Spillovers of US Interest Rates

Monetary Policy & Information Effects*

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This Draft November 1, 2022, First Draft: August 2nd 2021

Abstract

This paper quantifies the international spillovers of US monetary policy by exploiting the high-frequency movement of multiple financial assets around FOMC announcements. I use the identification strategy introduced by Jarociński and Karadi [2020], which exploits both the high frequency movements of interest rates and the S&P 500, to identify two FOMC shocks: a pure US monetary policy and an information disclosure shock. These two FOMC shocks have intuitive and very different international spillovers over both Emerging and Advanced Economies. On the one hand, a US tightening caused by a pure US monetary policy shock leads to an economic recession, an exchange rate depreciation and tighter financial conditions. On the other hand, a tightening of US monetary policy caused by the FOMC disclosing positive information about the state of the US economy leads to an economic expansion, an exchange rate appreciation and looser financial conditions. I argue that ignoring the disclosure of information by the FOMC biases the impact of a US monetary policy tightening and may explain recent atypical findings which suggest an expansionary effect of US monetary policy shocks on the rest of the world.

Keywords: Monetary policy, Emerging markets, Exchange Rates, Monetary Policy Spillovers.
JEL Codes: F40, F41, E44, E51.

*I would like to thank the Monetary and Fiscal History of Latin America project of the Becker Friedman Institute for their generous financial support. Particularly, I would like to thank Edward R. Allen, for supporting my research.

1 Introduction

The international spillovers of US monetary policy is a classic question in international macroeconomics, going back to Fleming [1962], Mundell [1963], Dornbusch [1976] and Frenkel [1983]. The status of the US dollar as the global reserve currency, unit of account, invoice of international trade and its dominant role in financial markets implies that the Federal Open Market Committee's (FOMC) policy decisions have spillover effects on the rest of the world. In recent years, the conventional view that a US monetary tightening leads to negative international spillovers such as a recession, exchange rate depreciation and financial distress (Svensson and Van Wijnbergen [1989], Obstfeld and Rogoff [1995], Betts and Devereux [2000], Vicondoa [2019]), has been challenged. In fact, a recent literature has found opposite empirical results, an increase in the US monetary policy rate has been associated with a depreciation of the US dollar and an economic boom and looser financial conditions in the rest of the world (Stavrakeva and Tang [2019], Ilzetzki and Jin [2021]). In this paper, I show that the atypical dynamics documented in this recent literature are can be explained by the disclosure of information about the US economy that takes place around FOMC meetings. This "information disclosure" effect contaminates the identification of monetary policy shocks and biases the estimates of the international spillovers of US monetary policy shocks. Controlling for this information disclosure effect re-establishes the conventional view that a US monetary tightening leads to a recession, exchange rate depreciation and tighter financial conditions.

The recent literature estimating atypical effects of US monetary policy shocks has identified them using the standard high frequency identification strategy, i.e. as unexpected movements in interest rates around FOMC announcements, as in Gertler and Karadi [2015] and Nakamura and Steinsson [2018]. However, FOMC announcements both convey decisions about policy rates and disclose information about the present and future state of the US economy. Both Advanced (AE) and economies depend heavily on the US business cycle (for instance, because of its international trade with the US or because of the impact of the US economy on commodity goods' prices) or on the conditions in US financial markets (for example, due to the appetite for AEs and EMs' sovereign and corporate bonds and/or equity markets). As a result, these economies are affected by both the FOMC's policy decisions and the new information disclosed by the FOMC. Therefore, separately identifying US monetary policy shocks from information disclosure shocks is essential to study the impact of US monetary policy on EM economies.

In line with this argument, I estimate a panel SVAR model using an identification scheme that allows me to separate two FOMC shocks: a pure US monetary policy shock (MP shock) and an information-disclosure shock (ID shock). I tell them apart using the methodology introduced by Jarociński and Karadi [2020] which imposes sign restrictions on the co-movement of the high-frequency surprises of interest rates and the S&P 500 around FOMC meetings. This co-movement is informative as standard theory unambiguously predicts that a monetary policy tightening shock should lead to lower stock market valuation. This is because a monetary policy tightening decreases the present value of future dividends by increasing the discount rate and by deteriorating present and future firm's profits and dividends. Thus, MP shocks are identified as those innovations that produce a negative co-movement between these high-frequency financial variables. On the contrary, innovations generating a positive co-movement between the interest rates and the S&P 500 correspond to ID shocks. This is a shock that occurs systematically at the time of the central bank policy announcements, but that is different from the standard monetary policy shock. By separately identifying these two structural shocks into a panel SVAR, I find that MP shocks produce conventional international spillovers, i.e. a recession, exchange rate depreciation and financial distress. On the contrary, an ID shock produces an economic expansion, a brief exchange rate appreciation and looser financial conditions.

Then, I argue that the recently found atypical dynamics can be attributed by not controlling for systematic disclosure of information around FOMC meetings. I show that following the standard high frequency identification scheme to identify US interest rate shocks leads to dynamics which are an average of those arising from a MP and ID shock. In particular, this leads to a US interest rate tightening associated with a significant economic expansion for both AE and EM economies. Overall, I argue that not controlling for the information disclosure around FOMC meetings biases the quantifying of international spillovers of US interest rates.

Related literature. This paper relates to three main strands of literature. First, this paper contributes to a long strand of literature which has focused on identifying and quantifying the international spillovers of US monetary policy shocks and their transmission channels. A significant share of this literature has found that a US tightening is associated with an Emerging Market economic recession, an exchange rate depreciation or fall of the value of the country's currency and tighter overall financial conditions. Examples of this literature are Eichenbaum and Evans [1995] and Uribe and Yue [2006] using data from the 1980s, 1990s, and more recently Dedola et al. [2017], Vicondoa [2019] using data up to the late 2000s. During the rest of the paper I will refer to these results as the conventional view or impact of a US tightening on Emerging Markets. The contribution to this literature is twofold. First, this paper innovates by introducing an identification scheme that clearly purges any information content included in US monetary policy decisions and finds that conventional results still hold for a time sample of the 2000s and 2010s. Second, this paper contributes to the literature by empirically studying the international spillovers of the disclosure of information by the FOMC as a transmission channel of US interest rates. I show that this transmission channel is quantitatively sizable and has not been considered by the previous literature as a meaningful transmission channel of US interest rates.

This paper also relates to a more recent literature in international economics which have found an atypical association between the US interest rates and Emerging Markets' dynamics. Particularly, Ilzetzki and Jin [2021] argue that there has been a significant change over time in the transmission of US monetary policy shocks in Emerging Markets. The authors find that while in the 1980s and early 1990s a US tightening lead to the conventional results described in the previous paragraph, in the last two decades there has been a shift whereby increases in US interest rates depreciate the US dollar but stimulate the rest of the world economy. The authors label this shift as a puzzling change in the transmission of US interest rates. Consequently, in the rest of the paper I will refer to these responses of Emerging Markets to a US tightening as atypical dynamics. Another example of these atypical dynamics is Canova [2005] which finds that after a US tightening, Latin American currencies appreciate while the conventional view would expect a currency depreciation.[1] I contribute to this literature by introducing an identification scheme that deconstruct shocks around FOMC announcements following Jarociński and Karadi [2020]. This identification scheme allows me to identify an information disclosure shock which entirely explains the atypical dynamics found by this recent literature. Additionally, this identification scheme allows me to identify a pure US monetary policy shock, which re-establishes the results presented by the conventional view. Consequently, by deconstructing monetary policy shocks I am able to match both the conventional and atypical results.

Third, this paper relates to a recent literature which has studied the spillovers of US interest rates over the rest of the world by using identification strategies that control for possible informational effects around FOMC meetings. For instance, Degasperi et al. [2020] uses the identification strategy constructed by Miranda-Agrippino and Ricco [2021] which controls for potential "signalling information" effects around FOMC meetings. Another example is Camara and Ramirez-Venegas [2022] which uses the identification strategy constructed by Bauer and Swanson [2022] which controls for the Federal Reserve's "responding to news" informational effect. This paper's key contribution to the literature is that it actively seeks to identify the spillovers of the US interest rates through the systematic disclosure of information around FOMC meetings. Furthermore, this paper shows that this systematic information disclosure around FOMC meetings biases estimates of US monetary policy shocks using the standard high-frequency identification strategy, leading to the recent expansionary effect of US interest rate hikes on the rest of the world. While Degasperi et al. [2020] and Camara and Ramirez-Venegas [2022], suggest that informational effects may explain these recent puzzling dynamics, they do not seek to answer this question. I show that alternative identification strategies that seek to purge for any "informational effects" around FOMC meetings yield remarkably similar results to this paper's benchmark results. I take this result as evidence that

[1] Evidence of atypical dynamics can also be found in an influential paper of the conventional view as Uribe and Yue [2006]. In the working paper, the authors explore an identification scheme different from the one presented in the actual paper, which allows for real domestic variables to react contemporaneously to innovations in the US interest rate. Under this alternative identification strategy, the point estimate of the impact of a US-interest-rate shock on output and investment is slightly positive. This lead to adoption of a different identification scheme.

