Bond Market Views of the Fed*

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Abstract

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

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

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1 Introduction

The surge in inflation following the pandemic stands out as one of the most remarkable macroeconomic developments in recent years. U.S. consumer prices, which for decades grew at a stable rate close to the Federal Reserve's two percent annual target, 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 the increase in 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 the changes in the Federal Reserve's monetary policy framework taking place around this time. In August 2020, the Fed concluded its monetary policy framework review and adopted a *flexible average inflation targeting* framework, in which the Fed declared it would tolerate temporary deviations of inflation from its target.[1] Did these changes in the monetary policy framework affect private sector beliefs about how the Federal Reserve would tackle inflation going forward? To what extent did these changes in beliefs 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 markets data to detect shifts in the market 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 these shifts by combining this measurement with a standard New Keynesian model with regime switches in the monetary policy rule. We find that these changes in monetary policy played a first-order role during this period, accounting for the bulk of the observed increase in inflation. In particular, we estimate that inflation would have peaked at only 5% in 2021 if the Fed would have followed its historical reaction function.

To illustrate our approach to detecting shifts in the Fed's monetary stance, let's assume that the Federal Reserve follows a Taylor rule of the following form

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

where i_t is the Fed funds rate at date t, π_t is the inflation rate, $\tilde{y}_t$ is a measure of real

[1] Consistent with this statement, the Fed did not hike interest rates in 2021 despite the large increase in inflation, citing that these increases were due to "transitory factors".

economic activity (the output gap), and $\varepsilon_{m,t}$ is a monetary shock capturing transitory deviations of the policy rate from its "systematic" component.[2] Our objective is to test whether there was a shift in the Fed's reaction function after 2020. A major obstacle for this purpose is that we have very few observations of these variables in the post-2020 period, and the information content of these observations is quite limited given that nominal interest rates were at zero until March 2022. Our observation is that this issue can be mitigated by leveraging high-frequency bond market data.

From the term structure of interest rates for nominal and inflation-protected bonds, we can retrieve daily risk-neutral expectations of future nominal interest rates and inflation, $\mathbb{E}_t^Q[i_k]$ and $\mathbb{E}_t^Q[\pi_k]$ for $k > t$. We can then express the Taylor rule in the "*expectations space*" as

$$\Delta\mathbb{E}_t^Q[i_k] = \psi_\pi \Delta\mathbb{E}_t^Q[\pi_k] + \psi_y \Delta\mathbb{E}_t^Q[\tilde{y}_k] + \Delta\mathbb{E}_t^Q[\varepsilon_{m,k}], \tag{2}$$

where $\Delta\mathbb{E}_t^Q[x_k] \equiv \mathbb{E}_t^Q[x_k] - \mathbb{E}_{t-1}^Q[x_k]$ is the daily forecast revision of variable x in a future period k.[3] Equation (2) offers a simple framework to use high-frequency financial market data for the purpose of estimating the systematic component of monetary policy: every day, market participants revise their beliefs about future inflation and nominal interest rates, and equation (2) clarifies that the comovement between these variables provides information about the Fed reaction function.

Our empirical analysis starts by estimating an analog of equation (2) using ordinary least squares (OLS) over the 2000-2022, treating $\psi_y \Delta\mathbb{E}_t^Q[\tilde{y}_k] + \Delta\mathbb{E}_t^Q[\varepsilon_{m,k}]$ as an error term. We call this the "naive" estimator of ψ_π because it is potentially biased, due to the correlation between forecast revisions in inflation and the error term. Indeed, standard derivations show that the probability limit of this estimator is

$$\hat{\psi}_\pi^{OLS} \to \psi_\pi + \frac{\mathrm{Cov}\left(\Delta\mathbb{E}_t^Q[\pi_k], \psi_y \Delta\mathbb{E}_t^Q[\tilde{y}_k] + \Delta\mathbb{E}_t^Q[\varepsilon_{m,k}]\right)}{\mathrm{Var}\left(\Delta\mathbb{E}_t^Q[\pi_k]\right)}.$$

Using a sub-sample analysis, we show that the estimates of ψ_π are remarkably stable over time in the pre-pandemic period—around a value of 1.3—and experienced a sizable drop to 0.75 over the 2020-2022 subsample.

This finding is not necessarily indicative of a reduction in the Fed responsiveness to inflation, because the bias term may have also changed over time. Specifically, it is natural

[2]This specification of the Taylor rule is arguably too simple. In the paper, we will use one that includes empirically plausible features such as an interest rate smoothing component and a time-varying intercept.

[3]Equation (2) hold irrespective of other structural features, such as the demand and supply block of the economy, as long as the monetary authority follows a monetary rule as in equation (1). So, our empirical approach does not require assumptions about these features.

to expect a reduction in the correlation between $\Delta\mathbb{E}_t^Q[\pi_k]$ and $\Delta\mathbb{E}_t^Q[\tilde{y}_k]$ if supply shocks become more prevalent in the U.S. economy over the 2020-2022 period, as most of the recent literature suggests (Bernanke and Blanchard, 2023). That is, the naive estimator detects a decline in the comovement between expected inflation and expected nominal rates, but this may not reflect an underlying change in the Fed policy but rather a change in the type of shocks that the Fed faces.

In order to control for this concern, we test for the stability of the monetary policy rule across sub-samples by estimating equation (2) only using forecasts revisions in a narrow window around monetary events, such as Federal open market committee meetings, releases of the minutes of the meetings, and planned speeches by the Federal Reserve chairman. By doing so, we are conditioning on the same type of demand shock—a monetary shock—across different sub-samples. Using the canonical three-equations New Keynesian model, we show that this approach correctly identifies shifts in the monetary policy rule so long as the conditional correlation between expected inflation and the error term in equation (2) is constant across the two subsamples under the null hypothesis of no shift in the policy parameters. This would be the case if there were no other factor beside policy changes that could have affected the propagation of monetary shocks after 2020.[4]

We test for a structural break in the monetary policy rule in the data and document a sizable and significant reduction in the estimate of ψ_π in the post 2020 period. In addition, by varying the horizon of the forecast k, we show that these deviations are stronger when considering short- to medium-term expectations (1 to 5 years), and disappear when using longer-term expectations. We show that these results are robust to a number of sensitivity checks, including correcting for the presence of risk and liquidity premia in nominal and real bonds, the presence of an occasionally binding zero lower bound constraint, and the possibility of that monetary events may not just reflect monetary shocks due to a "Fed information effect". We then use a New Keynesian model as well as direct narrative evidence of the FOMC's change in policy stance to argue that this structural break in the estimates is attributable to a central bank that places less weight on inflation stabilization, and in particular to a reduction in the Taylor rule weight on current inflation, ψ_π.

In the second part of the paper we study the macroeconomic implications of the changes in financial markets' perception of the policy rule 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, mimicking the change in

[4] As we show in the paper, this would be true in the context of the baseline New Keynesian model if the slope of the Phillips curve, the elasticity of intertemporal substitution and the discount factor were constant across sub-samples.

the monetary policy framework announced in 2022. We discipline the parameters of the average inflation targeting 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%.

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 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 changes in the conduct of monetary policy. Specifically, we provide evidence that the adoption of the new monetary policy strategy had a sizable impact on investors' beliefs about the conduct of monetary policy that are implicit in bond prices.[5] In addition, we show that these shifts in beliefs are quite consequential for inflation dynamics when fed through a benchmark New Keynesian model.[6]

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 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 in what we label the *expectation space*. In addition, we show that the endogeneity concerns arising when

[5]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).

[6]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.

estimating monetary reaction functions—and that were addressed by Clarida, Gali, and Gertler (2000) using an instrumental variable approach—are not present when estimating reaction functions on expectation data.[7] Bauer, Pflueger, and Sunderam (2022) is also a recent paper that uses survey expectation data to estimate time-variation in the coefficients of a Taylor rule. Our approach is complementary because it uses a quite different variation in the data, and it is valid under a different set of assumptions.[8] See also Hamilton, Pruitt, and Borger (2011) and King and Lu (2022) for papers that have used expectation data—either market based or surveys—to quantify aspects of the conduct of monetary policy.

As we formally show in Section 2, the absence of market-based measures of output gap expectations and the presence of risk premia in bond prices introduce 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). Our finding that the bulk 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 covid pandemic. Our results are consistent with this view, but it is not necessary. The more dovish stance is also consistent with the adoption of an average inflation targeting regime emphasized by the Fed "strategy review". Relative to this work, our contribution is to provide direct evidence of the monetary policy shift using bond prices data.

[7] Cochrane (2011) argues that predictability of monetary shocks invalidates the instrumental variable approach. As we discuss in Section 2.2, this critique does not apply to our methodology, if the forecasting horizon is longer than the predictability of monetary shocks.

[8] Bauer, Pflueger, and Sunderam (2022) use the cross-sectional variation in expected future nominal interest rate, inflation, and the output gap among different professional forecasters to estimate the parameters of a Taylor rule—assumed to be constant across forecasters. We instead rely on time variation in the co-movement between market-based expectations of future nominal interest rates and inflation.

2 The data and conceptual framework

This section proceeds in two steps. Section 2.1 describes the data used in our empirical analysis and present some summary statistics. Section 2.2 discusses the difficulties inherent in testing for shifts in the conduct of monetary policy and presents our approach.

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 k-period nominal bond and by $r_t^{(k)}$ the zero-coupon yield on a k-period real bond. 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 March 31st 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.[9]

These data are useful for our purposes because they can be used to construct the expectation of the average short term interest rate and of the average inflation rate over the life-time of the bonds. Specifically, we have

$$i_t^{(k)} = \mathbb{E}_t^{\mathcal{Q}}\left[\frac{1}{k}\sum_{i=0}^{k-1} i_{t+i}^{(1)}\right] \equiv \mathbb{E}_t^{\mathcal{Q}}\left[\bar{i}_k\right] \tag{3}$$

$$IC_t^{(k)} = \mathbb{E}_t^{\mathcal{Q}}\left[\frac{1}{k}\sum_{i=1}^{k} \pi_{t+i}\right] \equiv \mathbb{E}_t^{\mathcal{Q}}\left[\overline{\pi}_k\right], \tag{4}$$

where π_t denotes the one-period inflation rate and $\mathbb{E}_t^{\mathcal{Q}}[\cdot]$ denotes the risk-neutral expectation conditional on time t information. Equations (3) and (4) follow from a no-arbitrage argument: in the absense of arbitrage opportunities, buying a k-period bond and following a strategy of rolling over one-period bonds for the next k periods must have equal (risk-adjusted) expected returns. Thus, the term structures of nominal yields and inflation compensation allows a real-time read on investors' expected nominal short rate and inflation paths.

[9] We end the sample then, because it is unclear whether lift-off constituted a return to the former "hawkish" regime or a continuation of the more "dovish" regime. Extending our sample to study this issue is an avenue for future work.

