Monetary Policy without Moving Interest Rates: The Fed Non-Yield Shock*

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Abstract

Existing high-frequency monetary policy shocks explain surprisingly little variation in stock prices and exchange rates around FOMC announcements. At the same time, both of these asset classes display heightened volatility relative to non-announcement times—even after residualizing with respect to the entire yield curve. Motivated by these observations, we use a heteroskedasticity-based procedure to estimate a "Fed non-yield shock" which is orthogonal to yield changes and is identified from excess volatility in the S&P 500 and various dollar exchange rates. A positive Fed non-yield shock raises stock prices in the U.S. and around the globe, depreciates the dollar, reduces the VIX and many other risk-related measures, and lowers U.S. convenience yields. Our shock is essentially uncorrelated with previous monetary policy shocks and implies that the Fed moves asset prices through channels that are not spanned by the yield curve.

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1 Introduction

No matter how we measure [monetary policy] surprises or how much delay we allow for the response, we can only explain up to about 10 percent of the daily variation in risk appetite. While some of the variation in risk appetite on days with FOMC announcements is certainly driven by news unrelated to monetary policy, it is hard to argue that all, or even most, of the remaining 90 percent of the daily variation in risk appetite is unrelated to monetary policy.

— Bauer, Bernanke, and Milstein (2023)

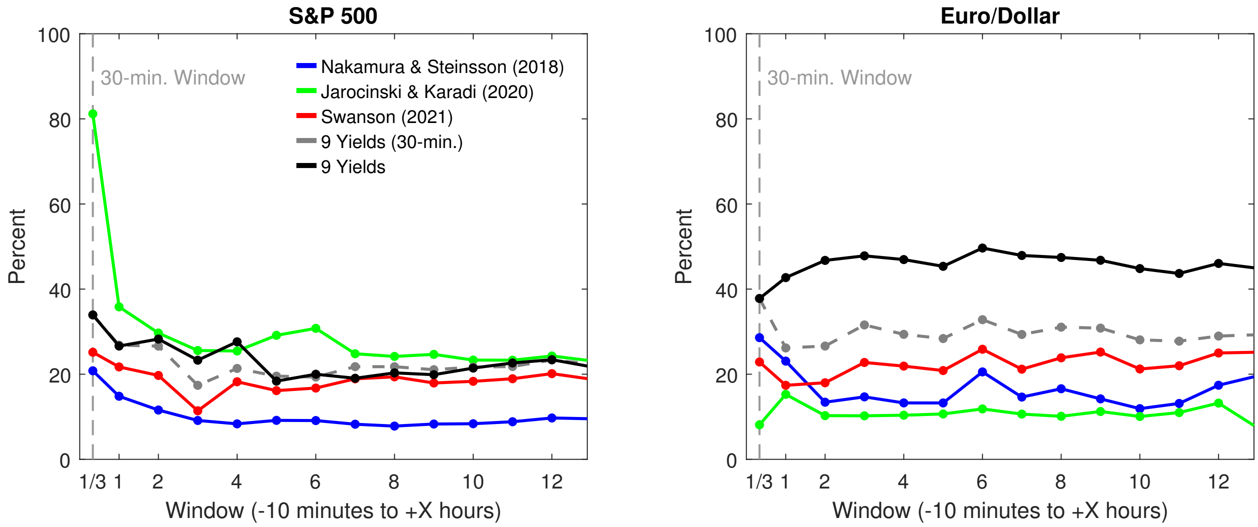
High-frequency monetary policy shocks à la Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005) have puzzlingly low explanatory power for prices of equities and currencies—two asset classes that are crucial for understanding the monetary transmission mechanism. These high-frequency shocks are constructed from unexpected interest rate changes over narrow windows around FOMC announcements and have become the workhorse shocks for empirical research in monetary economics. Although, by construction, they account for most of the variation in the yield curve over the event window, their explanatory power for changes in stock prices and exchange rates is surprisingly low.

Figure 1 illustrates this point by plotting the R-squared of various high-frequency shocks for the S&P 500 and the Euro-Dollar exchange rate. The horizontal axis measures the length of the event window around FOMC announcements. As the figure shows, Nakamura and Steinsson's (2018) single shock (blue line) and Swanson's (2021) three shocks (red line) explain less than 30 percent of the variation at all horizons up to 13 hours after the shock. Adding more yield-based shocks does not substantially raise this explanatory power. Specifically, regressing changes in the stock market or the exchange rate on nine yield surprises covering the entire yield curve up to 30 years adds little explanatory power. This is the case regardless of whether we construct the yield changes over 30-minute windows (grey line) or whether we increase the window length to match the window of the dependent variable (black line).

One potential avenue to address this issue is to introduce what the literature has termed "information effects" (Romer and Romer, 2000). If central bank communication reveals private information on economic fundamentals, the observed behavior of stock markets or exchange rates is also needed to estimate monetary policy shocks (Jarociński and Karadi, 2020; Gürkaynak, Kara, Kısacıkoğlu, and Lee, 2021).[1] Besides the fact that some research

[1] Other names for information effects in the literature are information shocks, signaling effects or Delphic forward

Figure 1: Explanatory Power of Yield Curve around FOMC Announcements



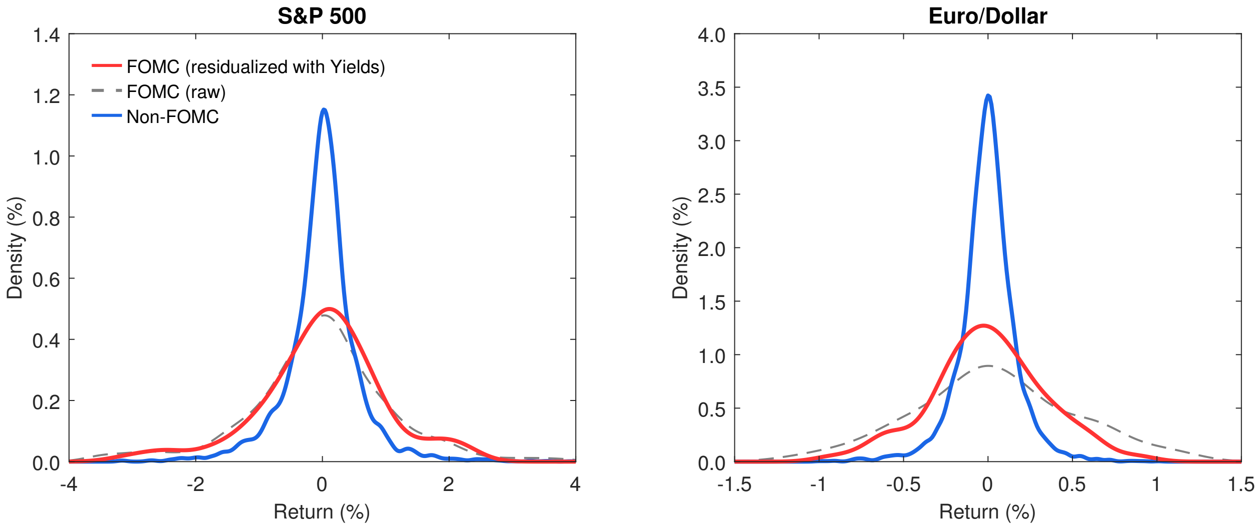
Notes: This figure shows the R^2 values of regressing the log-return around FOMC announcements of the front-month S&P E-mini futures contracts (left panel) and the Euro-Dollar exchange rate (right panel) on various different high-frequency shocks. The window over which returns are constructed is expanding along the horizontal axis. The full sample ranges from January 1996 to April 2023. See text for details on the shocks.

has challenged the importance of information effects (e.g., Bauer and Swanson, 2023), Figure 1 shows that they do not resolve the explanatory power puzzle. Specifically, the explanatory power of Jarociński and Karadi's (2020) shocks (green line), which are constructed from 30-minute changes in yields and stock prices, falls sharply when considering longer windows. Further, these shocks have very low explanatory power for exchange rates throughout. This point echoes findings by Gürkaynak et al. (2021, p.1) who conclude that "even after conditioning on possible information effects driving longer term interest rates, there appear to be other drivers of exchange rates."

Since both stocks and exchange rates are substantially more volatile than bond yields, the unexplained variation could simply reflect news unrelated to monetary policy. Indeed, (Swanson, 2021, p.13) attributes the low explanatory power of yield curve changes for the stock market to the "larger idiosyncratic volatility of stocks (...) relative to Treasuries". This contrasts with Bauer, Bernanke, and Milstein (2023) who question such an interpretation. The data suggests that the unexplained variation is not just noise. Specifically, Figure 2 shows that both stock prices and exchange rates exhibit much greater variance on announcement days than at similar times on non-announcement days—even after residualizing with

guidance.

Figure 2: Distribution of Returns for 6-Hour Window around FOMC Announcements



Notes: This figure shows the distribution of log-returns of the front-month S&P E-mini futures contracts (left panel) and the Euro-Dollar exchange rate (right panel). The dashed grey line with legend entry FOMC (raw) represents the distribution of log-returns around FOMC announcements. The full red line represents the same distribution around FOMC announcements after residualizing the returns with nine yield changes (see below for details). The full blue line represents the distribution around similar times on non-FOMC announcement days. The window over which returns are constructed goes from 10 minutes prior to the reference time to six hours after. The full sample ranges from January 1996 to April 2023. Appendix Figure C1 displays the distributions of returns for more window sizes. See text for details on the shocks.

respect to yield changes. This "excess variance" also points to an omitted dimension of monetary policy.

In this paper, we show that the unexplained variation in equities and exchange rates reflects a dimension of monetary policy that is not spanned by changes in the yield curve. We use a heteroskedasticity-based procedure to estimate a single latent shock from high-frequency movements in U.S. equities and various major U.S. dollar exchange rates. We call this shock the "Fed non-yield shock". It is by construction orthogonal to changes in the U.S. yield curve at any horizon and thus contrasts with shocks that affect the yield curve. We show that the non-yield shock is well-identified and that it captures much of the remaining variation in both equities and exchange rates. A positive Fed-non yield shock leads to an increase in global stock markets and a depreciation of the U.S. dollar against other currencies. These effects appear to be driven by a decrease in perceived risk, an increase in risk appetite, as well as decreases in U.S. convenience yields relative to other countries.

Related literature Our paper relates to a long literature in monetary economics, which aims to identify exogenous variation in monetary policy, i.e., "monetary policy shocks", to study the monetary transmission mechanism. Early work constructed shocks from historical narratives (e.g., Friedman and Schwartz, 1963; Romer and Romer, 2004) or vector autoregressions (VARs) (e.g., Christiano, Eichenbaum, and Evans, 1999; Uhlig, 2005). More recent work predominantly measures shocks from high-frequency financial market data following the seminal work by Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005). These shocks have been used, extended, and adapted in a variety of high-frequency applications (e.g., Nakamura and Steinsson, 2018; Swanson, 2021; Lunsford, 2020; Lewis, 2023) or in combination with lower-frequency times series methods (e.g., Gertler and Karadi, 2015; Caldara and Herbst, 2019; Paul, 2020; Miranda-Agrippino and Ricco, 2021). We contribute to this literature by proposing a method that extracts shocks that are informative about a novel and under-researched dimension of monetary policy.

The most closely related papers are Cieslak and Schrimpf (2019), Jarociński and Karadi (2020), and Kroencke, Schmeling, and Schrimpf (2021). Building on prior work by Romer and Romer (2000), Cieslak and Schrimpf (2019) and Jarociński and Karadi (2020) rationalize the unexplained stock market variation around FOMC announcements with information effects. While the mapping between their information shocks and our non-yield shock is not straightforward, we show below that our shock is orthogonal to those by Jarociński and Karadi (2020). Kroencke, Schmeling, and Schrimpf (2021) also construct a monetary policy shock that is orthogonal to yield changes based on risky asset prices and interpret this shock as a "risk shift". While our non-yield shock is conceptually similar to the risk shift, several differences in methodology and implementation ultimately imply that the risk shift explains less than a quarter of the variation of our non-yield shock. We provide a more detailed comparison below.

We also contribute to a fast-growing literature studying the effects of monetary policy on risk perceptions and risk appetite, which are often referred to as the *risk-taking channel* of monetary policy. On the empirical side much work has documented that monetary policy affects risk premia (e.g., Bernanke and Kuttner, 2005; Hanson and Stein, 2015; Gertler and Karadi, 2015). Subsequent work has begun to incorporate these mechanisms into theoretical frameworks (e.g., Alvarez, Atkeson, and Kehoe, 2009; Drechsler, Savov, and Schnabl, 2018; Kekre and Lenel, 2022).[2] We add to this literature by showing that monetary policy has more powerful effects on risk perceptions and risk appetite than previously thought. Our findings further help understand the *exchange rate channel* of monetary policy (e.g., Eichenbaum and Evans, 1995; Faust and Rogers, 2003; Gürkaynak et al., 2021). Specifically, we show

[2] See Bauer, Bernanke, and Milstein (2023) for a comprehensive review of this literature.

that risk premia are not only important for unconditional exchange fluctuations (e.g., Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011; Hassan and Mano, 2019), but also for the monetary policy transmission to exchange rates.

In the context of the risk-taking channel, it is important to emphasize that our results differ from those in the literature as our non-yield shock leaves interest rates initially unaffected. More recently, Bauer, Lakdawala, and Mueller (2022) show that FOMC announcements can affect risk premia through policy uncertainty and Cieslak and McMahon (2023) document a link between the Fed's policy deliberations and risk premia. While their analyses and focus are distinct from ours, their results also emphasize the effects of "non-traditional" monetary policy on risk premia.

Lastly, our paper contributes to a body of work in international economics studying flight-to-safety or flight-to-quality episodes—or more broadly the link between safe assets, U.S. dollar, and risk premia. Recent work in this literature includes Maggiori (2017), Caballero and Farhi (2018), Baele, Bekaert, Inghelbrecht, and Wei (2020), Kekre and Lenel (2021), Jiang, Krishnamurthy, and Lustig (2021), and Engel and Wu (2023). We contribute to this literature by showing that monetary policy can potentially generate such flight-to-safety behavior in international markets.

Roadmap The remainder of the paper is structured as follows. The next section presents our empirical framework and discusses how we identify the Fed non-yield shock. Section 3 documents the importance of the non-yield shock for global asset prices. Section 4 provides a framework to interpret the shock as well as additional responses. Lastly, Section 5 concludes.

2 The Fed Non-yield Shock

In this section, we introduce the Fed non-yield shock. We begin with laying out the estimation framework and discuss the underlying identification assumptions. We also discuss what the estimation procedure does in a relatively general class of models and how the non-yield shock can arise. We subsequently turn to the data as well as specification choices, and also report tests on the strength of the identifying variation. We conclude this section with presenting the estimated shock series.

2.1 Framework

In conventional high-frequency event-study designs, the estimating equation is

$$\Delta p_{i,t} = \beta_i s_t^y + \varepsilon_{i,t}, \qquad \text{for } t \in F. \tag{1}$$

In this specification $\Delta p_{i,t}$ is the high-frequency return on asset i around the time-t FOMC announcement and F denotes the set of dates/times of FOMC announcements.[3] Further, s_t^y is a vector of k monetary policy shocks that pass through the yield curve (henceforth, "yield shocks"), and β_i is the corresponding vector of coefficients. Following Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005), a large literature constructs s_t^y using changes in interest rate futures around announcements. Consistent with conventional economic theory, this framework estimates the effects of monetary policy as captured by changes in interest rates, that is, the yield curve.

However, as noted in the introduction, both the low explanatory power of yield shocks and the elevated volatility of asset prices are puzzling and potentially indicative of an unobserved dimension of monetary policy. Thus, instead of (1), we consider the following specification in our analysis

$$\Delta p_{i,t} = \beta_i s_t^y + \gamma_i s_t^{ny} + \varepsilon_{i,t}, \qquad \text{for } t \in F, \tag{2}$$

where s_t^{ny} denotes the latent non-yield shock. Hence, this specification allows for the possibility that information released during the FOMC announcement affects stocks and exchange rates through a channel that is separate from interest rates. For the estimation we will assume that both s_t^y and s_t^y are uncorrelated with the error $\varepsilon_{i,t}$ ($Cov\left[s_t^y, \varepsilon_{i,t}\right] = Cov\left[s_t^{ny}, \varepsilon_{i,t}\right] = 0$). We will further assume that s_t^{ny} is orthogonal to s_t^y ($Cov\left[s_t^y, s_t^{ny}\right] = 0$). We will discuss the implications of this latter assumption for the interpretation of the non-yield shock below.

To recover s_t^{ny}, we apply a heteroskedasiticty-based approach (Rigobon, 2003). In the context of this application, the underlying idea is that on trading days, on which there is no announcement, asset returns at similar times as FOMC announcements should neither include s_t^y nor s_t^{ny}, but be otherwise comparable. Formally,

$$\Delta p_{i,t} = \varepsilon_{i,t}, \qquad \text{for } t \in NF, \tag{3}$$

where NF denotes the set of non-announcement dates/times. We will also make use of

[3] The setup also depends on the length of the event window which we omit for ease of notation. We return to this point below.

the fact that we can directly measure s_t^y from interest rate futures following the previous literature. Under the assumption that s_t^{ny} and s_t^y are orthogonal, we can then identify the non-yield shock from heightened stock market and exchange rate volatility relative to non-announcement days.

We estimate s_t^{ny} via maximum likelihood using the Kalman filter following Gürkaynak, Kısacıkoğlu, and Wright (2020). The observation equation for asset i combines equations (2) and (3) and is given by

$$\Delta p_{i,t} = \beta_i s_t^y + \gamma_i d_t s_t^{ny} + \varepsilon_{i,t}.$$

Here, $d_t = 1\,(t \in F)$ is an announcement indicator, and s_t^{ny} is independently and identically normally distributed with zero mean and unit variance. The variance is normalized to one since γ_i is otherwise only identified up to scale.[4]

In principle, we could recover our non-yield shock from a single asset. However, our motivating facts in the introduction suggests that a common non-yield shock affects different assets and even different asset classes. Further, employing a broader set of assets increases the estimation precision of the non-yield shock. In the case of multiple assets, the observation equation is

$$\Delta p_t = \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t, \tag{4}$$

where p_t, β, γ, and ε_t denote the appropriately dimensioned matrices capturing $p_{i,t}$, β_i, γ_i, and $\varepsilon_{i,t}$. We assume ε_t is independently and identically normally distributed with a diagonal variance-covariance matrix. Details on the estimation framework are available in Appendix A.

2.2 Identification and Interpretation

We now summarize the key identification assumptions that allow us to estimate the non-yield shock s_t^{ny} based on equation (4): (i) the change in asset prices on non-FOMC announcements days do not include monetary policy news but are otherwise comparable to changes on announcement days, (ii) the change of the yield curve around FOMC announcements is entirely driven by monetary policy shocks, and vector s_t^y is able to capture all these shocks, (iii) the relationship between the yield curve and the stock market is stable over the sample period. (iv) The non-yield shock s_t^{ny} is orthogonal to all yield shocks s_t^y.