Finally, while the main focus of Degasperi et al. [2020] and Camara and Ramirez-Venegas [2022] is to study the transmission channels of US interest rates, they disregard the transmission of US interest rates through informational effects. In this paper, I show that this is sizeable transmission channel, leading to quantitatively large spillovers on the rest of the world.[2]

2 Data, Methodology & Identification Strategy

In this section, I describe the construction of datasets, present details on the panel SVAR methodology used and delineate the identification strategy used across the paper. Section 2.1 describes in detail the different datasets and their sources. Section 2.2 describes the main empirical methodology used, presenting the key underlying assumptions, the structure of the model and the estimation procedure. Section 2.3 describes the identification strategies used to quantify the impact of the two different US monetary policy shocks.

2.1 Data Description

First, I describe the sample of AE and EM countries, the different datasets used across the paper to construct out sample of macroeconomic and financial variables, and the source of the high-frequency surprises and FOMC shocks.

The benchmark specification analyzes the international transmission of US monetary spillovers on 4 Advanced Economies and 8 Emerging Markets at the monthly frequency for the period January 2004 to December 2016. Table 1 presents the different countries in the analysis. The reasoning behind this choice of time sample is twofold. First, a main motivation of this paper is to be able to explain and deconstruct the atypical dynamics found after a US tightening in recent times. Consequently, I estimate the empirical models during a time period where the abnormal dynamics are found in previous papers.[3] The second reason is the lack of data availability for Emerging Market economies in the late 1990s and early 2000s. Additionally, during the late 1990s and early 2000s several EM economies experienced significant monetary and fiscal policy changes (for instance the implementation of inflation targetting regimes and fiscal policy rules).[4] Thus, to construct a rich but balanced panel, I start the sample in January 2004.

[2]While this paper innovates by presenting an empirical analysis of the international spillovers of the FOMC's disclosure of information, the theoretical literature has already studied its potential impacts, see Ahmed et al. [2021].

[3]For instance, Ilzetzki et al. [2017] founds that the puzzling dynamics arise during the 1990s and remain during the 2000s.

[4]An example of these policy changes is that around a third of emerging and developing countries shifted from pro-cyclical to counter-cyclical fiscal policies between the late 1990s to the early 2000s.

Table 1: Country List

Emerging Markets	Advanced Economies
Brazil	Australia
Chile	Canada
Colombia	Japan
Indonesia	South Korea
Mexico	
Peru	
Philippines	
South Africa	

Second, I describe the sources and datasets used to construct my sample. In order to construct a harmonized dataset of macroeconomic and financial variables for both AE and EM economies, I source all of the datasets from the IMF, which guarantees that the variables in the dataset are constructed following closely related methodologies. Variables “industrial production”, “consumer price index”, “nominal exchange rate with respect to the US dollar”, ”equity index” and “lending rates” are sourced from the IMF's International Financial Statistics dataset.[5] While constructing a harmonized dataset is key for estimating a panel model, it also prevents me from easily expanding the number of countries in my sample for a considerable time window.

Lastly, I describe the source of the high frequency surprises used to construct the two FOMC shocks in Section 2.3. I follow Jarocinski [2020] and define the high frequency surprise of the interest rate as the first principal component of the 30 minute window surprises in interest rate derivatives with maturities up to 1 year. In particular, I use the first principal component of the surprises in the current month and 3-month Fed Funds Futures and the 2, 3, and 4 quarters ahead 3-month eurodollar futures.[6] For the stock market surprise, I use the 30 minute window surprise in the S&P 500 index. This data is sourced directly from the dataset constructed by Jarocinski [2020].[7]

[5]In Section 4 I estimate the SVAR models using a variable specification which is tailored for Emerging Market economies. In particular, I introduce a “Commodity Terms of Trade Index” and the EMBI Spreads index. The “Commodity Terms of Trade Index” sourced from the Gruss and Kebhaj [2019], accessed from the IMF's “Macroeconomic and Financial Data” dataset. The variable “EMBI Spreads” is constructed by JP Morgan and can be sourced from the IMF or from the World Bank's Global Economic Monitor.

[6]Other papers exploiting the first principal component of surprises in different interest rates are, among others, Gürkaynak et al. [2004] and Nakamura and Steinsson [2018].

[7]Both the time series and the the structural shocks and the replication codes to compute shocks can be directly downloaded from the authors' website. See https://marekjarocinski.github.io/.

2.2 Methodology

Next, I describe the panel SVAR model methodology estimated across the paper. The model specification is a pooled panel SVAR as presented by Canova and Ciccarelli [2013]. This type of model considers the dynamics of several countries simultaneously, but assuming that the dynamic coefficients are homogeneous across units, and coefficients are time-invariant. In this framework, this implies that country i's variables only depend on structural shocks and the lagged values of country i's variables. Although the possible interactions and interdependencies across countries is an interesting topic on itself, I abstract from this possibility in this paper. In Section 4 I discuss heterogeneous responses across different countries by partitioning the benchmark sample across different dimensions.

In its most general form, a panel SVAR model comprises of N countries or units, n endogenous variables, p lagged values and T time periods. The pooled panel SVAR model can be written as

$$\begin{aligned}
\begin{pmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{N,t} \end{pmatrix} &= C + \begin{pmatrix} A^1 & 0 & \cdots & 0 \\ 0 & A^1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A^1 \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{N,t-1} \end{pmatrix} + \cdots \\
&+ \begin{pmatrix} A^p & 0 & \cdots & 0 \\ 0 & A^p & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A^p \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{N,t-p} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \vdots \\ \epsilon_{N,t} \end{pmatrix}
\end{aligned} \tag{1}$$

where $y_{i,t}$ denotes an $n \times 1$ vector of n endogenous variables of country i at time t and A^j is an $n \times n$ matrix of coefficients providing the response of country i to the j^{th} lag at period t. Note that by assuming that $A^j_1 = A^j_n = A^j$ for $j = 1, \ldots, n$ implies the assumption that the estimated coefficients are common across countries. C is a $Nn \times 1$ vector of constant terms which are also assumed to be common across countries. Lastly, $\epsilon_{i,t}$ is an $n \times 1$ vector of residuals for the variables of country i, such that

$$\epsilon_{i,t} \sim \mathcal{N}\left(0, \Sigma_{ii,t}\right)$$

with

$$\begin{aligned}
\epsilon_{ii,t} &= \mathbb{E}\left(\epsilon_{i,t}\epsilon'_{i,t}\right) = \Sigma_c \quad \forall i \\
\epsilon_{ij,t} &= \mathbb{E}\left(\epsilon_{i,t}\epsilon'_{j,t}\right) = 0 \quad \text{for } i \neq j
\end{aligned}$$

The last two equations imply that, as for the model's auto-regressive coefficients, the innovation's variance is equal across countries.

Next, I describe the different type of variables that comprise vector y_t. This vector is comprised of two types of variables: m_t which denote either high-frequency surprises of interest rates around thirty minute windows of FOMC announcements, or the recovered structural FOMC shocks described in Section 2.3; and $\tilde{y}_t$ which denotes the vector of country i specific variables. In my benchmark specification $\tilde{y}_t$ is comprised of five variables: (i) the nominal exchange rate with the US dollar, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) and an equity index.

The models is estimated using Bayesian tools with a standard Normal-Wishart prior over the auto-regressive coefficient and the innovation volatilities and using 12 lags, i.e., $p = 12$. The hyper-parameter which govern the overall tightness and lag decay of the variance prior are set to 0.1 and 1 respectively, typical values on the literature (see Dieppe et al. [2016]). The model results are based on 10,000 iterations of the Gibbs sampler, discarding the first 2,000 simulations for convergence.[8]

2.3 Identification Strategy

Lastly, I describe the identification strategy that allows me to recover two distinct FOMC shocks and estimate their impact on both AE and EM economies. The identification strategy combines the two structural FOMC shocks recovered by using the identification methodology developed by Jarociński and Karadi [2020] and Jarocinski [2020] with a standard Choleski ordering identification strategy.

The identification strategy introduced by Jarociński and Karadi [2020] exploit the high-frequency surprises of multiple financial instruments to recover two distinct FOMC shocks: a pure monetary policy (MP) shock and an information disclosure (ID) shock. In particular, the authors impose sign restrictions conditions on the co-movement of the high-frequency surprises of interest rates and the S&P 500 around FOMC meetings. This co-movement is informative as standard theory unambiguously predicts that a monetary policy tightening shock should lead to lower stock market valuation. This is because a monetary policy tightening decreases the present value of future dividends by increasing the discount rate and by deteriorating present and future firm's profits and dividends. Thus, MP shocks are identified as those innovations that produce a negative co-movement between these high-frequency financial variables. On the contrary, innovations generating a positive co-movement between interest rates and the S&P 500 correspond to ID shocks.

Note that imposing a sign restriction over the co-movement of the high-frequency surprises of the interest rates and the S&P 500 does not uniquely identify the underlying structural shocks. In terms of Jarociński and Karadi [2020] and Jarocinski [2020], there are "different rotations" of the decomposition matrix that satisfy the sign restriction condition. Previous papers have chosen different approaches to deal with this non-uniqueness.[9] For my

[8]Details of the model's estimation procedure, prior and posterior computation are in Appendix B.