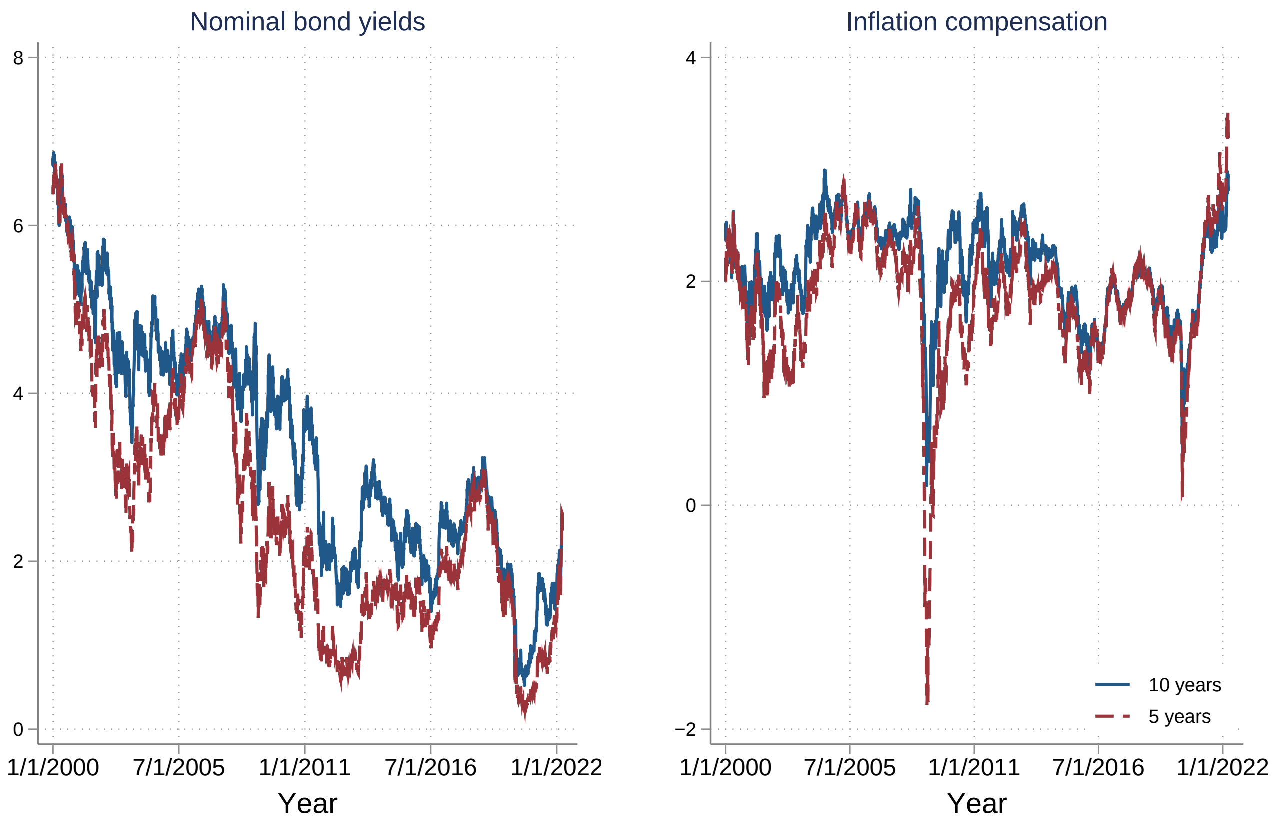
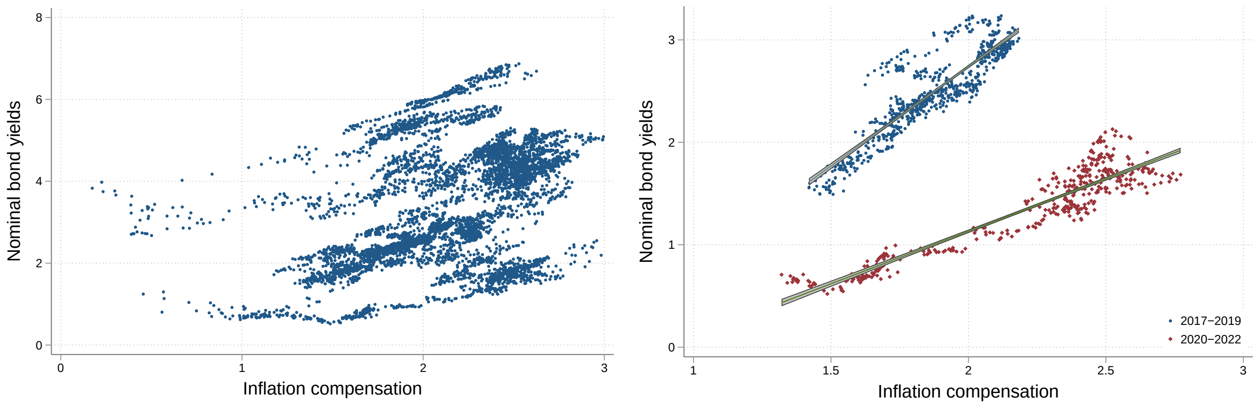


Figure 1: Nominal bond yields and Inflation compensation

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.

In our baseline results we will treat the risk-neutral expectations as equal to "physical"—or real-world—expectations. 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, respectively (see Kim and Wright (2005), Piazzesi and Swanson (2008) Adrian, Crump, and Moench (2013), Abrahams, Adrian, Crump, Moench, and Yu (2016), and D'Amico, Kim, and Wei (2018) among many others). In a sensitivity analysis, we will attempt to control for movements in risk premia to make sure they are not driving our results.

Figure 1 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 downwards 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 inflation compensation episodes stand out as outliers: during the financial



(a) Full sample

(b) Three years sub-samples

Figure 2: Nominal bond yields vs Inflation compensation

Notes: Panel (a) shows a scatter plot of 10-year inflation compensation and nominal Treasury yields over the full January 3, 2020 through March 31, 2022 sample, while panel (b) shows similar scatter plots but for sub-samples that cover 2017-2019 and 2020-2022. The data are from Gürkaynak, Sack, and Wright (2007, 2010).

crisis in 2008 and 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 that these periods affect our results, we exclude 2008 and the first half of 2020 (January 1 to July 31st) from our sample.[10]

In the next subsection we will discuss how we can use data on expected nominal interest rates and inflation to test whether financial markets changed their views about the Fed's stance on inflation after 2020. Before moving there, it is useful to look at the comovement of these two variables and how their relationships changed over time. In our sample, expected future nominal rates and expected future inflation comove positively, although only weakly so: the regression of expected nominal rates onto inflation expectations in our sample has an R^2 of about 13 percent. Panel (a) of Figure 2 visualizes this pattern. The positive relationship is to be expected: if the monetary authority behaves according to the Taylor principle, we should see nominal interest rates move more than one-for-one with the rate of inflation, so the slope of that relationship should typically be positive and greater than one. The relationship in panel (a) of Figure 2 does indeed imply a slope coefficient greater than one, but—as already mentioned—the relationship is quite weak.

[10]In the sensitivity analysis, we will construct risk-neutral expectations of future nominal interest rates and future inflation using swap contracts, which are arguably less affected by this differential liquidity premium. Our main results will be quite similar when using these alternative measures.

The weak association between the two variables is the result of the slow-moving downward drift in nominal interest rates observed over the sample period, which is not met by a corresponding downward trend in inflation. One indication that this is indeed the reason for the weak relationship comes from panel (b) of Figure 2, where we plot the same graph for shorter sub-samples, 2017-2019 and 2020-2022. In those sub-samples, the relationship is much stronger with R^2's above ninety percent. This indicates that it is quite important to account for low frequency movements in nominal interest rates when using the data.

Panel (b) of Figure 2 also shows that the *slope* of the relationship between expected nominal interest rates and expected inflation was lower in the 2020-2022 sub-sample relative to the 2017-2019 sub-sample. The 2020-2022 sub-sample followed the Fed's strategy review, which ultimately led to the adoption of "average inflation targeting". In what follows, we discuss to what extent changes in the slope of the relation between expected nominal interest rates and expected inflation are indicative of a shift in financial markets' perception over the Fed's stance on inflation.

2.2 Identifying shifts in the monetary policy rule

We assume that financial markets believe that monetary policy is governed by a Taylor rule,

$$i_t = \rho_i i_{t-1} + (1-\rho_i)\left[i_t^\star + \psi_\pi\left(\pi_t - \pi^\star\right) + \psi_y \tilde{y}_t\right] + \varepsilon_{m,t}, \tag{5}$$

where i_t is the nominal interest rate prevailing at time t, $(\pi_t - \pi^\star)$ is the deviation of inflation from its target, $\tilde{y}_t$ the output gap, $i_t^\star$ is the "natural" interest rate—the nominal interest rate prevailing in an economy with no price rigidities—and $\varepsilon_{m,t}$ is a monetary shock. In what follows, we discuss how we can use the data presented in the previous sub-section to test for a shift in the Fed reaction function.

Taking expectations under the risk-neutral measure of both side of equation (5) in year k, and first-differencing with respect to t—$\Delta\mathbb{E}_t^Q[x_k] = \mathbb{E}_t^Q[x_k] - \mathbb{E}_{t-1}^Q[x_k]$—we obtain

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

In what follows, we assume that forecast revisions to the natural interest rate are neglegible at daily frequencies, that is $\Delta\mathbb{E}_t^Q[i_k^\star] = 0$. We believe this assumption is reasonable, as most of the literature considers the natural rate of interest $i_t^\star$ to be a very slow-moving process.[11]

[11] See, for example, Laubach and Williams (2003, 2016) and Del Negro, Giannone, Giannoni, and Tambalotti (2017).

Given this assumption, and the fact that equation (6) holds for every k, we have

$$\Delta\mathbb{E}_t^Q\left[\bar{i}_k - \rho_i \bar{i}_{k-1}\right] = \psi_\pi \Delta\mathbb{E}_t^Q\left[(1-\rho_i)\overline{\pi}_k\right] + \psi_y \Delta\mathbb{E}_t^Q\left[(1-\rho_i)\overline{\tilde{y}}_k\right] + \Delta\mathbb{E}_t^Q\left[\overline{\varepsilon}_{m,k}\right], \tag{7}$$

where $\overline{x}_k$ is the average of variable x between now and year k. Notice that forecasts revisions about future monetary shocks would appear in equation (7) even if we were to assume that monetary shocks were not serially correlated. This is because expectations are taken with respect to the risk-neutral and not the physical measure: to the extent that monetary shocks are correlated with the economy's stochastic discount factor, and to the extent that the price of risk moves over time, we can observe time variation in $\Delta\mathbb{E}_t^Q\left[\overline{\varepsilon}_{m,k}\right]$ even in presence of transitory monetary shocks.

In Section 2.1 we described how we obtained data on $\mathbb{E}_t^Q[\bar{i}_k]$ and $\mathbb{E}_t^Q[\overline{\pi}_k]$ for different k's. In addition, we have reliable estimates of ρ_i from previous research. We now discuss to what extent we can use equation (7) and the bond market data to infer shifts in the Fed reaction function.

