NBER WORKING PAPER SERIES

MONETARY POLICY WITHOUT MOVING INTEREST RATES: THE FED NON-YIELD SHOCK

Christoph Boehm
T. Niklas Kroner

Working Paper 32636
http://www.nber.org/papers/w32636

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2024, Revised September 2025

We thank Borağan Aruoba, Anna Cieslak, Pierre De Leo, Thomas Drechsel, Refet Gürkaynak, Tarek Hassan, Diego Känzig, Sebnem Kalemli-Ozcan, Rohan Kekre (discussant), Paymon Khorrami, Burçin Kısacıkoğlu, Benjamin Knox, Arvind Krishnamurthy, Moritz Lenel (discussant), Daniel Lewis (discussant), Matteo Maggiori, Michael McMahon, Tyler Muir, Xuhui Pan (discussant), Dejanir Silva, Adi Sunderam, Eric Swanson, Jenny Tang, Rosen Valchev, Rossen Valkanov (discussant), Annette Vissing-Jorgensen, Linyan Zhu (discussant), as well as seminar and conference participants at NBER SI 2024, NBER AP Fall 2024, AFA 2024, SEA 2024, Wake Forest Macro Workshop 2024, AEA 2025, MFA 2025, Frontiers of Macroeconomics, SFS Cavalcade NA 2025, Banque de France Conference, SED 2025, Dallas Fed, BYU, Bank of Israel, Fed Board, George Washington, Bilkent, UCSD, UT Austin, and Maryland for helpful comments. We thank Shaily Acharya for excellent research assistance. The views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Board or the Federal Reserve System, or the National Bureau of Economic Research.

Monetary Policy without Moving Interest Rates: The Fed Non-Yield Shock
Christoph Boehm and T. Niklas Kroner
NBER Working Paper No. 32636
June 2024, Revised September 2025
JEL No. E43, E44, E52, E58, F31, G10

ABSTRACT

Existing high-frequency monetary policy shocks explain surprisingly little variation in stock prices and exchange rates around FOMC announcements. Further, both of these asset classes display heightened volatility relative to non-announcement times. 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. The non-yield shock has large effects on global markets, with a positive non-yield shock raising U.S. and foreign stock prices, depreciating the dollar, and increasing commodity prices. At the same time, the shock leaves global yields unaffected. Further results indicate that the non-yield shock transmits mostly through risk premia. The existence of the non-yield shock generally has implications for how monetary policy shocks can be identified, raising concerns about the validity of many common approaches.

Christoph Boehm
University of Texas at Austin
Department of Economics
and NBER
chris.e.boehm@gmail.com

T. Niklas Kroner
Federal Reserve Board of Governors
t.niklas.kroner@gmail.com

1 Introduction

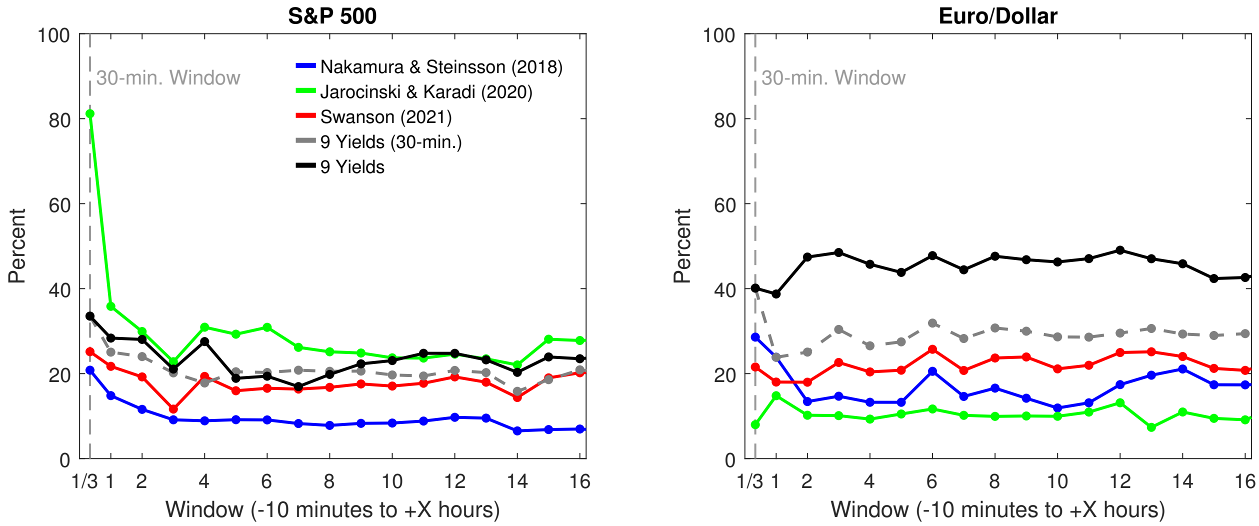
> *No matter how we measure [monetary policy] surprises or how much delay we allow for the response, we can only explain up to about 10 percent of the daily variation in risk appetite. While some of the variation in risk appetite on days with FOMC announcements is certainly driven by news unrelated to 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 16 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 rationalize such low explanatory power 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 identify monetary policy shocks

Figure 1: Explanatory Power of Yield Curve around FOMC Announcements



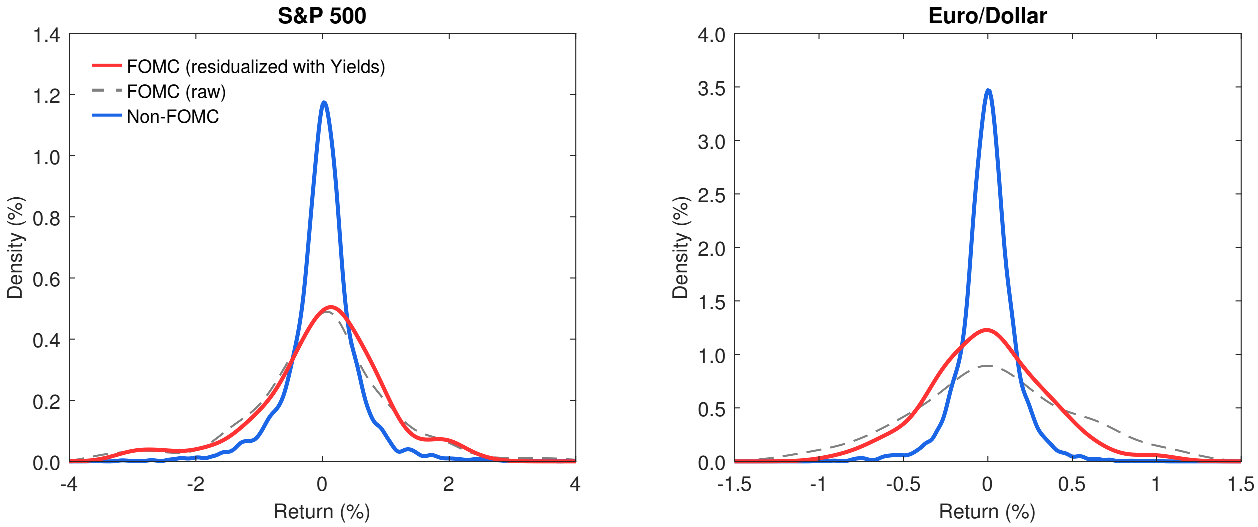
Notes: This figure shows the R^2 of regressing the log-return of the front-month S&P E-mini futures contracts (left panel) and the Euro-Dollar exchange rate (right panel) around FOMC announcements on various different high-frequency shocks. The window over which returns are constructed is expanding as indicated on the horizontal axis. The full sample ranges from January 1996 to July 2025. See text for details on the shocks.

(Jarociński and Karadi, 2020; Gürkaynak, Kara, Kısacıkoğlu, and Lee, 2021).[1] Besides the fact that some research 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 of the S&P 500. 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

[1]Other terms for information effects in the literature are information shocks, signaling effects or Delphic forward 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 begins 10 minutes prior to the reference time and ends six hours after. The full sample ranges from January 1996 to July 2025.

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 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 begin our analysis by laying out the estimation framework. Different from the standard event study framework, which assumes that yields capture all changes in monetary policy over the event window, we allow for a latent shock to affect stock prices and exchange rates. The defining feature of this shock is that it is orthogonal to yield changes—giving it its name, the Fed non-yield shock. To estimate it, we use intraday data on U.S. stock prices and major U.S. dollar exchange rates and apply a heteroskedasticity-based identification procedure together with the Kalman filter (Rigobon, 2003; Gürkaynak, Kısacıkoğlu, and Wright, 2020). Statistical tests show that the employed asset prices all exhibit excess variance around FOMC announcements. It turns out that a single non-yield shock explains a large chunk of the variation in both stock prices and exchange rates unexplained by yields. A positive non-yield shock raises U.S. stock prices and depreciates the dollar.

Using daily data, we go on to document that the non-yield shock has large and significant effects on financial markets around the globe. In a sample of 40 countries, a one standard deviation non-yield shock moves international stock prices by 49 basis points, on average, in a two-day window around the announcement. Almost all countries have statistically significant individual effects. In addition, the dollar responds by 35 basis points, on average, relative to a basket of 30 foreign currencies. The non-yield shock also affects commodity prices and capital flows into emerging market economies. When compared to commonly used high-frequency monetary policy shocks from the literature (i.e., those in Figure 1), the non-yield shock generally has larger effects. In contrast with prior shocks, however, it leaves global yields unaffected. The non-yield shock therefore captures very different variation from existing monetary policy shocks.

The non-yield shock affects asset prices predominantly through changes in risk premia. Following a one-standard deviation positive non-yield shock, implied volatility measures of major international stock markets fall by 2.3 percent, on average, and implied volatility measures of major currencies by 1.4 percent. Alternative measures of equity risk premia experience similar declines. In the case of exchange rates, changes in convenience yields explain a modest but statistically significant share of around 17 percent of the overall response. The contributions of risk-free rates and expected future dividends to the observed stock price response are both small and insignificant throughout. Non-yield shocks therefore appear to trigger changes in global risk-on/risk-off behavior. The effects of negative shocks resemble flight-to-safety episodes as characterized by Baele, Bekaert, Inghelbrecht, and Wei (2020).

Though economically important by various metrics, neither the interpretation of the non-yield shock nor the consequences of its existence are immediately clear. To make progress on these questions, we present a simple framework that helps clarify the nature of the non-yield shock and what its presence implies for the identification of structural monetary policy shocks.[2] Our framework shows that the non-yield shock is, in general, a reduced form monetary policy shock. That is, it is a linear combination of the unobserved structural monetary policy shocks. The non-yield shock admits a structural interpretation only as a special case. We present an equivalence result that characterizes whether the non-yield shock is structural. It implies that there are two possible interpretations of our non-yield shock.

[2]We use the term structural monetary policy shocks as referring to exogenous disturbances in structural models that arise from particular central bank actions (e.g., exogenous deviations from a policy rule).

Under the first interpretation, there exists a structural monetary policy shock that does not affect the yield curve. The non-yield shock then equals this structural monetary policy shock (up to a sign flip). The equivalence result also shows that the non-yield shock is structural if and only if the remaining structural shocks are identifiable from the yield curve alone. Extracting monetary policy shocks solely from the yield curve—as pioneered by Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005)—may then remain valid despite the presence of the non-yield shock. Under this interpretation, the non-yield shock is simply an additional dimension of monetary policy that has large effects on global equity prices, exchange rates, and other outcomes. As we discuss below, a theoretical mechanism, which could rationalize this interpretation in a knife-edge case, is that the Fed credibly announces more decisive policy reactions in adverse states of the world going forward.

Under the second interpretation, the non-yield shock is not structural and may therefore lack a clear interpretation. In this case, structural monetary policy shocks are not identifiable from the yield curve alone. Intuitively, the yield curve alone does not contain enough information to recover the true structural disturbances. Identification requires the use of additional information, such as other asset prices or the non-yield shock itself. An example of this case is a world with information effects as in Jarociński and Karadi (2020). The non-yield shock arises in the presence of information effects since the two structural shocks, a "pure" monetary policy shock and an "information" shock, are not spanned by the yield curve. In practice, however, the non-yield shock is uncorrelated with those by Jarociński and Karadi (2020), as already hinted at by Figure 1. This suggests that information effects *as currently estimated* cannot explain the non-yield shock.

While the non-yield shock can arise in a range of economic environments and its precise origin remains uncertain, we show that it is related to Fed communications. In particular, we find that larger shock magnitudes are associated with FOMC announcements that are (i) accompanied by press conferences, (ii) paired with a release of the Summary of Economic Projections, and (iii) delivered under Chairman Ben Bernanke—a strong advocate of more transparent communications. Although these results provide some guidance for the interpretation of the non-yield shock, more research is needed to better explain the non-yield shock and to model it within a structural framework.

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) or in combination with lower-frequency times series methods (e.g., Gertler and Karadi, 2015; 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 not spanned by the yield curve.

Within this line of work, the most closely related papers are Jarociński and Karadi (2020) and Kroencke, Schmeling, and Schrimpf (2021). Building on prior work by Romer and Romer (2000), Jarociński and Karadi (2020) rationalize the unexplained stock market variation around FOMC announcements with information effects.[3] We show that within their framework, their shocks and our non-yield shock should be closely related. In practice, it turns out, they are orthogonal. 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". Although our non-yield shock is conceptually similar to the risk shift, differences in objectives, applied methodology, and implementation ultimately imply that the risk shift explains only about a quarter of the variation of our non-yield shock. We therefore conclude that the variation captured by the non-yield shock is largely new.

By documenting that our non-yield shock has strong effects on financial markets through risk premia, we contribute to several strands of empirical research on the monetary policy transmission mechanism. Regarding the transmission of U.S. monetary policy to the stock market, various papers emphasize the risk premium channel.[4] For example, Bernanke and Kuttner (2005) find that the risk premium accounts for the lion's share of the stock market reaction to yield-based shocks, Bekaert, Hoerova, and Lo Duca (2013) document strong effects on the VIX, and Miranda-Agrippino and Rey (2020) argue that U.S. monetary policy affects global stocks through investors' risk-taking behavior. More recently, Nagel and Xu (2024) push back on prior evidence, arguing that traditional monetary policy shocks affect the stock market mostly through changes in yields. We demonstrate in this paper that the responses to yield-based shocks only capture a relatively small share of the overall market reaction. Our findings therefore imply that the majority of the stock market response to

[3]Other papers follow similar approaches (e.g., Cieslak and Schrimpf, 2019; Lewis, 2025).

[4]See Bauer, Bernanke, and Milstein (2023) and Knox and Vissing-Jorgensen (2025) for literature reviews.

FOMC announcements is driven by risk premia. They also relate to evidence from monetary policy news on non-announcement days, which suggests that the effects of monetary policy on the stock market may operate more strongly through risk premia than previously recognized (e.g., Cieslak and McMahon, 2023).

Recent work demonstrates that changes in currency risk premia and convenience yields—both reflecting deviations from uncovered interest parity (UIP)—potentially play an important role for the transmission of monetary policy to exchange rates.[5] Mueller, Tahbaz-Salehi, and Vedolin (2017) provide evidence of substantial currency risk premia around FOMC announcements, while Jiang, Krishnamurthy, and Lustig (2021) show that yield-based shocks affect convenience yields. As noted above, Gürkaynak et al. (2021) find that exchange rate reactions to FOMC announcements are not well explained by yield-based shocks, even when accounting for Jarociński and Karadi's (2020) information effects—a result we confirm in Figure 1. We find that the large majority of exchange rate reactions to the Fed non-yield shocks reflect changes in UIP deviations. This implies that risk premia and convenience yields are not only important for unconditional exchange rate fluctuations (e.g., Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011; Engel and Wu, 2023), but also for the transmission of monetary policy to exchange rates.

The existence of the non-yield shock and its affects on asset prices are not easily explained by mechanisms commonly studied in the monetary policy literature. There are, however, links to adjacent areas of research. As noted above, one potential way to rationalize our shock is that the Fed makes credible promises about state-contingent policy interventions either explicitly or implicitly through other actions. Such promises are also discussed and studied by Cieslak, Morse, and Vissing-Jorgensen (2019) and Haddad, Moreira, and Muir (2025). Research on flight-to-safety episodes may provide a fruitful avenue for better understanding the non-yield shock (e.g., Maggiori, 2017; Caballero and Farhi, 2018; Kekre and Lenel, 2024). The joint response of risk premia, the U.S. dollar, and convenience yields to a negative non-yield shock resembles in many ways typical flight-to-safety episodes.

Lastly, by documenting the existence of our non-yield shock, we relate to work on macro-finance term structure models. These models typically imply that all structural shocks are spanned by the current yield curve, so that observed yields are sufficient statistics for forecasting all macro and financial variables. Empirically, however, several studies find evidence, which is *prima facie* inconsistent with this prediction (e.g., Ludvigson and Ng, 2009; Duffee,

[5]There is, of course, a large literature studying the more conventional transmission channels of monetary policy to exchange rates. Engel (2014) provides an overview of earlier work.

2011; Joslin, Priebsch, and Singleton, 2014). This has led some to conclude that models featuring spanning are rejected by the data. Others argue that measurement error in observed yields or certain econometric issues can potentially rationalize the evidence (e.g., Cieslak and Povala, 2015; Bauer and Rudebusch, 2017; Bauer and Hamilton, 2018). Analogous to this literature, our evidence can be interpreted in one of two ways. One interpretation is that the non-yield shock arises because observed yield changes do not span all structural monetary policy shocks. An alternative interpretation is that measurement error in observed yields prevents the identification of structural monetary policy shocks, and the non-yield shock captures variation in the true latent yields. For the remainder of this paper, we adopt the first perspective by assuming that yields are observed without measurement error following most of the literature on high-frequency identification.[6]

Roadmap The remainder of the paper is structured as follows. The next section presents our empirical framework and estimates the non-yield shock. Section 3 documents the importance of the non-yield shock for global asset prices and examines the channels through which it transmits. In Section 4, we discuss how the non-yield shock can arise and what its presence implies for the identification of structural monetary policy shocks. Lastly, Section 5 briefly discusses the link between Fed communications and the non-yield shock, and subsequently 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 then turn to the data and explain specification choices before conducting tests on the strength of the identifying variation. We conclude this section with presenting the estimated shock series and several robustness checks.

2.1 Framework

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

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

[6] Although this assumption is adopted in virtually the entire literature on high-frequency identification of monetary policy shocks and it is thought that measurement error in observed yields is generally small (e.g., Bekaert, Hodrick, and Marshall, 1997), we are not aware of any empirical work that has demonstrated that measurement error in yields is unimportant for the identification of structural monetary policy shocks.

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.[7] 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. The coefficient vector β_i can be consistently estimated by Ordinary Least Squares (OLS) if the surprise s_t^y is uncorrelated with the error $\varepsilon_{i,t}$.

The economic interpretation of β_i depends on why yields s_t^y change during the event window. Under the common assumption that monetary policy exclusively affects current and future interest rates, β_i captures the causal effect of these *structural monetary policy shocks* on the asset price of interest (Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005; Swanson, 2021). More generally, β_i captures the causal effects of *reduced-form monetary policy shocks*. For instance, in Jarociński and Karadi's (2020) framework, in which the structural monetary policy shocks are a "pure" and an "information" shock, β_i captures the effect of a linear combination of these two shocks on the return of asset i.

As noted in the introduction, both the low explanatory power of yield shocks and the elevated volatility of asset prices around announcements are puzzling and 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, which is assumed to be orthogonal to s_t^y ($Cov\left[s_t^y, s_t^{ny}\right] = 0$). Hence, this specification allows for the possibility that information released during FOMC announcements affects stocks and exchange rates but is not fully captured by interest rates. At this point, we do not take a stance on how the non-yield shock can arise in the data, but focus on its existence. We return to the interpretation of the non-yield shock in Section 4.

To estimate γ_i, 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

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

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.[8] We will also make use of the fact that we can directly measure s_t^y from interest rate futures following the previous literature. Under the assumptions that (i) s_t^y and s_t^{ny} are orthogonal to one another and (ii) both s_t^y and s_t^{ny} 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 can then identify γ_i from heightened stock market and exchange rate volatility relative to non-announcement days.

We recover s_t^{ny} using the Kalman filter via maximum likelihood estimation 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, $d_t = 1\left(t \in F\right)$ 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.[9]

In principle, we could recover our non-yield shock from a single asset. However, the motivating facts in the introduction apply to different assets and even different asset classes. In addition, we document a third fact in Appendix C.4, which is that the correlations between stock returns and exchange rates increase substantially on announcement days relative to non-announcement days and so do the correlations between different dollar exchange rates. The evidence therefore points toward a common driving force that raises the volatility of asset prices around FOMC announcements. Since employing a broader set of assets increases the estimation precision of the non-yield shock, we consider a multivariate version of the

[8] The assumption that there is no monetary policy news on non-announcement days is stricter than required and we make it mostly for expositional clarity. It is sufficient for the estimation to assume that there is more monetary policy news on announcement days than on non-announcement days, which we confirm with statistical tests below. Swanson and Jayawickrema (2024) show that speeches of the Fed chair and other forms of Fed communication on non-announcement days also affect financial markets.

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

observation equation in which all asset prices are driven by a common non-yield shock:

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

Here, p_t, β, γ, and ε_t denote the appropriately dimensioned matrices capturing $p_{i,t}$, β_i, γ_i, and $\varepsilon_{i,t}$. In our baseline analysis we assume that ε_t is independently and identically normally distributed with a diagonal variance-covariance matrix.[10] Details on the estimation framework are available in Appendix B.

2.2 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 typically 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. 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 avoid simultaneity bias and omitted variable bias arising from other news released during the event window (Gürkaynak, Sack, and Swanson, 2005). In addition, tighter windows typically imply sharper differences in variances, which are necessary for heteroskedasticity-based estimators (Lewis, 2022). A wider window, on the other hand, includes the subsequent press conference, which other work has found 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

[10] We present a robustness check with an unrestricted variance-covariance matrix in Appendix Table 4, which shows very similar results.

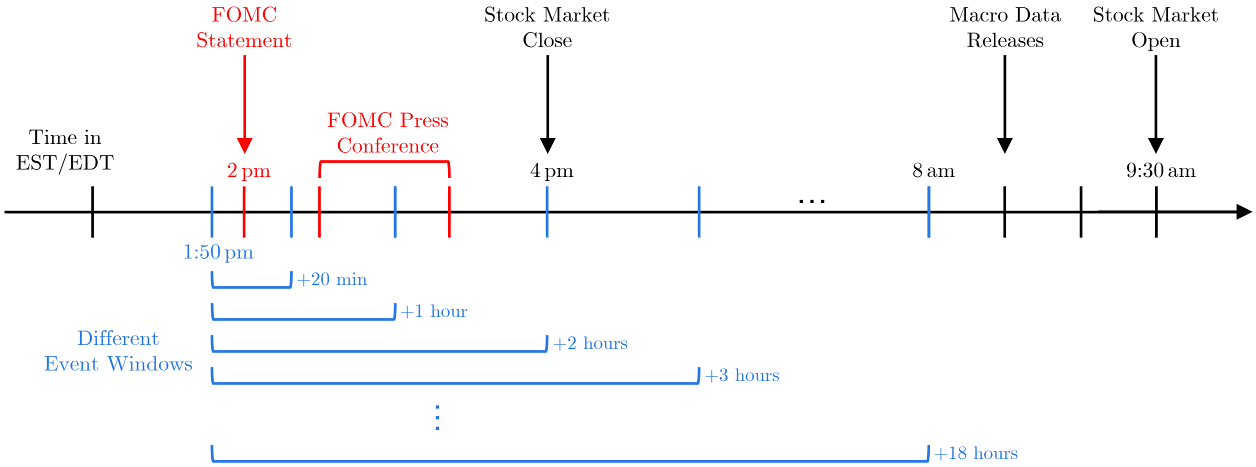
and multiple asset prices that we view as appropriate *a priori*. Good data coverage plays an important role for the selection of asset prices in this step. We subsequently perform pre-tests for differences in variances by asset price and window length to finalize our baseline specification.

Sample Period Our sample period ranges from January 1996 to July 2025. We obtain dates and times of FOMC announcements from *Bloomberg* and cross-check them with information from the Federal Reserve website, and data from prior papers. The announcement sample F includes a total of 240 observations over this period. With very few exceptions, the FOMC announcements occur at 2:15 pm EST (Eastern Standard Time) until January 2013 and at 2:00 pm EST thereafter. The non-announcement sample *NF* comprises 5565 observations on regular trading days for which we use a timestamp of 2:15 pm EST. Appendix A.1 provides more details on the sample construction.

Event Windows All event windows we consider begin 10 minutes prior to the release. Such a short time period before the announcement is important to circumvent simultaneity problems which would arise, for instance, if the Fed responded to asset price movements within the event window. Further, such a short time span before the announcement avoids omitted variable bias, which could arise if asset prices and the impending policy decision both responded to news. The shortest window we consider 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 a 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

Figure 3: Overview of Event Study Windows



Notes: This figure presents a timeline of events on a typical FOMC day together with the different event study windows we consider.

yields,

$$s_t^{y(\ell)} = \Big[\; MP1_t^{(\ell)} \quad MP2_t^{(\ell)} \quad ED2_t^{(\ell)} \quad ED3_t^{(\ell)} \quad ED4_t^{(\ell)} \quad T2Y_t^{(\ell)} \quad \dots \\ T5Y_t^{(\ell)} \quad T10_t^{(\ell)} \quad T30_t^{(\ell)} \; \Big]'. \tag{5}$$

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 *London Stock Exchange Group (LSEG) Tick History* database (formerly known as Thomson Reuters or Refinitiv Tick History). In Appendix A.2, we provide details on the construction and show that all our surprises closely match those of previous studies.

Note that we could alternatively estimate a factor model via principal components as done in previous work (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Swanson, 2021) and use the first few components in the estimation. 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. 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 if we replace the nine yield changes with their first three principal components (see robustness section in Appendix C). 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, we require 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 *LSEG 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 (2025) 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 extended their trading hours in 2011. We therefore use the first and second closest E-mini S&P 500 futures contract to represent stock markets in our analysis. While this may appear limiting, the results in Boehm and Kroner (2025) suggest that international and U.S. stock markets respond very similarly to U.S. news. We will confirm this point below in Section 3 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.[11] We drop the Chinese Renminbi, Indian Rupee, Taiwanese Dollar, Brazilian Real, and Korean Won due to the poor quality of the

[11] https://data.bis.org/topics/DER/tables-and-dashboards/BIS,DER_D11_3,1.0 (accessed on August 26, 2025).

Table 1: Asset Prices Used as Dependent Variables For Estimation

Name	Abbreviation	Ticker	Sample	Observations	
				FOMC	Non-FOMC
Stock Index Futures					
E-mini S&P 500 front month	ES1	ESc1	1997–2025	224	5195
E-mini S&P 500 second month	ES2	ESc2	1997–2025	193	4367
U.S. Dollar Exchange Rates					
Euro	EUR	EUR=	1998–2025	213	5029
Japanese Yen	JPY	JPY=	1996–2025	236	5527
British Pound	GBP	GBP=	1996–2025	237	5527
Australian Dollar	AUD	AUD=	1996–2025	237	5529
Canadian Dollar	CAD	CAD=	1996–2025	234	5527
Swiss Franc	CHF	CHF=	1996–2025	235	5533
Singapore Dollar	SGD	SGD=	1996–2025	228	5253
Swedish Krona	SEK	SEK=	1996–2025	231	5442
Norwegian Krone	NOK	NOK=	1996–2025	235	5496
New Zealand Dollar	NZD	NZD=	1996–2025	236	5509
Mexican Peso	MXN	MXN=	1996–2025	208	4777
South African Rand	ZAR	ZAR=	1996–2025	232	5277
Polish Zloty	PLN	PLN=	1996–2025	205	4759
Total				239	5539

Notes: This table shows the asset prices employed as dependent variables in our analysis. The data is from *LSEG Tick History*. For all series, the sample period ends in July 2025. The U.S. Dollar exchanges rates are listed in descending order of turnover of the foreign currency based on the BIS Triennial Central Bank Survey (see footnote 11). *Abbreviation* refers to the abbreviation used in this paper, and *Ticker* refers to the Reuters Instrument Code (RIC). *Observations* denote the number of observations for the 14-hour window employed in the baseline estimation.

intraday data. Further, we exclude the Hong Kong Dollar and the Danish Krone as they are pegged to the U.S. dollar and the Euro, respectively. This leaves us with 13 U.S. Dollar exchange rates. All exchange rates are measured as mid-market rates. Figure 2 provides an overview of the 15 asset prices we consider for our baseline specification. In our analysis, we will use log-differences of these asset prices. Appendix A.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 verify that we have sufficient identifying variation in the selected asset prices. To do so, we use the equivalence of 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 $\phi_{i,t}$, defined as

$$\phi_{i,t} \equiv \Delta p_{i,t} - \beta_i s_t^y = \gamma_i s_t^{ny} + \varepsilon_{i,t}, \qquad \text{for } t \in F, \tag{6}$$

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

In practice, we first estimate β_i by OLS and then construct the residual.[12]

With this alternative formulation, we can directly test for sufficient variation to identify the non-yield shock. Specifically, we study the excess variance of $\phi_{i,t}^{(\ell)}$ on FOMC days. The residual $\phi_{i,t}$ is constructed based on yield shocks $s_t^{y(\ell)}$, as defined in (5), and the ℓ-hour log-return of asset price $\Delta p_{i,t}^{(\ell)}$ in Table 1. We then test the null hypothesis that the variances on FOMC and non-FOMC days are equal, $H_0 : \frac{V_F(\phi_{i,t}^{(\ell)})}{V_{NF}(\phi_{i,t}^{(\ell)})} = 1$, against the two-sided alternative that they are not equal, $H_1 : \frac{V_F(\phi_{i,t}^{(\ell)})}{V_{NF}(\phi_{i,t}^{(\ell)})} \neq 1$.

Table 2 reports the variance ratios for each asset i and event window ℓ, along with the stars indicating the significance levels based on the Brown and Forsythe (1974) robust test statistic. Unlike the classic F-test of the equality of variances, this robust version allows the data to be generated by a non-normal distribution.[13] A green background indicates that we can reject the null hypothesis at the one percent level, while a red background indicates that we cannot reject it at that level.