[9]For instance, Jarociński and Karadi [2020] include the high frequency surprises of the interest rates and

benchmark specification, I follow the approach introduced by Jarocinski [2020] to deal with this non-uniqueness problem and pin down the decomposition by imposing 0.88 ratio between the variance of the MP shock and the variance of the high-frequency interest rate surprise.[10] Following this procedure allows me to recover the time series of the two FOMC shocks and introduce them into the panel SVAR model in Section 3 and into a Local Projection regression as shown in Section 4 as a robustness check. Also, in Section 4 I show that results remain qualitatively and quantitatively similar when using different approaches to deal with this non-uniqueness problem.

In order to identify and quantify the international spillovers of the two FOMC shocks over the rest of world I combine the recovered FOMC shocks with a standard Choleski identification strategy. I order the vector of identified structural shocks m_t first with the vector of country i specific macroeconomic and financial variables second. Within the vector m_t is order the two FOMC shocks with i^{MP} first and i^{ID} second. *A priori*, this implies that the first ordered FOMC shock is allowed to contemporaneously impact the second ordered FOMC shock but the latter does not impact the former on impact. Given that by construction these shocks are mutually orthogonal these ordering decisions should only lead to efficiency losses and do not introduce any systematic bias. In Section 4, I show that results hold and are quantitatively similar when re-ordering the shocks in vector m_t and by estimating the impact of each FOMC shock separately by defining vector m_t as containing only one of the two FOMC shocks at a time.

3 Spillovers of Monetary Policy & Information Effects

This section presents the main results of this paper. I estimate and quantify the impact of the two FOMC shocks: a pure monetary policy (MP) shock and an information disclosure (ID) shock. I compare the resulting impulse response functions with those arising from following the standard identification strategy ("Standard HFI") of only using the high-frequency surprise of the policy interest rate. First, I show that the two FOMC shocks have completely opposite spillovers over the rest of the world. Second, I argue that the presence of information disclosure shocks biases the results arising from the standard identification strategy and may explain recently found atypical dynamics.

First, I start by testing whether the deconstruction of US interest rate movements into the two distinct FOMC shocks matter for quantifying the spillovers of US monetary

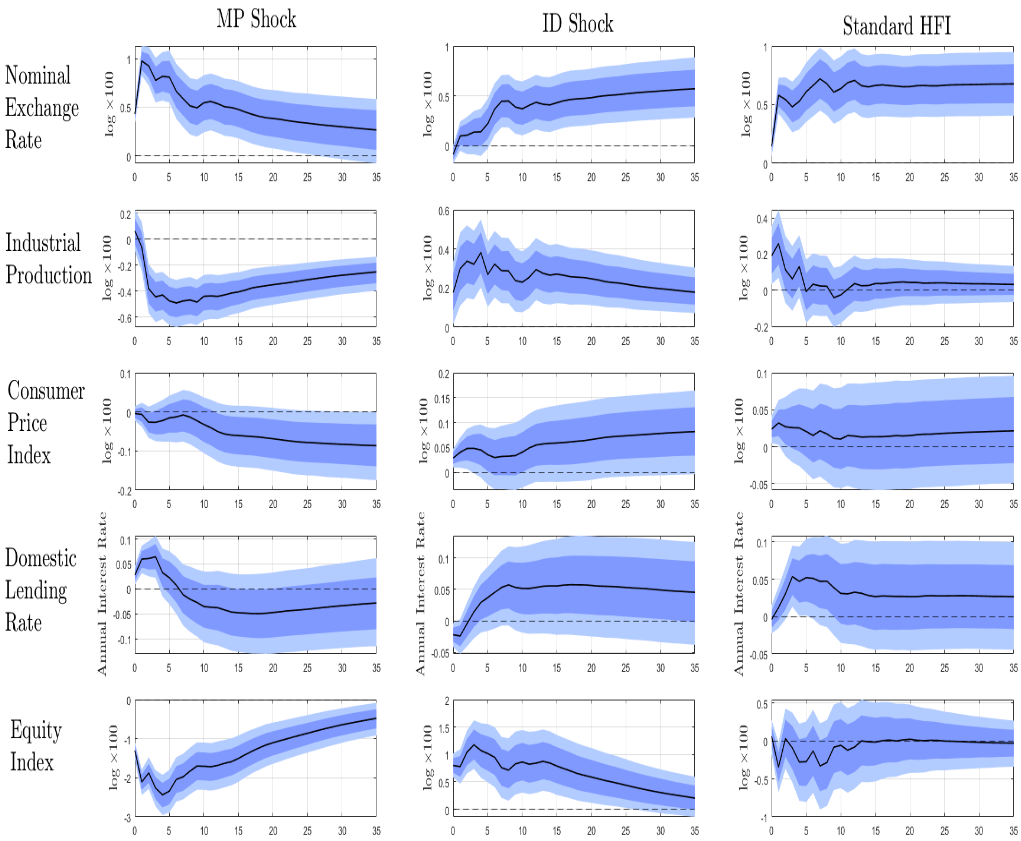
the S&P 500 in their VAR and specify an agnostic flat prior over the space of admissible rotations. Andrade and Ferroni [2021] use the average admissible rotation angle for a similar decomposition. Jarocinski [2020] recovers the structural shocks by choosing a rotational angle that imposes a relationship between the relative variances of the MP shock and that of the high-frequency surprises of the interest rate.

[10] In Appendix B.2 I present the different steps of this procedure by following the methodology introduced by Jarocinski [2020].

policy. The first and second columns of Figure 1 present the impulse response functions of the macroeconomic and financial variables to a MP and ID shock, respectively. Comparing

Figure 1: Impulse Response to One-Standard-Deviation Shock

Benchmark Specification



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock, the middle column presents the results for the ID or "Information Disclosure" shock, and the last column presents the results for the interest rate composite high frequency surprise or "Standard HFI". In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

the figures across these two columns leads to a first important conclusion. This is that the identification scheme based on sign restriction of the US high-frequency financial surprises separately identifies two distinct economic shocks. If the co-movement between the high frequency of the policy interest rate composite and the S&P 500 was uninformative, the impulse response functions presented in the first and second columns of Figure 1 should exhibit the same results. Comparing the results presented in these figures, it is straightforward to conclude that this is not the case. For instance, the behavior of the industrial production index is completely opposite across figures, with a MP shock leading to a persistent decline in industrial output and a ID shock leading to a persistent increase in it. Hence, correctly identifying the different FOMC shocks is crucial to accurately quantify the spillovers of US monetary policy shocks.

Next, I describe in greater detail the impulse response functions. The first column of Figure 1 shows the responses of domestic macro and financial variables to a MP shock. First, Panel 1.1 shows that a one-standard-deviation MP shock leads to a 50 basis point depreciation on impact of the nominal exchange rate. The nominal exchange rate further depreciates during the first 6 months after the shock, reaching a level 100 basis points greater to the pre-shock levels. This depreciation continues to be significantly different from zero even 3 years after the initial shock. Panel 2.1 in the second row shows that after a brief two month expansion, the industrial production index shows a hump shaped, persistent decrease, reaching a level 30 basis point below its pre-shock levels 10 months after the initial shock. Furthermore, this decrease in industrial production persists even 3 years after the initial shock. Panel 3.1 shows that a MP shock does not lead to a significant response of the consumer price index. *A priori*, a MP shock affects consumer prices through two opposite channels. On the one hand, the nominal exchange rate depreciation increases the domestic price of imported goods. On the other hand, the economic recession (shown by the drop in industrial production) may reduce inflationary pressures. Panel 4.1 on the fourth row shows that a MP shock leads to a short-lived increase in domestic lending rates to the private sector. This increase peaks between 3 and 5 months after the initial shock at 10 basis points above pre-shock levels, quickly returning to this level 10 months after the initial shock. Finally, Panel 5.1 on the last row shows that a MP shock leads to a significant and persistent drop in the equity index. This drop is between 100 and 200 basis points during the first 6 months after the initial shock. Moreover, the drop in the equity index is persistent, remaining below its pre-shock levels 3 years after the initial shock.[11]

The spillovers of a ID shock are completely opposite to those of a MP shock. The second column of Figure 1 presents the impulse response functions of a one-standard-deviation ID shock. Panel 1.2 shows that a ID shock leads to a 10 basis points appreciation of the exchange rate on impact. The appreciation of the exchange rate remains significant for the first 2 months after the initial shock. Afterwards, the nominal exchange rate slowly turns to a mild depreciation between 15 and 36 months after the initial shock. Panel 2.2 shows that the industrial production index shows a persistent hump shaped expansion. After a 10 basis point increase on impact, industrial output increases to a level 40 basis point above pre-shock levels. Additionally, industrial output remains 20 basis points above pre-shock levels 3 years after the shock. Panel 3.2 shows that the consumer price index increases on impact between 25 and 50 basis points. This index exhibits a moderate increase even 3 years after the initial shock. Panel 4.2 shows that domestic lending rates decrease for the first 5 months after the

[11] A possible concern arising from the dynamics of the equity index on Panel 5.1 of Figure 1 is that the drop in the equity index is driven by the depreciation of the nominal exchange rate, shown in Panel 1.1. Note that, as described in Appendix A the equity index is defined in domestic currency. Furthermore, the drop in the equity index is between 50% and 100% greater in magnitude than the increase in the nominal exchange rate. Thus, Panel 5.1 shows that the equity index drops in value both in domestic currency and in US dollars.