The identification problem. To understand the identification problem consider applying naively ordinary least square (OLS) to equation (7), leaving $\psi_y \Delta\mathbb{E}_t^Q\left[(1-\rho_i)\overline{\tilde{y}}_k\right] + \Delta\mathbb{E}_t^Q\left[\overline{\varepsilon}_{m,k}\right]$ as an error term. The probability limit of this estimator would be

$$\hat{\psi}_\pi^{\text{OLS}} \to \psi_\pi + \frac{\text{Cov}\left(\Delta\mathbb{E}_t^Q[\overline{\pi}_k], \psi_y \Delta\mathbb{E}_t^Q\left[\overline{\tilde{y}}_k\right]\right)}{\text{Var}\left(\Delta\mathbb{E}_t^Q[\overline{\pi}_k]\right)} + \frac{\text{Cov}\left(\Delta\mathbb{E}_t^Q[(1-\rho_i)\overline{\pi}_k], \Delta\mathbb{E}_t^Q\left[\overline{\varepsilon}_{m,k}\right]\right)}{\text{Var}\left(\Delta\mathbb{E}_t^Q[(1-\rho_i)\overline{\pi}_k]\right)}. \tag{8}$$

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. In addition, as inflation typically bears a risk premium, one should also expect a correlation between $\Delta\mathbb{E}_t^Q[(1-\rho_i)\overline{\pi}_k]$ and $\Delta\mathbb{E}_t^Q\left[\overline{\varepsilon}_{m,k}\right]$, which also introduces a bias in the OLS estimator of ψ_π.

The bias may also vary over time due to structural changes that affect the covariance pattern between expected inflation and the error term. For example, the first component of the bias should be smaller in periods during which supply shocks are prevalent because this type of shocks induce a negative comovement between output and inflation—leading to a smaller covariance between the two.

This identification problem is particularly relevant in our application. Figure 3 reports the point estimate of $\hat{\psi}_\pi^{\text{OLS}}$ along with a 95% confidence interval for 5 different sub-samples: 2000-2004, 2005-2009, 2010-2014, 2015-2019, 2020-2022. We can see that the relation be-

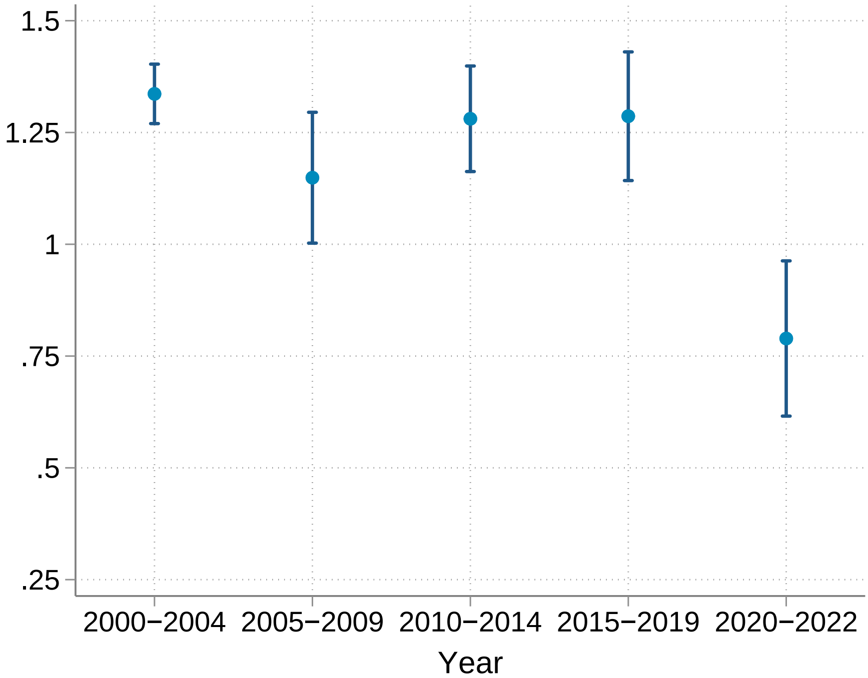


Figure 3: OLS estimates of ψ_π in equation (7)

Notes: The figure plots the resulting coefficients from regressions of daily changes in 10-year Treasury yields onto daily changes in 10-year inflation compensation over the indicated sub-samples. Confidence intervals are constructed based on standard errors that are robust to heteroscedasticity and autocorrelation.

tween expected nominal interest rates and expected inflation has been remarkably stable for twenty years, with $\hat{\psi}_\pi^{\text{OLS}}$ centered around 1.25. We can also see a sharp weakening of this relation in the last sub-sample, with $\hat{\psi}_\pi^{\text{OLS}}$ dropping to 0.78. Given the previous discussion, this drop does not necessarely reveal a reduction in the responsiveness of nominal interest rates to current inflation—a decline in ψ_π, as it could also be the product of other developments, such as an increase in the importance of supply shocks post 2020.

Our approach. We now show that, despite the identification problem discussed above, it is still possible to use equation (7) to test for a structural break in $\hat{\psi}_\pi^{OLS}$ and learn whether there was a shift in the perceived monetary stance of the Federal Reserve after 2020. Rather than estimating equation (7) using the full sample, we propose to estimate this relation only using forecasts revisions of future nominal interest rates and inflation that occur around the "monetary events" that took place in our sample (e.g. FOMC meetings), which are broadly interpreted in the literature as monetary shocks. So, the key idea of our test is that, by conditioning on these events, we control for possible confounding effects—such as an increase in the prevalence of supply shocks—that may explain a fall over time in $\hat{\psi}_\pi^{OLS}$ via the bias term.

More formally, and letting D_t be a dummy variable equal to 1 if t is after 2020:M8 and zero otherwise, we will estimate

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

where $\Delta \mathbb{E}_t^{Q,m}[x_k]$ denotes the revision in forecast of variable x in year k computed on a one-day window around the monetary events in our sample. The choice of August 2020 as the beginning of the structural break is natural since this is when the Fed released the statement outlining the new monetary policy framework. We combine the pre-2020 period into a single regime because this period was characterized by a remarkable stability in the relation between expected nominal rates and expected inflation, as seen in Figure 3. The parameter d represents the difference in $\hat{\psi}_\pi^{OLS}$ pre- and post-August 2020. Our approach consists of testing the null hypothesis that $d = 0$, and interpreting its rejection as evidence of a shift in the Fed monetary policy rule after August 2020.

To understand why this procedure can correctly detect a shift in the monetary policy rule, suppose that there was no shift in policy. 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 $(\bar{i}_k, \overline{\pi}_k, \overline{\eta}_k)$ in equation (9) would be independent of D_t, including the bias term. In Appendix A we show that, under these assumptions, the OLS estimator of d has an asymptotically normal distribution centered around zero. Therefore, even though $\hat{\psi}_\pi^{OLS}$ is asymptotically biased, we can still test the null hypothesis that d equalled zero and interpret its rejection as evidence of a shift in the monetary policy rule across the two sub-samples.

The logic of this approach is that by conditioning on the same type of shock (a monetary shock) before and after the pandemic, we are effectively holding constant the asymptotic bias of the OLS estimator across the two sub-samples *under the null hypothesis of no shift in the monetary policy rule*. Therefore, any statistical difference in $\hat{\psi}_\pi^{\text{OLS}}$ before and after 2020 must come from a change in the underlying perceived monetary policy rule.

This approach is correct under the assumption that—absent a shift in the Fed policy rule—the propagation of monetary shocks to the rest of the economy would have been the same before and after 2020:M8. We now turn to study our empirical strategy within the context of a New Keynesian model, in order to understand what this assumption implies for the structural parameters of the model.

The bias in the standard New Keynesian model. To better understand our empirical strategy, suppose that the data are generated from the standard log-linearized three-equations New Keynesian model, which we outline in Appendix B, and consider estimating equation (7) conditioning on monetary shocks. The following result characterizes the probability limit of $\hat{\psi}_{\pi}^{\text{OLS},m}$ as a function of the model's structural parameters.

Proposition 1. *Consider the log-linearized three-equations New Keynesian model. Suppose that $\rho_y > \rho_m$, where ρ_m is the autocorrelation of monetary policy shocks and $\rho_y \in (0,1)$ is the solution to*

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

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, as $k \to \infty$, we have

$$\hat{\psi}_\pi^{OLS,m} \to \psi_\pi + \psi_y\frac{(1-\beta\rho_y)}{\kappa}. \tag{11}$$

Because we are considering the limiting case as the forecasting horizon grows arbitrarely large, $k \to \infty$, we have that the asymptotic bias of $\hat{\psi}_\pi^{OLS,m}$ only depends on the correlation between forecasts updates about inflation and the output gap conditional on monetary shocks. From equation (11) we can see that this correlation 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 hitting the economy, which as discussed earlier could explain the fall in $\hat{\psi}_\pi^{\text{OLS}}$ documented in Figure 3, 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 is also helpful in clarifying what assumptions we need in order to interpret a change in $\hat{\psi}_\pi^{\text{OLS,m}}$ across two sub-samples as a evidence in favour of a change in the monetary policy rule. Looking at the expression in (11), we need the slope of the Phillips curve κ and the preference parameters β and σ to be constant across the two sub-samples. If that was the case, then a change in $\hat{\psi}_\pi^{\text{OLS,m}}$ across two sub-periods could only come from changes in the policy parameters $(\psi_y, \psi_\pi, \rho_i)$.

2.3 Discussion

Before moving to estimation, it is useful to discuss further our empirical approach.

There are two main aspects of our empirical test. First, by taking expectations of *future* variables, we resolve one of the key identification issue that arises when estimating Taylor rules, the dependence between the variables in the systematic component of the monetary rule (π_t and $\tilde{y}_t$) and the unobserved monetary shock $\varepsilon_{m,t}$. Abstracting from the presence of risk-premia, this would be true for any future date k as long as $\varepsilon_{m,t}$ is not serially correlated. When monetary shocks are serially correlated, the forecast horizon becomes important: as long as k is large enough relative to the predictability of the error terms, $\mathbb{E}_t[\varepsilon_{m,k}]$ will be close to zero, and we could apply our methodology. Indeed, in Proposition 1 we allow $\varepsilon_{m,t}$ to be an AR(1) process, but the correlation between expected future inflation and expected future monetary shocks can be made arbitrarely close to zero as the forecast horizon k increases. In practice, monetary shocks appear to be only mildly serially correlated (see Coibion and Gorodnichenko (2012) for example), suggesting that k need not be too large in our application.

