifts in the Fed's reaction function, 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 at date t, π_t is the inflation rate, $\pi^\star$ is the inflation target, $i^\star$ is the "natural" nominal interest rate, and $\varepsilon_{m,t}$ is an i.i.d. monetary shock capturing transitory deviations of the policy rate from its systematic component. We will later discuss how this approach extends to more comprehensive statistical descriptions of monetary policy, including features such as interest rate smoothing, a time-varying intercept, and an output gap component.

Our objective is to test whether the private sector's view of the Fed's reaction function changed after 2020—in this simple case a shift in ψ_π—and, if a change is identified, to determine the perceived duration of this new "regime".[1] This is hard to do using *realized* data: we only have a few observations of short-term nominal interest rates and inflation in the post-2020 period, and their informational content is limited given that nominal interest rates were at the zero lower bound until March 2022. In addition, such a short time period does not allow one to measure the perceived persistence of the new policy regime, as for that we would need multiple spells.

One key insight of our paper is that these challenges can be addressed by leveraging high-frequency bond market data. Specifically, we can take time-t expectations of nominal interest rates and inflation at some future date $k > t$ and express the Taylor rule (1) as

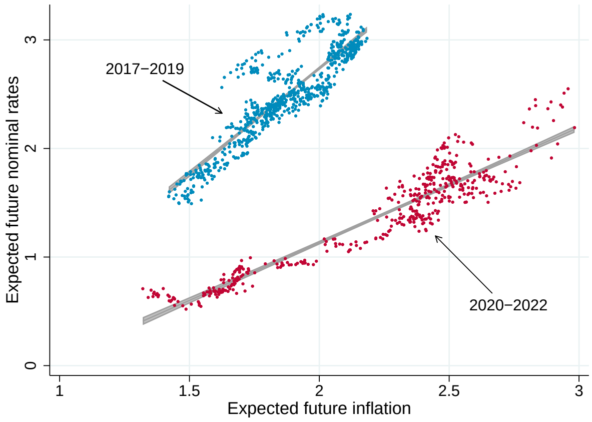
$$\Delta\mathbb{E}_t[i_k] = \psi_\pi \Delta\mathbb{E}_t[\pi_k], \tag{2}$$

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. From the term structure of nominal and inflation-protected bonds, we can retrieve daily "risk-neutral" expectations of these variables, and use them to construct proxies for the variables in equation (2).

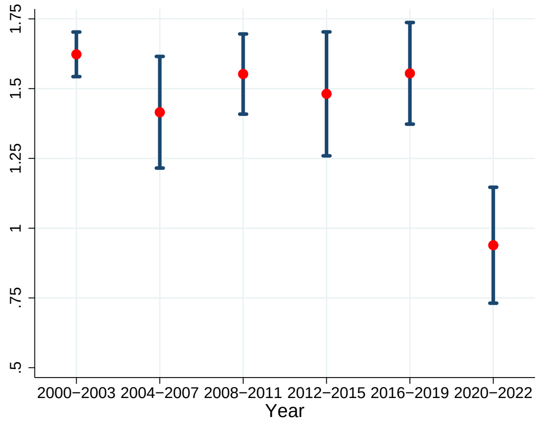
Every day, market participants revise their beliefs about *future* inflation and future nominal interest rates, and equation (2) clarifies that the comovement between these forecast updates is informative about the markets' beliefs on the Fed's reaction function. In addition, expectations data allow us to address the two challenges described above. First, expected future nominal interest rates move over time even if current interest rates are at the zero lower bound; for this reason, the former are more informative than the latter for the purpose of detecting shifts in the policy rule. Second, by varying the forecast horizon k we can obtain information on how long investors expected a change in ψ_π to persist.

We start our empirical analysis by studying the relationships between market-implied expectations of future nominal interest rates and future inflation. We document two main facts, which we report in Figure 1. First, as we can see from panel (a) of the figure, there is a remarkably strong linear relationship between these two variables, suggesting that a simple

[1]As we will discuss later in the paper, a change in the monetary policy rule in a baseline New Keynesian model is more consequential for output and inflation when it is expected to be in place for longer. Therefore, measuring the persistence of the shift in the monetary policy rule is a critical input for answering the question that we pose in this paper.



(a) $\mathbb{E}_t[\bar{i}_{t,k}]$ 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). Panel (b) reports estimates of ψ_π in different sub-samples. See Section 2 for a description of the data and the estimation of ψ_π.

Taylor rule as that of equation (1) is a good framework to process these data. Second, the slope of this relationship in the 2020-2022 period was much flatter than that of preceding years. Indeed, ordinary least squares (OLS) estimates of ψ_π reveal a remarkable stability in this coefficient up to the pandemic—-which was centered around a value of 1.5 for almost twenty years—and a sizable drop afterward, see panel (b) of Figure 1. In addition, when varying the maturity of bonds, we find that these shifts in the slope are relevant for a forecast horizon of up to 5 years and are not statistically significant at longer horizons.

From the perspective of equation (1), this evidence indicates that financial markets perceived the Fed after 2020 to be systematically less responsive to movements in current inflation than before in the short-medium term—a perceived change in the Fed reaction function. However, there are other plausible explanations not related to a change in Fed policy that could also explain a weaker relationship between the expected future nominal interest rate and expected future inflation. In the paper, we review these alternative hypotheses and find that our main results hold even after we control for those.

First, the Taylor rule of equation (1) could be misspecified, and the reduction in the OLS estimates of ψ_π could be the result of this misspecification rather than an actual shift in the policy of the Federal reserve. Specifically, suppose that the Taylor rule in (1) also included an output gap component, in line with the dual mandate of the Fed. Then, the

OLS estimates of ψ_π would be asymptotically biased,

$$\hat{\psi}_\pi^{OLS} \xrightarrow{p} \psi_\pi + \psi_y \frac{\text{Cov}\left(\Delta\mathbb{E}_t[\pi_k], \Delta\mathbb{E}_t[\hat{y}_k]\right)}{\text{Var}\left(\Delta\mathbb{E}_t[\pi_k]\right)},$$

where $\hat{y}_k$ denotes the output gap. A lower $\hat{\psi}_\pi^{OLS}$ across sub-samples could then be the result of a reduction in the correlation between inflation and the output gap rather than a change in the conduct of monetary policy. This explanation is consistent with the view that supply shocks have become more prevalent in the U.S. economy over the 2020-2022 period (Bernanke and Blanchard, 2023), as they move output and inflation in opposite direction.

In order to control for this concern, we test for the stability of the monetary policy rule across sub-samples by estimating ψ_π only using forecasts revisions in a window around "monetary events", such as releases of statements and minutes of Federal open market committee meetings. To the extent that these events identify forecast updates conditional on monetary shocks, we could use these data to test for a structural break in their relationship and be robust to the aforementioned criticism—as we would be conditioning on the *same* type of demand shock before and after the break. Following this approach, we still find a sizable and significant reduction in the estimate of ψ_π in the post-2020 period.

In addition to a potential misspecification of the policy rule, other factors could explain a weaker relationship between expected nominal interest rates and expected inflation. For instance, this weakening could result from a higher prevalence of the zero lower bound constraint post-2020 or changes in the pattern of risk and liquidity premia in financial markets, making risk-neutral expectations a less reliable proxy for actual expectations. We show that our key findings remain robust even after accounting for these concerns. First, our main results persist when excluding the [0-2] year forward horizon, which is most affected by expectations of the zero lower bound constraint (Mertens and Williams, 2021). Second, most of the estimated effects are concentrated in the [3-5] year forward horizon and diminish as we move to longer maturities. If risk premia were driving these patterns, we would instead expect the effects to be more pronounced at longer horizons, as bond risk premia are highly correlated across maturities and tend to increase with maturity (Cochrane and Piazzesi, 2005).

Finally, we study the macroeconomic implications of these perceived changes in the Fed reaction function by enriching the canonical three-equations New Keynesian model with a two-regime monetary policy rule: a traditional Taylor rule and an average inflation targeting rule in which nominal interest rates respond to deviations of a backward-looking average inflation from its target—a way of capturing a key feature of the new framework announced in 2020. We discipline the parameters of this regime via indirect inference by fitting the evidence discussed earlier and 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 responded according to the historical Taylor rule: at peak, annualized inflation would have reached 5% in this scenario instead of the observed 9%.

We show that the large effects of these policy changes on inflation in the baseline New Keynesian model are due to the interplay of two forces. First, the shift to a less responsive policy regime lowers expectations of real interest rates in the short and medium run. Second, we show that inflation in the baseline New Keynesian model is extremely sensitive to changes in future real interest rates, with the responsiveness *increasing* in the horizon, a feature that is due to the interplay between the "forward guidance puzzle" (Del Negro, Giannoni, Patterson et al., 2012) and the forward-looking nature of inflation via the Phillips curve—a forward guidance puzzle "squared". While we believe that the model's implications for the effects of the policy shift on the term structure of interest rates are realistic, as they are informed by our empirical analysis, the sensitivity of inflation to long-term real interest rates implied by this class of models is likely too large, making these results an upper bound on the role of monetary policy during this episode.

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.[2] 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

[2]This finding contrasts the quite limited impact that the Federal Reserve's announcements of the new strategy had on household expectations, see Coibion, Gorodnichenko, Knotek, and Schoenle (2023).

[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 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.

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 during this episode.

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. King and Lu (2022) use the term structure of inflation expectations by professional forecasters to estimate the reputation of the central bank within the context of a model where the policymaker's type is private information, while Mertens and Zhang (2023) solve a New Keynesian model in terms of risk-neutral expectations and estimate it using the term structure of nominal and real yields. Campos, Fernández-Villaverde, Nuño, and Paz (2024) use market-implied expectations of nominal interest rates and inflation to measure the perceived policy response to changes in the natural rate of interest.

The paper more connected 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.

As we formally show in Section 3, the absence of market-based measures of output gap expectations introduces a source of bias when trying to estimate the Fed reaction function. As we explained earlier, it is still possible to test for shifts in the monetary policy rule using 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 these monetary events to test for shifts in the *systematic* component of the Fed reaction function rather than to measure monetary shocks and their propagation on 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. For example, 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 Dovishness to an increase in the amount of unfunded fiscal spending during the pandemic. Our results are consistent with this view, although our interpretation links the change in the perceived Dovishness to the adoption of the flexible average inflation targeting regime. 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

This section is divided in three parts. Section 2.1 describes the data used in the empirical analysis. Section 2.2 presents our approach to detect shifts in the Fed reaction function and presents the baseline results. Section 2.3 discusses the results in light of the policy changes introduced by the Federal Reserve in August 2020.

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 a real bond maturing k years from date t. The difference between these two reflects the inflation compensation required by investors for holding the inflation risk embedded 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 February 28th, 2022. 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 end the sample right at the lift-off from the zero lower bound period.[4]

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 life-time of the bonds. Specifically, from standard asset pricing relationships, we have

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

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

where $\bar{i}_{t,k}$ and $\bar{\pi}_{t,k}$ denote average nominal interest rate and inflation over the next k years, $\mathbb{E}_t\left[\cdot\right]$ denotes the expectation conditional on time t information, and $\eta_{t,k}$ and $\iota_{t,k}$ are, respectively, the risk premium embedded in nominal and real bonds with a residual maturity of k years. Equations (3) and (4) show that the term structures of nominal yields and inflation compensation contain potentially useful information for a real-time read on the future path of nominal short term interest rates and inflation expected by investors.

In our baseline results, we will ignore time-variation in the term and inflation risk premium and treat daily changes in nominal bond yields and inflation compensation as forecast revisions of future nominal interest rates and future inflations. That is, we will assume that $\eta_{t,k}$ and $\iota_{t,k}$ are constant over time. This assumption is not innocuous: several studies have found evidence that nominal bond yields and inflation compensation also reflect time-varying term and inflation risk premiums, especially conditioning on changes in monetary policy shocks, see 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) among many others. In Section 3, we will explicitly control for time variation in risk premia.

Figure 2 plots the time series of the nominal bond yield and the inflation compensation measure for bonds with time to maturity of five and ten years. Nominal yields have trended downward for most of the sample. The inflation compensation measure has been fluctuating around two percent, with a sustained period of low inflation expectations between 2015 and 2020 and values substantially above this number during the recovery from the pandemic. Two episodes stand out as outliers: during the financial crisis in 2008 and

[4]We end the sample then because it is unclear whether the market interpreted the rapid lift-off of interest rates as a return to the former monetary regime or not. Bauer, Pflueger, and Sunderam (2024) detect an increase in the sensitivity of nominal interest rates to inflation after March 2023 using both survey data and—similarly to our analysis—market-based expectations. See also Kroner (2023). Extending our sample to study this issue is an avenue for future work.

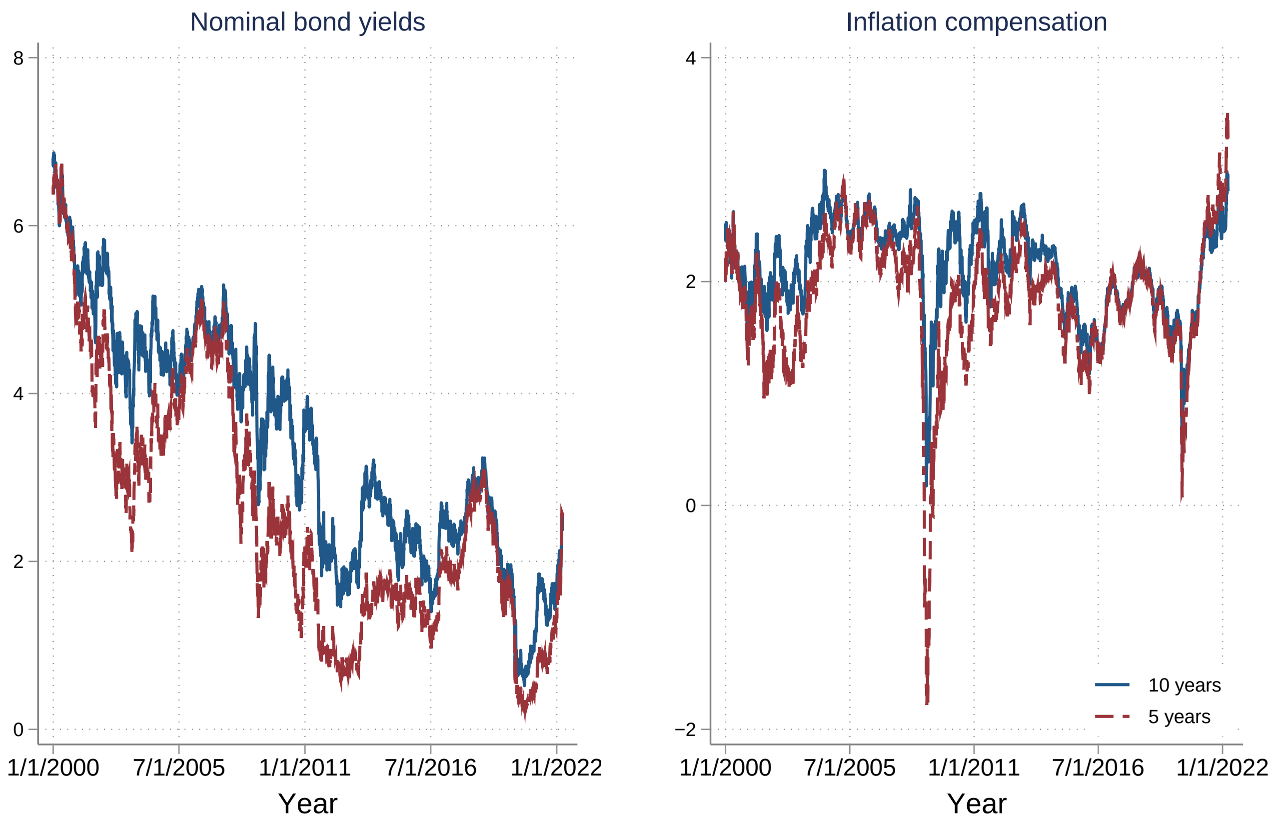


Figure 2: Nominal bond yields and Inflation compensation

Notes: The left panel plots 5- and 10-year zero-coupon nominal Treasury yields, while the right panel plots 5- and 10-year inflation compensation (the difference between nominal Treasury and TIPS yields). The data are from Gürkaynak, Sack, and Wright (2007, 2010) and cover the period January 2000 through March 2022.

the Covid outbreak in early 2020, inflation compensation measures plummeted. TIPS, at times, trade at a discount compared to nominal Treasury securities due to their relative illiquidity, which leads to a downward bias in the expected inflation measure computed using $IC_t^{(k)}$. The sharp declines in 2008 and in the first half of 2020 most likely reflected an increase in this liquidity discount due to the financial turmoil rather than a genuine reduction in inflation expectations. To avoid these periods affecting our results, we exclude 2008 and the first half of 2020 (January 1 to July 31st) from our sample.