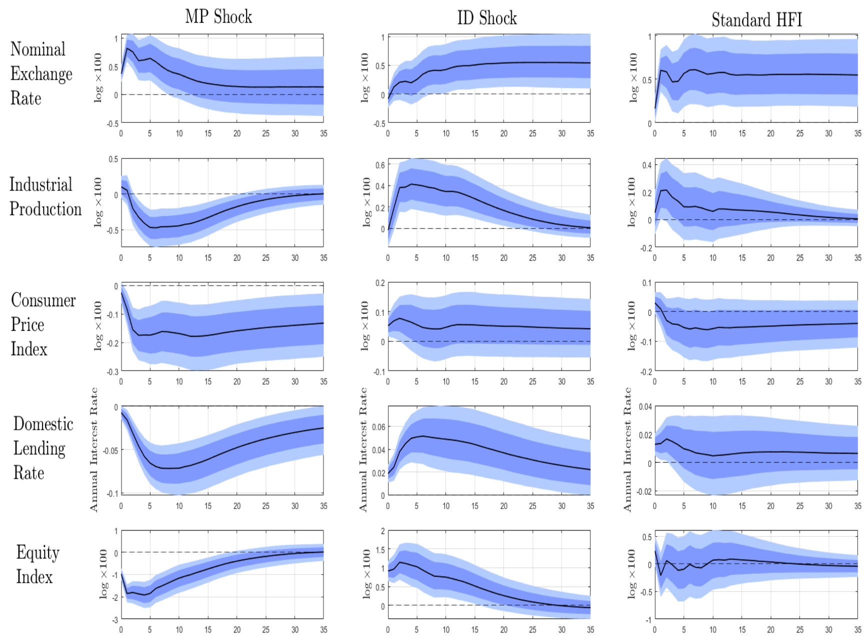
initial shocks. This initial decrease in domestic lending rates accompanied with a higher inflation (see Panel 3.2) suggests that real rates exhibit a decrease after a FOMC interest rate hike caused by an ID shock. Lastly, Panel 5.2 shows that a ID shock leads to a persistent increase in the equity index. The index jumps 100 basis points on impact, reaching a peak of 200 basis points above pre-shock levels 4 months after the initial shock. The significant and persistent expansion in the equity index accompanied with lower lending rates provide evidence of an ID shock leading to looser financial conditions. Overall, the first and second columns of Figure 1 show that the two FOMC shocks lead to almost completely opposite impulse response functions for the full sample of countries.

Next, I argue that following the "Standard HFI" strategy, using only the high-frequency surprise of the policy interest rate composite, may lead to biased impulse response functions. In particular, I replace the benchmark specification of vector m_t which contains the two FOMC shocks with the high-frequency surprise of the policy interest rate composite and of the S&P 500 index. The third column of Figure 1 exhibits the impulse response functions under this identification strategy. Across the different variables, the impulse responses are an average of the responses presented for the MP and ID shocks in the first and middle columns. Most shockingly, the "Standard HFI" strategy leads to a qualitatively different response of the industrial production index from that arising after a MP shock. Under the "Standard HFI" strategy, the industrial production exhibits a one-year increase above pre-level shocks. On impact, industrial production increases by 20 basis points, peaking close to 25 basis points in the following two months. Furthermore, there are notable quantitative differences in the impulse response functions of other variables. Panel 1.3 shows that under the "Standard HFI" strategy, the nominal depreciation is 50% smaller than that implied by a MP shock (25 versus 50 basis points). This quantitative difference continues during the first year after the shock. Consequently, following the "Standard HFI" strategy may lead to underestimating the depreciation of the exchange rate after a pure US monetary policy shock. Another quantitative difference emerges in Panel 5.3, shows that under the "Standard HFI" strategy, the equity index exhibits a small drop with wide uncertainty bounds.

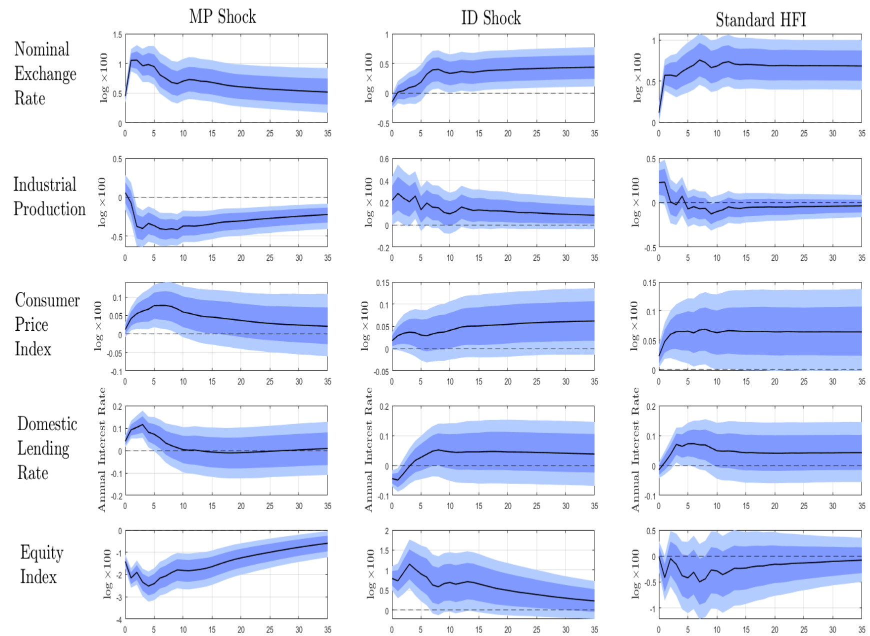
Lastly, I test whether the results are driven by the composition of countries in the sample. Figure 2 shows the resulting impulse response functions for a sample of Advanced Economies (on the left panel in Figure 2a) and Emerging Market economies on the right panel in Figure 2b separately. Across the two sub-samples, the main results presented in Figure 1 hold, with the two FOMC shocks leading to completely opposite dynamics and the "Standard HFI" leading to a weighted average of them. Still, there are some noticeable differences. First, after an MP shock, Emerging Market economies exhibit a persistent increase in the consumer price index while Advanced Economies exhibit a significant drop. As argued by García-Cicco and García-Schmidt [2020] and Auclert et al. [2021], Emerging Market economies depend relatively more in imported goods for both consumer and intermediate input goods. Thus, one would expect that greater exchange rate pass through in EMs relative to AE, all else equal. Similarly, the impact of a MP shock on domestic lending rates is different across the two sub-samples. While lending rates in AE moderately decrease by 5 basis points, they sharply increase in EMs, peaking above 10 basis points. This may be driven by Emerging Market economies having relatively less sophisticated and smaller domestic financial markets and, thus, exhibiting a relatively greater dependence on international financial markets than AE (see Dages et al. [2000], Broner et al. [2013], Cortina et al. [2018], Abraham et al. [2020]). While lending rates decrease for Advanced Economies, the fact that industrial production and equity indexes decrease for both country sub-samples suggests that a MP shock leads to overall tighter financial conditions.

Figure 2: Impulse Response to One-Standard-Deviation Shock

Separate Samples for Adv. & Emerging Economies



(a) Advanced Economies



(b) Emerging Market Economies

Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. Figure 2a on the left presents the results for the panel of "Advanced Economies" comprised of: Australia, Canada, Japan and South Korea. Figure 2b presents the results for the panel of "Emerging Market Economies" comprised of: Brazil, Chile, Colombia, Indonesia, Mexico, Peru, Philippines and South Africa. Each figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock, the middle column presents the results for the ID or "Information Disclosure" shock, and the last column presents the results for the interest rate composite high frequency surprise or "Standard HFI". In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

To summarize, by introducing an identification scheme which deconstruct US interest rates movements into two different FOMC shocks, I am able to show that an increase in US interest rates may have completely different spillovers on the rest of the world depending on the underlying economic shock. While a pure monetary policy shock leads to conventional results, an information disclosure shock leads to an economic expansion, an exchange rate appreciation and looser financial conditions. Moreover, I argued that following a "Standard HFI" strategy underestimates the spillovers of a US monetary policy shock and leads to atypical dynamics, such as an expansion of economic activity. Lastly, I showed that these results are present for both the sub-samples of Advanced and Emerging Market economies with only minor caveats.

4 Additional Results & Robustness Checks

This section presents additional results and robustness checks that complement and validate the findings presented in Section 3. First, I show that the main results are also present using local projection techniques a la Jordà [2005] to estimate impulse response functions. Second, I show that the main results are robust when using different ordering identification assumptions between the two FOMC shocks. Third, I show that the main results are robust to using different approaches to deal with the non-uniqueness problem inherent to the sign-restriction identification strategy. Fourth, I show that the main results are also robust to using a variable specification particular for Emerging Markets. Lastly, I briefly describe potential sources of quantitatively heterogeneity in the spillovers of the two FOMC shocks.