Second, we perform our analysis based only on revisions in forecasts that arise around monetary events. As we have argued earlier, this allows us to control for the identification problem arising due to the correlation between inflation and the error term. Estimating features of the Taylor rule 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.[12]

It is also worth pointing out that we are testing the null hypothesis of no structural break in policy rule and in the transmission mechanism of monetary policy. And so just observing a change in d doesn't necessarily imply a structural break in conduct of monetary policy. For example, a steepening of the Phillips curve, as suggested by Benigno and Eggertsson (2023), can affect the transmission mechanism of monetary policy and hence imply the structural break. In the next two sections, we argue that the changes in structural parameters needed to account for the estimated bias are implausible large. Thus, we will argue that the structural break is due to a change in the conduct of monetary policy. This

[12]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.

could be either due to a change in ψ_π, ψ_y or ρ_i. When moving to the structural analysis, our approach will consist in specifying an alternative regime for the monetary policy rule based on the idea of average inflation targeting, as suggested during the Fed Strategy Review, and parametrize its coefficient via indirect inference to replicate our numerical estimates of d. We will assume there that ψ_y and ρ_i are unchanged, since, as we argue in section 3.3, changes in these parameters are unlikely to account for the data.

3 Empirical analysis

Having presented the data and our strategy, we now move to the empirical analysis. Section 3.1 reports the results of our test. We find a significant and sizable reduction in the coefficient ψ_π during the 2020-2022 period. In addition, we show that these differences are more pronounced when considering short to medium term expectations (five years ahead), while they almost disappear when considering long term expectations (between six and ten years ahead). Together, these findings are consistent with financial markets expecting a temporary monetary stance that places less weight on current inflation stabilization. In section 3.2 we conduct an extensive sensitivity analysis of these results. Finally, section 3.3 discusses to what extent our findings are consistent with the revision of the monetary policy framework carried out by the Federal Reserve in August 2020.

3.1 Baseline results

We estimate equation (9) by OLS. In our baseline, we consider k to be equal to ten years ahead. In order to estimate equation (9) we need to take a stance on the numerical value for ρ_i. We set it to 0.90 at quarterly frequency, consistent with previous literature and with our own estimates of Section 3.2, but will verify later the robustness of our results to different assumptions about ρ_i.

The coefficient d represents the difference in the sensitivity of expected nominal interest rates to expected inflation in the two sub-samples, and we are interested in testing the null hypothesis that $d = 0$. Table 1 reports the results. Column (1) reports the estimates of ψ_π and d when considering the full sample. Consistent with the results reported in Figure 3, the OLS estimate of ψ_π is centered at 1.28 in the pre-2020 sample, and it drops by 0.49 after 2020, with both coefficients being precisely estimated.

As discussed earlier, we cannot interpret the weakening in the relation between expected nominal interest rates and expected inflation as evidence of a policy shift, as it could also be explained by a larger prevalence of supply shocks in the second sub-period. To control for

Table 1: Testing for a shift in the Fed stance on inflation

	(1) Full sample	(2) Monetary events
ψ_π	1.28***	1.11***
	(0.03)	(0.09)
d	−0.49***	−0.79**
	(0.09)	(0.36)
R^2	0.41	0.28
N. obs.	4019	455

Note: The table reports the resulting coefficients from a regression of daily changes in 10-year Treasury yields onto daily changes in 10-year inflation compensation and daily changes in 10-year inflation compensation interacted with a dummy that takes the value one post-2020. The regression specification is in equation (9). The first column reports the results from the full sample, while the second column restricts the sample to days with monetary events such as FOMC meetings, releases of FOMC minutes, and speeches on monetary policy by the Fed chair. 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.

this alternative explanation, we estimate equation (9) restricting the sample to "monetary events". These are defined as days during which the Federal Reserve releases the statement or the minutes of a planned FOMC meeting, or during which the Fed chairman delivers a speech on monetary policy at a planned event. Over the 2000-2022 sample, we have 455 of such events. The second column of Table 1 reports the estimates of equation (9) when using only these events. Also in this case, we find a weaker relation between expected nominal interest rates and expected inflation post 2020: the point estimates for d is -0.79, and we can reject the null hypothesis that $d = 0$ at conventional levels. Under the assumptions discussed in Section 2.2, this result suggests that financial markets perceived a shift toward a more Dovish stance over inflation after August 2020.

So far we have seen that financial markets perceived expected nominal interest rates to be significantly less sensitive to expected inflation post 2020. Through the lens of Taylor-type monetary rule, this suggests a shift to a policy regime characterized by a weaker weight on deviations from current inflation. We now ask: how persistent financial markets expected this monetary policy regime to be? To answer this question, we use the term structure of our data and estimate equation (9) for different k's. Specifically, we split the ten years averages considered in the baseline specification into two pieces: expected average inflation and nominal interest rates between now and five years from now, and expectations between six and ten years from now. Figure 4 reports the coefficient d for these two specifications,

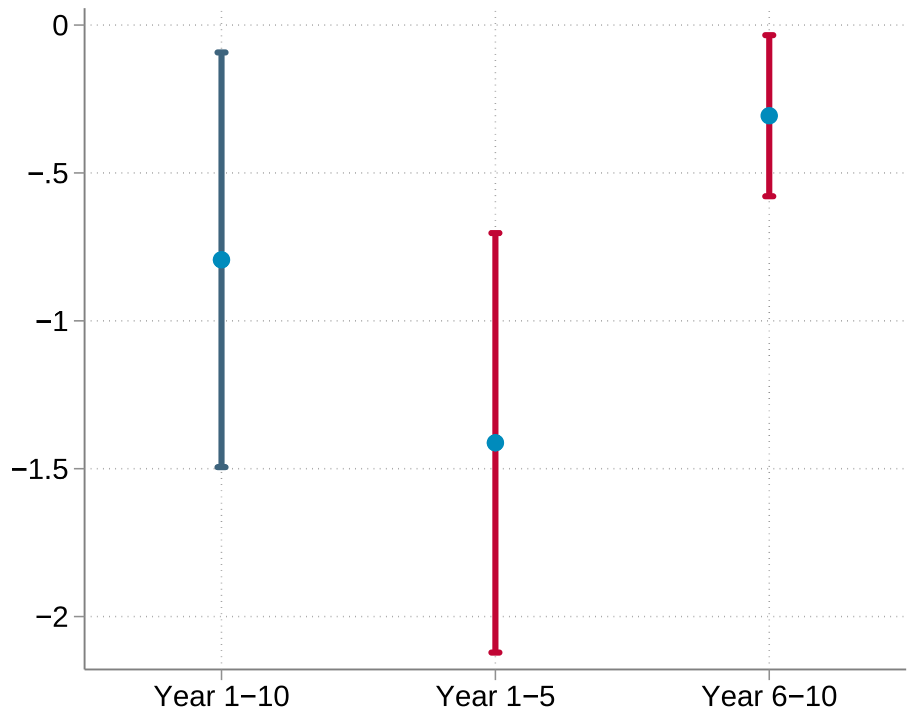


Figure 4:

Notes: The figure breaks the decline in the coefficient from a regression of daily changes in 10-year nominal Treasury yields onto daily changes in 10-year inflation compensation over the post-2020 sample into the contributions from a regression of daily changes in 5-year nominal Treasury yields onto daily changes in 5-year inflation compensation and from a regression of daily changes in 5-year nominal Treasury rate in five years' time onto daily changes in 5-year inflation compensation in five years' time. Confidence intervals are constructed based on standard errors that are robust to heteroscedasticity and autocorrelation.

along with a 95% confidence interval. We can see from the figure that the largest deviations after 2020 arise for short to medium term expectations (year one to five), while financial markets did not expect these deviations to persist in the longer term: the coefficient d is only marginally different from zero when looking at expectations between year six to ten.

3.2 Sensitivity analysis

So far we have documented a significant reduction of the elasticity of nominal interest rates to current inflation after 2020. In addition, we have provided evidence that financial markets expected this shift in the conduct of monetary policy to be transitory. In this section, we check the robustness of these two results to a number of measurement issues.

The zero lower bound. The presence of the zero lower bound implies, by construction, a reduced sensitivity of nominal interest rates to inflation changes when the former are near zero. 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.

We control for this issue by explicitly allowing for the possibility of a zero lower bound (ZLB) constraint, 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

$$\mathbb{E}_t[i_k] = \rho_i \mathbb{E}_t[i_{k-1}] + (1-\rho_i)\left\{\mathbb{E}_t[i_k^\star] + \psi_\pi \mathbb{E}_t[\pi_k - \pi^\star] + \psi_y \mathbb{E}_t[\tilde{y}_k]\right\} + f\left(\frac{\mathbb{E}_t[\hat{i}_k]}{\sigma_m}\right)\sigma_m, \quad (12)$$

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 (12) to modify our test. Specifically, consider a first order approximation of equation (12) around the point $\mathbb{E}_t[\pi_k] = \pi^\star$, $\mathbb{E}_t[\tilde{y}_k] = 0$, $\mathbb{E}_t[i_k^\star] = \bar{i}^\star$ and $\mathbb{E}_t[i_{k-1}] = \bar{i}_{k-1}$.[13] We then have

$$\mathbb{E}_t\left[i_k\right] = \left(1 + \frac{1}{\sigma} f_k'\right)\left\{\rho_i \mathbb{E}_t[i_{k-1}] + (1-\rho_i)\left\{\mathbb{E}_t[i_k^\star] + \psi_\pi \mathbb{E}_t[\pi_k - \pi^\star] + \psi_y \mathbb{E}_t[\tilde{y}_k]\right\}\right\}, \quad (13)$$

with

$$f_k' = f'\left(\frac{\rho_i \bar{i}_{k-1} + (1-\rho_i)\bar{i}^\star}{\sigma}\right).$$

The term in f_k' is negative and tends to be large in absolute value when the approximation point, $\rho_i \bar{i}_{k-1} + (1-\rho_i)\bar{i}^\star$, 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 will infer a larger ψ_π the closer we expect to be to the ZLB.[14]

Importantly, f_k' is known up to $\bar{i}_{k-1}$, $\bar{i}^\star$ and σ. Our approach consists of two steps. First,

[13] An alternative approach would be to use equation (12) 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 $\mathbb{E}_t[i_k^\star]$ and $\mathbb{E}_t[\tilde{y}_t]$. Rather than following this route, we approximate equation (12) to first-order and apply the same methods employed previously to control for these two unobservables.

[14] To see this point clearly, consider the special case in which $\rho_i = 0$, $\psi_y = 0$ and $\mathbb{E}_t[i_k^\star] = 0$. Then, a consistent estimator of ψ_π would be $\psi_\pi^{OLS}/(1 + \frac{1}{\sigma}f_k')$. So, holding ψ_π^{OLS} constant, the smaller is f_k' the larger the inferred ψ_π.

we use data to calibrate these three parameters in order to obtain numerical values for $\{f'_k\}$ for each k. Specifically, we average the Laubach and Williams (2016) indicator of the natural interest rate and add 2% inflation to obtain a value for $\bar{i}^{\star}$, and use the sample average of $\mathbb{E}_t^Q[i_{k-1}]$ to set $\bar{i}_{k-1}$. Importantly, we let the values of $\bar{i}_{k-1}$ and $\bar{i}^{\star}$ to vary across the two sub-samples, so as to allow for expectations of a binding ZLB to differ in the pre and post pandemic period. We then set $\sigma = 0.03$, which is in the upper range of the estimates for the standard deviation of monetary shocks at the annual frequency. We use these values to compute $\{f'_k\}$ for both sub-samples, and use these coefficients along with equation (13) to obtain an expression for the revision in expectations about the average of the short term rate over the next k years

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

This expression is the equivalent of equation (7) in presence of the ZLB constraint, and we will use it to test for the stability of ψ_π in the sample.

