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

Christoph E. Boehm
UT Austin and NBER

T. Niklas Kroner
Federal Reserve Board

This draft: August 29, 2024
First draft: March 25, 2021

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. A positive non-yield shock raises stock prices in the U.S. and around the globe, depreciates the dollar against all major currencies, increases global commodity prices, and leads to net capital inflows into emerging market economies. The non-yield shock is essentially uncorrelated with previous monetary policy shocks and its effects are large in comparison. Its strong effects on the VIX and other risk-related measures point towards a dominant risk premium channel. We show that the non-yield shock can be related to Fed communications and that its existence has implications for the identification of structural monetary policy shocks.

JEL Codes: E43, E44, E52, E58, F31, G10

Keywords: Federal Reserve, Monetary Policy, Stock Market, Exchange Rates, Asset Prices, Risk Premia, Information Effects, High-frequency Identification

*We thank Borağan Aruoba, Anna Cieslak, Pierre De Leo, Thomas Drechsel, Refet Gürkaynak, Tarek Hassan, Diego Känzig, Sebnem Kalemli-Ozcan, Burçin Kısacıkoğlu, Benjamin Knox, Arvind Krishnamurthy, Moritz Lenel (discussant), Matteo Maggiori, Michael McMahon, Tyler Muir, Adi Sunderam, Eric Swanson, Jenny Tang, Rosen Valchev, Annette Vissing-Jorgensen, as well as seminar and conference participants at NBER SI 2024, AFA 2024, Dallas Fed, and Maryland for helpful comments. We thank Shaily Acharya for excellent research assistance, as well as Anna Cieslak, Thomas Drechsel, Marek Jarociński, Benjamin Knox, Lee Smith, and Eric Swanson for generously sharing their data with us. A previous version of this paper was circulated under the title "Beyond the Yield Curve: Understanding the Effect of FOMC Announcements on the Stock Market". 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.

1 Introduction

> *No matter how we measure [monetary policy] surprises or how much delay we allow for the response, we can only explain up to about 10 percent of the daily variation in risk appetite. While some of the variation in risk appetite on days with FOMC announcements is certainly driven by news unrelated to monetary policy, it is hard to argue that all, or even most, of the remaining 90 percent of the daily variation in risk appetite is unrelated to monetary policy.*
>
> — Bauer, Bernanke, and Milstein (2023)

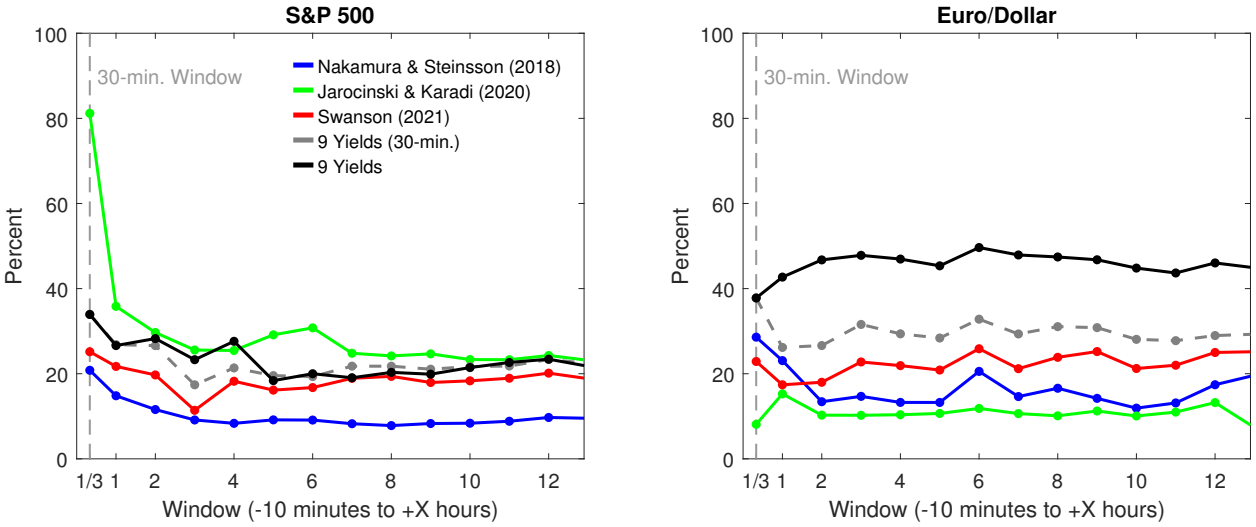
High-frequency monetary policy shocks à la Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005) have puzzlingly low explanatory power for prices of equities and currencies—two asset classes that are crucial for understanding the monetary transmission mechanism. These high-frequency shocks are constructed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

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

One potential avenue to 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 (Jarociński and Karadi, 2020; Gürkaynak, Kara, Kısacıkoğlu, and Lee, 2021).[1] Besides the

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

Figure 1: Explanatory Power of Yield Curve around FOMC Announcements



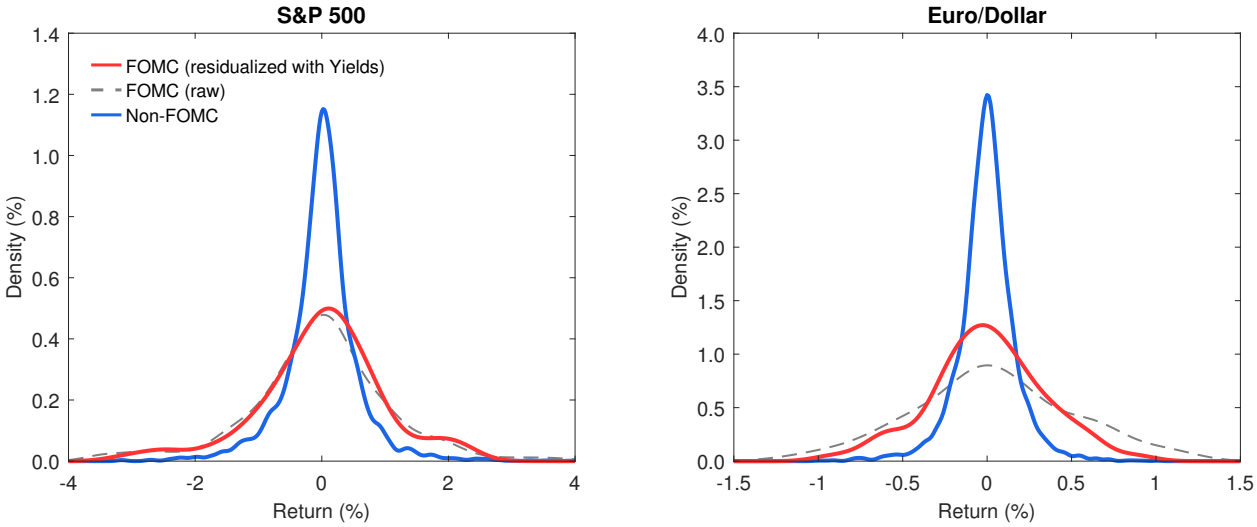
Notes: This figure shows the R^2 of regressing the log-return of the front-month S&P E-mini futures contracts (left panel) and the Euro-Dollar exchange rate (right panel) around FOMC announcements on various different high-frequency shocks. The window over which returns are constructed is expanding as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

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. Further, these shocks have very low explanatory power for exchange rates throughout. This point echoes findings by Gürkaynak et al. (2021, p.1) who conclude that "even after conditioning on possible information effects driving longer term interest rates, there appear to be other drivers of exchange rates."

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

guidance.

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



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

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

In this paper, we show that the unexplained variation in equities and exchange rates reflects a dimension of monetary policy that is not spanned by changes in the yield curve. We 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 non-yield shock. We estimate its effect on U.S. stock prices and various U.S. dollar exchange rates using a heteroskedasticity-based identification procedure (Rigobon, 2003) and the non-yield shock itself using the Kalman filter (Gürkaynak, Kısacıkoğlu, and Wright, 2020). Identification tests show that the non-yield shock is strongly identified. Importantly, we find 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. and foreign stock prices and depreciates the dollar.

We show that the non-yield shock has large and significant effects on international financial markets. In a sample of 40 countries, a one standard deviation non-yield shock moves international stock prices by around 45 basis points, on average, in a two-day window around the announcement. The dollar responds by over 30 basis points relative to foreign currencies. These effects of the non-yield shock are greater in magnitude when compared to the effects of commonly used high-frequency monetary policy shocks from the literature (Nakamura and Steinsson, 2018; Swanson, 2021; Jarociński and Karadi, 2020).

We present a simple model that helps clarify the nature of the non-yield shock and what its presence implies for the identification of structural monetary policy shocks. The model makes clear that the non-yield shock is, in general, a reduced form monetary policy shock. That is, it is a linear combination of the 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.

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. Commonly used identification schemes such as those in Kuttner (2001), Gürkaynak, Sack, and Swanson (2005), and the literature that followed may then remain valid despite 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 and exchange rates. One would expect that it should be possible to relate large realizations of the non-yield shock to concrete policy actions if the non-yield shock is indeed structural.

Under the second interpretation, the non-yield shock is not structural and may therefore lack a clear link to policy actions. 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.

The yield shock is largely unexplained by existing monetary policy shocks from the liter-

ature. This finding is expected for identification schemes, which exclusively focus on interest rates (e.g., Romer and Romer, 2004; Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005, and the literature that followed). However, we further show that shocks that are identified using variation from additional asset prices—such as those by Jarociński and Karadi (2020)—also explain only small shares of the variation in the non-yield shock. Hence, we conclude that the dimension(s) of monetary policy captured by the non-yield shock are largely new. The remainder of the paper tries to better understand the origins and effects of the non-yield shock.

To do so, we look for clues on what the non-yield shock captures and whether we can tie it to concrete policy actions. We show that the non-yield shock has strong and significant effects on a variety of risk-related measures, such as implied volatility measures of stocks (e.g., the VIX) and exchange rates, as well as various measures of risk premia used in the literature. The evidence therefore points toward a dominant risk premium channel. The non-yield shock is also associated with changes in implied interest rate volatility. This suggests that changes in monetary policy uncertainty may generate the non-yield shock—at least in part.

Lastly, we show that the non-yield shock can be statistically linked to Fed communications. Specifically, our results indicate that more communication, for instance through press conferences, is associated with greater shock magnitudes. Further, discussion of risk-related or global economic topics appears to generate variation in the non-yield shock. While these results provide some guidance for the interpretation of the non-yield shock, we acknowledge that more research is needed to fully understand how to best interpret and model the non-yield shock in 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; Lunsford, 2020; Lewis, 2023) or in combination with lower-frequency times series methods (e.g., Gertler and Karadi, 2015; Caldara and Herbst, 2019; Paul, 2020; Miranda-Agrippino and Ricco, 2021). We contribute to this

literature by proposing a method that extracts shocks that are informative about a novel and under-researched dimension of monetary policy not spanned by the yield curve.

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

We also contribute to a fast-growing literature studying the effects of monetary policy on risk perceptions and risk appetite, which are often referred to as the *risk-taking channel* of monetary policy. On the empirical side much work has documented that monetary policy affects risk premia (e.g., Bernanke and Kuttner, 2005; Hanson and Stein, 2015; Gertler and Karadi, 2015). Subsequent work has begun to incorporate these mechanisms into theoretical frameworks (e.g., Alvarez, Atkeson, and Kehoe, 2009; Drechsler, Savov, and Schnabl, 2018; Kekre and Lenel, 2022).[2] We add to this literature by showing that monetary policy has more powerful effects on risk perceptions and risk appetite than previously thought. Our findings further help understand the *exchange rate channel* of monetary policy (e.g., Eichenbaum and Evans, 1995; Faust and Rogers, 2003; Gürkaynak et al., 2021). Specifically, we show that risk premia are not only important for unconditional exchange fluctuations (e.g., Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011; Hassan and Mano, 2019), but also for the monetary policy transmission to exchange rates.

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

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

of "non-traditional" monetary policy on risk premia.

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

Roadmap The remainder of the paper is structured as follows. The next section presents our empirical framework and estimates the non-yield shock. Section 3 documents the importance of the non-yield shock for global asset prices. 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. Section 5 provides evidence on the dominant channels through which the non-yield shock affects asset prices and links it to Fed communications. Lastly, Section 6 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 present the data and specification choices before conducting tests on the strength of the identifying variation. We conclude this section with presenting the estimated shock series.

2.1 Framework

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

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

In this specification $\Delta p_{i,t}$ is the high-frequency return on asset i around the time-t FOMC announcement and F denotes the set of dates/times of FOMC announcements.[3] Further, s_t^y is a vector of k monetary policy shocks that pass through the yield curve (henceforth, "yield shocks"), and β_i is the corresponding vector of coefficients. Following Kuttner (2001)

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

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 potentially indicative of an unobserved dimension of monetary policy. Thus, instead of (1), we consider the following specification in our analysis

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

where s_t^{ny} denotes the latent non-yield shock, 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 include s_t^y nor s_t^{ny}, but be otherwise comparable. Formally,

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

where NF denotes the set of non-announcement dates/times. We will also make use of the fact that we can directly measure s_t^y from interest rate futures following the previous literature. Under the assumption that s_t^y and s_t^{ny} are orthogonal, 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, $d_t = 1\,(t \in F)$ is an announcement indicator, and s_t^{ny} is independently and identically normally distributed with zero mean and unit variance. The variance is normalized to one since γ_i is otherwise only identified up to scale. We assume that both s_t^y and s_t^{ny} are uncorrelated with the error $\varepsilon_{i,t}$ ($Cov\left[s_t^y, \varepsilon_{i,t}\right] = Cov\left[s_t^{ny}, \varepsilon_{i,t}\right] = 0$), which is standard in the literature and plausible if the event windows are sufficiently narrow to prevent simultaneity and omitted variable bias in the estimation.[4]

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

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

where p_t, β, γ, and ε_t denote the appropriately dimensioned matrices capturing $p_{i,t}$, β_i, γ_i, and $\varepsilon_{i,t}$. In our baseline estimation we assume that ε_t is independently and identically normally distributed with a diagonal variance-covariance matrix.[5] Details on the estimation framework are available in Appendix A.