Local projection results. I start by showing that the main results presented in Section 3 are robust to estimating the impulse response functions to the two FOMC shocks using local projection techniques a la Jordà [2005]. The first empirical specification, which I label as "Pooled Specification", has the following form

$$y_{i,t+h} = \beta_h^{MP} i_t^{\text{MP}} + \beta_h^{ID} i_t^{\text{ID}} + \sum_{j=1}^{J_y} \delta_i^j y_{i,t-j} + \sum_{j=1}^{J_x} \alpha_i^j x_{i,t-j} + \sum_{j=1}^{J_i} \left(\phi_i^j i_{t-j}^{\text{MP}} + \varphi_i^j i_{t-j}^{\text{ID}} \right) + \epsilon_{i,t} \quad (2)$$

where $y_{i,t+h}$ is country i's outcome of variable at a horizon of h months from date t. Coefficients β_h^{MP} and β_h^{ID} give the impulse response of outcome variable y at horizon h of a pure monetary policy (MP) and of an information disclosure (ID) shock, respectively. The specification includes J_y lags of the outcome variable, y_i, J_x lags of the other "country specific" variables x_i and J_i lags of the FOMC shocks. I select the number of lags by computing the Schwarz's Bayesian information criterion (SBIC) selection statistic for each country separately. I set $J_y = J_x = J_i$ equal to 1 as it is the optimal number of lags according to the SBIC statistic for all but one country.[12] I also estimate it using the "Standard HFI" by replacing

[12]The exception is Indonesia, for which the SBIC statistic suggest the choice of 2 lags. As a robustness check, I computed the Hannan and Quinn information criterion statistic which also suggest using one lag for the vast majority of countries in my sample.

i_t^{MP} and i_t^{ID} with the high-frequency surprises of the policy interest rate and the S&P 500.[13]

I also estimate the following empirical specifications

$$y_{i,t+h} = \beta_h^{MP} i_t^{\text{MP}} + \beta_h^{ID} i_t^{\text{ID}} + \sum_{j=1}^{J_y} \delta_i^j y_{i,t-j} + \sum_{j=1}^{J_x} \alpha_i^j x_{i,t-j} + \sum_{j=1}^{J_i} \left(\phi_i^j i_{t-j}^{\text{MP}} + \varphi_i^j i_{t-j}^{\text{ID}}\right) + \Gamma_i + \Gamma_{i,t} + \epsilon_{i,t} \tag{3}$$

The specification given by Equation 3 includes country specific fixed effects given by Γ_c and includes a linear time trend given by $\Gamma_{i,t}$. The final specification, in Equation 3 is consistent with the specification estimated by Ilzetzki and Jin [2021]. The standard errors are clustered at the country and time level, which control for the fact that all countries are hit by the FOMC shocks simultaneously.

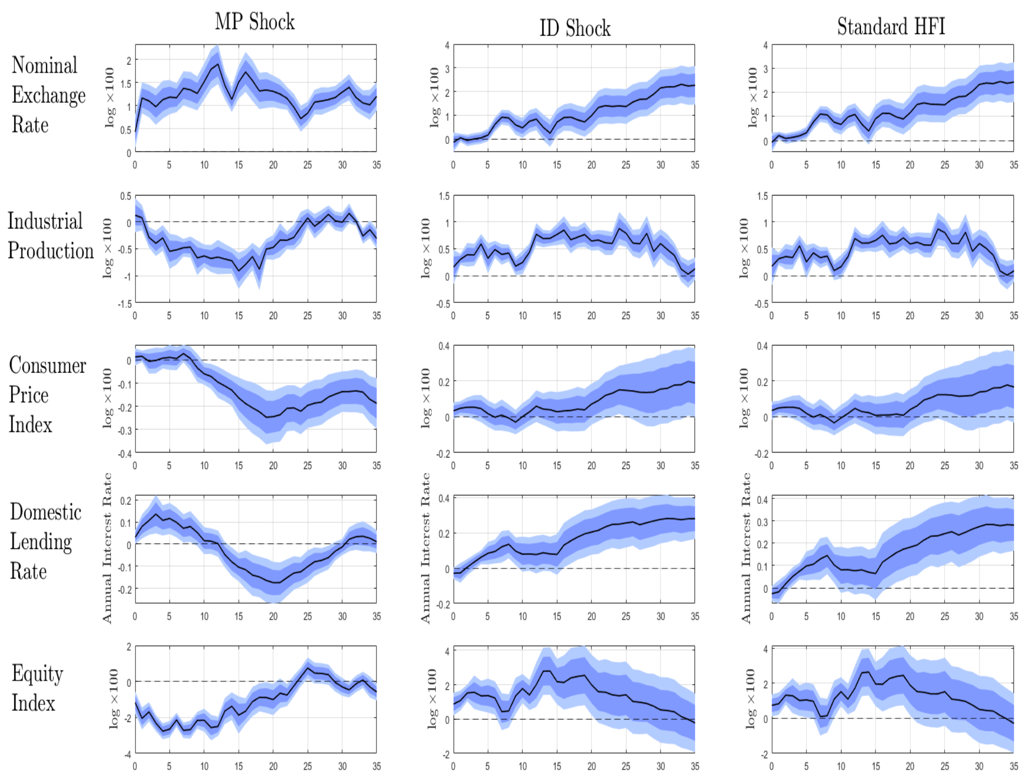
Figure 3 presents the impulse response functions of the macroeconomic and financial variables to the two FOMC shocks and following the "Standard HFI" strategy. First, by comparing the estimated dynamics on the first and second columns, it is clear that under a local projection methodology the two FOMC shocks still lead to opposite spillovers on the rest of the world. On the one hand, a MP shock lead to the conventional results of a drop in industrial output, a persistent nominal exchange rate depreciation and tighter financial conditions shown by higher lending rates and a drop in the equity index. On the other hand, an ID shock leads to a short lived nominal exchange rate appreciation, a persistent increase in the industrial production index and an increase in the equity index. Furthermore, results are quantitatively close to those presented in Section 3.

Secondly, the right-most column of Figure 3 shows that the estimated impulse response functions under the "Standard HFI" strategy lead to an average of the dynamics presented in the first two columns. Panel 3.1 shows that the nominal exchange rate does not depreciate on impact. Panel 3.2 shows that industrial production exhibits a persistent and significant expansion. Panels 3.3 and 3.4 show that domestic lending rates and the consumer price index exhibit moderate increases with wide uncertainty bounds. Finally, under the "Standard HFI" strategy, Panel 3.5 shows a moderate but significant expansion of the equity index. Thus, this identification approach which does not purge high-frequency surprises of policy interest rates of possible informational effects leads to atypical dynamics similar to those presented by Ilzetzki and Jin [2021] and to those exhibited in Section 3. These atypical dynamics, particularly the expansion of industrial output and the increase in the equity index, provide further evidence that the systematic disclosure of information around FOMC meetings may bias the identification and quantification of the impact of international spillovers of US monetary policy shocks.

Figure 12 in Appendix D shows that these results hold when estimated using specifications with country fixed effects and time trends. Furthermore, Figure 13 in Appendix

[13] Note that this specification of the "Standard HFI" is in line with the analogous specification for the SVAR model in Section 3.

Figure 3: Local Projection Impulse Response Functions
Pooled Specification



Note: The black solid line represents the point estimate of coefficient for either one of the two FOMC shocks, or the high-frequency surprise of the policy interest rate composite. The dark shaded area represents a 68% confidence intervals, and the light shaded are represents the 90% confidence intervals. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock, the middle column presents the results for the ID or "Information Disclosure" shock, and the last column presents the results for the interest rate composite high frequency surprise or "Standard HFI". In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure. For each shock, I standardize the coefficients such that they represent the dynamics of a one-standard deviation shock.

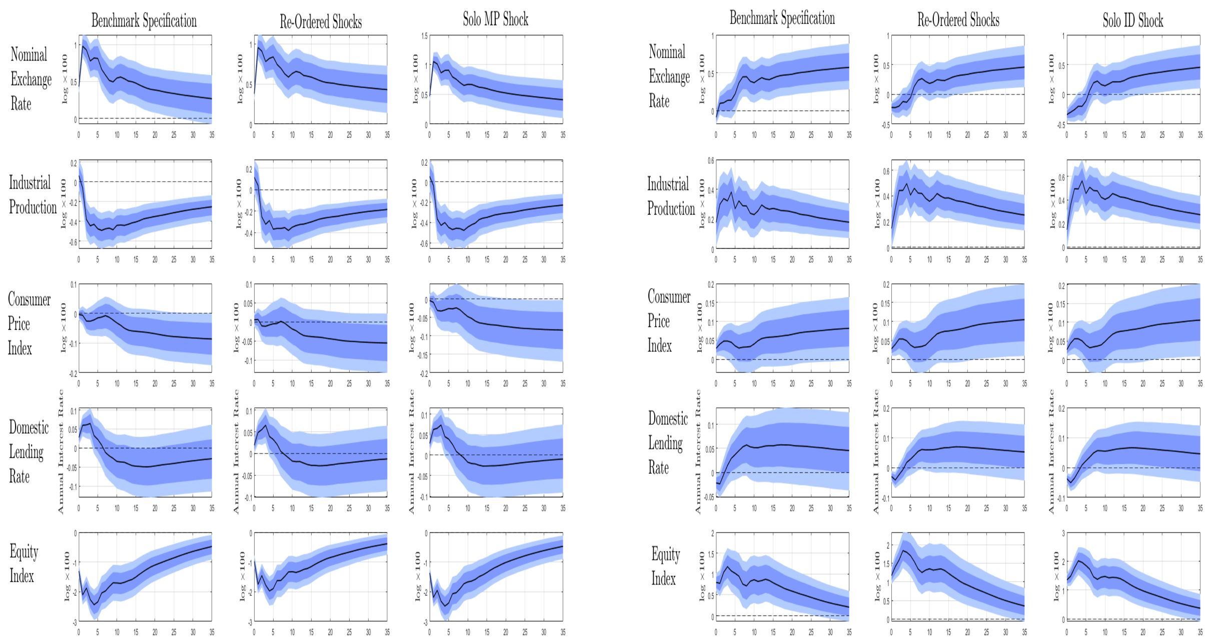
D shows the impulse response functions when introducing month-country fixed effects to the pooled panel local projection regression in Equation 2. Once more, the main results hold. Consequently, once I introduce the two FOMC shocks, any atypical dynamics that emerges from using the "Standard HFI" strategy disappears, even when estimating empirical specifications analogous to those which found these dynamics.