Column (2) of Table 2 reports the estimates of d for this specification. We can see that the 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-medium term expectations.

Fed information effect. An important step in our empirical strategy is that we condition on the same type of demand shock—a monetary shock—before and after 2020 when testing for the presence of a structural break in the conduct of monetary policy. This step requires that the monetary policy events that we consider reveal information about the conduct of monetary policy. 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).[15] 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

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

Table 2: Sensitivity analysis

	(1) Baseline	(2) ZLB	(3) Fed inf. effect	(4) Risk premia
d (10 year avg)	-0.79^{**}	-0.87^{*}	-1.12^{***}	-0.28^{**}
	(0.36)	(0.54)	(0.38)	(0.12)
d (5 year avg, 1-5)	-1.41^{***}	-2.08^{***}	-1.42^{***}	-0.99^{***}
	(0.36)	(0.60)	(0.38)	(0.26)
d (5 year avg, 6-10)	-0.36	-0.33	-0.52^{*}	-0.07^{**}
	(0.23)	(0.29)	(0.26)	(0.03)
N. obs.	455	455	210	455

Note: The table reports sensitivity analysis to the baseline results reported in Table 1 and Figure 4. Column (1) restates the baseline results, column (2) controls for proximity to the ZLB, column (3) controls for potential "Fed Information Effects", and column (4) controls for time-variation in term and inflation risk premiums. 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.

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 (3) in Table 2 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.[16]

Time-varying risk premia. As we discussed previously, time variation in the compensation for term and inflation risk may be responsible for daily variation in the risk-neutral expectations of future nominal interest rates and inflation used in our analysis. In what follows, we use methods developed in the literature to estimate movements in risk premia, and use these estimates to back out "actual" expectations about future nominal interest rates and inflation. We will then estimate equation (7) using actual rather than risk-neutral expectations. Doing so makes our approach more robust because, by using actual expectation, we eliminate part of the error term in equation (7), therefore reducing possible

[16] 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).

confounding forces.[17]

We compute actual inflation expectations at the daily frequency as follows. First, we 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 inflation, $\mathbb{E}_t^P[\overline{\pi}_k]$. Most asset pricing models, and certainly the popular Gaussian affine term structure models, imply that inflation compensation would reflect the underlying factors that drive inflation and therefore also actual inflation expectations. That is,

$$\mathbb{E}_t^P[\overline{\pi}_k] = f_{k,t}(X_t),$$

where $IC_t^{(k)} = g_{k,t}(X_t)$ is a function of the same underlying factors X_t. Instead of specifying and estimating an asset pricing model to obtain the function $f_{k,t}$, we follow the insight of Aronovich and Meldrum (2021) and approximate this function using local linear projections of the surveys onto the observable inflation compensation measures and nominal yields. These regressions are estimated on a seven year rolling sample to take into account the time-variation of f and potential non-linearities. We can then use the estimated parameters of this relation and our data on $IC_t^{(k)}$ to obtain *daily* actual expectations for inflation.[18] Appendix C.1 provides more details on this procedure and discusses the implied inflation risk premium 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 $\mathbb{E}_t^P[\bar{i}_k]$.

Column (4) in Table 2 reports the estimates of d when running our main specification on the risk premia-adjusted data. Although the baseline coefficient is smaller than in the raw financial market data, we continue to find a sizable and statistically significant drop in the regression coefficient on inflation expectations, especially at the five year horizon.[19]

[17] When using actual expectations the term $\Delta\mathbb{E}_t[\overline{\varepsilon}_{m,k}]$ would be close to zero when the forecasting horizon k is large enough.

[18] The survey started to ask the question about the average expected inflation rate over the next five years only in 2005Q3. So, we estimate the 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.

[19] A smaller coefficient is to be expected, as the estimation errors involved in the measurement of the actual expectations induces a measurement error for the regressors in equation (7), which bias the estimated coefficients towards zero.

Additional sensitivity analysis. We have performed additional sensitivity analysis which, for the sake of keeping the paper compact, we report in Appendix C.2.

In the benchmark specification, we fix the persistence parameter of the Taylor rule ρ_i to 0.90 at a quarterly frequency. In the sensitivity analysis, we perform the test under different values of ρ_i, varying between 0.7 and 0.95. We find that the estimated coefficient d is barely affected by those changes.

In a different exercise, we obtain risk-neutral expectations about future nominal interest rates and future inflation using OIS and Inflation swaps contracts, rather than nominal and real bond yields. This exercise is important because these measures are thought to be less contaminated of liquidity premia than the one we are currently using in the analysis. The analysis in the Appendix shows that we obtain very similar estimates for the coefficient d when estimating equation (9) using this data.[20]

3.3 Interpreting our estimate for d

In this section, we discuss how we interpret the estimates for the coefficient d in equation (9). As we argued above, under the null of hypothesis of no change in the perceived policy and in the transmission of monetary policy, the parameter d is equal to zero. Therefore, a non-zero estimate for d must come from either a change in the underlying perceived monetary policy rule or a change in other structural parameters that affect the transmission of monetary policy shocks. In particular, through the lens of the standard New Keynesian model, Proposition 1 shows that a non-zero d identifies changes in

$$\psi_\pi + \psi_y \frac{(1 - \beta\rho_y)}{\kappa}.$$

We will next argue that the negative estimate of d is attributable to a change in the perceived conduct of monetary policy and in particular to a reduction in ψ_π .

Changes in structural parameters other than the monetary authority's policy rules cannot credibly account for a large share of d because we would need implausibly large structural changes. For example, a steepening of the Phillips curve - an increase in κ - can contribute to a reduction in the bias term but, to match our estimate for d, κ should increase by a factor of more than 5.[21] The same is true for changes in the intertemporal elasticity of substitution and the discount factor that affect ρ_y.

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

[21] In our standard calibrated model, a simple back of the envelope calculation gives that an increase in κ from its calibrated value of .17 to .4 would produce a reduction in the bias term of about .35 relative to the .8 we estimated. If κ were 1 instead we would have a reduction in the bias term of about .6. (Note that κ is

We then interpret the negative d as an indicator of a new monetary policy stance that is less responsive to inflation. This is broadly consistent with the messages conveyed in the Federal Reserve's Statement on Longer-Run Goals and Monetary Policy Strategy (which followed the review of the monetary policy framework, sometimes just referred to as the "*strategy review*") and in the subsequent FOMC statements.[22] The Statement on Longer-Run Goals and Monetary Policy strategy, released in late August 2020, 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 meeting 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 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 indeed optimal to allow inflation to run above target after recovery to avoid downward spiral in inflation when the response of nominal interest rate is constrained.[23] Vice-chairman Clarida on 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 inflation pressures built in early 2021, the FOMC acknowledged that inflation had

itself a composite parameter, given by $\kappa = \left(\frac{1}{\nu} + \sigma\right) / [\phi(\overline{\mu} - 1)]$ where ν is the Frisch elasticity of the labor supply, ϕ is the Rotemberg adjust cost and $\overline{\mu}$ is the mean markup. Also, changes in κ have an indirect effect on the bias as ρ_y is a function of κ as shown in (10).)

[22] 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.

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

risen, but initially judged that these inflationary pressures were 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 then 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 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 is equivalent to a decrease in the inflation coefficient in the canonical Taylor rule.

Our results thus 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 relatively short forward horizons whereas it is mostly absent over long-run forward horizons. This is consistent with the Fed communications of temporary inflation overshoot ("for some time").

Note that this narrative evidence can also be consistent with a Taylor rule that has higher persistence, higher ρ_i. This can also account for a negative estimate for d in equation (9) because ρ_i affects the bias term via its influence on the coefficient ρ_y. However, since estimates of ρ_i in the pre-2020 period are already high: around .90 at our quarterly frequency. Thus, there is a limited scope for increase and this channel cannot account for the bulk of our estimate.[24]

Finally, a change in the bias term in (11) can also arise because of changes in the responsiveness of monetary policy to the output gap. In particular, a reduction in the bias post 2020 could be the result of a reduction in ψ_y. However, while a smaller response to the output gap result in a more dovish stance of inflation in response to a demand shock – like the monetary policy shock we are conditioning our estimates to – it results in a more hawkish stance in response to the markup or supply shocks that have been important in 2021-2022 as we will show in our quantitative exercise. Thus, attributing the negative estimate of d to a reduction in ψ_y would counterfactually result in a more aggressive response of nominal interest rates to the increase in inflation in 2020-2021.

[24] In our calibrated model, an increase in ρ_i from our baseline of .90 to .99 can account for a reduction in the bias term of only about .14.

4 Quantitative analysis

In the previous section we have presented evidence consistent with a shift toward a more Dovish monetary policy stance. In this section, we use a standard New Keynesian model to quantify the macroeconomic implications of this policy 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 one-third of the observed increase in inflation.

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

$$\sum_{t=0}^{\infty} \beta^t \int_{s^t} \tilde{\theta}\left(s^t\right) U\left(C\left(s^t\right), L\left(s^t\right)\right) p\left(s^t \mid s_0\right) ds^t, \tag{14}$$

where β is the discount factor and $\tilde{\theta}\left(s^t\right)$ is a preference shock, our "demand shock".