[4] Note that our baseline model has no intercept following Gürkaynak, Kısacıkoğlu, and Wright (2020) as we assume that our employed ℓ-hour changes are mean-zero in population which is true in our sample. In Appendix Table A1, we check this assumption by estimating our non-yield shock with demeaned data. The results are almost identical.

Assumptions (i) and (ii) are conventional in the high-frequency literature. Without a regime change, assumption (iii) is always satisfied up to a first order. However, some prior work indicates that the relationship between the yield curve and asset prices may be time-varying due to the zero lower bound (ZLB). We therefore show in our robustness analysis in Appendix A.3 that to the extent that assumption (iii) is violated, the consequences for our estimation are relatively inconsequential—in line with findings by Swanson (2021).

Assumption (iv) is key for the interpretation of the non-yield shock. To understand what this assumption implies for the non-yield shock, consider the following model that generates the data over the narrow windows on which the estimation procedure is implemented. Specifically, suppose the true model is

$$\begin{pmatrix} s_t^y \\ \Delta p_t \end{pmatrix} = \begin{pmatrix} A_y \\ A_p \end{pmatrix} z_t + \begin{pmatrix} 0 \\ \varepsilon_t \end{pmatrix}. \tag{5}$$

Here, s_t^y is a $k \times 1$ vector of yield shocks, Δp_t is a $n \times 1$ vector of stock price and exchange rate changes, z_t is a $r \times 1$ vector of structural monetary policy shocks which satisfy $Cov\left[z_t\right] = I_r$, ε_t is a $n \times 1$ vector of non-monetary drivers of stock prices and currencies over the window in question, and A_y and A_p are matrices capturing how yield changes, stock price changes, and exchange rate changes depend on the structural monetary policy shocks. Since we initially leave these matrices unrestricted, this model is quite general. The only restrictions we impose on this data generating process is that the endogenous variables linearly depend on the state variables and that yield changes are not affected by non-monetary drivers within narrow windows.

Applying our estimation procedure to this data generating process in the population—or more precisely, a slightly more general procedure that allows for multiple non-yield shocks—implies that

$$\Delta p_t = \beta s_t^y + \Gamma s_t^{ny} + \varepsilon_t, \tag{6}$$

where

$$\beta = A_p A_y' \left(A_y A_y'\right)^{-1}, \tag{7}$$

provided that A_y is of rank $k \leq r$. In words, β is the matrix of projection coefficients obtained by projecting Δp_t on s_t^y. Further, for a coefficient matrix Γ that is pinned down by the estimation procedure, the non-yield shock is implicitly defined as satisfying equation

$$\Gamma s_t^{ny} = A_p \left(I - A_y' \left(A_y A_y'\right)^{-1} A_y\right) z_t. \tag{8}$$

It follows from equation (8) that the non-yield shock is in general a *reduced form monetary policy shock*. It is a reduced form shock, because it is a linear combination of the structural monetary policy shocks z_t. (This is most clearly seen for the case in which Γ is invertible.) While reduced form shocks are generally difficult to interpret, equation (8) also makes clear that the non-yield shock is *only* a function of the structural monetary policy shocks z_t. That is, for the data generating process considered here, the estimation procedure correctly separates the monetary policy shocks z_t from the non-monetary disturbances ε_t, so that the non-yield shocks are unaffected by the non-monetary disturbances.[5]

Plugging expressions (7) and (8) into equation (6) gives

$$\Delta p_t = \underbrace{A_p A_y' \left(A_y A_y'\right)^{-1} A_y}_{\text{Effect passing through yields}} z_t + \underbrace{A_p \left(I - A_y' \left(A_y A_y'\right)^{-1} A_y\right)}_{\text{Effect orthogonal to yield changes}} z_t + \varepsilon_t. \tag{9}$$

This expression shows that our estimation procedure decomposes the effects of the structural monetary policy shocks z_t on Δp_t into a part that passes through the yield curve and a part that does not pass through the yield curve (the orthogonal complement). The properties of projections imply that if A_y is of rank $k \leq r$, then $A_y' \left(A_y A_y'\right)^{-1} A_y$ is of rank k and $I_r - A_y' \left(A_y A_y'\right)^{-1} A_y$ is of rank $r - k$ (see Davidson and MacKinnon, 2004, p. 61). Hence, if there are k yield shocks and we detect $r - k$ non-yield shocks in the data, then there must be r structural monetary policy shocks.

The following special cases help build intuition. First, suppose that the number of yield shocks equals the number of structural monetary policy shocks, $k = r$, and that A_y is of full rank. Then (i) the structural monetary policy shocks can be identified from the yield curve alone, $z_t = \left(A_y\right)^{-1} s_t^y$, and (ii) there are no non-yield shocks. These are the cases considered in Kuttner (2001), Gürkaynak, Sack, and Swanson (2005), and Swanson (2021).

Second, suppose that the vector of structural monetary policy shocks z_t can be partitioned into a $k \times 1$ vector z_t^1 and a $(r-k) \times 1$ vector z_t^2, which – and this is the key assumption for this special case – does not affect yields. Partitioning $A_y = \begin{bmatrix} A & 0 \end{bmatrix}$, where A is a $k \times k$ matrix of full rank, it follows that (i) $z_t^1 = A^{-1} s_t^y$, that is, the k structural monetary policy shocks z_t^1 can be identified from the yield curve, and (ii) the $r - k$ non-yield shocks are *structural* shocks, $s_t^{ny} = z_t^2$. Hence, while the non-yield shock is in general a reduced form monetary policy shock, it is structural in this special case.[6]

[5] Of course, this is a property of estimating the non-yield shock in the population. In finite samples, there will be estimation error.

[6] Note that this second special case is also consistent with the identification procedures by Kuttner (2001), Gürkaynak, Sack, and Swanson (2005), and Swanson (2021), although they do not identify the $r - k$ non-yield

Lastly, consider the special case of Jarociński and Karadi (2020). Specifically, suppose that there are two structural monetary policy shocks $z_t = \begin{bmatrix} z_t^{\text{pure}} & z_t^{\text{info}} \end{bmatrix}'$, where z_t^{pure} is the pure monetary policy shock and z_t^{info} is the information shock. These two shocks are identified from the co-movement of one interest rate, $k = 1$, and the S&P 500, $n = 1$. The key assumptions are that a pure monetary policy shock has opposite effects on interest rates and stock prices while the information shock moves interest rates and stock prices in the same direction. Formally, these restrictions are captured as $A_y = \begin{bmatrix} a & b \end{bmatrix}$ and $A_y = \begin{bmatrix} -c & d \end{bmatrix}$ for strictly positive (but unknown) constants a, b, c, d.

Straightforward algebra shows that in this case

$$s_t^{ny} = \frac{1}{\sqrt{a^2 + b^2}} \left(-b z_t^{\text{pure}} + a z_t^{\text{info}} \right).$$

That is, the non-yield shock is a linear combination of the pure and the information shock. Note that this is a testable prediction: If the true data generating process follows the identification assumptions of Jarociński and Karadi (2020), and we implement our estimation procedure on the resulting data, then the non-yield shock should be a linear combination of the pure and the information shock. One would expect that a regression of the non-yield shock on the pure and the information shock should deliver a high R-squared. We will test this prediction below.

An important point that follows from these special cases is that, if at least one non-yield shock is present in the data—which is what we will argue below—then identification strategies, which identify monetary policy shocks from data on yields alone, will generally fail to uncover the true structural monetary policy disturbances. The reason is that the yield curve alone does not contain sufficient information to recover these shocks. An example of this is the special case of Jarociński and Karadi (2020) just discussed. In that case only a single short-term yield is used in the estimation, which – and continuing to use the notation introduced for that special case – satisfies

$$s_t^y = a z_t^{\text{pure}} + b z_t^{\text{info}}.$$

Hence, the single yield shock is insufficient to recover the two true structural shocks. This point is more general. In fact, and conditional on there being at least one non-yield shock in the data, the only exception is the second special case above, in which the non-yield shocks are structural monetary policy shocks. In that case, changes in the yield curve are sufficient

shocks to the extent that they exist.

to recover k structural monetary policy shocks.

2.3 Specification and Data

The estimation of the non-yield shock requires, among other things, a choice of the window length as well as a selection of informative asset prices.

While previous high-frequency, intraday studies commonly use windows of 20, 30, or 60 minutes around announcements, we also consider longer windows. Given the amount of information contained in the FOMC announcements as well as in the subsequent press conferences, we expect that stock and currency markets might need more time to fully incorporate all information.[7] In order to find the optimal window length, we therefore attempt to balance the trade-off between capturing more information and introducing too much noise. A tighter window is known to circumvent econometric issues arising from other news releases (Gürkaynak, Sack, and Swanson, 2005) and to strengthen the identification with heteroskedasticity-based approaches (Lewis, 2022). A wider window, on the other hand, includes the subsequent press conference, which other papers find to be important for asset prices (e.g., Gorodnichenko, Pham, and Talavera, 2023), and allows the market to fully process the information released in both the FOMC announcements and the press conferences.

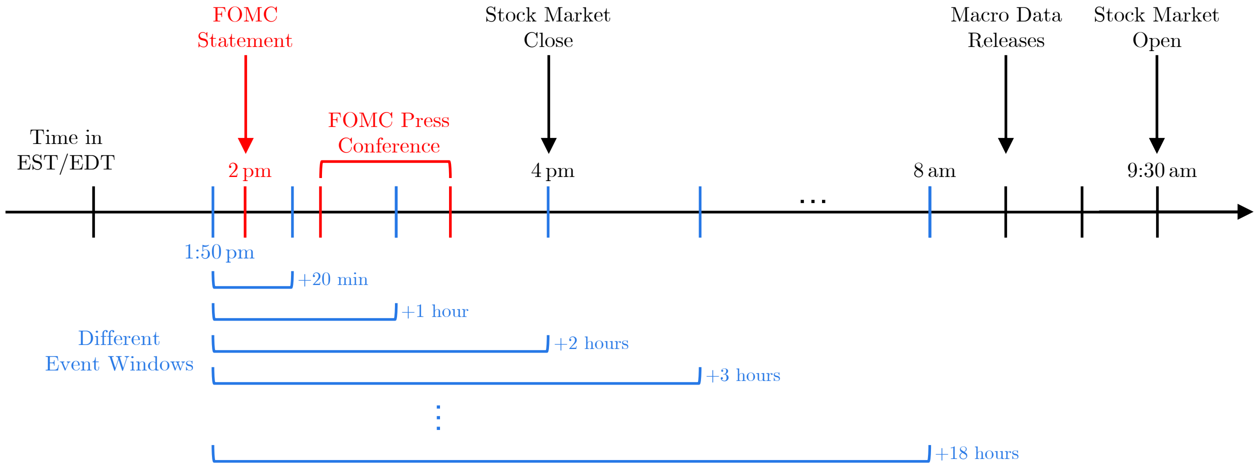
A similar trade-off applies to the selection of asset prices. If an asset price strongly responds to the non-yield shock, including it in the estimation will generally provide information on the shock and thereby improve estimation precision. On the other hand, asset prices that respond to the non-yield shock only weakly, or not at all, will largely add noise to the estimation. Asset prices with poor data coverage are also unlikely to benefit the estimation.

We therefore proceed in two steps. In a first step, we consider a range of window lengths and multiple asset prices that we consider as appropriate *a priori*. Good data coverage plays an important role for the selection of asset prices in this step. We subsequently perform pre-tests on the strength of the identifying variation by asset price and window length to finalize our baseline specification.

Sample Period Our sample period ranges from January 1996 to April 2023. We obtain dates and times of FOMC announcements from *Bloomberg* and cross-check them with infor-

[7] Note that this is not necessarily important if our interest lies in understanding only the high-frequency effects as pointed out by Bauer and Swanson (2023). However, we are also interested in studying the lower-frequency effects of our non-yield shock.

Figure 3: Overview of Event Study Windows



Notes: This figure shows timeline of a typical FOMC day including the different event study windows we consider.

mation from the Federal Reserve website, and data from prior papers. The announcement sample F includes a total of 220 observations over this period. With very few exceptions, the FOMC announcements are released at 2:15 pm EST (Eastern Standard Time) until January 2013 and at 2:00 pm EST thereafter. The non-announcement sample NF comprises 5085 observations on regular trading days for which we use a timestamp of 2:15 pm EST. Appendix B.1 provides more details on the sample construction.

Event Windows All event windows we consider begin 10 minutes prior to the release. The shortest ends 20 minutes after the FOMC release and hence matches the typical 30-minute window used in the literature. After that, we consider a window ending 60 minutes after the FOMC release and then proceed in one hour increments. Throughout the paper, we use *ℓ-hour window* to refer to the window ending ℓ hours after the release and write *ℓ-hour return* to describe the return over that window. Overall, we consider 19 event windows, i.e., $\ell \in \left\{\frac{1}{3}, 1, 2, ..., 18\right\}$. The 18-hour window is the widest and ends at 8 am EST on the next day so that U.S. macroeconomic data releases, which often occur 8:30 am, are not included for any window length. Figure 3 provides an visualization of this argument.

Yield Shocks Our estimation procedure of s_t^{ny} partials out all variation arising from yield shocks s_t^y. As shown by Gürkaynak, Sack, and Swanson (2005) and Swanson (2021), among others, FOMC announcements potentially affect the yield curve through different channels leading to complex and multidimensional effects. To capture these effects, we construct for a given event window length ℓ the vector $s_t^{y(\ell)}$ from the following nine surprises across different yields,

$$s_t^{y(\ell)} = \begin{bmatrix} MP1_t^{(\ell)} & MP2_t^{(\ell)} & ED2_t^{(\ell)} & ED3_t^{(\ell)} & ED4_t^{(\ell)} & T2Y_t^{(\ell)} & \ldots \\ & & T5Y_t^{(\ell)} & T10_t^{(\ell)} & T30_t^{(\ell)} \end{bmatrix}'. \tag{10}$$

In this expression $MP1_t^{(\ell)}$ and $MP2_t^{(\ell)}$ are surprises in the expected federal funds rate after the current and subsequent FOMC meeting. Both are constructed from federal funds futures contracts. Further, $ED2_t^{(\ell)}$, $ED3_t^{(\ell)}$, and $ED4_t^{(\ell)}$ are surprises in the implied rates from Eurodollar futures capturing revisions of the expected 3-month US Dollar LIBOR from two to four quarters out. All five measures ($MP1_t^{(\ell)}$, $MP2_t^{(\ell)}$, $ED2_t^{(\ell)}$, $ED3_t^{(\ell)}$, and $ED4_t^{(\ell)}$) are standard in the literature (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018), and cover surprises in the yield curve of maturities up to 14 months. For longer horizons, we use implied rates from Treasury futures of horizons two ($T2_t^{(\ell)}$), five ($T5_t^{(\ell)}$), ten ($T10_t^{(\ell)}$), and thirty years ($T30_t^{(\ell)}$) (Gürkaynak, Kısacıkoğlu, and Wright, 2020). All high-frequency data is obtained from the *Thomson Reuters Tick History* database. In Appendix B.2, we provide details on the construction and show that all our surprises closely match those of previous studies.

Note that we could alternatively allow for noise in each of the nine surprises by first estimating a factor model via principal components as done in previous work (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Swanson, 2021). However, we prefer to use all raw surprises as our baseline. The main reason is that this approach is more conservative in the context of our application since it makes sure that the non-yield shock does not pick up any information captured in the yield curve over the estimation window (this will be confirmed in our robustness analysis in Appendix A.3). An added benefit is that we do not need to take a stance on how many shocks adequately capture the effects of monetary policy shocks on the yield curve. It turns out, however, that the non-yield shock is almost identical when replacing the nine yield changes with their three principal components (see robustness section in Appendix A.3). This is consistent with the findings by Swanson (2021).

Equities and Exchange Rates We focus on equities and exchange rates as our outcome variables for the following two reasons: First, both asset classes are, aside from yields, the most studied ones in the empirical monetary policy literature. They also feature prominently in many models. Second, to conduct our analysis with varying window lengths, our analysis requires securities that are sufficiently liquid outside of regular trading hours. Currencies typically trade around the clock on regular trading days. Further, stock index futures are traded outside of regular trading hours for a handful of countries, including the U.S. As before, all high-frequency data comes from the *Thomson Reuters Tick History* database.

With regard to stock index futures, we have access to contracts for the U.S. and several other advanced economies (see Boehm and Kroner (2023) for a list of considered futures contracts). However, only the E-mini S&P 500 futures contracts have sufficient data quality to construct returns over the different window sizes of interest to us. This is mostly because trading hours of many international futures contracts extend beyond the trading hours of the underlying stock market only by several of hours. The same issue arises for VIX futures, which only recently extended their trading hours. We therefore use the first and second closest E-mini S&P 500 futures contracts to represent stock markets in our analysis. While this may appear limiting, the results in Boehm and Kroner (2023) suggest that international and U.S. stock markets respond very similarly to U.S. news. We will confirm this interpretation below in Section 3.1 where we study a broader range of stock indexes.

Motivated by the need for sufficiently liquid assets, we consider in the forex market the U.S. Dollar exchange rates against the 20 currencies with the highest turnover of over-the-counter (OTC) foreign exchange instruments according to the 2022 Bank of International Settlements (BIS) Triennial Central Bank Survey.[8] We drop the Chinese Yuan and Indian Rupee due to the poor quality of the intraday data, leaving us with 18 U.S. Dollar exchange rates. Figure 2 provides an overview of the 20 asset prices we consider for our baseline specification. Note that all these asset prices will be expressed in log-differences throughout our analysis. Appendix B.3 provides details on how these returns are constructed.

Baseline Specification We next turn to the second specification step, in which we select the event window and the final set of asset prices. This step is based on pre-tests on the strength of the identifying variation for a given asset price i and event window length ℓ.

The pre-tests use the equivalence between the one-step Kalman filter estimation of (4) and a two-step procedure (Gürkaynak, Kısacıkoğlu, and Wright, 2020), which applies the Rigobon (2003) heteroskedasticity estimator to the residual $\phi_{i,t}$, where $\phi_{i,t}$ is given by

$$\phi_{i,t} \equiv \Delta p_{i,t} - \beta_i s_t^y = \gamma_i s_t^{ny} + \varepsilon_{i,t} \quad \text{for } t \in F,$$

after estimating β_i by OLS, and

$$\phi_{i,t} \equiv \Delta p_{i,t} = \varepsilon_{i,t} \quad \text{for } t \in NF.^{9}$$

[8] `https://stats.bis.org/statx/srs/table/d11.3` (accessed on September 10, 2023).