Robustness checks to shock ordering. The benchmark specification sets a specific order between the two FOMC shocks inside the vector of variables m_t, as described in Section 2.3. Next, I show that the main results presented in Section 3 are qualitatively and quantitatively robust to changes in the ordering and specification of vector m_t.

The benchmark specification specified that within the vector m_t of FOMC structural shocks, the MP shock is ordered first and the ID shock coming in second. While by construction the two FOMC shocks are orthogonal to each other, introducing them into the SVAR model may lead to spurious correlations due to the finite sample and the imposition of ordering strategies. A first test of the potential biases introduced by this identification strategy is to study the impulse response functions of the FOMC shock on each other. Figure 11 in Appendix D presents the impulse response functions of the benchmark specification for the two FOMC shocks and the set of macroeconomic and financial variables. Under the benchmark ordering strategy, the impact of the FOMC structural shocks on the other shock is small (an order of magnitude smaller than the driving shock) and with uncertainty bounds containing the non-significant response.

To test the robustness of the benchmark results I re-estimate the impulse response functions using two alternative specifications of vector m_t. Figure 4 shows that the main

Figure 4: Robustness Check under Alternative Shock Ordering



(a) MP Shock

(b) ID Shock

Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The dashed red line presents the median response of the benchmark specifications presented in Figure 1. Each figure is comprised of 6 sub-figures ordered in three rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) equity index. The first column presents the results when ordering the ID shock first and the MP shock second, and the second column presents the dynamics for a specification with m_t containing only the MP or the ID shock. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

results are robust to re-ordering the two FOMC shocks, i.e. $m_t = [i_t^{ID} i_t^{MP}]$; and to estimating the model by introducing these shocks one at a time, i.e. estimating the impulse response functions with only one shock at a time with $m_t = [i_t^{MP}]$ and $m_t = [i_t^{ID}]$, separately, one at a time.

Figure 4a presents the impulse response functions of an MP shock for the nominal exchange rate, the industrial production and the equity index for two alternative specifications of vector m_t. These three variables are chosen as they show the most significant opposite dynamics under the benchmark specification. Figure 14 in Appendix D presents the results for the full set of variables. For ease of comparison with the results presented in Section 3, I plot the median response of the benchmark specification in a dashed red line. The left column presents the impulse response functions that emerge from re-ordering the shocks, i.e. ordering vector m_t such as the ID shock is ordered first and the MP shock second. The right column of Figure 4a presents the impulse response results when defining m_t as only containing the MP shock. In both columns, the red dashed line represents the median impulse response from the benchmark specification presented in Figure 1 in Section 3. The main results hold under the two alternative specifications of m_t with an MP shock leading to an exchange rate depreciation, a reduction of industrial output and a drop in the equity index. Quantitatively, there are minor differences with the median response of the benchmark specification laying within the different specifications 90% credibility areas. Figure 4b carries out the analogous robustness check for the ID shock, with the main results holding for the two alternative specifications.

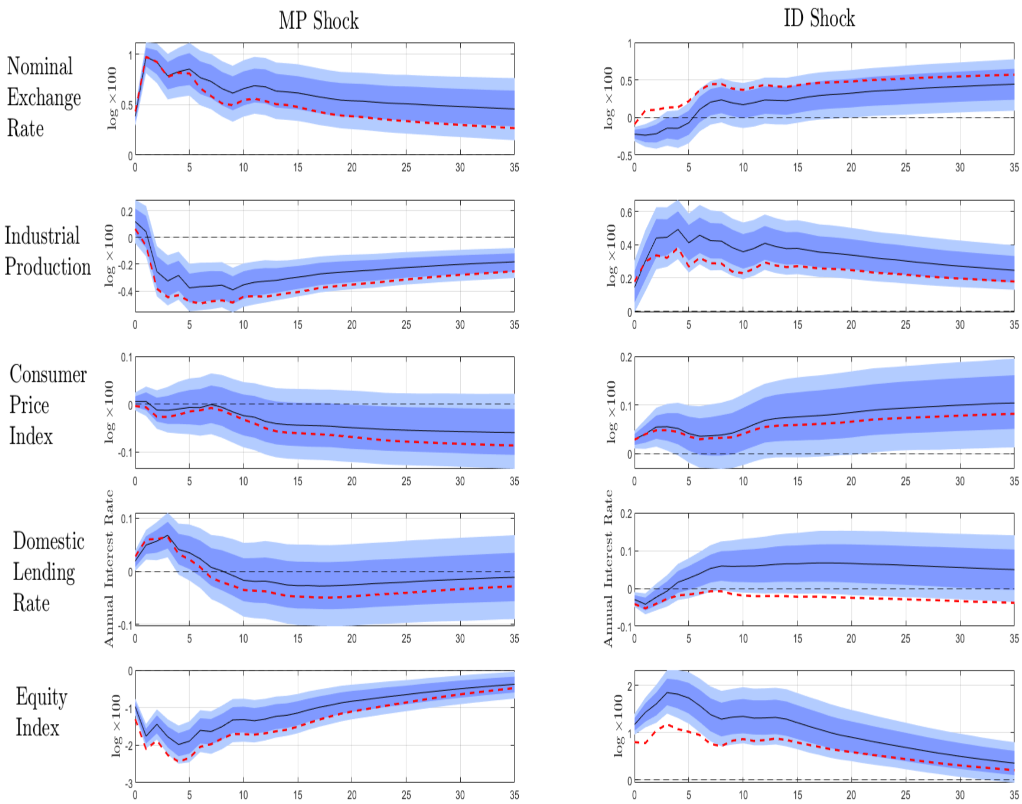
Robustness checks to structural shock recovery. The benchmark specification has the two FOMC shocks recovered by the median rotation matrix that satisfies the sign-restriction conditions. As stressed in Section 2.3, the sign restriction identification scheme implies a non-uniqueness problem when recovering the underlying structural shocks. Next, I show that the paper's main results are robust to changes in the angle of rotation of the decomposition matrix that recovers the structural FOMC shocks.

Under the benchmark specification, the FOMC shocks are recovered following the approach introduced by Jarocinski [2020]. The first robustness test I carry out is recovering the median shock (or median angle) which satisfy the sign-restrictions. This alternative strategy recovers the structural shocks by imposing an equal weight on the MP and ID shocks in explaining the variance of the high frequency movements of the interest rate composite.[14]

Figure 5 presents the resulting impulse response of this robustness check. For ease of comparison I plot the median response of the benchmark specification in a red dashed line. Altogether, the main results presented in Section 3 are robust to this different method to deal with the non-uniqueness problem inherent to the sign-restriction identification strategy. For instance, the median response of the benchmark specification is within the uncertainty bounds of this alternative specification. There are only subtle quantitative differences with the benchmark specifications. On the one hand, under the alternative specification the impact of a MP shock on industrial production and the equity index is quantitatively larger. On the

[14] Appendix B.2 presents details on this procedure. Furthermore, in Appendix B.2 describes how different rotation angles relate to the relative importance of each structural FOMC shock.

Figure 5: Impulse Response to One-Standard-Deviation Shock
Median Shock Specification



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 10 sub-figures ordered in five rows and two columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock, the last or right column presents the results for the ID shock. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

other hand, the quantitative impact of a ID shock on the same variables is relatively larger under the benchmark specification. These differences between specifications make intuitive sense as the alternative specifications puts relatively more weight into ID shocks than the benchmark case.

As a final robustness check I re-estimate the SVAR model from Section 3 using two alternative rotations: (i) the 75^{th} and (ii) the 25^{th} percentiles of the matrices of rotations which satisfy the sign-restriction conditions. Figure 15 in Appendix D presents the results for the full set of variables. Once more, the main results presented in Section 3 hold with results qualitatively in line with those presented under the benchmark specification. Results are quantitatively robust as 90% credibility intervals are different from zero. In consequence, it is fair to state the main results hold under different approaches that recover the underlying structural FOMC shocks which meet the sign-restriction conditions.