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

$$Y\left(s^t\right) = \left(\int_0^1 y_i\left(s^t\right)^{\frac{1}{\mu(s^t)}} di\right)^{\mu(s^t)} \tag{15}$$

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 labor and a linear technology,

$$y_i\left(s^t\right) = n_i\left(s^t\right) \tag{16}$$

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 (14) 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 (15) 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

$$y_i\left(s^t\right) = \left(\frac{P_i\left(s^t\right)}{P\left(s^t\right)}\right)^{\frac{\mu\left(s^t\right)}{1-\mu\left(s^t\right)}} Y\left(s^t\right) \tag{17}$$

and the price index is given by

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

Intermediate good producers. Each intermediate good is supplied by a monopolistically competitive firm who uses labor to operate the the linear technology (16). 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

$$\max_{\{P_i(s^t),y_i(s^t),n_i(s^t)\}} \sum_{t=0}^{\infty} \int_{s^t} Q\left(s^t\right) \left[P_i\left(s^t\right) y_i\left(s^t\right) - W\left(s^t\right) n_i\left(s^t\right) - \frac{\kappa}{2} \left[\frac{P_i\left(s^t\right)}{P_i\left(s^{t-1}\right)\left(1+\overline{\pi}\right)} - 1 \right]^2 \right] ds^t \tag{18}$$

subject to (16) and (17) and where the nominal stochastic discount factor is

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

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

$$\begin{aligned} 1+i\left(s^t\right) = &\left(1+i\left(s^{t-1}\right)\right)^{\rho_i} \\ &\times \left\{ \left(1+\bar{i}\right) \left[\frac{1+\xi_t \pi\left(s^t\right) + \left[1-\xi_t\right] \overline{\pi}_t\left(s^t\right)}{1+\pi^{\star}} \right]^{\psi_\pi(\xi_t)} \left(\frac{Y\left(s^t\right)}{\overline{y}} \right)^{\psi_y} \right\}^{1-\rho_i} \exp\left\{\sigma_m \varepsilon_m\left(s_t\right)\right\} \end{aligned} \tag{19}$$

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 "average inflation targeting" adopted after the Federal Reserve strategy review in 2020. 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 (18) with $P\left(s^t\right) = P_i\left(s^t\right)$, iii) the nominal interest rate satisfies the Taylor rule (19), iv) markets clear in that

$$L\left(s^{t}\right)=Y\left(s^{t}\right)=C\left(s^{t}\right)+\frac{\phi}{2}\left(\frac{\pi\left(s^{t}\right)-\pi^{\star}}{1+\pi^{\star}}\right)^{2} \tag{20}$$

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

$$1=\left(1+i_{t}\left(s^{t}\right)\right)\beta\int\left[\theta\left(s^{t+1}\right)\frac{U_{c}(s^{t+1})}{U_{c}(s^{t})}\frac{1}{1+\pi_{t+1}\left(s^{t+1}\right)}\right]p\left(s^{t+1}|s^{t}\right)ds^{t+1} \tag{21}$$

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

$$\tilde{\pi}\left(s^{t}\right)=\frac{1}{\phi\left(\mu\left(s^{t}\right)-1\right)}Y\left(s^{t}\right)\left[\mu\left(s^{t}\right)w\left(s^{t}\right)-1\right]+\int Q\left(s^{t+1}\mid s^{t}\right)\tilde{\pi}\left(s^{t+1}\right)p\left(s^{t+1}|s^{t}\right)ds^{t+1} \tag{22}$$

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 (19), (20), (21), and (22) given the stochastic processes for the shocks in the economy.

4.2 Estimation

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

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

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 to χ^{-1} to 1.2 so that consumption and output are equal to 1 the deterministic steady state. We set the inflation target to 2% annual, $\pi^\star = .005$, 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 we leave to Appendix E.1 a detailed description of the estimation, let us summarize here the key parts of our approach and discuss the results. 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 $\left[\kappa, \rho_i, \psi_\pi(H), \psi_y\right]$ along with the shock processes on this sub-sample. The observables are the de-trended logarithm of real GDP, the nominal interest rate, and the CPI inflation.[25] We approximate the model's policy functions using a first-order perturbation around the deterministic steady state of the single regime model and estimate the structural parameters with Bayesian methods. 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. This is the case in our application because—in any given point in time—the likelihood of transitioning from the H to D regime is very close to zero. The resulting estimates, reported in panel B of Table 3, are broadly consistent with previous studies.

In the second step, we choose the remaining parameters governing the Dovish regime—$\psi_\pi(D)$ and P_{DD}—to match the high frequency evidence of Section 3.1. The empirical targets are the point estimates of d in equation (9) when using 1-5 years averages and 6-10 years averages, reported in Figure 4. The model implied statistics are computed via simulation. We fix all the parameters of the first step at their posterior mean and, for a candidate value of $\psi_\pi(D)$ and P_{DD}, solve the model and simulate long trajectories for $\mathbb{E}_t^m[\bar{\hat{i}}_k - \rho_i \bar{\hat{i}}_{k-1}]$ and $\mathbb{E}_t^m[\overline{\pi}_k]$.[26] We then estimate equation (9) on these simulated trajectories, with D_t taking a

[25] All these series are available at FRED, see Appendix D for a complete description.

[26] We set $\varepsilon_{\theta,t}$ and $\varepsilon_{\mu,t}$ to zero in all our simulations in order to compute expectations conditional on monetary shocks.

Table 3: Model parameters

Panel A: **Fixed parameters**		
	Value	Notes
σ	1.000	Intertemporal elasticity of substitution of 1
ν	1.000	Frish 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
$\psi_\pi(D)$	1.00	Point estimates of d, 1-5 yrs. **Data: -1.41, Model: -1.52**
P_{DD}	0.85	Point estimates of d, 6-10 yrs. **Data: -0.30, Model: -0.04**

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 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.

value of 1 when the economy is currently in the D regime and zero otherwise. Panel C of Table 3 reports the numerical value of the parameters and an indicator of model fit. We can see that the model can replicate the large observed deviations in the sensitivity of expected nominal interest rates to expected inflation between the two regimes, with this gap closing when considering a longer horizon. To achieve that, the model needs a much smaller value of ψ_π in the D regime, 1.00 vs 2.49, and a conditional probability of remaining in the D regime of 85%.

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 trajectory 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 panel of Figure 5 reports data for inflation, nominal interest rates and de-trended output for the period of analysis. We can see the rise in inflation and in output, with the Fed funds rate being fixed at zero throughout this event. The bottom panel of the figure reports the posteriod mean of the realized shocks. In order to reproduce the observed pattern for the data, the model needs a decline in the rate of time preference—a positive "demand" shock—and an unusually large increase in price markups charged by firms in the first few quarters—a negative "supply" shocks. The former contributes to the strong output 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 reduced form analysis, we find evidence of a switch to the *D*ovish regime, especially during the last two quarters of 2021: by then, the historical Taylor rule would have predicted positive interest rates as both inflation and the output gap where above their targets, so the model infers a switch to the average inflation targeting regime. Interestingly, the model does not need unusually large monetary shocks to fit the data, as the realization of $\varepsilon_{m,t}$ is in most periods within one standard deviation from its mean. This indicates that the *D*ovish monetary rule that we specify fits the realized data on inflation, output and nominal interest rates in the episode as well as the traditional Taylor rule fits *historical* realizations of these variables.

Equipped with the realization of the shock processes we can now use the model to perform a counterfactual. Specifically, we feed the model with the realization of $\{\hat{\theta}_t, \hat{\mu}_t, \varepsilon_{m,t}\}$ we have just estimated, but recompute the path of endogenous variable keeping the monetary regime at H. This experiment answers the question of how would nominal interest rates, inflation and output have behaved if the Federal Reserve did not implement the shift

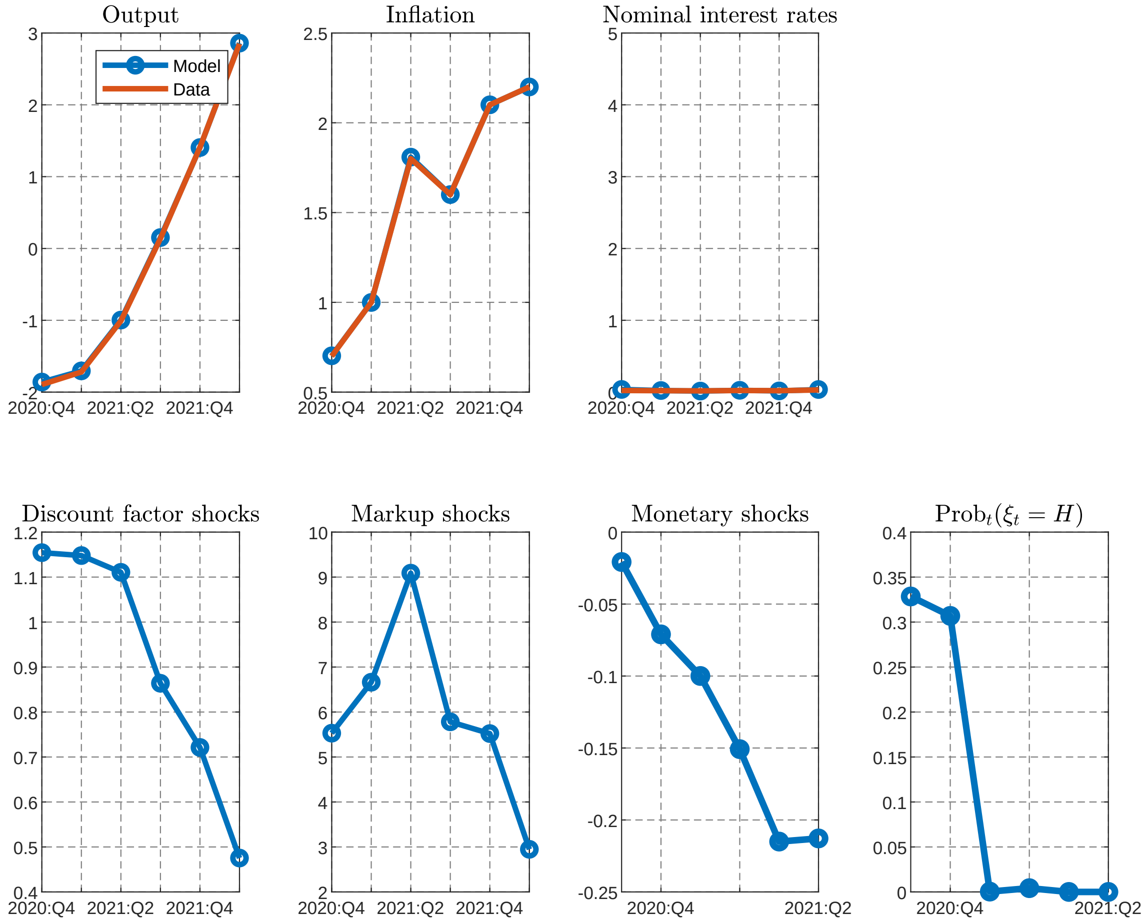


Figure 5: Path of observables and structural shocks: 2020:Q3-2022:Q1

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 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.

to average inflation targeting. The circled line in Figure 6 reports the model implied path for these three variables—which by construction is equal to that of the model—while the circled line reports their value in the counterfactual. We can see that under the H monetary regime the Federal reserve would have increased interest rates throughout the episode instead of keeping them at zero. The effects on output and inflation would have been sizable: by the end of 2021, output would have been approximately three percentage points and inflation five percentage points below their observed value.