[9] As shown by Gürkaynak, Kısacıkoğlu, and Wright (2020), both approaches lead to slightly different results when

Table 1: Overview of Left-hand-side Asset Prices

Name	Abbreviation	Ticker	Sample	Observations	
				FOMC	Non-FOMC
Stock Index Futures					
E-mini S&P 500 front month	ES1	ESc1	1997–2023	208	4779
E-mini S&P 500 second month	ES2	ESc2	1997–2023	198	4578
U.S. Dollar Exchange Rates					
Euro	EUR	EUR=	1998–2023	197	4577
Japanese Yen	JPY	JPY=	1996–2023	220	5084
British Pound	GBP	GBP=	1996–2023	219	5084
Australian Dollar	AUD	AUD=	1996–2023	219	5084
Canadian Dollar	CAD	CAD=	1996–2023	218	5085
Swiss Franc	CHF	CHF=	1996–2023	219	5084
Hong Kong Dollar	HKD	HKD=	1996–2023	205	4604
Singapore Dollar	SGD	SGD=	1996–2023	212	4814
Swedish Krona	SEK	SEK=	1996–2023	214	4994
Korean Won	KRW	KRW=	1996–2023	123	2632
Norwegian Krone	NOK	NOK=	1996–2023	219	5048
New Zealand Dollar	NZD	NZD=	1996–2023	220	5064
Mexican Peso	MXN	MXN=	1996–2023	220	5078
Taiwan Dollar	TWD	TWD=	1996–2023	115	2435
South African Rand	ZAR	ZAR=	1996–2023	215	4837
Brazilian Real	BRL	BRL=	1996–2023	207	4739
Danish Krone	DKK	DKK=	1996–2023	217	5048
Polish Zloty	PLN	PLN=	1996–2023	188	4333

Notes: This table shows the asset prices considered as left-hand variables in our analysis. The data is from *Thomson Reuters Tick History*. For all series, the sample period ends in April 2023. The U.S. Dollar exchanges rates are listed in descending order in terms of turnover of the foreign currency based on the BIS Triennial Central Bank Survey. All exchange rates are converted so that they are in foreign currency per U.S. dollar. *Abbreviation* refers to the abbreviation used in the paper, and *Ticker* refers to the Reuters Instrument Code (RIC).

With this alternative formulation, we can use Lewis's (2022) test for weak identification, which is based on the idea that a heteroskedasticity estimator can be rewritten as an instrumental variable problem (Rigobon and Sack, 2004). With some abuse of notation, let $\Delta p_{i,t}^{(\ell)}$ be the ℓ-hour log-return of an asset price i in Table 1, and let $\phi_{i,t}^{(\ell)}$ be the corresponding residual constructed based on yield shocks $s_t^{y(\ell)}$ as defined in (10). We can then construct

more than one series is included in Δp_t. The reason for that is that the Kalman filter takes the covariance of the assets in Δp_t into account while the two-step procedure can only be implemented for a single asset at a time.

for each asset price i and event window ℓ, the following F-statistic

$$F_i^{(\ell)} = \frac{\left(\hat{\Pi}_i^{(\ell)}\right)^2 \left(\sum_{t=1}^{T} \left(z_{i,t}^{(\ell)}\right)^2\right)^2}{\sum_{t=1}^{T} \left(z_{i,t}^{(\ell)}\right)^2 \left(\hat{\nu}_{i,t}^{(\ell)}\right)^2}, \tag{11}$$

where $\hat{\Pi}_i^{(\ell)}$ and $\hat{\nu}_{i,t}^{(\ell)}$ are OLS estimates from the first stage

$$\phi_{i,t}^{(\ell)} = \Pi_i^{(\ell)} z_{i,t}^{(\ell)} + \nu_{i,t}^{(\ell)},$$

with the instrumental variable $z_{i,t}^{(\ell)}$, satisfying

$$z_{i,t}^{(\ell)} = \left[1\left(t \in F^{(\ell)}\right) \times \frac{T^{(\ell)}}{T_F^{(\ell)}} - 1\left(t \in NF^{(\ell)}\right) \times \frac{T^{(\ell)}}{T_{NF}^{(\ell)}}\right] \phi_{i,t}^{(\ell)}.$$

Here, $T^{(\ell)}$ is the total number of observations, $T_F^{(\ell)}$ is the number of observations in the announcement sample $F^{(\ell)}$, and $T_{NF}^{(\ell)}$ is the number of observations in the non-announcement sample $NF^{(\ell)}$.

Table 2 reports the F-statistics for each asset price i and event window ℓ. A green background indicates that we can reject the null hypothesis that the maximum asymptotic bias from a weak instrument exceeds 5 percent, while a red background indicates that we cannot reject it. The robust critical value of the hypothesis test is 37.42 and is taken from Montiel Olea and Pflueger (2013). Note that this test is conservative for at least two reasons: First, it uses the *maximum* asymptotic bias. Second, the robust critical value by Montiel Olea and Pflueger (2013) is the highest critical value for a given bias level, while the critical value is decreasing in the number of effective degrees of freedom.

Table 2 shows that for short windows the identifying variation is excellent across almost all assets, while for longer windows we cannot reject a weak-instrument bias for most assets. Based on these results, we can now jointly select a set of assets and a window length ℓ for our baseline specification. Since we expect that a larger event window and more assets improve the estimation of the non-yield shock, our objective is—loosely—to jointly maximize the event window ℓ and the number of assets n while passing the weak instrument test for each asset $i = 1, ..., n$.

Based on this criterion, we select the 13-hour window for our estimation and the 15 asset prices in Table 2 that pass the weak instrument test for this window length. That is, we

Table 2: Selection of Event Window Based on Weak Instrument Test

Window	ES1	ES2	EUR	JPY	GBP	AUD	CAD	CHF	HKD	SGD	SEK	KRW	NOK	NZD	MXN	TWD	ZAR	BRL	DKK	PLN
20 min.	162	107	1508	509	627	1401	888	826	11	1262	983	968	783	959	310	693	542	165	1633	1066
1 hour	114	73	1114	322	751	815	669	535	12	683	881	622	585	718	193	181	321	79	931	767
2 hours	159	95	621	249	405	481	455	521	11	421	386	164	329	404	107	253	428	88	853	514
3 hours	143	96	561	157	375	432	360	425	3	221	257	554	208	251	132	56	249	41	669	377
4 hours	133	87	533	81	369	377	282	403	5	417	237	117	253	234	106	18	229	24	566	444
5 hours	164	122	582	68	330	321	368	403	6	200	281	51	274	226	115	16	208	15	551	384
6 hours	142	109	403	36	275	201	361	232	9	134	174	48	221	154	163	25	222	10	349	263
7 hours	132	107	383	26	256	177	307	271	12	102	216	43	274	148	75	6	179	2	333	249
8 hours	126	92	326	16	264	152	338	211	17	91	204	53	281	140	85	3	117	0	341	218
9 hours	118	89	389	10	207	136	307	242	6	66	180	18	244	120	64	1	195	6	391	241
10 hours	84	75	285	15	156	108	359	194	10	62	160	28	217	80	119	8	144	8	277	224
11 hours	90	75	244	10	122	102	329	177	8	53	181	9	179	91	163	3	119	0	213	310
12 hours	106	87	164	3	98	81	219	108	4	48	132	8	137	71	133	1	66	4	161	144
13 hours	117	107	113	6	70	87	241	75	5	49	65	17	83	68	133	4	42	3	119	75
14 hours	84	90	67	2	55	61	167	46	6	37	16	17	27	58	73	9	30	3	65	40
15 hours	56	50	64	0	24	34	115	34	1	15	16	18	26	31	52	18	17	5	56	40
16 hours	48	39	42	0	22	28	111	35	1	6	9	6	14	26	58	26	12	34	40	19
17 hours	43	24	33	0	25	29	79	29	1	9	8	6	13	51	67	24	10	3	29	21
18 hours	44	33	36	3	25	21	56	26	3	5	7	12	15	39	48	28	12	8	26	19

Notes: This table shows the results of the first-stage F-tests. For a given event window (row) and asset price (column), the table shows the F-statistic as constructed in (11). The event windows are explained above and the asset price abbreviations are explained in Table 1. *Green* background indicates that we can reject the null hypothesis that the maximum asymptotic bias from a weak instrument exceeds 5 percent, and *red* indicates that we cannot reject it. The robust critical value of the hypothesis test is 37.42 and is taken from Montiel Olea and Pflueger (2013). The highlighted window shows the 13-hour window employed in our estimation where we include the 15 asset prices for which we can reject the null hypothesis.

estimate s_t^{ny} based on equation (4) for $\Delta p_t = \Delta p_t^{(13)}$ and $s_t^y = s_t^{y(13)}$. Here, the yield shocks $s_t^{y(13)}$ are given by equation (10) for $\ell = 13$, and the left-hand side vector of asset prices is

$$\begin{aligned}\Delta p_t^{(13)} = \Big[\; & \Delta ES1_t^{(13)} \quad \Delta ES2_t^{(13)} \quad \Delta EUR_t^{(13)} \quad \Delta GBP_t^{(13)} \quad \Delta AUD_t^{(13)} \quad \Delta CAD_t^{(13)} \quad \ldots \\ & \Delta CHF_t^{(13)} \quad \Delta SGD_t^{(13)} \quad \Delta SEK_t^{(13)} \quad \Delta NOK_t^{(13)} \quad \Delta NZD_t^{(13)} \quad \ldots \\ & \Delta MXN_t^{(13)} \quad \Delta ZAR_t^{(13)} \quad \Delta DKK_t^{(13)} \quad \Delta PLN_t^{(13)} \; \Big]'.\end{aligned} \tag{12}$$

Note that due to missing data for the left-hand side variables the samples sizes differ slightly across the event windows reported in Table 2. For our baseline sample and relative to the total number of observations reported above, we loose 22 observations. More specifically, we are left with 5064 non-FOMC days (instead of 5085), and 219 FOMC days (instead of 220).

Table 3: Estimation Results

Return (bp)	ES1	ES2	EUR	GBP	AUD	CAD	CHF	SGD
Fed non-yield shock	61.73***	65.57***	38.68***	33.39***	61.03***	36.04***	31.86***	22.60***
	(3.69)	(3.73)	(1.30)	(1.32)	(2.14)	(1.32)	(1.18)	(0.97)
R^2 without shock	0.21	0.19	0.45	0.30	0.25	0.25	0.43	0.28
R^2 with shock	0.52	0.59	0.91	0.84	0.86	0.82	0.80	0.67
Return (bp)	SEK	NOK	NZD	MXN	ZAR	DKK	PLN	
Fed non-yield Shock	45.47***	47.29***	59.87***	35.22***	56.19***	38.59***	52.42***	
	(1.44)	(1.52)	(2.25)	(1.88)	(2.09)	(1.30)	(1.86)	
R^2 without shock	0.41	0.41	0.28	0.30	0.36	0.44	0.33	
R^2 with shock	0.90	0.91	0.76	0.65	0.79	0.90	0.88	

Notes: This table shows the results of specification (4), $\Delta p_t = \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$, estimated via the Kalman filter and based on the 13-hour window. The first row displays coefficient vector γ, i.e., the effect of Fed non-yield shock s_t^{ny} on each of the 15 series in Δp_t. Coefficients are in basis points per standard deviation shock, and standard errors are in parentheses. Exchange rates are expressed in U.S. dollars so that an increase reflects a depreciation of the U.S. dollar relative to the local currency. The R^2 values are obtained from announcement day regressions of the respective dependent variable on (i) yield shocks s_t^y, and (ii) yield shocks s_t^y and non-yield shock s_t^{ny}. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Abbreviations of asset prices are explained in Table 1.

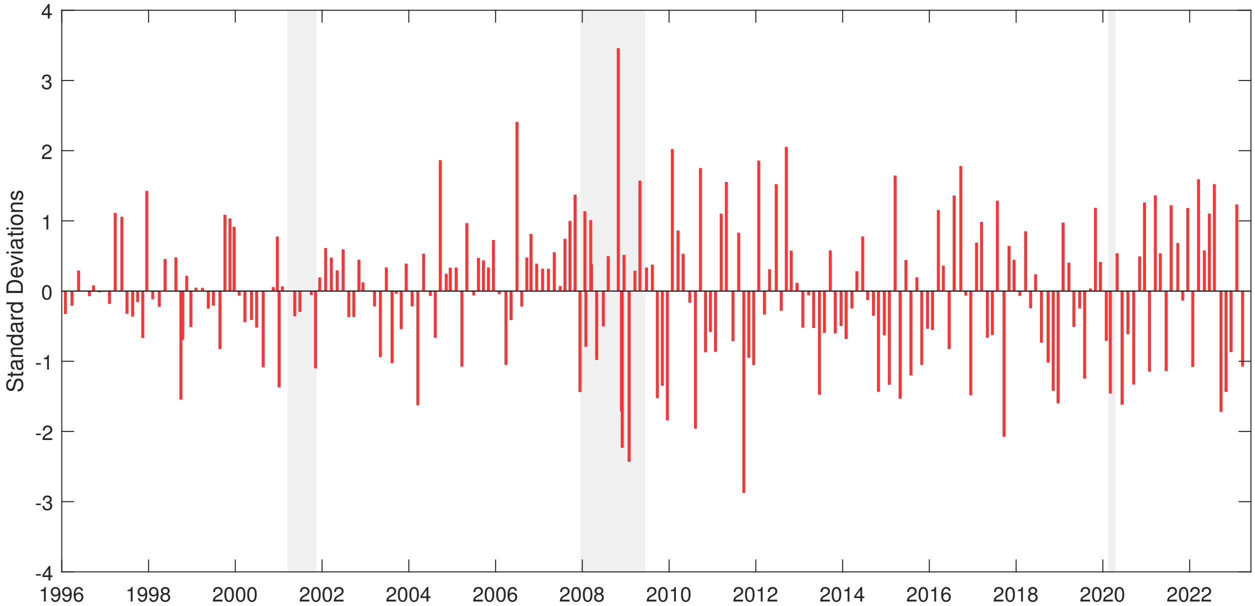
2.4 Results

We now turn to the results of our baseline estimation, which are shown in Table 3. Two findings stand out. First, as conjectured, the estimates imply that there is indeed a common factor. For each of the 15 asset prices, our non-yield shock more than doubles the explained variation. For some exchange rates it even triples the R-squared, explaining almost the entire variation in the 13-hour window. Hence, a single factor can account for a large part of the unexplained variation in these asset prices. However, it also worth noting that for the majority of assets a non-negligible share of the variation remains unexplained. This suggests that assuming that the entirety of asset returns around FOMC announcements is driven by monetary policy, as done by some previous papers, might be not innocuous.

Second, the estimated effects of the Fed non-yield shock, i.e., the $\hat{\gamma}_i$, are all highly statistical significant at the one percent level.[10] They are also quite sizable. A one-standard deviation non-yield shock leads to a 62 basis points increase in the E-mini S&P 500 front month futures contract (*ES1*) as well as a 39 and 60 basis points appreciation of the U.S. Dollar against the Euro (*EUR*) and New Zealand Dollar (*NZD*), respectively. For comparison, we regress the same 13-hour returns on Swanson's (2021) three monetary policy shocks.

[10] Heteroskedasticity-robust standard errors are obtained from the likelihood estimation. Details are provided in Appendix A.

Figure 4: Time Series of Fed Non-yield Shock



Notes: This figure displays the time series of the Fed non-yield shock over the sample period. Grey bars indicate NBER recession periods.

For the E-mini S&P 500 front-month futures contract (*ES1*), the federal funds rate shock has the largest effect leading to a 70 basis points decline. For the exchange rates, the forward guidance shock has the largest effects leading to a 26 basis points and 39 basis points appreciation of the U.S. Dollar against the Euro (*EUR*) and New Zealand Dollar (*NZD*), respectively. The Fed non-yield shock therefore has comparable effects on the stock market to previous monetary policy shocks but larger effects on exchange rates.

Note that the explanatory power of our nine yield shocks for exchange rates, i.e., the R^2 without the Fed non-yield shock, is somewhat greater than in previous high-frequency event studies despite using a wider window. This suggests that our non-yield shock is conservatively estimated in the sense that we likely take out too much rather than too little variation attributable to yield changes. We return to this point in the robustness section, where we re-estimate our non-yield shocks with the first three principal components of the nine surprises used here.

Figure 4 shows the time series of the estimated non-yield shock. As is clear from the figure, the series displays substantial variation throughout our sample period. Further, there are no extreme outliers. All observations are within four standard deviations, and we have roughly an equal number of positive (106) and negative (113) observations.

Comparison with previous shocks To understand how novel our Fed non-yield shock is, we compare our shock to other shocks in the literature that are also constructed based on financial market data. In particular, for a given paper, we regress the Fed non-yield shock on the shocks constructed by that paper. Table 4 displays the findings of this exercise for different papers. Several points are worth noting: First, the shocks based entirely on interest rates such as Nakamura and Steinsson (2018) (NS 2018), Swanson (2021) (Sw 2021), and Bu, Rogers, and Wu (2021) (BRW 2021), are indeed orthogonal to our non-yield shock. Second, our shock is orthogonal to the shocks by Jarociński and Karadi (2020), who also use the S&P 500 in their estimation. This implies that our shock does not pick up the central bank information effects as measured by Jarociński and Karadi (2020). Third, the shocks by Kroencke, Schmeling, and Schrimpf (2021) and Lewis (2023) have the most explanatory power with 23 and 17 percent, respectively. This is unsurprising since the former paper directly uses stocks and exchange rates to extract their factors, and the latter paper uses stocks in the estimation and allows for four dimensions of monetary policy shocks. Nonetheless, neither of these shocks can explain more than 23 percent of the variation of our non-yield shock. Lastly, we also show that our shock is uncorrelated with the Romer and Romer (2004) shock and a cleaned version by Aruoba and Drechsel (2022). Overall, our shock reflects to a large extent variation, which has not been directly explored in the prior literature.

Table 4: Explanatory Power of Previous Monetary Policy Shocks for Fed Non-yield Shock

Specification: $s_t^{ny} = \beta\, shocks_t^x + \varepsilon_t$

	High-Frequency						Romer & Romer	
$shocks_t^x$	NS 2018	JK 2020	Sw 2021	KSS 2021	BRW 2021	Le 2023	RR 2004	AD 2022
No. of Shocks	1	2	3	3	1	4	1	1
R^2	0.00	0.00	0.01	0.23	0.02	0.17	0.02	0.01
Observations	104	167	187	112	185	191	91	91

Notes: This table shows the explanatory power of different set of monetary policy shocks for our non-yield shock. Each column shows the results for different set of shocks on right-hand side taken from a given paper in the literature. Abbreviations: NS 2018—Nakamura and Steinsson (2018); JK 2020—Jarociński and Karadi (2020); Sw 2021—Swanson (2021); KSS 2021—Kroencke, Schmeling, and Schrimpf (2021); BRW 2021—Bu, Rogers, and Wu (2021); Le 2023—Lewis (2023); RR 2004—Romer and Romer (2004); AD 2022—Aruoba and Drechsel (2022).