Table 2 shows that for short windows the identifying variation is excellent for all assets, while for longer windows the variance ratios decrease. Based on these results, we next select the window length for our baseline specification. Since we expect that a longer 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.

Based on this criterion, we select the 14-hour window for our estimation. That is, we estimate s_t^{ny} based on equation (4) for $\Delta p_t = \Delta p_t^{(14)}$ and $s_t^y = s_t^{y(14)}$. Here, the yield shocks $s_t^{y(14)}$ are given by equation (5) for $\ell = 14$, and the left-hand side vector of asset prices is

$$\begin{aligned} \Delta p_t^{(14)} = \Big[\; & \Delta ES1_t^{(14)} \;\; \Delta ES2_t^{(14)} \;\; \Delta EUR_t^{(14)} \;\; \Delta GBP_t^{(14)} \;\; \Delta AUD_t^{(14)} \;\; \Delta CAD_t^{(14)} \;\; \ldots \\ & \Delta CHF_t^{(14)} \;\; \Delta SGD_t^{(14)} \;\; \Delta SEK_t^{(14)} \;\; \Delta NOK_t^{(14)} \;\; \Delta NZD_t^{(14)} \;\; \ldots \\ & \Delta MXN_t^{(14)} \;\; \Delta ZAR_t^{(14)} \;\; \Delta DKK_t^{(14)} \;\; \Delta PLN_t^{(14)} \; \Big]'. \end{aligned} \tag{7}$$

Note that we have some missing data for the asset prices in vector $\Delta p_t^{(14)}$. This leads samples sizes to differ not only across assets (as shown in Table 1) but also across event win-

[12] As shown by Gürkaynak, Kısacıkoğlu, and Wright (2020), both approaches lead to slightly different results when more than one series is included in Δp_t. The reason 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.

[13] In our baseline, we use the test statistic based on the 10 percent trimmed mean. The test results are essentially unchanged for Brown and Forsythe's (1974) alternative suggestion of using the median.

Table 2: Testing for Excess Variance around FOMC Announcements

Window	ES1	ES2	EUR	JPY	GBP	AUD	CAD	CHF	SGD	SEK	NOK	NZD	MXN	ZAR	PLN
20 min.	2.8***	2.6***	6.8***	4.0***	4.8***	5.9***	5.1***	5.6***	6.1***	6.0***	4.7***	5.1***	3.6***	4.3***	5.4***
1 hour	2.7***	2.5***	5.8***	3.8***	4.7***	5.2***	5.0***	4.7***	5.2***	5.5***	4.4***	5.1***	3.3***	3.8***	4.9***
2 hours	2.9***	2.7***	4.8***	3.7***	3.9***	4.1***	4.2***	4.2***	4.2***	4.0***	3.8***	4.0***	2.4***	3.5***	4.7***
3 hours	3.0***	3.1***	4.5***	3.1***	3.8***	4.1***	3.7***	4.0***	3.4***	3.3***	3.1***	3.6***	2.5***	3.2***	3.9***
4 hours	2.8***	2.8***	4.4***	2.6***	3.9***	3.8***	3.6***	3.9***	4.1***	3.3***	3.4***	3.7***	2.5***	3.3***	4.2***
5 hours	3.1***	3.2***	4.6***	2.4***	3.6***	4.0***	3.7***	4.1***	3.1***	3.6***	3.7***	3.4***	2.5***	3.2***	4.5***
6 hours	3.0***	2.8***	4.1***	2.3***	3.2***	3.4***	3.7***	3.5***	2.8***	3.2***	3.5***	3.2***	2.8***	3.4***	3.7***
7 hours	3.0***	3.1***	4.1***	2.2***	3.1***	3.2***	3.5***	3.7***	2.8***	3.4***	3.5***	2.6***	2.2***	3.4***	4.0***
8 hours	2.8***	2.8***	3.6***	1.8***	3.0***	2.7***	3.4***	3.3***	2.6***	2.9***	3.2***	2.6***	2.3***	2.8***	3.3***
9 hours	2.7***	2.7***	3.6***	1.7***	2.8***	2.5***	3.4***	3.2***	2.2***	2.9***	3.2***	2.6***	2.3***	3.3***	3.5***
10 hours	2.6***	2.7***	3.3***	1.7***	2.6***	2.4***	3.5***	2.9***	2.2***	2.8***	3.1***	2.3***	2.7***	3.1***	3.2***
11 hours	2.6***	2.5***	3.1***	1.6***	2.4***	2.4***	3.4***	2.8***	2.1***	2.8***	2.8***	2.3***	2.8***	2.6***	3.3***
12 hours	2.6***	2.5***	2.7***	1.4***	2.2***	2.3***	2.9***	2.3***	2.0***	2.5***	2.6***	2.1***	2.6***	2.4***	2.6***
13 hours	2.6***	2.6***	2.3***	1.5***	2.2***	2.3***	3.1***	2.2***	2.0***	2.0***	2.3***	2.1***	2.4***	1.9***	2.2***
14 hours	2.3***	2.5***	2.0***	1.2***	2.0***	2.1***	2.8***	1.8***	1.8***	1.6***	1.8***	1.9***	2.0***	1.8***	1.9***
15 hours	2.2***	2.2***	2.0***	1.1**	1.6***	1.9***	2.4***	1.8***	1.5***	1.6***	1.8***	1.7***	1.9***	1.6***	1.9***
16 hours	2.1***	1.9***	1.9***	1.2***	1.6***	1.8***	2.5***	1.8***	1.3***	1.4***	1.7***	1.8***	1.9***	1.5***	1.7***
17 hours	2.1***	1.7***	1.8***	1.0*	1.6***	1.7***	2.2***	1.7***	1.4***	1.5***	1.7***	2.0***	2.0***	1.5***	1.8***
18 hours	2.0***	1.8***	1.8***	1.3***	1.6***	1.6***	2.1***	1.7***	1.3***	1.5***	1.7***	2.0***	1.9***	1.4***	1.7***

Notes: This table shows the excess variance of the dependent variables around FOMC announcements. For a given event window (row) and asset price (column), the table shows the ratio of the variance on announcement days relative to non-announcement days of the residuals as constructed in equation (6). The event windows are explained in the text and the asset price abbreviations in Table 1. A *green* background indicates that we can reject the null hypothesis that the variances are equal at the one percent level, and *red* indicates that we cannot reject it. ***, **, and * indicate significance at the 1, 5, and 10 percent level of the corresponding Brown and Forsythe (1974) robust test statistic for a two-sided test. The highlighted 14-hour window is chosen for our baseline specification.

dows. Relative to the total number of observations reported above, we loose 27 observations in our baseline sample. More specifically, we are left with 5539 non-FOMC days (instead of 5565), and 239 FOMC days (instead of 240).

2.3 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 all assets except the Japanese Yen, the non-yield shock more than doubles the explained variation. For some exchange rates it more than triples the R-squared, explaining over 80 percent of variation over the 14-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

Table 3: Estimation Results

Return (bp)	ES1	ES2	EUR	JPY	GBP	AUD	CAD	CHF
Non-yield Shock	57.96***	63.96***	36.49***	11.85***	32.88***	60.59***	36.23***	31.95***
	(3.43)	(3.59)	(1.32)	(1.63)	(1.26)	(1.96)	(1.35)	(1.21)
R^2 without shock	0.20	0.19	0.46	0.54	0.32	0.28	0.25	0.43
R^2 with shock	0.50	0.56	0.86	0.58	0.78	0.86	0.81	0.76
Return (bp)	SGD	SEK	NOK	NZD	MXN	ZAR	PLN	
Non-yield Shock	23.12***	43.77***	46.05***	59.46***	36.18***	57.46***	50.34***	
	(0.95)	(1.38)	(1.60)	(2.20)	(1.90)	(2.29)	(1.80)	
R^2 without shock	0.32	0.43	0.40	0.30	0.33	0.34	0.40	
R^2 with shock	0.73	0.87	0.85	0.77	0.66	0.76	0.87	

Notes: This table shows the results of our baseline estimation (specification (4)), $\Delta p_t = \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t$. 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. Exchange rates are expressed in U.S. dollars per foreign currency so that an increase reflects a depreciation of the U.S. dollar. The R^2 are obtained from event study regressions of the respective dependent variable on (i) yield shocks s_t^y, and (ii) yield shocks s_t^y and the 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.

is driven by monetary policy, as done by some previous work, might not be innocuous.[14]

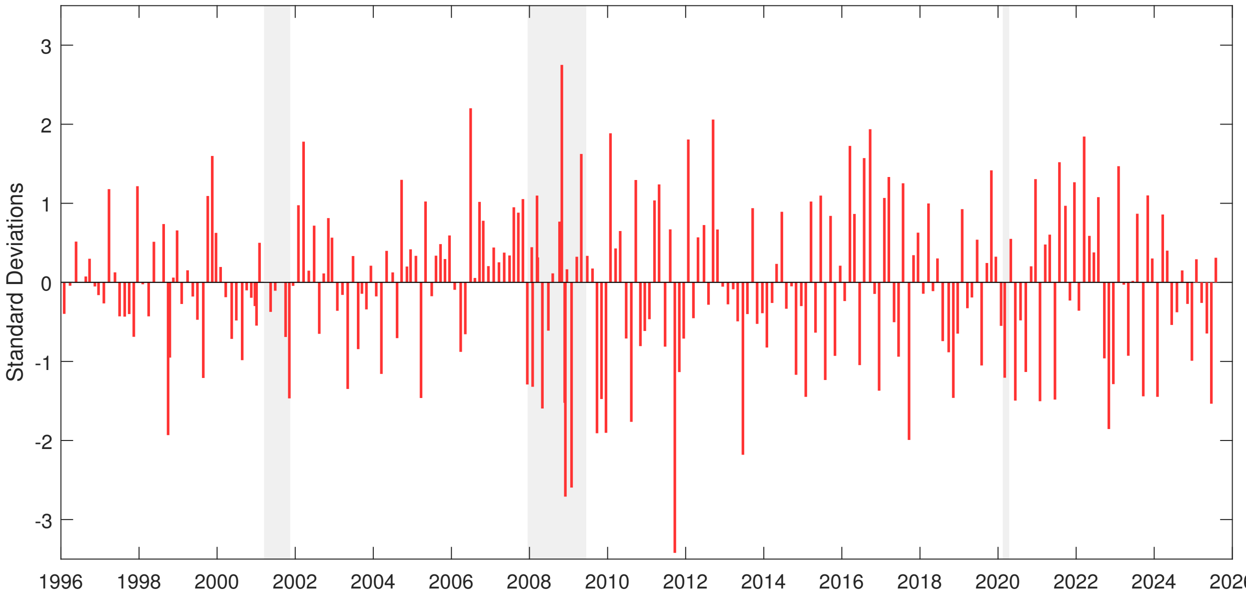
Second, the estimated effects of the Fed non-yield shock, i.e., the $\hat{\gamma}_i$, are all highly statistically significant at the one percent level.[15] They are also sizable. For example, a one-standard deviation non-yield shock leads to a 58 basis points increase in the E-mini S&P 500 front month futures contract (*ES1*) as well as a 36 and 59 basis points depreciation of the U.S. Dollar against the Euro (*EUR*) and New Zealand Dollar (*NZD*), respectively. We provide a comparison of the effect sizes to those of other monetary policy shocks in the next section.

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. There are no extreme outliers. All observations are within four standard deviations. Further, we have roughly an equal number of positive (116) and negative (123) observations. The autocorrelation of the non-yield shock series is -0.03 ($p > 0.6$).

[14]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.

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

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.

2.4 Sensitivity Analysis

We now discuss a variety of checks that assess the sensitivity of our baseline estimates. In summary, we show that the non-yield shock is a robust feature of the data. The detailed results of these analyses are provided in Online Appendix C.

Alternative Assumptions To assess the sensitivity of our non-yield shock to a range of choices made for the baseline specification, we re-estimate it under alternative versions of equation (4). First, we allow for an unrestricted variance-covariance matrix of the error term (*Generalized Covariance*). This case accommodates the possibility of drivers that may cause systematic movements on both announcement and non-announcement days—referred to as "ever-present factors" by Gürkaynak, Kısacıkoğlu, and Wright (2020). Second, Swanson and Jayawickrema (2024) show that yield shocks may also occur on non-FOMC days. Hence, we allow yield shocks to occur on non-FOMC days (*Non-FOMC Days Purified*). Third, we consider a specification with a common intercept for both FOMC and non-FOMC days (*Intercept*), and another that allows for different intercepts across regimes (*Intercept for each Regime*). These specifications address concerns that the non-yield shock might capture overnight drifts documented by Hu, Pan, Wang, and Zhu (2022) and Boyarchenko, Larsen, and Whelan (2023). Lastly, we summarize the yield shocks using three yield curve

Table 4: Robustness of Fed Non-Yield Shock

Alternative Assumptions	Baseline	Generalized Covariance	Non-FOMC Days Purified	Intercept	Intercept for each Regime	3 Yield Factors
Correlation with baseline shock	1.00	0.90	1.00	1.00	1.00	0.93
Average R^2						
without shock	0.35	0.35	0.35	0.34	0.34	0.27
with shock	0.75	0.67	0.75	0.75	0.75	0.73
Observations	239	239	239	239	239	239
Nonlinearities	Second-order	Pos. & Neg.	Interactions with Yield Shocks			
	Yield Shocks	Yield Shocks	ZLB	Unempl. Rate	Ind. Prod.	VIX
Correlation with baseline shock	0.93	0.93	0.91	0.92	0.88	0.89
Average R^2						
without shock	0.29	0.28	0.29	0.28	0.30	0.31
with shock	0.75	0.74	0.74	0.74	0.74	0.74
Observations	239	239	239	239	239	239
Nonlinearities	Interactions with Yield Shocks					
	Monetary Policy Uncertainty	Intermediary Health	Stock-Bond Correlation	Pre-FOMC Drift	Investor Attention	All
Correlation with baseline shock	0.90	0.93	0.92	0.90	0.93	0.78
Average R^2						
without shock	0.32	0.30	0.29	0.31	0.27	0.53
with shock	0.74	0.76	0.74	0.75	0.75	0.82
Observations	239	206	239	231	215	191

Notes: This table shows the results of our robustness analyzes. We re-estimate alternate versions of specification (4). The details on each specification are provided in the text and in Online Appendix C. 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 the independent variables without non-yield shock (*without shock*) and with non-yield shock (*with shock*). Further, we report the correlation of our re-estimated series with our baseline one.

factors, extracted from the nine series following the methodology by Swanson (2021) (*3 Yield Factors*). Although there is no specific concern, we test whether our preferred choice of summarizing the information in the yield curve is robust to this alternative. The results in the top panel of Table 4 show that the baseline estimates of the non-yield shock are indeed robust.[16]

Allowing for Nonlinearities The baseline specification (4) assumes that yield shocks affect stock prices and exchange rates linearly. Substantial nonlinearities could contribute to the

[16] Residualizing the left-hand variables with respect to all nine yield shocks and then extracting the first principal component from these residuals (using a standard expectation–maximization algorithm to handle missing observations) produces an almost identical non-yield shock. (The correlation with the baseline series is 0.997.)

low explanatory power of yield shocks observed in Figure 1 and, consequently, to the existence of the non-yield shock. To check this concern, we use the same three yield curve factors just discussed and estimate a variety of non-linear specifications. Summarizing the yield curve with these three factors avoids overfitting, which could arise if we instead used all nine yield surprises directly. The left-hand-side variables remain the same 15 asset prices as in the baseline.

We start by considering second-order terms of the three yield shocks (*Second-order Yield Shocks*), i.e., squares and interactions of the three yield factors, as well as sign-dependent effects (*Pos. & Neg. Yield Shocks*). In addition, we examine state-dependent effects by interacting the three yield shocks with a variety of economic variables. We consider a broad set of variables motivated by prior work emphasizing different monetary policy mechanisms. First, we interact the yield shocks with a zero-lower-bound indicator (*ZLB*). To capture nonlinearities related to real economic slack, we interact the shocks with the unemployment rate (*Unempl. Rate*) and the industrial production index (*Ind. Prod.*). We also estimate specifications with interactions with a range of financial variables: the VIX (*VIX*); a monetary policy uncertainty measure (*Monetary Policy Uncertainty*); a measure of intermediary sector health (*Intermediary Health*); the stock-bond correlation (*Stock-Bond Correlation*); the pre-FOMC drift (*Pre-FOMC Drift*); and a measure of investor attention (*Investor Attention*). Online Appendix C.2 provides details on these variables and the underlying rationales for implementing these robustness checks.

The middle and bottom panels of Table 4 display the results. None of the nonlinearities materially affects the estimates shock series. The last column of the bottom panel shows results for a specification, which includes all interaction terms jointly (in addition to the main terms of the three yield factors and, of course, the main terms of the interaction variables). This specification has 39 variables plus the non-yield shock on the right-hand side of the estimation equation. Even though the number of observations drops by 48 due to missing data, raising overfitting concerns, the non-yield shock still adds around 30 percentage points of explanatory power. In summary, the non-yield shock does not appear to be driven by the nonlinearities in the yield curve considered here.

The Event Window Length In Online Appendix C.3, we also examine the sensitivity of the non-yield shock to the 14-hour window used in the baseline. Specifically, we re-estimate the shock using asset price changes over the other 18 event window lengths considered above. In essence, we find that the precise event window does not matter: the non-yield shocks estimated using windows around the 14-hour baseline are highly correlated with the baseline shock. Only for very narrow windows below two hours in length does the correlation with the baseline non-yield shock drop off. This suggests that either the information takes time to accurately be priced and/or that the press conference provides valuable additional information for markets.

3 Empirical Implications of the Fed Non-Yield Shock

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. The objective is twofold. First, we demonstrate that the non-yield shock has large effects on global stock prices, various dollar exchange rates, and commodity prices, among others. These effects are greater than those of other monetary policy shocks studied in the literature, highlighting its economic significance. Second, we show that the non-yield shock predominantly operates through changes in equity risk premia for stocks and a combination of changes in currency risk premia and convenience yields for exchange rates.

To assess the implications of the non-yield shock we estimate event study regressions of the form

$$\Delta^d x_{c,t} = \alpha_c + \delta s_t^{ny} + \eta_{c,t}, \qquad \text{for } t \in F, \tag{8}$$

where $\Delta^d x_{c,t}$ is a generic dependent variable. In the case of stock price indexes and currencies, the dependent variable is the 2-day log-difference in the stock price 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. We also study the effects on various other asset prices, such as commodity prices, for which the dependent variable has no cross-sectional dimension. In these cases the subscripts c in equation (8) are redundant. 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. Constructing the difference over these two days ensures that all information captured by the non-yield shock becomes available between the beginning and end-point of the window.

Unless noted otherwise, the data comes from *Bloomberg*. Appendix A.4 provides details on these 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 releases. To mitigate the influence of such extreme values, we winsorize the 2-day returns at the top and bottom 1 percent.

When estimated on data with a cross-sectional dimension, the coefficient δ in specification (8) captures a pooled effect. It masks, however, potential heterogeneity in the responses across countries. We therefore also estimate specifications of the form

$$\Delta^d x_{c,t} = \alpha_c + \delta_c s_t^{ny} + \eta_{c,t}, \qquad \text{for } t \in F, \tag{9}$$

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

3.1 The Importance of the Non-Yield Shock for Financial Markets

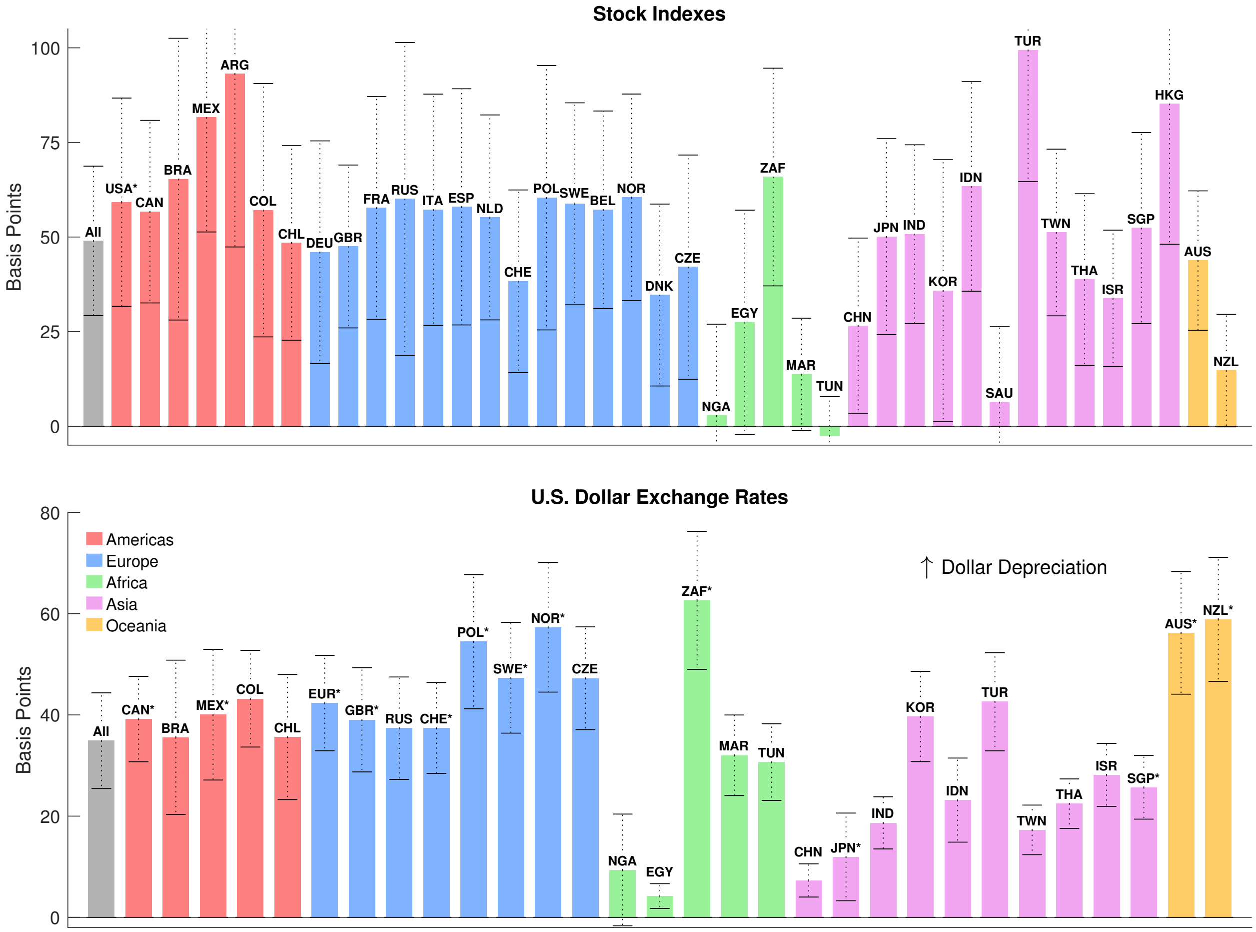
We next document the transmission of our non-yield shock to important financial markets. Much research has examined the effects of yield-based monetary policy shocks on various asset classes, including equities (see, e.g., Bernanke and Kuttner, 2005; Miranda-Agrippino and Rey, 2020), foreign exchange rates (see, e.g., Eichenbaum and Evans, 1995; Gürkaynak et al., 2021), and commodities (e.g., Frankel, 2008). Since our shock is orthogonal to yield shocks, however, these prior estimates are unlikely to provide any guidance about the effects of the non-yield shock.

Effects on Global Stock Prices We begin with estimating the effects of the Fed non-yield shock on international stock markets. The top panel of Figure 5 illustrates the estimates of equations (8) and (9) with the 2-day log-difference of countries' stock price indexes as the dependent variable. The pooled estimate, depicted by the leftmost grey bar, shows that a one standard deviation positive non-yield shock raises international stock markets by 49 basis points, on average. This effect is highly statistically significant. Further, almost all stock indexes increase after a positive non-yield shock—making it a driver of the global financial cycle (Rey, 2013; Miranda-Agrippino and Rey, 2020; Boehm and Kroner, 2025). This is the case even though foreign stock market data is not used in the estimation of the shock, that is, there is no mechanical reason for such effects. Taken together, the magnitude and uniformity of these effects is striking: They imply that shocks with a one standard deviation size (which are common, see Figure 4) change the global stock market capitalization by almost half a percent.

Effects on Exchange Rates We next turn to the effects of the non-yield shock on exchange rates. The bottom panel of Figure 5 shows the estimates of equations (8) and (9), where the dependent variables are now 2-day log-changes of various dollar exchange rates.[17] Again, all exchange rates are expressed in U.S. dollars per unit of foreign currency so that an increase

[17] We exclude the Argentine Peso, Saudi Riyal, and Hong Kong Dollar, as these currencies were pegged to the U.S. dollar for most of the sample period. We also exclude the Danish Krone, as it is pegged to the Euro.

Figure 5: Effects of Fed Non-yield Shock on Stock and Exchange Rate Markets



Notes: This figure shows the response of international stock indexes (top) and U.S. dollar exchange rates (bottom) to a one standard deviation positive Fed non-yield shock. The dependent variable is the 2-day return on the stock index or exchange rate of country c, expressed in basis points. Exchange rates are in U.S. dollars per unit of foreign currency so that an increase reflects a depreciation of the U.S. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ from equation (8), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (9). Black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country. We winsorize each 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 A3.

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 35 basis points, on average. While the U.S. dollar depreciates against all currencies considered here, there is large heterogeneity in the effect sizes. For instance, the U.S. dollar depreciates by around 60 basis points vis-à-vis the South African Rand, the New Zealand dollar, and the Australian dollar. In comparison, there is a much smaller change in the value of the U.S. dollar relative to the Egyptian Pound or the Chinese Renminbi, which is somewhat unsurprising considering that both currencies are heavily managed. Note that all exchange rates, which are included in the estimation of the non-yield shock, are marked with asterisks in Figure 5. The fact that the U.S. dollar also depreciates against currencies such as the Korean Won and the Turkish Lira, which are not included in the shock estimation, indicates that the effects of the non-yield shock are quite broad.

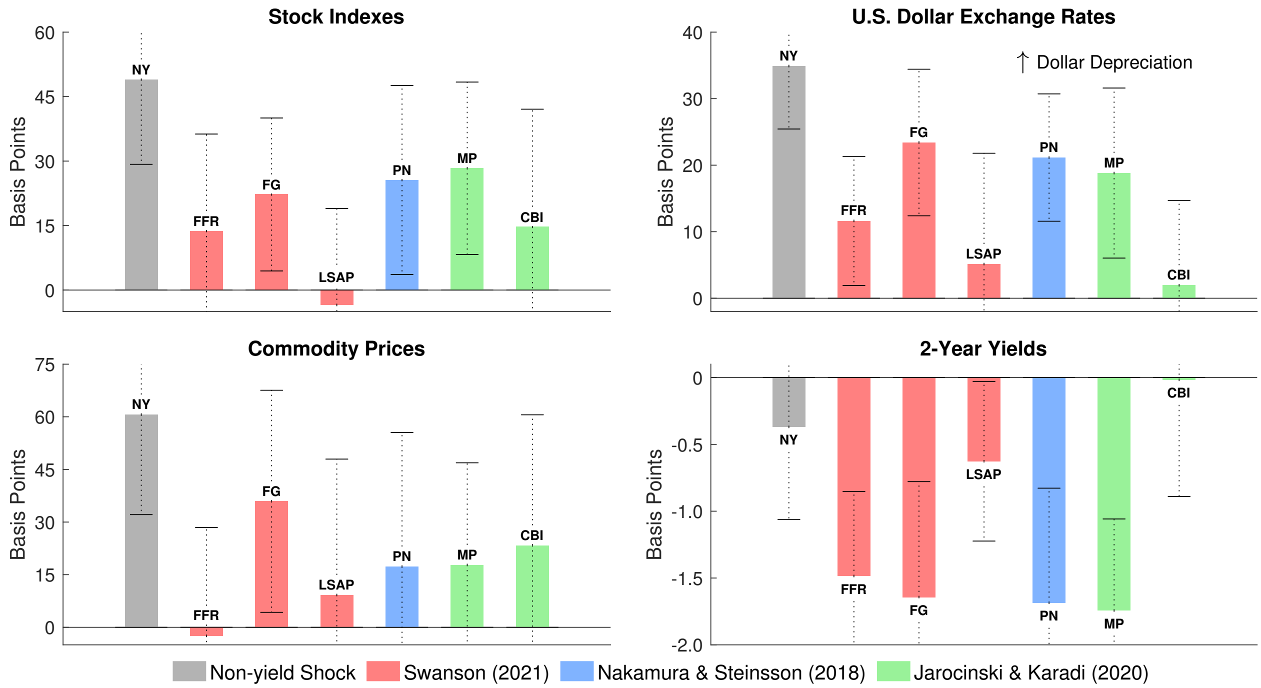
Effects on Other Markets In Appendix D, we also study the effects on a range of other markets. We first show that our non-yield shock has no statistically or economically significant effects on international local-currency government bond yields (see Appendix Figure D1). This point is not implied by the construction of the non-yield shock since foreign bond yields are not used in the estimation of the shock. Further, we document that a positive non-yield shock has positive and significant effects on commodity prices, with very large effects for precious metals and oil (see Appendix Figure D2). Considering the pivotal role of commodity prices in explaining global economic fluctuations (e.g., Fernández, Schmitt-Grohé, and Uribe, 2017), these results further underscore the importance of our non-yield shock. We also find that emerging market economies experience capital inflows following a positive non-yield shock (see Appendix Figure D3). Appendix D also provides additional results for other asset prices.[18]

Comparison with Previous Monetary Policy Shocks To benchmark the economic importance of the non-yield shock, we next compare its effects with those of other commonly used monetary policy shocks in the literature. Specifically, we re-estimate the pooled specification (8) for stock indexes and U.S. dollar exchange rates after replacing the non-yield shock with other monetary policy shocks. In addition, we compare the effects on commodity prices (measured by the S&P Commodity Index) and 2-year yields (measured by the pooled effect on various countries' 2-year local-currency government bond yields). As in the introduction, we compare the non-yield shock to shocks from Nakamura and Steinsson (2018), Jarociński and Karadi (2020), and Swanson (2021).