Note that our baseline specification (4) assumes that the changes in stock prices and exchange rates *linearly* depend on the yield shocks s_t^y as captured by coefficient vector β. The presence of substantial non-linearities in yield shocks could lead to a misspecification problem.[6] We will therefore present various robustness checks in Section 2.3 that alleviate such concerns.

[4] 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 A1, we check this assumption by estimating our non-yield shock with demeaned data. The results are almost identical.

[5] We present a robustness check with an unrestricted variance-covariance matrix in Appendix Table A1, which shows very similar results.

[6] We will show in Section 4 that time variation in the composition of structural shocks, as for instance in Jarociński and Karadi (2020), can be captured with our framework and does therefore not lead to a misspecification problem.

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.

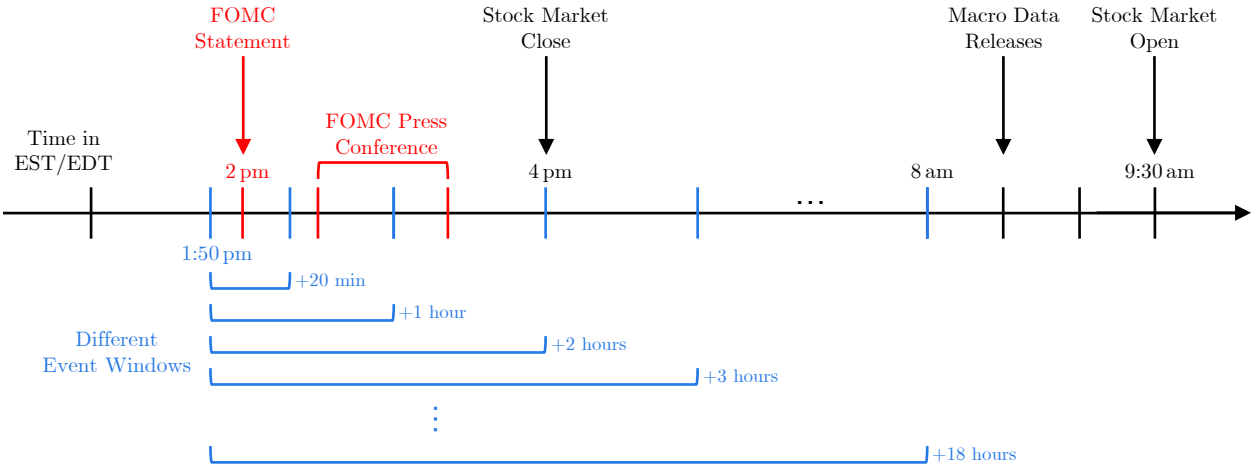
While previous high-frequency, intraday studies typically use windows of 20, 30, or 60 minutes around announcements, we also consider longer windows. Given the amount of information contained in the FOMC announcements as well as in the subsequent press conferences, we expect that stock and currency markets 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). Tighter windows further strengthen the identification with heteroskedasticity-based approaches (Lewis, 2022). A wider window, on the other hand, includes the subsequent press conference, which other papers find to be important for asset prices (e.g., Gorodnichenko, Pham, and Talavera, 2023), and allows the market to fully process the information released in both the FOMC announcements and the press conferences.

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

We therefore proceed in two steps. In a first step, we consider a range of window lengths and multiple asset prices that we 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 on the strength of the identifying variation by asset price and window length to finalize our baseline specification.

Sample Period Our sample period ranges from January 1996 to April 2023. We obtain dates and times of FOMC announcements from *Bloomberg* and cross-check them with information from the Federal Reserve website, and data from prior papers. The announcement sample F includes a total of 220 observations over this period. With very few exceptions, the FOMC announcements are released at 2:15 pm EST (Eastern Standard Time) until January 2013 and at 2:00 pm EST thereafter. The non-announcement sample NF comprises

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.

5085 observations on regular trading days for which we use a timestamp of 2:15 pm EST. Appendix B.1 provides more details on the sample construction.

Event Windows All event windows we consider begin 10 minutes prior to the release. 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 yields,

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

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 *Thomson Reuters Tick History* database. In Appendix B.2, we provide details on the construction and show that all our surprises closely match those of previous studies.

Note that we could alternatively allow for noise in each of the nine surprises by first estimating a factor model via principal components as done in previous work (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Swanson, 2021). However, we prefer to use all raw surprises as our baseline. The main reason is that this approach is more conservative in the context of our application since it makes sure that the non-yield shock does not pick up any information captured in the yield curve over the estimation window. 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 A.4). 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 *Thomson Reuters Tick History* database.

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

Motivated by the need for sufficiently liquid assets, we consider in the forex market the U.S. Dollar exchange rates against the 20 currencies with the highest turnover of over-the-counter (OTC) foreign exchange instruments according to the 2022 Bank of International Settlements (BIS) Triennial Central Bank Survey.[7] We drop the Chinese Yuan and Indian Rupee due to the poor quality of the intraday data, leaving us with 18 U.S. Dollar exchange rates. Figure 2 provides an overview of the 20 asset prices we consider for our baseline specification. Note that all these asset prices will be expressed in log-differences throughout our analysis. Appendix B.3 provides details on how these returns are constructed.

Baseline Specification We next turn to the second specification step, in which we select the event window and the final set of asset prices. This step is based on pre-tests on the strength of the identifying variation for a given asset price i and event window length ℓ. Specifically, we use Lewis's (2022) test for weak identification, which recasts the estimation as an instrumental variable problem and produces a first-stage F-statistic that can be used to assess the strength of the identifying variation. We provide details on this tests in Appendix A.3.

Table 2 reports the F-statistics for each asset price i and event window ℓ. A green background indicates that we can reject the null hypothesis that the maximum asymptotic bias from a weak instrument exceeds 5 percent, while a red background indicates that we cannot reject it. The robust critical value of the hypothesis test is 37.42 and is taken from

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

Table 1: Asset Prices for Consideration as Dependent Variables

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

Notes: This table shows the asset prices considered as dependent variables in our analysis. The data is from *Thomson Reuters Tick History*. For all series, the sample period ends in April 2023. The U.S. Dollar exchanges rates are listed in descending order in terms of turnover of the foreign currency based on the BIS Triennial Central Bank Survey (see footnote 7). *Abbreviation* refers to the abbreviation used in this paper, and *Ticker* refers to the Reuters Instrument Code (RIC).

Montiel Olea and Pflueger (2013). Note that this test is conservative for at least two reasons: First, it uses the *maximum* asymptotic bias. Second, the robust critical value by Montiel Olea and Pflueger (2013) is the highest critical value for a given bias level, while the critical value is decreasing in the number of effective degrees of freedom.

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

Table 2: First-stage F-statistics from Weak Instrument Test

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

Notes: This table shows the results of the first-stage F-tests. For a given event window (row) and asset price (column), the table shows the F-statistic as constructed in equation (A4). 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 maximum asymptotic bias from a weak instrument exceeds 5 percent, and *red* indicates that we cannot reject it. The robust critical value of the hypothesis test is 37.42 and is taken from Montiel Olea and Pflueger (2013). The highlighted 13-hour window is chosen for our baseline specification where we include the 15 asset prices which pass the weak identification test.

asset $i = 1, ..., n$.

Based on this criterion, we select the 13-hour window for our estimation and the 15 asset prices in Table 2 that pass the weak instrument test for this window length. That is, we estimate s_t^{ny} based on equation (4) for $\Delta p_t = \Delta p_t^{(13)}$ and $s_t^y = s_t^{y(13)}$. Here, the yield shocks $s_t^{y(13)}$ are given by equation (5) for $\ell = 13$, and the left-hand side vector of asset prices is

$$\begin{aligned}\Delta p_t^{(13)} = \Big[& \Delta ES1_t^{(13)} \quad \Delta ES2_t^{(13)} \quad \Delta EUR_t^{(13)} \quad \Delta GBP_t^{(13)} \quad \Delta AUD_t^{(13)} \quad \Delta CAD_t^{(13)} \quad ... \\ & \Delta CHF_t^{(13)} \quad \Delta SGD_t^{(13)} \quad \Delta SEK_t^{(13)} \quad \Delta NOK_t^{(13)} \quad \Delta NZD_t^{(13)} \quad ... \\ & \Delta MXN_t^{(13)} \quad \Delta ZAR_t^{(13)} \quad \Delta DKK_t^{(13)} \quad \Delta PLN_t^{(13)} \Big]'. \end{aligned} \tag{6}$$

Note that we have some missing data for the asset prices in vector $\Delta p_t^{(13)}$. This leads samples sizes to differ not only across assets (as shown in Table 1) but also across event windows. Relative to the total number of observations reported above, we loose 22 observations in our baseline sample. More specifically, we are left with 5064 non-FOMC days (instead of 5085), and 219 FOMC days (instead of 220).

Table 3: Estimation Results

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

Notes: This table shows the results of 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.

2.3 Results

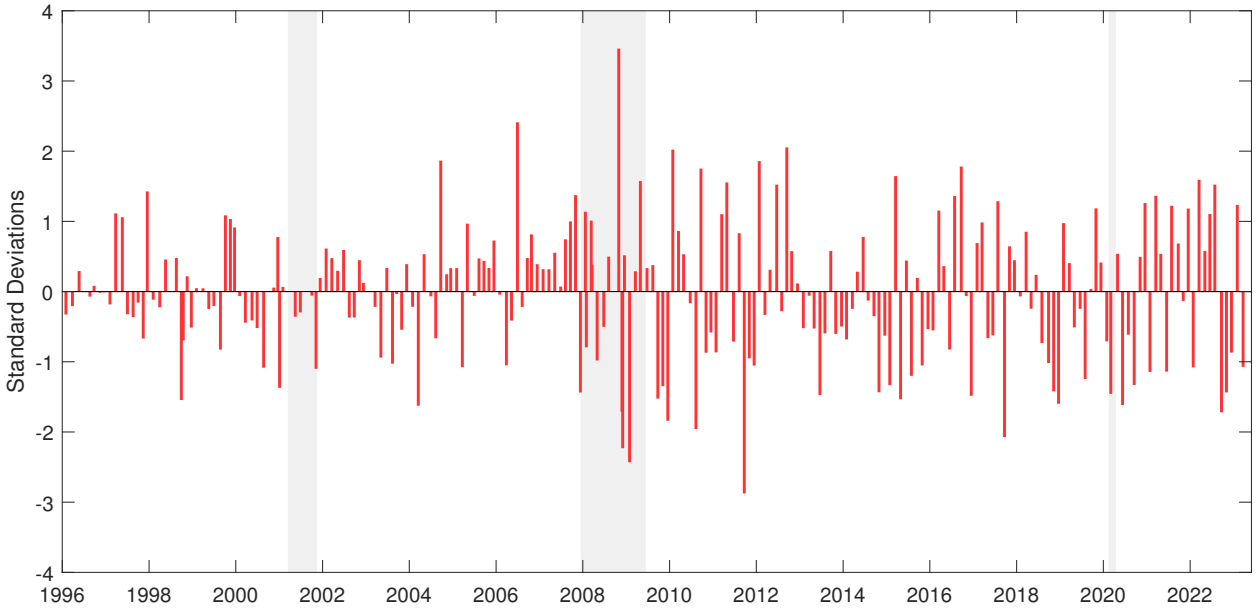
We now turn to the results of our baseline estimation, which are shown in Table 3. Two findings stand out. First, as conjectured, the estimates imply that there is indeed a common factor. For each of the 15 asset prices, our non-yield shock more than doubles the explained variation. For some exchange rates it more than triples the R-squared, explaining almost the entire variation in the 13-hour window. Hence, a single factor can account for a large part of the unexplained variation in these asset prices. However, it also worth noting that for the majority of assets a non-negligible share of the variation remains unexplained. This suggests that assuming that the entirety of asset returns around FOMC announcements is driven by monetary policy, as done by some previous work, might be not innocuous.[8]

Second, the estimated effects of the Fed non-yield shock, i.e., the $\hat{\gamma}_i$, are all highly statistical significant at the one percent level.[9] They are also quite sizable. A one-standard deviation non-yield shock leads to a 62 basis points increase in the E-mini S&P 500 front month futures contract (*ES1*) as well as a 39 and 60 basis points depreciation of the U.S.

[8]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.

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

Figure 4: Time Series of Fed Non-yield Shock



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

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 (106) and negative (113) observations. The autocorrelation of the non-yield shock series is -0.07 ($p > 0.2$).

Robustness We briefly summarize several robustness checks. Appendix Table A1 shows that the baseline estimates of the non-yield shock are robust across a variety of alternative specifications choices. Specifically, we show that our shock is very similar when (i) allowing for a generalized covariance matrix in the estimation, (ii) allowing yield shocks to be present on non-FOMC days, (iii) using three yield curve factors as in Swanson (2021), as well as (iv) including intercepts in the estimation specification.