2.2 Identifying shifts in the monetary policy rule

For our baseline analysis we assume that monetary policy is governed by the following rule

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

where i_τ is the nominal interest rate prevailing in year τ, $(\pi_\tau - \pi^\star)$ is the deviation of inflation from its target, $i^\star_\tau$ is the "natural" interest rate—the nominal interest rate prevailing in an economy with no price rigidities—and $\varepsilon_{m,\tau}$ is a transitory deviation from the rule—a monetary shock. In what follows, we discuss how we can use the data presented earlier to detect changes in the Fed reaction function.

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

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

We then make two assumptions that we think are reasonable when working with the variables expressed in first-difference, and that allow us to further simplify equation (6).

First, we assume that forecast revisions of future monetary policy shocks are also small, $\Delta\mathbb{E}_t\left[\varepsilon_{m,k}\right] = 0$. This assumption clearly holds for most days in our sample—as, on a typical day, there are no forecast revisions about $\varepsilon_{m,k}$—and it is more generally satisfied as long as the forecast horizon k is large compared to the persistence of the monetary policy shocks. For example, if monetary shocks follow an AR(1) process with persistence ρ_m, then the forecast revisions conditional on a monetary shock of size δ_t at date t would be $\Delta\mathbb{E}_t\left[\varepsilon_{m,k}\right] = (\rho_m)^k\,\delta_t$, which will be close to zero as long as k is large relative to ρ_m. In practice, monetary shocks commonly estimated in the literature display only mild serial correlation (see Coibion and Gorodnichenko (2012) for example), suggesting that k need not be too large for this second assumption to be reasonable.

Second, we assume that daily forecast revisions of the natural interest rate are negligible at daily frequencies, that is $\Delta\mathbb{E}_t[i^\star_k] = 0$. We think this is reasonable since most of the literature considers the natural rate of interest $i^\star_t$ to be a very slow-moving process driven by secular forces, such as demographics and the patterns of capital flows across countries, see, for example, Laubach and Williams (2003, 2016) and Del Negro, Giannone, Giannoni, and Tambalotti (2017).

Given these two assumptions and the fact that equation (6) holds for every k, we have

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

where $\overline{x}_{t,k}$, is the average of variable x between now and k years ahead of now, 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 will consider expectations constructed using nominal and inflation-protected bond yields with a residual maturity of ten years.

In order 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 percentile. 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 $\Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right]$.[5] We can then estimate ψ_π over different sub-samples and check whether the monetary policy rule perceived by financial markets investors changed over time.

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.[6]

Column (1) of 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. Indeed, we cannot reject the null hypothesis that $\psi_\pi=1.55$ in any of these sub-periods at conventional levels. Even more remarkably, we observe a sizable fall in the coefficient post-2020, with a point estimate of 1.02.

Next, we exploit the term structure of the data and estimate equation (8) using expectations constructed over relatively short-term ([0-2] years forward), medium-term ([3-5] years forward), and long-term ([6-10] years forward) horizons.[7] The results are reported in columns (2)-(4) of Table 1.

This exercise reveals an interesting pattern. Column (2)—which reports the results for the [0-2] horizon—shows that the coefficient ψ_π is generally smaller and it exhibits more variation over time compared to the baseline specification. Notably, nominal interest rates were not sensitive to changes in inflation compensation over the 2012-2015 subsample,

[5]As we discuss in Section 3.4, our main results are robust to varying ρ_i in the empirically plausible range between 0.7 and 0.9.

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

[7]Note that we need to use TIPS with a residual maturity of 2 years in order to construct inflation compensation at the $[0,2]$ and $[3,5]$ forward horizon. Because short-maturity TIPS were not traded in the earlier part of our sample, we estimate these specifications only using post-2003 data.

Table 1: Estimates of equation (8)

	(1) 10 years averages	(2) [0-2] years	(3) [3-5] years	(4) [6-10] years
$\psi_{\pi,2000-2003}$	1.63^{***}			1.61^{***}
	(0.04)			(0.07)
$\psi_{\pi,2004-2007}$	1.41^{***}	1.21^{***}	2.11^{***}	1.67^{***}
	(0.10)	(0.18)	(0.20)	(0.11)
$\psi_{\pi,2008-2011}$	1.55^{***}	1.03^{***}	2.41^{***}	2.02^{***}
	(0.07)	(0.14)	(0.13)	(0.09)
$\psi_{\pi,2012-2015}$	1.48^{***}	-0.06	1.94^{***}	2.11^{***}
	(0.11)	(0.12)	(0.18)	(0.14)
$\psi_{\pi,2016-2019}$	1.55^{***}	1.06^{***}	1.87^{***}	1.87^{***}
	(0.09)	(0.18)	(0.16)	(0.12)
$\psi_{\pi,2020-2022}$	1.02^{***}	0.06	1.07^{***}	1.50^{***}
	(0.11)	(0.18)	(0.20)	(0.14)
R^2	0.41	0.07	0.26	0.34
N	4019	3249	3249	4019

Note: The top panel of the table reports the estimates of $\psi_{\pi,s}$ in equation (8) while the bottom panel reports estimates of ψ_π and d in equation (9). Expectations are constructed using bond yields with a residual maturity of ten years. The table reports robust standard errors in parenthesis. One star indicates significance at the 10 percent level, two starts indicate significance at the 5 percent level, and three stars indicate significance at the 1 percent level.

with ψ_π closely resembling the values observed in the 2020-2022 subsample. We believe that these observations—the small slope and its variation over time—can be attributed to the presence of the zero lower bound constraint on nominal interest rates. As we will discuss in Section 3.3, the presence of a binding zero lower bound biases the coefficient ψ_π in equation (5) downward, particularly when expectations of the constraint binding in the future are high. Moreover, Mertens and Williams (2021) show that the zero lower bound was a significant determinant of U.S. short-term nominal interest rate forecasts over the 2012-2014 period. This suggests that focusing on a short-term forward horizon may not be ideal for estimating shifts in the policy rule.

Importantly, our key result holds when using [3-5] years and [6-10] years forward expectations, which are likely unaffected by the presence of the zero lower bound constraint (Mertens and Williams, 2021). In column (3), we see that ψ_π fluctuates minimally around a value of 2 up to 2020 before dropping to 1.07 in the 2020-2022 sub-period. Column (4) shows a similar pattern when using expectations of future interest rates and future inflation 6 to 10 years ahead, though the decline in ψ_π is smaller compared to that observed for the 3-5 year horizon

To summarize, the 2020-2022 period exhibited a sharp decline in the sensitivity of nominal interest rates to inflation, as estimated using bond market data. This decline is evident not only in shorter-term expectations but also in medium-term and, to a lesser extent, longer-term expectations—a pattern that distinguishes the behavior of these variables during the 2020-2022 sample relative to the preceding twenty years. Viewed through the lens of the Taylor rule in equation (5), this suggests that bond market investors believed the Federal Reserve would respond more weakly to shocks affecting current inflation going forward.

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 3 reports the point estimate of d in equation (9) along with a 99% confidence interval for the baseline specification ([0-10] years forward), and for two specifications that use medium-term ([0-5] years forward) and longer-term ([6-10] years forward) expectations. Consistent with the results in Table 1, the point estimate of d in the baseline is -0.54 with a tight confidence interval. The figure also shows that the largest deviations occur for short- to medium-term expectations (up to year five) while financial markets did not expect these deviations to persist in the longer term. For expectations between year six and ten, the coefficient d is closer to zero, with a point estimate of -0.30, and not significantly different from it at 1% significance level.

2.3 Discussion

So far, we have documented two main results. First, there has been a substantial change in the relationship between nominal bond yields and inflation compensation, with their correlation becoming substantially weaker in the post 2020 period. Second, the weakening is especially large when looking at shorter maturities.

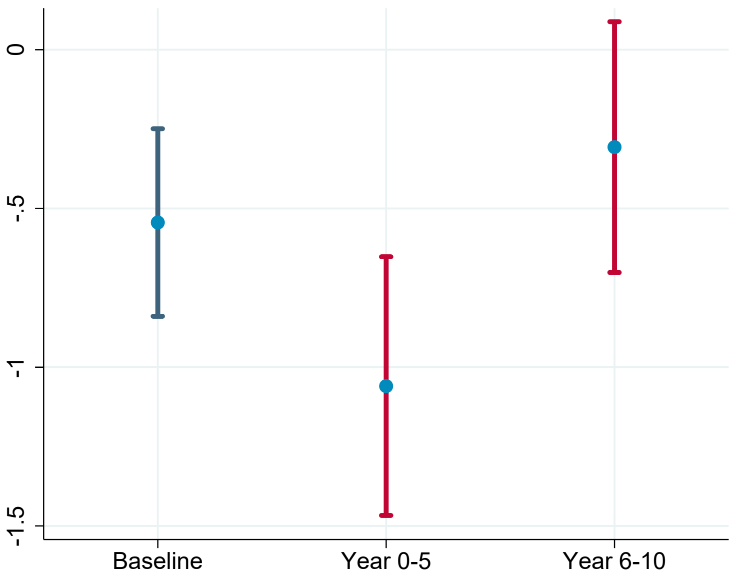


Figure 3: Medium-term vs. long-term expectations

Notes: The figure reports point estimates and 99% confidence intervals for the coefficient d in equation (9) estimated using: i) expectations of nominal interest rates and inflation averaged over the next ten year; ii) expectations of nominal interest rates and inflation averaged over the next five year; iii) expectations of nominal interest rates and inflation averaged between the next six and ten years. Confidence intervals are constructed based on standard errors that are robust to heteroscedasticity and autocorrelation.

When interpreted through the lens of the Taylor rule in equation (5), these findings suggest a temporary shift to a more "Dovish" policy toward inflation. We believe that this interpretation is broadly consistent with the messages conveyed in the Federal Reserve's Statement on Longer-Run Goals and Monetary Policy Strategy in August 2020 (which followed the review of the monetary policy framework, sometimes just referred to as the "*strategy review*") and in the subsequent Federal Open Market Committee (FOMC) statements.[8] The Statement on Longer-Run Goals and Monetary Policy strategy declared that:

> *"[...] the Committee seeks to achieve inflation that averages 2 percent over time, and therefore judges that, following periods when inflation has been running persistently below 2 percent, appropriate monetary policy will likely aim to achieve inflation moderately above 2 percent for some time."*

The FOMC statements following the meetings between September 2020 and December 2021 struck a similar tone, stating that

> *"[...] the Committee will aim to achieve inflation moderately above 2 percent for some time so that inflation averages 2 percent over time and longer-term inflation expectations*

[8]The Statement on Longer-Run Goals and Monetary Policy Strategy is available on the Board's website at https://www.federalreserve.gov/monetarypolicy/files/fomc_longerrungoals.pdf.

remain well anchored at 2 percent."

This language was new, as the FOMC had previously communicated a symmetric flexible inflation target, rather than the new flexible *average* inflation target.

The reasoning behind this change was that in a low-inflation environment, with frequent spells of interest rates at the effective lower bound (ELB), it is optimal to allow inflation to run above the target after a recovery to avoid a downward spiral in inflation when the response of nominal interest rate is constrained.[9] Vice-chairman Clarida, in a speech in August 2020, declared:

"[...] in a world of low r^* in which adverse aggregate demand shocks are expected to drive the economy in at least some downturns to the ELB. In this case, which is obviously relevant today, economic analysis indicates that flexible inflation-targeting monetary policy cannot be relied on to deliver inflation expectations that are anchored at the target, but instead will tend to deliver inflation expectations that, in each business cycle, become anchored at a level below the target."

When inflationary pressures began to build in early 2021, the FOMC acknowledged the rise in inflation but initially assessed these pressures as transitory. The FOMC statements between April 2021 and December 2021 stated that

"Inflation has risen, largely reflecting transitory factors."

Per the new strategy, the aim was to let inflation run moderately above two percent for some time and have inflation fall back only as the transitory factors faded.

The new strategy thus suggests that the FOMC intended to tolerate above-target inflation for a while, with a delayed return of inflation to the target. This could be interpreted as a temporarily lower coefficient on inflation deviations from the target in the standard Taylor-type policy rule. Davig and Foerster (2023) indeed show that communicating such a delay in the return of inflation to the target can be represented as a decrease in the inflation coefficient in the canonical Taylor rule.

Our results in the previous section suggest that bond market investors appear to have understood and priced in the new policy strategy, as we find that the market pricing of inflation and interest rate expectations are consistent with a weaker central bank response to inflation. We also find that this effect is predominant at medium-term forward horizons, whereas it is mostly absent over long-run forward horizons. This is consistent with the Fed's messaging about a temporary inflation overshoot ("for some time").

[9] See for example Eggertsson and Woodford (2003), Eggertsson (2006), and Werning (2012).

This discussion does not imply that a change in the policy framework is necessary for financial markets to update their view on monetary policy. Indeed, many other central banks in advanced economies did not promptly respond to the increase in inflation observed post covid, and financial markets may have changed their view about their reaction function even in the absence of an official change in their monetary policy strategy. Bocola (2024) for example documents a much smaller sensitivity of nominal bond yields to inflation compensation in the euro area post 2020.[10]

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—and pointed out that this interpretation is consistent with the Fed's discussion and implementation of flexible average inflation targeting.

In this section, we put this interpretation under scrutiny. Specifically, we discuss three plausible confounding factors that could explain the same facts documented in Section 2 even in the absence of a shift in the monetary policy regime: the presence of the output gap in the Taylor rule (5), time-varying risk premia, and the possibility of an occasionally binding zero lower bound constraint. We propose ways to control for these confounding factors and show that our main results survive this sensitivity analysis.

3.1 Controlling for the output gap

Our analysis thus far was based on a Taylor rule that responded only to inflation. In practice, the Federal Reserve has a dual mandate to achieve price stability and maximum employment, and it is customary in the literature to include in the Fed's reaction function also indicators of economic activity—such as the output gap or the unemployment rate. An important question is how a misspecification of the Fed reaction function would affect our results and whether we can correct for such a misspecification.

[10] The interpretation given is that rising debts post-Covid made public finance sustainability a more pressing consideration for the European Central Bank, constraining its ability to raise nominal interest rates aggressively.