Figure 6 shows that the non-yield shock has the largest effects on international stock markets, exchange rates, and commodity prices among all shocks considered here. For example, a one standard deviation federal funds rate shock from Swanson (2021), which is essentially the Kuttner (2001) shock and the target rate shock from Gürkaynak, Sack, and Swanson (2005), leads to a 14 basis points change in international stock prices. This contrasts with

[18] In Appendix Figure D4, we report results for inflation compensations. We find that a positive non-yield shock leads to a small but significant increase in U.S. inflation compensations, while inflation compensations in other countries remain largely unaffected.

Figure 6: Effects of Fed Non-yield Shock and Other Monetary Policy Shocks



Notes: This figure compares the response of international asset prices to our Fed non-yield shock with the responses to other monetary policy shocks. For stock prices, exchange rates, and yields, each bar denotes a pooled effect, i.e., the estimate of the common coefficient δ from equation (8) for a given dependent variable and monetary policy shock of interest. For commodity prices, each bar denotes the effect of a monetary policy shock on the S&P GS Commodity Index. The dependent variable is always the 2-day change in the asset price of interest, expressed in basis points. All shocks have been standardized and signed to have a negative pooled effect on the 2-year yields. The black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country (or heteroskedasticity-robust in the case of commodity prices). All dependent variables are winsorized at the top and bottom 1 percent. Shock Abbreviations: NY—Fed non-yield; FFR—Federal Funds Rate; FG—Forward Guidance; LSAP—Large-scale Asset Purchase; PN—Policy News; MP—Monetary Policy; CBI—Central Bank Information.

the Fed non-yield shock, which has an effect size of 49 basis points per one standard deviation shock. The fact that the non-yield shock has the strongest effect on commodity prices among all shocks is remarkable, given that no commodity prices are used in the estimation of the non-yield shock. At the same time, the non-yield shock does not have significant effects on global yields, as discussed above, whereas most shocks from the prior literature, of course, do affect foreign yields. Overall, the results in Figure 6 underscore both the economic significance of the non-yield shock and the fact that it does not drive yields.

3.2 The Channels of the Non-Yield Shock

We now turn to the channels through which the non-yield shock transmits to financial markets. As before, we focus on stock prices and exchange rates, which both have wellestablished asset pricing decompositions. We provide details on these decompositions in Appendices D.5–D.7.

Global Stock Prices According to the classic Campbell and Shiller (1988) approximation, changes in stock prices can be decomposed into changes in (1) expected future dividends, (2) expected future risk-free rates, and (3) expected future risk premia. Whereas greater expected future dividends raise stock prices, increases in risk-free rates and equity premia lower them. We use this decomposition to understand the channels through which the non-yield shock affects stock prices. Its implementation requires the use of empirical proxies to measure each of the three components.[19] Due to data availability, we limit our analysis to the following seven countries: the U.S., Canada, the Euro Area, the U.K., Switzerland, Japan, and Australia.

Following prior work (e.g., Boyd, Hu, and Jagannathan, 2005), we use countries' 10-year government bond yields as proxies for their expected future risk-free rates over the next ten years. To gauge expected future dividends, we construct a measure of dividend expectations over the same horizon using dividend swap data from Goldman Sachs (Manley and Mueller-Glissmann, 2008).[20] Appendix D.5 provides details on these data and the construction of our measure. Note that the dividend data are available only for the U.S., the Euro Area, the U.K., and Japan. Lastly, we use 30-day option-implied stock volatilities—i.e., the VIX for the United States and its analogs for other countries—to proxy for equity risk premia. As shown by Martin (2017), implied stock market volatility is tightly linked to equity risk premia.

With these measures in hand, we regress their (log-)changes on the non-yield shock using versions of specification (8). The top panel of Table 5 presents the results. For completeness, we first report the pooled effect on the seven countries' stock indexes—a subset of the sample underlying the results in Figure 5. The non-yield shock has a positive and significant effect on the stock prices of these countries and the magnitude of the effect, 50 basis points, is similar to the earlier estimate. The adjacent column reports the effect on 10-year yields. As discussed above, the non-yield shock does not significantly impact longer-term yields. The next column shows the effect on expected future dividends. Perhaps surprisingly, it is small and statistically insignificant. Finally, the last column shows that the non-yield shock has a strong and highly significant effect on implied volatilities. A one-standard deviation increase

[19] Conducting a full decomposition of stock prices is unfortunately not feasible without making strong assumptions. As Knox and Vissing-Jorgensen (2022) show, fully decomposing the U.S. stock market using observables is not possible due to data limitations. These constraints are even more severe for other countries.

[20] We thank Christian Mueller-Glissmann for sharing the data with us.

in the non-yield shock lowers implied volatilities by 2.3 percent, on average. Hence, equity risk premia decline following a positive non-yield shock. In Appendix Figure D5 we show that the effects on each component are largely comparable across countries.

While these estimates suggest a substantial role for the risk premium channel and smaller roles for the risk-free rate and expected future dividend channels, we can make more precise statements by calculating the contributions of these yield and dividend changes to the overall stock price response. To do so, we apply a stock price elasticity of -10 to the 10-year yield and the elasticity of +0.5 to the measure of 10-year expected dividends.[21] These values are relatively large (in absolute value) in comparison to prior estimates from the literature, implying that we likely overstate the contributions of expected risk-free rates and dividends over the next 10-years (see Appendix D.5 for derivations). For implied volatilities, our proxies of expected future risk premia, an analogous elasticity is not available.

Multiplying the estimates with the associated elasticities allows us to quantify the contribution of expected yields and dividends to the overall stock price change (see last row of the top panel of Table 5). Following a one standard deviation non-yield shock, the change in the 10-year yields explains 0.9 basis points of the 50 basis point change in stock price indexes. Analogously, the change in expected dividends explains 3 basis points of the 50 basis point change in stock price indexes. Together, these two channels account for about 8 percent (=3.87/50.40) of the overall response. Hence, changes in expected risk-free rates and dividend expectations over the next ten years cannot explain meaningful amounts of the observed change in stock prices.[22]

The evidence therefore points to a strong risk premium channel. In particular, the estimates suggest that the non-yield shock primarily transmits to stock prices through a reduction in uncertainty, an increase in investors' willingness to bear risk, or both.[23] We provide additional evidence for this interpretation in Appendix Table D2. There, we show that a positive non-yield shock leads to a significant drop in the 2-year U.S. equity premium

[21] The difference between these elasticities can be understood as follows: the expected 1-year risk-free rate one year ahead mechanically discounts all dividends beyond one year. As a result, a change in the expected 1-year risk-free rate has an almost one-to-one effect on stock prices, implying an elasticity of roughly 10 for the 10-year yield. In contrast, a change in the expected 1-year dividend one year ahead affects only that year's cash flow directly and does not mechanically alter the path of future dividends.

[22] Moreover, these numbers make clear that reasonable changes in the assumed elasticities, or a somewhat sluggish response in the underlying dividend swaps (which are not traded on centralized exchanges), would not alter this conclusion. One caveat, however, is that due to data limitations we only estimate the contribution of expected risk-free rates and dividends up to 10 years out. It is possible that stock prices are affected by changes in risk-free rates and expected future dividends beyond 10 years.

[23] 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.

Table 5: The Channels of the Fed Non-Yield Shock

Stock Index Decomposition (bp)	Stock Index	10-Year Yield	10-Year Dividend Expectation	30-Day Implied Stock Volatility
Fed non-yield shock	50.40***	0.09	5.97	-231.54***
	(10.45)	(0.42)	(8.72)	(47.51)
R^2	0.09	0.00	0.00	0.07
Observations	1673	1668	560	1329
Stock price effect		0.89	+2.98	+?
Exchange Rate Decomposition (bp)	U.S. Dollar Exchange Rate	10-Year Yield Diff. (Foreign-U.S.)	10-Year U.S. Convenience Yield	30-Day Implied FX Volatility
Fed non-yield shock	37.68***	-0.23	-0.62**	-139.02***
	(4.23)	(0.55)	(0.26)	(40.42)
R^2	0.14	0.00	0.02	0.05
Observations	1434	1428	1042	1389
Exchange rate effect		-2.33	+6.22	+?
Countries included: U.S., Canada, Euro Area, U.K., Switzerland, Japan, Australia				

Notes: The table reports the pooled effects of our non-yield shock on various asset prices, i.e., estimates of common coefficient δ of equation (8). The dependent variables are either 2-day changes (for 10-year yields) or 2-day log changes, expressed in basis points, and are intended to proxy the different channels through which the non-yield shock affects stock prices. See text for details. Standard errors are clustered by announcement. We winsorize each country-level series at the top and bottom 1 percent. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Appendix Figures D5 and D6 display the underlying country-by-country estimates for the top and bottom panels, respectively.

measure of Martin (2017). The decline is economically sizable and accounts for around 60 percent of the overall U.S. stock market effect. Further, we document that risk aversion and uncertainty indicators of Bekaert and Hoerova (2014) and Bekaert, Engstrom, and Xu (2022), all decrease significantly following a positive non-yield shock.

Exchange Rates We next perform an analogous exercise to examine the channels through which the non-yield shock affects exchange rates. Specifically, we follow recent work by Jiang, Krishnamurthy, and Lustig (2021), among others, and use a decomposition that extends earlier frameworks (e.g., Clarida and Gali, 1994; Froot and Ramadorai, 2005) by allowing for deviations from both uncovered interest parity (UIP) and covered interest parity (CIP). According to this decomposition, the foreign country's currency appreciates relative to the U.S. dollar when (1) its risk-free rates are expected to rise relative to U.S. rates, (2) expected convenience yields for holding U.S. bonds relative to the foreign ones decline, or (3) expected currency risk premia associated with holding the foreign currency relative to the U.S. dollar decline. Note that the latter two components would be zero if UIP and CIP held.

To take the decomposition to the data, we use differences in 10-year government bond yields to proxy for expected risk-free rate differentials over the next ten years. In particular, we construct for each of the six countries the difference between their 10-year yield and the U.S. counterpart. To proxy for expected U.S. convenience yields, we use the 10-year "U.S. Treasury premium" series from Du, Im, and Schreger (2018), which measure the convenience yield on U.S. Treasuries relative to the convenience yields on 10-year government bonds of other countries. Lastly, we use 30-day option-implied currency volatilities to get a sense of exchange rate risk premia. The theoretical link between implied currency volatility and currency risk premia is less direct than that of equities.[24] Nonetheless, empirical work typically documents a positive relationship between option-implied currency volatilities and currency risk premia (Lyons, 1988; Bhansali, 2007; Jurek, 2014).

We then regress two-day changes (or log changes) in these proxies on the non-yield shock using specification (8). The bottom panel of Table 5 reports the estimates. The first column shows that the non-yield shock leads to a statistically significant depreciation of the U.S. dollar against the six exchange rates considered here. The adjacent column reports the effect on 10-year yield differentials (foreign minus U.S.). These differentials are essentially unaffected by the non-yield shock—as expected, given the results reported above. In contrast, the non-yield shock significantly reduces the 10-year U.S. convenience yield, that is, the additional non-monetary yield investors attach to U.S. Treasuries relative to their foreign counterparts. A one-standard-deviation increase in the non-yield shock lowers this relative convenience yield by 0.6 basis points. Lastly, the non-yield shock induces a strong and significant decline in implied currency volatilities: a one-standard deviation increase reduces implied volatility by 1.4 percent, on average, suggesting a fall in exchange rate risk premia.

To better assess the quantitative importance of yield differentials and U.S. convenience yields for the overall effects on exchange rates, we multiply these estimates with their associated elasticities. We use an elasticity of +10 for the 10-year yield differentials and -10 for the 10-year U.S. convenience yields (see Appendix D.6 for derivations). As in the case of stock prices, an analogous elasticity for the implied volatility measures is not available. The last row of the bottom panel of Table 5 shows that the non-yield shock's effect on 10-year yield differentials and U.S. convenience yields translates into exchange rate movements of approx-

[24] Ideally, one would use a financial instrument that directly captures the covariance between the exchange rate and the stochastic discount factor. Kremens and Martin (2019), for example, employ quanto index contracts to proxy for currency risk premia. Unfortunately, their data is only available at the monthly frequency, which makes it unsuitable for our high-frequency setting.

imately -2.3 and 6.2 basis points, respectively. While the contribution passing through yield differentials is quantitatively unimportant, changes in U.S. convenience yields account for a nontrivial share of around 17 percent (=6.22/37.68) of the observed exchange rate response. A large portion of the response, however, remains unexplained. Given the pronounced decline in implied currency volatilities, the evidence once again points to the importance of a risk premium channel in driving the exchange rate response to the non-yield shock.

3.3 Discussion

In summary, global stock markets rise after a positive non-yield shock and the dollar depreciates. These effects are large in comparison to other shocks and are driven predominantly by changes in risk premia. In the case of exchange rates, changes in U.S. convenience yields also explain 17 percent of the overall response. Expected future dividends, by contrast, are largely unaffected by the non-yield shock and can therefore not explain the observed stock market response. Further, a positive non-yield shock leads to an increase in commodity prices and capital flows into emerging markets.

These results suggest that a positive non-yield shock shares many features with the onset of a global "risk-on" episode. Riskier asset classes—such as global stocks and foreign government bonds—appear to become more attractive through a combination of lower risk premia and relatively higher convenience yields on foreign bonds. The sharp rise in commodity prices is not only consistent with a risk premium channel (Etula, 2013), but also points to a strong transmission to emerging markets (Fernández, González, and Rodriguez, 2018). The observed capital inflows into emerging market economies following a positive non-yield shock further support this interpretation. They also echo prior work finding global risk measures to be important drivers of capital flows (Forbes and Warnock, 2012). Overall, the effects of a positive non-yield shock resemble in many ways the flip side of the "flight-to-safety" episodes studied in Baele et al. (2020), during which investors prefer both safer assets and assets with greater liquidity.

Baele et al. (2020) emphasize that flight-to-safety episodes are typically accompanied by a divergence between bond and equity risk premia. Consistent with this pattern, we document in Appendix Table D3 that term premium measures are not significantly affected by our non-yield shock. Hence, our results also point to some disconnect between bond and currency risk premia—a relationship studied by recent works (e.g., Greenwood, Hanson, Stein, and Sunderam, 2023). Finally, the table shows that implied interest rate volatilities—often interpreted as proxies for monetary policy uncertainty—decline following a positive non-yield shock. This finding is reminiscent of earlier work showing that yields do not fully capture interest rate volatility (Collin-Dufresne and Goldstein, 2002; Cieslak and Povala, 2016).

4 Theoretical Implications of the Fed Non-Yield Shock

This section discusses several theoretical issues related to the non-yield shock. We focus in particular on the following two questions. First, under what conditions does the non-yield shock exist? Second, what does the presence of the non-yield shock imply for the identification of structural monetary policy shocks? To answer these questions, we introduce a simple theoretical framework and implement our estimation procedure on data generated from this model. Using a relationship predicted by the model, we then compare the non-yield shock to previously identified monetary policy shocks from the literature. It turns out that a substantial amount of information associated with FOMC announcements is contained in the non-yield shock but has not been captured by prior shocks. Details on this section and proofs are relegated to Appendix E.

4.1 Framework and Estimation

Suppose that the data over narrow event windows around monetary policy announcements is generated by the model

$$\begin{pmatrix} s_t^y \\ \Delta p_t \end{pmatrix} = \begin{pmatrix} A_y \\ A_p \end{pmatrix} z_t + \begin{pmatrix} 0 \\ \varepsilon_t \end{pmatrix}. \tag{10}$$

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, and z_t is a $r \times 1$ vector of structural monetary policy shocks which satisfy $Cov\left[z_t\right] = I_r$ and are zero on non-event days. Further, 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. This model is quite general. The main restrictions we impose on this data generating process is that the endogenous variables linearly depend on the shocks z_t and that yield changes are not affected by non-monetary drivers within narrow windows. In line with our implementation, we also assume for some of the results below that $n \geq r \geq k$, that A_y is of full row rank (k), and that A_p of full column rank (r).

In the context of this framework, the yield shocks s_t^y are best thought of as representing the first k principal components of observed changes in the yield curve over the event window. For instance, we could have $k = 3$ principal components, as suggested by Swanson (2021).[25] Further, the structural monetary policy shocks z_t should be thought of as representing interpretable shocks that the empirical monetary policy literature has studied. Specifically, the vector z_t could contain elements representing (i) surprise deviations from a policy rule ("conventional monetary policy shocks"); (ii) communications about the future path of the policy rate ("forward guidance"); (iii) news on asset purchases ("quantitative easing"); (iv) the revelation of private information about economic fundamentals ("Fed information effects"); or (v) a monetary policy response in the presence of a misperceived reaction function ("Fed response to news effects"). Note that at this point we do not take a stance on which of these shocks are contained in z_t. Nor can we rule out that there could be other structural monetary policy shocks. We highlight this potential set of shocks only to facilitate interpretation.

We now apply our estimation procedure to data generated from equation (10)—or more precisely, we apply a slightly more general procedure that allows for multiple non-yield shocks. For presentational clarity, we perform this estimation on an infinite sample so that there is no estimation error. The estimating equation is

$$\Delta p_t = \beta s_t^y + \Gamma s_t^{ny} + \varepsilon_t, \tag{11}$$

for $t \in F$. Γ is now a matrix with n rows and a number of columns equal to the number of non-yield shocks in the vector s_t^{ny}.

Since the non-yield shocks are orthogonal to the yield shocks, an estimate of β can be obtained by projecting Δp_t on s_t^y on announcement dates/times. Doing so yields

$$\beta = A_p A_y' \left(A_y A_y'\right)^{-1}, \tag{12}$$

provided that A_y is of rank $k \leq r$. Further, for a coefficient matrix Γ that is determined by the parameters of the model (see Appendix E for details), the non-yield shocks are implicitly defined as satisfying equation

$$\Gamma s_t^{ny} = A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right) z_t. \tag{13}$$

Note that the orthogonality between s_t^y and s_t^{ny} is reflected in the annihilator matrix $I_r -$

[25] This interpretation is preferable over interpreting s_t^y directly as changes in yields, because it implies that the identification problems of Gürkaynak, Sack, and Swanson (2005) and Swanson (2021) are nested as special cases. It further avoids technical difficulties that arise if there are more yields than structural monetary policy shocks.

$A_y' \left(A_y A_y'\right)^{-1} A_y$, which residualizes with respect to the yield curve.

It follows from equation (13) that non-yield shocks are in general *reduced form monetary policy shocks*. Non-yield shocks are reduced form shocks, because they are linear combinations 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 (13) also makes clear that the non-yield shocks are only functions of the structural monetary policy shocks z_t. Since the non-yield shocks do not depend on the non-monetary disturbances ε_t, they are reduced form *monetary policy* shocks.

Plugging expressions (12) and (13) into equation (11) and using that $s_t^y = A_y z_t$ from equation (10) gives

$$\Delta p_t = \underbrace{A_p A_y' \left(A_y A_y'\right)^{-1} A_y}_{\text{Effects passing through yields}} z_t + \underbrace{A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right)}_{\text{Effects orthogonal to yield changes}} z_t + \varepsilon_t. \tag{14}$$

This expression shows that the estimation procedure decomposes the effects of the structural monetary policy shocks z_t on the stock prices and exchange rates contained in 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).

4.2 How can Non-Yield Shocks Arise?

As equations (13) and (14) make clear, the existence of non-yield shocks depends on the rank of the annihilator matrix $I_r - A_y' \left(A_y A_y'\right)^{-1} A_y$. If all structural monetary policy shocks z_t are spanned by the yield curve, then the rank of $I_r - A_y' \left(A_y A_y'\right)^{-1} A_y$ is zero and no non-yield shock exists. By contrast, if not all structural monetary policy shocks are spanned by the yield curve, then the rank of $I_r - A_y' \left(A_y A_y'\right)^{-1} A_y$ is strictly positive. At least one non-yield shock then exists and can be obtained from equation (13) provided that the vector Δp_t contains sufficiently many informative asset prices (so that A_p is of full column rank). Hence, the key condition for the non-yield shock to exist is that not all structural monetary policy shocks are spanned by the yield curve. The properties of projections further imply the following result.

Proposition 1. *Suppose $n \geq r \geq k$, A_y is of full row rank, and A_p is of full column rank. Then the number of non-yield shocks equals the number of structural monetary policy shocks r minus the number of yield shocks k.*

Two points follow immediately from this proposition and the preceding discussion. First, no single monetary policy shock can simultaneously account for the yield curve movements and the non-yield shock observed in the data. To rationalize the existence of both, it is therefore necessary to think about combinations of multiple structural shocks. Second, several commonly studied shocks are unlikely to give rise to non-yield shocks since they are spanned by yield curve factors. For instance, conventional monetary policy shocks to the target rate (Kuttner, 2001) and communications about the future conduct of policy, such as forward guidance (Gürkaynak, Sack, and Swanson, 2005) or announcements of asset purchases (Swanson, 2021), will not generate non-yield shocks either individually or jointly, as they are likely to be spanned by the yield curve.

We next turn to examples, in which non-yield shocks exist. One set of potential explanations involves varying forms of Fed information effects—that is, cases in which the Fed's actions reveal private information about economic fundamentals. In the case most commonly studied in the literature, the Fed reveals information about the future path of the economy through its choice of interest rates (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). For example, an unexpected tightening could reveal that the Fed's assessment of the economic outlook is better than previously expected. As a result, the private sector may revise its growth forecast and expected future dividends upwards. We emphasize that a slight variation of this narrative can also generate a non-yield shock and is more consistent with our findings. Specifically, the Fed's interest rate decision could reveal information about *recession tail risk* with minimal effect on the expected growth rate and expected dividends. Prior work has shown that such downside risks are particularly reflected in risk premia (e.g., Ang, Chen, and Xing, 2006), which is consistent with our findings in Section 3. To the best of our knowledge, such "third-moment information effects" have not yet been directly explored in the literature.

To spell out explicitly how information effects can generate non-yield shocks, consider the case of Jarociński and Karadi (2020).

Example 1. *In Jarociński and Karadi's (2020) framework, there are two structural monetary policy shocks* $z_t = \begin{pmatrix} z_t^{pure} & z_t^{info} \end{pmatrix}'$*, 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* $A_y = \begin{pmatrix} a & b \end{pmatrix}$ *and* $A_p = \begin{pmatrix} -c & d \end{pmatrix}$ *for strictly positive (but unknown) constants* a, b, c, d.

Writing out $s_t^y = A_y z_t$ *from equation* (10) *for this example gives*

$$s_t^y = a z_t^{pure} + b z_t^{info}. \tag{15}$$

Further, with two structural monetary policy shocks and only one yield, it is clear that yields cannot span the structural shocks. Hence, one non-yield shock exists in this case. Straightforward algebra (provided in Appendix E) shows that this non-yield shock takes the form

$$s_t^{ny} = \pm \frac{1}{\sqrt{a^2 + b^2}} \left(-b z_t^{pure} + a z_t^{info} \right). \tag{16}$$

Hence, the yield shock and the non-yield shock in this example are both linear combinations of the pure and the information shock.

Information effects are not the only possible explanation for the non-yield shock. Given the mixed empirical evidence on such effects—specifically, on the formulation emphasizing effects on expected growth rates and dividends (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020)—one might instead consider the possibility that financial markets learn about systematic aspects of monetary policy. For instance, as argued by Bauer and Swanson (2023), markets could update their beliefs about the Fed's reaction function upon observing a particular policy decision. If some interest rate decisions trigger such updating while others do not, then it is conceivable that observed yield changes do not contain sufficient information to span both types of shocks—similar to the case with information effects just discussed. A non-yield shock will then exist. More concretely, consider the possibility that the Fed reveals information about policy rate decisions, its reaction function, or asset purchases in *specific states of the world*. Haddad, Moreira, and Muir (2025) provide evidence for such state-contingent promises in the context of the Fed's asset purchases. Further, as discussed in Cieslak, Morse, and Vissing-Jorgensen (2019), the Fed could promise to lower interest rates more aggressively in bad states of the world. If this promise convinces markets that such adverse states are then less likely to occur, the effect on the expected path of interest rates is ambiguous (and zero in a knife-edge case). At the same time, the combination of the policy promise and the reduced probability of adverse states to occur both push stock prices up, leading to a disconnect between yield curve and stock market reactions. We next formalize a specific version of this case.[26]

[26] A limitation of this example is that the underlying macroeconomic model must be non-linear due to the state-dependent monetary policy response, while the data generating process (10) is linear.

Example 2. *Suppose that there are four structural monetary policy shocks collected in the vector* $z_t = \begin{pmatrix} z_t^{target} & z_t^{path} & z_t^{QE} & z_t^{promise} \end{pmatrix}'$, *where* z_t^{target}, z_t^{path}, *and* z_t^{QE} *are shocks to the Fed funds target rate, its path, and large scale asset purchases as in Swanson (2021), and* $z_t^{promise}$ *captures credible promises to change monetary policy reactions in adverse states of the world. Suppose further that* s_t^y *includes three yield curve factors,* $k = 3$, *and* Δp_t *includes an unspecified number of stock price and exchange rate changes. In the knife-edge case just discussed, the promise to intervene more decisively in bad states of the world leaves current and expected interest rates unchanged. This restriction is captured with a column of zeros in the matrix* A_y, *so that* $A_y = \begin{pmatrix} A & 0_{3\times 1} \end{pmatrix}$, *where* A *is a* 3×3 *matrix. There are no restrictions on* A_p. *Using equations (10) and (13), it is straightforward to show that*

$$\begin{aligned} s_t^y &= A \begin{pmatrix} z_t^{target} \\ z_t^{path} \\ z_t^{QE} \end{pmatrix}, \\ s_t^{ny} &= \pm z_t^{promise}. \end{aligned} \tag{17}$$

We conclude from this example that certain state-contingent promises could also be the source of the non-yield shock.

4.3 Implications for the Identification of Structural Monetary Policy Shocks

We next discuss what the existence of the non-yield shock implies for the identification of structural monetary policy shocks.

One useful implication of Proposition 1 is that it allows us to measure the number of structural monetary policy shocks in the data. 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. Swanson (2021) estimates that there are $k = 3$ factors in the yield curve around FOMC announcements and we estimate that there is one non-yield shock.[27] This implies that there are $r = 4$ structural monetary policy shocks. More precisely, four structural monetary policy shocks are needed to accurately describe the behavior of yields, stock prices, and exchange rates around FOMC announcements. A useful conclusion is therefore that identification schemes of structural monetary policy shocks should generally aim to identify four structural shocks.

In the case of one non-yield shock ($r = k + 1$), as in our empirical analysis, the following

[27] There will not be more than one non-yield shock because the combined R^2 of yield and non-yield shocks reported in Table 3 are quite large.

equivalence result holds:

Proposition 2. *Suppose that $r = k + 1$, A_y is of full row rank, and A_p is of full column rank. Then the following statements are equivalent:*

1. *There exists a structural shock that does not affect the yield curve.*

2. *k structural monetary policy shocks are identifiable from the yield curve alone.*

3. *There is one non-yield shock and it has a structural interpretation.*

The intuition of the equivalence of points 1. and 2. is as follows. If all r structural monetary policy shocks in z_t affect the yield curve, then the $k = r - 1$ yield factors do not contain sufficient information to recover z_t. This is because we have $k = r - 1$ linear equations, but r unknowns. Identifiability is only given if one of the structural monetary policy shocks does not affect the yield curve. In this case, the system of $k = r - 1$ equations only contains $k = r - 1$ unknowns and it has a unique solution if matrix A_y has rank k. Note that the proposition makes a statement about *identifiability* (formally defined in Appendix E). The actual identification of shocks typically requires additional assumptions about the matrix A_y (see, e.g., Gürkaynak, Sack, and Swanson, 2005; Swanson, 2021). The equivalence of points 1. and 3. follows from the fact that the non-yield shock is constructed to be orthogonal to the yield shocks.

Proposition 2 implies that there are two possible interpretations of the non-yield shock. Under to the first interpretation, the non-yield shock is structural. As in Example 2, which is a specific case of this interpretation, the vector of structural monetary policy shocks z_t can be partitioned into a $k \times 1$ vector z_t^1 and a scalar z_t^2, which does not affect yields. Partitioning $A_y = \begin{pmatrix} A & 0_{k\times 1} \end{pmatrix}$, 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 in z_t^1 are identifiable from the yield curve alone, and (ii) the non-yield shock is *structural*, $s_t^{ny} = \pm z_t^2$. Hence, while the non-yield shock is in general a reduced form monetary policy shock, it is structural in this special case.

If the non-yield shock is structural, identification schemes that construct the remaining k structural monetary policy shocks from yields alone can principally remain valid despite the presence of the non-yield shock. Such identification schemes include, among many others, Kuttner (2001); Gürkaynak, Sack, and Swanson (2005) and Swanson (2021). In addition, if the non-yield shock is indeed structural, it should be possible to tie large realizations to concrete policy actions, which cause the observed asset price responses documented in Sections 2.3 and 3. We highlight that the assumption that a particular central bank action leaves interest rates unchanged is strong. As Example 2 on state-contingent policy promises demonstrates, it is possible to construct such examples, but they rely on the knife-edge assumption that opposing effects on expected interest rates cancel exactly.

The second interpretation is that the non-yield shock is strictly a reduced form shock. In this case, identification schemes based on yields alone cannot recover the remaining k structural monetary policy shocks and any attempt to do so would only recover linear combinations of structural shocks. Further, if the non-yield shock is a reduced-form shock, it can serve as an input for identification schemes to recover structural shocks—together with yield shocks.