The baseline specification (4) assumes that the effects of yield shocks on stock prices and exchange rates are linear. Substantial nonlinearities could drive the low explanatory power of yield shocks illustrated in Figure 1 and therefore potentially the existence of the non-yield shock. We check this concern by regressing our baseline non-yield shock on yields while

allowing for non-linear effects. Appendix Table A2 shows that the non-yield shock cannot be explained by (i) squares and interactions of yield shocks, (ii) yield shocks whose effect may vary with their signs, as well as interactions of the yield shocks with (iii) the VIX, (iv) the unemployment rate, or (v) a zero lower bound (ZLB) indicator.

3 The Response of Financial Markets around the World

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

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

$$\Delta^d x_{c,t} = \alpha_c + \delta s_t^{ny} + \eta_{c,t}, \qquad \text{for } t \in F, \tag{7}$$

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

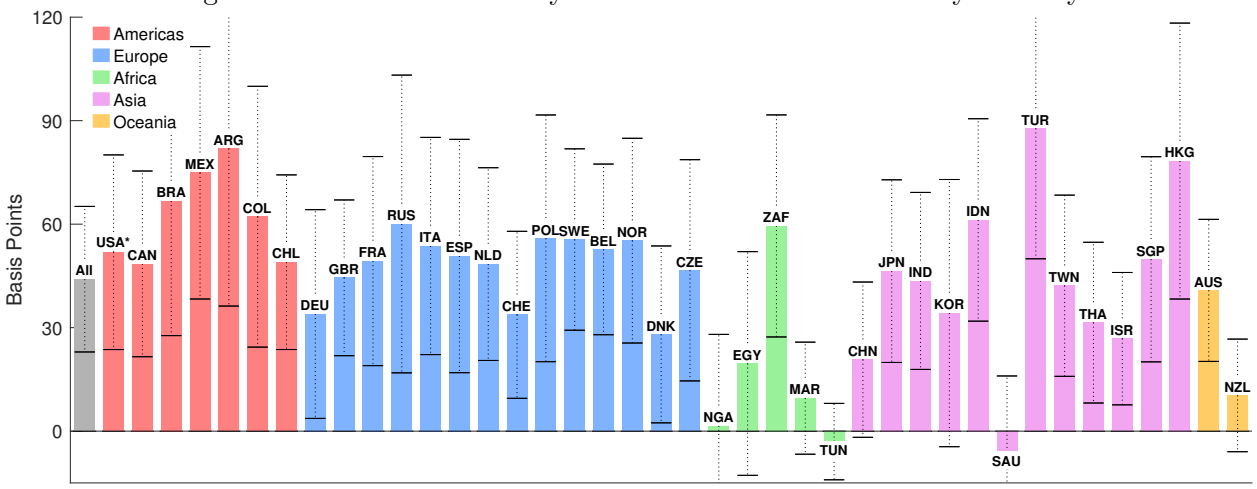
If not otherwise noted, the data comes from *Bloomberg*. Appendix B.4 provides details on this data. Note that we do not exclude any data during periods of financial market stress. However, some of our daily series display extremely large changes in episodes of high market volatility, which are unrelated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

The pooled effect δ, estimated from specification (7), is informative about the average effect on international stock markets. It masks, however, potential heterogeneity in the responses across countries. We therefore also estimate the specification

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

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

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



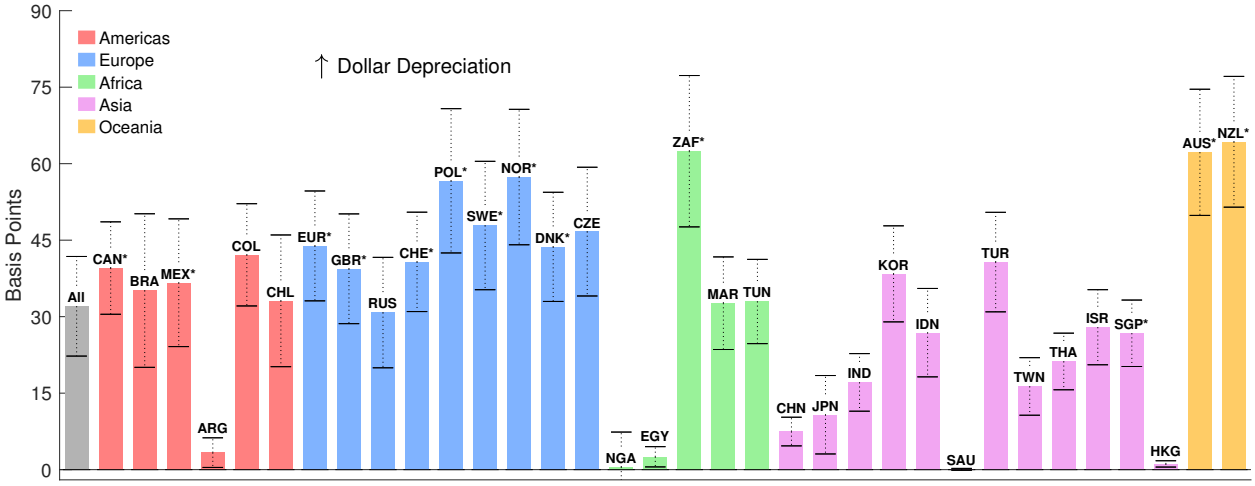
Notes: This figure shows the response of international stock indexes to a one standard deviation positive Fed non-yield shock. The dependent variable is the 2-day return on the stock index of country c, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ from equation (7), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (8). The black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country. We winsorize each country-level return series at the top and bottom 1 percent. * denotes asset prices which have been used in the shock estimation. Abbreviations of asset prices are explained in Appendix Table B3.

3.1 Stock Markets

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

Figure 5 illustrates the estimates of equations (7) and (8) with the 2-day log-difference of countries' stock 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 44 basis points, on average. This effect is highly significant. Further, the non-yield shock generates co-movement in stock prices – making it a driver of the global financial cycle (Rey, 2013; Miranda-Agrippino and Rey, 2020; Boehm and Kroner, 2023). Almost all stock indices increase after a positive non-yield shock. This is the case even though foreign stock market data is not used in the estimation of the non-yield shock. There is some heterogeneity in effect sizes across regions. Countries in North America, South America, and Europe respond most consistently to the non-yield shock. This contrasts with

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



Notes: This figure shows the response of U.S. dollar exchange rates to the Fed non-yield shock. The dependent variable is the 2-day return of the exchange rate, expressed in basis points. Exchange rates are in U.S. dollars per unit of foreign currency so that an increase reflects a depreciation of the U.S. dollar. The leftmost, grey bar shows the pooled effect, i.e., the estimate of the common coefficient δ from equation (7), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (8). The black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country. We winsorize each currency return series at the top and bottom 1 percent. * denotes asset prices which have been used in the shock estimation. Abbreviations of asset prices are explained in Appendix Table B3.

countries in Africa, Asia, and Oceania, which display more heterogeneity in the estimated effect sizes.

3.2 Exchange Rates

We next turn to the effects of the non-yield shock on exchange rates.[10] Specifically, we estimate pooled and country-specific effects based on equations (7) and (8), where the dependent variables are now 2-day log-changes of various exchange rates.

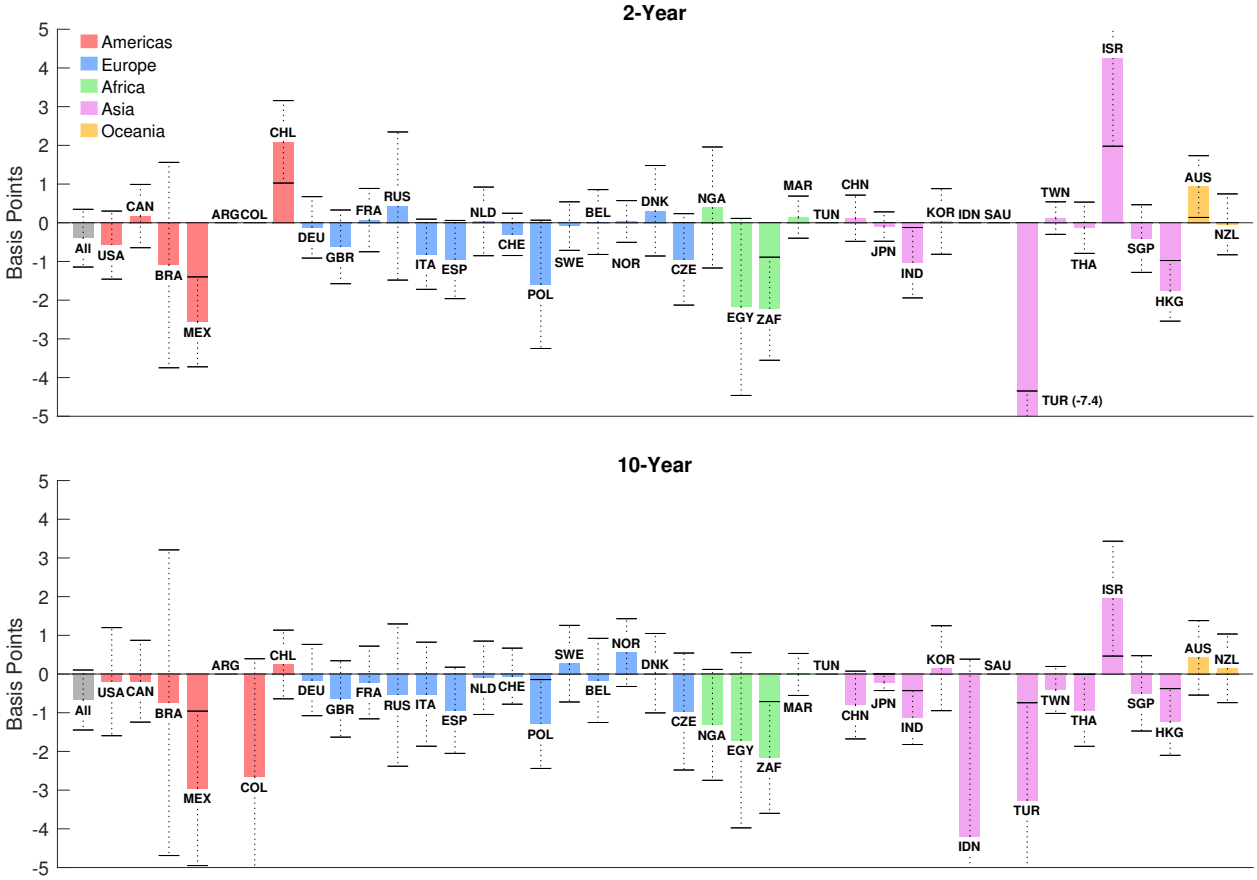
Figure 6 shows the estimates. All exchange rates are expressed in U.S. dollars per unit of foreign currency so that an increase reflects a depreciation of the U.S. dollar. As the figure shows, a one standard deviation positive Fed non-yield shock leads the U.S. dollar to depreciate against other currencies by 32 basis points, on average. While the U.S. dollar depreciates against all currencies considered here, there is large heterogeneity in effect sizes. For instance, the U.S. dollar depreciates by more than 60 basis points vis-à-vis the South African Rand, the New Zealand dollar, and the Australian dollar. In comparison, there is essentially no change in the value of the U.S. dollar relative to the Saudi Riyal or the

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

Hong Kong Dollar. Note that all exchange rates, which are included in the estimation of the non-yield shock, are marked with asterisks in Figure 6. The fact that the U.S. dollar also depreciates against currencies such as the Czech Koruna and the Turkish Lira, which are not included in the shock estimation, indicates that the effects of the non-yield shock are quite broad.

3.3 Bond Markets

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



Notes: This figure shows the response of international government bond yields to the Fed non-yield shock. The dependent variable is the 2-day change in local-currency government bond yields, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of the common coefficient δ from equation (7), while the remaining bars show the country-specific effects, i.e., the estimates of coefficients δ_c from equation (8). The black error bands depict 95 percent confidence intervals, where standard errors are two-way clustered by announcement and by country. We winsorize each country's series at the top and bottom 1 percent. Abbreviations of asset prices are explained in Appendix Table B3.

Next, we study the effects of the non-yield shock on bond markets. Since the Fed non-

yield shock is by construction orthogonal to surprise changes in the U.S. yield curve within a 13-hour window around FOMC announcements, we expect no or only small effects on U.S. bond markets within a 2-day window as well.[11] *A priori* less clear, however, are the reactions of international bond yields to the non-yield shock.

Figure 7 shows the effects on the yields of 2-year and 10-year local-currency denominated government bonds. These estimates are obtained from specifications (7) and (8) with the 2-day changes in yields on the left-hand side. As the figure shows, the pooled effects are economically small and statistically insignificant. Since the standard errors are small, this amounts to a "tight zero". Only for a handful of countries are the effects different from zero. Government bond yields in Mexico and Turkey, for instance, fall significantly after a positive non-yield shock. Yields in Israel, by contrast, increase.

3.4 Commodity Markets

In this section, we study the effects of the Fed non-yield shock on commodity prices. Prior papers documented the pivotal role of commodity prices in explaining economic fluctuations. For example, Fernández, Schmitt-Grohé, and Uribe (2017) show that commodity prices are a fundamental source of global output fluctuations, while Reinhart and Reinhart (2009) find that commodity prices can be generally associated with financial crises. As our non-yield shock is orthogonal to the yield curve, previous papers which have documented the response of commodity prices to yield-based monetary policy shocks (e.g., Frankel, 2008) are unlikely to be informative about the effects of the non-yield shock.