Emerging Market variable specification. Next, I show that the main results are robust to an alternative variable specification which is tailored for Emerging Market economies. The benchmark variable specification described in Section 2.1 and used to estimate the main results in Section 3 is chosen to reflect key macroeconomic and financial variables of both Advanced Economies and Emerging Markets. The literature which has studied the spillovers of US interest rates specifically on Emerging Markets usually applies a variable specification which reflect key characteristics of these economies (see Uribe and Yue [2006] and Vicondoa [2019]). I follow this literature and replace the domestic lending rates with the EMBI spreads and introduce a commodity terms of trade index.[15]

Figure 6 presents the result of this robustness check. Overall, the main results still hold with the MP and ID shock leading to qualitatively opposite international spillovers. However, the main insight from exercise is that EMBI spreads and the commodity terms of trade index react significantly different to the two FOMC shocks. On the one hand, a MP shock leads to a sharp increase in EMBI spreads and persistent drop in the commodity terms of trade index. On the other hand, an ID shocks leads to a significant decrease in EMBI spreads and mild increase in commodity terms of trade. These results suggest that a MP shock leads to tighter financial conditions while a ID shock leads to looser financial conditions in Emerging Market economies, in line with the results presented in Section 3.

Potential sources of heterogeneous impact of US interest rate spillovers. Following, I describe two potential sources of quantitatively heterogeneity in the international impact of US interest rates: (i) countries' exchange rate regimes and (ii) countries' reliance on the export of commodity goods. I briefly comment how previous literature has theorized that these country characteristics may influence the quantitative impact of the spillovers of US interest rates and describe my results.

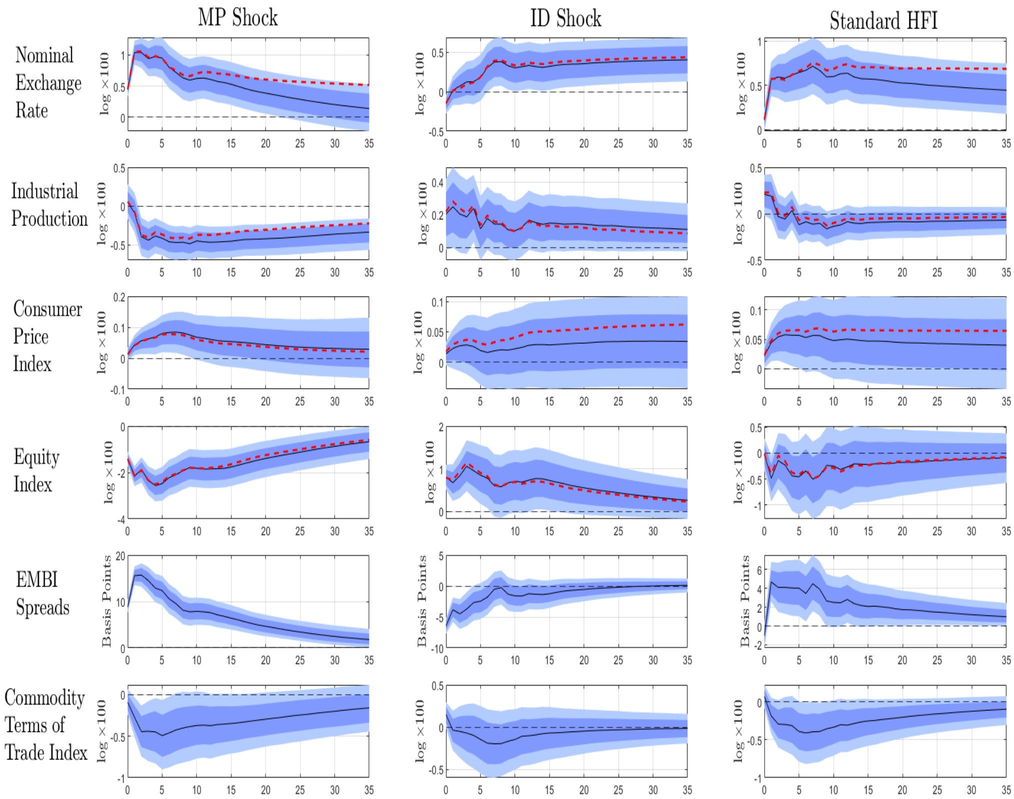
First, I study whether countries' exchange rate regimes may influence the quantitative impact of the spillovers of US interest rates. The advantages and disadvantages of different exchange rate regimes is a classic yet still open question in international economics (see Mundell [1963], Levy-Yeyati and Sturzenegger [2003], Edwards and Yeyati [2005]). Moreover, the evidence is also mixed in terms of exchange rate regimes shaping the impact of US interest rates. On the one hand, Di Giovanni and Shambaugh [2008] provides evidence that for a panel of advanced economies the impact of higher foreign interest rates lead to a recession for countries with a fixed exchange rate. On the other hand, Rey [2015] argues that economies can not insulate from the US interest rate, even with flexible exchange rate regimes.[16]

I carry two different partitions of the countries in the sample according to their

[15] The "Commodity Terms of Trade Index" sourced from the Gruss and Kebhaj [2019], accessed from the IMF's "Macroeconomic and Financial Data" dataset. The variable "EMBI Spreads" is constructed by JP Morgan and can be sourced from the IMF or from the World Bank's Global Economic Monitor.

[16] Dedola et al. [2017] and Degasperi et al. [2020] also present evidence that the impact of US interest rates is similar across countries with different exchange rate regimes.

Figure 6: Impulse Response to One-Standard-Deviation Shock
EM Specification



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The dashed red line represents the median response under the benchmark specification for a sample of only Emerging Market economies. The figure is comprised of 12 sub-figures ordered in 6 rows and two columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production, (iii) consumer price index, (iv) EMBI spreads, (v) equity index, (vi) Commodity Terms of Trade Index. The first or left column presents the results for the MP or "Pure US Monetary Policy"shock, the second or right column presents the results for the ID or "Information Disclosure" shock. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

exchange rate regimes. The first compares the resulting dynamics between a sample of only Peru versus the rest of the countries in the sample. The Peruvian Central Bank actively and publicly intervenes in foreign exchange rate markets to stabilize the nominal exchange rate. Also, the Peruvian case has been considered as a case study for the benefits and costs of FX interventions (see Rossini et al. [2019], Castillo et al. [2021] and Camara et al. [2021]).[17] Figures 16 and 17 in Appendix D presents the impulse response functions to the MP and ID shocks for each sub-sample. On the one hand, across the two FOMC shocks, Peru exhibits a lower impact on the nominal exchange rate and on domestic lending rates as expected given its Central Bank interventions in foreign markets. The more moderate impact on the nominal exchange rate and domestic lending is particularly significant when comparing with a sample

[17] Furthermore, under the exchange rate regime classification by Ilzetzki et al. [2017], the country falls under tight or narrow exchange rate management.

of Emerging Markets which excludes Peru (right-most column of Figures 16 and 17). On the other hand, the median response on industrial production are quantitatively close, while the impact on the equity index is significantly greater for Peru.

The second country partition groups Peru and Indonesia as countries with a "dirty float" exchange rate regime versus the rest of the countries in the sample. The grouping of Peru and Indonesia is motivated by both countries being classified as "*tight*" exchange rate managers according to Ilzetzki et al. [2017]. Figures 18 and 19 in Appendix D shows the impulse response functions of the MP and ID shock for each sub-sample, respectively. The insights of the first partition specification still hold.

Second, I study whether a country's share of commodity goods in total exports matters for the transmission of US interest rate spillovers. This is motivated by the impact of US interest rates in commodity prices as suggested by Figure 6 and a vast literature (see for instance, Akram [2009] and Frankel [2014]). In order to test the potential role of commodity goods as a source of heterogeneity in the spillovers of US interest rates I partition the sample of Emerging Market economies into "High Commodity Dependence" and "Low Commodity Dependence" countries. This partition is based on countries' share of commodity goods in their export basket as constructed by the UNCTAD's "The State of Commodity Dependence" for the year 2016.[18] The high commodity dependence sample is comprised of Brazil, Chile, Colombia and Peru; while the low commodity dependence sample is comprised of Indonesia, Mexico and South Africa.

Figures 20 and 21 present the impulse response functions for the high and low commodity dependence samples for a MP and ID shock, respectively. I plot a dashed red line with the median response for the sample of Emerging Market economies (see Figure 6). First, the high commodity dependence sample exhibits a significantly greater response of their commodity terms of trade index than the low commodity dependence sample to both FOMC shocks. *A priori*, this could lead to an overall greater impact of the spillovers of US interest rates. However, this does not seem to be the case. In response to a MP shock, the low commodity dependence sample exhibits a greater nominal exchange rate depreciation, a greater pass through to consumer prices, a greater increase in EMBI spreads and a larger drop in the equity index, than the high commodity dependence sample. Similar dynamics arise in response to a ID shock. While this may be driven by large commodity exporters being having a greater tradable sector than other countries which reduces the economic contraction necessary to adjust to a given cut-off capital outflow, as suggested by Cavallo and Frankel [2008], I leave this question for future research.