Robustness We implement a number of robustness checks. In Appendix A.3, we show that the baseline estimates of the non-yield shock are robust across a variety of alternative estimation specifications. Specifically, we show that our shock is very similar when (i) allowing for other unobserved factors unrelated to FOMC releases, (ii) allowing yield shocks to be present on non-FOMC days, (iii) using three yield curve factors as in Swanson (2021), (iv) including intercepts in the estimation specification, as well as (v) accounting for the ZLB periods in the estimation.

3 The Response of Financial Markets around the World

In this section, we study the high-frequency effects of the Fed non-yield shock on a broad range of asset prices around the world. We focus on international stock markets, currencies, and government bond yields.

We estimate two types of specifications. First, we estimate a cross-country pooled effect from the event study regression

$$\Delta^d x_{c,t} = \alpha_c + \delta s_t^{ny} + \eta_{c,t} \qquad \text{for } t \in F, \tag{13}$$

where $\Delta^d x_{c,t}$ is a generic dependent variable. In the case of stock indexes and currencies, the dependent variable is the 2-day log-difference in the stock index or currency of country c around the FOMC announcement at time t. When studying government bond yields, the dependent variable is the 2-day change in the yield. Throughout this section we consider 2-day changes, which are constructed from the closing price of the day before the FOMC announcement and the closing price of the day after the announcement. We study 2-day changes to ensure that all information captured by the non-yield shock becomes available between the beginning and end-point of this window.

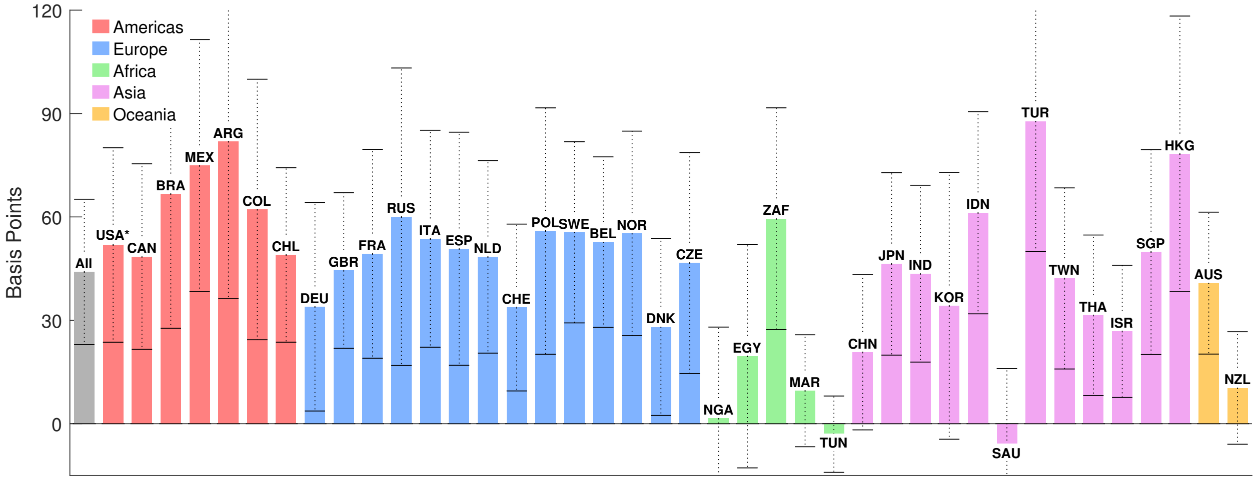
If not otherwise noted, the data comes from *Bloomberg*. Appendix B.4 provides details on this data. Note that we do not exclude any data during periods of financial market stress. However, some of our daily series display extremely large changes in episodes of high market volatility, which are unrelated to the FOMC release itself. To mitigate the influence of such extreme values, we winsorize the 2-day returns at the top and bottom 1 percent.

The pooled effect δ, estimated from specification (13), is informative about the average effect on international stock markets. It masks, however, potential heterogeneity in the responses across countries. We therefore also estimate the specification

$$\Delta^d x_{c,t} = \alpha_c + \delta_c s_t^{ny} + \eta_{c,t} \qquad \text{for } t \in F, \tag{14}$$

where the coefficients of interest, δ_c, are now country-specific.

Figure 5: Effects of Fed Non-yield Shock on Stock Markets by Country



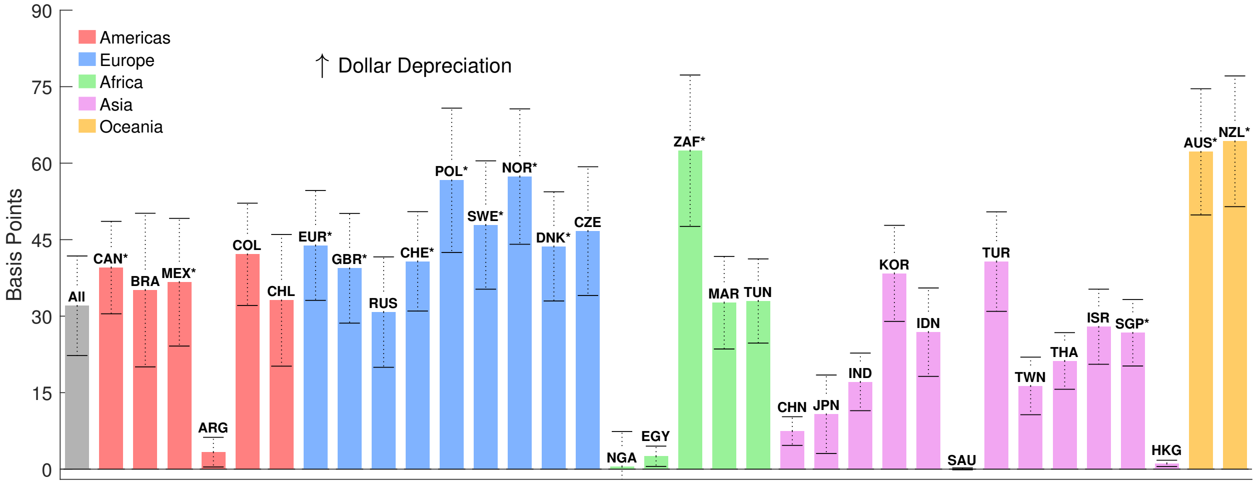
Notes: This figure shows the response of international stock indexes to the Fed non-yield shock. The dependent variable is the 2-day return on the stock index of country c, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ from equation (13), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (14). The black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country. We winsorize each country-level return series at the top and bottom 1 percent. * denotes asset prices which have been used in the shock estimation. Abbreviations of asset prices are explained in Appendix Table B3.

3.1 Stock Markets

We begin with estimating the effects of the Fed non-yield shock on international stock markets. Various papers have documented the effects of yield-based monetary policy shocks on domestic and international stock markets (see, e.g., Bernanke and Kuttner, 2005; Miranda-Agrippino and Rey, 2020). Since our shock is orthogonal to yield shocks, however, these prior estimates are unlikely to be informative about the effects of the non-yield shock.

Figure 5 illustrates the estimates of equations (13) and (14) with the 2-day log-difference of countries' stock indexes as the dependent variable. The pooled estimate, depicted by the leftmost grey bar, implies that a one standard deviation positive non-yield shock raises international stock markets by 44 basis points, on average. This effect is highly significant. Further, the non-yield shock generates co-movement in asset prices. Almost all stock indices increase after a positive non-yield shock. This is the case even though foreign stock market data is not used in the estimation of the non-yield shock. There is some heterogeneity in effect sizes across regions. Countries in North America, South America, and Europe respond most consistently to the non-yield shock. This contrasts with countries in Africa and Asia, which display more heterogeneity in the estimated effect sizes.

Figure 6: Effects of Fed Non-yield Shock on U.S. Dollar Exchange Rates



Notes: This figure shows the response of U.S. dollar exchange rates to the Fed non-yield shock. The dependent variable is the 2-day return of the exchange rate, expressed in basis points. Exchange rates are expressed in U.S. dollars per unit of foreign currency so that an increase reflects a depreciation of the U.S. dollar relative to the foreign currency. The leftmost, grey bar shows the pooled effect, i.e., the estimate of the common coefficient δ from equation (13), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (14). The black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country. We winsorize each country-level return series at the top and bottom 1 percent. * denotes asset prices which have been employed in the shock estimation. Abbreviations of asset prices are explained in Appendix Table B3.

3.2 Exchange Rates

We next turn to the effects of the non-yield shock on exchange rates.[11] Specifically, we estimate pooled and country-specific effects based on equations (13) and (14), where the dependent variables are now 2-day log-changes of various exchange rates.

Figure 6 shows the estimates. All exchange rates are expressed in U.S. dollars per unit of foreign currency so that an increase reflects a depreciation of the U.S. dollar. As the figure shows, a one standard deviation positive Fed non-yield shock leads the U.S. dollar to depreciate against other currencies by 32 basis points, on average. While the U.S. dollar depreciates against all currencies considered here, there is large heterogeneity in effect sizes. For instance, the U.S. dollar depreciates by more than 60 basis points vis-à-vis the South African Rand, the New Zealand dollar, and the Australian dollar. In comparison, the U.S. dollar depreciation against multiple other currencies is much smaller. Note that all exchange rates, which are included in the estimation of the non-yield shock, are marked with asterisks in Figure 6. The fact that the U.S. dollar also depreciates against currencies such as the

[11] For prior work on monetary policy and exchange rates see, e.g., Eichenbaum and Evans (1995).

Czech Koruna and the Turkish Lira, which are not included in the shock estimation, indicates that the effects of the non-yield shock are quite broad.

3.3 Bond Markets

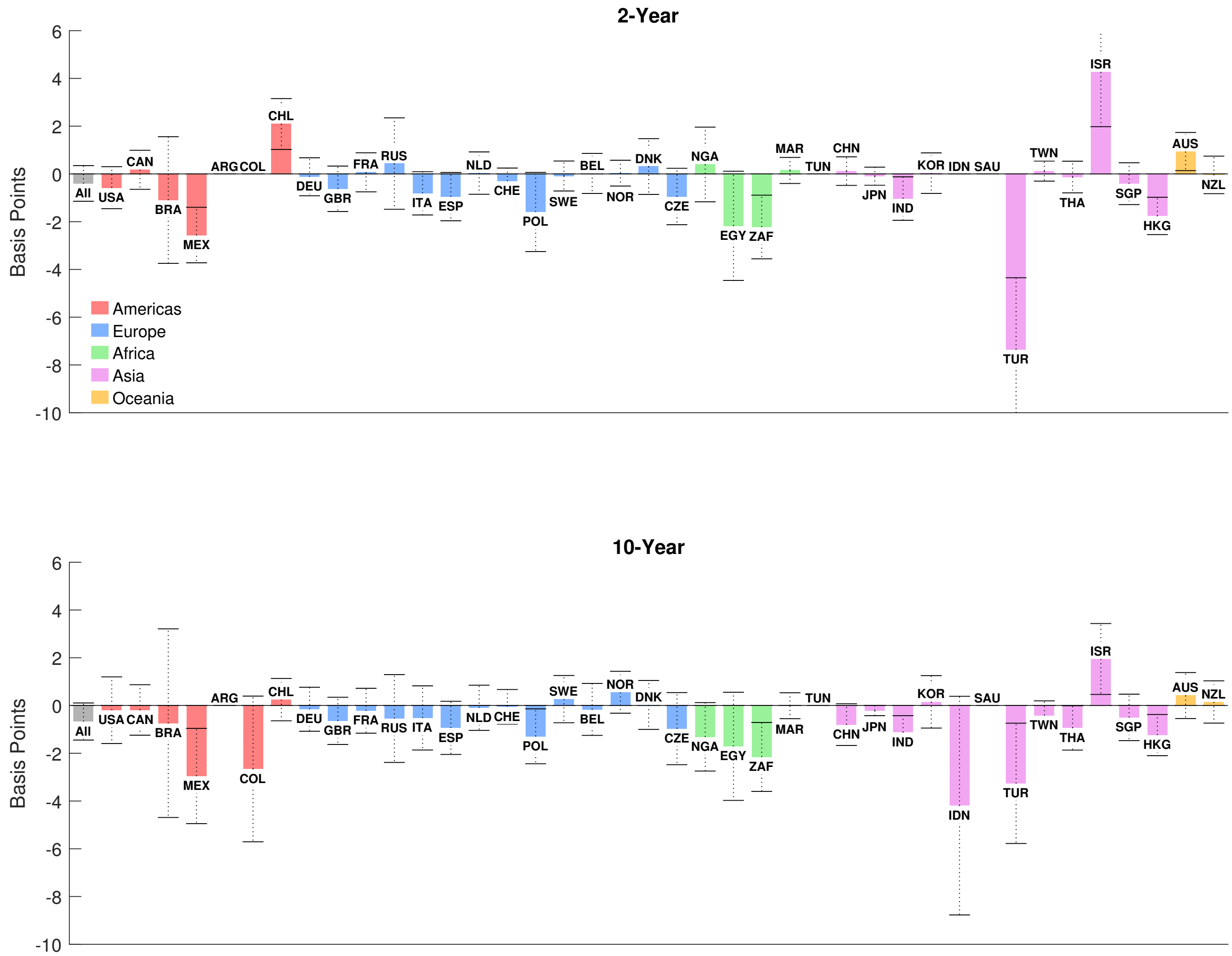
Lastly, we study the effects of the non-yield shock on bond markets. Since the Fed non-yield shock is by construction orthogonal to surprise changes in the U.S. yield curve within a 13-hour window around FOMC announcements, we expect no or small effects on U.S. bond markets within a 2-day window as well.[12] *A priori* less clear, however, are the reactions of international bond yields to the non-yield shock.

Figure 7 shows the effects on the yields of 2-year and 10-year local-currency denominated government bonds. These estimates are obtained from specifications (13) and (14) with the 2-day changes in yields on the left-hand side. As the figure shows, the pooled effects are economically small and statistically insignificant. Since the standard errors are small, this amounts to a "tight zero". Only for a handful of countries are the effects different from zero. Government bond yields in Mexico and Turkey, for instance, fall significantly after a positive non-yield shock. Yields in Israel, by contrast, increase.

In summary, a positive non-yield shock raises international stock prices, it depreciates the U.S. dollar against a large number of foreign currencies, and it leaves most government bond yields approximately unchanged.

[12] We show in Appendix Table C1 that the Fed non-yield shock has no discernible effects on the U.S. yield curve in a 2-day window using both data from *Bloomberg* as well as Gürkaynak, Sack, and Wright (2007).

Figure 7: Effects of Fed Non-yield Shock on Bond Yields



Notes: This figure shows the response of international government bond yields to the Fed non-yield shock. The dependent variable is the 2-day change in local-currency government bond yields, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of the common coefficient δ from equation (13), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (14). The black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country. We winsorize each country's series at the top and bottom 1 percent. Abbreviations of asset prices are explained in Appendix Table B3.

4 Interpreting the Shock

After documenting the importance of the Fed non-yield shock for international financial markets, we now seek to understand why these asset prices respond. To do so, we combine basic asset pricing theory with data on a variety of indicators that are informative about the underlying channels.

4.1 Asset Pricing Framework

First, as shown by Boyd, Hu, and Jagannathan (2005), stock prices decompose into its three fundamental components: a risk-free interest rate, a risk premium, and a growth expectations component:

$$\Delta p_{c,t} \approx pd_c \Big(\underbrace{\Delta g_{c,t}}_{\text{growth expectations}} - \underbrace{\Delta ep_{c,t}}_{\text{equity premium}} - \underbrace{\Delta r^f_{c,t}}_{\text{risk-free rate}} \Big) \tag{15}$$

In this decomposition $\Delta p_{c,t}$ is the observed change in the stock price index of country c, $\Delta g_{c,t}$ is the change in the weighted average of expected future growth rates of cash flows, $\Delta ep_{c,t}$ is the change of the equity (risk) premium, $\Delta r^f_{c,t}$ is the change in the interest rate on long-term risk-free claims, and pd_c is a positive constant (the average price-dividend ratio).

Second, following Jiang, Krishnamurthy, and Lustig (2021), Kalemli-Özcan and Varela (2021), and Obstfeld and Zhou (2022), we decompose the nominal exchange rate as follows:

$$\Delta e_{c,t} = - \underbrace{\Delta\left(r^f_{US,t} - r^f_{c,t}\right)}_{\text{interest rate differential}} - \underbrace{\Delta\left(\lambda_{US,t} - \lambda_{c,t}\right)}_{\text{convenience yield differential}} - \underbrace{\Delta rp_{c,t}}_{\text{risk premium}} . \tag{16}$$

In this expression, $e_{c,t}$ is the log of the exchange rate, which is measured in U.S. dollars per unit of foreign currency of country c. As before, Δ denotes the difference over the window length of the event study. Turning to the right-hand side, $\Delta\left(r^f_{US,t} - r^f_{c,t}\right)$ is the change in the interest differential between U.S. and foreign long-term risk-free claims. Further, $\Delta\left(\lambda_{US,t} - \lambda_{c,t}\right)$ is the change in the convenience yield of the U.S. dollar bond relative to the foreign bond. Lastly, $\Delta rp_{c,t}$ denotes the change in the excess return of an investor borrowing in dollars and purchasing a foreign-currency denominated bond.[13] Increases in (i) U.S. risk-free rates relative to foreign risk-free rates, (ii) the U.S. convenience yield relative to the foreign convenience yield, and (iii) the risk premium all appreciate the dollar.

This framework helps interpret the Fed non-yield shock. By construction, the shock is orthogonal to changes in the US risk-free rate. This implies that $\Delta r^f_{US,t} = 0$ in equation (16). Further, as shown in Section 3.3, foreign bond yields display no systematic response pattern to the non-yield shock. Instead, the pooled effect is close to zero and precisely estimated. We interpret this lack of response as implying that for most countries $\Delta r^f_{c,t} \approx 0$ in equations (15) and (16). This implies that the observed stock price changes in response to the Fed non-yield shock must follow from a change in growth expectations and/or the equity risk

[13]This decomposition assumes that the expectation of the exchange rate is constant in the limit, so that $\Delta E_t \left[\lim_{T\to\infty} e_{c,t+T}\right] = 0$.

premium. Further, the exchange rate responses must arise from a change in the relative convenience yield and/or the currency risk premium. We next explore the changes in these components in greater detail.

4.2 Risk, Uncertainty, and Risk Appetite

We begin with investigating the role of risk and uncertainty as well as risk appetite for explaining the effects of the Fed non-yield shock on foreign stock markets and currencies. Note that we use the terms "risk" and "uncertainty" interchangeably to describe actual or perceived changes in the second moments of the underlying fundamentals. We use "risk appetite" (or "risk aversion" as the flipside) to describe changes in investors' preference to bear risk. Appendix Table B4 provides the sources of the underlying data in this section.

We first study the effects on option-implied stock market volatility indexes, such as the VIX, which measure risk aversion and uncertainty. To do so, we estimate a pooled effect as well as country-specific effects using versions of equations (13) and (14), with the VIX and other countries' implied volatility indexes as dependent variables.