We illustrate both of these points for Example 1 (the Jarociński and Karadi (2020) case). As equation (15) makes clear, the yield shock s_t^y alone is not sufficient to identify the two structural monetary policy shocks z_t^{pure} and z_t^{info}, even if a and b were known. There is one equation and two unknowns. As a result, there are infinitely many combinations of z_t^{pure} and z_t^{info} satisfying equation (15). In addition to the yield shock, the non-yield shock s_t^{ny} is required to uniquely pin down the two structural shocks—as well as knowledge of the constants a and b. With two equations and two unknowns, the system can be inverted to recover z_t^{pure} and z_t^{info}. Interestingly, knowledge of c and d is not directly required for identification although the derivation necessitates that they are not both zero.[28]

4.4 Common Variation with Previous Monetary Policy Shocks

We continue with relating the non-yield shock to monetary policy shocks constructed in previous work. The theoretical foundation for doing so comes from equation (13). This equation shows that non-yield shocks are always linear functions of the structural monetary policy shocks. Hence, if previous shocks have captured similar variation as our non-yield shock, then regressing the non-yield shock on these shocks should deliver high explanatory power.[29]

Table 6 displays the R-squared from regressions of the non-yield shock on different sets of monetary policy shocks from the literature. First, shocks constructed from yields (Nakamura and Steinsson (2018) (NS 2018), Swanson (2021) (Sw 2021), Bu, Rogers, and Wu (2021) (BRW 2021)) or otherwise centered on interest rates (Romer and Romer (2004) (RR

[28] We note that using the non-yield shock to identify structural monetary policy shocks has an advantage over using a single asset such as the change in the S&P 500 (Jarociński and Karadi, 2020). The reason is that the non-yield shock is purified of the non-monetary noise ε_t (partially so in finite samples with multiple assets in vector Δp_t).

[29] To see this more concretely, return to Example 1—the Jarociński and Karadi (2020) case. In this example the non-yield shock is a linear combination of the pure and the information shock (equation 16). Hence, if these two shocks captured similar variation as the non-yield shock, then the R-squared from a regression of the non-yield shock on the pure and the information shock should be high.

Table 6: Explanatory Power of Previous Monetary Policy Shocks for Fed Non-yield Shock

Specification: $s_t^{ny} = \beta \, shocks_t^x + \varepsilon_t$								
	Yields					Yields + other Assets		
$shocks_t^x$	RR 2004	NS 2018	Sw 2021	BRW 2021	AD 2022	JK 2020	KSS 2021	Le 2025
No. of Shocks	1	1	3	1	1	2	3	4
R^2	0.01	0.00	0.01	0.03	0.00	0.00	0.25	0.14
Observations	91	104	188	185	91	168	113	192

Notes: This table shows the explanatory power of different sets of monetary policy shocks for our non-yield shock. Each column displays the results for a different set of shocks. *Yields* refers to papers which identify shocks purely from changes in interest rates. *Yields + other Assets* refers to papers which identify shocks from changes in yields and other asset prices. Abbreviations: AD 2022—Aruoba and Drechsel (2022); BRW 2021—Bu, Rogers, and Wu (2021); JK 2020—Jarociński and Karadi (2020); KSS 2021—Kroencke, Schmeling, and Schrimpf (2021); Le 2025—Lewis (2025); NS 2018—Nakamura and Steinsson (2018); RR 2004—Romer and Romer (2004); Sw 2021—Swanson (2021).

2004), Aruoba and Drechsel (2022) (AD 2022)) are indeed orthogonal to our non-yield shock. This property is, of course, in large part the result of constructing the non-yield shock as orthogonal to yields. Since our sample, window length, etc., differ from these studies, and Romer and Romer (2004) and Aruoba and Drechsel (2022) use no high-frequency data at all, however, the lack of explanatory power shown in Table 6 is not *ex-ante* guaranteed.

Second, shocks constructed from yields as well as other asset prices do not explain substantial shares of the non-yield shock either. The shocks by Jarociński and Karadi (2020), which are based on one short-term yield factor and the S&P 500, have no explanatory power for the non-yield shock. This result is surprising, given that information effects can generate non-yield shocks as shown in Example 1 above. While differences in the implementation, such as window length (14 hours for the non-yield shock versus 30 minutes in Jarociński and Karadi (2020)), the set of assets used (we use exchange rates in addition to the S&P 500), and differences in the estimation procedure (e.g., Jarociński and Karadi's (2020) shocks are only set identified) will almost certainly drive the R-squared below one, the R-squared of zero suggests that the information effect *as modeled by Jarociński and Karadi (2020)* is an unlikely candidate to generate the non-yield shock.

The only shocks that have some predictive power for the non-yield shock are those by Kroencke, Schmeling, and Schrimpf (2021) and Lewis (2025). Specifically, Kroencke, Schmeling, and Schrimpf's (2021) risk-shift together with two yield curve factors has an R-squared of 25 percent. Further, Lewis's (2025) four shocks have a combined R-squared of 14 percent. Given that both of these sets of shocks also use stock prices and exchange rates in their construction, however, the R-squared are again surprisingly modest. We conclude from this exercise that the large majority of variation contained in the non-yield shock has not been captured in the prior literature. Further, it appears that how precisely variation from stock prices and exchange rate is used in the construction of monetary policy shocks matters a great deal.

5 Concluding Remarks

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 the Fed non-yield shock—a shock that is orthogonal to yield changes. A positive realization leads to large increases in global stock as well as commodity prices, and a sizable depreciation of the dollar. Further, the non-yield shock triggers substantial movements in proxies of risk premia, suggesting that these asset prices are predominantly affected through changes in investors' risk-taking behavior.

Based on a simple framework, we then show that the non-yield shock has a structural interpretation if there exists a structural monetary policy shock that does not affect yields. In this knife-edge case, the presence of the non-yield shock has no immediate implications for the identification of structural monetary policy shocks except that it adds an additional dimension that has large effects on certain asset classes. In general, however, the non-yield shock is not structural, and its existence implies that structural monetary policy shocks cannot be identified from the yield curve alone. The reason is that the yield curve lacks sufficient information.

These findings raise the concern that the transmission mechanism of monetary policy to the economy could be less well understood than commonly thought. At the heart of the problem is that the interest rate changes we observe around FOMC announcements reflect a multi-dimensional set of new information. If observed interest rate changes are accompanied by the release of private information about the state of the economy, by new information about the systematic conduct of monetary policy, or the like, the estimated effects on economic outcomes are confounded. Our findings also suggest that even state-of-the-art identification strategies—which are principally designed to address this concern—are unlikely to be fully successful, as none of the associated shock series explain meaningful shares of the non-yield shock.

How can future research build on these findings? A natural step forward is to combine our non-yield shock with the first three principal components of the yield curve in an identification scheme. As our discussion in Section 4 makes clear, however, the challenge is that there are many plausible economic mechanisms that could potentially generate the non-yield shock. As a result, an intermediate step is likely required, which aims to first narrow down the set of plausible mechanisms. Here, our findings in Section 3 yield first insights. One robust result of our analysis is that risk premia are key for the transmission of the non-yield shock. Another one is that dividends are not. This suggests that conventional formulations of the information effects framework are unlikely explanations for the non-yield shock.

We have also begun with linking the non-yield shock to Fed communications. While a full analysis is beyond the scope of this paper, we provide an initial examination in Online Appendix F. There, we show that the magnitude of the non-yield shock is positively associated with several proxies of communication intensity. For example, FOMC announcements accompanied by a Summary of Economic Projections release, or those under Chairman Bernanke—a strong advocate of central bank communications—tend to be associated with larger non-yield shocks. So are FOMC announcements with statements or press conferences. On the other hand, we also find that the non-yield shock is essentially uncorrelated with more sophisticated measures of FOMC communications from prior work, highlighting the difficulty of linking asset price movements to interpretable communication measures. More work is therefore required to articulate plausible identification schemes based on the non-yield shock.

References

Ang, Andrew, Joseph Chen, and Yuhang Xing. 2006. “Downside Risk.” *The Review of Financial Studies* 19 (4):1191–1239.

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 and James D Hamilton. 2018. “Robust bond risk premia.” *The Review of Financial Studies* 31 (2):399–448.

Bauer, Michael D and Glenn D Rudebusch. 2017. “Resolving the spanning puzzle in macro-finance term structure models.” *Review of Finance* 21 (2):511–553.

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, Robert J Hodrick, and David A Marshall. 1997. "On biases in tests of the expectations hypothesis of the term structure of interest rates." *Journal of Financial Economics* 44 (3):309–348.

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

Bekaert, Geert, Marie Hoerova, and Marco Lo Duca. 2013. "Risk, uncertainty and monetary policy." *Journal of Monetary Economics* 60 (7):771–788.

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.

Bhansali, Vineer. 2007. "Volatility and the carry trade." *Journal of Fixed Income, Winter* .

Boehm, Christoph E and T Niklas Kroner. 2025. "The US, economic news, and the global financial cycle." *Review of Economic Studies* :rdaf020.

Boyarchenko, Nina, Lars C Larsen, and Paul Whelan. 2023. "The overnight drift." *The Review of Financial Studies* 36 (9):3502–3547.

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.

Brown, Morton B and Alan B Forsythe. 1974. "Robust tests for the equality of variances." *Journal of the American statistical association* 69 (346):364–367.

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.

Campbell, John Y and Robert J Shiller. 1988. "The dividend-price ratio and expectations of future dividends and discount factors." *The review of financial studies* 1 (3):195–228.

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, Adair Morse, and Annette Vissing-Jorgensen. 2019. "Stock returns over the FOMC cycle." *The Journal of Finance* 74 (5):2201–2248.

Cieslak, Anna and Pavol Povala. 2015. "Expected returns in Treasury bonds." *The Review of Financial Studies* 28 (10):2859–2901.

———. 2016. "Information in the term structure of yield curve volatility." *The Journal of Finance* 71 (3):1393–1436.

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

Clarida, Richard and Jordi Gali. 1994. "Sources of real exchange-rate fluctuations: How important are nominal shocks?" In *Carnegie-Rochester conference series on public policy*, vol. 41. Elsevier, 1–56.

Collin-Dufresne, Pierre and Robert S Goldstein. 2002. "Do bonds span the fixed income markets? Theory and evidence for unspanned stochastic volatility." *The Journal of Finance* 57 (4):1685–1730.

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

Duffee, Gregory R. 2011. "Information in (and not in) the term structure." *The Review of Financial Studies* 24 (9):2895–2934.

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. 2014. "Exchange rates and interest parity." *Handbook of international economics* 4:453–522.

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

Etula, Erkko. 2013. "Broker-dealer risk appetite and commodity returns." *Journal of Financial Econometrics* 11 (3):486–521.

Fernández, Andrés, Andrés González, and Diego Rodriguez. 2018. "Sharing a ride on the commodities roller coaster: Common factors in business cycles of emerging economies." *Journal of International Economics* 111:99–121.

Fernández, Andrés, Stephanie Schmitt-Grohé, and Martín Uribe. 2017. "World shocks, world prices, and business cycles: An empirical investigation." *Journal of International Economics* 108:S2–S14.

Forbes, Kristin J and Francis E Warnock. 2012. "Capital flow waves: Surges, stops, flight, and retrenchment." *Journal of international economics* 88 (2):235–251.

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.

Froot, Kenneth A and Tarun Ramadorai. 2005. "Currency returns, intrinsic value, and institutional-investor flows." *The Journal of Finance* 60 (3):1535–1566.

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.

Greenwood, Robin, Samuel Hanson, Jeremy C Stein, and Adi Sunderam. 2023. "A quantity-driven theory of term premia and exchange rates." *The Quarterly Journal of Economics* 138 (4):2327–2389.

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, 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.

Haddad, Valentin, Alan Moreira, and Tyler Muir. 2025. “Whatever It Takes? The Impact of Conditional Policy Promises.” *American Economic Review* 115 (1):295–329.

Hu, Grace Xing, Jun Pan, Jiang Wang, and Haoxiang Zhu. 2022. “Premium for heightened uncertainty: Explaining pre-announcement market returns.” *Journal of Financial Economics* 145 (3):909–936.

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.

Joslin, Scott, Marcel Priebsch, and Kenneth J Singleton. 2014. “Risk premiums in dynamic term structure models with unspanned macro risks.” *The Journal of Finance* 69 (3):1197–1233.

Jurek, Jakub W. 2014. “Crash-neutral currency carry trades.” *Journal of Financial Economics* 113 (3):325–347.

Kekre, Rohan and Moritz Lenel. 2024. “The Flight to Safety and International Risk Sharing.” *American Economic Review* 114 (6):1650–91.

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

———. 2025. “The effect of the federal reserve on the stock market: Magnitudes, channels and shocks.” *Available at SSRN 5233918* .

Kremens, Lukas and Ian Martin. 2019. “The quanto theory of exchange rates.” *American Economic Review* 109 (3):810–843.

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

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. 2025. “Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Effects.” *The Review of Economics and Statistics* 107 (4):1086–1103.

Ludvigson, Sydney C and Serena Ng. 2009. “Macro factors in bond risk premia.” *The Review of Financial Studies* 22 (12):5027–5067.

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.

Manley, Richard and Christian Mueller-Glissmann. 2008. “The market for dividends and related investment strategies (corrected).” *Financial Analysts Journal* 64 (3):17–29.

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* .

Mueller, Philippe, Alireza Tahbaz-Salehi, and Andrea Vedolin. 2017. “Exchange rates and monetary policy uncertainty.” *The Journal of Finance* 72 (3):1213–1252.

Nagel, Stefan and Zhengyang Xu. 2024. “Movements in yields, not the equity premium: Bernanke-kuttner redux.” Tech. rep., National Bureau of Economic Research.

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.

Rey, Helene. 2013. “Dilemma not trilemma: the global cycle and monetary policy independence.” Proceedings - Economic Policy Symposium - Jackson Hole, Federal Reserve Bank of Kansas City.

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

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 and Vishuddhi Jayawickrema. 2024. “Speeches by the fed chair are more important than fomc announcements: An improved high-frequency measure of us monetary policy shocks.” *Unpublished Manuscript* .

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.

Online Appendix

for

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

September 15, 2025

Christoph E. Boehm
UT Austin and NBER

T. Niklas Kroner
Federal Reserve Board

Table of Contents

A Data 3
A.1 Sample Construction 3
A.2 Yield Shocks 3
A.3 Left-hand-side Asset Prices for Estimation 7
A.4 Daily Financial Market Data from Bloomberg and LSEG 8
A.5 Other Data 11
A.6 Capital Flows 12

B Estimation 16
B.1 Setup 16
B.2 Estimation Algorithm 16

C Sensitivity Analysis 19
C.1 Alternative Assumptions 19
C.2 Allowing for Nonlinearities and Time-varying Coefficients 20
C.3 The Event Window Length 21
C.4 Common Factor Structure 21

D Financial Market Analysis 24
D.1 Bond Yields 24
D.2 Commodity Prices 25
D.3 Capital Flows 26
D.4 Inflation Compensations 27

*The views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Board or the Federal Reserve System.
Email: chris.e.boehm@gmail.com and t.niklas.kroner@gmail.com.

D.5 Stock Market Channels 27
D.6 Exchange Rate Channels 31
D.7 Additional Results on Risk Premium Channel 34

E Theoretical Framework 37
E.1 Data Generating Process 37
E.2 Assumptions on Estimation Framework 37
E.3 Estimation and Proofs 38

F The Role of Fed Communications 48
F.1 Data Construction 48
F.2 Analysis 49
F.3 Communication Measures From Prior Work 51

References 52

A Data

A.1 Sample Construction

FOMC days Our sample of FOMC announcements ranges from January 1996 to July 2025. 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 *LSEG Tick History*. These outages are more common in the early sample period but otherwise completely random, hence mitigating concerns of sample selection. As a result of such outages, we exclude the two scheduled FOMC announcements on July 1, 1998, and August 21, 2001, and the unscheduled meeting on April 18, 2001. We are then left with 240 observations.

Non-FOMC days Our sample of non-FOMC day ranges from January 1996 to July 2025. We use 2:15 pm EST as the reference time around which we construct these event windows 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 *LSEG Tick History*. These outages are more common in the early sample period but otherwise completely random. 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 5565 observations.

A.2 Yield Shocks

For each FOMC announcement day, we construct nine yield shocks which capture the effects of monetary policy on the yield curve. To construct these, we employ intraday data on interest rate futures from *LSEG Tick History*. The sample period ranges from January 1996 to July 2025. 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., $\tau = t$ if $t \in F$. 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 $\ell^- = 2$ and $\ell^+ = 4$.

Table A1: Overview of Intraday Interest Rate Futures Data

Variable in Text	Underlying Instruments	RICs	Sample
$MP1$	Federal Funds Rate Futures	FFc1–FFc2	1996–2025
$MP2$	Federal Funds Rate Futures	FFc3–FFc4	1996–2025
$ED2$	2-Quarter Eurodollar/SOFR Futures	EDcm2/SRAcm3	1996–2025
$ED3$	3-Quarter Eurodollar/SOFR Futures	EDcm3/SRAcm4	1996–2025
$ED4$	4-Quarter Eurodollar/SOFR Futures	EDcm4/SRAcm5	1996–2025
$T2$	2-Year Treasury Futures	TUc1/TUc2	1996–2025
$T5$	5-Year Treasury Futures	FVc1/FVc2	1996–2025
$T10$	10-Year Treasury Futures	TYc1/TYc2	1996–2025
$T30$	30-Year Treasury Futures	USc1/USc2	1996–2025

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 *LSEG Tick History*. *RIC* refers to the Reuters Instrument Code, which uniquely identifies each instrument. Abbreviations: SOFR—Secured Overnight Financing Rate.

A.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

$$MP1_\tau^{(\ell)} = \frac{m_0}{m_0 - d_0}\left(ff_{\tau+\ell}^1 - ff_{\tau-10}^1\right), \tag{A1}$$

where $ff_{\tau-10}^1$ and $ff_{\tau+\ell}^1$ 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 (A1). 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 $\frac{m_0}{m_0-d_0}\left(ff_{\tau+\ell}^1 - ff_{\tau-10}^1\right)$ 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., $MP1_\tau^{(\ell)} = ff_{\tau+\ell}^2 - ff_{\tau-10}^2$. This avoids multiplying by a large factor, $\frac{m_0}{m_0-d_0}$. 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

$$MP2_{\tau}^{(\ell)} = \frac{m_1}{m_1 - d_1}\left[\left(ff_{\tau+\ell}^{j(1)} - ff_{\tau-10}^{j(1)}\right) - \frac{d_1}{m_1} MP1_{\tau}^{(\ell)}\right], \tag{A2}$$

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 (A2). 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., $MP2_{\tau}^{(\ell)} = ff_{\tau+\ell}^{j(1)+1} - ff_{\tau-10}^{j(1)+1}$.

A.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 (2025) 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 $p_{\zeta}^{ed^j}$ be the price at time ζ of the jth nearest quarterly Eurodollar futures contract (March, June, September, December), then the expiration date of $p_{\zeta}^{ed^j}$ is between j and $j-1$ quarters in the future at any given point in time. Further, the implied rate is given by $ed_{\zeta}^{j} = 100 - p_{\zeta}^{ed^j}$. For a given FOMC announcement τ, we calculate the difference in the implied rate

$$EDj_{\tau}^{(\ell)} = ed_{\tau+\ell}^{j} - ed_{\tau-10}^{j}, \text{ for } j \in \{2, 3, 4\}, \tag{A3}$$

where $ed_{\tau-10}^{j}$ and $ed_{\tau+\ell}^{j}$ 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, $EDj^{(\ell)}_\tau = ed^j_{\tau+\ell} - ed^j_{\tau-10}$,.

A.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.,

$$T2^{(\ell)}_\tau = -\left(p^{t2^1}_{\tau+\ell} - p^{t2^1}_{\tau-10}\right)/2. \tag{A4}$$

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).

A.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 extreme outliers.

A.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 A2 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 A2: Comparison of Interest Rate Surprises with Previous Papers

	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						0.99			
T5							0.99		
T10								0.99	
T30									0.98
Observations	105	105	105	105	105	78	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 14-hour windows for our shock estimation.

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

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

$$\Delta p_{i,t}^{(\ell)} = \log(p_{i,t+\ell}) - \log(p_{i,t-10}), \tag{A5}$$

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

A.4 Daily Financial Market Data from Bloomberg and LSEG

Table A3: 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	1996–2025			USGG2YR Index	1996–2025	USGG10YR Index	1996–2025
Canada	CAN	SPTSX Index	1996–2025	CAD Curncy	1996–2025	GTCAD2Y Govt	1996–2025	GTCAD10Y Govt	1996–2025
Brazil	BRA	IBOV Index	1996–2025	BRL Curncy	1996–2025	*BR2YT=RR	2002–2025	*BR10YT=RR	1998–2025
Mexico	MEX	MEXBOL Index	1996–2025	MXN Curncy	1996–2025	GTMXN2Y Govt	2011–2025	*MX10YT=RR	2002–2025
Argentina	ARG	MERVAL Index	1996–2025						
Colombia	COL	COLCAP Index	2002–2025	COP Curncy	1996–2025	*CO2YT=RR	2002–2025	*CO10YT=RR	2002–2025
Chile	CHL	IPSA Index	1996–2025	CLP Curncy	1996–2025	*CL2YT=RR	2007–2025	*CL10YT=RR	2007–2025
Europe									
Euro Area	EUR	SX5E Index	1996–2025	EUR Curncy	1996–2025				
Germany	DEU	DAX Index	1996–2025			GTDEM2Y Govt	1996–2025	GTDEM10Y Govt	1996–2025
United Kingdom	GBR	UKX Index	1996–2025	GBP Curncy	1996–2025	GTGBP2Y Govt	1996–2025	GTGBP10Y Govt	1996–2025
France	FRA	CAC Index	1996–2025			GTFRF2Y Govt	1996–2025	GTFRF10Y Govt	1996–2025
Russia	RUS	IMOEX Index	1997–2025	RUB Curncy	1996–2025	*RU2YT=RR	2001–2023	*RU10YT=RR	2003–2023
Italy	ITA	FTSEMIB Index	1998–2025			*IT2YT=RR	1998–2025	*IT10YT=RR	1996–2025
Spain	ESP	IBEX Index	1996–2025			*IT2YT=RR	1998–2025	*IT10YT=RR	1996–2025
Netherlands	NLD	AEX Index	1996–2025			*NL2YT=RR	1996–2025	*NL10YT=RR	1996–2025
Switzerland	CHE	SMI Index	1996–2025	CHF Curncy	1996–2025	*CH2YT=RR	1996–2025	*CH10YT=RR	1996–2025
Poland	POL	WIG20 Index	1996–2025	PLN Curncy	1996–2025	*PO2YT=RR	1998–2025	*PO10YT=RR	1999–2025
Sweden	SWE	OMX Index	1996–2025	SEK Curncy	1996–2025	*SE2YT=RR	1996–2025	*SE10YT=RR	1996–2025
Belgium	BEL	BEL20 Index	1996–2025			*BE2YT=RR	1996–2025	*BE10YT=RR	1996–2025
Norway	NOR	OBX Index	1996–2025	NOK Curncy	1996–2025	GTNOK2Y Govt	2007–2025	*NO10YT=RR	1996–2025
Denmark	DNK	KFX Index	1996–2025			*DK2YT=RR	1996–2025	*DK10YT=RR	1996–2025
Czech Republic	CZE	PX Index	1996–2025	CZK Curncy	1996–2025	*CZ2YT=RR	1998–2025	*CZ10YT=RR	2000–2025
Africa									
Nigeria	NGA	NGXINDX Index	1998–2025	NGN Curncy	1996–2025	*NG2YT=RR	2008–2025	*NG10YT=RR	2007–2025
Egypt	EGY	EGX30 Index	1998–2025	EGP Curncy	1996–2025	*EG2YT=RR	2016–2025	*EG10YT=RR	2010–2025
South Africa	ZAF	TOP40 Index	1996–2025	ZAR Curncy	1996–2025	*ZA2YT=RR	2007–2025	*ZA10YT=RR	1996–2025
Morocco	MAR	MOSENEW Index	1996–2025	MAD Curncy	1996–2025	*MA2YT=RR	2012–2025	*MA10YT=RR	2012–2025
Tunisia	TUN	TUSISE Index	1999–2025	TND Curncy	1996–2025				
Asia									
China	CHN	SHCOMP Index	1996–2025	CNY Curncy	1996–2025	*CN2YT=RR	2000–2025	*CN10YT=RR	2000–2025
Japan	JPN	NKY Index	1996–2025	JPY Curncy	1996–2025	GTJPY2Y Govt	1996–2025	GTJPY10Y Govt	1996–2025
India	IND	NIFTY Index	1996–2025	INR Curncy	1996–2025	*IN2YT=RR	1997–2025	*IN10YT=RR	1998–2025
Korea	KOR	KOSPI Index	1996–2025	KRW Curncy	1996–2025	GTKRW2Y Govt	1999–2025	GTKRW10Y Govt	2001–2025
Indonesia	IDN	JCI Index	1996–2025	IDR Curncy	1996–2025			*ID10YT=RR	2003–2025
Saudi Arabia	SAU	SASEIDX Index	1996–2025						
Turkey	TUR	XU100 Index	1996–2025	TRY Curncy	1996–2025	*TR2YT=RR	2005–2025	*TR10YT=RR	2010–2025
Taiwan	TWN	TWSE Index	1996–2025	TWD Curncy	1996–2025	*TW2YT=RR	1998–2025	*TW10YT=RR	1998–2025
Thailand	THA	SET Index	1996–2025	THB Curncy	1996–2025	*TH2YT=RR	2000–2025	*TH10YT=RR	2001–2025
Israel	ISR	TA125 Index	1996–2025	ILS Curncy	1996–2025	*IS2YT=RR	2006–2025	*IS10YT=RR	2002–2025
Singapore	SGP	STI Index	1999–2025	SGD Curncy	1996–2025	*SG2YT=RR	1996–2025	*SG10YT=RR	1998–2025
Hong Kong	HKG	HSI Index	1996–2025			*HK2YT=RR	1997–2025	*HK10YT=RR	1996–2025
Oceania									
Australia	AUS	AS51 Index	1996–2025	AUD Curncy	1996–2025	*AU2YT=RR	1996–2025	*AU10YT=RR	1996–2025
New Zealand	NZL	NZSE50FG Index	2001–2025	NZD Curncy	1996–2025	*NZ2YT=RR	1996–2025	*NZ10YT=RR	1996–2025

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

Table A4: Daily Cross-Country Data—Part II

Countries	ISO	30–Day Implied Stock Volatility		30–Day Implied FX Volatility		Breakeven Inflation Rate	
		Ticker	Sample	Ticker	Sample	Ticker	Sample
Americas							
United States	USA	VIX Index	1996–2025			USGGBE02/ USGGBE10 Index	2004–2025 1998–2025
Canada	CAN	VIXI Index	2017–2025	USDCADV1M Curncy	1998–2025	CDGGBE10 Index	2008–2025
Europe							
Euro Area	EUR	V2X Index	1999–2025	EURUSDV1M Curncy	1998–2025	EUSWI2/ EUSWI10 Curncy	2004–2025 2004–2025
Germany	DEU					DEGGBE02/ DEGGBE10 Index	2011–2025 2009–2025
United Kingdom	GBR	IVIUK Index	2000–2025	GBPUSDV1M Curncy	1996–2025	UKGGBE02/ UKGGBE10 Index	1996–2025 1996–2025
Switzerland	CHE	V3X Index	1999–2025	USDCHFV1M Curncy	1996–2025		
Sweden	SWE					SKGGBE02/ SKGGBE10 Index	2002–2025 2004–2025
Asia							
Japan	JPN	VXJ Index	1996–2025	USDJPYV1M Curncy	1996–2025	JYGGBE02/ JYGGBE10 Index	2012–2025 2004–2025
Oceania							
Australia	AUS	AS51VIX Index	2008–2025	AUDUSDV1M Curncy	1996–2025	ADGGBE02/ ADGGBE10 Index	2003–2025 2000–2025

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 the IMF World Economic Outlook (WEO) database.

Table A5: Daily Commodity Prices and Implied Interest Rate Volatilities

Name	Ticker	Sample
Commodity Prices		
S&P GSCI Total	SPGSCI Index	1996-2025
S&P GSCI Energy	SPGSEN Index	1996-2025
S&P GSCI Precious Metals	SPGSPM Index	1996-2025
S&P GSCI Industrial Metals	SPGSIN Index	1996-2025
S&P GSCI Agriculture & Livestock	SPGSAL Index	1996-2025
WTI Oil—Front-month Futures Contract	CL1 Comdty	1996-2025
Brent Oil—Front-month Futures Contract	CO1 Comdty	1996-2025
Gold—Gold/USD Dollar Exchange Rate	XAU Curncy	1996-2025
Silver—Silver/USD Dollar Exchange Rate	XAG Curncy	1996-2025
Implied Interest Rate Volatility Indexes		
Merrill Lynch Option Volatility Estimate (MOVE)	MOVE Index	1996-2025
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 Table D2 and Table D2. The data is from *Bloomberg*. For each series, we report sample period (*Sample*) and Bloomberg identifier (*Ticker*).

Table A6: 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 in 2022.