To investigate the response of commodity prices to our shock, we estimate the specification

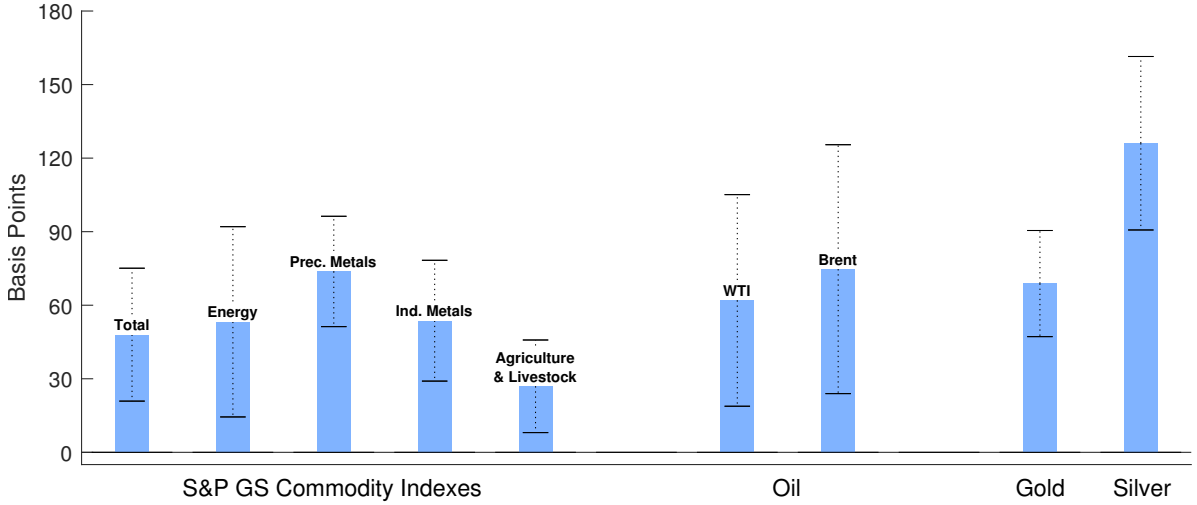
$$\Delta^d x_t = \alpha + \delta s_t^{ny} + \eta_t, \qquad \text{for } t \in F, \tag{9}$$

where $\Delta^d x_t$ is the 2-day log-change in the commodity index or price of interest around the FOMC announcement at time t. In our analysis, we focus on S&P GS commodity indexes to cover the full range of commodities. Appendix Table B6 provides an overview of the commodities underlying each index. We also report separately results for three popular commodity prices: oil, gold, and silver.

Figure 8 illustrates the estimation results. First and foremost, the Fed non-yield shock leads to significant increases in commodities prices on average and across all classes. Further, the effects are strongest for energy and metals.

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

Figure 8: Effects of Fed Non-yield Shock on Commodity Prices



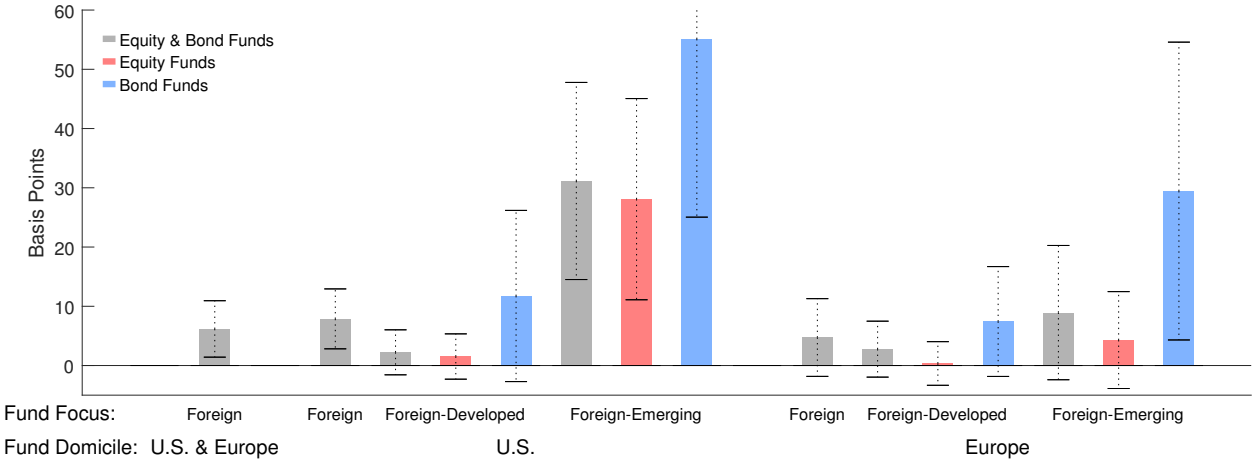
Notes: This figure shows the response of different commodity indexes and prices to the non-yield shock. Commodity price changes are expressed in basis points. Each bar shows the effect on a given commodity price or index, i.e., the estimate of coefficient δ of equation (9) with the 2-day log-change of the commodity price or index of interest on the left-hand side. The black error bands depict 95 percent confidence intervals, where standard errors are clustered by announcement. We winsorize each dependent variable at the top and bottom 1 percent. More details on commodity prices are provided in Appendix Table B5 and B6.

3.5 International Capital Flows

After focusing on asset prices so far, we now study the effects of the Fed non-yield shock on capital flows. Capital flows are an important aspect of the international financial system as they are often seen as integral to understanding financial crises, in particular in emerging market economies (e.g., Reinhart and Reinhart, 2009). Prior papers have studied the effects of yield-based monetary policy shocks on capital flows (e.g., Bruno and Shin, 2015). These estimates, however, are unlikely to be informative about the effects of the non-yield shock due to its orthogonality to yield shocks.

To study capital flows, we employ the funds flow data from Emerging Portfolio Fund Research (EPFR) which covers mutual funds and exchange-traded funds (ETFs). Importantly, it provides data at a daily frequency beginning in 2007. As shown by prior papers, 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 net flows by funds' dominant asset class (equities or bonds), geographic investment focus (developed or emerging

Figure 9: 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 (9). 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.

markets), and domicile. We concentrate on funds domiciled in the U.S. and Western Europe which cover approximately 94 percent of the assets in our sample. That way, we can easily exclude domestic funds, i.e., funds which focus on investments in their country of domicile, as we are interested in international capital flows.

To estimate the effects of our non-yield, we rerun equation (9), where the dependent variables are capital flows across different groups of funds. 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. Further, each flow is expressed in basis points of the total net assets managed by the underlying group of funds. We provide more details on the dataset and the construction of our flow series in Appendix B.5.

Figure 9 displays the estimation results. First and foremost, the figure shows that a positive Fed non-yield shock generally leads to capital inflows from abroad. On average, a one-standard deviation positive Fed non-yield shock causes a 6 basis points inflow (leftmost bar). The effects are driven by the 31 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 through bond funds. More broadly, our findings echo prior evidence

documenting that factors besides interest rates are crucial in understanding capital flows. For example, Forbes and Warnock (2012) argue that global risk is an important driver of capital flows.

3.6 Comparison with Previous Monetary Policy Shocks

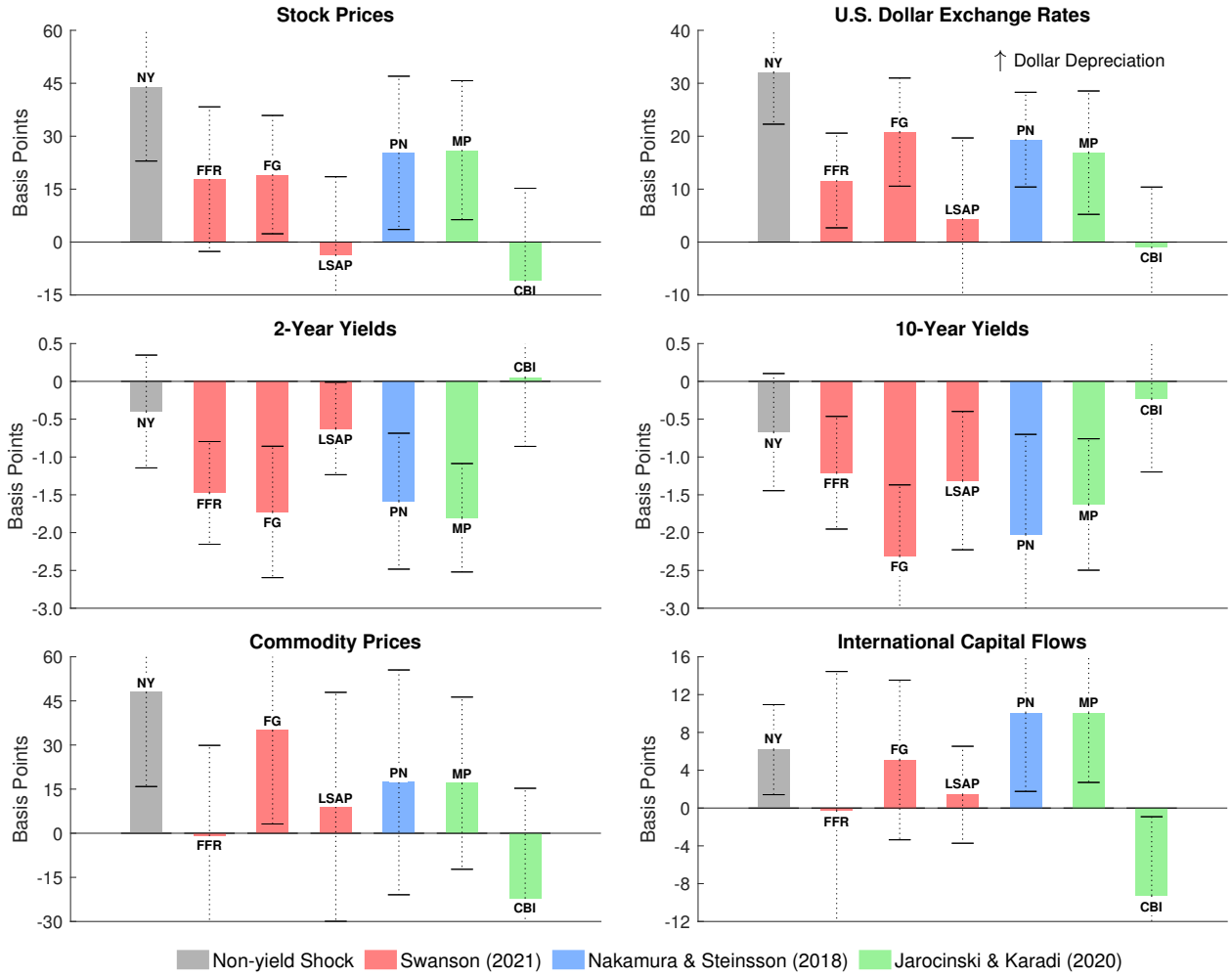
To assess the importance of our non-yield shock, we next compare its effects with the effects of other commonly used monetary policy shocks in the literature. To so do, we re-estimate the pooled specification (7) and specification (9) replacing the non-yield shock with other monetary policy shocks. As in the introduction, we consider shocks from Nakamura and Steinsson (2018), Jarociński and Karadi (2020), and Swanson (2021). Figure 10 shows the estimates. For comparison, the figure also plots the pooled effects of the non-yield shock from Figures 5–7, the effect on the S&P GS Commodity Index from Figure 8, as well as the effect on the foreign capital flow of U.S. & European funds from Figure 9.

Three points stand out. First, the non-yield shock has the largest effects on international stock markets and exchange rates among all shocks. For example, a one standard deviation federal funds rate shock by Swanson (2021), which is essentially the Kuttner (2001) shock and the target rate shock by Gürkaynak, Sack, and Swanson (2005), leads to an 18 basis points change in international stock prices, while the Fed non-yield has an effect of 44 basis points. Second, our non-yield shock has no significant effect on yields while most previous shocks strongly affect yields. Third, the non-yield shock has the strongest effects on commodity prices among all shocks, and a sizable effect on capital flows. These results underscore both the economic significance and the particular nature of our non-yield shock.

3.7 Summary

A positive non-yield shock raises international stock prices, it depreciates the U.S. dollar against a large number of foreign currencies, and it leaves most government bond yields approximately unchanged. Further, we document that the non-yield shock increases commodity prices, and leads to foreign capital inflows, in particular into emerging markets. Overall, the non-yield shock's effects are consistent with a global shift in risk sentiment—an interpretation we further corroborate in Section 5.

Figure 10: 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 the first four panels (stocks, exchange rates, and yields), each bar denotes the pooled effect, i.e., the estimate of the common coefficient δ from equation (7), for a given monetary policy shock of interest. For commodity prices and capital flows, each bar denotes the effect of a monetary policy shock on the S&P GS Commodity Index and on the foreign capital flow of U.S. & European funds, respectively. The dependent variable is always the 2-day change in the asset price of interest, expressed in basis points, except for the capital flow which we measure over a 1-week window. All shocks have been standardized and signed to have a negative effect on the 10-year yield. 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. 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.

4 Implications for the Identification of Monetary Policy Shocks

This section discusses what the presence of the non-yield shock implies for the identification of structural monetary policy shocks. To do so, we introduce a framework that clarifies how the non-yield shock can arise in the data and how it relates to the underlying structural shocks. We show that the non-yield shock is in general a reduced form monetary policy shock but can have a structural interpretation under specific assumptions. We also compare the non-yield shock to previously identified shocks in the literature. It turns out that a substantial amount of information associated with FOMC announcements has not been captured by previous shocks. Details on this section and proofs are relegated to Appendix D.

4.1 Framework

Suppose that the data over narrow event windows 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, 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, 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 that $n \geq r \geq k$, that A_y is of full row rank (k) and A_p of full column rank (r) for some of the results below. A useful way of thinking about the yield shocks s_t^y is that they represent the first k principal components of observed changes in the yield curve over the narrow event window. For instance, we could have $k = 3$ principal components as in Swanson (2021).