The left panel of Figure 8 displays the estimates. As the figure shows, the Fed non-yield shock leads to a decline in implied volatility indexes by 1.6 percent, on average. Except for France and Japan, all country-specific effects are significant at the 5 percent level. The effect on the VIX is the largest. These estimates imply that either uncertainty declines, investors' willingness to take risk rises, or both.

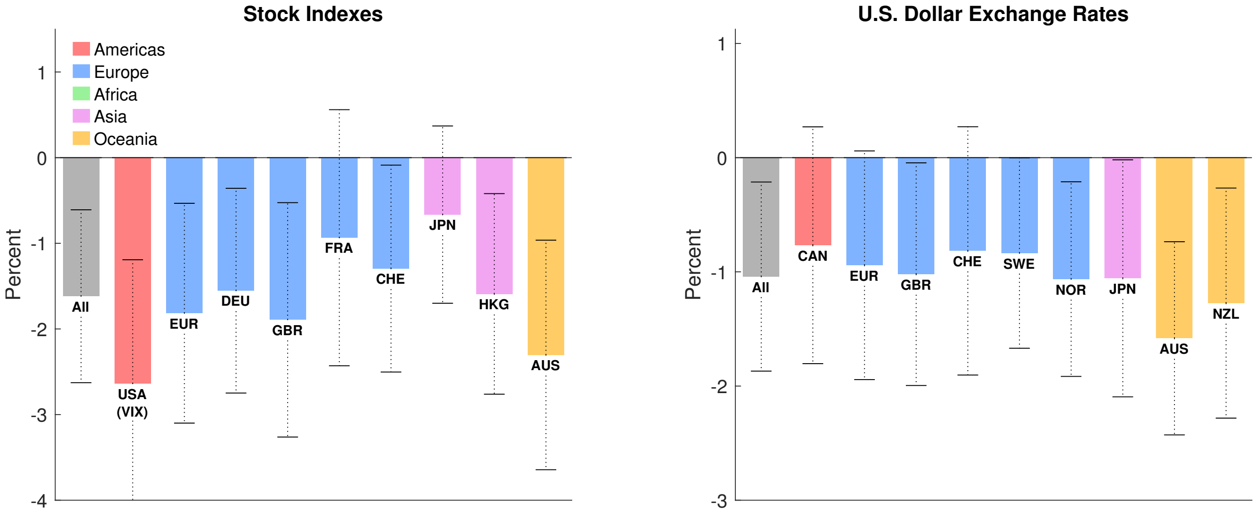
Uncertainty and risk-bearing capacity are also important for exchange rates (e.g., Lustig and Verdelhan, 2007). Due to the lack of high-frequency measures of expected excess returns on exchange rates, also referred to as uncovered interest rate (UIP) deviations, we use option-implied volatility to proxy for currency risk premia.[14] The right panel of Figure 8 shows the estimates of the pooled and county-specific effects. Similar to implied stock volatilities, the option-implied volatilities of U.S. dollar exchange rates fall following a positive non-yield shock. These responses suggest that currency risk premia explain part of the U.S. dollar movements observed after non-yield shocks.

To better understand these channels, we next turn to a variety of additional indicators for risk, risk appetite, interest rate volatility, and term premia. Specifically, we estimate the specification

$$\Delta^d x_t = \alpha + \delta s_t^{ny} + \eta_t, \qquad \text{for } t \in F, \tag{17}$$

[14] Lyons (1988) shows that option-implied volatilities are predictive of realized UIP deviations.

Figure 8: Effects of Fed Non-yield Shock on Implied Volatilities



Notes: This figure shows the response of option-implied volatilities for stocks (left panel) and exchange rates (right panel) to the Fed non-yield shock. The 2-day log-returns are expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ of equation (13), while the other bars show the country-specific effects, i.e., the estimates of coefficients δ_c of equation (14), where the left-hand sides are now 2-day returns of the stock and exchange rate implied volatility indexes. The black error bands depict 95 percent confidence intervals, where standard errors are clustered by announcement. We winsorize each country-level series at the top and bottom 1 percent. Abbreviations of asset prices are explained in Appendix Table B4.

with the different indicators as the dependent variables. Table 5 provides the estimates of this exercise. The first measure we consider is Martin's (2017) SVIX, a proxy for the equity premium at the 1-year horizon. While we observe a decline in the SVIX, it is relatively noisy. As emphasized above, the effects on the VIX can either come from changes in the price of risk (risk aversion) or the amount of risk (uncertainty). Bekaert and Hoerova (2014) provide a decomposition of the VIX into measures of risk aversion and uncertainty. We further study the effects on Bekaert, Engstrom, and Xu's (2022) measures, which are constructed from equities and corporate bonds. As our estimates show, a positive non-yield shock leads to a decline in risk aversion as well as uncertainty.

One underlying source of these results might be monetary policy uncertainty—a second moment effect. To investigate this hypothesis, we use the short-rate uncertainty (SRU) measure from Bauer, Lakdawala, and Mueller (2022), which measures option-implied volatility of the LIBOR, a benchmark short-term interest rate, over the next year. To capture longer-term uncertainty, we also use the Merrill Lynch Option Volatility Estimate (MOVE) index, which measures the 1-month ahead option-implied yield volatility of 2-year, 5-year, 10-year, and 30-year Treasuries, as well as the CBOE/CBOT 10-year U.S. Treasury Note Volatil-

Table 5: Effects of Fed Non-Yield Shock on Indicators of Risk, Uncertainty, and Term Premia

Return (%)	VIX	SVIX	Risk Aversion		Uncertainty	
			BH 2014	BEX 2022	BH 2014	BEX 2022
Fed non-yield shock	-2.64***	-0.56*	-3.25**	-1.68***	-2.14**	-0.64**
	(0.73)	(0.28)	(1.55)	(0.64)	(0.89)	(0.25)
R^2	0.07	0.03	0.02	0.06	0.05	0.03
Observations	219	216	208	217	210	217
Return (%)	Implied Interest Rate Vol.			Term Premium		
	SRU	MOVE	TYVIX	1-Year	2-Year	10-Year
Fed non-yield shock	-0.91***	-1.22***	-1.49***	0.42	0.35	1.03
	(0.33)	(0.44)	(0.55)	(0.28)	(0.47)	(0.98)
R^2	0.04	0.03	0.04	0.02	0.00	0.01
Observations	199	219	141	219	219	219

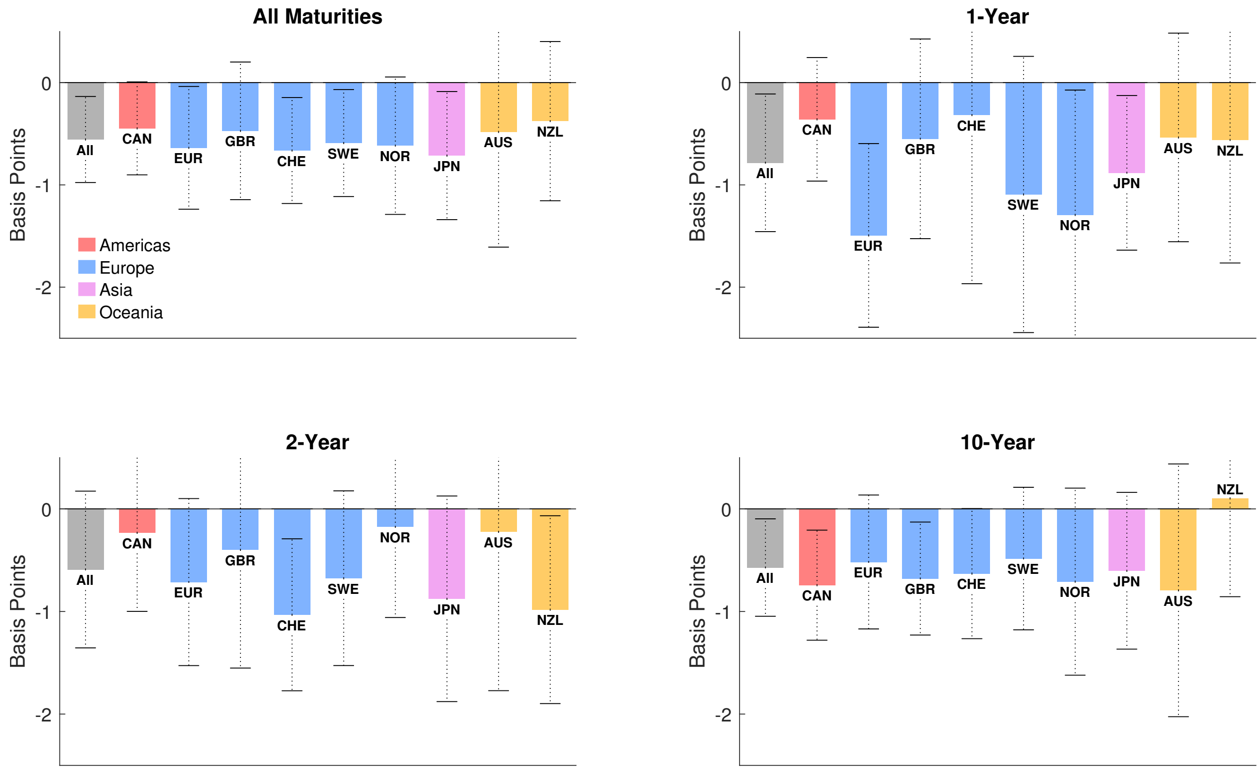
Notes: This table presents estimates of δ from specification (17), where the left-hand side variables are now 2-day log-changes of risk and uncertainty indicators, or 2-day changes in term premia measures. See the text for details on the employed variables. BH 2014 and BEX 2022 refer to the corresponding measures by Bekaert and Hoerova (2014) and Bekaert, Engstrom, and Xu (2022), respectively. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level. We winsorize each dependent variable at the top and bottom 1 percent.

ity (TYVIX) Index, which measures the 1-month ahead option-implied volatility of 10-year Treasury futures.

The bottom panel of Table 5 shows the estimates for all three implied interest rate volatility indexes. In all cases, the Fed non-yield shock leads to a significant decline in implied interest rate volatility. These estimates imply that the non-yield shock either directly captures changes in interest-rate volatility or affects various asset prices through a change in interest rate volatility.

Lastly, we study the effects on term premia. Using measures from Adrian, Crump, and Moench (2013), the table shows that the non-yield shock has no discernible effects on term premia. Note that the absence of an effect here is not implied by the identification assumption. While our estimation procedure implies that the non-yield shock is orthogonal to yield changes at all maturities, it does not imply that the non-yield shock is orthogonal to both expected future short-term rates and term premia. Nonetheless, the results in Table 5 indicate that term premia are largely unresponsive to the non-yield shock. Together with the orthogonalization with respect to yield changes, this implies that the non-yield shock leaves expected future short-term rates unchanged as well.

Figure 9: Effects of Fed Non-yield Shock on Convenience Yields



Notes: This figure shows the response of the U.S. convenience yield relative to other country's convenience yields to the Fed non-yield shock. The top-left panel shows joint effects for maturities starting at 1-year, i.e., 1-,2-,3-,5-,7-, and 10-year. The top-right panel displays coefficients for the 1-year, and the bottom-left and bottom-right panels for the 2-year and 10-year, respectively. The 2-day log-returns are expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ of equation (13), while the other bars show the country-specific effects, i.e., the estimates of coefficients δ_c of equation (14), where the left-hand sides are now 2-day returns of the stock and exchange rate implied volatility indexes. The black error bands depict 95 percent confidence intervals, where standard errors are clustered by announcement. We winsorize each country-level series at the top and bottom 1 percent. Abbreviations of asset prices are explained in Appendix Table B4.

4.3 Convenience Yields

To measure convenience yields we use the "U.S. Treasury premium" series from Du, Im, and Schreger (2018). The Treasury premium measures the convenience yields of U.S. Treasuries relative to other countries' convenience yields on government bonds, i.e., $\lambda_{US,t} - \lambda_{c,t}$ in equation (16). For example, an increase implies that the convenience yield of the U.S. Treasury increases relative to the convenience yield of country c's government bond.

Following Du, Im, and Schreger (2018), we focus on 10 currencies of advanced economies for which convenience yields can be constructed in a relative clean manner. Figure 9 displays the effects of the Fed non-yield shock on convenience yields for various maturities.[15] The results show that the non-yield shock typically leads to a decrease of the Treasury premium. The effects are broadly similar across maturities. Drawing on decomposition (16), these results suggest that the dollar depreciation documented in Figure 6 is partly driven by a reduction in the relative convenience yield of treasuries.

4.4 Summary

To summarize, the Fed non-yield shock is orthogonal to U.S. yields by construction and also largely leaves foreign interest rates unchanged. Instead, it reflects changes in risk appetite as measured by proxies for equity and currency risk premia. These changes could to be driven—at least in part—by changes in interest rate volatility. In addition, the non-yield shock affects convenience yields.

5 Conclusion

In this paper we argue that U.S. monetary policy affects asset prices through channels that are not captured by interest rates. Motivated by the facts that (i) yield-based monetary policy shocks have little explanatory power for stocks and currencies around FOMC announcements and (ii) that stocks and currencies display elevated variances around these announcements, we use a heteroskedasticity-based procedure to estimate a Fed non-yield shock. Econometric tests show that this shock is strongly identified. It further explains a large chunk of the unexplained variation in stock prices and currencies.

A positive Fed non-yield shock raises international stock prices and depreciates the dollar against various foreign currencies. These effects are driven by changes in actual or perceived risk and risk appetite as well as changes in convenience yields. While the level of interest rates both in the U.S. and foreign countries remains largely unchanged after non-yield shocks, our estimates imply that changes in interest rate volatility can potentially rationalize these findings—at least in part.

References

Adrian, Tobias, Richard K Crump, and Emanuel Moench. 2013. "Pricing the term structure with linear regressions." *Journal of Financial Economics* 110 (1):110–138.

[15] We do not consider the 3-month maturity as it is constructed differently compared to the rest and much more volatile during the Great Recession.

Alvarez, Fernando, Andrew Atkeson, and Patrick J Kehoe. 2009. "Time-varying risk, interest rates, and exchange rates in general equilibrium." *The Review of Economic Studies* 76 (3):851–878.

Aruoba, S Boragan and Thomas Drechsel. 2022. "Identifying monetary policy shocks: A natural language approach." .

Baele, Lieven, Geert Bekaert, Koen Inghelbrecht, and Min Wei. 2020. "Flights to safety." *The Review of Financial Studies* 33 (2):689–746.

Bauer, Michael D, Ben S Bernanke, and Eric Milstein. 2023. "Risk appetite and the risk-taking channel of monetary policy." *Journal of Economic Perspectives* 37 (1):77–100.

Bauer, Michael D, Aeimit Lakdawala, and Philippe Mueller. 2022. "Market-based monetary policy uncertainty." *The Economic Journal* 132 (644):1290–1308.

Bauer, Michael D. and Eric T. Swanson. 2023. "An Alternative Explanation for the "Fed Information Effect"." *American Economic Review* 113 (3):664–700.

Bekaert, Geert, Eric C Engstrom, and Nancy R Xu. 2022. "The time variation in risk appetite and uncertainty." *Management Science* 68 (6):3975–4004.

Bekaert, Geert and Marie Hoerova. 2014. "The VIX, the variance premium and stock market volatility." *Journal of econometrics* 183 (2):181–192.

Bernanke, Ben S and Kenneth N Kuttner. 2005. "What explains the stock market's reaction to Federal Reserve policy?" *The Journal of finance* 60 (3):1221–1257.

Boehm, Christoph E and T Niklas Kroner. 2023. "The US, economic news, and the global financial cycle." Tech. rep., National Bureau of Economic Research.

Boyd, John H, Jian Hu, and Ravi Jagannathan. 2005. "The stock market's reaction to unemployment news: Why bad news is usually good for stocks." *The Journal of Finance* 60 (2):649–672.

Bu, Chunya, John Rogers, and Wenbin Wu. 2021. "A unified measure of Fed monetary policy shocks." *Journal of Monetary Economics* 118:331–349.

Caballero, Ricardo and Emmanuel Farhi. 2018. "The safety trap." *The Review of Economic Studies* 85 (1):223–274.

Caldara, Dario and Edward Herbst. 2019. "Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svars." *American Economic Journal: Macroeconomics* 11 (1):157–92.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans. 1999. "Monetary policy shocks: What have we learned and to what end?" *Handbook of macroeconomics* 1:65–148.

Cieslak, A and M McMahon. 2023. "Tough talk: The Fed and the risk premia."

Cieslak, Anna and Andreas Schrimpf. 2019. "Non-monetary news in central bank communication." *Journal of International Economics* 118:293–315.

Davidson, Russell and James G MacKinnon. 2004. *Econometric theory and methods*, vol. 5. Oxford University Press New York.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2018. "A model of monetary policy and risk premia." *The Journal of Finance* 73 (1):317–373.

Du, Wenxin, Joanne Im, and Jesse Schreger. 2018. "The us treasury premium." *Journal of International Economics* 112:167–181.

Eichenbaum, Martin and Charles L Evans. 1995. "Some empirical evidence on the effects of shocks to monetary policy on exchange rates." *The Quarterly Journal of Economics* 110 (4):975–1009.

Engel, Charles and Steve Pak Yeung Wu. 2023. "Liquidity and exchange rates: An empirical investigation." *The Review of Economic Studies* 90 (5):2395–2438.

Faust, Jon and John H Rogers. 2003. "Monetary policy's role in exchange rate behavior." *Journal of Monetary Economics* 50 (7):1403–1424.

Frankel, Jeffrey A. 2008. *The Effect of Monetary Policy on Real Commodity Prices*. University of Chicago Press, 291–333.

Friedman, Milton and Anna Jacobson Schwartz. 1963. *A monetary history of the United States, 1867-1960*, vol. 9. Princeton University Press.

Gertler, Mark and Peter Karadi. 2015. "Monetary policy surprises, credit costs, and economic activity." *American Economic Journal: Macroeconomics* 7 (1):44–76.

Gorodnichenko, Yuriy, Tho Pham, and Oleksandr Talavera. 2023. "The voice of monetary policy." *American Economic Review* 113 (2):548–584.

Gürkaynak, Refet, Brian Sack, and Eric Swanson. 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements." *International Journal of Central Banking* 1 (1).

Gürkaynak, Refet S. 2005. "Using federal funds futures contracts for monetary policy analysis." .

Gürkaynak, Refet S, A Hakan Kara, Burçin Kısacıkoğlu, and Sang Seok Lee. 2021. "Monetary policy surprises and exchange rate behavior." *Journal of International Economics* 130:103443.

Gürkaynak, Refet S, Burçin Kısacıkoğlu, and Jonathan H Wright. 2020. "Missing Events in Event Studies: Identifying the Effects of Partially Measured News Surprises." *American Economic Review* 110 (12):3871–3912.

Gürkaynak, Refet S, Brian Sack, and Jonathan H Wright. 2007. "The US Treasury yield curve: 1961 to the present." *Journal of monetary Economics* 54 (8):2291–2304.