A.5 Other Data

Monetary Policy Shocks

- Aruoba and Drechsel (2022)—privately shared
- Bu, Rogers, and Wu (2021)—journal website
- Jarociński and Karadi (2020)—privately shared
- Kroencke, Schmeling, and Schrimpf (2021)—journal website
- Lewis (2025)—author website
- Nakamura and Steinsson (2018)—author website
- Romer and Romer's (2004)—updated by Aruoba and Drechsel (2022) (privately shared)
- Swanson (2021)—author website

Miscellaneous

- Updated Adrian, Crump, and Moench (2013) term premium measures—New York Fed website
- Updated Bauer, Lakdawala, and Mueller (2022) monetary policy uncertainty measure—San Francisco Fed website
- Monetary policy uncertainty measure from Bundick, Herriford, and Smith (2024)—privately shared
- U.S. Treasury premium measures from Du, Im, and Schreger (2018)—author website
- Data and code from Gürkaynak, Kısacıkoğlu, and Wright (2020)—journal link
- Updated Gürkaynak, Sack, and Wright (2007) nominal yields from Federal Reserve Board website
- Updated Martin (2017) equity premium measures from Knox and Vissing-Jorgensen (2022)—privately shared
- Data on dividends swaps from Goldman Sachs (Manley and Mueller-Glissmann, 2008)—privately shared
- FOMC sentiment measure from Gardner, Scotti, and Vega (2022)—author website
- Facial expression measure from Curti and Kazinnik (2023)—journal website
- Voice tone measure from Gorodnichenko, Pham, and Talavera (2023)—journal website
- Uncertainty and risk aversion measures from Bekaert and Hoerova (2014)—author website
- Uncertainty and risk aversion measures from Bekaert, Engstrom, and Xu (2022)—author website

A.6 Capital Flows

A.6.1 Overview of EPFR data

Since April 2007, EPFR provides for each weekday d updates on the funds in its database. Let $\{d_f, g_f, a_f\}$ describe funds which have domicile d_f, geographic investment focus g_f, and dominant asset class a_f. Then EPFR provides the following aggregate series for funds $\{d_f, g_f, a_f\}$:

- $\text{flow}(d_f, g_f, a_f)_d$: total flow into or out of the funds in U.S. dollar.
- $\text{AUM}(d_f, g_f, a_f)_d$: total net assets under management of the funds in U.S. dollar.
- $\text{flow}(d_f, g_f, a_f)_d^{\%}$: total flow into or out of the funds in percentage of total net assets, i.e.,

$$\text{flow}(d_f, g_f, a_f)_d^{\%} = 100\frac{\text{flow}(d_f, g_f, a_f)_d}{\text{AUM}(d_f, g_f, a_f)_{d-1}}.$$

- $\text{flow}(d_f, g_f, a_f)_d^{c\%}$: cumulative total flow into or out of the funds in percentage of total net assets, i.e.,

$$\text{flow}(d_f, g_f, a_f)_d^{c\%} = 100\left(1 + \frac{\text{flow}(d_f, g_f, a_f)_0^{\%}}{100}\right)\left(1 + \frac{\text{flow}(d_f, g_f, a_f)_1^{\%}}{100}\right)\cdots\left(1 + \frac{\text{flow}(d_f, g_f, a_f)_d^{\%}}{100}\right).$$

EPFR constructs their aggregate series in the following manner:

1. For each fund f, EPFR constructs the variables $\text{flow}_{f,d}$ and $\text{AUM}_{f,d}$ based on the underlying data funds provide to them.
2. EPFR classifies each fund along several dimensions. The fund's domicile is based on where the fund is registered. If two-thirds (or more) of the fund's holdings fall under a specific asset class, EPFR associates the fund with that asset class. The geographic investment focus is determined based on the country risk exposure of the fund's holdings.
3. Based on the classifications, EPFR aggregates the fund-level variables accordingly, i.e.,

$$\text{flow}(d_f, g_f, a_f)_d = \sum_{f\in\{d_f,g_f,a_f\}} \text{flow}_{f,d} \quad \text{and} \quad \text{AUM}(d_f, g_f, a_f)_d = \sum_{f\in\{d_f,g_f,a_f\}} \text{AUM}_{f,d}.$$

A.6.2 Construction of Capital Flow Series

Formula For each FOMC announcement ($t \in F$) and group of funds $\{d_f, g_f, a_f\}$, we construct the capital flow over a 1-week window as follows

$$\text{flow}(d_f, g_f, a_f)_t = \text{flow}(d_f, g_f, a_f)_{d_t+5}^{c\%} - \text{flow}(d_f, g_f, a_f)_{d_t-1}^{c\%}, \tag{A6}$$

where d_t is the weekday of FOMC announcement at time t.

Economics behind formula Let us assume that there is one representative asset which funds $\{d_f, g_f, a_f\}$ own quantity $q(d_f, g_f, a_f)_d$ of and which has a price of $p(d_f, g_f, a_f)_d^{fc}$ in the funds' preferred currency and a price of $p(d_f, g_f, a_f)_d$ in U.S. dollars. To simplify the exposition, we will write variables as $x_d = x(d_f, g_f, a_f)_d$ in the following. Assets under management can be rewritten as

$$\text{AUM}_d = p_d q_d,$$

and flow as

$$\begin{aligned}
\text{flow}_d &= fxr_{d,d-1}^{fc} p_d^{fc} (q_d - q_{d-1}) \\
&= \frac{1}{2}\left(p_d + \frac{p_d^{fc}}{p_{d-1}^{fc}} p_{d-1}\right)(q_d - q_{d-1}),
\end{aligned}$$

where EPFR uses the average exchange rate over d and $d-1$ to convert the flows into dollars, i.e., $fxr_{d,d-1}^{fc} = \frac{1}{2}\left(\frac{p_d}{p_d^{fc}} + \frac{p_{t-1}}{p_{d-1}^{fc}}\right)$. Hence, we have

$$\begin{aligned}
\text{flow}_d^{\%} &= \frac{\frac{1}{2}\left(p_d + \frac{p_t^{fc}}{p_{d-1}^{fc}} p_{d-1}\right)(q_d - q_{d-1})}{p_{d-1} q_{d-1}} \\
&= \frac{1}{2}\left(\frac{p_d}{p_{d-1}} + \frac{p_d^{fc}}{p_{d-1}^{fc}}\right)\frac{q_d - q_{d-1}}{q_{d-1}} \\
&= \Delta^1 p_d \times \Delta^1 q_d,
\end{aligned}$$

where $\Delta^k p_d = \frac{1}{2}\left(\frac{p_{d+k-1}}{p_{d-1}} + \frac{p_{d+k-1}^{fc}}{p_{d-1}^{fc}}\right)$ and $\Delta^k q_d = \frac{q_{d+k-1} - q_{d-1}}{q_{d-1}}$. Note that equation (A6) can be written as

$$\begin{aligned}
\text{flow}_t &= \text{flow}_{d_t+5}^{c\%} - \text{flow}_{d_t-1}^{c\%} \\
&= 100 \times \text{flow}_{d_t-1}^{c\%}\left[\left(1 + \frac{\text{flow}_{d_t}^{\%}}{100}\right) \times \left(1 + \frac{\text{flow}_{d_t+1}^{\%}}{100}\right) \times \cdots \times \left(1 + \frac{\text{flow}_{d_t+5}^{\%}}{100}\right) - 1\right].
\end{aligned}$$

If we do a first-order approximation around $\overline{\text{flow}^{c\%}} \approx 1$ and $\overline{\text{flow}^{\%}} \approx 0$, we get

$$\begin{aligned}
\text{flow}_t \approx\ & 100 \times \overline{\text{flow}^{c\%}}\left[\left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) \times \cdots \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) - 1\right] \\
& + 100 \times \left[\left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) \times \cdots \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) - 1\right]\left(\text{flow}_{d_t-1}^{c\%} - \overline{\text{flow}^{c\%}}\right) \\
& + 100 \times \overline{\text{flow}^{c\%}}\left[\frac{1}{100} \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) \times \cdots \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right)\right]\left(\text{flow}_{d_t}^{\%} - \overline{\text{flow}^{\%}}\right)
\end{aligned}$$

$$
\begin{aligned}
& +100 \times \overline{\text{flow}^{c\%}} \left[\frac{1}{100} \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right) \times \cdots \times \left(1 + \frac{\overline{\text{flow}^{\%}}}{100}\right)\right] \left(\text{flow}^{\%}_{d_t+1} - \overline{\text{flow}^{\%}}\right) \\
& +... \\
\text{flow}_t \quad \approx \quad & \text{flow}^{\%}_{d_t} + \text{flow}^{\%}_{d_t+1} + \text{flow}^{\%}_{d_t+2} + \text{flow}^{\%}_{d_t+3} + \text{flow}^{\%}_{d_t+4} + \text{flow}^{\%}_{d_t+5}
\end{aligned}
$$

Further, note that a first-order approximation of $\text{flow}^{\%}_{d_t} = \Delta^1 p_{d_t} \times \Delta^1 q_{d_t}$ around $\overline{\Delta^1 p} = 1$ and $\overline{\Delta^1 q} = 0$ is given by

$$
\begin{aligned}
\text{flow}^{\%}_{d_t} & \approx \overline{\Delta^1 q} \left(\Delta^1 p_{d_t} - \overline{\Delta^1 p}\right) + \overline{\Delta^1 p} \left(\Delta^1 q_{d_t} - \overline{\Delta^1 q}\right) \\
\text{flow}^{\%}_{d_t} & \approx \Delta^1 q_{d_t},
\end{aligned}
$$

which allows us to write

$$
\begin{aligned}
\text{flow}_t & \approx \Delta^1 q_{d_t} + \Delta^1 q_{d_t+1} + \Delta^1 q_{d_t+2} + \Delta^1 q_{d_t+3} + \Delta^1 q_{d_t+4} + \Delta^1 q_{d_t+5} \\
& \approx \Delta^6 q_{d_t} - \Delta^1 q_{d_t+1} \Delta^1 q_{d_t} - \Delta^1 q_{d_t+2} \Delta^2 q_{d_t} - \Delta^1 q_{d_t+3} \Delta^3 q_{d_t} - \Delta^1 q_{d_t+4} \Delta^4 q_{d_t} - \Delta^1 q_{d_t+5} \Delta^5 q_{d_t}.
\end{aligned}
$$

Lastly, a first-order approximation around $\overline{\Delta^k q} = 0$ yields

$$
\begin{aligned}
\text{flow}_t & \approx \left(\Delta^6 q_{d_t} - \overline{\Delta^6 q_{d_t}}\right) - \overline{\Delta^1 q_d} \left(\Delta^1 q_{d_t+1} - \overline{\Delta^1 q_d}\right) - ... \\
\text{flow}_t & \approx \Delta^6 q_{d_t}
\end{aligned}
$$

Hence, we have

$$
\text{flow}(d_f, g_f, a_f)_t \approx \frac{q(d_f, g_f, a_f)_{d_t+5} - q(d_f, g_f, a_f)_{d_t-1}}{q(d_f, g_f, a_f)_{d_t-1}},
$$

which means that our employed capital flow series does indeed measure—up to a first order—the change in the quantity of the funds' assets.

Implementation details We obtain the following series directly from EPFR:

$$
\text{flow}(d_f, g_f, a_f)_d \quad \text{for} \quad d_f \in \{\text{US}, \text{WE}\}, g_f \in \{\text{US}, \text{WE}, \text{DM}, \text{EM}\}, a_f \in \{\text{B}, \text{E}\},
$$

and

$$
\text{AUM}(d_f, g_f, a_f)_d \quad \text{for} \quad d_f \in \{\text{US}, \text{WE}\}, g_f \in \{\text{US}, \text{WE}, \text{DM}, \text{DM}\}, a_f \in \{\text{B}, \text{E}\},
$$

where US stands for *United States*, WE for *(Western) Europe*, DM for *Developed Markets*, and EM for *Emerging Markets*, B for *Bond*, and E for *Equity*. We focus on U.S.- and European-domiciled funds as these cover almost the entirety of the dataset (93 percent of the assets over the sample period), and this restriction allows us to easily take out domestic flows. Further, as done by previous papers (e.g., Converse, Levy-Yeyati, and Williams, 2023), we concentrate on equity and bond funds which are by far the two largest groups covered by EPFR and also seen as most representative of overall capital flows.

In order to construct (A6), we need to first construct $\text{flow}(d_f, g_f, a_f)^{\%}_{d_t}$. In particular, we need to construct flows for *Foreign Developed Markets* (FDM) so that domestic flows are subtracted out. In the following, we describe the construction of $\text{flow}(d_f, g_f, a_f)^{\%}_{d_t}$ for each case. Once we have $\text{flow}(d_f, g_f, a_f)^{\%}_{d_t}$, it is straightforward to construct $\text{flow}(d_f, g_f, a_f)^{c\%}_{d_t}$ and the final series $\text{flow}(d_f, g_f, a_f)_t$.

- U.S. or European Domicile ($d_f \in \{US, WE\}$), Foreign-Developed Markets (g_f = FDM), Equity or Bond ($a_f \in \{\text{B}, \text{E}\}$):

$$\begin{aligned}\text{flow}(d_f, \text{FDM}, a_f)^{\%}_{d_t} &= \frac{\text{flow}(d_f, \text{FDM}, a_f)_{d_t}}{\text{AUM}(d_f, \text{FDM}, a_f)_{d_t}} \\ &= \frac{\text{flow}(d_f, DM, a_f)_{d_t} - \text{flow}(d_f, d_f, a_f)_{d_t}}{\text{AUM}(d_f, DM, a_f)_{d_t-1} - \text{AUM}(d_f, d_f, a_f)_{d_t-1}}.\end{aligned}$$

- U.S. or European Domicile ($d_f \in \{US, WE\}$), Foreign-Developed Markets (g_f = FDM), Equity and Bond ($a_f = \text{B+E}$):

$$\text{flow}(d_f, \text{FDM}, \text{B+E})^{\%}_{d_t} = \frac{\text{flow}(d_f, \text{FDM}, \text{E})_{d_t} + \text{flow}(d_f, \text{FDM}, \text{B})_{d_t}}{\text{AUM}(d_f, \text{FDM}, \text{E})_{d-1} + \text{AUM}(d_f, \text{FDM}, \text{B})_{d-1}}.$$

- U.S. or European Domicile ($d_f \in \{US, WE\}$), Foreign-Emerging Markets (g_f = FDM), Equity or Bond ($a_f \in \{\text{B}, \text{E}\}$):

$$\text{flow}(d_f, \text{EM}, a_f)^{\%}_{d_t} = \frac{\text{flow}(d_f, \text{EM}, a_f)_{d_t}}{\text{AUM}(d_f, \text{EM}, a_f)_{d_t-1}}.$$

- U.S. or European Domicile ($d_f \in \{US, WE\}$), Foreign-Emerging Markets (g_f = EM), Equity and Bond ($a_f = \text{B+E}$):

$$\text{flow}(d_f, \text{EM}, \text{B+E})^{\%}_{d_t} = \frac{\text{flow}(d_f, \text{EM}, \text{E})_{d_t} + \text{flow}(d_f, \text{EM}, \text{B})_{d_t}}{\text{AUM}(d_f, \text{EM}, \text{E})_{d-1} + \text{AUM}(d_f, \text{EM}, \text{B})_{d-1}}.$$

- U.S. or European Domicile ($d_f \in \{US, WE\}$), Foreign Markets (g_f = FDM+EM), Equity and Bond ($a_f = \text{B+E}$):

$$\begin{aligned}&\text{flow}(d_f, \text{FDM+EM}, \text{B+E})^{\%}_{d_t} \\ &\quad= \frac{\text{flow}(d_f, \text{FDM+EM}, \text{B+E})_{d_t}}{\text{AUM}(d_f, \text{FDM+EM}, \text{B+E})_{d_{t-1}}} \\ &\quad= \frac{\text{flow}(d_f, \text{FDM}, \text{E})_{d_t} + \text{flow}(d_f, \text{FDM}, \text{B})_{d_t} + \text{flow}(d_f, \text{EM}, \text{E})_{d_t} + \text{flow}(d_f, \text{EM}, \text{B})_{d_t}}{\text{AUM}(d_f, \text{FDM}, \text{E})_{d_t\text{-}1} + \text{AUM}(d_f, \text{FDM}, \text{B})_{d_t\text{-}1} + \text{AUM}(d_f, \text{EM}, \text{E})_{d_t\text{-}1} + \text{AUM}(d_f, \text{EM}, \text{B})_{d_t\text{-}1}}.\end{aligned}$$

- U.S. and European Domicile (d_f = US+WE), Foreign Markets (g_f = FDM+EM), Equity and Bond ($a_f = \text{B+E}$):

$$\text{flow}(\text{US+WE}, \text{FDM+EM}, \text{B+E})^{\%}_{d_t} = \frac{\text{flow}(\text{US}, \text{FDM+EM}, \text{B+E})_{d_t} + \text{flow}(\text{WE}, \text{FDM+EM}, \text{B+E})_{d_t}}{\text{AUM}(\text{US}, \text{FDM+EM}, \text{B+E})_{d_{t-1}} + \text{AUM}(\text{WE}, \text{FDM+EM}, \text{B+E})_{d_{t-1}}}.$$

B Estimation

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

B.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*

$$\Delta p_t = \beta s_t^y + \gamma d_t s_t^{ny} + \varepsilon_t, \tag{B1}$$

where $p_t = \begin{bmatrix} p_{1,t} & \dots & p_{n,t} \end{bmatrix}'$, $\beta = \begin{bmatrix} \beta_1' & \dots & \beta_n' \end{bmatrix}'$, $\gamma = \begin{bmatrix} \gamma_1 & \dots & \gamma_n \end{bmatrix}'$, and $\varepsilon_t = \begin{bmatrix} \varepsilon_{1,t} & \dots & \varepsilon_{n,t} \end{bmatrix}'$. Further, $\beta_i = \begin{bmatrix} \beta_{1,i} & \dots & \beta_{k,i} \end{bmatrix}$, and the yield shocks $s_t^y = \begin{bmatrix} s_{1,t}^y & \dots & s_{k,t}^y \end{bmatrix}'$ 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

$$s_t^{ny} \sim \text{i.i.d. } N\left(0,1\right). \tag{B2}$$

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 $\theta = \begin{bmatrix} \beta & \gamma & \Sigma_\varepsilon \end{bmatrix}$. The goal is to estimate the unobserved factor s_t^{ny}, given a set of parameters $\hat{\theta}$, which are estimated by maximum likelihood.

B.2 Estimation Algorithm

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

$$\begin{aligned} \mathcal{L}\left(\theta\right) = -\frac{1}{2}\sum_{t=1}^{T} \Big\{ & 1\left(d_t = 1\right)\left[\left(\Delta p_t - \beta s_t^y\right)'\left(\Sigma_\varepsilon + \gamma\gamma'\right)^{-1}\left(\Delta p_t - \beta s_t^y\right) + \log\left(\left|\Sigma_\varepsilon + \gamma\gamma'\right|\right)\right] \\ & + 1\left(d_t = 0\right)\left[\Delta p_t' \Sigma_\varepsilon^{-1} \Delta p_t + \log\left(\left|\Sigma_\varepsilon\right|\right)\right] \Big\} \end{aligned} \tag{B3}$$

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 (B3) 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 (B1) 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, as it is only identified up to a sign 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.

C Sensitivity Analysis

In this section, we detail the robustness analyses discussed in Section 2.4. In Sections C.1 and C.2 describe the re-estimations underlying Table 4, while in Section C.3 investigates the role of the event window in our estimation. Finally, Section C.4 documents the increase in cross-asset correlation underlying our findings.

C.1 Alternative Assumptions

We begin by relaxing various assumptions in the baseline specification. Notably, for these re-estimations, the left-hand-side variables remain the same 15 asset prices as in the baseline. The top panel of Table 4 summarizes the results.

Generalized Covariance Following Gürkaynak, Kısacıkoğlu, and Wright (2020), we also estimate a version with an unrestricted variance-covariance matrix of ε_t instead of the diagonal matrix under the baseline:

$$\Delta p_t = \beta s_t^y + \gamma d_t s_t^{ny} + \tilde{\varepsilon}_t,$$

where $\tilde{\varepsilon}_t \sim N(0, \tilde{\Sigma}_\varepsilon)$ and $\tilde{\Sigma}_\varepsilon$ is a unrestricted variance-covariance matrix.

Non-FOMC Days Purified We now conduct a robustness check allowing yield shocks, s_t^y, to be present during non-announcement days. Specifically, instead of estimating equation (4), we estimate:

$$\Delta p_t = \beta s_t^y + \delta \tilde{s}_t^y + \gamma d_t s_t^{ny} + \varepsilon_t,$$

where

$$\tilde{s}_t^y = \begin{cases} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} & \text{for } t \in F \\ \begin{bmatrix} MP1_t & MP2_t & ED2_t & ED3_t & ED4_t & T2Y_t & T5Y_t & T10_t & T30_t \end{bmatrix} & \text{for } t \in NF. \end{cases}$$

This specification allows yield shocks to have different effects on FOMC and non-FOMC days. However, the nine surprises in s_t^y and $\tilde{s}_t^y$ are constructed identically on announcement and non-announcement days. We implement this specification by regressing Δp_t on $\tilde{s}_t^y$ on non-FOMC days (via OLS) and then run the Kalman filter based on the purified changes, i.e., the residuals from this regression.

Intercepts Since our baseline specification (4) does not include an intercept, we also estimate alternative versions that incorporates intercepts. These specifications address concerns that financial market drifts might be inadvertently captured by our estimation procedure. Specifically, we consider one specification with intercepts for both FOMC and non-FOMC days:

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

and another specification that allows for different intercepts on FOMC and non-FOMC 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 15-dimensional vectors. Both models are implemented by demeaning each series before estimation: in the first case, the mean is taken over both announcement and non-announcement days, while in the second, separate means are calculated for each. After demeaning, both models are estimated using the Kalman filter.

3 Yield Factors In the baseline version, we use nine interest rate surprises to summarize yield shocks (s_t^y). We now summarize yield shocks using three yield curve factors ($\hat{s}_t^y$), which are extracted from the nine series following the methodology in Swanson (2021). Specifically, we first extract the first three principal components from s_t^y and then rotate the factors so that the first corresponds to a federal funds rate shock $\hat{s}_t^{FFR}$, the second to a forward guidance shock $\hat{s}_t^{FG}$, and the third to a large-scale asset purchase shock $\hat{s}_t^{LSAP}$. With three yield curve factors $\hat{s}_t^y = \begin{bmatrix} \hat{s}_t^{FFR} & \hat{s}_t^{FG} & \hat{s}_t^{LSAP} \end{bmatrix}$ at hand, we can then estimate:

$$\Delta p_t = \beta \hat{s}_t^y + \gamma d_t s_t^{ny} + \varepsilon_t.$$

C.2 Allowing for Nonlinearities and Time-varying Coefficients

We now analyze the extent to which our non-yield shock captures nonlinearities in response to yield shocks or the effects of time-varying coefficients. The three yield factors effectively summarize yield curve shocks, explaining 89 percent of the variation in the nine surprises. Therefore, we use them to implement various nonlinear specifications without the overfitting concerns that would arise if we instead used the nine yield surprises. Notably, for these re-estimations, the left-hand-side variables remain the same 15 asset prices as in the baseline.

Second-order Yield Shocks First, we consider second-order terms of the three yield shocks, i.e., squared shocks and interactions across shocks. Specifically, we estimate the following equation:

$$\Delta p_t = \beta \hat{s}_t^y + \delta \hat{s}_t^{y,2} + \gamma d_t s_t^{ny} + \varepsilon_t,$$

where $\hat{s}_t^{y,2} = \begin{bmatrix} \left(\hat{s}_t^{FFR}\right)^2 & \left(\hat{s}_t^{FG}\right)^2 & \left(\hat{s}_t^{LSAP}\right)^2 & \hat{s}_t^{FFR} \times \hat{s}_t^{FG} & \hat{s}_t^{FFR} \times \hat{s}_t^{LSAP} & \hat{s}_t^{FG} \times \hat{s}_t^{LSAP} \end{bmatrix}$.

Positive and Negative Yield Shocks We also allow the shocks to have different effects for positive and negative values. Specifically, we estimate the following specification:

$$\Delta p_t = \beta \hat{s}_t^y + \delta \hat{s}_{t,pos}^y + \psi d_{t,pos} + \gamma d_t s_t^{ny} + \varepsilon_t,$$

where $\hat{s}_{t,pos}^y = \begin{bmatrix} d_{t,pos}^{FFR} \hat{s}_t^{FFR} & d_{t,pos}^{FG} \hat{s}_t^{FG} & d_{t,pos}^{LSAP} \hat{s}_t^{LSAP} \end{bmatrix}$ and $d_{t,pos} = \begin{bmatrix} d_{t,pos}^{FFR} & d_{t,pos}^{FG} & d_{t,pos}^{LSAP} \end{bmatrix}$ with $d_{t,pos}^x = 1\left(\hat{s}_t^x > 0\right)$.

Interactions with Yield Shocks Lastly, we allow the effects of the shocks to vary with the level of different variables. Specifically, we estimate:

$$\Delta p_t = \beta \hat{s}_t^y + \delta \left(\hat{s}_t^y \times Z_t\right) + \psi d_t Z_t + \gamma d_t s_t^{ny} + \varepsilon_t,$$

where Z_t is the vector of interaction variables. We consider the following variables:

1. a *ZLB indicator* to capture nonlinearities at the zero lower bound;

2. the *empirical cumulative distribution function of the unemployment rate* (see Boehm and

Kroner (2025) for details on the construction) or the *log of the industrial production index*, both intended to capture slack in the real economy;

3. the *log of the VIX*, capturing risk appetite and uncertainty in financial markets;

4. the *log of the monetary policy uncertainty measure* from Bauer, Lakdawala, and Mueller (2022), which reflects option-implied policy rate uncertainty over the next year;

5. the *intermediary capital risk factor* from He, Kelly, and Manela (2017), used as a proxy for the health of the intermediary sector;

6. the *3-month stock-bond correlation*, constructed as in Campbell, Pflueger, and Viceira (2020), intended to broadly capture whether the economic environment is predominantly driven by demand or supply shocks;

7. the *Pre-FOMC drift*, constructed following Lucca and Moench (2015), to investigate whether the non-yield shock is related to this anomaly;

8. the *investor attention measure* from Kroner (2025), used to capture shifts in market focus toward FOMC announcements.

To mitigate concerns about simultaneity, we use lagged values—either from the day or the month prior to the FOMC announcement.

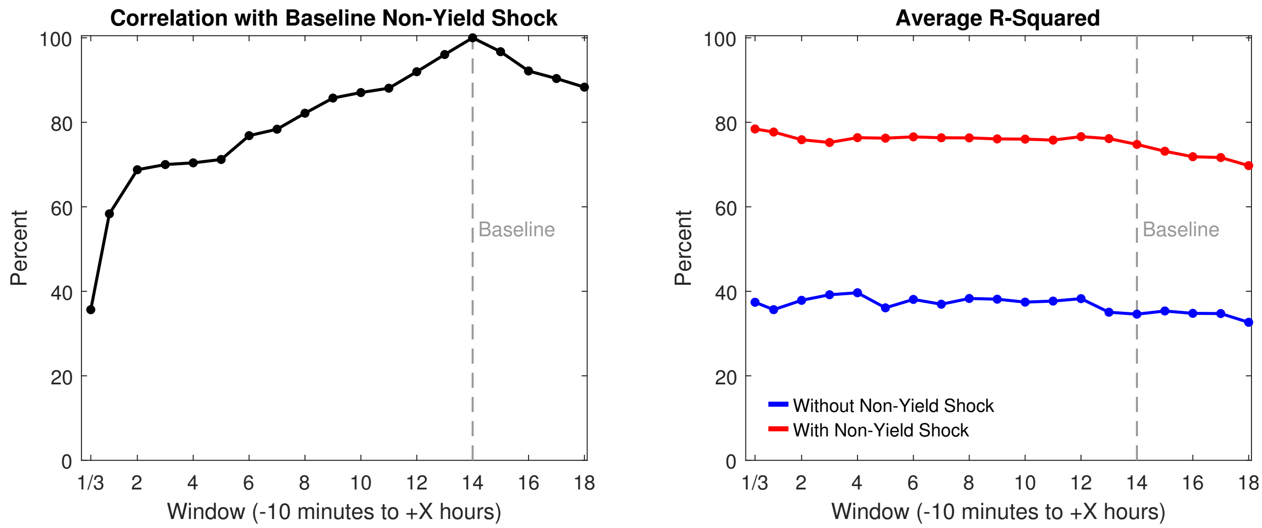
C.3 The Event Window Length

We now assess the role of the 14-hour event window used in our baseline estimation. To do so, we re-estimate the non-yield shock for each of the 19 event windows considered in Section 2, holding the set of 15 asset prices fixed. Figure C1 shows the correlation of these alternative series with the baseline (left panel) and the additional explanatory power provided by the non-yield shock under each window length (right panel). The correlation is generally high for windows close to the 14-hour baseline, suggesting robustness to moderate changes in window length. However, the correlation drops below 70 percent when using shorter windows below two hours. The explanatory power of the yield curve factors (blue line) is relatively stable across all window lengths, and the additional explanatory power from the non-yield shock (red line) is similarly consistent. In sum, these results suggest that the non-yield shock is not an artifact of the particular event window chosen in the baseline.

C.4 Common Factor Structure

We now investigate our finding that a single non-yield shock accounts for nearly all of the remaining variation in the employed asset prices. While we demonstrated prior to estimation that these asset prices exhibit excess volatility, this alone does not imply that the additional variation can be captured by a single factor. To explore this further, we examine how the correlation matrix of asset price returns differs between FOMC and non-FOMC days. Table C1 displays the difference in these correlation matrices. Consistent with our baseline estimation, the top panel shows the correlation

Figure C1: Fed Non-Yield Under Alternative Event Study Windows



Notes: This figure shows the correlation of the baseline Fed non-yield shock series with alternative series estimated using different event study windows (left panel), as well as the average R^2 for the respective window lengths (right panel). The R^2 values are constructed as the average R^2 values from announcement day regressions of each of the 15 asset prices on the independent variables without non-yield shock (*without shock*) and with non-yield shock (*with shock*). The window over which returns are constructed is expanding as indicated on the horizontal axis. The full sample ranges from January 1996 to July 2025.

matrix of residualized asset price returns on FOMC days minus the corresponding matrix for non-FOMC days. As a robustness check, the bottom panel displays the difference in residualized asset price returns for non-FOMC days under our *non-FOMC days purified* scenario. Both panels clearly demonstrate that the correlation across asset returns increases substantially on FOMC days. This rise in co-movement suggests that the excess volatility is indeed attributable to a common factor. It also confirms that the high explanatory power of our non-yield shock is not an artifact of the estimation procedure, but rather a genuine feature of the data.