We now apply our estimation procedure to this data generating process in the population—or more precisely, a slightly more general procedure that allows for multiple non-yield shocks. The estimating equation is

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

for $t \in F$. Estimating β in the population yields

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

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

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

The orthogonality assumption between s_t^y and s_t^{ny} is reflected in the annihilator matrix $I_r - A_y' \left(A_y A_y'\right)^{-1} A_y$, which residualizes with respect to the yield curve.

It follows from equation (13) that the 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 shock is only a function 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.

4.2 Dimensions of Monetary Policy

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

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

This expression shows that our estimation procedure decomposes the effects of the structural monetary policy shocks z_t on Δp_t into a part that passes through the yield curve and a part that does not pass through the yield curve (the orthogonal complement). The properties of projections then 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.*

Hence, if there are k yield shocks and we detect $r-k$ non-yield shocks in the data, then there must be r structural monetary policy shocks. Note that the framework allows for the possibility that no non-yield shock exists (if $r=k$).

4.3 Two Interpretations of the Non-yield Shock

In the case of one non-yield shock ($r=k+1$), as in our empirical analysis, the following 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 shocks 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*. 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. This implies that 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—and this is the key assumption for this interpretation—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, k structural monetary policy shocks 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 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 above as well as Section 5.1 below.

The second interpretation is that the non-yield shock is 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 point with an example.

Consider the case of Jarociński and Karadi (2020). In their framework, there are two structural monetary policy shocks $z_t = \begin{pmatrix} z_t^{\text{pure}} & z_t^{\text{info}} \end{pmatrix}'$, 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. Equation (10) then implies that

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

Further, straightforward algebra shows that in this case one non-yield shock exists and takes the form

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

Hence, the yield shock and the non-yield shock are both linear combinations of the pure and the information shock. Clearly, a single yield shock s_t^y 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. In addition to the yield shock, the non-yield shock s_t^{ny}, and hence the S&P 500, is required—as well as knowledge of the constants a and b. Interestingly, knowledge of c and d is not directly required for identification although the derivation necessitates that they are not both zero. Relative to directly using a small number of asset prices, such as a single stock price change

Table 4: 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 2023
No. of Shocks	1	1	3	1	1	2	3	4
R^2	0.02	0.00	0.01	0.02	0.01	0.00	0.23	0.17
Observations	91	104	187	185	91	167	112	191

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 2023—Lewis (2023); NS 2018—Nakamura and Steinsson (2018); RR 2004—Romer and Romer (2004); Sw 2021—Swanson (2021).

(Jarociński and Karadi, 2020), the non-yield shock has the advantage that it is purified of the noise ε_t (partially so in finite samples).

Note that equation (16) has a testable prediction. If the true data generating process follows the identification assumptions of Jarociński and Karadi (2020), and we implement our estimation procedure on the resulting data, then the non-yield shock should be a linear combination of the pure and the information shock. A regression of the non-yield shock on the pure and the information shock should deliver a high R-squared. Of course, such a relationship holds more generally. As equation (13) shows, the non-yield shock is generally a linear function of the structural shocks. We proceed in the next section with relating our non-yield shock to prior monetary policy shocks from the literature.

4.4 Common Variation with Previous Monetary Policy Shocks

To do so we regress the non-yield shock on monetary policy shocks constructed in previous work. Table 4 displays the findings of this exercise. 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 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 4 is not *ex-ante* guaranteed.

Second, the shocks by Jarociński and Karadi (2020), who also use the S&P 500 in their

estimation, are orthogonal to our shock, while the shocks by Kroencke, Schmeling, and Schrimpf (2021) and Lewis (2023) have explanatory powers of only 23 and 17 percent, respectively, despite the fact that they directly use stocks and exchange rates in the construction of their shocks. We conclude from this exercise that the large majority of variation that is captured by the non-yield shock has not been directly explored in the prior literature.

5 Understanding the Non-yield Shock

In this section we present evidence on the origins of the non-yield shock as well as the dominant channels through which it affects asset prices.

5.1 Evidence from Asset Prices

Having documented the importance of the Fed non-yield shock for international financial markets in Section 3, we now seek to understand why these asset prices respond. To do so, we combine basic asset pricing theory with data on a variety of indicators that are informative about the underlying channels.

5.1.1 Framework

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

$$\Delta p_{c,t} \approx pd_c \Big(\underbrace{\Delta g_{c,t}}_{\text{growth expectations}} - \underbrace{\Delta ep_{c,t}}_{\text{equity premium}} - \underbrace{\Delta r^f_{c,t}}_{\text{risk-free rate}} \Big) \tag{17}$$

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

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

$$\Delta e_{c,t} = - \underbrace{\Delta \left(r^f_{US,t} - r^f_{c,t} \right)}_{\text{interest rate differential}} - \underbrace{\Delta \left(\lambda_{US,t} - \lambda_{c,t} \right)}_{\text{convenience yield differential}} - \underbrace{\Delta rp_{c,t}}_{\text{risk premium}} . \tag{18}$$

In this expression, $e_{c,t}$ is the log of the exchange rate, which is measured in U.S. dollars per

unit of foreign currency of country c. As before, Δ denotes the difference over the window length of the event study. Turning to the right-hand side, $\Delta\left(r^f_{US,t} - r^f_{c,t}\right)$ is the change in the interest differential between U.S. and foreign long-term risk-free claims. Further, $\Delta\left(\lambda_{US,t} - \lambda_{c,t}\right)$ is the change in the convenience yield of the U.S. dollar bond relative to the foreign bond. Lastly, $\Delta rp_{c,t}$ denotes the change in the excess return of an investor borrowing in dollars and purchasing a foreign-currency denominated bond.[12] Increases in (i) U.S. risk-free rates relative to foreign risk-free rates, (ii) the U.S. convenience yield relative to the foreign convenience yield, and (iii) the risk premium all appreciate the dollar.

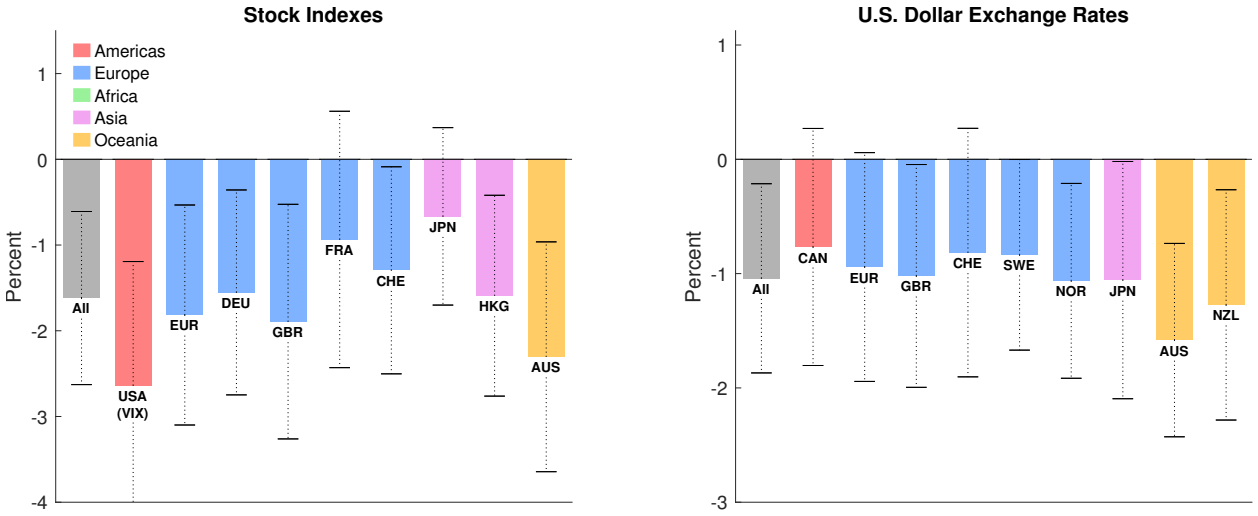
This framework helps interpret the Fed non-yield shock. By construction, the shock is orthogonal to changes in the U.S. interest rates. We verify below that the non-yield shock also leaves risk-free rates unchanged, so that $\Delta r^f_{US,t} = 0$ in equation (18). Further, as shown in Section 3.3, foreign bond yields display no systematic response pattern to the non-yield shock. Instead, the pooled effect is close to zero and precisely estimated. We interpret this lack of response as implying that for most countries $\Delta r^f_{c,t} \approx 0$ in equations (17) and (18). This implies that the observed stock price changes in response to the Fed non-yield shock must follow from a change in growth expectations and/or the equity risk premium. Further, the exchange rate responses must arise from a change in the relative convenience yield and/or the currency risk premium. We next explore the changes in these components in greater detail.

5.1.2 Interest Rates

As noted above, neither U.S. nor foreign yields are affected by the non-yield shock. In Appendix C.1, we provide more evidence on the effects of the Fed non-yield shock on interest rates. First, we show that not only yields but also forward rates are unaffected by the shock. Further, we investigate the response of inflation compensations and real yields. For the U.S., we find some evidence that our a positive non-yield shock leads to increases in inflation compensation. However, the effects are small and the economic interpretation is not straightforward, as TIPS liquidity premia seem to be driving the results rather than inflation expectations. Internationally, inflation compensations do not respond to our shock. Based on this evidence, we conclude that neither real nor nominal interest rates are much affected by the Fed non-yield shock and hence are not of first-order importance for the interpretation of the non-yield shock.

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

Figure 11: Effects of Fed Non-yield Shock on Implied Volatilities



Notes: This figure shows the response of option-implied volatilities for stocks (left panel) and exchange rates (right panel) to the Fed non-yield shock. The dependent variables are constructed as 2-day log-returns, expressed in basis points. The leftmost, grey bar shows the pooled effect, i.e., the estimate of common coefficient δ of equation (7), while the other bars show the country-specific effects, i.e., the estimates of coefficients δ_c of equation (8). The black error bands depict 95 percent confidence intervals, where standard errors are clustered by announcement. We winsorize each country-level series at the top and bottom 1 percent. Abbreviations of asset prices are explained in Appendix Table B4.

5.1.3 Risk Premia

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

We first study the effects on option-implied stock market volatility indexes, such as the VIX, which measure risk aversion and uncertainty. To do so, we estimate a pooled effect as well as country-specific effects using versions of equations (7) and (8), with changes in the VIX and other countries' implied volatility indexes as dependent variables.

The left panel of Figure 11 displays the estimates. As the figure shows, the Fed non-yield shock leads to a decline in implied volatility indexes by 1.6 percent, on average. Except for France and Japan, all country-specific effects are significant at the 5 percent level. The effect on the VIX is the largest. These estimates imply that either uncertainty declines, investors'

willingness to take risk rises, or both.

Uncertainty and risk-bearing capacity are also important for exchange rates (e.g., Lustig and Verdelhan, 2007). Due to the lack of high-frequency measures of expected excess returns on exchange rates, also referred to as uncovered interest rate (UIP) deviations, we use option-implied volatility to proxy for currency risk premia.[13] The right panel of Figure 11 shows the estimates of the pooled and county-specific effects. Similar to implied stock volatilities, the option-implied volatilities of U.S. dollar exchange rates fall following a positive non-yield shock. These responses suggest that currency risk premia explain part of the U.S. dollar movements observed after non-yield shocks.

To better understand these channels, we next turn to a variety of additional indicators for risk, risk appetite, interest rate volatility, and term premia. Specifically, we re-estimate equation (9) with the different indicators as the dependent variables. Table 5 provides the estimates of this exercise. The first measure we consider is Martin's (2017) SVIX, a proxy for the equity premium at the 1-year horizon. While we observe a decline in the SVIX, it is relatively noisy. As emphasized above, the effects on the VIX can either come from changes in the price of risk (risk aversion) or the amount of risk (uncertainty). Bekaert and Hoerova (2014) provide a decomposition of the VIX into measures of risk aversion and uncertainty. We further study the effects on Bekaert, Engstrom, and Xu's (2022) measures, which are constructed from equities and corporate bonds. As our estimates show, a positive non-yield shock leads to a decline in risk aversion as well as uncertainty.

We next study the effects on term premia. Using measures from Adrian, Crump, and Moench (2013) and Kim and Wright (2005), the middle panel of Table 5 shows that the non-yield shock has no discernible effects on term premia. Note that the absence of an effect here is not implied by the identification assumption. While our estimation procedure implies that the non-yield shock is orthogonal to yield changes at all maturities, it does not imply that the non-yield shock is orthogonal to both expected future short-term rates and term premia. Nonetheless, the results in Table 5 indicate that term premia are largely unresponsive to the non-yield shock. Together with the orthogonalization with respect to yield changes, this implies that the non-yield shock leaves expected future short-term rates unchanged as well (see also Appendix C.1).