Hanson, Samuel G and Jeremy C Stein. 2015. "Monetary policy and long-term real rates." *Journal of Financial Economics* 115 (3):429–448.

Hassan, Tarek A and Rui C Mano. 2019. "Forward and spot exchange rates in a multi-currency world." *The Quarterly Journal of Economics* 134 (1):397–450.

Jarociński, Marek and Peter Karadi. 2020. "Deconstructing Monetary Policy Surprises—The Role of Information Shocks." *American Economic Journal: Macroeconomics* 12 (2):1–43.

Jiang, Zhengyang, Arvind Krishnamurthy, and Hanno Lustig. 2021. "Foreign safe asset demand and the dollar exchange rate." *The Journal of Finance* 76 (3):1049–1089.

Kalemli-Özcan, Şebnem and Liliana Varela. 2021. "Five facts about the uip premium." Tech. rep., National Bureau of Economic Research.

Kekre, Rohan and Moritz Lenel. 2021. "The flight to safety and international risk sharing." Tech. rep., National Bureau of Economic Research.

———. 2022. "Monetary policy, redistribution, and risk premia." *Econometrica* 90 (5):2249–2282.

Knox, Benjamin and Annette Vissing-Jorgensen. 2022. "A stock return decomposition using observables." .

Kroencke, Tim A, Maik Schmeling, and Andreas Schrimpf. 2021. "The FOMC risk shift." *Journal of Monetary Economics* 120:21–39.

Kroner, Niklas. 2023. "Inflation and Attention: Evidence from the Market Reaction to Macro Announcements." *Available at SSRN 4527424* .

Kuttner, Kenneth N. 2001. "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market." *Journal of monetary economics* 47 (3):523–544.

Lewis, Daniel J. 2022. "Robust inference in models identified via heteroskedasticity." *The Review of Economics and Statistics* 104 (3):510–524.

Lewis, Daniel J. 2023. "Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Effects." *The Review of Economics and Statistics* :1–46.

Lunsford, Kurt G. 2020. "Policy Language and Information Effects in the Early Days of Federal Reserve Forward Guidance." *American Economic Review* 110 (9):2899–2934.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan. 2011. "Common risk factors in currency markets." *The Review of Financial Studies* 24 (11):3731–3777.

Lustig, Hanno and Adrien Verdelhan. 2007. "The cross section of foreign currency risk premia and consumption growth risk." *American Economic Review* 97 (1):89–117.

Lyons, Richard K. 1988. “Tests of the foreign exchange risk premium using the expected second moments implied by option pricing.” *Journal of International Money and Finance* 7 (1):91–108.

Maggiori, Matteo. 2017. “Financial intermediation, international risk sharing, and reserve currencies.” *American Economic Review* 107 (10):3038–3071.

Martin, Ian. 2017. “What is the Expected Return on the Market?” *The Quarterly Journal of Economics* 132 (1):367–433.

Miranda-Agrippino, Silvia and Hélène Rey. 2020. “US Monetary Policy and the Global Financial Cycle.” *The Review of Economic Studies* Rdaa019.

Miranda-Agrippino, Silvia and Giovanni Ricco. 2021. “The transmission of monetary policy shocks.” *American Economic Journal: Macroeconomics* .

Montiel Olea, José Luis and Carolin Pflueger. 2013. “A robust test for weak instruments.” *Journal of Business & Economic Statistics* 31 (3):358–369.

Nakamura, Emi and Jón Steinsson. 2018. “High-frequency identification of monetary non-neutrality: the information effect.” *The Quarterly Journal of Economics* 133 (3):1283–1330.

Obstfeld, Maurice and Haonan Zhou. 2022. “The Global Dollar Cycle.” .

Paul, Pascal. 2020. “The time-varying effect of monetary policy on asset prices.” *Review of Economics and Statistics* 102 (4):690–704.

Rigobon, Roberto. 2003. “Identification through heteroskedasticity.” *Review of Economics and Statistics* 85 (4):777–792.

Rigobon, Roberto and Brian Sack. 2004. “The impact of monetary policy on asset prices.” *Journal of Monetary Economics* 51 (8):1553–1575.

Romer, Christina D. and David H. Romer. 2000. “Federal Reserve Information and the Behavior of Interest Rates.” *American Economic Review* 90 (3):429–457.

Romer, Christina D and David H Romer. 2004. “A new measure of monetary shocks: Derivation and implications.” *American economic review* 94 (4):1055–1084.

Swanson, Eric T. 2021. “Measuring the effects of federal reserve forward guidance and asset purchases on financial markets.” *Journal of Monetary Economics* .

Uhlig, Harald. 2005. “What are the effects of monetary policy on output? Results from an agnostic identification procedure.” *Journal of Monetary Economics* 52 (2):381–419.

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A Estimation Appendix

This appendix provides details on the estimation of our "non-yield shock". Our estimation and code is adapted from Gürkaynak, Kısacıkoğlu, and Wright (2020).

A.1 Setup

Our estimation framework can be written as a state-space model. The estimation equation (4) for the n asset case, restated here for convenience, is the *measurement equation*

$$\Delta p_t = \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t, \tag{A1}$$

where $p_t = [\begin{array}{ccc} p_{1,t} & \dots & p_{n,t} \end{array}]'$, $\beta = [\begin{array}{ccc} \beta_1' & \dots & \beta_n' \end{array}]'$, $\gamma = [\begin{array}{ccc} \gamma_1 & \dots & \gamma_n \end{array}]'$, and $\varepsilon_t = [\begin{array}{ccc} \varepsilon_{1,t} & \dots & \varepsilon_{n,t} \end{array}]'$. Further, $\beta_i = [\begin{array}{ccc} \beta_{1,i} & \dots & \beta_{k,i} \end{array}]$, and the yield shocks $s_t^y = [\begin{array}{ccc} s_{1,t}^y & \dots & s_{k,t}^y \end{array}]'$ as well as the announcement indicator $d_t = 1\,(t \in F)$ are exogenous. The announcement indicator d_t gives rise to time-varying coefficients γd_t. We assume that ε_t is independently and identically normally distributed with zero mean and a diagonal variance-covariance matrix Σ_ε. The (degenerate) *transition equation* is given by

$$s_t^{ny} \sim \text{i.i.d. } N\,(0,1)\,. \tag{A2}$$

The variance is normalized to one since γ is otherwise only identified up to scale. The parameters of the system are summarized by the parameter vector $\theta = \left[\begin{array}{ccc} \beta & \gamma & \Sigma_\varepsilon \end{array}\right]$. The goal is to estimate the unobserved factor s_t^{ny}, given a set of parameters $\hat{\theta}$, which are estimated by maximum likelihood.

A.2 Estimation Algorithm

We estimate s_t^{ny} by using the Kalman filter to obtain the log-likelihood function of the model,

$$\begin{aligned}\mathcal{L}\,(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\Big\{ & 1\,(d_t = 1)\left[(\Delta p_t - \beta s_t^y)'\left(\Sigma_\varepsilon + \gamma\gamma'\right)^{-1}(\Delta p_t - \beta s_t^y) + \log\left(\left|\Sigma_\varepsilon + \gamma\gamma'\right|\right)\right] \\ & + 1\,(d_t = 0)\left[\Delta p_t'\Sigma_\varepsilon^{-1}\Delta p_t + \log\left(\left|\Sigma_\varepsilon\right|\right)\right]\Big\}\end{aligned} \tag{A3}$$

and then maximize it via the following EM algorithm:

1. Start with initial guess for the parameters $\theta^{(0)}$, where

$$\beta^{(0)} = \beta^{OLS} = \left(s_t^{y\prime} s_t^y\right)^{-1} s_t^{y\prime}\Delta p_t$$

$$\Sigma_\varepsilon^{(0)} = diag\left(E_t\left[\left(\Delta p_t - \beta^{(0)} s_t^y\right)^2\right]\right)$$

$$\gamma^{(0)} = [\underbrace{0.01\ \dots\ 0.01}_{n \text{ times}}].$$

2. Run Kalman filter: The updating equations are given by

$$s_{t|t}^{ny(j)} = \gamma^{(j-1)\prime} F_t^{-1} v_t d_t,$$

$$q_{t|t}^{(j)} = 1 - \gamma^{(j-1)\prime} F_t^{-1} \gamma^{(j-1)} d_t,$$

where

$$F_t = \left(\gamma\gamma' d_t + \Sigma_{\varepsilon}^{(j-1)} \right),$$

$$v_t = \Delta p_t - \beta^{(j-1)} s_t^y,$$

and $q_{t|t}^{(j)}$ is the MSE of $s_{t|t}^{ny(j)}$, i.e. $q_{t|t}^{(j)} = E\left[\left(s_t^{ny} - s_{t|t}^{ny(j)} \right) \left(s_t^{ny} - s_{t|t}^{ny(j)} \right)' \right]$. The log-likelihood (A3) can then be written as

$$\begin{aligned} \mathcal{L}(\theta)^{(j)} &= \sum_{t=1}^{T} \mathcal{L}_t(\theta)^{(j)} \\ &= \sum_{t=1}^{T} \left(-\frac{1}{2} \right) \left[\log(2\pi) + \log|F_t| + v_t' F_t^{-1} v_t \right] \\ &= -\frac{T}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \log|F_t| - \frac{1}{2} \sum_{t=1}^{T} v_t' F_t^{-1} v_t. \end{aligned}$$

3. Run Kalman smoother: Due to the non-degenerate form of the transition equation, the smoothed estimates are equal to the filtered ones:

$$\begin{aligned} s_{t|T}^{ny(j)} &= s_{t|t}^{ny(j)}, \\ q_{t|T}^{(j)} &= q_{t|t}^{(j)}. \end{aligned}$$

4. Calculate $\theta^{(1)}$: Let us define $\omega = \begin{bmatrix} \beta & \gamma \end{bmatrix}$ such that the measurement equation (A1) can be written as $\Delta p_t = \omega x_t + \varepsilon_t$. Further, let $x_{t|T}^{(j)} = \begin{bmatrix} s_t^{y\prime} & s_{t|T}^{ny(j)} \end{bmatrix}'$ and $Q_{t|T}^{(j)} = diag\begin{pmatrix} 0 & q_{t|T}^{(j)} \end{pmatrix}$, then $\theta^{(1)}$ is given by

$$\begin{aligned} \omega^{(j)} &= \left(\sum_{t=1}^{T} \left(E_T\left(x_t x_t' \right) \right) \right)^{-1} \sum_{t=1}^{T} E_T\left(x_t' \Delta p_t \right) \\ &= \left(\sum_{t=1}^{T} \left(x_{t|T} x_{t|T}' + Q_{t|T}^{(j)} \right) \right)^{-1} \sum_{t=1}^{T} x_{t|T}' \Delta p_t, \end{aligned}$$

and

$$\begin{aligned}\Sigma_{\varepsilon}^{(j)} &= diag\left(\frac{1}{T}\sum_{t=1}^{T} E_T\left(\Delta p_t - \omega^{(j)} x_t\right)^2\right) \\ &= diag\left(\frac{1}{T}\sum_{t=1}^{T}\left(\Delta p_t - \omega^{(j)} x_{t|T}\right)^2 + \omega^{(j)\prime}\sum_{t=1}^{T} Q_{t|T}^{(j)}\omega^{(j)}\right).\end{aligned}$$

5. Repeat step 2-4 until the improvement in the log-likelihood is below a certain threshold. Let j^* denote the final iteration of the algorithm. Then the final parameter estimates are given by $\hat{\theta} = \theta^{(j^*)}$ with $\hat{\gamma} = \gamma^{(j^*)}$ being reported in Table 3. The non-yield shock series is given by $\hat{s}_t^{ny} = s_{t|T}^{ny(j^*)}$.

6. Construction of heteroskedasticity-robust standard errors of $\hat{\theta}$: The formula for the variance-covariance matrix of the parameters is given by

$$Cov(\hat{\theta}) = \left(HG^{-1}H\right)^{-1},$$

where

$$H = -\sum_{t=1}^{T}\frac{\partial^2 \mathcal{L}_t(\hat{\theta})}{\partial\hat{\theta}\partial\hat{\theta}'}$$

and

$$G = \sum_{t=1}^{T}\frac{\partial \mathcal{L}_t(\hat{\theta})}{\partial\hat{\theta}}\left(\frac{\partial \mathcal{L}_t(\hat{\theta})}{\partial\hat{\theta}}\right)'.$$

The matrices H and G are computed by plugging in small deviations from $\hat{\theta}$, i.e., $\partial\hat{\theta}$, into the Kalman filter.

Remarks

- Gürkaynak, Kısacıkoğlu, and Wright (2020) show that the parameter vector θ is identified. To achieve that, we need to assume that non-yield shock has a variance of one since it is only identified up to scale. Further, we normalize the first element of γ to be positive since it is only identified up to signing convention.

- We have missing observations in Δp_t which the code can handle since the updating equations of Kalman filter can be adequately adjusted depending on the available data for period t. If there are no missing values, we have $\hat{\beta} = \beta^{OLS}$ and s_t^y and s_t^{ny} are fully orthogonal.

A.3 Robustness

In this section, we analyze the robustness of our baseline series of the Fed non-yield shock by estimating alternate specifications of equation (4). In the following, we discuss each robustness exercise in detail. Table A1 summarizes the results. Note that the left-hand side variables are always the same 15 asset prices as in the baseline version.

Table A1: Robustness of Fed Non-Yield Shock

	Baseline	Generalized Covariance	Non-FOMC Days Purified	3 Yield Curve Factors	Intercept	Intercept for each Regime	Subperiods	
							Non-ZLB	ZLB
Correlation with Baseline Shock	1.00	0.94	1.00	0.94	1.00	1.00	0.96	0.88
Average R^2								
without shock	0.33	0.33	0.33	0.26	0.33	0.33	0.34	0.52
with shock	0.79	0.74	0.79	0.77	0.79	0.79	0.76	0.86
Observations	219	219	219	219	219	219	149	70

Notes: This table shows the results of our robustness analyzes. We re-estimate alternate versions of baseline specification (4), $\Delta p_t = \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$, using the Kalman filter. The left-hand side variables are always the same 15 variables used in the baseline analysis. The R^2 values are constructed as the average R^2 values from announcement day regressions of each of the 15 asset prices on (i) yield shocks s_t^y, and (ii) yield shocks s_t^y and non-yield shock s_t^{ny}. Further, we report the correlation of our re-estimated series with our baseline one for the overlapping sample period.

Generalized Covariance Following Gürkaynak, Kısacıkoğlu, and Wright (2020), we also estimate a version with an unrestricted variance-covariance matrix of ε_t in (4) instead of the diagonal matrix under the baseline. This specification allows for the possibility of ever-present factors, i.e., drivers which lead to systematic movements on announcement and non-announcement days. As column two of Table A1 illustrates, the shock is very close to the baseline one indicating our estimation is robust to allowing for other unobserved factors which are not related to the FOMC announcement.

Non-FOMC Days Purified We also do a robustness check in which we allow monetary policy shocks, s_t^y, to be present during times non-announcement days. That is, instead of equation (3), we now have for each asset price i

$$\Delta p_{i,t} = \tilde{\beta}_i s_t^y + \varepsilon_{i,t}, \qquad \text{for } t \in NF, \tag{A4}$$

while the other equations are unchanged. Note that we allow s_t^y to have a difference effect on FOMC days and non-FOMC days. However, the nine surprises in s_t^y are constructed the same way on announcement and non-announcement days. We implement this specification by estimating (A4) by OLS and then run the Kalman filter based on the purified changes, i.e., the residuals of regression (A4). Column three of of Table A1 displays the results. The non-yield shock is essentially unchanged which is consistent with the, on average, low explanatory power of yields for exchange rates and stock prices on non-announcement days. In other words, the exploited variation is very similar to the baseline estimation.

3 Yield Curve Factors We also change the data series used for s_t^y in our estimation. While we use nine interest rate surprises in the baseline version, we now employ three yield curve factors instead. These factors are extracted from the nine series via principal components analysis as in Swanson (2021). The three factors explain 90 percent of the variation in the nine series. With the yield curve factors at hand, we can estimate the model. The fourth column of Table A1 shows the results of this exercise. The estimated shock his very highly correlated with the baseline series. One thing worth point out is that the average explanatory power of the three factors for the asset returns drops to 26 percent, while the explanatory power including the non-yield shock is 77 percent—almost as much as in the baseline estimation. This may indicate that the Fed non-yield shock in this alternative specification is contaminated with changes in the yield curve that are not captured accurately by the three principal components. The high correlation also suggests that our baseline version is robust to allowing for noise in the yield curve surprises by using the first three principal components instead.

Intercepts As our baseline specification (4) includes no intercept, we also estimate the baseline specification including intercepts, $\Delta p_t = \alpha + \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$, and intercepts for each regime, i.e., announcement and non-announcement days, $\Delta p_t = \alpha_0 + d_t \alpha_1 + \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$. Note that α, α_0, and α_1 are n-dimensional vectors. Both models are implemented by demeaning each series prior to estimation, where in the first case the mean over both announcement and non-announcement days is taken, and in the second model a separate mean is calculated for announcement and non-announcement days. After the both models can be estimated estimated via the Kalman filter. Columns five and six of Table A1 display the results. In essence, the intercepts do not affect our results consistent with the employed returns in stocks and exchange rates having a mean close to zero over our sample period.

ZLB Subperiods We next analyze the stability of our analysis over our sample period with particular emphasis on the impact of the zero-lower-bound episodes. To do so, we first split our sample of FOMC days into two groups, ZLB and non-ZLB, based on the target range of federal funds rate being between 0 and 25 basis points. We then estimate our non-yield sock for each group separately, where the set of non-FOMC days is always unchanged compared to the baseline estimation. The last two columns of Table A1 display the results of each estimation. The last rows show the number of observations indicating the proportion of each subperiod in our sample. Both shock series are highly correlated with the baseline series. The correlation of the ZLB version is somewhat lower. Looking at the average R^2 value without the shock, the relationship between yield shocks and asset returns affected by the ZLB resulting in increased R^2 values. At the same time, overfitting concerns arise considering the sample size and number of yield shocks. On top, the non-yield shock at the ZLB has still a correlation of almost 90 percent with the baseline one. Overall, the results indicate that around FOMC announcements, the relationship between the yield curve and the asset returns is mostly stable throughout our sample consistent with the findings in Swanson (2021).

B Data Appendix

B.1 Sample Construction

FOMC days Our sample of FOMC announcements ranges from January 1996 until April 2023. We obtain dates and times of the FOMC press releases from *Bloomberg*, which we cross-check with information the Federal Reserve website, and data from Gürkaynak, Sack, and Swanson (2005) and Jarociński and Karadi (2020). Based on our sample of scheduled and unscheduled announcements, we remove dates for which the intraday data has large time gaps due to outages from *Thomson Reuters Tick History*. These outages are more common in the early sample period but otherwise completely random mitigating concerns of sample selection. As a result, we exclude the two scheduled FOMC announcements on July 1, 1998, and August 21, 2001, and the unscheduled meeting on April 18, 2001. We end up with 220 observations.