To study this question, we assume that the Fed follows the rule

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left[i_t^\star + \psi_\pi\left(\pi_t - \pi^\star\right) + \psi_y \hat{y}_t\right] + \varepsilon_{m,t}, \tag{10}$$

where $\hat{y}_t$ is the output gap, and ψ_y is an indicator of how sensitive nominal interest rates are to changes in $\hat{y}_t$. Applying the same steps discussed in Section 2.2, we obtain the relation

$$\Delta\mathbb{E}_t\left[\bar{i}_{t,k} - \rho_i \frac{k-1}{k}\bar{i}_{t,k-1}\right] = \psi_\pi \Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\pi}_{t,k}\right] + \psi_y \Delta\mathbb{E}_t\left[(1-\rho_i)\overline{\hat{y}}_{t,k}\right]. \tag{11}$$

If we were to estimate equation (11) using only data on expected nominal interest rates and inflation—as we did in the previous section—the probability limit of the OLS estimator of ψ_π would be

$$\hat{\psi}_\pi^{\text{OLS}} \xrightarrow{p} \psi_\pi + \psi_y \frac{\text{Cov}\left(\Delta\mathbb{E}_t[\overline{\pi}_{t,k}], \Delta\mathbb{E}_t\left[\overline{\hat{y}}_{t,k}\right]\right)}{\text{Var}\left(\Delta\mathbb{E}_t[\overline{\pi}_{t,k}]\right)}. \tag{12}$$

As long as expected inflation and the expected output gap are correlated, and the Fed moves nominal interest rates partly to stabilize the output gap ($\psi_y > 0$)—both of which are empirically plausible—the OLS estimator of ψ_π will be asymptotically biased.

This bias term may also vary over time due to structural changes affecting the covariance between inflation and the output gap. These structural changes could then explain the drop in $\hat{\psi}_\pi^{OLS}$ in the 2020-2022 period that we documented in the previous section. Specifically, the bias term should be smaller in sub-samples during which supply shocks are prevalent because these shocks induce a negative comovement between output and inflation. So, rather than indicating a change in the Fed reaction function, the fall in $\hat{\psi}_\pi^{OLS}$ could just reflect the expectation that the Fed would be facing more supply-side shocks going forward than they did in the past. This is also a plausible alternative explanation of our findings, given the well-documented disruptions in supply chains induced by the pandemic and the energy shocks associated with the war in Ukraine.

In what follows, we propose a strategy to address this identification problem and test for a shift in the perceived monetary stance of the Federal Reserve after 2020. Rather than trying to estimate the coefficient ψ_π across the two sub-samples—which is not feasible given the identification problem just described—we will use the estimates of d in equation (9) to test the *null hypothesis of no change in the monetary policy rule*. Specifically, we propose to estimate equation (9) only using forecasts revisions around the "monetary events" that took place in our sample (e.g. FOMC meetings), which are broadly interpreted in the literature as monetary shocks. We will then test the hypothesis that $d = 0$ and interpret a rejection of this hypothesis as evidence of a change in the perceived monetary policy rule.

The key idea of this approach is that, by conditioning on monetary events, we can control for possible confounding effects—such as an increase in the size of supply shocks—that may explain a fall over time in $\hat{\psi}_{\pi}^{OLS}$ via the bias term.

To understand why this procedure can detect a shift in the monetary policy rule even in the presence of these confounding factors, suppose that there was no change in the Fed reaction function between the two sub-samples. Assume further that no other change took place in 2020 that could have affected the propagation of a monetary shock to the rest of the economy. Then, the joint distribution of $(\bar{i}_{t,k}, \overline{\pi}_{t,k}, \overline{y}_{t,k})$ *conditional on a monetary shock* would be independent of D_t—which would imply that the bias term in equation (12) is constant over the two sub-samples. Under these assumptions, the OLS estimator of d in equation (9)—the difference between ψ_{π} in the two sub-samples—would follow a normal distribution centered around zero asymptotically (see Appendix A). Therefore, we can test the null hypothesis that d equaled zero and interpret a rejection as evidence of a shift in the monetary policy rule across the two sub-samples.

Column (2) of Table 2 reports the estimates of d in equation (9) when using forecast revisions around monetary events. These are defined as days during which the Federal Reserve releases the statement or minutes of a planned FOMC meeting, or when the Fed chairman delivers a speech on monetary policy at a planned event. Over the 2000-2022 sample, we have 455 such events. Consistent with our previous analysis, we continue to observe a significant weakening in the relationship between expected future nominal interest rates and expected future inflation after August 2020, with this effect being most pronounced at the five year forecast horizon. Since we are conditioning on the same type of shock—a monetary shock—both before and after 2020, we are more confident that these results reflect a shift in the perceived monetary policy rule rather than a change in the nature of shocks the U.S. economy faced post-2020.[11]

Discussion. It is useful to think about the procedure just described through the lens of the canonical New Keynesian model. Suppose that our data were generated by the standard log-linearized three-equations New Keynesian model, which we outline in Appendix B, and consider estimating equation (11) only using expectations of future nominal interest rates and future inflation conditional on monetary shocks. The following result characterizes the probability limit of $\hat{\psi}_{\pi}^{\mathrm{OLS},m}$ as a function of the model's structural parameters.

[11]Our approach would not be valid if market surprises around monetary policy events reflect information about the current state of the economy that markets learn from policy officials—a so called "Fed information effect", see Nakamura and Steinsson (2018). In Appendix C.2 we use the insights of Jarociński and Karadi (2020) to refine our sample by excluding monetary events likely associated with these information spillovers. Our main results remain robust to this additional sensitivity check.

Table 2: Sensitivity analysis

	(1) Baseline	(2) Monetary events	(3) Risk premia	(4) ZLB
d (10 year avg)	-0.54^{***}	-0.88^{**}	-0.27	-0.35^{*}
	(0.11)	(0.43)	(0.19)	(0.20)
d (5 year avg, 1-5)	-1.05^{***}	-1.94^{***}	-1.05^{***}	-1.25^{***}
	(0.15)	(0.50)	(0.12)	(0.27)
d (5 year avg, 6-10)	-0.13	-0.26	0.16^{***}	0.19
	(0.10)	(0.30)	(0.04)	(0.14)
N. obs.	4019	455	4019	4019

Note: The table reports the estimates of d in equation (9) under different specifications. Column (1) restates the baseline results reported in Section 2. Column (2) estimates equation (9) using only daily changes in nominal bond yields and inflation compensation around monetary events. Column (3) controls for time-variation in term and inflation risk premiums. Column (4) controls for proximity to the zero lower bound. Standard errors are robust to heteroscedasticity and autocorrelation. One star indicates significance at the 10 percent level, two starts indicate significance at the 5 percent level, and three stars indicate significance at the 1 percent level.

Proposition 1. *Consider the log-linearized three-equations New Keynesian model. Let $\rho_y \in (0,1)$ be the solution to*

$$\rho_y = \rho_i - (1-\rho_i)\frac{1}{\sigma}\frac{\rho_y\left(\psi_\pi \frac{\kappa}{1-\beta\rho_y} + \psi_y\right)}{\left(1-\rho_y - \frac{1}{\sigma}\frac{\kappa}{1-\beta\rho_y}\rho_y\right)} \tag{13}$$

where κ is the slope of the Phillips curve, β is the rate of time preference of the representative household, and σ is the inverse of the elasticity of intertemporal substitution. Let $\mathbb{E}_t^m[\xi_k]$ be the forecast update for variable ξ at date $k > t$ given that we learn of a realization of the monetary shock at date t,

$$\mathbb{E}_t^m[\xi_k] \equiv \mathbb{E}[\xi_k|\mathcal{I}^t, \varepsilon_{m,t}] - \mathbb{E}[\xi_k|\mathcal{I}^t].$$

Consider a linear projection of $\mathbb{E}_t^m\left[\hat{i}_k - \rho_i\hat{i}_{k-1}\right]$ on a constant and $\mathbb{E}_t^m\left[(1-\rho_i)\hat{\pi}_k\right]$, and denote by $\hat{\psi}_\pi^{OLS,m}$ the projection coefficient. Then, the probability limit of $\hat{\psi}_\pi^{OLS,m}$ is

$$\hat{\psi}_\pi^{OLS,m} \xrightarrow{p} \psi_\pi + \psi_y\frac{(1-\beta\rho_y)}{\kappa}. \tag{14}$$

From equation (14), we can see that the estimate of ψ_π is asymptotically biased even when we condition on monetary policy shocks. The proposition shows that this bias depends on some of the structural parameters of the model: the policy parameters $(\psi_y, \psi_\pi, \rho_i)$, the slope of the Phillips curve κ, the rate of time preference β and the elasticity of intertemporal substitution σ.

Importantly, the bias does not depend on the parameters of the other shocks hitting the economy. So, an increase in the variance of supply shocks, which as discussed earlier could explain the fall in $\hat{\psi}_\pi^{\text{OLS}}$ documented in Table 1, does not affect the probability limit of $\hat{\psi}_\pi^{\text{OLS,m}}$. In this sense, conditioning on monetary shocks makes it easier to detect shifts in the monetary policy rule.

Proposition 1 also helps clarify the additional assumptions needed to interpret a change in $\hat{\psi}_\pi^{\text{OLS,m}}$ across the two sub-samples as evidence of a change in the monetary policy rule. As discussed earlier, we need the bias term in equation (12) to be constant across the two sub-samples *under the null hypothesis of no change in the monetary policy rule*. This requires that other structural parameters that affect the propagation of monetary shocks are constant over the horizon of our analysis. Looking at the expressions in (13) and (14), we need the slope of the Phillips curve κ and the preference parameters β and σ to be constant across the two sub-samples. Recent papers have emphasized a steepening of the Phillips curve after 2020 (Benigno and Eggertsson, 2023), something that could potentially rationalize a fall in $\hat{\psi}_\pi^{\text{OLS,m}}$ even in absence of an actual shift in the monetary policy rule. However, a simple back of the envelope calculation suggests that κ would need to increase by a factor of five to explain our findings quantitatively.[12] Similarly, we would need somewhat unplausibly large changes in σ and β to rationalize a fall in $\hat{\psi}_\pi^{\text{OLS,m}}$ across sub-samples without an actual change in the monetary policy rule.

Estimating features of the Fed reaction function by conditioning on a monetary shock may appear counterintuitive at first: after all, it is the presence of monetary shocks in the Taylor rule that creates an endogeneity problem, which has led researchers to use other type of structural shocks as instrumental variables to estimate the parameters, see Debortoli, Galí, and Gambetti (2020). By looking at future outcomes, however, we can exploit the variation induced by a monetary shock and learn something about the systematic component of the Taylor rule.[13]

Finally, while under our assumption a non-zero d must come from changes in the underlying monetary policy rule, this test does not tell us which parameter of the policy rule is

[12]Plugging in standard values for the other parameters, we need κ to increase by a factor of 4.88 to lead to a reduction in the bias term of about 0.6, which is roughly consistent with our estimates of d in Table 2.

[13]Conditional on a monetary shock at time t, $\mathbb{E}_t[i_k - \rho_i i_{k-1}]$ depends only on the systematic component of the Taylor rule as long as $k > t$ and the monetary shocks are not serially correlated. Therefore, it is possible to learn the parameters of the Taylor rule by looking at the relation between $\mathbb{E}_t[i_k - \rho_i i_{k-1}]$ and movements in inflation and the output gap induced by a monetary shock.

changing. Indeed, from equation (14) we can see that the bias term depends on $(\rho_i, \psi_\pi, \psi_y)$, so potentially a change in either of them can account for a non-zero d. Consistent with the discussion in Section 2.3, in the quantitative analysis of Section 4 we will consider a monetary policy rule that alternates between two regimes—a historical Taylor rule given by equation (10), and an average inflation targeting regime in which the monetary authority responds to deviations of average inflation from a target. Importantly, we will estimate the parameters of the average inflation targeting regime via indirect inference by matching, in model simulated data, the point estimates of the coefficient d at different forecasting horizons.

3.2 Controlling for time-varying risk 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 the term premium and the inflation risk premium are constant over time. In what follows, we discuss to what extent the presence of time-varying risk premia on nominal and real bonds affects our results and how we can control for these movements.

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

$$\Delta \left[i_t^{(k)} - \rho_i \frac{k-1}{k} i_t^{(k-1)} \right] = \psi_\pi \Delta \left[(1-\rho_i) IC_t^{(k)} \right] + \varepsilon_t, \tag{15}$$

where ε_t is a function of the term premium $\eta_{t,k}$ and inflation risk premium $\iota_{t,k}$,

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

Similarly to what happens for the output gap, the presence of risk premia in bond markets introduces a bias in 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 daily movements in the term premium and in the inflation risk premium, 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 measures of expectations that are "purified" from risk premia.

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 asset pricing models imply that the inflation risk premium reflects 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 the surveys expectation 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.[14] Appendix C.1 provides more details on this procedure and discusses the properties of the inflation risk 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 $\mathbb{E}_t[\overline{i}_{t,k}]$.

Column (3) in Table 2 reports the estimates of d when using the risk 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 1-5 years horizon, with the coefficient being identical to the one in the baseline specification.

3.3 Controlling for the zero lower bound constraint

The presence of the zero lower bound (ZLB) constraint implies, by construction, a reduced sensitivity of nominal interest rates to inflation changes when the former are expected to

[14]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 coefficient 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.

be near zero in the future. So, rather than an indication of a reduction in ψ_π post-2020, our results could be due to a binding or near-binding zero lower bound in this subsample.

In Table 1, we have already shown that our results survive when excluding from the analysis the [0-2] forward horizon—the most affected by the ZLB. In this section, we control for this issue more explicitly by allowing for the possibility of a ZLB constraint when specifying the monetary policy rule and by modifying our empirical strategy accordingly. Specifically, we assume that the Taylor rule in equation (5) holds for the "shadow" interest rate $\hat{i}_t$, while the observed interest rate is related to this shadow rate by the relation

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

Assuming further that $\varepsilon_{m,t}$ is a Gaussian i.i.d. random variable with mean 0 and variance σ_m, we have that the expected future short term rate at year k is given by

$$\mathbb{E}_t[i_{t+k}] = \rho_i \mathbb{E}_t[i_{t+k-1}] + (1-\rho_i)\left\{\mathbb{E}_t[i^\star_{t+k}] + \psi_\pi \mathbb{E}_t[\pi_{t+k} - \pi^\star]\right\} + f\left(\frac{\mathbb{E}_t[\hat{i}_{t+k}]}{\sigma_m}\right)\sigma_m, \quad (16)$$

where $f(x) = \varphi(x)/[1-\Phi(x)]$, with $\varphi(.)$ and $\Phi(.)$ being, respectively, the probability density function and the cumulative density function of the standard normal random variable.

We use equation (16) to modify our test. Specifically, consider a first order approximation of equation (16) around the point $\mathbb{E}_t[\pi_{t+k}] = \pi^\star$, $\mathbb{E}_t[i^\star_{t+k}] = \bar{i}^\star$ and $\mathbb{E}_t[i_{t+k-1}] = \bar{i}_{t,k-1}$.[15] We then have

$$\mathbb{E}_t\left[i_{t+k}\right] = \left(1 + \frac{1}{\sigma_m} f'_k\right)\left\{\rho_i \mathbb{E}_t[i_{t+k-1}] + (1-\rho_i)\left\{\mathbb{E}_t[i^\star_{t+k}] + \psi_\pi \mathbb{E}_t[\pi_{t+k} - \pi^\star]\right\}\right\}, \quad (17)$$

with

$$f'_k = f'\left(\frac{\rho_i \bar{i}_{t+k-1} + (1-\rho_i)\bar{i}^\star}{\sigma_m}\right).$$

The term in f'_k is negative and tends to be large in absolute value when the approximation point, $\rho_i \bar{i}_{t,k-1} + (1-\rho_i)\bar{i}^\star$, is close to zero. This is intuitive: the smaller $\rho_i \bar{i}_{k-1} + (1-\rho_i)\bar{i}^\star$ relative to the size of the monetary shocks, the more likely that the zero lower bound constraint will bind in year k. From this expression, we can also see how the presence of the ZLB affects our inference on ψ_π: for a given correlation between $\mathbb{E}_t[i_k]$ and $\mathbb{E}_t[\pi_k]$, we

[15] An alternative approach would be to use equation (16) and non-linear least squares to test the stability of ψ_π over time. However, in this approach we would need to have a proxy for the neutral interest rate $\mathbb{E}_t[i^\star_k]$. Rather than following this route, we approximate equation (16) to a first-order and apply the same methods employed previously to control for these two unobservables.

will infer a larger ψ_π the closer we expect to be to the ZLB.[16]

Importantly, f'_k is known up to $\bar{i}_{t,k-1}$, $\bar{i}^\star$ and σ_m. Our approach consists of two steps. First, we use data to calibrate these three parameters in order to obtain numerical values for $\{f'_k\}$ for each k. Specifically, we use the sample average of the Laubach and Williams (2016) indicator of the natural interest rate, add 2% inflation to obtain a value for $\bar{i}^\star$, and use the sample average of $\mathbb{E}_t[i_{t+k-1}]$ to set $\bar{i}_{t,k-1}$. Importantly, we let the values of $\bar{i}_{t,k-1}$ and $\bar{i}^\star$ vary across the two sub-samples, so as to allow for expectations of a binding ZLB to differ in the pre and post-pandemic periods. To be conservative, we set $\sigma_m = 0.03$ which is twice as large as the typical estimate of the standard deviation of monetary policy shocks.[17] We use these values to compute $\{f'_k\}$ for both sub-samples and use these coefficients along with equation (17) to obtain an expression for the revision in expectations about the average of the short term rate over the next k years

$$\Delta\mathbb{E}_t[\bar{i}_{t,k}] - \frac{1}{k}\sum_{j=1}^{k}\left(1+\frac{1}{\sigma_m}f'_j\right)\rho_i\Delta\mathbb{E}_t[i_{t+j-1}] = \psi_\pi\frac{1}{k}\sum_{j=1}^{k}\left(1+\frac{1}{\sigma_m}f'_j\right)(1-\rho_i)\Delta\mathbb{E}_t[\pi_{t+j}].$$

This expression is the equivalent 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 (4) of Table 2 reports the estimates of d for this specification. We can see that the results are robust to controlling for the presence of the ZLB constraint, as we find significant differences in ψ_π across the two sub-samples, especially when we consider short to medium-term expectations.