The evidence this far indicates that premia of riskier assets such as stocks and exchange rates decrease following our non-yield shock, while premia of U.S. bonds are mostly unaffected. Hence, the results suggest that our non-yield shock either leads to higher risk-

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

Table 5: Effects of Fed Non-Yield Shock on Indicators of Risk Premia

Return (%)	VIX	SVIX	Risk Aversion		Uncertainty	
			BH 2014	BEX 2022	BH 2014	BEX 2022
Fed non-yield shock	-2.64***	-0.56*	-3.25**	-1.68***	-2.14**	-0.64**
	(0.73)	(0.28)	(1.55)	(0.64)	(0.89)	(0.25)
R^2	0.07	0.03	0.02	0.06	0.05	0.03
Observations	219	216	208	217	210	217
Return (bp)	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	0.35	1.03	-0.05	-0.08	-0.01
	(0.28)	(0.47)	(0.98)	(0.15)	(0.25)	(0.49)
R^2	0.02	0.00	0.01	0.00	0.00	0.00
Observations	219	219	219	219	219	219
Return (%)	Implied Interest Rate Volatility					
	EDX1	SRU	MOVE	TYVIX		
Fed non-yield shock	-2.38***	-0.91***	-1.22***	-1.49***		
	(0.62)	(0.33)	(0.44)	(0.55)		
R^2	0.02	0.04	0.03	0.04		
Observations	193	199	219	141		

Notes: This table presents estimates of δ from specification (9), 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, ACM 2013, BH 2014, and BEX 2022 refer to the corresponding measures by Kim and Wright (2005), Bekaert and Hoerova (2014), Adrian, Crump, and Moench (2013), 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.

tolerance of investors or incorporates risk-related information, which is not captured in the yield changes. One potential explanation might be that our non-yield shock captures monetary policy uncertainty—an aspect of monetary policy, which has recently received increased attention (e.g., Husted, Rogers, and Sun, 2020; De Pooter, Favara, Modugno, and Wu, 2021; Bauer, Lakdawala, and Mueller, 2022; Bundick, Herriford, and Smith, 2024).

To investigate this hypothesis, we employ uncertainty measures based on option-implied interest rate volatility. 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.

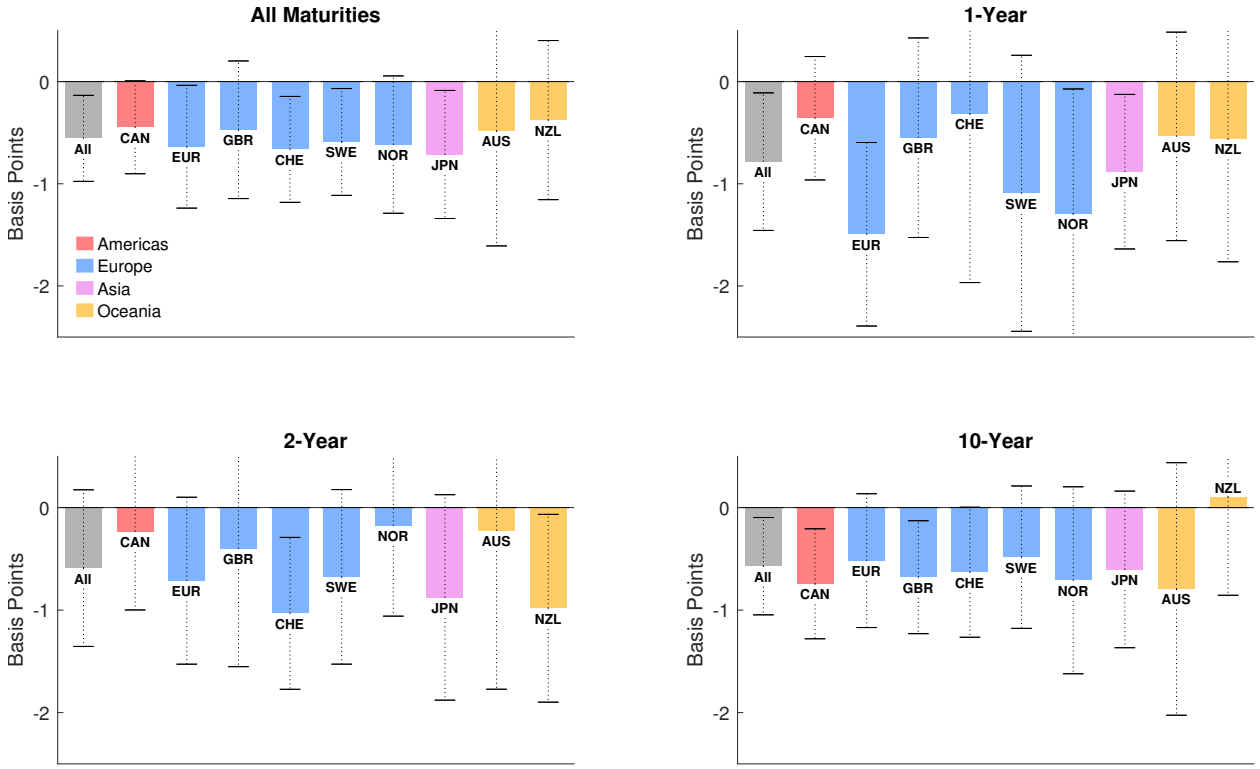
The bottom panel of Table 5 shows the estimates for all four implied interest rate volatility indexes. In all cases, the Fed non-yield shock leads to a significant decline in implied interest rate volatility, with the strongest effects on the EDX1 measure, i.e., policy-rate uncertainty over the very near term. These estimates imply that the non-yield shock either directly captures changes in interest-rate volatility or 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. These results also imply that information on interest rate uncertainty is not fully captured in the yield curve, echoing findings of prior work in the literature.

5.1.4 Convenience Yields

To measure convenience yields we use the "U.S. Treasury premium" series from Du, Im, and Schreger (2018). The Treasury premium measures the convenience yields of U.S. Treasuries relative to other countries' convenience yields on government bonds, i.e., $\lambda_{US,t} - \lambda_{c,t}$ in equation (18). For example, an increase implies that the convenience yield of the U.S. Treasury increases relative to the convenience yield of country c's government bond.

Following Du, Im, and Schreger (2018), we focus on 10 currencies of advanced economies for which convenience yields can be constructed in a relative clean manner. Figure 12 displays the effects of the Fed non-yield shock on convenience yields for various maturities.[14] The results show that the non-yield shock typically leads to a decrease of the Treasury premium. The effects are broadly similar across maturities. Drawing on decomposition (18), these results suggest that the dollar depreciation documented in Figure 6 is partly driven by a reduction in the relative convenience yield of treasuries.

Figure 12: Effects of Fed Non-yield Shock on Convenience Yields



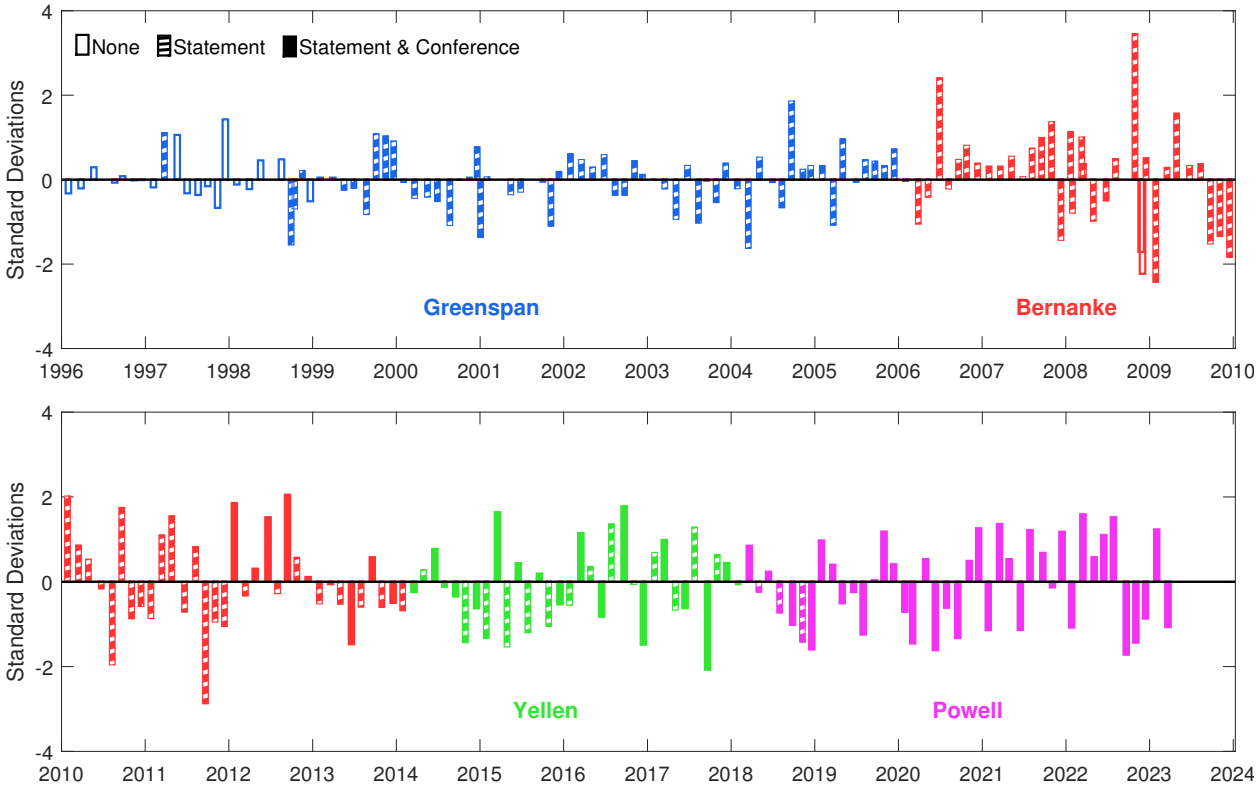
Notes: This figure shows the response of U.S. convenience yields relative to foreign countries' convenience yields to the Fed non-yield shock. The top-left panel shows effects pooled across maturities, for maturities starting at 1-year, i.e., 1-,2-,3-,5-,7-, and 10-year. The top-right panel displays coefficients for the 1-year maturity, whereas the bottom-left and bottom-right panels for the 2-year and 10-year maturities, respectively. The dependent variables are 2-day log-returns, expressed in basis points. The leftmost, grey bars show effects pooled across countries, i.e., the estimate of common coefficient δ of equation (7), while the other bars show the country-specific effects, i.e., the estimates of coefficients δ_c of equation (8). The black error bands depict 95 percent confidence intervals, where standard errors are clustered by announcement. We winsorize each country-level series at the top and bottom 1 percent. Abbreviations of asset prices are explained in Appendix Table B4.

5.2 The Role of Fed Communication

We next seek to understand whether the Federal Reserve's communication on FOMC days is linked to our Fed non-yield shock. Relating asset price movements to specific aspects of the FOMC statement or the press conference is a challenging task and an active literature works on this very question (e.g., Gorodnichenko, Pham, and Talavera, 2023). In the following analysis, we study several dimensions through which Fed communication may cause the Fed non-yield shock.

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

Figure 13: 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.

We begin with a visualization. Figure 13 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.[15]

We therefore proceed with a more formal analysis. Specifically, we regress the abso-

[15] Of our 219 announcements, 23 come without a statement. Except for two during the Great Recession, all of them are before May 1999 when statements were not a regular part of FOMC announcements. We have 63 announcements with press conferences. They were introduced in 2012 and are part of every scheduled meeting since 2019.

lute value of our non-yield shock on a variety of communication-related variables using the specification

$$|s_t^{ny}| = \alpha + \beta x_t + \eta_t \qquad \text{for } t \in F, \tag{19}$$

where x_t is a generic vector of independent variables. We use the absolute value of the non-yield shock as the dependent variable since we hypothesize that the independent variables in x_t raise the magnitude of the shocks while they have no prediction for the sign. Note that throughout the analysis we include a recession indicator as a control to mitigate concerns that the results are driven by recession-specific factors.

We begin with regressing the absolute value of the non-yield shock on two indicator variables. The first indicator equals one on announcement days, which are accompanied by a statement, while the other equals one if the announcement is accompanied by a press conference. The first column of Table 6 shows that both statement and press conference are associated with greater shock magnitudes. For example, announcements with statements have shocks that are 0.26 standard deviations greater than on announcement days without statements. Column two of Table 6 shows that shock magnitudes were greater under the three most recent chairs when compared to the period under chairman Greenspan (omitted base group). This is consistent with the view that the Federal Reserve's communication greatly expanded when Bernanke became chairman. When considering all indicators jointly as shown in column three, only the coefficients on the chairmen remain significant, with Bernanke's one standing out as the largest and most significant.

We next investigate whether specific topics are linked to the magnitude of the non-yield shock. Based on our results this far, we focus on the following three topics: financial, risk-related, and international. To construct each of these topics, we use the term frequency-inverse document frequency (tf-idf) measure of relevant words in the FOMC statement and the press conference. The tf-idf is a widely used statistic in text analysis and measures the importance of a word or group of words in a given document. It takes into account both the frequency of the words in the document as well as the rarity of the words across documents. Details on the construction of the tf-idf measures are available in Appendix B.7.

To measure discussions related to financial markets, we construct td-idfs for words associated with the word stem "financ". Column four of Table 6 displays the estimates of equation (19) with these measures on the right-hand side. We find for FOMC statements that more discussion of financial conditions is indeed linked to variation of our non-yield shock. Column five shows the estimates using td-idfs for words with stems "uncertain" or "risk" and column six presents similarly the estimates for words with stems "international" or "glob". For both

topics, we find evidence that they are associated with more variation in our non-yield shock. Overall, the results are consistent with our non-yield shock being caused by new information in the context of financial, risk-related, and/or international developments.

Lastly, we consider equation (19) with all measures included in the same specification. Column seven of Table 6 displays the estimates of this exercise. Clearly, multiple coefficients become insignificant in the joint specification although none of the individually significant effects change signs. The three regressors whose effects remain significant are the press conference indicator, the chairman Bernanke indicator, and the tf-idf measure of international discussions in the FOMC statement. The potential importance of the press conference for financial markets is consistent with prior papers (e.g., Gorodnichenko, Pham, and Talavera, 2023),[16] and the strong effects of the Bernanke indicator is consistent with the expansion of Fed communication under his chairmanship (Yellen, 2012). Since discussions of international conditions are less frequent they may be more surprising, which could explain the significance of this topic.