Table C1: Difference in Asset Price Correlations between FOMC and Non-FOMC Days

Corr(FOMC Days, Residualized) - Corr(Non-FOMC Days, Raw)

	ES1	ES2	EUR	JPY	GBP	AUD	CAD	CHF	SGD	SEK	NOK	NZD	MXN	ZAR	PLN
ES1	0.00														
ES2	0.00	0.00													
EUR	0.17	0.17	0.00												
JPY	0.15	0.15	0.10	0.00											
GBP	0.23	0.23	0.13	0.08	0.00										
AUD	0.23	0.22	0.25	0.10	0.23	0.00									
CAD	0.17	0.18	0.18	0.15	0.22	0.17	0.00								
CHF	0.23	0.21	0.07	0.03	0.12	0.26	0.15	0.00							
SGD	0.10	0.09	0.17	0.16	0.21	0.15	0.19	0.16	0.00						
SEK	0.17	0.17	0.05	0.13	0.09	0.22	0.18	0.14	0.14	0.00					
NOK	0.16	0.13	0.09	0.15	0.13	0.23	0.12	0.19	0.15	0.07	0.00				
NZD	0.20	0.22	0.20	0.12	0.18	0.11	0.12	0.23	0.09	0.18	0.22	0.00			
MXN	0.08	0.07	0.18	0.24	0.16	0.15	0.14	0.23	0.12	0.19	0.15	0.16	0.00		
ZAR	0.10	0.13	0.22	0.21	0.23	0.19	0.17	0.24	0.14	0.19	0.19	0.19	0.09	0.00	
PLN	0.16	0.15	0.09	0.18	0.17	0.24	0.18	0.16	0.18	0.09	0.10	0.19	0.14	0.14	0.00

Corr(FOMC Days, Residualized) - Corr(Non-FOMC Days, Residualized)

	ES1	ES2	EUR	JPY	GBP	AUD	CAD	CHF	SGD	SEK	NOK	NZD	MXN	ZAR	PLN
ES1	0.00														
ES2	0.00	0.00													
EUR	0.14	0.15	0.00												
JPY	0.06	0.05	0.10	0.00											
GBP	0.22	0.22	0.13	0.07	0.00										
AUD	0.25	0.25	0.23	0.06	0.23	0.00									
CAD	0.19	0.20	0.17	0.11	0.22	0.18	0.00								
CHF	0.15	0.14	0.06	0.05	0.11	0.23	0.13	0.00							
SGD	0.10	0.09	0.17	0.13	0.21	0.15	0.19	0.15	0.00						
SEK	0.17	0.17	0.04	0.10	0.09	0.23	0.19	0.11	0.15	0.00					
NOK	0.16	0.14	0.09	0.13	0.13	0.23	0.12	0.17	0.15	0.07	0.00				
NZD	0.21	0.23	0.19	0.10	0.18	0.11	0.13	0.21	0.10	0.18	0.22	0.00			
MXN	0.10	0.09	0.17	0.19	0.16	0.16	0.15	0.20	0.12	0.20	0.16	0.16	0.00		
ZAR	0.13	0.15	0.21	0.17	0.23	0.20	0.18	0.21	0.14	0.19	0.19	0.20	0.10	0.00	
PLN	0.16	0.16	0.09	0.15	0.17	0.24	0.18	0.14	0.18	0.09	0.10	0.19	0.15	0.15	0.00

Notes: The tables show changes in the correlation matrices of 14-hour returns for the 15 asset prices used in the estimation. The top table displays the correlation matrix of 14-hour returns on FOMC days—residualized with respect to the yield shocks—minus the correlation matrix of 14-hour returns on non-FOMC days. The bottom table displays the correlation matrix of 14-hour residualized returns on FOMC days minus the correlation matrix of 14-hour residualized returns on non-FOMC days.

D Financial Market Analysis

In this appendix, we provide additional details related to Section 3. Sections D.1 through D.4 present further estimates of the effects of the non-yield shock on major financial markets. Sections D.5 and D.6 describe the analytical frameworks underlying the transmission channels of the non-yield shock and report additional associated results. Finally, Section D.7 presents supporting evidence for the risk premium channel.

D.1 Bond Yields

U.S. We start by studying the effects of our Fed non-yield shock on various U.S. interest rates. Since the Fed non-yield shock is by construction orthogonal to surprise changes in the U.S. yield curve within a 14-hour window around FOMC announcements, we expect no or only small effects on U.S. bond markets within a 2-day window as well. As Table D1 shows, our shock has indeed no discernible effects on nominal yields as well as nominal forward rates.

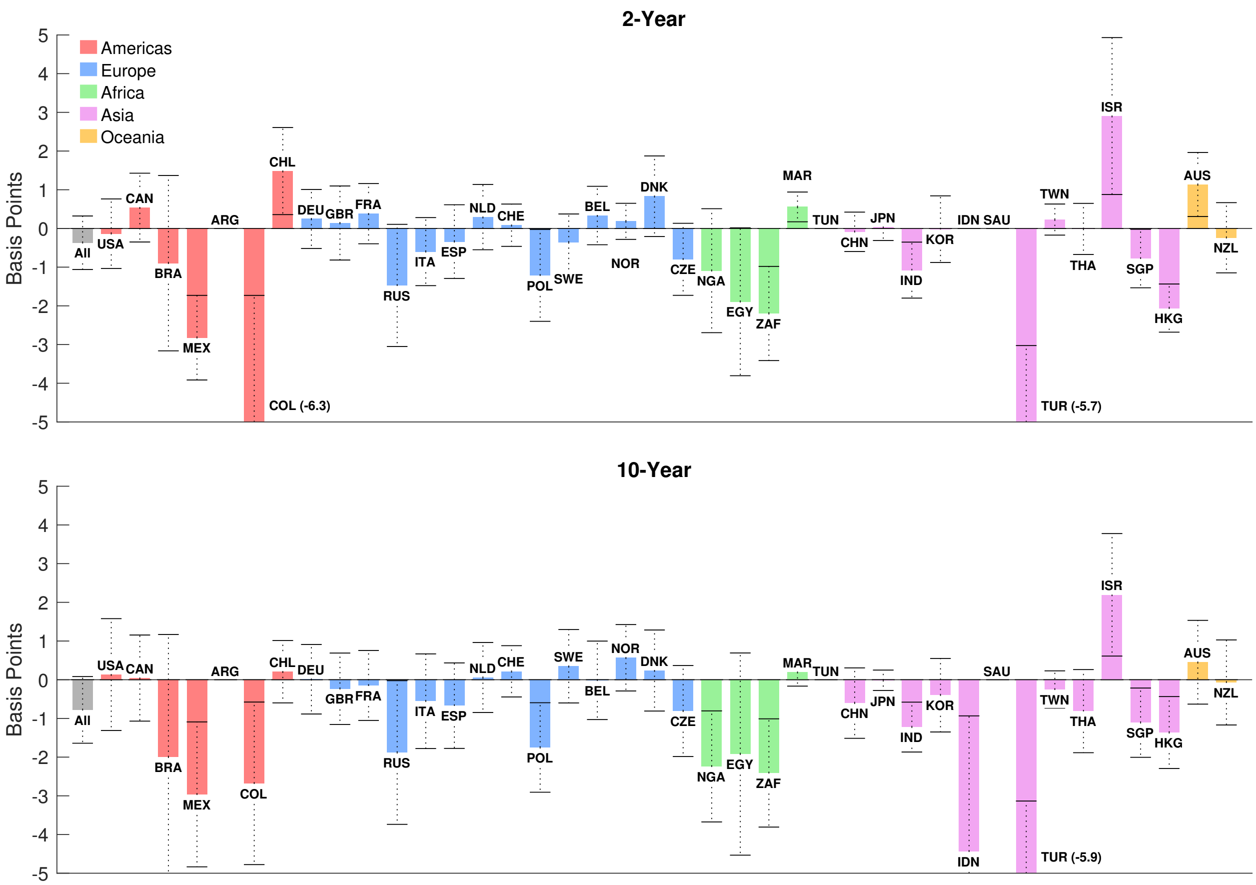
Table D1: Effects of Fed Non-Yield Shock on U.S. Yields

Change (bp)	1 Month	3 Month	6 Month	1 Year	2 Year	5 Year	10 Year	20 Year	30 Year
Yield—Bloomberg									
Fed non-yield shock	-0.41	-0.61	-0.24	0.04	-0.13	-0.18	0.41	-0.54	0.76
	(0.60)	(0.65)	(0.51)	(0.44)	(0.57)	(0.80)	(0.87)	(1.63)	(0.82)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Observations	196	239	239	239	239	239	239	42	239
Yield—GSW 2007									
Fed non-yield shock				0.30	-0.11	-0.17	0.46	0.77	0.90
				(0.44)	(0.58)	(0.78)	(0.89)	(0.82)	(0.70)
R^2				0.00	0.00	0.00	0.00	0.01	0.01
Observations				239	239	239	239	239	239
Instantaneous Forward Rate—GSW 2007									
Fed non-yield shock					-0.65	0.48	1.25	1.04	
					(0.89)	(1.13)	(1.11)	(0.85)	
R^2					0.00	0.00	0.01	0.01	
Observations					239	239	239	239	

Notes: This table presents estimates of δ from specification (8), 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 two panels display estimates for yields and instantaneous forward rates 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.

Global While the non-yield shock is orthogonal to the U.S. yield curve, it is *a priori* less clear what the reactions of international bond yields are. Figure D1 shows the effects on the yields of international 2-year and 10-year local-currency denominated government bonds. These estimates are obtained from specifications (8) and (9) 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 also 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.

Figure D1: Effects of Fed Non-yield Shock on Bond Yields

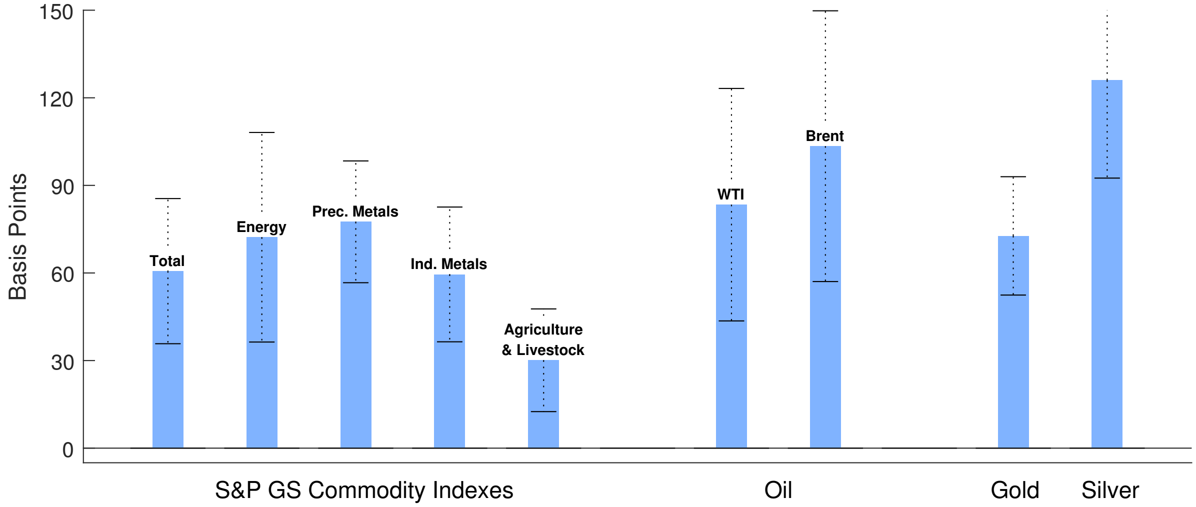


Notes: This figure shows the response of international government bond yields to the Fed non-yield shock. The dependent variable is the 2-day change in local-currency government bond yields, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of the common coefficient δ from equation (8), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (9). 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 Table A3.

D.2 Commodity Prices

We next study the effects of our non-yield shock on commodity prices. To do so, we employ the widely-used S&P GS commodity indexes. Table A6 provides details on the underlying commodities for each index. We also report separately results for three key commodity prices: oil, gold, and silver. Figure D2 shows the estimates. The Fed non-yield shock leads to significant increases in commodity prices, both on average and across all major categories. The effects are particularly

Figure D2: 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 bar shows the effect on a given commodity price or index, i.e., the estimate of coefficient δ of equation (8) 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 the data are provided in Table A5 and A6.

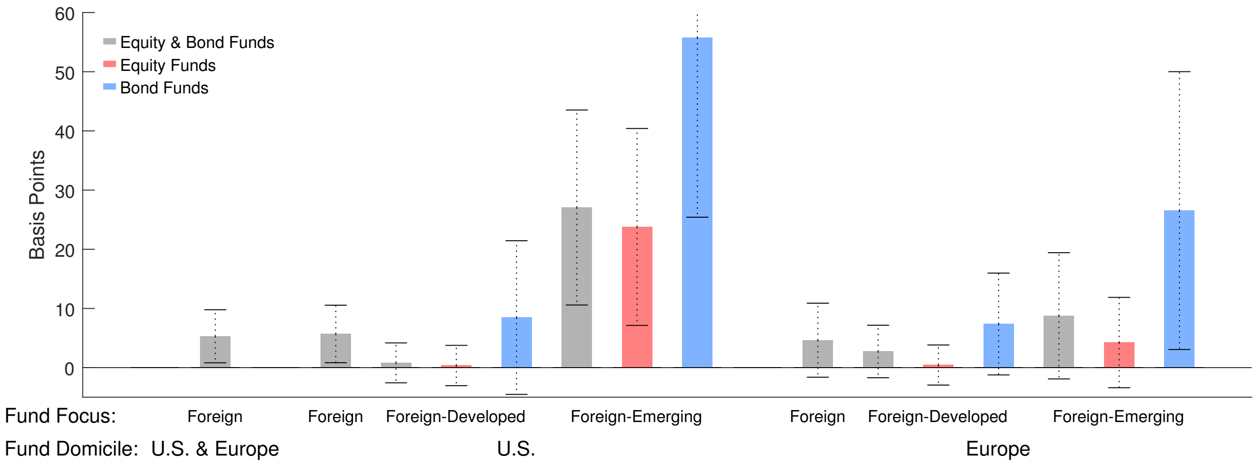
pronounced for energy and metals. The point estimate for silver suggests a greater than one percent response to a one standard deviation non-yield shock. Overall, these findings show that the non-yield shock strongly transmits to commodity markets.

D.3 Capital Flows

We next study the effects of the Fed non-yield shock on capital flows. To do so, we employ the funds flow data from Emerging Portfolio Fund Research (EPFR), which covers mutual funds and exchange-traded funds (ETFs). This data source provides daily data from 2007 onwards. As shown by prior work, EPFR's funds flow data is able to broadly match flow dynamics of more comprehensive datasets, such as the Treasury International Capital (TIC) data (Jotikasthira, Lundblad, and Ramadorai, 2012) or the IMF balance of payments data (Miao and Pant, 2012).

For our analysis, we employ EPFR's aggregate flow series, which allow us to differentiate flows by funds' dominant asset class (equities or bonds), geographic investment focus (developed or emerging markets), and domicile. We concentrate on funds domiciled in the U.S. and Western Europe, which cover approximately 93 percent of the assets in our sample. To isolate international capital flows, we then exclude funds with a domestic investment focus, i.e., funds which focus on investments in their country of domicile. As asset quantities likely respond more sluggishly than prices, we measure each flow over a 1-week window around FOMC announcements—from 1 day before to 7 days after an announcement. Each flow is expressed in basis points of the total net assets managed by the underlying group of funds. Estimates are based on equation (8). We provide more details on the dataset and the construction of our flow series in Section A.6.

Figure D3: Effects of Fed Non-yield Shock on International Capital Flows



Notes: The figure shows the responses of capital flows to the Fed non-yield shock. The dependent variable is a capital flow for a set of funds, measured over a 1-week window around FOMC announcements and expressed in basis points of the funds' total net assets. Each bar shows the effect on a given capital flow, i.e., the estimate of coefficient δ of equation (8). For a given capital flow, *Fund Domicile* refers to the domicile of the underlying funds, whereas *Fund Focus* refers to the geographic focus of the funds' investments. 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.

Figure D3 displays the estimates. The figure shows that a positive Fed non-yield shock typically leads to capital inflows into foreign economies. On average, a one-standard deviation positive Fed non-yield shock causes a 5 basis points inflow (leftmost bar). The effects are driven largely by the substantial 27 basis points inflows from U.S.-domiciled funds into emerging markets. For both U.S.- and European-domiciled funds, the strongest inflows into emerging markets come from bond funds.

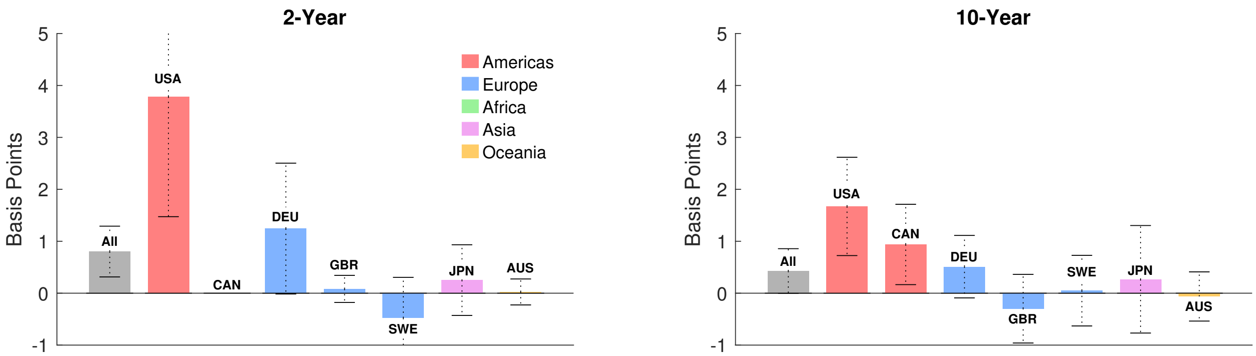
D.4 Inflation Compensations

In this appendix, we investigate the responses of inflation compensations to the non-yield shock. Figure D4 displays the effects on inflation compensations at the 2-year and 10-year horizon. As the figure shows, a positive one-standard deviation non-yield shock leads to an increase in U.S. inflation compensations of 1.7 basis points at the 10-year horizon, and an increase of 3.8 basis points at the 2-year horizon. Foreign inflation compensations are mostly unaffected. Together with the fact that changes in inflation compensations could be driven by liquidity or inflation risk premia rather than inflation expectations these relatively small effects suggest a limited role of the inflation channel for understanding our non-yield shock.

D.5 Stock Market Channels

Decomposition To decompose stock prices, we use the classic Campbell and Shiller (1988) approximation. As shown in Campbell (2017, p. 135), Campbell and Shiller's (1988) approximate

Figure D4: Effects of Fed Non-yield Shock on Breakeven Inflation Rates



Notes: This figure shows the response of international inflation compensations to the Fed non-yield shock. The dependent variable is the 2-day change in local inflation compensation measure, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of the common coefficient δ from equation (8), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (9). 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.

log-linear present value model implies that country c's stock index at time τ can be expressed as

$$p^s_{c,\tau} = \text{constant } + \sum_{j=0}^{\infty} \rho_c^j \left(1-\rho_c\right) E_\tau d_{c,\tau+1+j} - \sum_{j=0}^{\infty} \rho_c^j E_\tau r^s_{c,\tau+1+j},$$

where $p^s_{c,\tau}$ denotes the log of country c's stock index at time τ, $E_\tau d_{c,\tau+1+j}$ is the log of country c's expected dividends over the next year j-years ahead, and $E_\tau r^s_{c,\tau+1+j}$ denotes the expected 1-year log-return on country c's stock index j-years ahead. Lastly, ρ_c is a log-linearization parameter for country c, defined as a function of the long-run average dividend-price ratio $\overline{d_c - p^s_c}$, specifically, $\rho_c = \frac{1}{1+\exp\left(\overline{d_c - p^s_c}\right)}$.

Along the lines of Bernanke and Kuttner (2005, p. 1255), we decompose the expected log-return as the sum of the risk-free rate and the equity premium:

$$E_{\tau+j} r^s_{c,\tau+1+j} = y_{c,\tau+j} + ep_{c,\tau+j},$$

where $y_{c,\tau+j}$ is the 1-year expected risk-free rate of country c j-years ahead and $ep_{c,\tau+j}$ denotes the 1-year equity premium (expected excess return) on country c's stock index j-years in the future, i.e., $ep_{c,\tau+j} \equiv E_{\tau+j} er_{c,\tau+1+j}$ with $er_{c,\tau+1+j}$ being the excess return. Using the law of iterated expectations, the present-value expression for the log stock index can then be written as

$$p^s_{c,\tau} = \text{constant } - \sum_{j=0}^{\infty} \rho_c^j E_\tau y_{c,\tau+j} + \sum_{j=0}^{\infty} \rho_c^j \left(1-\rho_c\right) E_\tau d_{c,\tau+1+j} - \sum_{j=0}^{\infty} \rho_c^j E_\tau ep_{c,\tau+j}.$$

Lastly, let t be the time of the FOMC announcement and Δ^d the 2-day change around the

FOMC announcement. We can then write the 2-day log-change in country c's stock index as

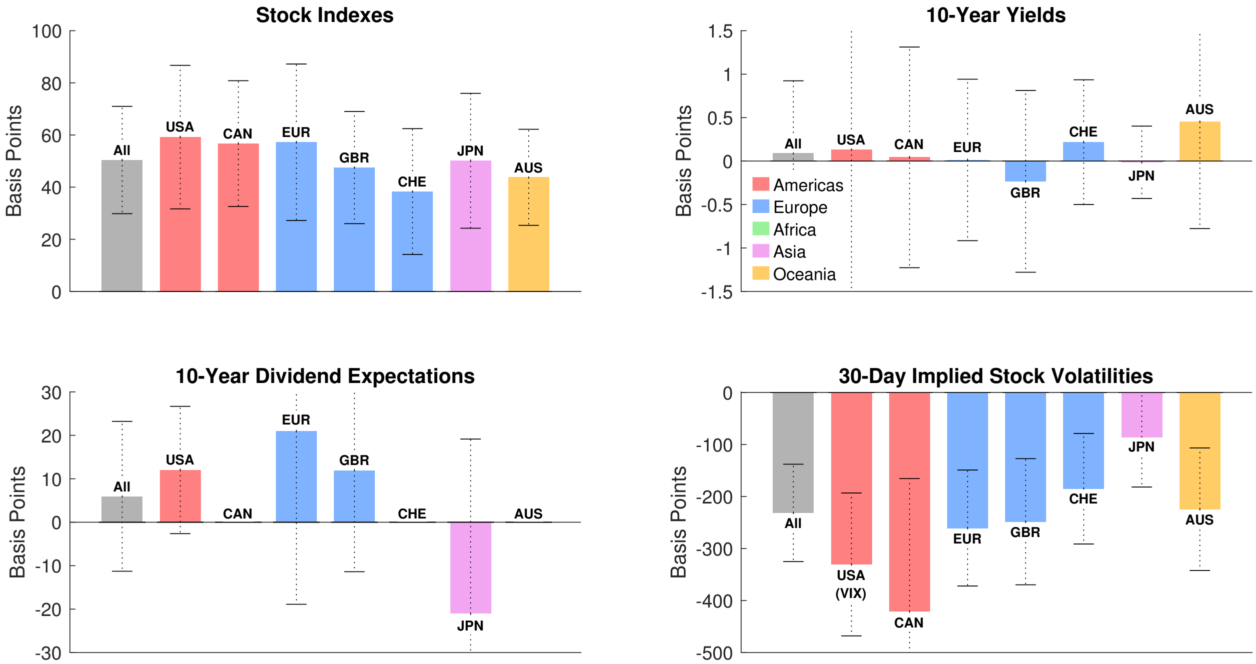
$$\Delta^d p^s_{c,t} = \underbrace{-\sum_{j=0}^{\infty} \rho_c^j \Delta^d E_t y_{c,t+j}}_{\substack{\text{changes in expected} \\ \text{risk-free rates}}} + \underbrace{\sum_{j=0}^{\infty} \rho_c^j \left(1-\rho_c\right) \Delta^d E_t d_{c,t+1+j}}_{\text{changes in expected dividends}} - \underbrace{\sum_{j=0}^{\infty} \rho_c^j \Delta^d E_t ep_{c,t+j}}_{\substack{\text{changes in expected} \\ \text{equity risk premia}}}. \tag{D1}$$

Construction of Dividend Expectations To gauge expected future dividends, we construct a measure of dividend expectations over a 10-year horizon using dividend swap data on stock indexes provided by Goldman Sachs (Manley and Mueller-Glissmann, 2008). Dividend swaps are essentially the over-the-counter counterparts of exchange-traded dividend futures, allowing investors to trade expected dividend payments over a given horizon. Consider, for example, the 2009 S&P 500 dividend swap traded on March 9, 2006. At the end of 2009, the swap buyer receives the sum of dividends paid by S&P 500 companies in 2009 (the floating leg), while the seller receives the price of the swap agreed upon on March 9, 2006 (the fixed leg). The swap price, therefore, reflects the market's expectations on March 9, 2006 of the total dividends to be paid by S&P 500 firms in 2009.

Compared to dividend futures, dividend swaps were introduced earlier, allowing us to use a substantially longer sample period in our analysis. In our case, the data extends back to 2004 and covers the U.S. (S&P 500), Euro Area (Euro Stoxx 50), U.K. (FTSE 100), and Japan (Nikkei). To construct our 10-year measure of dividend expectations, we proceed in two steps. First, we generate constant-horizon (1-year ahead) prices for maturities up to 10 years by linearly interpolating dividend swap prices for two consecutive calendar years. Second, we compute the 10-year dividend expectations by averaging the 1-year ahead prices over the next 10 years.

Country-specific Effects Figure D5 displays the pooled effects reported in the top panel of Table 5, along with the underlying country-specific estimates. As shown in the figure, the strong pooled effect on stock indexes is not driven by any single country. The same holds for the small and insignificant effects on 10-year yields and dividend expectations—none of the individual countries exhibit significant responses for either variable. For implied volatilities, the largest effect is observed for the VIX, often regarded as the key gauge of global risk sentiment. Moreover, countries with stronger stock price responses tend to also exhibit larger declines in implied volatility, consistent with the notion of a dominant risk premium channel. An exception is Japan, where the response of implied volatility is relatively muted compared to its stock index reaction.

Figure D5: Effects of Fed Non-yield Shock on Stock Index Components



Notes: This figure shows the underlying estimates of Table 5 for the stock market. The figure shows the Fed non-yield shock's effects on stock indexes (top-left panel), 10-year yields (top-right panel), 10-year dividend expectations (bottom-left panel), and 30-day option-implied stock volatilities (bottom-right panel). The dependent variables are constructed as 2-day returns or log-returns, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ of equation (8), while the other bars show the country-specific effects, i.e., the estimates of coefficients δ_c of equation (9). 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.

Calculation of Elasticities In order to apply the decomposition in the context of our non-yield shock, we rewrite equation (D1) in terms of country c's 10-year risk-free rate and 10-year dividend expectations. These two objects that can be measured in the data, as discussed in the main text. Doing so allows us to obtain an approximate answer regarding the relative importance of the interest rate and dividend channels.

Let $\Delta^d y_{c,t}^{10}$ be the 2-day change in the 10-year risk-free rate and $\Delta^d d_{c,t}^{10}$ be the 2-day log-change in the 10-year dividend expectations, i.e.,

$$\Delta^d y_{c,t}^{10} = \frac{1}{10} \sum_{j=0}^{9} \Delta^d E_t y_{c,t+j} \quad \text{and} \quad \Delta^d d_{c,t}^{10} = \frac{1}{10} \sum_{j=0}^{9} \Delta^d E_t d_{c,t+1+j}.$$

Next, take the discounted sums of yields and dividends from expression (D1), truncate them after

9 years and approximate them as follows:

$$\sum_{j=0}^{9} \rho_c^j \Delta^d E_t y_{c,t+j} \approx 10\Delta^d y_{c,t}^{10} \quad \text{and} \quad \sum_{j=0}^{9} \rho_c^j \Delta^d E_t d_{c,t+1+j} \approx 10\Delta^d d_{c,t}^{10}.$$

Both of these approximations are exact for $\rho_c = 1$ and remain accurate for values of ρ_c close to but below 1. In the data, ρ_c is typically found to be in the range from 0.95 to 0.99, suggesting that our proxies are relatively precise.[1] Using these approximations in (D1) yields:

$$\begin{aligned}\Delta^d p_{c,t}^s \approx & -10\Delta^d y_{c,t}^{10} - \sum_{j=10}^{\infty} \rho_c^j \Delta^d E_t y_{c,t+j} \\ & + (1-\rho_c)\, 10\Delta^d d_{c,t}^{10} + \sum_{j=10}^{\infty} \rho_c^j (1-\rho_c)\, \Delta^d E_t d_{c,t+1+j} \\ & - \sum_{j=0}^{\infty} \rho_c^j \Delta^d E_t ep_{c,t+j}. \end{aligned} \tag{D2}$$

Based on (D2), we can derive the following elasticities of country c's stock index with respect to the 10-year risk-free rate expectations and 10-year dividend expectations:

$$\frac{\Delta^d p_{c,t}^s}{\Delta^d y_{c,t}^{10}} = -10 \quad \text{and} \quad \frac{\Delta^d p_{c,t}^s}{\Delta^d d_{c,t}^{10}} = (1-\rho_c)\, 10 = 0.5,$$

where we used $\rho_c = 0.95$ to be conservative, i.e., to rather overstate than to understate the contribution of dividend expectations.

D.6 Exchange Rate Channels

Decomposition To decompose exchange rates, we follow Jiang, Krishnamurthy, and Lustig (2021), Kalemli-Özcan and Varela (2021), and Obstfeld and Zhou (2022). These papers extend earlier frameworks (e.g., Clarida and Gali, 1994; Froot and Ramadorai, 2005) by allowing for deviations from both UIP and CIP. To understand the decomposition, it is helpful to begin with the expected carry trade return at time τ for U.S. investors borrowing in U.S. dollars and investing in country c for one year:

$$\underbrace{fp_{c,\tau}}_{\substack{\text{currency} \\ \text{risk premium}}} + \underbrace{\lambda_{c,\tau}}_{\substack{\text{convenience yield of holding U.S.} \\ \text{bond relative to country c's bond}}} = \underbrace{y_{c,\tau} + E_t p_{c,\tau+1}^f - p_{c,\tau}^f}_{\substack{\text{dollar return of investing} \\ \text{in country c's bond}}} - \underbrace{y_{US,\tau}}_{\substack{\text{return on} \\ \text{U.S. bond}}}. \tag{D3}$$

Here, $p_{c,\tau}^f$ is the log of country c's U.S. dollar exchange rate, measured in U.S. dollars per unit of foreign currency of country c; $y_{c,\tau}$ and $y_{US,\tau}$ denote the one-year risk-free rates in country

[1] For example, Campbell (2017, p. 134) states that ρ_c is in the range $0.95-0.96$ for the U.S.; Cuthbertson, Hayes, and Nitzsche (1997) estimate $\rho_c = 0.95$ for the U.K.; Cuthbertson and Hyde (2002) find $\rho_c = 0.97$ for Germany and $\rho_c = 0.95$ for France; and Hausman and Wieland (2014) report $\rho_c = 0.99$ for Japan.

c and the U.S., respectively; $fp_{c,\tau}$ is the risk premium that U.S. investors require for holding country c's currency for one year; and $\lambda_{US,\tau}$ represents the additional convenience yield that U.S. investors obtain from holding the U.S. bond relative to country c's bond for one year. Note that $fp_{c,\tau} = \lambda_{US,\tau} = 0$ if both UIP and CIP hold.