3.4 Additional sensitivity

We conducted additional sensitivity analyses, which are presented in Appendix C.2 to keep the main paper concise.

In the benchmark specification, we fix the persistence parameter of the Taylor rule ρ_i to 0.80 at an annual frequency. In the sensitivity analysis, we estimate equation (9) under different values of ρ_i, varying it between 0.7 and 0.9. We find that the estimated coefficient d is only marginally affected by these changes.

In a different exercise, we obtain risk-neutral expectations about future nominal interest rates and future inflation using overnight index swaps (OIS) and inflation-linked contracts (ILC), rather than nominal and real bond yields. This exercise is valuable because these

[16] To see this point, consider the special case in which $\rho_i = 0$ and $\mathbb{E}_t[i^\star_{t+k}] = 0$. Then, a consistent estimator of ψ_π would be $\psi_\pi^{OLS}/(1+\frac{1}{\sigma}f'_k)$. Holding ψ_π^{OLS} constant, the smaller is f'_k the larger the inferred ψ_π.

[17] This is conservative because a higher value of σ_m will tend to magnify differences between f'_k across regimes.

measures are thought to be less contaminated by the presence of liquidity premia and convenience yields relative to those that we are currently using in the analysis. As shown in the Appendix, we obtain very similar estimates for the coefficient d when estimating equation (9) using this data.[18]

4 Quantitative analysis

In the previous section we have presented evidence consistent with a perceived shift toward a more Dovish 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 4.1 presents the model, while section 4.2 discusses the estimation of its parameters. Section 4.3 uses the estimated model to measure the drivers of inflation during the recovery phase after the pandemic. By applying the particle filter, we show that the model explains the observed rise in inflation via a combination of negative supply shocks, increasing demand, and a switch toward the Dovish policy regime. We find that this shift in monetary policy accounts for roughly half of the observed increase in inflation.

Note that in the model, we take the view that the perceived change in policy was caused by a shift in the actual policy rule. However, one could model this as only a change in perceived policy while keeping actual policy unchanged. We show that our results are mostly driven by expectations of future monetary policy rather than a differing path for realized interest rates.

4.1 The model

Time is discrete and indexed by $t = 0, 1, ...$ The economy is populated by a continuum of identical and infinitely lived households, final good producers, intermediate good producers, and a monetary authority. Let s_t be the exogenous state of the economy. Let $s^t = (s_0, ..., s_t)$ be the history of events up through and including period t, and $p\left(s^t \mid s^{t-k}\right)$ be the probability of a history s^t given s^{t-k}.

Preferences and technology. Households have preferences over consumption, $c\left(s^t\right)$, and hours worked, $l\left(s^t\right)$ given by

$$\sum_{t=0}^{\infty} \beta^t \int_{s^t} \tilde{\theta}\left(s^t\right) U\left(C\left(s^t\right), L\left(s^t\right)\right) p\left(s^t \mid s_0\right) ds^t, \tag{18}$$

[18] We do not use swaps in the baseline analysis because of a data limitation issue, as reliable data on those contracts are available only for a subset of the 2000-2022 period and for fewer maturities.

where $U(C,L)$ has standard properties, β is the discount factor and $\tilde{\theta}\left(s^t\right)$ is a preference shock, our "demand shock".[19]

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

$$Y\left(s^t\right) = \left(\int_0^1 y_i\left(s^t\right)^{\frac{1}{\mu\left(s^t\right)}} di\right)^{\mu\left(s^t\right)} \tag{19}$$

where $\mu\left(s^t\right) > 1$ is related to the constant elasticity of substitution across varieties, $\epsilon(s^t)$, by the following relation: $\mu(s^t) = \epsilon(s^t)/[\epsilon(s^t) - 1]$. Time-variation in $\mu(s^t)$ will generate shifts in the Phillips curve. So, we will equivalently refer to $\mu(s^t)$ as the "supply shock".

The intermediate goods are produced using a linear technology,

$$y_i\left(s^t\right) = n_i\left(s^t\right) \tag{20}$$

where $n_i\left(s^t\right)$ denotes the labor utilized in the production of good i. Feasibility requires that $\int n_i(s^t)di = L(s^t)$.

Households. The stand-in household chooses consumption, leisure, and bond holdings to maximize (18) subject to their budget constraints

$$P\left(s^t\right) C\left(s^t\right) + B\left(s^{t+1}\right) \leq W\left(s^t\right) L\left(s^t\right) + \left(1 + i\left(s^t\right)\right) B\left(s^t\right) + \Pi\left(s^t\right)$$

where $P\left(s^t\right)$ is the price level, $W\left(s^t\right)$ is the nominal wage rate, $i\left(s^t\right)$ is the nominal interest rate, and $\Pi\left(s^t\right)$ denotes profits from the monopolistically competitive firms owned by stand-in household.

Final good producers. The final good is produced by competitive firms who choose inputs $y_i\left(s^t\right)$ to maximize

$$P\left(s^t\right) Y\left(s^t\right) - \int_0^1 P_i\left(s^t\right) y_i\left(s^t\right) di$$

where $Y\left(s^t\right)$ is given by (19) and $P_i\left(s^t\right)$ the price of intermediate good i. Using this problem, we can derive the demand function for variety i

$$y_i\left(s^t\right) = \left(\frac{P_i\left(s^t\right)}{P\left(s^t\right)}\right)^{\frac{\mu\left(s^t\right)}{1-\mu\left(s^t\right)}} Y\left(s^t\right) \tag{21}$$

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

and the price index is given by

$$P\left(s^t\right) = \left(\int_0^1 P_i\left(s^t\right)^{\frac{1}{1-\mu(s^t)}}\right)^{1-\mu\left(s^t\right)}.$$

Intermediate good producers. Each intermediate good is supplied by a monopolistically competitive firm that uses labor to operate the linear technology (20). The firm faces quadratic adjustment costs when changing their prices relative to the inflation target of the monetary authority $\pi^\star$,

$$\frac{\phi}{2}\left[\frac{P_i\left(s^t\right)}{P_i\left(s^{t-1}\right)\left(1+\pi^\star\right)}-1\right]^2.$$

Intermediate goods firms are owned by the stand-in household and discount profits using their stochastic discount factor. The problem of each intermediate goods firm is

$$\max_{\{P_i(s^t),y_i(s^t),n_i(s^t)\}} \sum_{t=0}^{\infty}\int_{s^t} Q\left(s^t\right)\left[P_i\left(s^t\right)y_i\left(s^t\right) - W\left(s^t\right)n_i\left(s^t\right) - \frac{\phi}{2}\left[\frac{P_i\left(s^t\right)}{P_i\left(s^{t-1}\right)\left(1+\overline{\pi}\right)}-1\right]^2\right]ds^t \quad (22)$$

subject to (20) and (21) and where the nominal stochastic discount factor is

$$Q\left(s^t\right) = \beta^t\frac{\tilde{\theta}(s^t)}{\tilde{\theta}(s_0)}\frac{U_c\left(s^t\right)/P(s^t)}{U_c\left(s_0\right)/P(s_0)}p\left(s^t|s_0\right).$$

Monetary policy. The monetary authority follows a Taylor rule with Markov switching regimes. There are two possible regimes $\xi \in \{H, D\}$. We think of regime H(awk) as a regime in which the monetary authority targets current inflation, while D(ove) is a regime in which the monetary authority targets a backward-looking average of inflation over a certain horizon. In particular, we have

$$\begin{aligned}1+i\left(s^t\right) = \left(1+i\left(s^{t-1}\right)\right)^{\rho_i} \times \Bigg\{ & \left(1+\bar{i}\right)\left[\frac{1+\mathbb{1}(\xi_t=H)\pi\left(s^t\right)+\mathbb{1}(\xi_t=D)\overline{\pi}_t\left(s^t\right)}{1+\pi^\star}\right]^{\psi_\pi(\xi_t)} \\ & \left(\frac{Y\left(s^t\right)}{\overline{y}}\right)^{\psi_y}\Bigg\}^{1-\rho_i} \times \exp\left\{\sigma_m\varepsilon_m\left(s_t\right)\right\} \quad (23)\end{aligned}$$

where $\bar{i}$ is the steady-state interest rate, $\pi^\star$ is the inflation target, $\overline{y}$ is the (constant) output under flexible prices, $\overline{\pi}_t\left(s^t\right) = \sum_{j=0}^{N}\pi_{t-j}\left(s^{t-j}\right)$ is average inflation over the previous N periods and $\varepsilon_m\left(s_t\right)$ is the monetary policy shock.

There are two differences between the regimes. First, in the H regime, the monetary authority aims to bring inflation at its target level $\pi^{\star}$ on a period-by-period basis, while in the D regime, that is true on average. This is a parsimonious way of capturing the adoption of the flexible average inflation targeting adopted after the Federal Reserve strategy review in 2020.[20] Second, we allow the responsiveness of nominal rates to inflation—$\psi_{\pi}(\xi_t)$—to vary across the two regimes.

Equilibrium. Given lagged prices and nominal interest rate, an equilibrium is a set of household's allocations $\left\{C\left(s^t\right), L\left(s^t\right), B\left(s^t\right)\right\}$, prices $\left\{P\left(s^t\right), W\left(s^t\right), i\left(s^t\right)\right\}$ such that i) the households' allocation solves the stand-in household's problem, ii) the price for the final good solves (22) with $P\left(s^t\right) = P_i\left(s^t\right)$, iii) the nominal interest rate satisfies the Taylor rule (23), iv) markets clear in that

$$L\left(s^t\right) = Y\left(s^t\right) = C\left(s^t\right) + \frac{\phi}{2}\left(\frac{\pi\left(s^t\right) - \pi^{\star}}{1+\pi^{\star}}\right)^2 \tag{24}$$

and $B\left(s^t\right) = 0$ as nominal bonds are in zero-net supply.

As is standard, the behavior of households and firms can be summarized by an Euler equation

$$1 = \left[1 + i_t\left(s^t\right)\right] \beta \int \left[\theta\left(s^{t+1}\right) \frac{U_c(s^{t+1})/U_c(s^t)}{1+\pi_{t+1}\left(s^{t+1}\right)}\right] p\left(s^{t+1}|s^t\right) ds^{t+1} \tag{25}$$

where $\theta\left(s^{t+1}\right) = \tilde{\theta}\left(s^{t+1}\right)/\tilde{\theta}\left(s^t\right)$, and a New Keynesian Phillips curve

$$\tilde{\pi}\left(s^t\right) = \frac{Y\left(s^t\right)\left[\mu\left(s^t\right) w\left(s^t\right) - 1\right]}{\phi\left[\mu\left(s^t\right) - 1\right]} + \beta \int \left[\theta\left(s^{t+1}\right) \frac{U_c(s^{t+1})/U_c(s^t)}{1+\pi_{t+1}\left(s^{t+1}\right)}\right] \tilde{\pi}\left(s^{t+1}\right) p\left(s^{t+1}|s^t\right) ds^{t+1} \tag{26}$$

where

$$\tilde{\pi}\left(s^t\right) = \left(\frac{\pi\left(s^t\right) - \pi^{\star}}{1+\pi^{\star}}\right)\left(\frac{1+\pi\left(s^t\right)}{1+\pi^{\star}}\right)$$

and $w\left(s^t\right) = -U_L\left(s^t\right)/U_c\left(s^t\right)$ is the real wage. Thus, the equilibrium can be characterized by a sequence $\left\{C_t\left(s^t\right), L\left(s^t\right), Y\left(s^t\right), \pi\left(s^t\right), i\left(s^t\right)\right\}$ that satisfies (23), (24), (25), and (26) given the stochastic processes for the shocks in the economy.

[20] The discussion in Section 2.3 clarified that flexible average inflation targeting prescribes a limited response when current inflation is above target following periods during which inflation has been consistently below targets due to a binding zero lower bound constraint. In our formulation, this behavior would be approximated by a shift to the D regime in conjunction with an initial condition of $\bar{\pi}(s^t) < \pi^{\star}$—as that would generate persistently low nominal interest rates even if inflation is currently above target.

4.2 Estimation

We now discuss the estimation of the model. We assume the following utility function

$$U(C,L) = \frac{C^{1-\sigma}}{1-\sigma} - \chi \frac{L^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}.$$

The exogenous state variables are $s_t = (\xi_t, \varepsilon_{m,t}, \mu_t, \theta_t)$. 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 $\hat{\mu}_t = \log(\mu_t)$,

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

where ε_θ and ε_μ are standard normal random variables.

The structural parameters are those governing preferences and technology, $[\sigma, \beta, \nu, \chi, \phi, \overline{\mu}]$, those governing policy, $[\pi^\star, \rho_i, \psi_y, \psi_\pi(H), \psi_\pi(D), N]$ and those governing the evolution of the shocks, $[\mathbf{P}, \sigma_\mu, \rho_\theta, \sigma_\theta, \rho_\mu, \sigma_\mu]$. We fix a subset of these parameters at conventional values. In particular, we assume that $\sigma = \nu = 1$, we set the average markup $\overline{\mu} = 1.2$ and normalize the preference parameter χ to $1/1.2$ so that consumption and output are equal to 1 in the deterministic steady state. We set the inflation target to 2% annually, $\pi^\star = .005$, and $\beta = .995$. so that the model roughly matches the average inflation and nominal interest rates in our sample. We fix the probability of transitioning from H to D to 0.006, which gives us an expected duration of the H regime of roughly 40 years, interpreting it as the monetary policy regime post-Volcker. Finally, we fix $N = 12$, implying that a period of three years for the averaging of inflation in the D regime, see Hebden, Herbst, Tang, Topa, and Winkler (2020).

For the other parameters, we proceed in two steps. While a detailed description of the estimation is provided in Appendix E.1, we summarize the key aspects of our approach and discuss the results here. First, we assume that for the 1984:Q1-2019:Q4 time period, the policy-maker was of a single type $\xi = H$ and we estimate the shock processes as well as the parameters $[\phi, \rho_i, \psi_\pi(H), \psi_y]$ on this sub-sample. The observables are the de-trended logarithm of employment, nominal interest rate, and the CPI inflation.[21] We approximate the model's policy functions using a first-order perturbation around the deterministic steady

[21] All these series are available at FRED, see Appendix D for a complete description. In our model, there is an equivalence between output and worked hours. We use employment data in the analysis rather than direct measures of output because the former have proved to be more predictive of inflation in recent years.