6 Conclusion

In this paper we argue that U.S. monetary policy affects asset prices through channels that are not captured by interest rates. Motivated by the facts that (i) yield-based monetary policy shocks have little explanatory power for stocks and currencies around FOMC announcements and (ii) that stocks and currencies display elevated variances around these announcements, we use a heteroskedasticity-based procedure to estimate a Fed non-yield shock. Econometric tests show that this shock is strongly identified. A positive non-yield shock raises global stock prices and depreciates the dollar. Relative to other commonly used monetary policy its effects on these asset classes are large.

We further 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 case the presence of the non-yield shock has no immediate implications for the identification of structural monetary policy shock 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 because the yield curve lacks sufficient information.

[16] Note that since we only have 23 announcements without a statement over our sample period, the statement indicator cannot be as precisely estimated as the one for the press conference.

Table 6: Predictive Power of Fed Communication for Fed Non-Yield Shock

Dependent variable: $\lvert s_t^{ny} \rvert$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(Statement)	0.26**		0.07				0.13
	(0.12)		(0.12)				(0.14)
1(Press Conference)	0.22**		0.06				0.53**
	(0.08)		(0.15)				(0.26)
1(Bernanke)		0.46***	0.44***				0.32***
		(0.10)	(0.11)				(0.12)
1(Yellen)		0.36***	0.31**				0.10
		(0.11)	(0.13)				(0.16)
1(Powell)		0.46***	0.38**				0.09
		(0.09)	(0.17)				(0.20)
Discussion of *Financial Issues*							
Statement				4.27***			1.33
				(1.13)			(1.29)
Press Conference—Statement				-0.09			-4.03
				(2.90)			(3.06)
Press Conference—Q&A				1.41			-4.00
				(2.32)			(3.35)
Discussion of *Risk-related Issues*							
Statement					-1.81		-1.73
					(1.16)		(1.35)
Press Conference—Statement					3.57**		2.17
					(1.78)		(2.25)
Press Conference—Q&A					-0.04		-3.95
					(1.99)		(3.06)
Discussion of *Global Issues*							
Statement						5.67***	3.81**
						(1.36)	(1.86)
Press Conference—Statement						-0.33	-1.87
						(4.31)	(4.34)
Press Conference—Q&A						-2.65	-1.60
						(3.81)	(4.71)
Recession Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.15	0.15	0.10	0.05	0.09	0.20
Observations	219	219	219	219	219	219	219

Notes: The table presents estimates of different specifications of equation (19). The dependent variable is always the absolute value of the Fed non-yield shock, whereas the set of independent variables varies as indicated in the table. See text and Appendix B.7 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.

The non-yield shock triggers substantial movements in measures of risk aversion and uncertainty, suggesting that the main channel through which the non-yield shock affects asset prices is through risk premia. One possibility consistent with our findings is that Fed actions affect interest rate uncertainty. Further, information effects can principally generate the non-yield shock. However, we also showed that Jarociński and Karadi's (2020) series have no explanatory power for the non-yield shock. Therefore, explaining the non-yield shock with information effects would require a modification of the information effects framework. While we demonstrate that the non-yield shock can be related to Fed communications, more work is needed to fully understand its origins.

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.

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

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

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

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

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

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

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

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

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

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

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

Bruno, Valentina and Hyun Song Shin. 2015. "Capital flows and the risk-taking channel of monetary policy." *Journal of Monetary Economics* 71:119–132.

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.

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

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

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

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

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

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.

d'Amico, Stefania, Don H Kim, and Min Wei. 2018. "Tips from TIPS: the informational content of Treasury Inflation-Protected Security prices." *Journal of Financial and Quantitative Analysis* 53 (1):395–436.

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

De Pooter, Michiel, Giovanni Favara, Michele Modugno, and Jason Wu. 2021. "Monetary policy uncertainty and monetary policy surprises." *Journal of International Money and Finance* 114:102401.

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

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

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

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

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

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.

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

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

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

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

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

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

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

———. 2010. "The TIPS yield curve and inflation compensation." *American Economic Journal: Macroeconomics* 2 (1):70–92.

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

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

Husted, Lucas, John Rogers, and Bo Sun. 2020. "Monetary policy uncertainty." *Journal of Monetary Economics* 115:20–36.

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.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Reinhart, Carmen M and Vincent R Reinhart. 2009. "Capital flow bonanzas: An encompassing view of the past and present." In *NBER international seminar on macroeconomics*, vol. 5. The University of Chicago Press Chicago, IL, 9–62.

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.

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

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

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

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

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

Yellen, Janet L. 2012. "Revolution and evolution in central bank communications." *Speech given at the University of California Haas School of Business, Berkeley, California November* 13 (0).

For online publication

A Estimation Appendix

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

A.1 Setup

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

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

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

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

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

A.2 Estimation Algorithm

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

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

and then maximize it via the following EM algorithm:

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

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

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

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

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

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

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

where

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

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

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

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

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

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

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

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

and

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

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

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

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

where

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

and

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

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

Remarks

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

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

A.3 Test for Weak Identification

The pre-tests use the equivalence between the one-step Kalman filter estimation of (4) and a two-step procedure (Gürkaynak, Kısacıkoğlu, and Wright, 2020), which applies the Rigobon (2003)

heteroskedasticity estimator to the residual $\phi_{i,t}$, where $\phi_{i,t}$ is given by

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

after estimating β_i by OLS, and

$$\phi_{i,t} \equiv \Delta p_{i,t} = \varepsilon_{i,t} \quad \text{for } t \in NF.^{17}$$

With this alternative formulation, we can use Lewis's (2022) test for weak identification, which is based on the idea that a heteroskedasticity estimator can be rewritten as an instrumental variable problem (Rigobon and Sack, 2004). With some abuse of notation, let $\Delta p_{i,t}^{(\ell)}$ be the ℓ-hour log-return of an asset price i in Table 1, and let $\phi_{i,t}^{(\ell)}$ be the corresponding residual constructed based on yield shocks $s_t^{y(\ell)}$ as defined in (5). We can then construct for each asset price i and event window ℓ, the following F-statistic

$$F_i^{(\ell)} = \frac{\left(\hat{\Pi}_i^{(\ell)}\right)^2 \left(\sum_{t=1}^T \left(z_{i,t}^{(\ell)}\right)^2\right)^2}{\sum_{t=1}^T \left(z_{i,t}^{(\ell)}\right)^2 \left(\hat{\nu}_{i,t}^{(\ell)}\right)^2}, \tag{A4}$$

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

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

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

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

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

A.4 Robustness

A.4.1 Re-estimation under Alternative Assumptions

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

Generalized Covariance Following Gürkaynak, Kısacıkoğlu, and Wright (2020), we also estimate a version with an unrestricted variance-covariance matrix of ε_t in (4) instead of the diagonal

[17] 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 for that is that the Kalman filter takes the covariance of the assets in Δp_t into account while the two-step procedure can only be implemented for a single asset at a time.

Table A1: Robustness of Fed Non-Yield Shock

	Baseline	Generalized Covariance	Non-FOMC Days Purified	3 Yield Curve Factors	Intercept	Intercept for each Regime
Correlation with Baseline Shock	1.00	0.94	1.00	0.94	1.00	1.00
Average R^2						
without shock	0.33	0.33	0.33	0.26	0.33	0.33
with shock	0.79	0.74	0.79	0.77	0.79	0.79
Observations	219	219	219	219	219	219

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

matrix under the baseline. This specification allows for the possibility of ever-present factors, i.e., drivers which lead to systematic movements on announcement and non-announcement days. As column two of Table A1 illustrates, the shock is very close to the baseline one indicating our estimation is robust to allowing for other unobserved factors which are not related to the FOMC announcement.

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

$$\Delta p_{i,t} = \tilde{\beta}_i s_t^y + \varepsilon_{i,t}, \qquad \text{for } t \in NF, \tag{A5}$$

while the other equations are unchanged. Note that we allow s_t^y to have a difference effect on FOMC days and non-FOMC days. However, the nine surprises in s_t^y are constructed the same way on announcement and non-announcement days. We implement this specification by estimating (A5) by OLS and then run the Kalman filter based on the purified changes, i.e., the residuals of regression (A5). Column three of of Table A1 displays the results. The non-yield shock is essentially unchanged which is consistent with the, on average, low explanatory power of yields for exchange rates and stock prices on non-announcement days. In other words, the exploited variation is very similar to the baseline estimation.

3 Yield Curve Factors We also change the data series used for s_t^y in our estimation. While we use nine interest rate surprises in the baseline version, we now employ three yield curve factors instead. These factors are extracted from the nine series via principal components analysis as in Swanson (2021). The three factors explain 90 percent of the variation in the nine series. With the yield curve factors at hand, we can estimate the model. The fourth column of Table A1 shows the results of this exercise. The estimated shock his very highly correlated with the baseline

series. One thing worth point out is that the average explanatory power of the three factors for the asset returns drops to 26 percent, while the explanatory power including the non-yield shock is 77 percent—almost as much as in the baseline estimation. This may indicate that the Fed non-yield shock in this alternative specification is contaminated with changes in the yield curve that are not captured accurately by the three principal components. The high correlation also suggests that our baseline version is robust to allowing for noise in the yield curve surprises by using the first three principal components instead.

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

A.4.2 The Role of Nonlinearities

We now analyze to what extent our non-yield shock captures nonlinearities with respect to the yield curve shocks. To do so, we regress our non-yield shock on various variables, which capture important nonlinearities, to see how much variation of the non-yield shock can be explained by nonlinearities. We start by re-estimating Swanson's (2021) three shocks over our sample period and based on the 13-hour changes. With the three yield shocks at hand, we can capture different nonlinearities in a parsimonious way.

Specifically, we consider five separate specifications. First, we consider second-order terms of the three yield shocks, i.e., squared shocks and interactions across shocks. Second, we allow for the shocks to have different effects for positive and negative observations. Third, fourth, and fifth, we allow the effects of the shocks to depend on the level of the VIX, the unemployment rate, and the zero lower bound, respectively. As Table A2 illustrates, none of the nonlinearities considered can explain more the 6 percent of our non-yield shock.

Table A2: Robustness of Fed Non-Yield Shock to Nonlinearities

Dependent variable: s_t^{ny}	Second-order Shocks	Positive Shocks	VIX	Unemployment Rate	ZLB
R^2	0.01	0.03	0.05	0.04	0.06
FFR shock	-0.11	0.10	0.00	-0.19**	0.02
FG shock	-0.03	0.13	-0.05	0.08	0.03
LSAP shock	-0.01	0.13	0.04	0.07	-0.10
FFR shock^2	-0.04				
FG shock^2	-0.04				
LSAP shock^2	0.01				
FFR shock × FG shock	-0.04				
FFR shock × LSAP shock	-0.03				
FG shock × LSAP shock	0.01				
1(FFR shock > 0)		-0.40**			
1(FG shock > 0)		-0.13			
1(LSAP shock > 0)		-0.12			
FFR shock × 1(FFR shock > 0)		-0.09			
FG shock × 1(FG shock > 0)		-0.19			
LSAP shock × 1(LSAP shock > 0)		-0.11			
$log(VIX)$			-0.05		
FFR shock × $log(VIX)$			-0.04		
FG shock × $log(VIX)$			0.14		
LSAP shock × $log(VIX)$			-0.10		
F_t^u				-0.01	
FFR shock × F_t^u				-0.24***	
FG shock × F_t^u				0.12	
LSAP shock × F_t^u				0.00	
1(ZLB)					0.12
FFR shock × 1(ZLB)					-1.81**
FG shock × 1(ZLB)					0.10
LSAP shock × 1(ZLB)					0.37**
Constant	0.03	0.52**	-0.01	0.00	0.02
Observations	219	219	219	219	219

Notes: The table shows estimates of regressing the Fed non-yield shock on various variables which capture different nonlinearities. Each column shows the estimates of a separate regression. For brevity, the standard errors of the coefficients are omitted. ***, **, and * indicate significance at the 1, 5, and 10 percent level. See text for more details on the specifications.

B Data Appendix

B.1 Sample Construction

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

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

B.2 Yield Shocks

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

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

Table B1: Overview of Intraday Interest Rate Futures Data

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

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

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

B.2.1 Federal Funds Futures

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

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

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

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 (B1). The construction is done in the followings steps:

1. For each available time ζ, calculate the implied federal funds rate, i.e. $ff_\zeta^1 = 100 - p_\zeta^{ff^1}$.
2. Calculate $\frac{m_0}{m_0-d_0}\left(ff_{\tau+\ell}^1 - ff_{\tau-10}^1\right)$ 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 large $\frac{m_0}{m_0-d_0}$. For example, for the FOMC announcement on January 29, 2014, we have $d_0 = 29$, $m_0 = 31$, and hence $31 - 29 + 1 = 3 < 7$.

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

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

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

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

B.2.2 Eurodollar/SOFR Futures

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

Let $p_\zeta^{ed^j}$ 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

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

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

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

B.2.3 Treasury Futures

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

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

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

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

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

B.2.4 Treatment of Missing Observations

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

B.2.5 Validation

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

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

Table B2: 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						0.94			
T5							0.91		
T10								0.95	
T30									0.93
Observations	105	105	105	105	105	77	94	93	94

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

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

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

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

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

B.4 Daily Financial Market Data

Table B3: Daily Cross-Country Data—Part I

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

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

Table B4: Daily Cross-Country Data—Part II

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

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

Table B5: Daily Commodity Prices and Implied Interest Rate Volatilities

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

Notes: This table shows the daily asset prices considered as outcome variables in Table 5 and Table 8. The data is from *Bloomberg*. For each series, we report sample period (*Sample*) and Bloomberg identifier (*Ticker*).