To understand why we get these large effects recall that the filtering exercise suggests that this period is characterized by an increase in markup shocks (negative supply shock) and a reduction of $\hat{\theta}$ (positive demand shock). To understand the effects of these shocks

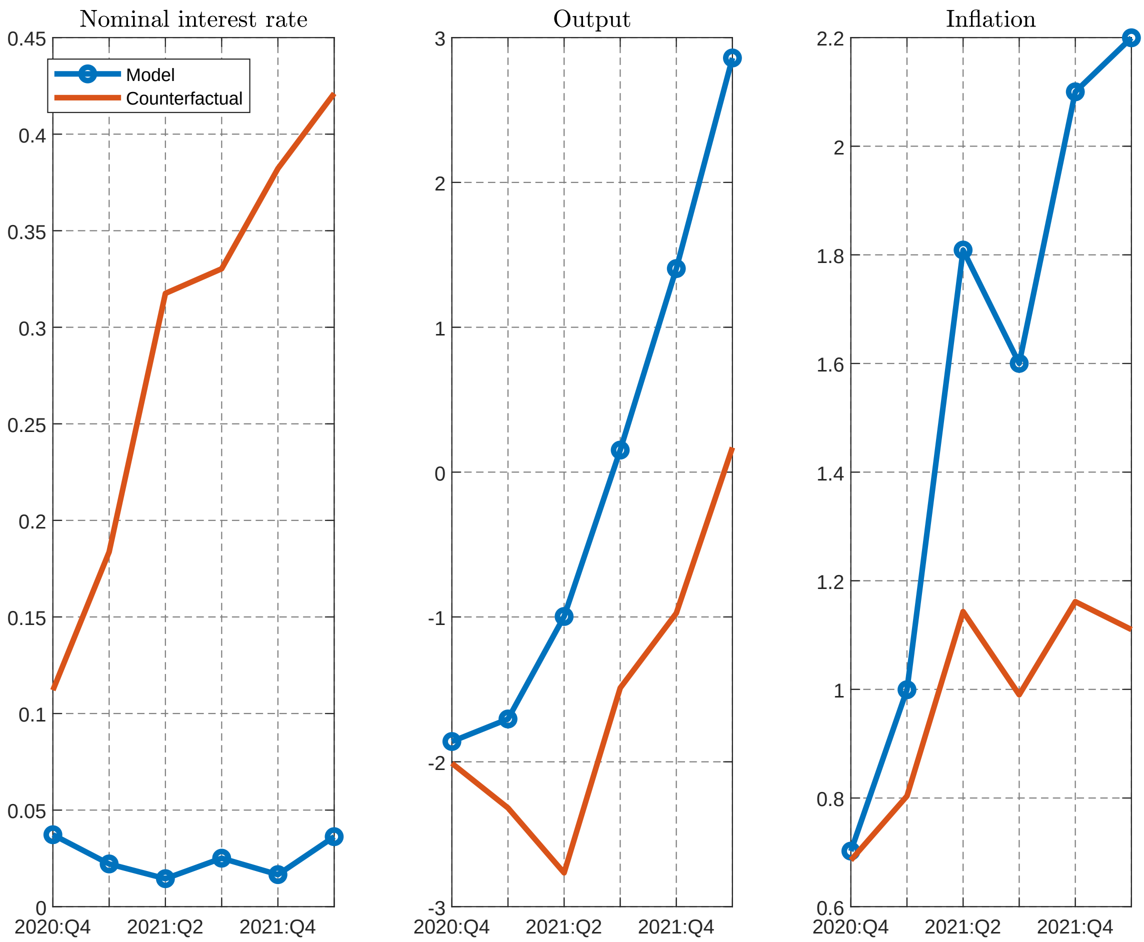


Figure 6: Nominal interest rates, output and inflation under H regime

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.

under the two regimes we contrast their impulse response functions.

Consider first the markup shock. If we iterate forward on the linearized Phillips curve, we have

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

A negative supply shock, an increase in $\sum_{j=0}^{\infty} \beta^j \mathbb{E}_t[\hat{\mu}_{t+j}]$, as we saw in 2021, directly increases inflation. If interest rates respond less to changes in inflation, this will imply a smaller reduction in the discounted expected value of future output through the household Euler equation. Thus, a positive innovation for the markup will lead to higher inflation and higher output in the average inflation targeting regime relative to the H regime.

This is shown in Figure xx which plots the impulse response to a markup shock.

Next consider the demand shock. If we iterate forward on the linearized Euler equation, we have

$$\hat{y}_t = -\frac{1}{\sigma}\sum_{j=0}^{\infty}\mathbb{E}_t[\hat{i}_{t+j} - \hat{\pi}_{t+1+j}] - \frac{1}{\sigma}\sum_{j=0}^{\infty}\mathbb{E}_t[\hat{\theta}_{t+1+j}].$$

A positive demand shock, a reduction in $\sum_{j=0}^{\infty}\mathbb{E}_t[\hat{\theta}_{t+1+j}]$, directly increases output. This generates inflationary pressure through an increase in the real wage and if the interest rate responds less to a change in inflation, this will again lead to a rise in inflation relative to the case in which there is a stronger response. This is shown in Figure xx which plots the impulse response to a reduction in $\hat{\theta}$. These two effects account for why we have higher inflation and output under the Dovish regime relative to the counterfactual Hawkish regime.

5 Conclusion

This paper has proposed a novel method to measure the systematic component of monetary policy using bond markets 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, thus providing a real time reading of financial markets' views on the monetary stance on inflation. When applying our methodology to U.S. data, we document that financial markets had remarkably stable expectations about the behavior of the Federal Reserve over the 2000-2020 period, but substantially revised them in conjunction of the adoption of the flexible average inflation targeting framework in 2020.

We have also showed how to 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 the bulk 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.

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Appendix

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

[to be continued]

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

$$\hat{y}_t = \mathbb{E}_t\left[\hat{y}_{t+1}\right] - \frac{1}{\sigma}\left(\hat{i}_t - \mathbb{E}_t\left[\hat{\pi}_{t+1} - \hat{\theta}_{t+1}\right]\right) \qquad \text{(Euler)}$$

$$\hat{\pi}_t = \beta\mathbb{E}_t\left[\hat{\pi}_{t+1}\right] + \kappa\hat{y}_t + \kappa\hat{\mu}_t \qquad \text{(NKPC)}$$

$$\hat{i}_t = \rho_i\hat{i}_{t-1} + (1-\rho_i)\left\{\psi_\pi\hat{\pi}_t + \psi_y\hat{y}_t\right\} + \hat{m}_t \qquad \text{(Taylor)}$$

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.[27] 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 all the shocks follow independent AR(1) processes:

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

The bounded solution to this system can be represented by policy functions that are linear in the state variables, $[\hat{i}_{t-1}, \hat{\theta}_t, \hat{\mu}_t, \hat{x}_t]$. We can write the policy functions for nominal

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

interest rates and the output as

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

$$y_t = a_y \hat{i}_{t-1} + \mathbf{b}_y \cdot \omega_t, \tag{A.2}$$

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

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

$$a_i = \rho_i - (1-\rho_i)\frac{1}{\sigma}\frac{a_i\left(\psi_\pi \frac{\kappa}{1-\beta a_i} + \psi_y\right)}{\left(1 - a_i - \frac{1}{\sigma}\frac{\kappa}{1-\beta a_i} a_i\right)} \tag{A.3}$$

with $|a_i| < 1$.

We now prove Proposition 1, restated here for convenience:

Proposition. *Consider the log-linearized three-equations New Keynesian model. 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. Suppose that $a_i > \rho_m$, where ρ_y is the solution to (A.3). Then, as $k \to \infty$, we have

$$\hat{\psi}_\pi^{OLS,m} \to \psi_\pi + \psi_y \frac{(1-\beta\rho_y)}{\kappa}. \tag{A.4}$$

Proof. From the linearity of (Taylor) it follows that

$$\hat{\psi}_\pi^{OLS,m} \to \psi_\pi + \frac{\text{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}], \psi_y \mathbb{E}_t^m[\hat{y}_{t+k}] + \mathbb{E}_t^m[\hat{m}_{t+k}]\right)}{\text{Var}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}]\right)}. \tag{A.5}$$

$$= \psi_\pi + \psi_y \frac{\text{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}], \mathbb{E}_t^m[\hat{y}_{t+k}]\right)}{\text{Var}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}]\right)} + \rho_m^k \frac{\text{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}], \hat{m}_t\right)}{\text{Var}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}]\right)}$$

Lets first focus on the term $\frac{\text{Cov}(\mathbb{E}_t^m[\hat{\pi}_{t+k}], \mathbb{E}_t^m[\hat{m}_{t+k}])}{\text{Var}(\mathbb{E}_t^m[\hat{\pi}_{t+k}])}$ and express it 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

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

Combining these two equations with (A.2) yields

$$\hat{y}_t = \rho_y \hat{y}_{t-1} + \mathbf{c} \cdot \omega_{t-1} + \mathbf{b}_y \cdot \omega_t, \tag{A.6}$$

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.2) and (A.6) to compute the revision in the forecast of $\hat{y}_{t+k}$ conditional on an innovation ε_{mt} in period t. From (A.2), the instantaneous update is

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

Iterating (A.6) forward, we have

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

Therefore,

$$\begin{aligned} \mathbb{E}^m_t\left[y_{t+k}\right] =& \rho^k_y \mathbb{E}^m\left[y_t\right] + b_{ym} \sum_{j=0}^{k-1} \rho^j_y \mathbb{E}^m\left[\hat{m}_{t+k-j}\right] + c_m \sum_{j=0}^{k-1} \rho^j_y \mathbb{E}^m\left[\hat{m}_{t+k-1-j}\right] \\ =& \left(\rho^k_y b_{ym} + b_{ym} \sum_{j=0}^{k-1} \rho^j_y \rho^{k-j}_m + c_m \sum_{j=0}^{k-1} \rho^j_y \rho^{k-1-j}_m\right) \varepsilon_{m,t} \\ =& \left(\rho^k_y b_{ym} + \frac{\left(b_{ym}\rho_m + c_m\right)}{\left(\rho_m - \rho_y\right)} \left(\rho^k_m - \rho^k_y\right)\right) \varepsilon_{x,t} \end{aligned} \tag{A.7}$$

where the second equality follows from

$$\mathbb{E}^m_t\left[\hat{m}_{t+j}\right] = \rho^j_m \varepsilon_{x,t},$$

and the last one from

$$\sum_{j=0}^{k-1} \rho^j_y \rho^{k-j}_m = \rho_m \frac{\rho^k_m - \rho^k_y}{\rho_m - \rho_y}$$

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,

$$\begin{aligned}
\mathbb{E}_t^m\left[\hat{\pi}_{t+k}\right] &= \kappa \sum_{j=0}^{\infty} \beta^j \mathbb{E}_t^m\left[\hat{y}_{t+k+j}\right] \\
&= \kappa \sum_{j=0}^{\infty} \beta^j \left(\rho_y^{k+j} b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\rho_m^k - \rho_y^k\right)\right)\varepsilon_{m,t} \\
&= \kappa \left(\frac{\rho_y^k}{1-\beta\rho_y} b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\frac{\rho_m^k}{(1-\beta\rho_m)} - \frac{\rho_y^k}{(1-\beta\rho_y)}\right)\right)\varepsilon_{m,t} \qquad \text{(A.8)}
\end{aligned}$$