Table 3: 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	0.833	Normalize output to 1 in steady state			
$\overline{\mu}$	1.200	20% markup in steady state			
$\pi^\star$	0.005	Inflation target of 2%			
β	0.995	Annualized real interest rate of 2% in steady state			
N	12.000	3 year horizon when averaging inflation in the D regime			
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.
ϕ	58.35	[39.94,75.97]	Gamma	80.00	10.00
$\psi_\pi(H)$	2.52	[2.09,2.95]	Normal	1.50	0.50
ψ_y	0.29	[0.18,0.39]	Normal	1.50	0.50
ρ_i	0.90	[0.87,0.92]	Beta	0.50	0.29
ρ_μ	0.83	[0.73,0.93]	Beta	0.50	0.29
ρ_θ	0.94	[0.92,0.97]	Beta	0.50	0.29
$\sigma_\mu \times 100$	2.67	[1.85,3.48]	InvGamma	1.00	Inf
$\sigma_\theta \times 100$	0.17	[0.14,0.20]	InvGamma	1.00	Inf
$\sigma_m \times 100$	0.18	[0.15,0.20]	InvGamma	1.00	Inf
Panel C: **Parameters of Dovish rule**					
	Value	Notes			
$\psi_\pi(D)$	0.66	Point estimates of d, 1-5 yrs. **Data: -1.00, Model: -1.00**			
P_{DD}	0.83	Point estimates of d, 6-10 yrs. **Data: 0.00, Model: -0.03**			

Note: The Table reports the numerical value of the parameters that we use for the counterfactual exercise. A subset of parameters, reported in Panel A, are fixed to conventional values from the literature. The remaining parameters are estimated using a two-step procedure detailed in Appendix E.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 value of the parameters obtained in the second step.

state of the single regime model and estimate the structural parameters with Bayesian methods. 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.[22] The resulting estimates are broadly consistent with previous studies,

[22]This is the case in our application because—at any given point in time—the likelihood of transitioning

see panel B of Table 3.

In the second step, we estimate the remaining parameters of the Dovish regime—$\psi_\pi(D)$ and P_{DD}—to match the high frequency evidence presented in the previous sections. We choose as empirical targets d in equation (9) estimated using only monetary events: as argued earlier, these statistics are more indicative of an actual change in monetary policy in the presence of Taylor rules that feature an output gap component, like the one in the model. Specifically, we target a value of d equal to -1 for expectations over the 1-5 years horizon, and a value of d equal to 0 for the 6-10 years horizon. These numbers are conservative given the estimates in column (2) of Table 2. See Appendix E for a description of how we compute these objects in the model.

Panel C of Table 3 reports the numerical value of the parameters and an indicator 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 much smaller value of ψ_π in the D regime, 0.66 vs 2.49, and a conditional probability of remaining in the D regime of 83%.

4.3 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 we estimate the path 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: any difference between the actual and the counterfactual trajectories isolates the effect of the shift in the monetary policy rule on the outcome of interest. See Appendix E.2 for a description of these two steps.

The top panels of Figure 4 report the data for the period of analysis. We can observe a sharp increase in output and the large inflation spikes that characterized the recovery from the pandemic in the US, while nominal interest rate were kept persistently at zero throughout this period. The bottom panels of the figure report the (average) of the trajectories of the shocks that rationalize the data.

To reproduce the observed patterns in output, inflation, and nominal interest rates, the model requires a gradual recovery in household demand—represented by a declining path

from the H to D regime is very close to zero.

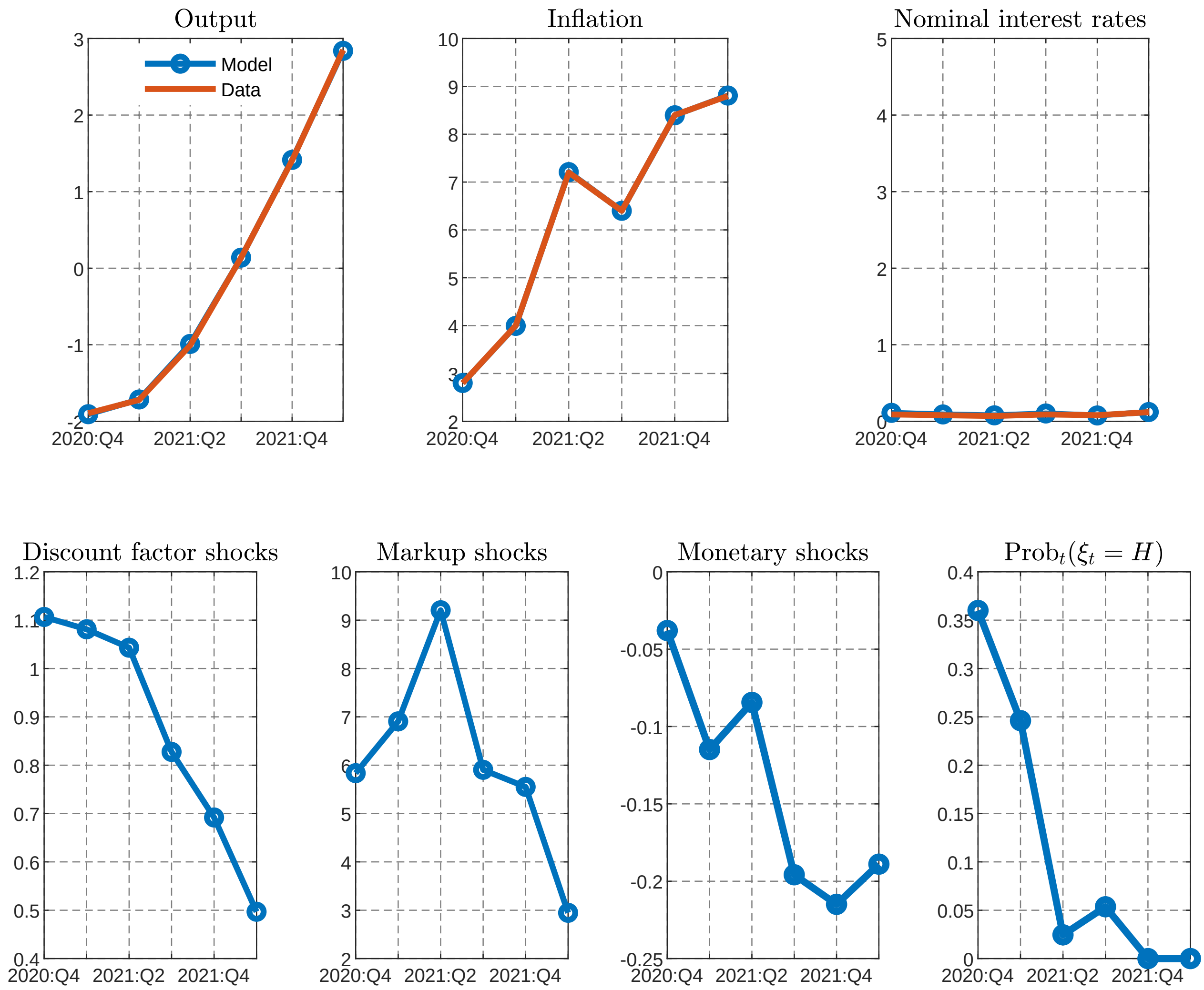


Figure 4: Event study, 2020:Q3-2022:Q1

Notes: The solid lines report the data used in the experiment. The circled lines report the posterior mean of the filtered series for the model counterpart and for the associated realization of the shocks generating that trajectory. Inflation and nominal interest rates are reported in (annualized) percentage points, and output is reported in percentage point deviations from its trend. The structural shocks are reported in percentage points deviations from their steady-state value. The bottom-right panel reports the probability of being in the H regime.

of $\hat{\beta}$ returning to its steady-state level—and an unusually large negative supply shock through the first half of 2021, as evidenced by the trajectory of the markup shocks. The former contributes to the strong recovery observed during the event, while the latter is needed to fit the increase in inflation observed during this period.

In addition, and consistent with our empirical analysis, we find evidence of a switch to the D regime. By 2021:Q2, the historical Taylor rule would have predicted substantially higher interest rates than observed, given that inflation was at 7% and output had nearly returned to its trend. Thus, the model infers a switch to the average inflation targeting

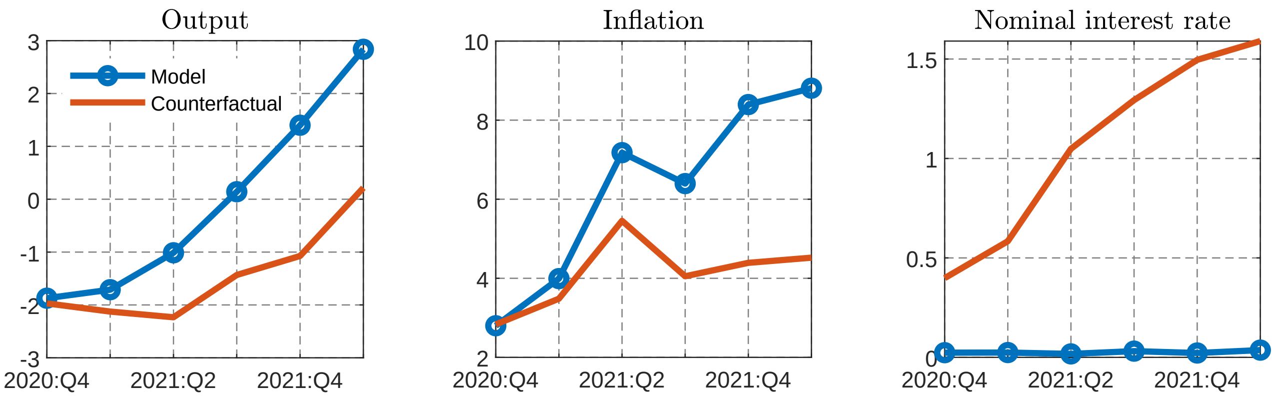


Figure 5: Output, inflation and nominal interest rate under the H regime

Notes: The circled lines report output, nominal interest rates and inflation during the event. Nominal interest rates and inflation are reported in percentage points, and output in percentage points deviations from their trend. The solid line reports the posterior men of the same variable in the counterfactual economy in which the monetary authority did not change to average inflation targeting—$\xi_t = H$ throughout the event.

regime, which, under our parametrization, results in a more inertial path for nominal interest rates, keeping them closer to zero. Interestingly, the model does not need unusually large monetary shocks to fit the data, as the realization of $\varepsilon_{m,t}$ in most periods falls within one standard deviation from its mean. This indicates that the Taylor rule that we have specified is not only consistent with the empirical evidence on expectations we have documented in Section 2 and 3, but it also fits realized data on output, inflation and nominal interest rates in our episode as well as the traditional Taylor rule fits historical realizations of these variables.

With the realized shock processes in hand, we can now use the model to perform a counterfactual analysis. Specifically, we input the estimated values of $\{\hat{\theta}_t, \hat{\mu}_t, \varepsilon_{m,t}\}$ into the model, but compute the path of the endogenous variables under a counterfactual scenario where $\xi_t = H$ in all periods during this episode. This experiment, therefore, estimates how the economy would have evolved if there had been no shift in the Fed's policy rule.

The solid lines in Figure 5 report the path for output, inflation, and nominal interest rates in the counterfactual. In contrast with the realized observations, the nominal interest rate would have been above zero and would have increased steadily throughout the episode under the H regime. The model tells us that the impact of this policy change on output and inflation would have been sizable: by the end of 2021, output would have been approximately three percentage points and inflation four percentage points below their observed value.

In order to understand why inflation is so sensitive to changes in the monetary regime, we can iterate forward the linearized Phillips curve (26) and the Euler equation (25) to obtain

$$\hat{y}_t = -\frac{1}{\sigma}\sum_{j=0}^{\infty}\mathbb{E}_t[\hat{r}_{t+j}] - \frac{1}{\sigma}\sum_{j=0}^{\infty}\mathbb{E}_t[\hat{\theta}_{t+1+j}], \tag{27}$$

$$\hat{\pi}_t = \kappa\sum_{j=0}^{\infty}\beta^j\mathbb{E}_t[\hat{y}_{t+j}] + \kappa\sum_{j=0}^{\infty}\beta^j\mathbb{E}_t[\hat{\mu}_{t+j}] \tag{28}$$

where $\hat{r}_{t+j} = \hat{i}_{t+j} - \mathbb{E}_{t+j}[\hat{\pi}_{t+j+1}]$ is the real interest rate at time $t+j$. Substituting equation (27) in (28), and using the fact that the path of the structural shocks is held constant in our counterfactual, we can then write the difference between the inflation rate under the D and the H regime as

$$\begin{aligned}\hat{\pi}_t^D - \hat{\pi}_t^{\mathrm{H}} &= -\frac{\kappa}{\sigma}\Big\{\left(\hat{r}_t^D - \hat{r}_t^H\right) + (1+\beta)\left[\mathbb{E}_t(\hat{r}_{t+1}|\xi_t = D) - \mathbb{E}_t(\hat{r}_{t+1}|\xi_t = H)\right] \\ &+ (1+\beta+\beta^2)\left[\mathbb{E}_t(\hat{r}_{t+2}|\xi_t = D) - \mathbb{E}_t(\hat{r}_{t+2}|\xi_t = H)\right] + \ldots\Big\},\end{aligned} \tag{29}$$

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

Equation (29) clarifies that the switch to the H regime in the counterfactual affects inflation at time t by changing the entire term structure of real interest rates. Since the slope of the Phillips curve is fairly flat in our parametrization ($\kappa = 0.10$), changes in *current* real interest rates have minimal impact on inflation at date t. However, the policy shift can still have sizable effects on current inflation because its sensitivity to expected future interest rates increases over the forward horizon, converging to $\frac{\kappa}{\sigma(1-\beta)}$ for very long-term real interest rates. This occurs because changes in expected future interest rates influence agents' expectations about future output gaps via equation (27), which, in turn, affect firms' current pricing decisions through the Phillips curve (28).

The circled line in Figure 6 plots the model implied term structure of real interest rate expectations averaged over the event. We can see that in the counterfactual scenario, real interest rate expectations over a two-year horizon are higher relative to those predicted by the model during the event. This is intuitive. The only difference between the two lines lies in the conduct of monetary policy, which in the event is characterized by the D regime while in the counterfactual by the H regime. Under the D regime, agents expect the monetary authority to respond more slowly to shocks that affect inflation relative to what they would expect under the H regime. Because the event is characterized by inflationary shocks, expectations of a slower response translate into expectations of lower real interest rates. These lower interest rates are expected to last for only 8 quarters due to the transitory nature of the D regime and the markup shocks. These movements in expected future real interest rates are not empirically implausible. Yields on TIPS with a residual maturity of

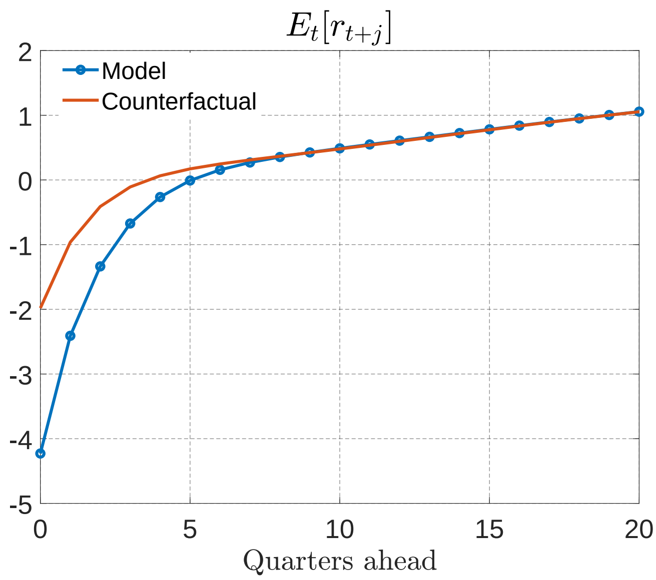


Figure 6: The term structure of real interest rates expectations

Notes: The circled lines report $\mathbb{E}_t[r_{t+j}]$ as a function of the maturity j averaged over the event. The solid line reports the same model objects in the counterfactual economy with $\xi_t = H$ throughout the event.

two years increased by 1.5% shortly after the lift-off event of March 2022, in the same order of magnitudes as those predicted by the model in Figure 6 if we interpreted the lift-off as a switch back to the H regime.