Table B6: Compositions of Commodity Indexes

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

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

B.5 Capital Flows

B.5.1 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.,

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

B.5.2 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

$$\text{flow}(d_f, g_f, a_f)_t = \text{flow}(d_f, g_f, a_f)_{d_t+5}^{c\%} - \text{flow}(d_f, g_f, a_f)_{d_t-1}^{c\%}, \tag{B6}$$

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 (B6) 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

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

which allows us to write

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

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

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

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 (94 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 (B6), 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 or Bond (a_f = 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 = 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 = 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 = 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.6 Data from other Papers

- Adrian, Crump, and Moench (2013): https://www.newyorkfed.org/research/data_indicators/term-premia-tabs#/overview
- Aruoba and Drechsel (2022): privately shared
- Bauer, Lakdawala, and Mueller (2022): https://www.michaeldbauer.com/files/mpu.csv
- Bu, Rogers, and Wu (2021): https://ars.els-cdn.com/content/image/1-s2.0-S0304393220301276-mmc1.csv
- Bundick, Herriford, and Smith (2024): privately shared
- Du, Im, and Schreger (2018): https://sites.google.com/view/jschreger/CIP?authuser=0
- d'Amico, Kim, and Wei (2018): https://www.federalreserve.gov/econres/notes/feds-notes/DKW_updates.csv
- Gürkaynak, Kısacıkoğlu, and Wright (2020): https://www.openicpsr.org/openicpsr/project/119697/version/V1/view
- Gürkaynak, Sack, and Wright (2007): https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html
- Gürkaynak, Sack, and Wright (2010): https://www.federalreserve.gov/data/tips-yield-curve-and-inflation-compensation.htm
- Jarociński and Karadi (2020): https://www.aeaweb.org/journals/dataset?id=10.1257/mac.20180090
- Kroencke, Schmeling, and Schrimpf (2021): https://ars.els-cdn.com/content/image/1-s2.0-S0304393221000258-mmc2.xls
- Lewis (2023): https://docs.google.com/spreadsheets/d/1l21TwrQpTY5cuqWH92oG-OQHQKpQt9Lm/edit#gid=227445324
- Martin (2017): Updated data from Knox and Vissing-Jorgensen (2022) (privately shared)
- Nakamura and Steinsson (2018): https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HZOXKN
- Romer and Romer's (2004): Updated data from Aruoba and Drechsel (2022) (privately shared)
- Swanson (2021): https://sites.socsci.uci.edu/~swanson2/papers/pre-and-post-ZLB-factors-extended.xlsx

B.7 Textual Analysis

We download the texts of the FOMC statements and press conferences directly from the Federal Reserve website.[18] We do a standard cleaning of the documents, where we remove headers, footers, and page numbers. For the press conference, we eliminate sentences that convey no relevant information such as the chair's initial greeting or its transitioning sentence to the Q&A. We have 219 FOMC announcements in total. 23 of these come without a statement which, except for two during the Great Recession, are all before May 1999 when statements were not a regular part of the FOMC. We have 63 announcements with press conferences. They were introduced in 2012 and became a regular part of each meeting in 2019. Press conferences include both an initial statement and subsequent Q&A which we treat as separate documents. Overall, a given announcement t has between zero and three documents (statement, press conference statement, and press conference Q&A) associated with it.

Let q be the set of terms of interest. The term frequency-inverse document frequency (tf-idf) of q in document d is then given by

$$\text{tf-idf}_{d,q} = \underbrace{\frac{Q_d(q)}{Q_d}}_{\text{term frequency of } q \text{ in } d} \times \underbrace{\left(\log \frac{1+D}{1+D(q)} + 1\right)}_{\text{inverse document frequency of } q},$$

where $Q_d(q)$ is the number of times terms in set q appear in document d, Q_d is the total number of terms in document d, $D(q)$ is the number of documents that contain terms in q, and D is the total number of documents in the sample.

Based on $\text{tf-idf}_{d,q}$, we can construct the announcement series used in our analysis. Specifically, we have for statements

$$\text{tf-idf}^{s}_{t,q} = 1(d \in t \cap d \in D_s)\ \text{tf-idf}_{d,q},$$

for press conference statements

$$\text{tf-idf}^{ps}_{t,q} = 1(d \in t \cap d \in D_{ps})\ \text{tf-idf}_{d,q},$$

and for press conference Q&As

$$\text{tf-idf}^{pq}_{t,q} = 1(d \in t \cap d \in D_{pq})\ \text{tf-idf}_{d,q}.$$

Note that D_s, D_{ps}, and D_{pq} denote the subsets of documents which are statements, press conference statements, and press conference Q&As, respectively.

[18] https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm (accessed on March 30, 2024).

C Additional Results

C.1 Effects on Yields and Inflation Compensation

We study the effects of our Fed non-yield shock on various interest rates and inflation compensations. In particular, we look at the effects on 2-day changes around FOMC announcements. We first show in Table C1 that our shock has no discernible effects on nominal yields as well as nominal forward rates. We then move to inflation compensations measured from Treasury Inflation-Protected Securities (TIPS) and inflation swap rates.

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

Change (bp)	1 Month	3 Month	6 Month	1 Year	2 Year	5 Year	10 Year	20 Year	30 Year
Yield—Bloomberg									
Fed non-yield shock	-0.48	-0.89	-0.54	-0.09	-0.58	-0.65	0.06	0.44	0.67
	(0.66)	(0.82)	(0.62)	(0.53)	(0.57)	(0.80)	(0.86)	(1.62)	(0.80)
R^2	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Observations	176	219	219	219	219	219	219	23	219
Yield—GSW 2007									
Fed non-yield shock				-0.06	-0.65	-0.67	0.16	0.62	0.79
				(0.51)	(0.60)	(0.79)	(0.89)	(0.81)	(0.70)
R^2				0.00	0.01	0.00	0.00	0.00	0.01
Observations				219	219	219	219	219	219
Instantaneous Forward Rate—GSW 2007									
Fed non-yield shock					-1.31	0.08	1.25	1.08	
					(0.91)	(1.11)	(1.12)	(0.82)	
R^2					0.01	0.00	0.01	0.01	
Observations					219	219	219	219	

Notes: This table presents estimates of δ from specification (9), 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.

In Table C2, we show that these generally increase following our non-yield shock. As nominal yields are unaffected, TIPS yields need to decrease which is also shown in the table. However, it is not clear that the non-yield shock leads necessarily to increases in inflation expectations. As shown by d'Amico, Kim, and Wei (2018), TIPS yield and inflation compensation (IC) can be decomposed as follows

$$\begin{aligned} \text{TIPS yield} &= \text{real yield} + \text{TIPS liquidity premium} \\ \text{TIPS IC} &= \text{expected inflation} + \text{inflation risk premium} - \text{TIPS liquidity premium}. \end{aligned}$$

Based on a no-arbitrage term structure model, d'Amico, Kim, and Wei (2018) also provide estimates

of each term in the decomposition. Table C2 shows the results for these terms. Based on d'Amico, Kim, and Wei (2018)'s estimates, the non-yield shock affects TIPS inflation compensations mostly through TIPS liquidity premia, rather than through expected inflation or inflation risk premia. However, this liquidity premium should not be able to explain why inflation swap rates are also increasing. Hence, the evidence based on US data is mixed as to whether our non-yield shock is affecting inflation expectations.

Table C2: Effects of Fed Non-Yield Shock on U.S. Inflation Compensation & Real Yields

Change (bp)	1 Year	2 Year	5 Year	10 Year	20 Year
TIPS Inflation Compensation		3.30**	1.73**	1.30**	0.97*
		(1.44)	(0.70)	(0.53)	(0.52)
Expected Inflation			-0.03	0.01	
			(0.21)	(0.18)	
Inflation Risk Premium			-0.06	0.01	
			(0.11)	(0.13)	
Liquidity Premium			-1.66**	-1.28***	
			(0.67)	(0.49)	
TIPS Yield		-4.11***	-2.68***	-1.47*	-0.76
		(1.48)	(0.95)	(0.85)	(0.76)
Real Yield			-0.50	-0.16	
			(0.48)	(0.58)	
TIPS Instantaneous Forward Rate		-3.81**	-0.58	-0.45	-0.51
		(1.77)	(1.27)	(0.88)	(0.77)
Inflation Swap Rate	0.41	2.48***	2.15***	1.48**	
	(1.26)	(0.95)	(0.62)	(0.72)	

Notes: Each estimate in this table comes from a separate version of (9), where only the left-hand side variable varies. Data on TIPS inflation compensations and TIPS yields comes from the updated dataset of Gürkaynak, Sack, and Wright (2010), whereas the inflation swap rates are from *Bloomberg*. The remaining variables are from the updated dataset of d'Amico, Kim, and Wei (2018). Since we employ 2-day changes, 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. Abbreviations: TIPS—Treasury Inflation Protected Security.

Hence, to figure out if inflation expectations are indeed a key channel of our non-yield shock, we move to international data on inflation compensations. Table C2 shows the results of this analysis. The estimates indicate that international inflation compensations are generally unaffected by our non-yield shock. Overall, we conclude that while our non-yield shock seems to have some positive effects on inflation compensation, the results indicate that the inflation channel is not an important part in understanding our non-yield shock.

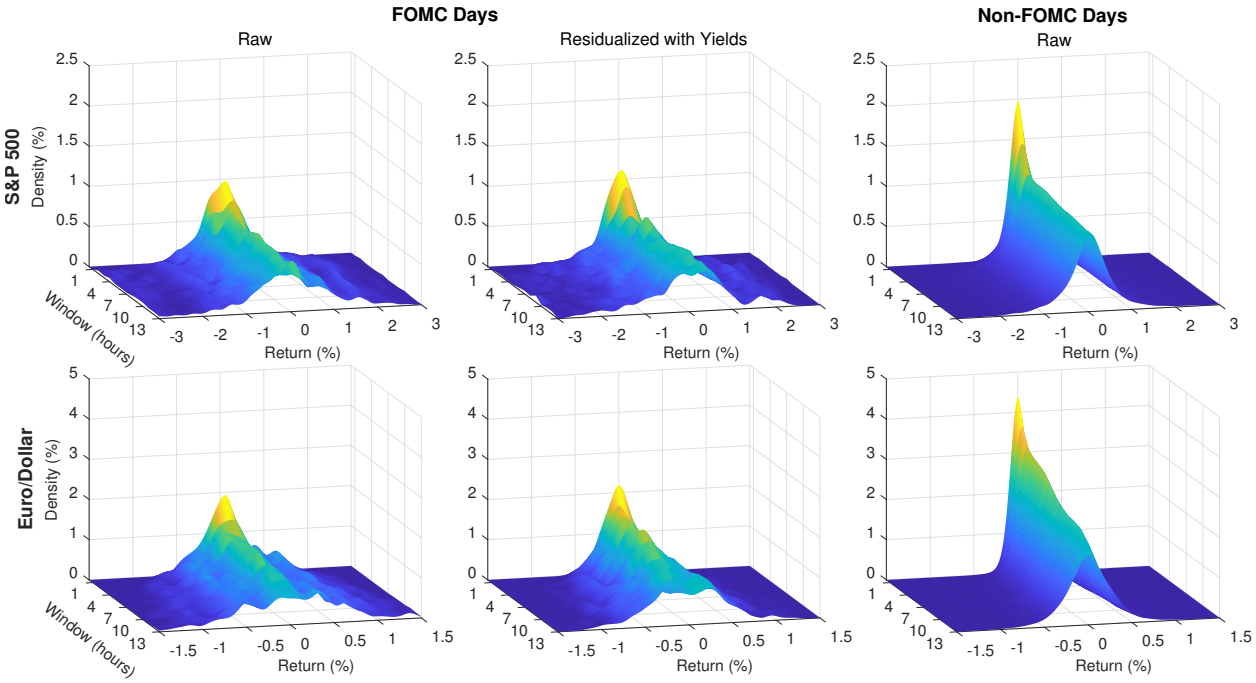
Table C3: Effects of Fed Non-Yield Shock on International Inflation Compensations

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

Notes: This table presents estimates of δ from specification (9), where the left-hand side variables are now 2-day log-changes in inflation swap or inflation breakeven rates. Heteroskedasticity-consistent standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level. We winsorize each dependent variable at the top and bottom 1 percent.

C.2 Miscellaneous Figures and Tables

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



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

D Framework Appendix

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.

D.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 prices and exchange rates.
- 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 $1 = n < r = 2$).

D.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.

D.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

$$\Delta p_t = \beta s_t^y + u_t. \tag{D1}$$

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 (D1) 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 structural shock $z_t \in \mathbb{R}^r$ 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,

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

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

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

   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*

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

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

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

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

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

□

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,

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

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. It follows from the data generating process (10) that

$$s_t^y = A_y z_t = \begin{bmatrix} A & 0 \end{bmatrix} \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix} = A z_t^1.$$

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

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

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

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

Then

$$s_t^y = \begin{pmatrix} A & B \end{pmatrix} \begin{pmatrix} z_t^1 \\ z_t^2 \end{pmatrix} = A z_t^1 + B z_t^2.$$

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

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

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

$$A_p \left(I_r - A_y' \left(A_y A_y' \right)^{-1} A_y \right) \begin{pmatrix} z_t^1 \\ 0 \end{pmatrix} = 0_{n \times 1} \tag{D2}$$

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

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

Condition (D2) 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 $B = 0_{k\times 1}$. □

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

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