Using equation (A.7) and (A.8), we have

$$\frac{\text{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_k], \mathbb{E}_t^m[\hat{y}_k]\right)}{\text{Var}\left(\mathbb{E}_t^m[\hat{y}_k]\right)} = \frac{\rho_y^k b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\rho_m^k - \rho_y^k\right)}{\kappa\left(\frac{\rho_y^k}{1-\beta\rho_y} b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\frac{\rho_m^k}{(1-\beta\rho_m)} - \frac{\rho_y^k}{(1-\beta\rho_y)}\right)\right)}. \qquad \text{(A.9)}$$

Under our assumption that $a_i = \rho_y > \rho_m$, we have

$$\begin{aligned}
\lim_{k\to\infty} \frac{\text{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_k], \mathbb{E}_t^m[y_k]\right)}{\text{Var}\left(\mathbb{E}_t^m[y_k]\right)} &= \lim_{k\to\infty} \frac{b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\left(\frac{\rho_m}{\rho_y}\right)^k - 1\right)}{\frac{\kappa}{1-\beta\rho_y}\left(b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\frac{\left(\frac{\rho_m}{\rho_y}\right)^k}{(1-\beta\rho_m)} - 1\right)\right)} \\
&= \frac{1-\beta\rho_y}{\kappa}
\end{aligned}$$

Next, consider the second term in the bias term in (A.5). We have

$$\begin{aligned}
\lim_{k\to\infty} \rho_m^k \frac{\text{Cov}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}], \hat{m}_t\right)}{\text{Var}\left(\mathbb{E}_t^m[\hat{\pi}_{t+k}]\right)} &= \lim_{k\to\infty} \rho_m^k \frac{1}{\kappa\left(\frac{\rho_y^k}{1-\beta\rho_y} b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\frac{\rho_m^k}{(1-\beta\rho_m)} - \frac{\rho_y^k}{(1-\beta\rho_y)}\right)\right)} \\
&= \lim_{k\to\infty} \left(\frac{\rho_m}{\rho_y}\right)^k \frac{1}{\kappa\left(\frac{1}{1-\beta\rho_y} b_{ym} + \frac{(b_{ym}\rho_m + c_m)}{(\rho_m - \rho_y)}\left(\frac{\left(\frac{\rho_m}{\rho_y}\right)^k}{(1-\beta\rho_m)} - \frac{1}{(1-\beta\rho_y)}\right)\right)} \\
&= 0
\end{aligned}$$

since $\rho_y > \rho_m$. Thus, substituting the last two expressions into (A.5) we have

$$\hat{\psi}_{\pi}^{OLS,m} \to \psi_\pi + \psi_y \frac{1-\beta\rho_y}{\kappa}$$

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,

$$\begin{aligned} \hat{i}_t &= a_i \hat{i}_{t-1} && \text{(A.10)} \\ \hat{y}_t &= a_y \hat{i}_{t-1} && \text{(A.11)} \end{aligned}$$

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

$$\hat{\pi}_t = \frac{\kappa}{1-\beta a_i}\hat{y}_t. \tag{A.12}$$

Substituting (A.10), (A.11) and (A.12 into (Taylor) yields

$$a_i = \rho_i + (1-\rho_i)\left\{\psi_\pi \frac{\kappa}{1-\beta a_i} + \psi_y\right\} a_y. \tag{A.13}$$

Next, substituting (A.10), (A.11) and (A.12 into (Euler) yields (note that $\hat{r}_t^n = 0$)

$$a_y = a_i a_y - \frac{1}{\sigma}\left(a_i - \frac{\kappa}{1-\beta a_i} a_i a_y\right). \tag{A.14}$$

Combining (A.13) and (A.14) yields

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

as wanted. □

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 3.2.

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 identification strategy requires high frequency variation in the data. Our approach, inspired by the recent paper of Aronovich and Meldrum (2021), consists then in using 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

$$SPF_t^{(n)} = \beta_{n,0} + \beta_{n,1} IC_t^{(2y)} + \beta_{n,2} IC_t^{(5y)} + \beta_{n,3} IC_t^{(10y)} + \beta_{n,4} i_t^{(2y)} + u_t^{(n)}, \tag{A.15}$$

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.[28]

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.15) to interpolate the surveys to daily values. The lower-left panel of Figure A-1 plots the implied daily values for the

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

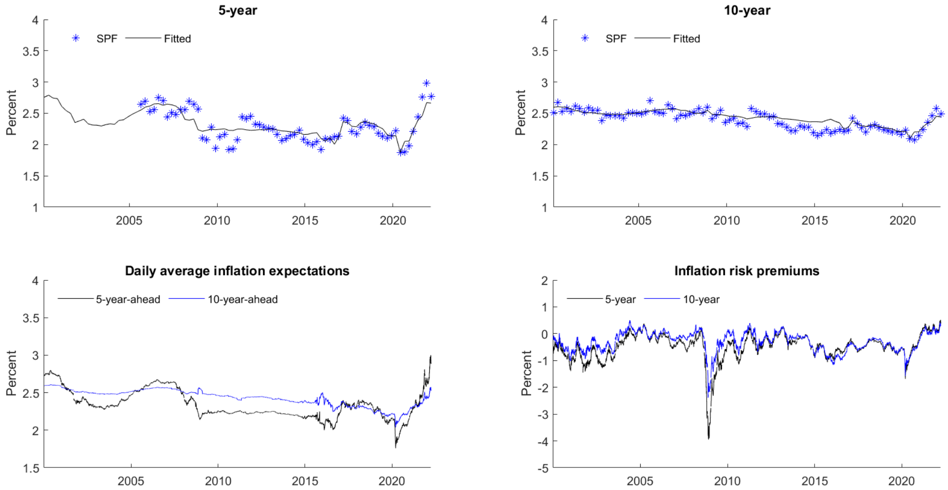

Figure A-1: Risk premia correction for inflation

Notes:

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 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 character-

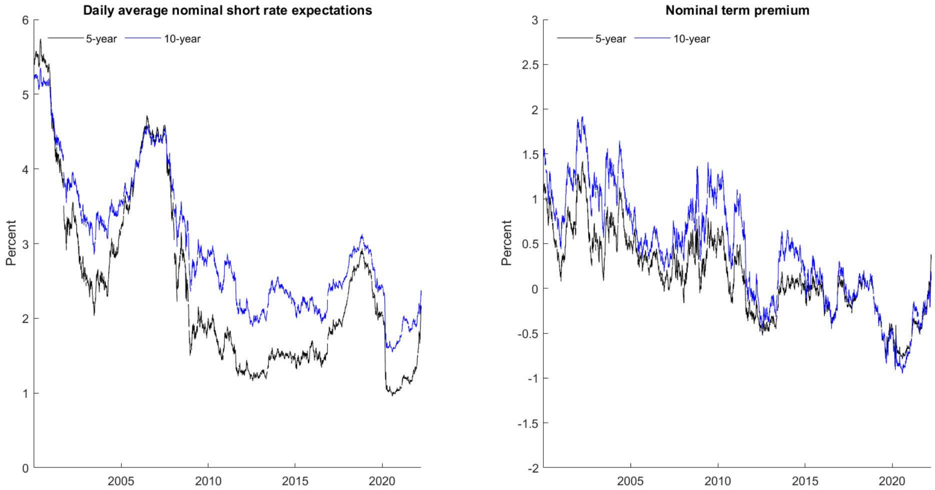

Figure A-2: Risk premia correction for nominal interest rates

Notes:

ized 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 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. In our baseline specification, we fixed $\rho = 0.9$ at a quarterly 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 $\rho = 0.7$ and $\rho = 0.95$, two rather extreme choices in both directions. The results show that our main result is intact and that point estimates are not vastly different if we vary our choice of ρ.

Table A-1: Robustness to choice of ρ

	(1) Baseline	(2) $\rho = 0.7$	(3) $\rho = 0.95$
d (10 year avg)	-0.79^{**}	-0.74^{**}	-0.88^{**}
	(0.36)	(0.31)	(0.43)
d (5 year avg, 1-5)	-1.41^{***}	-1.07^{***}	-1.94^{***}
	(0.36)	(0.27)	(0.51)
d (5 year avg, 6-10)	-0.36	-0.42^{**}	-0.26
	(0.23)	(0.19)	(0.30)
N. obs.	455	455	455

Note: The table reports sensitivity analysis to the baseline results reported in Table 1 and Figure 4. Column (1) restates the baseline results, column (2) uses $\rho = 0.7$, and column (3) uses $\rho = 0.95$. 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.

Robustness to potential liquidity premiums. Because the inflation compensation measure that we use in our baseline implementation is based on Nominal and TIPS yields, it is potentially affected by a liquidity premium. That is because there seems to be a preference for holding nominal bonds over TIPS due to their liquidity. 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.

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-in 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 $\mathbf{s}_t = (s_t, \hat{\imath}_{t-1}, \hat{\bar{\pi}}_{t-1}) = \left(\xi_t, \varepsilon_{m,t}, \mu_t, \theta_t, \hat{\imath}_{t-1}, \hat{\bar{\pi}}_{t-1}\right)$ where $\hat{\bar{\pi}}_{t-1}$ 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:

$$\begin{aligned} y_t &= T_1(\xi_t; \Theta) \cdot \mathbf{s}_t \\ s_t &= T_2(\xi_t; \Theta) \cdot \mathbf{s}_{t-1} + R(\xi_t; \Theta) \cdot \varepsilon_t \end{aligned} \tag{A.16}$$

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.[29] 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 3.1. 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

[29]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 3.1. 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 point estimates of the coefficient d_k in equation (9) reported in Figure 4 and their model-implied counterparts. The model-implied counterparts of d_k are computed via simulations. Specifically, we solve the two-regime model using the perturbation approach described in Foerster et al. (2016), and use the implied non-linear state space representation to simulate a time series for $\mathbb{E}_t^m[\bar{\hat{\pi}}_k]$ and $\mathbb{E}_t^m[\bar{\hat{i}}_k - \rho_i \bar{\hat{i}}_{k-1}]$, for k equal to 5 and 10 years ahead.[30] We then estimate equation (9) on the model-simulated data, with the dummy D_t being equal to one if the economy is in the D regime at time t and zero otherwise. We set the lenght of the simulation to $T = 300000$. The parameters $\psi_\pi(D)$ and $P_{D,D}$ are chosen to minimize an unweighted distance between the point estimate of d from the data and the one computed via simulations of the model. 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.16) to estimate the density of the state vector for each t.[31] The approximation is done via a set of pairs of particles and weights

[30] These conditional expectations are computed by setting in the simulations all the structural shocks in the economy, with the exception of monetary shocks, to zero.

[31] In order to run the particle filter, we add iid measurement errors to each variable in y_t. The variance of

$\{s_t^i, \tilde{w}_t^i\}_{i=1}^N$ 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: Resamplig. 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 5 in the main text reports the time series for the observables and the average for the latent states, computed using $\{s_t^i, \tilde{w}_t^i\}_{i=1}^N$

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 6 in the main text.

these measurement errors is set to 0.5% of the unconditional variance of the series.