Although the movements in real interest rates across the two regimes are empirically plausible, their effects on output and inflation should be interpreted with caution. From equation (29), we can see that movements in long-term real rates have large effects on inflation because of their outsized effects on the output gap—often referred to in the literature as the "forward guidance puzzle" (Del Negro et al., 2012)—and because of the forward-looking nature of inflation in the New Keynesian model. If one believes that these features result in excessive sensitivity to long-term interest rates, our results should be considered an upper bound on the effects of monetary policy on inflation. Caravello, McKay, and Wolf (2024) also document, using a semi-structural approach, that a shift in the monetary policy rule has sizable effects on the economy when considering the classic rational expectation New Keynesian model, and they show that introducing behavioral elements as in Gabaix (2020) reduces the sensitivity of inflation to these changes.[23] In future research, we plan to build on this insight and conduct our analysis in an economy that exhibits a more realistic sensitivity of inflation to current and future real interest rates.

[23]Other ways of reducing this sensitivity would be that of incorporating imperfect information as in Angeletos and Lian (2018) or introducing incomplete financial markets as in McKay, Nakamura, and Steinsson (2016).

5 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' 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 these expectations following the adoption of the flexible average inflation targeting framework in 2020.

We have also shown how we can use 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 the baseline New Keynesian model, we find that the shift to the flexible average inflation targeting regime accounts for around half of the increase in inflation observed during the sample. This result depends heavily on the details of the structural model that we used, which we kept quite simple for illustrative purposes. We believe that assessing the positive and normative implications of the documented shifts in the monetary policy rule in more quantitatively relevant models is a fruitful avenue for future research.

Going forward, it would be interesting to apply our framework to analyze how different countries adjusted their monetary policies in response to the pandemic. Although only the Federal Reserve formally changed its monetary policy framework, many other central banks in advanced economies refrained from responding to rising inflationary pressures in 2021, which may have influenced private sector views on their resolve to controlling inflation. In contrast, central banks in several emerging economies reacted more swiftly and experienced milder increases in inflation. 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 leave this exciting question for future research.

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Appendix

A The asymptotic distribution of the OLS estimator of $\hat{d}$ in equation (9)

Consider a sample of random variables $\{x_t, y_t\}$, with x being the treatment of interest and y being the outcome. There is a structural break in the sample, given by a deterministic sequence $\{D_t\}$ where $D_t = 0$ before the break, and $D_t = 1$ after the break. Suppose our goal is to estimate how the effect of x on y changes after the structural break happens. We will show that if the first and second moments, and the covariance of x and the errors are unchanged over the break, then, under appropriate regularity conditions, the estimator is consistent and we can use the usual OLS procedure with robust standard errors to test whether the treatment effect of x changes with the structural break.

More formally, we assume that the outcome y and treatment x satisfy

$$y_t = \alpha + \beta x_t + d x_t D_t + \eta_t$$

where η_t are the errors. We show the asymptotic properties of the test under serial independence assumption. We also assume that the variables are identically distributed conditional on D_t, but the distribution could differ before and after the break. The exceptions are that the first and second moments of η_t, x_t and their covariance, which we assume to be unchanged by the break. Additionally, we assume the relevant regularity conditions on finiteness of moments hold, without loss of generality we impose that the mean of errors is 0, and we assume that the share of observation in the sample from after the break converges to a number strictly between zero and one. Under these assumptions, we can consistently estimate d using OLS, the asymptotic distribution of the OLS estimator of d is normal, and the usual robust variance estimator converges to the asymptotic variance of the OLS estimator of d. The assumptions and the proof are formalized below.

Assumption 1. *Consider sequence of serially independent random variables $\{x_t, \eta_t\}$ and a deterministic sequence $\{D_t\}$ with $D_t \in \{0, 1\}$*

1. *The random vectors $\{(x_t, \eta_t)\}_t$ are serially independent.*
2. *Given $D \in \{0, 1\}$, the random variables $\{x_t, \eta_t\}_{t, D_t = D}$ are identically distributed .*
3. *Let $\mathbb{E}_D$ denote the expectation of a function of x_t, η_t for the subsample with $D_t = D$.*

$$\mathbb{E}_0[x] = \mathbb{E}_1[x], \qquad \mathbb{E}_0\left[x^2\right] = \mathbb{E}_1\left[x^2\right], \qquad \mathbb{E}_0\left[\eta^2\right] = \mathbb{E}_1\left[\eta^2\right], \qquad \mathbb{E}_0[\eta x] = \mathbb{E}_1[\eta x].$$

I.e. these moments are constant across the break. Denote the expectation for these moments by $\mathbb{E}$ instead of $\mathbb{E}_D$.

4. *For all $D \in \{0,1\}$, there is $\delta > 0$ s.t. $\mathbb{E}_D\left[\eta_t^{4+\delta}\right] < \infty, \mathbb{E}_D\left[x_t^{4+\delta}\right] < \infty$.*
5. $\mathbb{E}_0[\eta_t] = \mathbb{E}_1[\eta_t] = 0$.
6. $\sum_t D_t/T \to \theta \in (0,1)$.

Proposition 2. *Suppose that the sequence of random variables $\{y_t, x_t, \eta_t\}$ and the deterministic sequence $\{D_t\}$ with $D_t \in \{0,1\}$ satisfy*

$$y_t = \alpha + \beta x_t + d x_t D_t + \eta_t$$

Let $\hat{d}^{OLS}$ be the OLS estimator of d. Under the assumption 1, as $T \to \infty$

$$\sqrt{T}\left(\hat{d}^{OLS} - d\right) \xrightarrow{d} \mathcal{N}(0, \mathbb{V})$$

where

$$\mathbb{V} \equiv \sum_{D\in\{0,1\}} \left\{ \frac{(\theta(1-D) + (1-\theta)D)}{\theta(1-\theta)\mathbb{E}[x^2]^2} \mathbb{E}_D\left[\left((x_t\eta_t - \mathbb{E}[\eta x]) + \mathbb{E}[\eta x]\frac{(x_t - \mathbb{E}[x])\mathbb{E}[x] - (x_t^2 - \mathbb{E}[x^2])}{\mathrm{Var}(x)}\right)^2\right]\right\}.$$

Furthermore, we have that the OLS variance estimator converges in probability to $\mathbb{V}$.

Proof. Define $D_t \equiv D_t x_t$. By Frisch-Waugh-Lowell theorem, we have

$$\hat{d}^{OLS} = d + \left[D^{x\top} M D^x\right]^{-1} D^{x\top} M\eta,$$

where

$$M \equiv I - P, \qquad P \equiv Z\left(Z^\top Z\right)^{-1} Z, \qquad Z \equiv \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_T \end{bmatrix}.$$

Rearrange the equation to obtain

$$\sqrt{T}\left(\hat{d}^{OLS} - d\right) = \left[\frac{1}{T} D^{x\top} M D^x\right]^{-1} \sqrt{T}\frac{1}{T} D^{x\top} M\eta,$$

where

$$
\begin{aligned}
\sqrt{T}\frac{1}{T}D^{x\top}M\eta = {} & \sqrt{T}\left(\frac{1}{T}\sum_t D_t\left(x_t\eta_t - \mathbb{E}\left[\eta x\right]\right)\right) \\
& - \frac{\sum_t D_t}{T}\frac{\left(\frac{1}{T}\sum_i x_i^2\right)\left(\frac{1}{\sum_t D_t}\sum_{t:D_t=1}x_t\right) - \left(\frac{1}{\sum_t D_t}\sum_{t:D_t=1}x_t^2\right)\left(\frac{1}{T}\sum_i x_i\right)}{T^{-1}\sum_i x_i^2 - \left(T^{-1}\sum_i x_i\right)^2}\sqrt{T}\frac{1}{T}\sum_\ell \eta_\ell \\
& - \frac{\sum_t D_t}{T}\frac{\left(\frac{1}{\sum_t D_t}\sum_{t:D_t=1}x_t^2\right) - \left(\frac{1}{\sum_t D_t}\sum_{t:D_t=1}x_t\right)\frac{1}{T}\sum_i x_i}{T^{-1}\sum_i x_i^2 - \left(T^{-1}\sum_i x_i\right)^2}\sqrt{T}\left(\frac{1}{T}\sum_\ell \eta_\ell x_\ell - \mathbb{E}\left[\eta x\right]\right) \\
& - \frac{\sum_t D_t}{T}\frac{\left(\sqrt{T}\left(\frac{1}{T}\sum_i x_i^2 - \mathbb{E}\left[x^2\right]\right) + \sqrt{T}\left(\frac{1}{T}\sum_i x_i - \mathbb{E}\left[x\right]\right)\left(T^{-1}\sum_i x_i\right)\right]\Big)}{T^{-1}\sum_i x_i^2 - \left(T^{-1}\sum_i x_i\right)^2}\mathbb{E}\left[\eta x\right].
\end{aligned}
$$

Define

$$
W_t \equiv \begin{bmatrix} \eta_t \\ D_t\left(x_t - \mathbb{E}\left[x\right]\right) \\ D_t\left(x_t^2 - \mathbb{E}\left[x^2\right]\right) \\ D_t\left(x_t\eta_t - \mathbb{E}\left[\eta x\right]\right) \\ x_t - \mathbb{E}\left[x\right] \\ x_t^2 - \mathbb{E}\left[x^2\right] \\ x_t\eta_t - \mathbb{E}\left[\eta x\right] \end{bmatrix}.
$$

Note that the assumption (1) implies that Lyapunov's condition holds. By Lindeberg CLT, we have that

$$
\sqrt{T}\frac{1}{T}\sum_t W_t \xrightarrow{d} \mathcal{N}\left(0, \mathbf{V}\right),
$$

where

$$
\begin{aligned}
\mathbf{V} &= (1-\theta)\,\mathbb{E}_0\begin{bmatrix} \eta^2 & \mathbf{0} & \eta H^\top \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \eta H & \mathbf{0} & HH^\top \end{bmatrix} + \theta\mathbb{E}_1\begin{bmatrix} \eta^2 & \eta H^\top & \eta H^\top \\ \eta H & HH^\top & HH^\top \\ \eta H & HH^\top & HH^\top \end{bmatrix}, \\
H_t &\equiv \begin{bmatrix} \left(x - \mathbb{E}\left[x\right]\right) \\ \left(x^2 - \mathbb{E}\left[x^2\right]\right) \\ \left(x\eta - \mathbb{E}\left[\eta x\right]\right) \end{bmatrix},
\end{aligned}
$$

with $\mathbb{E}_D\left[f\left(x_t, \eta_t\right)\right]$ being the expectation $f\left(x_t, \eta_t\right)$ for t s.t. $D_t = D$. Next, we apply the Delta method. Define

$$G \equiv \begin{bmatrix} 0 \\ \frac{\mathbb{E}[x]}{\mathrm{Var}(x)}\mathbb{E}\left[\eta x\right] \\ -\frac{1}{\mathrm{Var}(x)}\mathbb{E}\left[\eta x\right] \\ 1 \\ -\frac{\theta\mathbb{E}[x]}{\mathrm{Var}(x)}\mathbb{E}\left[\eta x\right] \\ \frac{\theta}{\mathrm{Var}(x)}\mathbb{E}\left[\eta x\right] \\ -\theta \end{bmatrix}, \qquad g \equiv \begin{bmatrix} \frac{\mathbb{E}[x]}{\mathrm{Var}(x)}\mathbb{E}\left[\eta x\right] \\ -\frac{1}{\mathrm{Var}(x)}\mathbb{E}\left[\eta x\right] \\ 1 \end{bmatrix}.$$

Applying the Delta method, we obtain that

$$\sqrt{T}\frac{1}{T}D^{x\top}M\eta \xrightarrow{d} \mathcal{N}\left(0, G^{\top}\mathbf{V}G\right).$$

Finally, note that

$$\begin{aligned}\frac{1}{T}D^{x\top}MD^{x} = {} & \frac{\sum_t D_t}{T}\frac{1}{\sum_t D_t}\sum_h D_h x_h^2 - \frac{1}{T^{-1}\sum_i x_i^2 - \left(T^{-1}\sum_i x_i\right)^2} \\ & \left\{ \left(\frac{1}{T}\sum_i x_i^2\left(\frac{\sum_t D_t}{T}\frac{1}{\sum_t D_t}\sum_h D_h x_h\right) - \left(\frac{\sum_t D_t}{T}\frac{1}{\sum_t D_t}\sum_h x_h^2 D_h\right)\frac{1}{T}\sum_i x_i\right)\frac{\sum_t D_t}{T}\frac{1}{\sum_t D_t}\sum_\ell d_\ell x_\ell \right. \\ & \left. + \frac{\left(\left(\frac{\sum_t D_t}{T}\frac{1}{\sum_t D_t}\sum_h x_h^2 D_h\right) - \left(\frac{\sum_t D_t}{T}\frac{1}{\sum_t D_t}\sum_h D_h x_h\right)\frac{1}{T}\sum_i x_i\right)}{T^{-1}\sum_i x_i^2 - \left(T^{-1}\sum_i x_i\right)^2}\frac{\sum_t D_t}{T}\frac{1}{\sum_t D_t}\sum_\ell d_\ell x_\ell^2 \right\}.\end{aligned}$$

This converges in probability to

$$\theta\mathbb{E}\left[x^2\right] - 0 * \mathbb{E}\left[x\right] - \theta^2\mathbb{E}\left[x^2\right] = \theta\left(1-\theta\right)\mathbb{E}\left[x^2\right].$$

Hence

$$\sqrt{T}\left(\hat{d}^{OLS} - d\right) \xrightarrow{d} \mathcal{N}\left(0, \mathbb{V}\right).$$

where

$$\mathbb{V} \equiv \frac{G^{\top}\mathbf{V}G}{\theta^2\left(1-\theta\right)^2\mathbb{E}\left[x^2\right]^2}, \tag{A.1}$$

$$G^{\top}\mathbf{V}G = \left(1-\theta\right)\theta^2 g^{\top}\mathbb{E}_0\left[HH^{\top}\right]g + \left(1-\theta\right)^2\theta g^{\top}\mathbb{E}_1\left[HH^{\top}\right]g, \tag{A.2}$$

$$g^{\top}\mathbb{E}_D\left[HH^{\top}\right]g=\mathbb{E}_D\left[\left(\left(x_t\eta_t-\mathbb{E}\left[\eta x\right]\right)+\mathbb{E}\left[\eta x\right]\frac{\left(x_t-\mathbb{E}\left[x\right]\right)\mathbb{E}\left[x\right]-\left(x_t^2-\mathbb{E}\left[x^2\right]\right)}{\mathrm{Var}\left(x\right)}\right)^2\right], \tag{A.3}$$

with $D\in\{0,1\}$.The standard OLS estimator would posit that $\mathbb{E}\left[\eta x\right]=0$. Under $\mathbb{E}\left[\eta x\right]=0$, the estimand of the OLS variance estimator would correspond to

$$\frac{\theta\mathbb{E}_0\left[x^2\eta^2\right]+\left(1-\theta\right)\mathbb{E}_1\left[x^2\eta^2\right]}{\theta\left(1-\theta\right)\mathbb{E}\left[x^2\right]^2}.$$