Non-FOMC days Our sample of non-FOMC day ranges from January 1996 until April 2023. We use 2:15 pm EST as the reference time around which we construct our event windows around since most FOMC announcements in our sample are at that time. Our sample construction starts with all U.S. trading days over the period. We exclude all FOMC announcement days (scheduled and unscheduled). Since our window can range into the next business day, we also exclude Fridays. Further, we drop days with shortened trading hours before or around holidays (e.g., July 3 or December 24). We also remove dates for which the intraday data has large time gaps around 2:15 pm EST due to outages from *Thomson Reuters Tick History*. These outages are more common in the early sample period but otherwise completely random mitigating concerns of sample selection. Lastly, as done by Nakamura and Steinsson (2018), we drop the days of market turmoil following September 11, 2001, i.e., from September 11 till 22, and the days of the Lehman and AIG collapse, i.e., September 15 and 16, 2008, from our sample. We end up with 5085 observations.

B.2 Yield Shocks

For each FOMC announcement day, we construct nine yield shocks which capture the effects of monetary policy to the yield curve. To construct these, we employ intraday data on interest rate futures from *Thomson Reuters Tick History*. The sample period ranges from January 1996 and to April 2023. Table 1 provides an overview of the employed data. For each futures contract, we have a minute-by-minute series which we aggregate up to 5-minute intervals. Following previous papers, the first five variables $MP1$, $MP2$, $ED2$, $ED3$, $ED4$ cover surprises to maturities up to 14 months and are standard measures in the literature following Gürkaynak, Sack, and Swanson (2005). For longer horizons, we employ Treasury futures following Gürkaynak, Kısacıkoğlu, and Wright (2020).

In the following, we detail the construction of the yield shocks from the futures contracts. As discussed in the main text, we consider different event windows which range from 10 minutes prior to the release to ℓ hours after the release, where $\ell \in \left\{\frac{1}{3}, 1, 2, ..., 18\right\}$. Hence, we need to construct for each FOMC announcement and each window length a given yield shock. To ease notion, let τ be the times of FOMC announcements, i.e., for $t \in F$. Further, we define ℓ^- and ℓ^+ as the window adjacent to the window ℓ in our analysis, respectively. For example for a window of $\ell = 3$, we have

Table B1: Overview of Intraday Interest Rate Futures Data

Variable in Text	Underlying Instruments	RICs	Sample
$MP1$	Federal Funds Rate Futures	FFc1–FFc2	1996–2023
$MP2$	Federal Funds Rate Futures	FFc3–FFc4	1996–2023
$ED2$	2-Quarter Eurodollar/SOFR Futures	EDcm2/SRAcm3	1996–2023
$ED3$	3-Quarter Eurodollar/SOFR Futures	EDcm3/SRAcm4	1996–2023
$ED4$	4-Quarter Eurodollar/SOFR Futures	EDcm4/SRAcm5	1996–2023
$T2$	2-Year Treasury Futures	TUc1/TUc2	1996–2023
$T5$	5-Year Treasury Futures	FVc1/FVc2	1996–2023
$T10$	10-Year Treasury Futures	TYc1/TYc2	1996–2023
$T30$	30-Year Treasury Futures	USc1/USc2	1996–2023

Notes: This table provides an overview of the intraday data employed to construct the monetary policy surprises to the yield curve. The data comes from *Thomson Reuters Tick History*. *RIC* refers to the Reuters Instrument Code, which uniquely identifies each instrument. Abbreviations: SOFR—Secured Overnight Financing Rate.

$\ell^- = 2$ and $\ell^+ = 4$.

B.2.1 Federal Funds Futures

For given expiry month, a federal funds rate futures contract pays out, on the last day of the expiry month, 100 minus the average (effective) federal funds rate over the expiry month. Precisely, let $p_\zeta^{ff^j}$ be the price at time ζ of the $(j-1)$ month ahead federal funds futures contract. Then, the expected average federal funds rate of the $(j-1)$ month ahead at time ζ is calculated as $ff_\zeta^j = 100 - p_\zeta^{ff^j}$.

Federal Funds Rate Surprise—Current Meeting We calculate the federal funds rate meeting surprise $MP1_\tau^{(\ell)}$ as

$$MP1_\tau^{(\ell)} = \frac{m_0}{m_0 - d_0}\left(ff^1_{\tau+\ell} - ff^1_{\tau-10}\right), \tag{B1}$$

where $ff^1_{\tau-10}$ and $ff^1_{\tau+\ell}$ are the current month's implied federal funds rates from the last trade that occurred more than 10 minutes before the FOMC announcement and the first trade that occurred more than ℓ hours and less than ℓ^+ hours after the FOMC announcement, respectively. Further, m_0 is the total number of days in the month of announcement τ, and d_0 is the day of announcement τ. See Gürkaynak (2005) for a derivation of (B1). The construction is done in the followings steps:

1. For each available time ζ, calculate the implied federal funds rate, i.e. $ff_\zeta^1 = 100 - p_\zeta^{ff^1}$.
2. Calculate $\frac{m_0}{m_0-d_0}\left(ff^1_{\tau+\ell} - ff^1_{\tau-10}\right)$ for each FOMC announcement τ and event window ℓ.
3. If $m_0 - d_0 + 1 \leq 7$, i.e., the announcement occurs in the last seven days of the month, we use the change in the price of next month's fed funds futures contract, i.e. $MP1_\tau^{(\ell)} = ff^2_{\tau+\ell} - ff^2_{\tau-10}$.

This avoids multiplying by large $\frac{m_0}{m_0-d_0}$. For example, for the FOMC announcement on January 29, 2014, we have $d_0 = 29$, $m_0 = 31$, and hence $31 - 29 + 1 = 3 < 7$.

Federal Funds Rate Surprise—Next Meeting We calculate the revision in expectations at FOMC meeting τ about the federal funds rate change at FOMC meeting $\tau + 1$ as

$$MP2_\tau^{(\ell)} = \frac{m_1}{m_1 - d_1}\left[\left(ff_{\tau+\ell}^{j(1)} - ff_{\tau-10}^{j(1)}\right) - \frac{d_1}{m_1}MP1_\tau^{(\ell)}\right], \tag{B2}$$

where $ff_{\tau-10}^{j(1)}$ and $ff_{\tau+\ell}^{j(1)}$ are the implied rate of the federal funds rate futures contract for the month of the next scheduled FOMC meeting from the last trade that occurred more than 10 minutes before the FOMC announcement and the first trade that occurred more than ℓ hours and less than ℓ^+ hours after the FOMC announcement, respectively. Further, m_1 is the total number of days in the month of announcement $\tau + 1$, and d_0 is the day of announcement $\tau + 1$. Note that we have usually, $j(1) = \{3, 4\}$. With a little bit of an abuse of notation, $\tau + 1$ refers here to the next scheduled FOMC meeting at the time of announcement τ. Hence, ex-post there might be an unscheduled meeting in between those. See Gürkaynak (2005) for a derivation of (B2). The construction is done in the followings steps:

1. For a given FOMC announcement τ, find month of next scheduled FOMC meeting, i.e., $j(1)$.
2. Calculate $\frac{m_1}{m_1-d_1}\left[\left(ff_{\tau+\ell}^{j(1)} - ff_{\tau-10}^{j(1)}\right) - \frac{d_1}{m_1}MP1_\tau^{(\ell)}\right]$ for each announcement τ and event window ℓ.
3. If $m_1 - d_1 + 1 \leq 7$, i.e., the announcement occurs in the last seven days of the month, use the change in the price of next month's fed funds futures contract, i.e., $MP2_\tau^{(\ell)} = ff_{\tau+\ell}^{j(1)+1} - ff_{\tau-10}^{j(1)+1}$.

B.2.2 Eurodollar/SOFR Futures

Eurodollar futures are quarterly contracts which pay out 100 minus the 3-month U.S. dollar BBA LIBOR interest rate at the time of expiration. The last trading day is the second London bank business day (typically the Monday) before the third Wednesday of the last month of the expiry quarter. With the cessation of the LIBOR, we use the Secured Overnight Financing Rate (SOFR) futures which are the successor futures contracts at the Chicago Mercantile Exchange (CME). We follow Kroner (2023) and use them from April 2022 onwards as this the first month in which the trading volumes of the SOFR futures contracts exceed the ones of the corresponding Eurodollar futures. For simplicity, we describe in the following the construction with respect to the Eurodollar futures contracts. The SOFR futures are handled in the same manner.

Let p_ζ^{edj} be the price at time ζ of the jth nearest quarterly Eurodollar futures contract (March, June, September, December), then the expiration date of p_ζ^{edj} is between j and $j - 1$ quarters in the future at any given point in time. Further, the implied rate is given by $ed_\zeta^j = 100 - p_\zeta^{edj}$. For a given FOMC announcement τ, we calculate the difference in the implied rate

$$EDj_\tau^{(\ell)} = ed_{\tau+\ell}^j - ed_{\tau-10}^j, \text{ for } j \in \{2, 3, 4\}, \tag{B3}$$

where $ed^j_{\tau-10}$ and $ed^j_{\tau+\ell}$ are the implied rate of the jth nearest quarterly Eurodollar futures contract from the last trade that occurred more than 10 minutes before the FOMC announcement and the first trade that occurred more than ℓ hours and less than ℓ^+ hours after the FOMC announcement, respectively. The construction is done in the followings steps:

1. For each ζ, calculate the implied rate, i.e. , $ed^j_\zeta = 100 - p^{edj}_\zeta$.
2. For a given FOMC announcement τ, calculate the difference in the implied rate of contract j, $EDj^{(\ell)}_\tau = ed^j_{\tau+\ell} - ed^j_{\tau-10}$,.

B.2.3 Treasury Futures

Treasury futures are quarterly contracts which obligate the seller to deliver a Treasury bond within a range of maturities to the buyer at the time of expiration. Let $p^{t2^j}_\zeta$ be the price at time ζ of the jth nearest quarterly 2-year Treasury futures contract. We then calculate the implied yield surprise around FOMC announcement τ by dividing the price change by the approximate duration of the underlying Treasury bond and flipping the sign of it, i.e.,

$$T2^{(\ell)}_\tau = -\left(p^{t2^1}_{\tau+\ell} - p^{t2^1}_{\tau-10}\right)/2. \tag{B4}$$

If the announcement τ is in the month of expiration (March, June, September, December) and prior to the expiration date, we employ the next closest contract, i.e., $T2^{(\ell)}_\tau = -\left(p^{t2^2}_{\tau+\ell} - p^{t2^2}_{\tau-10}\right)/2$, due to its higher liquidity. Similarly, we calculate the implied yield changes from 5-year, 10-year, and 30-year futures contracts, i.e.,

$$\begin{aligned} T5^{(\ell)}_\tau &= -\left(p^{t5^1}_{\tau+\ell} - p^{t5^1}_{\tau-10}\right)/4, \\ T10^{(\ell)}_\tau &= -\left(p^{t10^1}_{\tau+\ell} - p^{t10^1}_{\tau-10}\right)/7, \\ T30^{(\ell)}_\tau &= -\left(p^{t30^1}_{\tau+\ell} - p^{t30^1}_{\tau-10}\right)/15, \end{aligned}$$

where we use the approximate maturities as in Gürkaynak, Kısacıkoğlu, and Wright (2020).

B.2.4 Treatment of Missing Observations

For some of the interest rate futures contracts, the trading is sometimes sparse early in our sample. Hence, if a yield shock is missing for a given window ℓ, we take the shock of the next shorter window ℓ^-. The underlying assumption is that if no price is observed, the futures price did not change between ℓ^- and ℓ. We also apply this in the few very cases in which we have an extreme values.

B.2.5 Validation

To validate our data and our construction methodology, we compare our constructed variables with the ones of Nakamura and Steinsson (2018) and Gürkaynak, Kısacıkoğlu, and Wright (2020). Table B2 shows the correlation of each of our variables with the corresponding one by the prior paper.

To match the window lengths, we use 30-minute changes in the case of Nakamura and Steinsson (2018), ranging from 10 minutes before to 20 minutes after, and 20-minute changes in the case of Gürkaynak, Kısacıkoğlu, and Wright (2020), ranging from 5 minutes before to 15 minutes after. Note that both papers employ different data sources than us.

Table B2:

	NS 2018					GKW 2020			
	MP1	MP2	ED2	ED3	ED4	T2	T5	T10	T30
MP1	0.99								
MP2		0.93							
ED2			0.99						
ED3				0.99					
ED4					0.99				
T2						0.94			
T5							0.91		
T10								0.95	
T30									0.93
Observations	105	105	105	105	105	77	94	93	94

Notes: This table shows the correlation of our constructed interest rate surprises with the ones of Nakamura and Steinsson (2018) (NS 2018) and Gürkaynak, Kısacıkoğlu, and Wright (2020) (GKW 2020) for the overlapping FOMC announcements. To match the window lengths, we use 30-minute changes in the case of NS 2018, ranging from 10 minutes before to 20 minutes after, and 20-minute changes in the case of GKW 2020, ranging from 5 minutes before to 15 minutes after. Note that we use 13-hour windows for our shock estimation.

B.3 Left-hand-side Asset Prices for Estimation

We construct the ℓ-hour log-return of asset price i as

$$\Delta p_{i,t}^{(\ell)} = \log(p_{i,\tau+\ell}) - \log(p_{i,\tau-10}) \,, \tag{B5}$$

where $p_{i,\tau+\ell}$ is the last price that occurred more than 10 minutes before the FOMC announcement and $p_{i,\tau-10}$ is first price that occurred more than ℓ hours and less than ℓ^+ hours after the FOMC announcement, respectively. If we do not observe any price between ℓ and ℓ^+, we set . Note that our Kalman filter algorithm can handle missing observations in Δp_t as long as at lease one $\Delta p_{i,t}$ is available for each t. We also inspect the data for extreme values which we set to missing.

B.4 Daily Financial Market Data

Table B3: Daily Cross-Country Data—Part I

Countries	ISO	Stock Index		U.S. Dollar Exchange Rate		2-Year Govt. Bond Yield		10-Year Govt. Bond Yield	
		Ticker	Sample	Ticker	Sample	Ticker	Sample	Ticker	Sample
Americas									
United States	USA	SPX Index	1996-2023			USGG2YR Index	1996-2023	USGG10YR Index	1996-2023
Canada	CAN	SPTSX Index	1996-2023	CAD Curncy	1996-2023	GTCAD2Y Govt	1996-2023	GTCAD10Y Govt	1996-2023
Brazil	BRA	IBOV Index	1996-2023	BRL Curncy	1996-2023	*BR2YT=RR	2002-2023	*BR10YT=RR	1998-2023
Mexico	MEX	MEXBOL Index	1996-2023	MXN Curncy	1996-2023	GTMXN2Y Govt	2011-2023	*MX10YT=RR	2002-2023
Argentina	ARG	MERVAL Index	1996-2023	ARS Curncy	1996-2023				
Colombia	COL	COLCAP Index	2002-2023	COP Curncy	1996-2023	*CO2YT=RR	2002-2023	*CO10YT=RR	2002-2023
Chile	CHL	IPSA Index	1996-2023	CLP Curncy	1996-2023	*CL2YT=RR	2007-2023	*CL10YT=RR	2007-2023
Europe									
Euro Area	EUR			EUR Curncy	1996-2023				
Germany	DEU	DAX Index	1996-2023			GTDEM2Y Govt	1996-2023	GTDEM10Y Govt	1996-2023
United Kingdom	GBR	UKX Index	1996-2023	GBP Curncy	1996-2023	GTGBP2Y Govt	1996-2023	GTGBP10Y Govt	1996-2023
France	FRA	CAC Index	1996-2023			GTFRF2Y Govt	1996-2023	GTFRF10Y Govt	1996-2023
Russia	RUS	IMOEX Index	1997-2023	RUB Curncy	1996-2023	*RU2YT=RR	2001-2023	*RU10YT=RR	2003-2023
Italy	ITA	FTSEMIB Index	1998-2023			*IT2YT=RR	1998-2023	*IT10YT=RR	1996-2023
Spain	ESP	IBEX Index	1996-2023			*IT2YT=RR	1998-2023	*IT10YT=RR	1996-2023
Netherlands	NLD	AEX Index	1996-2023			*NL2YT=RR	1996-2023	*NL10YT=RR	1996-2023
Switzerland	CHE	SMI Index	1996-2023	CHF Curncy	1996-2023	*CH2YT=RR	1996-2023	*CH10YT=RR	1996-2023
Poland	POL	WIG20 Index	1996-2023	PLN Curncy	1996-2023	*PO2YT=RR	1998-2023	*PO10YT=RR	1999-2023
Sweden	SWE	OMX Index	1996-2023	SEK Curncy	1996-2023	*SE2YT=RR	1996-2023	*SE10YT=RR	1996-2023
Belgium	BEL	BEL20 Index	1996-2023			*BE2YT=RR	1996-2023	*BE10YT=RR	1996-2023
Norway	NOR	OBX Index	1996-2023	NOK Curncy	1996-2023	GTNOK2Y Govt	2007-2023	*NO10YT=RR	1996-2023
Denmark	DNK	KFX Index	1996-2023	DKK Curncy	1996-2023	*DK2YT=RR	1996-2023	*DK10YT=RR	1996-2023
Czech Republic	CZE	PX Index	1996-2023	CZK Curncy	1996-2023	*CZ2YT=RR	1998-2023	*CZ10YT=RR	2000-2023
Africa									
Nigeria	NGA	NGXINDX Index	1998-2023	NGN Curncy	1996-2023	*NG2YT=RR	2008-2023	*NG10YT=RR	2007-2023
Egypt	EGY	EGX30 Index	1998-2023	EGP Curncy	1996-2023	*EG2YT=RR	2016-2023	*EG10YT=RR	2010-2023
South Africa	ZAF	TOP40 Index	1996-2023	ZAR Curncy	1996-2023	*ZA2YT=RR	2007-2023	*ZA10YT=RR	1996-2023
Morocco	MAR	MOSENEW Index	1996-2023	MAD Curncy	1996-2023	*MA2YT=RR	2012-2023	*MA10YT=RR	2012-2023
Tunisia	TUN	TUSISE Index	1999-2023	TND Curncy	1996-2023				
Asia									
China	CHN	SHCOMP Index	1996-2023	CNY Curncy	1996-2023	*CN2YT=RR	2000-2023	*CN10YT=RR	2000-2023
Japan	JPN	NKY Index	1996-2023	JPY Curncy	1996-2023	GTJPY2Y Govt	1996-2023	GTJPY10Y Govt	1996-2023
India	IND	NIFTY Index	1996-2023	INR Curncy	1996-2023	*IN2YT=RR	1997-2023	*IN10YT=RR	1998-2023
Korea	KOR	KOSPI Index	1996-2023	KRW Curncy	1996-2023	GTKRW2Y Govt	1999-2023	GTKRW10Y Govt	2001-2023
Indonesia	IDN	JCI Index	1996-2023	IDR Curncy	1996-2023			*ID10YT=RR	2003-2023
Saudi Arabia	SAU	SASEIDX Index	1996-2023	SAR Curncy	1996-2023				
Turkey	TUR	XU100 Index	1996-2023	TRY Curncy	1996-2023	*TR2YT=RR	2005-2023	*TR10YT=RR	2010-2023
Taiwan	TWN	TWSE Index	1996-2023	TWD Curncy	1996-2023	*TW2YT=RR	1998-2023	*TW10YT=RR	1998-2023
Thailand	THA	SET Index	1996-2023	THB Curncy	1996-2023	*TH2YT=RR	2000-2023	*TH10YT=RR	2001-2023
Israel	ISR	TA125 Index	1996-2023	ILS Curncy	1996-2023	*IS2YT=RR	2006-2023	*IS10YT=RR	2002-2023
Singapore	SGP	STI Index	1999-2023	SGD Curncy	1996-2023	*SG2YT=RR	1996-2023	*SG10YT=RR	1998-2023
Hong Kong	HKG	HSI Index	1996-2023	HKD Curncy	1996-2023	*HK2YT=RR	1997-2023	*HK10YT=RR	1996-2023
Oceania									
Australia	AUS	AS51 Index	1996-2023	AUD Curncy	1996-2023	*AU2YT=RR	1996-2023	*AU10YT=RR	1996-2023
New Zealand	NZL	NZSE50FG Index	2001-2023	NZD Curncy	1996-2023	*NZ2YT=RR	1996-2023	*NZ10YT=RR	1996-2023

Notes: This table shows the daily asset prices considered as outcome variables in Section 3 by country. The data is from *Bloomberg* and *Refinitiv*. For each series, we report sample period (*Sample*) and the Bloomberg or Refinitiv identifier (*Ticker*). * denotes data from Refinitiv. Countries are listed by continent and descending order in terms of their 2022 nominal GDP (in U.S. dollars) taken from IMF World Economic Outlook (WEO) database.