Solving equation (D3) forward, we arrive at:

$$p^f_{c,\tau} = \sum_{j=0}^{\infty} E_\tau \left(y_{c,\tau+j} - y_{US,\tau+j}\right) - \sum_{j=0}^{\infty} E_\tau \lambda_{c,\tau+j} - \sum_{j=0}^{\infty} E_\tau fp_{c,\tau+j} + \lim_{j\to\infty} E_t p^f_{c,\tau+j}.$$

Let t be the time of the FOMC announcement and Δ^d the 2-day change around the FOMC announcement, then we can write the 2-day log-change in country c's U.S. dollar exchange rate as

$$\Delta^d p^f_{c,t} \;=\; \underbrace{\sum_{j=0}^{\infty} \Delta^d E_t \left(y_{c,t+j} - y_{US,t+j}\right)}_{\substack{\text{changes in expected risk-free rate}\\ \text{differentials}}} - \underbrace{\sum_{j=0}^{\infty} \Delta^d E_t \lambda_{c,t+j}}_{\substack{\text{changes in expected}\\ \text{U.S. convenience yields}}} - \underbrace{\sum_{j=0}^{\infty} \Delta^d E_t fp_{c,t+j}}_{\substack{\text{changes in expected}\\ \text{currency risk premia}}}, \tag{D4}$$

where we assumed that the expectation of the exchange rate is constant in the limit, so that $\lim_{j\to\infty} \Delta^d E_t p^f_{c,t+j} = 0$.

Country-specific Effects Figure D6 displays the pooled effects reported in the bottom panel of Table 5, along with the country-specific estimates of the countries in the sample. Several points stand out. First, the strong pooled effect on U.S. dollar exchange rates is not driven by any single country. Similarly, the small and insignificant effects on 10-year yield differentials are consistent across countries, with no country showing large or statistically significant responses. Further, for U.S. convenience yields and implied volatilities, countries with stronger exchange rate responses tend to exhibit larger declines in both measures—consistent with the interpretation that the non-yield shock operates operates through both of these channels. An exception is Japan, where the exchange rate response is relatively muted despite more pronounced reactions in convenience yields and implied volatility.

Calculation of Elasticities In order to apply the decomposition in the context of our non-yield shock, we rewrite equation (D4) in terms of the 10-year risk-free rate differential and the 10-year U.S. convenience yield—two objects that can be measured in the data, as discussed in the main text. This allows us to obtain an approximate quantification of the relative importance of the risk-free rates and convenience yields channels.

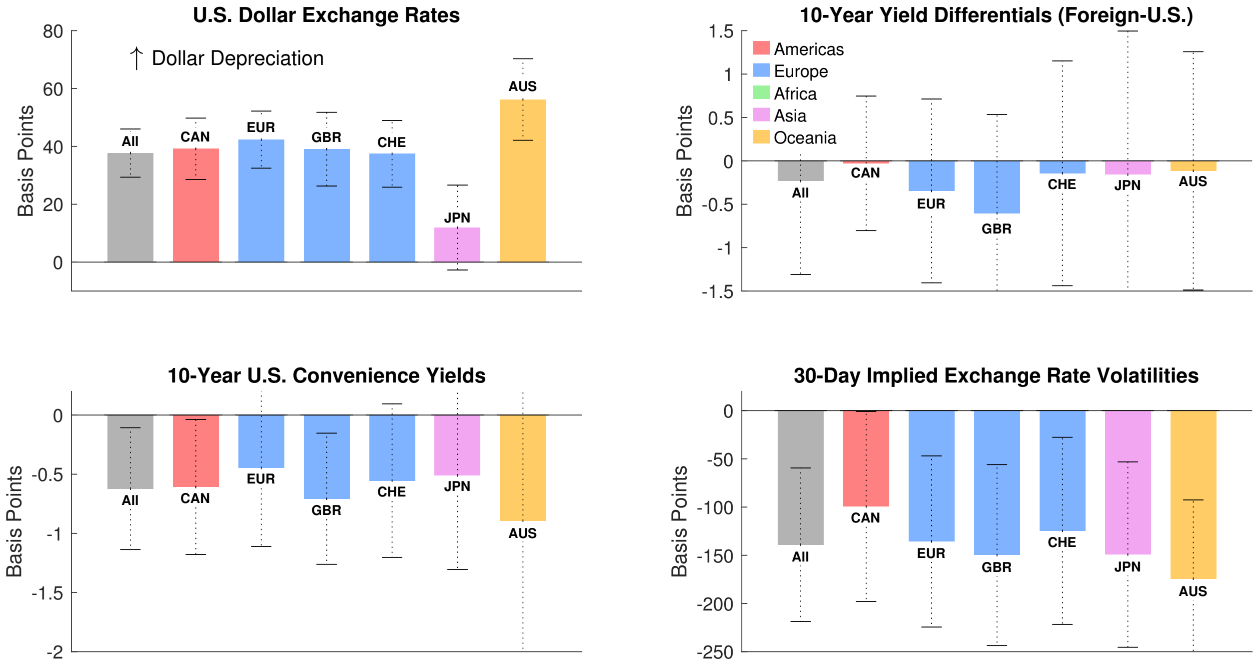
Let $\Delta^d \lambda^{10}_{c,t}$ be the 2-day log-change in the U.S. convenience yield relative to country c over 10 years, i.e.,

$$\Delta^d \lambda^{10}_{c,t} = \frac{1}{10} \sum_{j=0}^{9} \Delta^d E_t \lambda_{c,t+j}.$$

Analogously, let $\Delta^d(y^{10}_{c,t} - y^{10}_{US,t})$ be the 2-day change in the 10-year risk-free rate differentials, i.e.,

$$\Delta^d \left(y^{10}_{c,t} - y^{10}_{US,t}\right) = E_t \left(y^{10}_{c,t} - y^{10}_{US,t}\right) - E_{t-\Delta} \left(y^{10}_{c,t} - y^{10}_{US,t}\right)$$

Figure D6: Effects of Fed Non-yield Shock on Exchange Rate Components



Notes: This figure shows the underlying estimates of Table 5 for the exchange rates. The figure shows the Fed non-yield shock's effects on U.S. dollar exchange rates (top-left panel), 10-year yield differentials (top-right panel), 10-year U.S. convenience yields (bottom-left panel), and 30-day option-implied exchange rate volatilities (bottom-right panel). The dependent variables are constructed as 2-day returns or log-returns, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ of equation (8), while the other bars show the country-specific effects, i.e., the estimates of coefficients δ_c of equation (9). 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.

$$
\begin{aligned}
&= E_t y^{10}_{c,t} - E_{t-\Delta} y^{10}_{c,t} - \left(E_t y^{10}_{US,t} - E_{t-\Delta} y^{10}_{US,t} \right) \\
&= \Delta^d y^{10}_{c,t} - \Delta^d y^{10}_{US,t}.
\end{aligned}
$$

We can then rewrite the exchange rate decomposition in equation (D4) as

$$
\begin{aligned}
\Delta^d p^f_{c,t} =& 10\Delta^d \left(y^{10}_{c,t} - y^{10}_{US,t} \right) + \sum_{j=10}^{\infty} \Delta^d E_t \left(y_{c,t+j} - y_{US,t+j} \right) \\
& - 10\Delta^d \lambda^{10}_{c,t} - \sum_{j=10}^{\infty} \Delta^d E_t \lambda_{c,t+j} \\
& - \sum_{j=0}^{\infty} \Delta^d E_t fp_{c,\tau+j}.
\end{aligned} \tag{D5}
$$

Based on (D5), we arrive at the following elasticities of country c's exchange rate with respect

Table D2: Effects of Fed Non-Yield Shock on Indicators of U.S. Risk Premia

Change (bp)	Equity Premium		Risk Aversion		Uncertainty	
	1-Year	2-Year	BH 2014	BEX 2022	BH 2014	BEX 2022
Fed non-yield shock	-8.21**	-15.37***	-401.33***	-186.47***	-235.97***	-72.92***
	(3.80)	(5.60)	(140.24)	(62.16)	(84.71)	(22.53)
R^2	0.04	0.07	0.04	0.07	0.06	0.04
Observations	234	211	209	239	211	239

Notes: This table presents estimates of δ from specification (8), where the dependent variables are now 2-day changes or log-changes. We use Martin's (2017) equity premium measures. BH 2014, and BEX 2022 refer to the corresponding risk aversion and uncertainty 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.

to the 10-year risk-free rate differential and the 10-year U.S. convenience yield:

$$\frac{\Delta^d p^f_{c,t}}{\Delta^d (y^{10}_{c,t} - y^{10}_{US,t})} = 10 \quad \text{and} \quad \frac{\Delta^d p^f_{c,t}}{\Delta^d \lambda^{10}_{c,t}} = -10.$$

D.7 Additional Results on Risk Premium Channel

Measures of U.S. Equity Risk Premia To provide additional evidence on the risk premium channel, we study the effects on additional stock market-based indicators for risk and risk appetite (see Table D2). The first measures we consider are Martin's (2017) measures for the U.S. equity premium at the 1-year and 2-year horizon.[2] Consistent with the evidence in the main text, we observe a significant decline in U.S. equity premia following our non-yield shock. Using the stock price decomposition (D1), we see that the elasticity with respect to equity premia is the same as that with respect to yields. Hence, applying a elasticity of -2 to the 2-year U.S. equity premium implies an 35 basis points change in the U.S. stock market, or contribution of about 61 percent (=30.74/50.40). Table D2 also shows that the non-yield shock's effects on U.S. risk premia come both from declines in the price of risk (risk aversion) and the amount of risk (uncertainty). For that, we use the measures of Bekaert and Hoerova (2014), who decompose the VIX into risk aversion and uncertainty, and those of Bekaert, Engstrom, and Xu (2022), which are constructed from equities and corporate bonds.

U.S. Term Premia and Interest Rate Volatility We next study the effects on term premia. Employing the widely-used measures from Adrian, Crump, and Moench (2013) and Kim and Wright (2005), the top panel of Table D3 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 D3 indicate that term premia

[2] We thank Benjamin Knox for sharing updated series with us.

Table D3: Effects of Fed Non-Yield Shock on Term Premia and Implied Interest Rate Volatility

Change (%)	Term Premia—ACM 2013			Term Premia—KW 2005		
	1-Year	2-Year	10-Year	1-Year	2-Year	10-Year
Fed non-yield shock	0.42	0.39	1.03	0.03	0.04	0.14
	(0.27)	(0.41)	(0.93)	(0.14)	(0.21)	(0.39)
R^2	0.01	0.01	0.01	0.00	0.00	0.00
Observations	239	239	239	239	239	239

Change (%)	Implied Interest Rate Volatility			
	EDX1	SRU	MOVE	TYVIX
Fed non-yield shock	-2.62***	-0.89***	-1.40***	-1.68***
	(0.72)	(0.31)	(0.42)	(0.52)
R^2	0.03	0.04	0.04	0.05
Observations	194	229	239	142

Notes: This table presents estimates of δ from specification (8), where the dependent variables are now 2-day log-changes of risk and uncertainty indicators, or 2-day changes in term premium measures. See the text for details on the employed variables. KW 2005 and ACM 2013 refer to the corresponding measures by Kim and Wright (2005) and Adrian, Crump, and Moench (2013), 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.

are largely unresponsive to the non-yield shock. Together with the orthogonalization with respect to yield changes, this result then implies that the non-yield shock leaves expectations of future U.S. short-term rates also unchanged, consistent with the results in Table D1.

We also study the effects on option-implied interest rate volatility measures—often used as proxies for monetary policy uncertainty. We start with implied volatility from Eurodollar options, which are based on the LIBOR, a benchmark short-term interest rate, and thus capture short-rate uncertainty over the near term. In particular, we use the measure by Bundick, Herriford, and Smith (2024) (EDX1), which proxies uncertainty over the next half year, as well as the measure by Bauer, Lakdawala, and Mueller (2022) (SRU), which captures uncertainty 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 Volatility (TYVIX) Index, which measures the 1-month ahead option-implied volatility of 10-year Treasury futures.

The bottom panel of Table D3 shows the estimates for all four implied interest rate volatility indexes. In all cases, the Fed non-yield shock leads to a significant decline in implied interest rate volatility, with the strongest effects on the EDX1 measure, i.e., policy-rate uncertainty over the very near term. These estimates imply that the non-yield shock either directly captures changes in interest-rate volatility or that it affects various asset prices through a change in interest rate volatility. That being said, the implied interest rate volatility measures only explain a small amount of variation of our non-yield shock, indicating that our shock captures information beyond these measures. Note that these results are also reminiscent of the findings by Collin-Dufresne and Goldstein (2002) and Cieslak and Povala (2016) that information on interest rate uncertainty is not fully captured in the yield curve.

E Theoretical Framework

In this appendix, we provide details on the argument in Section 4. We begin with stating the assumptions on the data generating process. We then review the assumptions on the estimation procedure before implementing it on the data from the data generating process assumed here. Note that the estimation in Section 4 and this appendix is implemented in the population, that is, the argument abstracts from sampling error.

E.1 Data Generating Process

Suppose the data over narrow event windows is generated by the model (10), where

- 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 satisfying $E[z_t] = 0$ and $V[z_t] = I_r$ for $t \in F$, where I_r is the $r \times r$ identity matrix, and $z_t = 0$ for $t \in NF$.
- ε_t is a $n \times 1$ vector of non-monetary drivers of stock prices and exchange rates satisfying $E[\varepsilon_t] = 0$ and $E[\varepsilon_t \varepsilon_t'] = \Sigma_\varepsilon$ for all t. We additionally assume that $E[z_t \varepsilon_t'] = 0_{k\times n}$.
- A_y is a $k \times r$ matrix capturing the relationship between yield shocks s_t^y and structural shocks z_t. We assume that there are weakly fewer yield shocks than structural monetary policy shocks $k \leq r$, and that the rank of A_y is k.
- A_p is a $n \times r$ matrix capturing how stock price and exchange rate changes in Δp_t depend on the structural shocks z_t. For some results below we assume that $n \geq r$ and that the rank of A_p is r, although these two conditions are not generally necessary (the Jarociński and Karadi (2020) special case below has $1 = n < r = 2$).

E.2 Assumptions on Estimation Framework

The assumptions on the estimation framework are:

- The empirical model (11) is correctly specified.
- No monetary policy shocks exist during non-event windows: $s_t^y = 0$ and $d_t = 0$ for $t \in NF$.
- Orthogonality with non-monetary shocks: $E[s_t^y \varepsilon_t'] = 0$ and $E[s_t^{ny} \varepsilon_t'] = 0$.
- Orthogonality between yield and non-yield shocks: $E\left[s_t^y \left(s_t^{ny}\right)'\right] = 0$.
- Normalization: $V[s_t^{ny}] = I_{r-k}$.

Relative to the estimation framework described in Section 2, the framework here principally allows for more than one non-yield shock. The effects of the non-yield shock(s) are captured by Γ.

E.3 Estimation and Proofs

We now apply our estimation procedure to the data generating process (10).

The estimating equation is (11), where s_t^{ny} is unobserved. Letting $u_t := d_t\Gamma s_t^{ny} + \varepsilon_t$, we can write

$$\Delta p_t = \beta s_t^y + u_t. \tag{E1}$$

Then

$$E\left[u_t\left(s_t^y\right)'\right] = E\left[\left(d_t\Gamma s_t^{ny} + \varepsilon_t\right)\left(s_t^y\right)'\right] = d_t\Gamma E\left[s_t^{ny}\left(s_t^y\right)'\right] + E\left[\varepsilon_t\left(s_t^y\right)'\right] = 0,$$

where the last equality uses the assumptions that $E\left[s_t^y\varepsilon_t'\right] = 0$ and $E\left[s_t^y\left(s_t^{ny}\right)'\right] = 0$ imposed by the estimation procedure. Note that imposing the assumption $E\left[s_t^y\left(s_t^{ny}\right)'\right] = 0$ here implies that the non-yield shocks will be constructed to be orthogonal to the yield shocks.

Given the orthogonality between u_t and s_t^y, β can be estimated by OLS from equation (E1) for $t \in F$ in the population. This gives

$$\begin{aligned}
\beta &= E\left[\Delta p_t\left(s_t^y\right)'\right]\left(E\left[s_t^y\left(s_t^y\right)'\right]\right)^{-1} \\
&= E\left[\left(A_p z_t + \varepsilon_t\right)\left(A_y z_t\right)'\right]\left(E\left[A_y z_t\left(A_y z_t\right)'\right]\right)^{-1} \\
&= \left(A_p E\left[z_t z_t'\right] A_y' + E\left[\varepsilon_t z_t'\right] A_y'\right)\left(A_y E\left[z_t z_t'\right] A_y'\right)^{-1} \\
&= A_p A_y'\left(A_y A_y'\right)^{-1},
\end{aligned}$$

which is equation (12) in the text. Note that the second equality uses equation (10) and the fourth equality uses the facts that $V\left[z_t\right] = I_r$ and $E\left[z_t\varepsilon_t'\right] = 0$. The matrix $A_y A_y'$ is invertible because the rank of A_y is k.

Now the regression error is

$$\begin{aligned}
u_t &= \Delta p_t - \beta s_t^y \\
&= A_p z_t + \varepsilon_t - A_p A_y'\left(A_y A_y'\right)^{-1} A_y z_t \\
&= A_p\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right) z_t + \varepsilon_t.
\end{aligned}$$

Hence, to be consistent with equation (11), the non-yield shock must satisfy

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

This is equation (13) in the text. Note that the annihilator matrix $\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right)$ reflects the orthogonality between s_t^{ny} and s_t^y.

We can then rewrite the estimating equation as

$$\begin{aligned}
\Delta p_t &= \beta s_t^y + u_t \\
&= A_p A_y'\left(A_y A_y'\right)^{-1} A_y z_t + A_p\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right) z_t + \varepsilon_t.
\end{aligned}$$

This is equation (14) in the text. This equation shows that the estimation procedure decomposes the effect of the structural shocks z_t on Δp_t into a component that passes through the yield curve, $A_p A_y' \left(A_y A_y'\right)^{-1} A_y$, and a component that is orthogonal to the yield curve, $A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right)$.

Proposition 1. *Suppose $n \geq r \geq k$, A_y is of full row rank, and A_p is of full column rank. Then the number of non-yield shocks equals the number of structural monetary policy shocks r minus the number of yield shocks k.*

Proof. The projection matrix $A_y' \left(A_y A_y'\right)^{-1} A_y$ maps any vector of structural shocks $z_t \in \mathbb{R}^r$ into the space spanned by the columns of A_y', which is a k-dimensional subspace of $\mathbb{R}^r$. Similarly, the projection matrix $I_r - A_y' \left(A_y A_y'\right)^{-1} A_y$ maps any structural shock $z_t \in \mathbb{R}^r$ into the orthogonal complement of the space spanned by the columns of A_y', which is a $(r-k)$-dimensional subspace of $\mathbb{R}^r$ (see Davidson and MacKinnon, 2004, p. 61). If $n \geq r$ and A_p is of full column rank, then the matrix $A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right)$ maps the structural shock $z_t \in \mathbb{R}^r$ into a $(r-k)$-dimensional subspace of $\mathbb{R}^n$. Hence, there must be $r-k$ non-yield shocks. □

Taking the variance of equation (13) and imposing the normalizations $V\left[s_t^{ny}\right] = I_{r-k}$ as well as $V\left[z_t\right] = I_k$, we obtain

$$\Gamma\Gamma' = A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right) A_p'.$$

This expression defines Γ in the population. Note that the solution is not unique. For any orthogonal matrix U, if Γ solves the above equation, then $\tilde{\Gamma} = \Gamma U$ will also solve the above equation. In the case of one non-yield shock, this property implies that Γ and s_t^{ny} are both pinned down up to a sign flip. In what follows, we will mostly constrain ourselves to instances in which either $r = k$ so that no non-yield shock exists, or to the case where $r - k = 1$, so that there is one non-yield shock. In the case of one non-yield shock, we normalize the first coefficient of Γ to be positive (as in Gürkaynak, Kısacıkoğlu, and Wright, 2020).

It also follows that the rank of Γ must equal $r-k$. Since for any matrix A, $rank\left(A\right) = rank\left(AA'\right)$, and Proposition 1 implies that the rank of $A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right)$ is $r-k$, the rank of $A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right) A_p'$ must also be $r-k$. It follows then that $\Gamma\Gamma'$ must also have rank $r-k$ and so must Γ. We will use the property that Γ has full column rank below.

As in the data, Γ can be estimated from the excess variance on announcement days. Specifically, the variance of u_t on announcement days is

$$\begin{aligned}
V_F\left[u_t\right] &= V\left[A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right) z_t + \varepsilon_t\right] \\
&= A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right) V\left[z_t\right] \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right) A_p' + V\left[\varepsilon_t\right] \\
&= A_p \left(I_r - A_y' \left(A_y A_y'\right)^{-1} A_y\right) A_p' + V\left[\varepsilon_t\right].
\end{aligned}$$

On non-announcement days we have

$$V_{NF}\left[\Delta p_t\right] = V\left[\varepsilon_t\right].$$

Hence,

$$V_F[u_t] - V_{NF}[\Delta p_t] = A_p\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right) A_p' = \Gamma\Gamma',$$

so Γ can be estimated from the observables u_t for $t \in F$ and Δp_t for $t \in NF$.

Note that Section 4 and this appendix study the properties of our estimation procedure under the assumption that the empirical model is correctly specified. There is no form of misspecification. We briefly verify that all assumptions imposed by the estimation procedure hold. Specifically,

1. Given that $s_t^y = A_y z_t$ and how β, Γ, and s_t^{ny} are constructed, the empirical model (11) is correctly specified.

2. There are no monetary policy shocks during the non-event window, since $s_t^y = A_y z_t = 0$ for $t \in NF$ and $d_t = 0$ for $t \in NF$ by assumption.

3. $E[s_t^y \varepsilon_t'] = 0$ follows since

$$E\left[s_t^y \varepsilon_t'\right] = E\left[A_y z_t \varepsilon_t'\right] = A_y E\left[z_t \varepsilon_t'\right] = 0_{k\times n}.$$

   Further, $E[s_t^{ny}\varepsilon_t'] = 0$ whenever the non-yield shock exists. To see this, suppose that WLOG $E[s_t^{ny}\varepsilon_t'] = \Phi$ for some matrix $\Phi \in \mathbb{R}_{(r-k)\times n}$. Then pre-multiplying by Γ and using equation (13) gives

$$\Gamma\Phi = E\left[A_p\left(I - A_y'\left(A_y A_y'\right)^{-1} A_y\right) z_t \varepsilon_t'\right] = A_p\left(I - A_y'\left(A_y A_y'\right)^{-1} A_y\right) E\left[z_t \varepsilon_t'\right] = 0_{n\times n}.$$

   Now, for each column $m = 1, ..., n$ of the matrix Φ we have

$$\sum_{l=1}^{r-k} \gamma_l \phi_{lm} = 0_{n\times 1},$$

   where γ_l is the l'th column of Γ and ϕ_{lm} is the (l, m)-th element of Φ. Since the columns of Γ are linearly independent (see above), the only solution is $\phi_{lm} = 0$ for all $l = 1, ..., r-k$ and all $m = 1, ..., n$. Hence, $E[s_t^{ny}\varepsilon_t'] = 0_{(r-k)\times n}$.

4. Lastly, the non-yield shock is constructed to satisfy $E\left[s_t^y \left(s_t^{ny}\right)'\right] = 0$ and $V[s_t^{ny}] = I_{r-k}$.

Before turning to the proof of Proposition 2, we introduce what we mean by *identifiability* and prove one lemma.

Definition 1 (Identifiability)**.** *We say that k structural monetary policy shocks are identifiable from the yield curve alone if there exists a partition*

$$z_t = \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix}$$

where z_t^1 is a $k \times 1$ vector shocks and z_t^2 is a scalar, and an invertible matrix A satisfying $A_y =$

$\begin{pmatrix} A & B \end{pmatrix}$ *such that*

$$z_t^1 = A^{-1} s_t^y.$$

Hence, for the observable yield shocks s_t^y and an invertible matrix A, it is possible to solve for the k structural shocks in vector z_t^1.

Lemma 1. *Consider the partition of the $k \times (k+1)$ matrix A_y into a $k \times k$ matrix A and a $k \times 1$ vector B such that $A_y = \begin{pmatrix} A & B \end{pmatrix}$. Then*

$$I_r - A_y' \left(A_y A_y'\right)^{-1} A_y = \frac{1}{1 + B' \left(AA'\right)^{-1} B} \begin{pmatrix} A^{-1} BB' \left(A'\right)^{-1} & -A^{-1} B \\ -B' \left(A'\right)^{-1} & 1 \end{pmatrix}.$$

Proof. The proof follows from direct computation:

$$\begin{aligned} I_r - A_y' \left(A_y A_y'\right)^{-1} A_y &= I_r - \begin{bmatrix} A' \\ B' \end{bmatrix} \left(\begin{bmatrix} A & B \end{bmatrix} \begin{bmatrix} A' \\ B' \end{bmatrix} \right)^{-1} \begin{bmatrix} A & B \end{bmatrix} \\ &= I_r - \begin{bmatrix} A' \\ B' \end{bmatrix} \left(AA' + BB'\right)^{-1} \begin{bmatrix} A & B \end{bmatrix}. \end{aligned}$$

Next apply the Sherman-Morrison formula to obtain

$$\left(AA' + BB'\right)^{-1} = \left(AA'\right)^{-1} - \frac{1}{1 + B' \left(AA'\right)^{-1} B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1}.$$

Then

$$\begin{aligned}
&I_r - A_y' \left(A_y A_y'\right)^{-1} A_y \\
&= I_r - \begin{pmatrix} A' \\ B' \end{pmatrix} \left(\left(AA'\right)^{-1} - \frac{1}{1 + B' \left(AA'\right)^{-1} B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1} \right) \begin{pmatrix} A & B \end{pmatrix} \\
&= I_r - \begin{pmatrix} A' \left(\left(AA'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1} \right) \\ B' \left(\left(AA'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1} \right) \end{pmatrix} \begin{pmatrix} A & B \end{pmatrix} \\
&= I_r - \begin{pmatrix} A' \left(\left(AA'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1} \right) A & A' \left(\left(AA'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1} \right) B \\ B' \left(\left(AA'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1} \right) A & B' \left(\left(AA'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} \left(AA'\right)^{-1} BB' \left(AA'\right)^{-1} \right) B \end{pmatrix} \\
&= I_r - \begin{pmatrix} \left(I_k - \frac{1}{1+B'(AA')^{-1}B} A^{-1} BB' \left(A'\right)^{-1} \right) & \left(A^{-1} B - \frac{1}{1+B'(AA')^{-1}B} A^{-1} BB' \left(A'\right)^{-1} A^{-1} B \right) \\ \left(B' \left(A'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} B' \left(A'\right)^{-1} \left(A\right)^{-1} BB' \left(A'\right)^{-1} \right) & \frac{B'\left(AA'\right)^{-1}B}{1+B'(AA')^{-1}B} \end{pmatrix} \\
&= \begin{pmatrix} \frac{1}{1+B'(AA')^{-1}B} A^{-1} BB' \left(A'\right)^{-1} & -\left(A^{-1} B - \frac{1}{1+B'(AA')^{-1}B} A^{-1} BB' \left(A'\right)^{-1} A^{-1} B \right) \\ -\left(B' \left(A'\right)^{-1} - \frac{1}{1+B'(AA')^{-1}B} B' \left(A'\right)^{-1} \left(A\right)^{-1} BB' \left(A'\right)^{-1} \right) & 1 - \frac{B'\left(AA'\right)^{-1}B}{1+B'(AA')^{-1}B} \end{pmatrix} \\
&= \begin{pmatrix} \frac{1}{1+B'(AA')^{-1}B} A^{-1} BB' \left(A'\right)^{-1} & -A^{-1} B \left(1 - \frac{B'\left(A'\right)^{-1} A^{-1} B}{1+B'(AA')^{-1}B} \right) \\ -\left(1 - \frac{B'\left(A'\right)^{-1} (A)^{-1} B}{1+B'(AA')^{-1}B} \right) B' \left(A'\right)^{-1} & \left(1 - \frac{B'\left(AA'\right)^{-1}B}{1+B'(AA')^{-1}B} \right) \end{pmatrix}
\end{aligned}$$

$$= \frac{1}{1 + B' \left(AA'\right)^{-1} B} \left(\begin{array}{cc} A^{-1}BB' \left(A'\right)^{-1} & -A^{-1}B \\ -B' \left(A'\right)^{-1} & 1 \end{array} \right).$$

$\square$

Proposition 2. *Suppose that $r = k + 1$, A_y is of full row rank, and A_p is of full column rank. Then the following statements are equivalent:*

1. *There exists a structural shock that does not affect the yield curve.*

2. *k structural monetary policy shocks are identifiable from the yield curve alone.*

3. *There is one non-yield shock and it has a structural interpretation.*

Proof. We begin with showing that 1. implies 2.

Since there exists a structural shock that does not affect the yield curve, there exists a partition of z_t,

$$z_t = \left(\begin{array}{c} z_t^1 \\ z_t^2 \end{array} \right),$$

where z_t^1 is $k \times 1$ and z_t^2 is is a scalar such that z_t^2 has no effects on the yields. We can then write

$$A_y = \left(\begin{array}{cc} A & 0_{k \times 1} \end{array} \right).$$

Since A_y is of full row rank, the $k \times k$ matrix A must be invertible. It follows from the data generating process (10) that

$$s_t^y = A_y z_t = \left[\begin{array}{cc} A & 0 \end{array} \right] \left(\begin{array}{c} z_t^1 \\ z_t^2 \end{array} \right) = A z_t^1.$$

Since A is invertible, the k structural shocks in z_t^1 are identifiable from the yield curve alone: $z_t^1 = A^{-1} s_t^y$.