Suppose we were to estimate this by a naive OLS estimator. The OLS robust variance estimator would correspond to

$$\frac{\frac{\sum_t \mathbf{1}_{D_t=1}}{T}\frac{1}{\sum_t \mathbf{1}_{D_t=0}}\sum_{t:D_t=0}x_t^2\hat{\eta}_t^2+\frac{\sum_t \mathbf{1}_{D_t=0}}{T}\frac{1}{\sum_t \mathbf{1}_{D_t=1}}\sum_{t:D_t=1}x_t^2\hat{\eta}_t^2}{\frac{\sum_t \mathbf{1}_{D_t=1}}{T}\frac{\sum_t \mathbf{1}_{D_t=0}}{T}\left[\frac{1}{T}\sum_t x_t^2\right]^2}. \tag{A.4}$$

We will now show that this in fact converges to $G^{\top}\mathbf{V}G$. Define

$$U\equiv\begin{bmatrix}1 & x_1 & d_1x_1\\ \vdots & \vdots & \vdots\\ 1 & x_T & D_tx_T\end{bmatrix},\qquad U_t\equiv\begin{bmatrix}1 & x_t & D_tx_t\end{bmatrix},\qquad \delta\equiv\begin{bmatrix}\alpha\\ \beta\\ d\end{bmatrix}.$$

We now want to evaluate the probability limit of $\frac{1}{\sum_t \mathbf{1}_{D_t=D}}\sum_{t:D_t=D}x_t^2\hat{\eta}_t^2$ for $D\in\{0,1\}$. Note that

$$\begin{aligned}\sum_{t:D_t=D}x_t^2\hat{\eta}_t^2&=\sum_{t:D_t=D}x_t^2\left(y_t-\hat{\alpha}-\hat{\beta}x_t-\hat{d}^{OLS}x_tD_t\right)^2\\&=\sum_{t:D_t=D}x_t^2\left(\eta_t-U_t\left(\hat{\delta}-\delta\right)\right)^2\\&=\sum_{t:D_t=D}x_t^2\eta_t^2+\sum_{t:D_t=D}x_t^2\left[U_t\left(\hat{\delta}-\delta\right)\right]^2-2\sum_{t:D_t=D}x_t^2\eta_t\left[U_t\left(\hat{\delta}-\delta\right)\right],\end{aligned}$$

where we used $\hat{\delta}-\delta=\left(U^{\top}U\right)^{-1}U^{\top}\eta$. The probability limit of $\left(U^{\top}U\right)^{-1}U^{\top}\eta$ is given by

$$\left(U^{\top}U\right)^{-1}U^{\top}\eta\xrightarrow{p}\frac{1}{\mathbb{E}\left[x^2\right]\mathrm{Var}\left(x\right)\theta\left(1-\theta\right)}\begin{bmatrix}\left(-\mathbb{E}\left[x\right]\mathbb{E}\left[x^2\right]\theta\left(1-\theta\right)\right)\mathbb{E}\left[\eta x\right]\\ \mathbb{E}\left[x^2\right]\theta\left(1-\theta\right)\mathbb{E}\left[\eta x\right]\\ 0\end{bmatrix}.$$

Therefore $U_t\left(\hat{\delta}-\delta\right)=\frac{\mathbb{E}[\eta x]}{\mathrm{Var}(x)}\left(x_t-\mathbb{E}\left[x\right]\right)+o_p\left(1\right)$. Using this, we obtain that the probability of limit of $\frac{1}{\sum_t \mathbf{1}_{D_t=D}}\sum_{t:D_t=D}x_t^2\hat{\eta}_t^2$ is

$$\frac{1}{\sum_t \mathbf{1}_{D_t=D}}\sum_{t:D_t=D}x_t^2\hat{\eta}_t^2 \xrightarrow{p} \mathbb{E}_D\left[x^2\eta^2\right]+\left(\frac{\mathbb{E}\left[\eta x\right]}{\mathrm{Var}\left(x\right)}\right)^2\left(\mathbb{E}_D\left[x^4\right]-2\mathbb{E}_D\left[x^3\right]\mathbb{E}\left[x\right]+\mathbb{E}\left[x^2\right]\mathbb{E}\left[x\right]^2\right)$$
$$-2\frac{\mathbb{E}\left[\eta x\right]}{\mathrm{Var}\left(x\right)}\left(\mathbb{E}_D\left[x^3\eta\right]-\mathbb{E}_D\left[x^2\eta\right]\mathbb{E}\left[x\right]\right). \tag{A.5}$$

Note that we can rewrite this probability limit as

$$\mathbb{E}_D\left[x_t^2\eta_t^2\right]+\left(\frac{\mathbb{E}\left[\eta x\right]}{\mathrm{Var}\left(x\right)}\right)^2\left(\mathbb{E}_D\left[x^4\right]-2\mathbb{E}_D\left[x^3\right]\mathbb{E}\left[x\right]+\mathbb{E}\left[x^2\right]\mathbb{E}\left[x\right]^2\right)-2\frac{\mathbb{E}\left[\eta x\right]}{\mathrm{Var}\left(x\right)}\left(\mathbb{E}_D\left[x^3\eta\right]-\mathbb{E}_D\left[x^2\eta\right]\mathbb{E}\left[x\right]\right)$$
$$=\mathbb{E}_D\left[\left(\left(x_t\eta_t-\mathbb{E}\left[\eta x\right]\right)+\mathbb{E}\left[\eta x\right]\frac{\left(x_t-\mathbb{E}\left[x\right]\right)\mathbb{E}\left[x\right]-\left(x_t^2-\mathbb{E}\left[x^2\right]\right)}{\mathrm{Var}\left(x\right)}\right)^2\right].$$

Hence the limit of $\frac{1}{\sum_t \mathbf{1}_{D_t=D}}\sum_{t:D_t=D}x_t^2\hat{\eta}_t^2$ (A.5) corresponds to A.3. Combined with the fact that $\frac{1}{T}\sum_t x_t^2 \xrightarrow{p} \mathbb{E}\left[x^2\right]$, we have that the OLS estimator of variance (A.4) converges to $\mathbb{V}$ (A.1). □

B Proof of Proposition 1

Consider the textbook New-Keynesian model (Woodford, 2003; Galí, 2015) described in the main text with a single monetary policy regime. In the log-linearized model, the dynamics for the endogenous variables must satisfy

$$\hat{y}_t=\mathbb{E}_t\left[\hat{y}_{t+1}\right]-\frac{1}{\sigma}\left(\hat{i}_t-\mathbb{E}_t\left[\hat{\pi}_{t+1}-\hat{\theta}_{t+1}\right]\right) \tag{Euler}$$
$$\hat{\pi}_t=\beta\mathbb{E}_t\left[\hat{\pi}_{t+1}\right]+\kappa\hat{y}_t+\kappa\hat{\mu}_t \tag{NKPC}$$
$$\hat{i}_t=\rho_i\hat{i}_{t-1}+\left(1-\rho_i\right)\left\{\psi_\pi\hat{\pi}_t+\psi_y\hat{y}_t\right\}+\hat{m}_t \tag{Taylor}$$

where y_t, $\hat{\pi}_t$ and $\hat{i}_t$ are, respectively, output, inflation and nominal interest rates expressed in log-deviations from steady state; β is the rate of time preference, $1/\sigma$ is the intertemporal elasticity of substitution for the stand-in household, ρ_i, ψ_π, ψ_y are the parameters describing the Taylor rule, and κ the slope of the Phillips curve,

$$\kappa=\frac{Y_{ss}\left(\frac{1}{\nu}+\sigma\right)}{\phi\left(\overline{\mu}-1\right)}=\frac{\left(\frac{1}{\nu}+\sigma\right)}{\phi\left(\overline{\mu}-1\right)}$$

where ν is the Frisch-elasticity of labor supply.[24] The economy is perturbed by three shocks: a shock to households' preferences, $\hat{\theta}_t$, a markup shock, $\hat{\mu}_t$ and a monetary shock $\hat{m}_t$. We assume that the preference and the markup shocks follow independent AR(1) processes:

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

while we assume that the monetary shock is iid, $\hat{m}_t = \varepsilon_{m,t}$.

We now prove Proposition 1, restated here for convenience. (The statement of the proposition is unchanged if the monetary shocks are persistent, $\hat{m}_t = \rho_m \hat{m}_{t-1} + \sigma_m \varepsilon_{m,t}$, provided that $k \to \infty$ and $\rho_y > \rho_m$.)

Proposition. *Consider the log-linearized three-equations New Keynesian model. Let $\rho_y \in (0,1)$ be the solution to*

$$\rho_y = \rho_i - (1-\rho_i)\frac{1}{\sigma}\frac{\rho_y\left(\psi_\pi \frac{\kappa}{1-\beta\rho_y} + \psi_y\right)}{\left(1-\rho_y - \frac{1}{\sigma}\frac{\kappa}{1-\beta\rho_y}\rho_y\right)} \tag{A.6}$$

where κ is the slope of the Phillips curve, β is the rate of time preference of the representative household, and σ is the inverse of the elasticity of intertemporal substitution. Let $\mathbb{E}_t^m[\xi_k]$ be the forecast update for variable ξ at date $k > t$ given that we learn of a realization of the monetary shock at date t,

$$\mathbb{E}_t^m[\xi_k] \equiv \mathbb{E}[\xi_k|\mathcal{I}^t, \varepsilon_{m,t}] - \mathbb{E}[\xi_k|\mathcal{I}^t].$$

Consider a linear projection of $\mathbb{E}_t^m\left[\hat{i}_{t+k} - \rho_i \hat{i}_{t+k-1}\right]$ on a constant and $\mathbb{E}_t^m\left[(1-\rho_i)\hat{\pi}_{t+k}\right]$, and denote by $\hat{\psi}_\pi^{OLS,m}$ the projection coefficient. Then, the probability limit of $\hat{\psi}_\pi^{OLS,m}$ is

$$\hat{\psi}_\pi^{OLS,m} \to \psi_\pi + \psi_y \frac{(1-\beta\rho_y)}{\kappa}. \tag{A.7}$$

Proof. First, note that the bounded solution to the the log-linearized economy can be represented by policy functions that are linear in the state variables, $[\hat{i}_{t-1}, \hat{\theta}_t, \hat{\mu}_t, \hat{m}_t]$. We can write the policy functions for nominal interest rates and the output as

$$\hat{i}_t = a_i \hat{i}_{t-1} + \mathbf{b}_i \cdot \omega_t \tag{A.8}$$

$$y_t = a_y \hat{i}_{t-1} + \mathbf{b}_y \cdot \omega_t, \tag{A.9}$$

where $\mathbf{b}_r = (b_{r\theta}, b_{r\mu}, b_{rm})$, $r \in \{i, y\}$, $\omega_t = (\hat{\theta}_t, \hat{\mu}_t, \hat{m}_t)$ and the coefficients are functions of

[24] Steady state output, Y_{ss}, is normalized to 1.

model parameters. We will show next, using the method of undetermined coefficients, that a_i is the solution to

$$a_i = \rho_i - (1-\rho_i)\frac{1}{\sigma}\frac{a_i\left(\psi_\pi \frac{\kappa}{1-\beta a_i} + \psi_y\right)}{\left(1 - a_i - \frac{1}{\sigma}\frac{\kappa}{1-\beta a_i}a_i\right)} \tag{A.10}$$

with $|a_i| < 1$.

From the linearity of (Taylor) and the iid assumption on monetary shocks, it follows that

$$\hat{\psi}_\pi^{OLS,m} \to \psi_\pi + \psi_y \frac{\mathrm{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}], \mathbb{E}_t^m[\hat{y}_{t+k}]\right)}{\mathrm{Var}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}]\right)}. \tag{A.11}$$

We now express the bias, $\frac{\mathrm{Cov}(\mathbb{E}_t^m[\hat{\pi}_{t+k}], \mathbb{E}_t^m[\hat{m}_{t+k}])}{\mathrm{Var}(\mathbb{E}_t^m[\hat{\pi}_{t+k}])}$, in terms of the structural parameters of the model. Given the policy functions we have

$$\hat{y}_{t-1} = a_y \hat{i}_{t-2} + \mathbf{b}_y \cdot \hat{\omega}_{t-1},$$

and

$$\hat{i}_{t-1} = a_i \hat{i}_{t-2} + \mathbf{b}_i \cdot \hat{\omega}_{t-1}.$$

Combining these two equations with (A.9) yields

$$\hat{y}_t = \rho_y \hat{y}_{t-1} + \mathbf{c} \cdot \omega_{t-1} + \mathbf{b}_y \cdot \omega_t, \tag{A.12}$$

where $\mathbf{c} = \left(a_y \mathbf{b}_i - a_i \mathbf{b}_y\right)$ and $\rho_y = a_i$.

We now use equations (A.9) and (A.12) to compute the revision in the forecast of $\hat{y}_{t+k}$ conditional on an innovation ε_{mt} in period t. From (A.9), the instantaneous update is

$$\mathbb{E}_t^m[\hat{y}_t] = b_{ym}\varepsilon_{m,t}.$$

Iterating (A.12) forward, we have

$$\begin{aligned}
\hat{y}_{t+k} &= \rho_y \hat{y}_{t+k-1} + \mathbf{c} \cdot \omega_{t+k-1} + \mathbf{b}_y \cdot \omega_{t+k} \\
&= \rho_y^k \hat{y}_t + \sum_{j=0}^{k-1} \rho_y^j \left(\mathbf{b}_y \cdot \omega_{t+k-j}\right) + \sum_{j=0}^{k-1} \rho_y^j \left(\mathbf{c} \cdot \omega_{t+k-1-j}\right)
\end{aligned}$$

Therefore,

$$\begin{aligned}\mathbb{E}_t^m\left[y_{t+k}\right] =& \rho_y^k \mathbb{E}^m\left[y_t\right] + b_{ym}\sum_{j=0}^{k-1}\rho_y^j \mathbb{E}^m\left[\hat{m}_{t+k-j}\right] + c_m \sum_{j=0}^{k-1}\rho_y^j \mathbb{E}^m\left[\hat{m}_{t+k-1-j}\right] \\ =& \rho_y^{k-1}\left(\rho_y b_{ym} + c_m\right)\varepsilon_{m,t} \end{aligned} \tag{A.13}$$

where the second equality follows from $\mathbb{E}_t^m\left[\hat{m}_{t+j}\right] = 0$ for $j \geq 1$.

We now use the Phillips curve to obtain a similar expression for inflation. Solving (NKPC) forward, we have

$$\hat{\pi}_{t+k} = \kappa \sum_{j=0}^{\infty}\beta^j \mathbb{E}_{t+k}\left[\hat{y}_{t+k+j}\right] + \kappa\sum_{j=0}^{\infty}\beta^j \mathbb{E}_{t+k}\left[\hat{\mu}_{t+k+j}\right].$$

Then,

$$\begin{aligned}\mathbb{E}_t^m\left[\hat{\pi}_{t+k}\right] &= \kappa\sum_{j=0}^{\infty}\beta^j \mathbb{E}_t^m\left[\hat{y}_{t+k+j}\right] = \kappa\sum_{j=0}^{\infty}\beta^j\left(\rho_y^{k-1+j}\left(\rho_y b_{ym}+c_m\right)\right)\varepsilon_{m,t} \\ &= \kappa\frac{\rho_y^{k-1}}{1-\beta\rho_y}\left(\rho_y b_{ym}+c_m\right)\varepsilon_{m,t}\end{aligned} \tag{A.14}$$

Then, using equation (A.13) and (A.14), we have

$$\frac{\text{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_k], \mathbb{E}_t^m[\hat{y}_k]\right)}{\text{Var}\left(\mathbb{E}_t^m[\hat{y}_k]\right)} = \frac{1-\beta\rho_y}{\kappa} \tag{A.15}$$

as wanted.