Table B4: Daily Cross-Country Data—Part II

Countries	ISO	Implied Vol. Stock Index		Implied Vol. Exchange Rate		Dividend Futures		Inflation Swap Rate		Breakeven Inflation Rate	
		Ticker	Sample	Ticker	Sample	Ticker	Sample	Ticker	Sample	Ticker	Sample
Americas											
United States	USA	VIX Index	1996-2023							USGGBE02/ USGGBE05/ USGGBE10 Index	2004-2023 2002-2023 1998-2023
Canada	CAN			USDCADV1M Curncy	1998-2023	ASD1-ASD8 Index	2015/16- 2023	USSWIT2/ USSWIT5/ USSWIT10 Curncy	2004-2023 2004-2023 2004-2023	CDGGBE05/ CDGGBE10 Index	2016-2023 2008-2023
Europe											
Euro Area	EUR	V2X Index	1999-2023	EURUSDV1M Curncy	1998-2023	DED1-DED8 Index	2008/09- 2023	EUSWI2/ EUSWI5/ EUSWI10 Curncy	2004-2023 2004-2023 2004-2023		
Germany	DEU	V1X Index	1996-2023							DEGGBE02/ DEGGBE05/ DEGGBE10 Index	2011-2023 2008-2023 2009-2023
United Kingdom	GBR	IVIUK Index	2000-2023	GBPUSDV1M Curncy	1996-2023			BPSWIT2/ BPSWIT5/ BPSWIT10 Curncy	2004-2023 2004-2023 2004-2023	UKGGBE02/ UKGGBE05/ UKGGBE10 Index	1996-2023 1996-2023 1996-2023
France	FRA	VCAC Index	2000-2020								
Switzerland	CHE	V3X Index	1999-2023	USDCHFV1M Curncy	1996-2023						
Sweden	SWE			USDSEKV1M Curncy	1998-2023					SKGGBE02/ SKGGBE05/ SKGGBE10 Index	2002-2023 2004-2023 2004-2023
Norway	NOR			USDNOKV1M Curncy	1999-2023						
Asia											
Japan	JPN	VXJ Index	1996-2023	USDJPYV1M Curncy	1996-2023	INT1-INT8 Index	2010-2023			JYGGBE02/ JYGGBE05/ JYGGBE10 Index	2012-2023 2009-2023 2004-2023
Hong Kong	HKG	VHSI Index	2001-2020								
Oceania											
Australia	AUS	AS51VIX Index	2008-2020	AUDUSDV1M Curncy	1996-2023					ADGGBE02/ ADGGBE05/ ADGGBE10 Index	2003-2023 2000-2023 2000-2023
New Zealand	NZL			NZDUSDV1M Curncy	1997-2023						

Notes: This table shows the daily asset prices considered as outcome variables in Section 3 by country. The data is from *Bloomberg*. For each series, we report sample period (*Sample*) and Bloomberg identifier (*Ticker*). Countries are listed by continent and descending order in terms of their 2022 nominal GDP (in U.S. dollars) taken from IMF World Economic Outlook (WEO) database.

Table B5: Daily Commodity Prices and Implied Interest Rate Volatilities

Name	Ticker	Sample
Commodity Prices		
S&P GSCI Total	SPGSCI Index	1996-2023
S&P GSCI Energy	SPGSEN Index	1996-2023
S&P GSCI Precious Metals	SPGSPM Index	1996-2023
S&P GSCI Industrial Metals	SPGSIN Index	1996-2023
S&P GSCI Agriculture & Livestock	SPGSAL Index	1996-2023
WTI Oil—Front-month Futures Contract	CL1 Comdty	1996-2023
Brent Oil—Front-month Futures Contract	CO1 Comdty	1996-2023
Gold—Gold/USD Dollar Exchange Rate	XAU Curncy	1996-2023
Silver—Silver/USD Dollar Exchange Rate	XAG Curncy	1996-2023
Implied Interest Rate Volatility Indexes		
Merrill Lynch Option Volatility Estimate (MOVE)	MOVE Index	1996-2023
CBOE/CBOT 10-year U.S. Treasury Note Volatility (TYVIX)	TYVIX Index	2003-2020

Notes: This table shows the daily asset prices considered as outcome variables in Section 3. The data is from *Bloomberg*. For each series, we report sample period (*Sample*) and Bloomberg identifier (*Ticker*).

Table B6: Compositions of Commodity Indexes

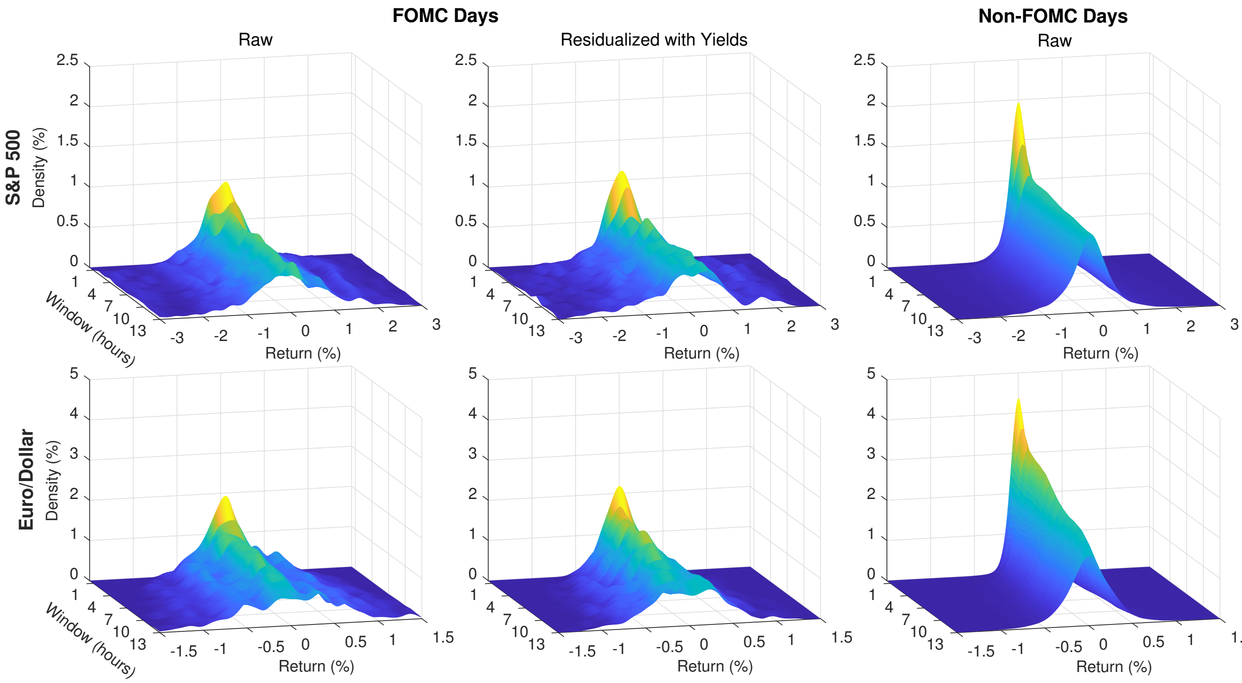
Energy		Industrial Metals		Precious Metals		Agriculture & Livestock	
Commodity	Weight	Commodity	Weight	Commodity	Weight	Commodity	Weight
WTI Crude Oil	20.34%	Aluminum	4.18%	Gold	5.33%	Chicago Wheat	3.64%
Heating Oil	3.50%	Copper	5.80%	Silver	0.64%	Kansas Wheat	1.40%
RBOB Gasoline	4.34%	Nickel	1.00%			Corn	6.54%
Brent Crude Oil	17.19%	Lead	0.66%			Soybeans	4.64%
Gasoil	4.78%	Zinc	1.08%			Coffee	0.83%
Natural Gas	3.33%					Sugar	1.81%
						Cocoa	0.36%
						Cotton	1.26%
						Lean Hogs	2.36%
						Live Cattle	3.76%
						Feeder Cattle	1.25%
Contribution to Total	53.48%		12.72%		5.97%		27.85%

Notes: This table shows the underlying commodity prices and corresponding weights for each of the S&P GS sector commodity indexes, as well as their contributions to the total index.

B.5 Data from other Papers

- Adrian, Crump, and Moench (2013): https://www.newyorkfed.org/research/data_indicators/term-premia-tabs#/overview
- Aruoba and Drechsel (2022): Updated data from Aruoba and Drechsel (2022) (privately shared)
- Bauer, Lakdawala, and Mueller (2022): https://www.michaeldbauer.com/files/mpu.csv
- Bu, Rogers, and Wu (2021): https://ars.els-cdn.com/content/image/1-s2.0-S0304393220301276-mmc1.csv
- Du, Im, and Schreger (2018): https://sites.google.com/view/jschreger/CIP?authuser=0
- Gürkaynak, Kısacıkoğlu, and Wright (2020): https://www.openicpsr.org/openicpsr/project/119697/version/V1/view
- Gürkaynak, Sack, and Wright (2007): https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html
- Jarociński and Karadi (2020): https://www.aeaweb.org/journals/dataset?id=10.1257/mac.20180090
- Kroencke, Schmeling, and Schrimpf (2021): https://ars.els-cdn.com/content/image/1-s2.0-S0304393221000258-mmc2.xls
- Lewis (2023): https://docs.google.com/spreadsheets/d/1l21TwrQpTY5cuqWH92oG-0QHQKpQt9Lm/edit#gid=227445324
- Martin (2017): Updated data from Knox and Vissing-Jorgensen (2022)
- Nakamura and Steinsson (2018): https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HZOXKN
- Romer and Romer's (2004): Updated data from Aruoba and Drechsel (2022) (privately shared)
- Swanson (2021): https://sites.socsci.uci.edu/~swanson2/papers/pre-and-post-ZLB-factors-extended.xlsx

Figure C1: Distributions of Asset Returns around FOMC and Non-FOMC Days



Notes: This figure shows return distributions around times of FOMC announcements and around comparable times on non-announcement trading days. Each panel displays distributions for different window lengths over which returns are constructed, where each window begins 10 minutes prior to the reference time and ends starting at 20 minutes up to 13 hours after the reference time. For each window size, the kernel density estimates integrate to one. The sample ranges from January 1996 to April 2023. Panels in the top row present results for the Euro-Dollar exchange rate, while panels in the bottom row for the front-month S&P 500 E-mini futures contracts. *Raw* refers to the returns, while *Residualized with Yields* refers to returns which orthogonalized by the entire yield curve. Details are provided in Section 2

C Additional Results

C.1 Commodities

In this section, we study the effects of the Fed non-yield shock on commodity prices. Similar to stocks and exchange rates, previous papers have documented the response of commodity prices to monetary policy shocks (e.g., Frankel, 2008). To investigate the response to our shock, we estimate specification (17) where $\Delta^d x_t$ is the 2-day log-change in the commodity index or price of interest around the FOMC announcement at time t. In our analysis, we focus on S&P GS commodity indexes to cover the full range of commodities. Appendix Table B6 provides an overview of the commodities underlying each index. We also report separately results for three popular commodity prices: oil, gold, and silver.

Figure C2 illustrates the estimation results. First and foremost, the Fed non-yield shock leads to significant increases in commodities prices on average and across all classes. Further, the effects are strongest for energy and metals.

Table C1: Effects of Fed Non-Yield Shock on U.S. Yields

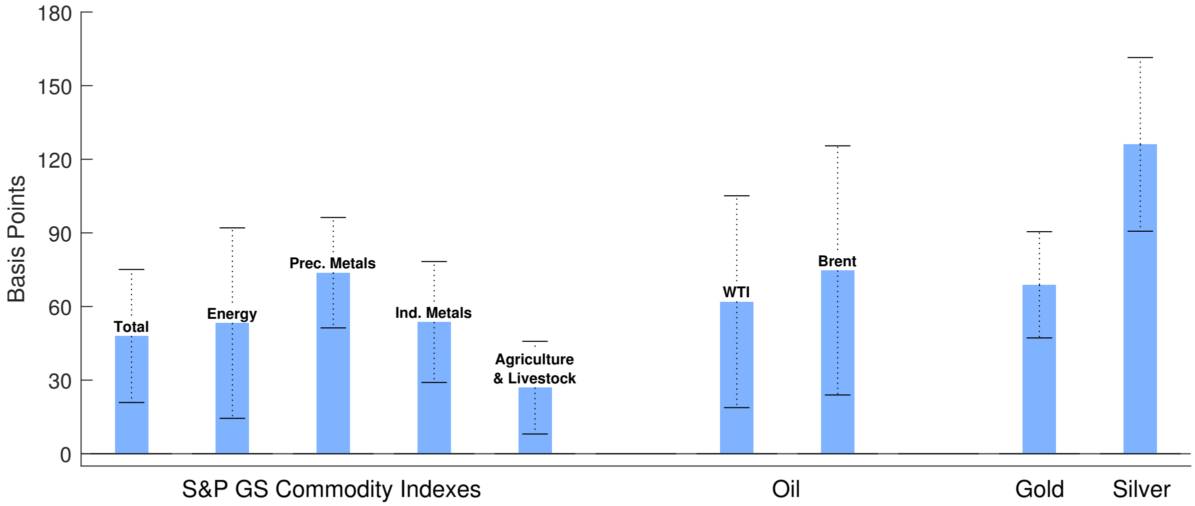
Change (bp)	1 Month	3 Month	6 Month	1 Year	2 Year	5 Year	10 Year	30 Year
Bloomberg								
Fed non-yield shock	-0.48	-0.89	-0.54	-0.09	-0.58	-0.65	0.06	0.67
	(0.66)	(0.82)	(0.62)	(0.53)	(0.57)	(0.80)	(0.86)	(0.80)
R^2	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01
Observations	176	219	219	219	219	219	219	219
GSW 2007								
Fed non-yield shock				-0.06	-0.65	-0.67	0.16	0.79
				(0.51)	(0.60)	(0.79)	(0.89)	(0.70)
R^2				0.00	0.01	0.00	0.00	0.01
Observations				219	219	219	219	219

Notes: This table presents estimates of δ from specification (17), where the left-hand side variables are now 2-day changes in U.S. government yields of different maturities. The top panel shows results for yields coming from *Bloomberg*, while the bottom panel displays estimates for yields taken from Gürkaynak, Sack, and Wright (2007). We winsorize the top and bottom 1 percent of each left-hand variable. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

C.2 Inflation Expectations

Finally, we study the inflation channel of our Fed non-yield shock. To do so, we employ both inflation swap and breakeven inflation rates. As before, we reestimate specification (17) with inflation swap and breakeven inflation rates as left-hand side variables. Table C2 displays the coefficient estimates. As the Table shows, we only find inflationary effects of our shock for the U.S. in a systematic fashion.

Figure C2: Effects of Fed Non-yield Shock on Commodity Prices



Notes: This figure shows the response of different commodity indexes and prices to the non-yield shock. Commodity price changes are expressed in basis points. Each bars show the effect on a given commodity price or index, i.e., the estimate of coefficient δ of equation (17) with the 2-day log-change of the commodity price or index of interest on the left-hand side. The black error bands depict 95 percent confidence intervals, where standard errors are clustered by announcement. We winsorize each dependent variable at the top and bottom 1 percent. More details on commodity prices are provided in Appendix Table B5 and B6.

Table C2: Effects of Fed Non-Yield Shock on Inflation Expectations

Return (bp)	Inflation Swap Rate			Breakeven Inflation Rate						
	USA	EUR	GBR	USA	CAN	DEU	JPN	GBR	AUS	SWE
2-Year										
Fed non-yield shock	2.48***	0.13	-0.37	3.83***		1.83*	0.23	0.13	0.08	-0.29
	(0.95)	(0.60)	(0.66)	(1.36)		(1.09)	(0.38)	(0.11)	(0.13)	(0.31)
R^2	0.07	0.00	0.00	0.12		0.05	0.00	0.00	0.00	0.00
Observations	153	158	157	151		95	85	216	158	168
5-Year										
Fed non-yield shock	2.15***	0.13	0.07	1.70**	0.62	0.68	0.20	-0.12	0.26	0.21
	(0.62)	(0.36)	(0.41)	(0.80)	(0.51)	(0.41)	(0.21)	(0.52)	(0.25)	(0.32)
R^2	0.10	0.00	0.00	0.05	0.02	0.03	0.01	0.00	0.00	0.00
Observations	153	155	155	173	52	115	111	217	187	157
10-Year										
Fed non-yield shock	1.48**	0.07	-0.26	1.31**	0.99**	0.33	0.24	-0.26	-0.10	-0.10
	(0.72)	(0.25)	(0.42)	(0.51)	(0.46)	(0.35)	(0.34)	(0.35)	(0.25)	(0.36)
R^2	0.06	0.00	0.00	0.04	0.05	0.01	0.01	0.00	0.00	0.00
Observations	153	155	155	201	120	111	155	219	187	157

Notes: This table presents estimates of δ from specification (17), where the left-hand side variables are now 2-day log-changes in inflation swap or inflation breakeven rates. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level. We winsorize each dependent variable at the top and bottom 1 percent.