We next show that 2. implies 1.

The data generating process implies that $s_t^y = A_y z_t$. WLOG partition

$$z_t = \left(\begin{array}{c} z_t^1 \\ z_t^2 \end{array} \right),$$

where z_t^1 is a $k \times 1$ vector of identifiable shocks and $z_t^2$is a scalar. Further, partition

$$A_y = \left(\begin{array}{cc} \underbrace{A}_{k \times k} & \underbrace{B}_{k \times 1} \end{array} \right).$$

Then

$$s_t^y = \left(\begin{array}{cc} A & B \end{array} \right) \left(\begin{array}{c} z_t^1 \\ z_t^2 \end{array} \right) = A z_t^1 + B z_t^2.$$

Since by assumption k shocks are identifiable from the yield curve, we have $z_t^1 = A^{-1} s_t^y$. Plugging this into the above equation gives

$$s_t^y = AA^{-1} s_t^y + Bz_t^2,$$

so that $Bz_t^2 = 0$ for all z_t^2. Hence, it must be that $B = 0$.

We next show that 1. implies 3.

Since there exists a structural shock that does not affect the yield curve, there exists a partition of z_t,

$$z_t = \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix},$$

where z_t^1 is $k \times 1$ and z_t^2 is is a scalar such that z_t^2 has no effects on the yields. We can then write

$$A_y = \begin{pmatrix} A & 0_{k\times 1} \end{pmatrix}.$$

Since A_y is of full row rank, the $k \times k$ matrix A must be invertible.

Plugging A_y into equation (13) gives

$$\begin{aligned}
\Gamma s_t^{ny} &= A_p \left(I_r - A_y' \left(A_y A_y' \right)^{-1} A_y \right) z_t \\
&= A_p \left(I_r - \begin{pmatrix} A' \\ 0 \end{pmatrix} \left(\begin{pmatrix} A & 0 \end{pmatrix} \begin{pmatrix} A' \\ 0 \end{pmatrix} \right)^{-1} \begin{pmatrix} A & 0 \end{pmatrix} \right) z_t \\
&= A_p \left(I_r - \begin{pmatrix} A' \\ 0 \end{pmatrix} (AA')^{-1} \begin{pmatrix} A & 0 \end{pmatrix} \right) z_t \\
&= A_p \left(I_r - \begin{pmatrix} A' (AA')^{-1} A & 0 \\ 0 & 0 \end{pmatrix} \right) \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix} \\
&= A_p \left(I_r - \begin{pmatrix} A' (A')^{-1} A^{-1} A & 0 \\ 0 & 0 \end{pmatrix} \right) \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix} \\
&= A_p \left(I_r - \begin{pmatrix} I_k & 0 \\ 0 & 0 \end{pmatrix} \right) \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix} \\
&= A_p \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix} \\
&= A_p \begin{pmatrix} 0 \\ z_t^2 \end{pmatrix}.
\end{aligned}$$

Further, partitioning A_p into a $n \times k$ matrix C and a $n \times 1$ vector D gives

$$\Gamma s_t^{ny} = \begin{pmatrix} C & D \end{pmatrix} \begin{pmatrix} 0 \\ z_t^2 \end{pmatrix},$$

and hence

$$\Gamma s_t^{ny} = D z_t^2.$$

Taking variances on both sides gives and using the normalizations that $V\left[s_t^{ny}\right]=1$ and that $V\left[z_t^2\right]=1$, we obtain

$$\Gamma\Gamma' = DD'.$$

Hence, $\Gamma = \pm D$ and $s_t^{ny} = \pm z_t^2$.

Lastly, we show that 3. implies 1.

WLOG partition the structural shocks z_t into a $k \times 1$ vector z_t^1 and a scalar z_t^2 such that

$$z_t = \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix}$$

and $s_t^{ny} = z_t^2$. (The case in which $s_t^{ny} = -z_t^2$ is analogous.) Then equation (13) implies that

$$\Gamma z_t^2 = A_p\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right)\begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix}.$$

Since this condition holds for all z_t^1 and z_t^2, it follows that

$$A_p\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right)\begin{pmatrix} z_t^1 \\ 0 \end{pmatrix} = 0_{n\times 1} \tag{E2}$$

for all z_t^1.

Next, partition $A_y = \begin{pmatrix} A & B \end{pmatrix}$, where A is $k \times k$ and B is $k \times 1$, and $A_p = \begin{pmatrix} C & D \end{pmatrix}$, where C is $n \times k$ and D is $n \times 1$. Then Lemma 1 implies that

$$\begin{aligned} A_p\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right) &= \frac{1}{1+B'\left(AA'\right)^{-1}B}\begin{pmatrix} C & D \end{pmatrix}\begin{pmatrix} A^{-1}BB'\left(A'\right)^{-1} & -A^{-1}B \\ -B'\left(A'\right)^{-1} & 1 \end{pmatrix} \\ &= \frac{1}{1+B'\left(AA'\right)^{-1}B}\begin{pmatrix} \left(CA^{-1}B - D\right)B'\left(A'\right)^{-1} & -CA^{-1}B + D \end{pmatrix}. \end{aligned}$$

Condition (E2) then becomes

$$\frac{1}{1+B'\left(AA'\right)^{-1}B}\left(CA^{-1}B - D\right)B'\left(A'\right)^{-1} z_t^1 = 0_{n\times 1}.$$

In order for this to hold for all z_t^1, it must be that

$$\left(CA^{-1}B - D\right)B'\left(A'\right)^{-1} = 0_{n\times k}.$$

(To see this, choose z_t^1 to be the different unit vectors.) Since A is invertible, it follows that

$$\left(CA^{-1}B - D\right)B' = 0_{n\times k}.$$

Let next

$$B' = \begin{pmatrix} b_1 & b_2 & ... & b_k \end{pmatrix}$$

so that

$$\left(CA^{-1}B - D\right) b_l = 0_{n\times 1}$$

for all $l = 1, ..., k$. Now suppose by contradiction that there is an $l \in \{1, ..., k\}$ such that $b_l \neq 0$, then we must have that

$$CA^{-1}B - D = 0_{n\times 1}.$$

But if this was true, then

$$\begin{aligned} A_p\left(I_r - A_y'\left(A_y A_y'\right)^{-1} A_y\right) &= \frac{1}{1 + B'\left(AA'\right)^{-1} B} \begin{pmatrix} \left(CA^{-1}B - D\right) B'\left(A'\right)^{-1} & -CA^{-1}B + D \end{pmatrix} \\ &= \begin{pmatrix} 0_{n\times k} & 0_{n\times 1} \end{pmatrix}, \end{aligned}$$

which, together with equation (13), implies that there is no non-yield shock. This is a contradiction. Hence, it must be that $B = 0_{k\times 1}$. □

Example 1: The special case of Jarociński and Karadi (2020)

In Jarociński and Karadi's (2020) framework, 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 $A_y = \begin{pmatrix} a & b \end{pmatrix}$ and $A_p = \begin{pmatrix} -c & d \end{pmatrix}$ for strictly positive (but unknown) constants a, b, c, d. Then the data generating process (10) implies that

$$s_t^y = A_y z_t = \begin{pmatrix} a & b \end{pmatrix} \begin{pmatrix} z_t^{\text{pure}} \\ z_t^{\text{info}} \end{pmatrix} = a z_t^{\text{pure}} + b z_t^{\text{info}}.$$

Further,

$$\begin{aligned} \Gamma s_t^{ny} &= A_p\left(I_2 - A_y'\left(A_y A_y'\right)^{-1} A_y\right) z_t \\ &= \begin{pmatrix} -c & d \end{pmatrix} \left(I_2 - \begin{pmatrix} a \\ b \end{pmatrix} \left(\begin{pmatrix} a & b \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix}\right)^{-1} \begin{pmatrix} a & b \end{pmatrix}\right) \begin{pmatrix} z_t^{\text{pure}} \\ z_t^{\text{info}} \end{pmatrix} \\ &= \begin{pmatrix} -c & d \end{pmatrix} \left(\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \frac{1}{a^2 + b^2} \begin{pmatrix} a^2 & ab \\ ab & b^2 \end{pmatrix}\right) \begin{pmatrix} z_t^{\text{pure}} \\ z_t^{\text{info}} \end{pmatrix} \\ &= \begin{pmatrix} -c & d \end{pmatrix} \begin{pmatrix} 1 - \frac{a^2}{a^2+b^2} & -\frac{ab}{a^2+b^2} \\ -\frac{ab}{a^2+b^2} & 1 - \frac{b^2}{a^2+b^2} \end{pmatrix} \begin{pmatrix} z_t^{\text{pure}} \\ z_t^{\text{info}} \end{pmatrix} \end{aligned}$$

$$
\begin{aligned}
&= \begin{pmatrix} -c & d \end{pmatrix} \begin{pmatrix} \frac{b^2}{a^2+b^2} z_t^{\text{pure}} - \frac{ab}{a^2+b^2} z_t^{\text{info}} \\ -\frac{ab}{a^2+b^2} z_t^{\text{pure}} + \frac{a^2}{a^2+b^2} z_t^{\text{info}} \end{pmatrix} \\
&= -c \left(\frac{b^2}{a^2+b^2} z_t^{\text{pure}} - \frac{ab}{a^2+b^2} z_t^{\text{info}} \right) + d \left(-\frac{ab}{a^2+b^2} z_t^{\text{pure}} + \frac{a^2}{a^2+b^2} z_t^{\text{info}} \right) \\
&= -\left(c\frac{b^2}{a^2+b^2} + d\frac{ab}{a^2+b^2} \right) z_t^{\text{pure}} + \left(c\frac{ab}{a^2+b^2} + d\frac{a^2}{a^2+b^2} \right) z_t^{\text{info}} \\
&= \frac{cb+da}{a^2+b^2} \left(-bz_t^{\text{pure}} + az_t^{\text{info}} \right).
\end{aligned}
$$

Taking the variance on both sides gives

$$
V\left[\Gamma s_t^{ny}\right] = V\left[\frac{cb+da}{a^2+b^2} \left(-bz_t^{\text{pure}} + az_t^{\text{info}} \right) \right].
$$

Then, using that $V\left[s_t^{ny}\right] = V\left[z_t^{\text{pure}}\right] = V\left[z_t^{\text{info}}\right] = 1$ and $Cov\left[z_t^{\text{pure}}, z_t^{\text{info}}\right] = 0$, we obtain

$$
\Gamma^2 = \left(\frac{cb+da}{a^2+b^2} \right)^2 \left(a^2+b^2\right),
$$

so that

$$
\Gamma = \pm \frac{cb+ad}{\sqrt{a^2+b^2}}.
$$

Note that if $c = d = 0$, then $\Gamma = 0$, which is why we ruled out this case by assumption.

Lastly, plugging back in gives

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

Example 2

In this example

$$
z_t = \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix},
$$

where $z_t^1 = \begin{pmatrix} z_t^{\text{target}} & z_t^{\text{path}} & z_t^{\text{QE}} \end{pmatrix}'$ and $z_t^2 = z_t^{\text{promise}}$. Further, z_t^{promise} has no effect on the yield curve so that $A_y = \begin{bmatrix} A & 0_{3\times 1} \end{bmatrix}$, where A is an invertible 3×3 matrix.

Then, using $s_t^y = A_y z_t$ from equation (10), we obtain

$$
s_t^y = \begin{bmatrix} A & 0 \end{bmatrix} \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix} = A \begin{pmatrix} z_t^{\text{target}} \\ z_t^{\text{path}} \\ z_t^{\text{QE}} \end{pmatrix}.
$$

Further, using equation (13),

$$
\Gamma s_t^{ny} = A_p \left(I_r - A_y' \left(A_y A_y' \right)^{-1} A_y \right) z_t
$$

$$= A_p \left(I_r - \begin{pmatrix} A' \\ 0 \end{pmatrix} \left(\begin{pmatrix} A & 0 \end{pmatrix} \begin{pmatrix} A' \\ 0 \end{pmatrix} \right)^{-1} \begin{pmatrix} A & 0 \end{pmatrix} \right) z_t$$

$$= A_p \begin{pmatrix} 0 \\ z_t^2 \end{pmatrix}.$$

(See the proof of Proposition 2 for details on the algebra underlying the last equality.) Now partitioning

$$A_p = \left[\underbrace{C}_{n\times k} \quad \underbrace{D}_{n\times 1} \right],$$

implies that $\Gamma s_t^{ny} = D z_t^2$. Taking variances and imposing that $V\left[s_t^{ny}\right] = V\left[z_t^2\right] = 1$ gives

$$\Gamma\Gamma' = DD',$$

and hence

$$\begin{pmatrix} \gamma_1^2 & \gamma_1\gamma_2 & ... & \gamma_1\gamma_n \\ \gamma_2\gamma_1 & \gamma_2^2 & ... & \gamma_2\gamma_n \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_n\gamma_1 & \gamma_n\gamma_2 & ... & \gamma_n^2 \end{pmatrix} = \begin{pmatrix} d_1^2 & d_1 d_2 & ... & d_1 d_n \\ d_2 d_1 & d_2^2 & ... & d_2 d_n \\ \vdots & \vdots & \ddots & \vdots \\ d_n d_1 & d_n d_2 & ... & d_n^2 \end{pmatrix}.$$

Clearly, $\Gamma = \pm D$. From $\Gamma s_t^{ny} = D z_t^2$ it follows that $s_t^{ny} = \pm z_t^2 = \pm z_t^{\text{promise}}$.

F The Role of Fed Communications

F.1 Data Construction

Statement Indicator The indicator equals one on announcement days that are accompanied by a policy statement, and zero otherwise. These statements were introduced in the late 1990s and soon after became a regular feature of every meeting. In our sample 217 of the 239 announcements include a statement.

Press Conference Indicator The indicator equals one if the announcement is accompanied by a press conference, and zero otherwise. Press conferences started in 2011 and were adopted as a regular feature starting in 2019. In our sample 85 of the 239 announcements include a press conference.

Fed Chair Indicator For each Chairman, we construct an indicator variable equal to one if the FOMC meeting took place under that Chair, and zero otherwise. Our sample covers 79 announcements under Chairman Greenspan, 68 under Chairman Bernanke, 32 under Chairwoman Yellen, and 60 under Chairman Powell.

SEP Factor The SEP summarizes the economic forecasts of the FOMC meeting participants (seven Governors and twelve Presidents of the regional Federal Reserve Banks). The SEP is provided for every second FOMC meeting. It was introduced in 2007 but has only been published without delay—on the day of the FOMC announcement—since 2011. In total, 57 out of 239 announcements in our sample were accompanied by the release of the SEP.

We focus on Table 1 of the SEP (typically found on page 1 or 2), which reports participants' forecasts for five variables—*real GDP growth*, *unemployment rate*, *PCE inflation*, *core PCE inflation*, and *federal funds rate*—across four forecast horizons: end of the current year, the subsequent two years, and the longer run. For each forecast, the table provides three summary statistics (the median, the central tendency—defined as the range excluding the three highest and three lowest forecasts—and the full range), along with the corresponding values from the previous SEP.

We summarize the information in the SEP's Table 1 constructing our $|\Delta \textit{Fed projections}|$ variable, which is the absolute value of a common factor estimated via principal component analysis (PCA).[3] The use of PCA is motivated by prior inspection of the data: changes in the forecasts are highly correlated across variables and forecast horizons. The $|\Delta \textit{Fed projections}|$ variable is constructed as follows:

1. Since the median is only reported from 2015 onward, we use the midpoint of the central tendency.[4]

2. For each variable, we construct constant forecast horizons (i.e., 1-year and 2-year ahead) based on the three end-of-year projections. This leaves us with three forecast horizons per variable: 1-year ahead, 2-year ahead, and long-run.

[3] A simple SEP indicator would lead to collinearity with the press conference variable, as the SEP began to be published concurrently with the introduction of press conferences.

[4] For periods where both the midpoint and median are available, they are highly correlated.

3. We compute the change in each forecast statistic relative to the previous SEP.[5]

4. We take the first principal component of the resulting panel of 42 series ($= 3 \times 3 \times 5 - 3$),[6] which explains 31 percent of the overall variation.

5. Finally, we take the absolute value of the first principal component (which is in standard deviations) to obtain our $|\Delta$*Fed projections*$|$ series. Using absolute values allows us to incorporate announcements without an SEP in a consistent manner by treating them as zero observations in the series.

F.2 Analysis

In this section, we investigate the role of Fed communications for our non-yield shock. We begin with a visualization. Figure F1 plots the time series of the non-yield shock and complements each observation with additional information on the Fed chair at the time of the shock as well as whether the announcement was accompanied by a statement and a press conference. Several points stand out. First, some of the largest observation occurred under the chairmanship of Ben Bernanke. In contrast, the magnitudes of the shock appear smallest under Alan Greenspan. Further, during the tenures of Yellen and Powell observations with press conference appear somewhat larger in magnitude. Since there are few announcement days without conference, however, it is difficult to draw firm conclusions from the figure alone.

We therefore proceed with a more formal analysis. Specifically, we test whether the magnitude of our shock series is associated with changes in the informational content of FOMC announcements which are easy to measure. To do so, we regress the absolute value of the non-yield shock on a range of information proxies using the following specification:

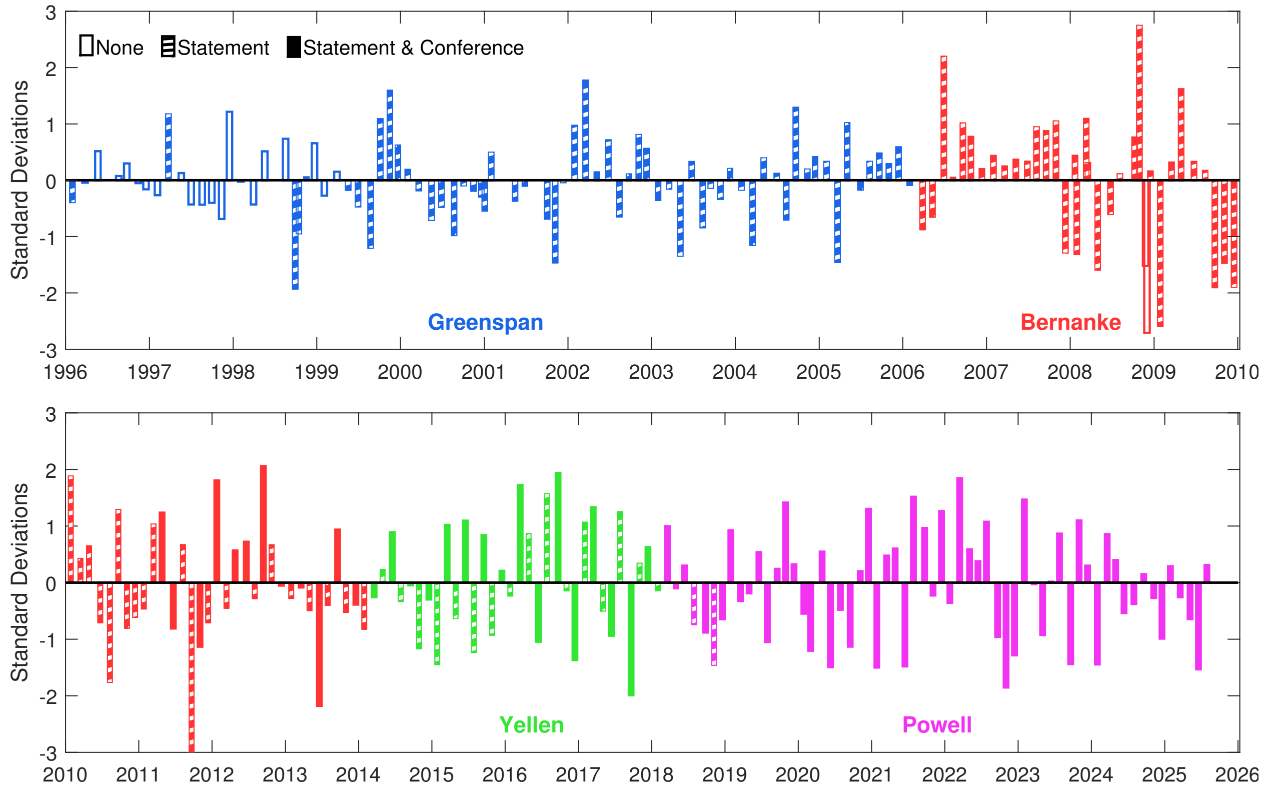
$$|s_t^{ny}| = \alpha + \beta x_t + \eta_t \qquad \text{for } t \in F, \tag{F1}$$

where x_t is a generic vector of independent variables. We use the absolute value of the non-yield shock as the dependent variable, as we hypothesize that the independent variables in x_t raise the magnitude of the shock but do not have a clear prediction for its direction. We consider four independent variables: (1) an FOMC statement indicator, (2) an FOMC press conference indicator, (3) a factor summarizing the forecast revisions in the published Summary of Economic Projections (SEP) ($|\Delta$*Fed projections*$|$), and (4) indicator variables for each Fed chairman. We also include a recession indicator as a control, as Figure F1 suggests that the Great Recession, in particular, may be associated with larger shock realizations.

Table F1 presents the results. The first three columns show that the presence of a statement, a press conference, and the release of SEP projections are each associated with larger shock magnitudes. In all three cases, we estimate a positive and highly significant effects. For example, announcements with press conferences are associated with shocks that are 0.18 standard deviations larger than those on announcement days without press conferences. The third column shows that

[5] For the federal funds rate, which began to be reported in 2015, we set changes to zero.
[6] The subtraction of 3 accounts for the absence of long-run forecasts for *Core PCE inflation*.

Figure F1: Fed Non-yield Shock across Fed Chairs and Types of FOMC Announcements



Notes: This figure displays the time series of the Fed non-yield shock over the sample period. The color coding indicates the chairmanship at the time and the shading whether the announcement was accompanied by a FOMC statement and press conference.

the magnitude of our non-yield shocks increases with the size of forecast revisions: a one standard deviation increase in the forecast revision factor is associated with a 0.15 standard deviation increase in the non-yield shock.

Columns four to seven of Table F1 show how each specific chair affected the magnitude of the shock relative to the other three chairs in the sample period. Here, the coefficients for Chairman Greenspan and Chairman Bernanke stand out, indicating a decline in non-yield shock variability under the former and an increase under the latter. This finding is consistent with Figure F1 and supports the common perception of limited policy communications under Chairman Greenspan and the substantial expansion of Fed communications under Chairman Bernanke. Column eight displays the results when running all indicators jointly. There, we see that only the coefficients on the SEP projection factor and on Chairman Bernanke remain highly significant, while the coefficients on statements and press conferences lose significance. That being said, all coefficients in Table F1 are robustly positive, consistent with the overall idea that information released by FOMC announcements helps to better explain the non-yield shock.

Table F1: Predictive Power of Information Released with FOMC Announcements

Dependent variable: $\lvert s_t^{ny} \rvert$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Statement)	0.26**							0.07
	(0.12)							(0.13)
1(Press Conference)		0.18**						0.11
		(0.08)						(0.14)
$\lvert\Delta$Fed Projections$\rvert$			0.15***					0.12***
			(0.04)					(0.03)
1(Greenspan)				-0.32***				Base Group
				(0.07)				Omitted
1(Bernanke)					0.24**			0.34***
					(0.10)			(0.11)
1(Yellen)						0.15		0.26*
						(0.10)		(0.13)
1(Powell)							0.06	0.10
							(0.08)	(0.16)
Recession Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.04	0.03	0.09	0.05	0.03	0.02	0.10
Observations	239	239	239	239	239	239	239	239

Notes: The table presents estimates of different specifications of equation (F1). The dependent variable is always the absolute value of the Fed non-yield shock (in standard deviations), whereas the set of independent variables varies as indicated in the table. See text for details on the construction of the independent variables. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

F.3 Communication Measures From Prior Work

We next examine whether our non-yield shock can be further linked to FOMC communications, beyond the simple measures considered above. In particular, we focus on three measures from prior studies. First, we use the sentiment measure from Gardner, Scotti, and Vega (2022), which is constructed from FOMC statement texts and aims to capture the Committee's assessment of the state of the economy. This measure is based on a dictionary-based textual analysis. Second, we incorporate the facial expression measure from Curti and Kazinnik (2023), which captures the Fed Chair's facial expressions during press conferences. This measure is derived using machine learning and facial recognition techniques applied to the press conference videos. Lastly, we include the voice tone measure from Gorodnichenko, Pham, and Talavera (2023), which uses machine learning to analyze the Fed Chair's vocal tone based on the press conference audio recordings.

The results are presented in Table F2. All communication measures are signed such that a positive value corresponds to positive sentiment, expression, or tone. Given the challenges in assigning signs to these variables, we also consider a specification using their absolute values. As the table shows, none of the measures exhibit a strong relationship with our non-yield shock. This is perhaps not surprising, as linking interpretable FOMC communications to asset price movements is a notoriously difficult task. Moreover, the sample sizes for the two measures based on press conferences are relatively small, which implies that firm statistical conclusions cannot be drawn.

Table F2: Predictive Power of Fed Communications Measures

	s_t^{ny}			$\|s_t^{ny}\|$		
	(1)	(2)	(3)	(4)	(5)	(6)
Text Sentiment	0.04					
	(0.09)					
Facial Expression		-0.03				
		(0.14)				
Voice Tone			0.02			
			(0.16)			
|Text Sentiment|				0.07		
				(0.10)		
|Facial Expression|					-0.09	
					(0.13)	
|Voice Tone|						-0.23
						(0.24)
R^2	0.00	0.00	0.00	0.00	0.01	0.02
Observations	168	47	36	168	47	36

Notes: The table presents estimates of different specifications of equation (F1). The dependent variable is either the Fed non-yield shock (1–3) or the absolute value of it (3–6). The independent variable is either Gardner, Scotti, and Vega's (2022) *Text Sentiment*, Curti and Kazinnik's (2023) *Facial Expression*, or Gorodnichenko, Pham, and Talavera's (2023) *Voice Tone* measure (or the absolute value thereof). All variables are in units of standard deviations and signed that they refer to positive sentiment, expression, or tone. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

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.

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

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

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. 2025. "The US, economic news, and the global financial cycle." *Review of Economic Studies* :rdaf020.

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

Bundick, Brent, Trenton Herriford, and A Lee Smith. 2024. "The Term Structure of Monetary Policy Uncertainty." *Journal of Economic Dynamics and Control* 160:104803.

Campbell, John Y. 2017. *Financial decisions and markets: a course in asset pricing.* Princeton University Press.

Campbell, John Y, Carolin Pflueger, and Luis M Viceira. 2020. "Macroeconomic drivers of bond and equity risks." *Journal of Political Economy* 128 (8):3148–3185.

Campbell, John Y and Robert J Shiller. 1988. "The dividend-price ratio and expectations of future dividends and discount factors." *The review of financial studies* 1 (3):195–228.

Cieslak, Anna and Pavol Povala. 2016. "Information in the term structure of yield curve volatility." *The Journal of Finance* 71 (3):1393–1436.

Clarida, Richard and Jordi Gali. 1994. "Sources of real exchange-rate fluctuations: How important are nominal shocks?" In *Carnegie-Rochester conference series on public policy*, vol. 41. Elsevier, 1–56.

Collin-Dufresne, Pierre and Robert S Goldstein. 2002. "Do bonds span the fixed income markets? Theory and evidence for unspanned stochastic volatility." *The Journal of Finance* 57 (4):1685–1730.

Converse, Nathan, Eduardo Levy-Yeyati, and Tomas Williams. 2023. "How ETFs amplify the global financial cycle in emerging markets." *The Review of Financial Studies* 36 (9):3423–3462.

Curti, Filippo and Sophia Kazinnik. 2023. "Let's face it: Quantifying the impact of nonverbal communication in FOMC press conferences." *Journal of Monetary Economics* 139:110–126.

Cuthbertson, Keith, Simon Hayes, and Dirk Nitzsche. 1997. "The behaviour of UK stock prices and returns: is the market efficient?" *The Economic Journal* 107 (443):986–1008.

Cuthbertson, Keith and Stuart Hyde. 2002. "Excess volatility and efficiency in French and German stock markets." *Economic Modelling* 19 (3):399–418.

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

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

Froot, Kenneth A and Tarun Ramadorai. 2005. "Currency returns, intrinsic value, and institutional-investor flows." *The Journal of Finance* 60 (3):1535–1566.

Gardner, Ben, Chiara Scotti, and Clara Vega. 2022. "Words speak as loudly as actions: Central bank communication and the response of equity prices to macroeconomic announcements." *Journal of Econometrics* 231 (2):387–409.

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, 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.

Hausman, Joshua K and Johannes F Wieland. 2014. "Abenomics: preliminary analysis and outlook." *Brookings Papers on Economic Activity* 2014 (1):1–63.

He, Zhiguo, Bryan Kelly, and Asaf Manela. 2017. "Intermediary asset pricing: New evidence from many asset classes." *Journal of Financial Economics* 126 (1):1–35.

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.

Jotikasthira, Chotibhak, Christian Lundblad, and Tarun Ramadorai. 2012. "Asset fire sales and purchases and the international transmission of funding shocks." *The Journal of Finance* 67 (6):2015–2050.

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

Kim, Don H and Jonathan H Wright. 2005. "An arbitrage-free three-factor term structure model and the recent behavior of long-term yields and distant-horizon forward rates." .

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. 2025. "How Markets Process Macro News: The Importance of Investor Attention." Tech. rep., Board of Governors of the Federal Reserve System (US).

Lewis, Daniel J. 2025. "Announcement-Specific Decompositions of Unconventional Monetary Policy Shocks and Their Effects." *The Review of Economics and Statistics* 107 (4):1086–1103.

Lucca, David O and Emanuel Moench. 2015. "The pre-FOMC announcement drift." *The Journal of Finance* 70 (1):329–371.

Manley, Richard and Christian Mueller-Glissmann. 2008. "The market for dividends and related investment strategies (corrected)." *Financial Analysts Journal* 64 (3):17–29.

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

Miao, Yanliang and Ms Malika Pant. 2012. *Coincident indicators of capital flows.* International Monetary Fund.

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." .

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* .