To complete the proof, we use the method of undetermined coefficients to express $\rho_y = a_i$ as a function of the model structural parameters. To do so, let's set the exogenous state variables at $t-1$ and t to zero. Therefore,

$$\hat{i}_t = a_i \hat{i}_{t-1} \tag{A.16}$$

$$\hat{y}_t = a_y \hat{i}_{t-1} \tag{A.17}$$

and recall that $\rho_y = a_i$. Using (NKPC) we have that

$$\hat{\pi}_t = \frac{\kappa}{1-\beta a_i}\hat{y}_t. \tag{A.18}$$

Substituting (A.16), (A.17) and (A.18) into (Taylor) yields

$$a_i = \rho_i + (1-\rho_i)\left\{\psi_\pi \frac{\kappa}{1-\beta a_i} + \psi_y\right\} a_y. \tag{A.19}$$

Next, substituting (A.16), (A.17) and (A.18 into (Euler) yields (note that $\hat{r}_t^n = 0$)

$$a_y = a_i a_y - \frac{1}{\sigma}\left(a_i - \frac{\kappa}{1-\beta a_i} a_i a_y\right). \tag{A.20}$$

Combining (A.19) and (A.20) yields

$$a_i = \rho_i - (1-\rho_i)\frac{1}{\sigma}\frac{a_i\left(\psi_\pi \frac{\kappa}{1-\beta a_i} + \psi_y\right)}{\left(1 - a_i - \frac{1}{\sigma}\frac{\kappa}{1-\beta a_i} a_i\right)}$$

completing the proof.

□

C Sensitivity analysis

C.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 **??**.

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 measure of actual, P-measure, expectations. Unfortunately, these survey are conducted on 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 expectation of future inflation—discussed in Section 3.2—and subsequently use the daily data on inflation compensation to obtain an high frequency measure of actual expectations. Specifically, we estimate the following relation

$$SPF_t^{(n)} = \beta_{n,0} + \beta_{n,1} IC_t^{(2y)} + \beta_{n,2} IC_t^{(5y)} + \beta_{n,3} IC_t^{(10y)} + \beta_{n,4} i_t^{(2y)} + u_t^{(n)}, \tag{A.21}$$

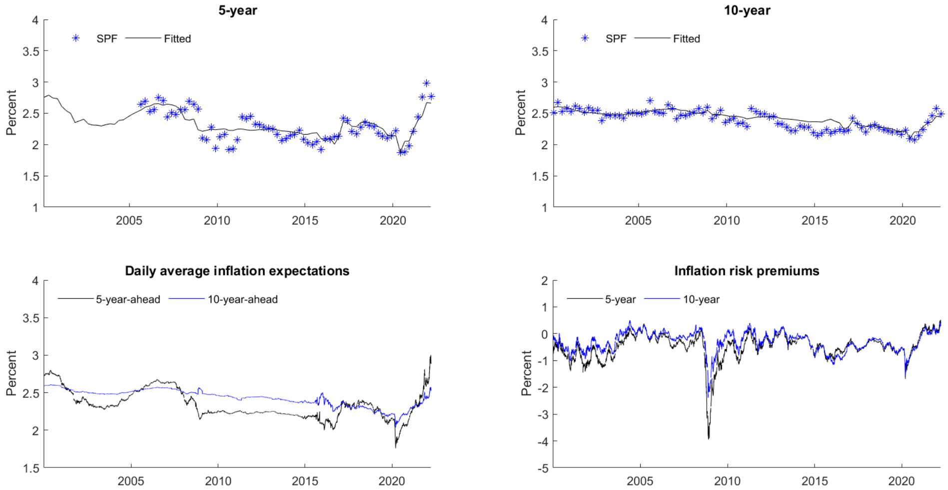

Figure A-1: Risk premia correction for inflation

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.[25]

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.21) to interpolate the surveys to daily values. The lower-left panel of Figure A-1 plots the implied daily values for the 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 $IRP_t^{(n)} = IC_t^{(n)} - S\hat{P}F_t^{(n)}$. In theory, the inflation risk premium should be positive

[25]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.

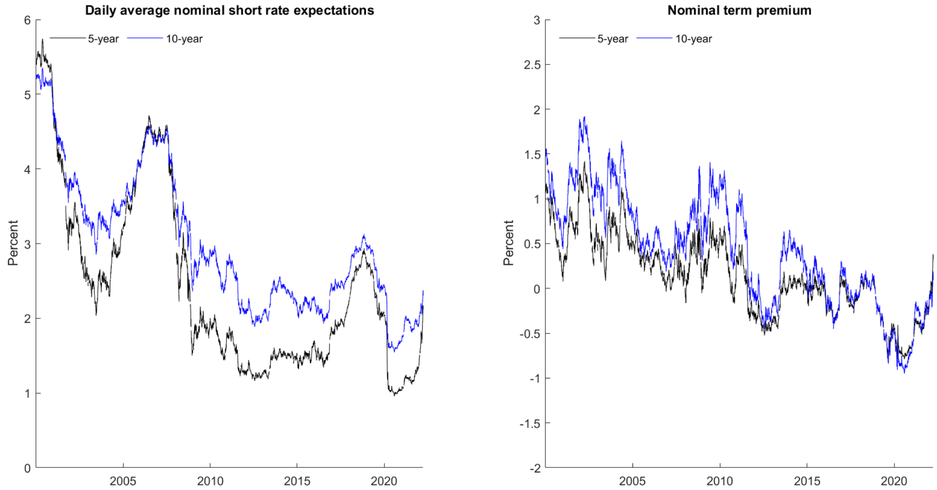

Figure A-2: Risk premia correction for nominal interest rates

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 negative 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 a similar questions for short-term nominal interest rates. In order to obtain a measure of the actual expectations of future nominal interest rate, we use the model of Kim and Wright (2005) to estimate of the nominal term premium. This is a standard affine term structure model and it is maintained by staff at the Federal Reserve Board, who makes the estimates available at daily frequency on the Federal Reserve Board website. The left panel of Figure A-2

Table A-1: Additional sensitivity

	(1) Baseline	(2) $\rho_i = 0.7$	(3) $\rho_i = 0.9$	(4) Information effect
d (10 year avg)	-0.54^{***}	-0.49^{***}	-0.64^{***}	-1.27^{***}
	(0.11)	(0.09)	(0.16)	(0.46)
d (5 year avg, 1-5)	-1.05^{***}	-0.83^{***}	-1.55^{***}	-1.98^{***}
	(0.15)	(0.12)	(0.25)	(0.53)
d (5 year avg, 6-10)	-0.13	-0.15^{*}	-0.06	-0.49
	(0.10)	(0.08)	(0.14)	(0.35)
N. obs.	4019	4019	4019	208

Note: The table reports sensitivity analysis to the baseline results reported in Table 2. Column (1) restates the baseline results, column (2) uses $\rho_i = 0.7$, column (3) uses $\rho_i = 0.9$, column (4) estimates equation (9) only on monetary events that satisfy the sign restrictions discussed in the text. Standard errors are robust to heteroscedasticity and autocorrelation. One star indicates significance at the 10 percent level, two starts indicate significance at the 5 percent level, and three stars indicate significance at the 1 percent level.

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.

C.2 Additional sensitivity

Robustness to choice of ρ_i. In our baseline specification, we fixed $\rho_i = 0.8$ at an annual frequency. To be sure that this choice is not critical for our results, we conduct a robustness exercise. Table A-1 presents the results if we instead set $\rho_i = 0.7$ and $\rho_i = 0.9$. The results show that our main result is intact and that point estimates are not vastly different if we vary our choice of ρ_i.

Robustness to the Fed information effect. In section 3.1 we have proposed a way to test for a structural break of the monetary policy rule even when the latter features an output gap component. The test consists in estimating equation (9) conditioning on "monetary events", and a key assumption for its validity is that during these days investors learn new information only about the conduct of monetary policy and not about the state of the economy. Some important contributions in the literature, however, suggest that surprises around these events also reflect that the central bank reveals its private information about the current state of the economy to investors, see Nakamura and Steinsson (2018).[26] This "Fed information effect" can confound the measurement of monetary shocks and invalidate our identification strategy, especially if the type of news about the state of the economy that are revealed around monetary announcements differ between the pre and post pandemic period.

We control for this "Fed information effect" by leveraging the insight in Jarociński and Karadi (2020): we compute innovations to stock prices around monetary events, and restrict the sample only to events with changes to short rate expectations and changes to stock prices (SP500 index) that are in opposite direction. The logic of this sign restriction is that, by focusing on those events, we mitigate the possibility of including events where the unexpected tightening of the Fed funds rate is caused by a revelation of positive news about the state of the economy. Column (4) in Table A-1 reports the estimates of d when we restrict the sample to these events. We can see that our two main empirical findings hold in this restricted sample too, and the point estimates are quite comparable to those reported in Table 2 in the main text.[27]

Robustness to potential liquidity premiums. Because the inflation compensation measure that we use in our baseline implementation is based on differences in the yields between nominal and inflation protected bonds, it is potentially affected by differences in liquidity premia/convenience yields on these assets due to a preference for holding nominal bonds over TIPS. This premium may vary over time, as investor may prefer more liquid assets in times of market stress, for example. Overnight Index Swaps (OIS) tied to the federal funds rate and inflation-linked swaps (ILS) should in principle reflect the same information as nominal bonds and the differential yield on nominal and real bonds. These swaps are thought to be less affected by liquidity premiums, but we also have a shorter sample of historical rates. We use the available sample to check the robustness of our results. For the robustness exercise, we implement the baseline regression but for the 5-year maturity, because we then have a reasonable long sample with both OIS and ILS rates available since March 2005. On this sample, we have a total of 332 monetary events. The regression yields $\hat{d} = -0.95$ with a t-stat of 2.23, thus similar in magnitude to our baseline results and statistically significant at the usual 5 percent level.

[26] Bauer and Swanson (2023) offer a critical view of the empirical relevance of this issue.

[27] Our results are robust to other types of sign restrictions consistent with the logic of Jarociński and Karadi (2020), for example restricting the sample to events characterized by a negative correlation between innovation to short rate expectations and expected future inflation (one year horizon).

D 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.

S&P500 Index, Not Seasonally Adjusted, daily values.

Inflation Expectations, Percent, Not Seasonally Adjusted, Quarterly values. The Survey of Professional Forecasters ask for average expected inflation over the next five and ten years.

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.

Overnight Index Swap (OIS) rates, Percent, Not Seasonally Adjusted, daily values. Maturities between 1 and 10 years. The swap contract is tied to the federal funds rates.

Inflation-Linked Swap (ILS) rates, Percent, Not Seasonally Adjusted, daily values. Maturities between 1 and 10 years. The swap contract is tied to US CPI.

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.

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

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

E Quantitative Analysis

In this Appendix we discuss details of the estimation of the New Keynesian model and of the main counterfactual reported in Section 4 of the paper.

E.1 Estimation of the New Keynesian model

We denote the state vector with $\mathbf{s}_t = (s_t, \hat{\imath}_{t-1}, \hat{\overline{\pi}}_{t-1}) = \left(\xi_t, \varepsilon_{m,t}, \mu_t, \theta_t, \hat{\imath}_{t-1}, \hat{\overline{\pi}}_{t-1}\right)$ where $\hat{\overline{\pi}}_{t-1}$ is the average inflation in the previous $N-1$ periods, and with Θ the vector collecting all the structural parameters of the model. The structural parameters are those governing preferences and technology, $[\sigma, \beta, \nu, \chi, \phi, \overline{\mu}]$, those governing policy, $[\pi^\star, \rho_i, \psi_y, \psi_\pi(H), \psi_\pi(D), N]$ and those governing the evolution of the shocks, $[\mathbf{P}, \sigma_\mu, \rho_\theta, \sigma_\theta, \rho_\mu, \sigma_\mu]$. 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:

$$\begin{aligned} y_t &= T_1(\xi_t; \Theta) \cdot \mathbf{s}_t \\ s_t &= T_2(\xi_t; \Theta) \cdot \mathbf{s}_{t-1} + R(\xi_t; \Theta) \cdot \varepsilon_t \end{aligned} \tag{A.22}$$

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, $[\sigma, \nu, \mu, \chi, \pi^\star, \beta]$ to conventional values, and fix $P_{H,D} = 0.006$ and $N = 12$. 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.[28] 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 and 3 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 3 reports the prior distribution for the model parameters and statistics

[28] The approach of estimating the single regime model is justified because its numerical solution is numerically very close to that of the two-regimes 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 quite low.

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 Markov chain. We generate 2 Markov chains of 500000 each and discard the first half of the draws.

Step 2. In the second step we choose the remaining parameters, $\psi_\pi(D)$ and $P_{D,D}$, so that the full model replicates the high frequency evidence in Section 2 and 3. For that purpose, we fix the parameters estimated in step 1 at the posterior mean and choose $\psi_\pi(D)$ and $P_{D,D}$ to reduce the distance between the estimates of the coefficient d in equation (9) and their model-implied counterparts. The model-implied counterparts of d_k are computed as follows. We solve the two-regime model using the perturbation approach described in Foerster et al. (2016), and using this solution we compute the change in the conditional expectation of nominal interest rates and future inflation k periods from now given that today we had a one standard deviation monetary shock and that the economy is in regime ξ, $\mathbb{E}^m[\bar{\hat{i}}_k - \rho_i \bar{\hat{i}}_{k-1}|\xi]$ and $\mathbb{E}^m[\bar{\hat{\pi}}_k|\xi]$. For each ξ, we then compute

$$\psi_\pi^k(\xi) = \frac{\mathbb{E}^m[\bar{\hat{i}}_k - \rho_i \bar{\hat{i}}_{k-1}|\xi]}{\mathbb{E}^m[(1-\rho_i)\bar{\hat{\pi}}_k|\xi]}.$$

The model implied d at horizon k is then defined as

$$d^k = \psi_\pi^k(\xi = D) - \psi_\pi^k(\xi = H).$$

The parameters $\psi_\pi(D)$ and $P_{D,D}$ are chosen to minimize an unweighted distance between the model implied d^k and our empirical targets. The results are reported in Panel C of Table 3.

E.2 Counterfactual

We now detail the counterfactual exercise of Section 4.3. 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 particle filter to the implied non-linear state space system in (A.22) to estimate the density of the state vector for each t.[29] 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:

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

Where $s_t^i = (\xi_t^i, \varepsilon_{m,t}^i, \mu_t^i, \theta_t^i)$ is a particle (a realization of the state vector) and $\tilde{w}_t^i$ its weight. The algorithm consists of 3 steps.

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

Step 1: Prediction. For each particle $i = 1, \ldots, N$, obtain a realization for the state vector $s_{t|t-1}^i$ given s_{t-1}^i by simulating the model forward.

Step 2: Filtering. Assign to each particle $s_{t|t-1}^i$ the weight $w_t^i = p(y_t|s_{t|t-1}^i)\tilde{w}_{t-1}^i$.

Step 3: Resampling. Rescale the weights $\{w_t^i\}_{i=1}^N$ so that they add up to one, and denote these rescaled values $\{\tilde{w}_t^i\}_{i=1}^N$. Sample N values of the state vector with replacement from $\{s_{t|t-1}^i, \tilde{w}_t^i\}_{i=1}^N$, and denote these draws by $\{s_t^i, \tilde{w}_t^i = 1\}_{i=1}^N$. If $t < T$, set $t = t + 1$ and go to Step 1. If not, stop.

We set $N = 3000000$. We apply the particle filter to our data for the 2020:Q3-2022:Q1 period and obtain an estimate for the probability density of the latent states. Figure 4 in the main text reports the time series for the observables and the average for the latent states, computed using $\{s_t^i, \tilde{w}_t^i\}_{i=1}^N$

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 the $\xi_t = H$ for the whole sample. This gives us the counterfactual path for output, inflation and nominal interest rate under the scenario in which the monetary authority kept operating using the historical rule during the recovery from the pandemic. The results of this counterfactual are reported in Figure 5 in the main text.

[29] In order to run the particle filter, we add iid measurement errors to each variable in y_t. The variance of these measurement errors is set to 0.5% of the unconditional variance of the series.