Comparison to alternative identification strategies. The macroeconomic literature has produced several different identification strategies which seek to purge for potential "informational effects" around FOMC meetings. Two examples of this literature are Miranda-

[18] For access to the UNCTAD report see `https://unctad.org/webflyer/state-commodity-dependence-2016`.

Agrippino and Ricco [2021] and Bauer and Swanson [2022]. The former follow an instrumental variable approach to control for any "signalling effect" through which the FOMC reacts to expected changes in macroeconomic and financial variables. The latter control for the "Fed Response to News" channel by orthogonalizing the high-frequency movements of interest rates around FOMC announcements to any key macroeconomic or financial information available prior to the FOMC meeting. In Appendix C, I compare the benchmark results of an MP shocks with those arising when following this two alternative identification strategies. Figure 10 show that the resulting impulse response functions are remarkably similar to the benchmark results presented in Figure 1. This result provides additional evidence that controlling for the information disclosed around FOMC meetings re-establishes the conventional view which associates an US interest rate hike with an economic recession, an exchange rate depreciation and tighter financial conditions in AE and EMs.

5 Conclusion

In this paper I have argued that the international spillovers of a US interest rates hike depend critically on the underlying structural shock that causes the tightening. Using the identification strategy proposed by Jarociński and Karadi [2020], I deconstruct FOMC shocks into a pure US monetary policy (MP) shock and an information disclosure (ID) shock. Introducing these FOMC shocks into a SVAR model with both Advanced and Emerging Market economies I find that the two shocks lead to qualitatively opposite spillovers. On the one hand, a MP shock leads to a nominal exchange rate depreciation, a persistent drop in industrial output and overall tighter financial conditions. On the other hand, a ID shock leads to a short lived exchange rate appreciation, a persistent expansion in industrial output and overall looser financial conditions.

Furthermore, I argue that following the standard high-frequency identification of US monetary policy leads to atypical spillover dynamics as it does not control for the systematic disclosure of information about the state of the US economy around FOMC announcements. I show that this identification strategy leads to impulse response functions which are an average of those resulting from the MP and ID shocks. In particular, under this identification strategy, a US interest rate tightening leads to a significant expansion of industrial production. Moreover, by not controlling for the disclosure of information, this identification strategy introduces an attenuates bias in terms of the quantitative impact US monetary policy shocks on the variables which do not show atypical dynamics.

Lastly, I show that the main results are robust to a battery of different model and sample specifications. Results hold when considering Advanced and Emerging Market economies separately, when estimating impulse response functions using local projection methodologies, and when estimating the model using a variable specification particular to

Emerging Market economies.

Acknowledgements:

I owe an unsustainable debt of gratitude to Giorgio Primiceri for his guidance and advice. I would also like to thank the comments by Martin Eichenbaum, Guido Lorenzoni and Larry Christiano. I would like to thank the Monetary and Fiscal History of Latin America project of the Becker Friedman Institute for their generous financial support. Particularly, I would like to thank Edward R. Allen, for supporting my research. I would like to thank the attendees of Northwestern University's macro lunch seminar, Javier Garcia Cicco, Husnu Dalgic and Yong Cai. Susan Belles provided helpful comments.

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A Data Details

In this section of the appendix I provide additional details on the construction of the sample used across the paper. The source of the macroeconomic and financial data used for the construction of the variables in the benchmark variable specification is the IMF's "International Financial Statistics".[19]

First, the benchmark specification is comprised of five variables:

1. Nominal Exchange Rate
2. Industrial Production index
3. Consumer Price Index
4. Lending Rate
5. Equity Index

Next, I present additional details for the construction of each of the variables

- Nominal Exchange Rate: The variable's full name at the IMF IFS data set is "Exchange Rates, National Currency Per U.S. Dollar, Period Average, Rate".
- Industrial Production Index: In order to construct countries' "Industrial Production Index" I rely on three variables of the IMF IFS' dataset:
  - Economic Activity, Industrial Production, Index
  - Economic Activity, Industrial Production, Seasonally Adjusted, Index
  - Economic Activity, Industrial Production, Manufacturing, Index

  Ideally, I would construct the variable "Industrial Production Index" by choosing only one of the variables mentioned above. However, this is impossible as countries do not report to the IMF all three of these variables for our time sample, January 2004 to December 2016. For instance, Peru provides neither the "Economic Activity, Industrial Production, Index" nor the "Economic Activity, Industrial Production, Seasonally Adjusted, Index", but does provide the "Economic Activity, Industrial Production, Manufacturing, Index". Visiting Peru's Central Bank statistics website, there is no "Industrial Production Index", but there is an "Industrial Production, Manufacturing Index", which coincides with the variable reported as "Economic Activity, Industrial Production, Manufacturing, Index" to the IMF.

[19] To access the IMF's IFS datasets go to https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b.

In order to deal with this, I establish the following priority between the three IMF IFS variables: (i) "Economic Activity, Industrial Production, Seasonally Adjusted, Index" (ii) "Economic Activity, Industrial Production, Index", (iii) "Economic Activity, Industrial Production, Manufacturing, Index". Table 2 below presents the IMF IFS variable used for each country. I believe that every one of the three variables considered reflects

Table 2: Construction of Industrial Production Index

Emerging Markets	
Brazil	Economic Activity, Industrial Production, Seasonally Adjusted, Index
Chile	Economic Activity, Industrial Production, Seasonally Adjusted, Index
Colombia	Economic Activity, Industrial Production, Seasonally Adjusted, Index
Indonesia	Economic Activity, Industrial Production, Manufacturing, Index
Mexico	Economic Activity, Industrial Production, Seasonally Adjusted, Index
Peru	Economic Activity, Industrial Production, Manufacturing, Index
Philippines	Economic Activity, Industrial Production, Manufacturing, Index
South Africa	Economic Activity, Industrial Production, Manufacturing, Index

Advanced Economies	
Australia	Economic Activity, Industrial Production, Seasonally Adjusted, Index
Canada	Economic Activity, Industrial Production, Seasonally Adjusted, Index
Japan	Economic Activity, Industrial Production, Seasonally Adjusted, Index
South Korea	Economic Activity, Industrial Production, Seasonally Adjusted, Index

the actual industrial production index. From Table 2, it is clear that when "Economic Activity, Industrial Production, Seasonally Adjusted, Index" is not available, the non-seasonally adjusted is also not available. Also, the fact that results are significant for Emerging Market Economies and Advanced Economies separately, see Figures 2b and 2a respectively, suggest that the paper's main results are not driven by the choice of variable. This conclusion also follows from the fact that the paper's main results are robust to the several sub-sample exercises carried out in Section 4.

- Consumer Price Index: Data for all countries except Australia is constructed using the variable "Prices, Consumer Price Index, All items, Index" from IMF IFS data set. Australia does not report a monthly CPI series to the IMF-IFS data set. Furthermore, the Australian Bureau of Statistics provides only quarterly data on their consumer price index.[20] Thus, for the case of Australia I proxy the monthly consumer price index by using the "Prices, Producer Price Index, All Commodities, Index". Once again, given that the paper's main results are robust to the different exercises that partition the sample, I believe that using this proxy variable does not guide any of the of the results presented in the paper.

- Lending Rate: For all countries I use the IMF-IFS' "Monetary and Financial Accounts, Interest Rates, Other Depository Corporations Rates, Lending Rates, Lending Rate,

[20]See https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/consumer-price-index-australia/jun-2022.

Percent per Annum" variable.

- Equity Index: In order to construct countries' "Equity Index" I rely on two variables of the IMF IFS' dataset:

  - Monetary and Financial Accounts, Financial Market Prices, Equities, Index
  - Monetary and Financial Accounts, Financial Market Prices, Equities, End of Period, Index

  I establish a priority: (i) "Monetary and Financial Accounts, Financial Market Prices, Equities, Index" (ii) "Monetary and Financial Accounts, Financial Market Prices, Equities, End of Period, Index". Again, the data coverage is not complete for all countries for the full sample period of January 2004 to December 2016. Table 3 presents index used for every country.

Table 3: Construction of Equity Index

Emerging Markets	
Brazil	Equities, End of Period, Index
Chile	Equities, Index
Colombia	Equities, End of Period, Index
Indonesia	Equities, Index
Mexico	Equities, End of Period, Index
Peru	Equities, End of Period, Index
Philippines	Equities, Index
South Africa	Equities, Index

Advanced Economies	
Australia	Equities, End of Period, Index
Canada	Equities, Index
Japan	Equities, Index
Korea, Rep. of	Equities, Index

Country classification for heterogeneity identification. Next, I describe the different classification/categorization of countries used in Section 4. In particular, I classified countries according to their exchange rate regimes and Emerging Market economies according to their commodity good dependence.

First, I classified/categorized countries according to their exchange rate regimes. In particular, I considered two partitions: (i) Peru vs the rest of the sample, (ii) Peru and Indonesia vs the rest of the sample. This sample partition is constructed following the exchange rate classification built by Ilzetzki et al. [2017] and additional evidence coming from both policy makers and other papers in the literature. Table 4 presents the exchange rate

Table 4: Exchange Rate Classification
Sourced from Ilzetzki et al. [2017]

Emerging Markets

Brazil	2003-2007: Freely Floating, 2008-2016: Managed Floating
Chile	2000-2007: De facto moving band that is narrower than or equal to +/-5%
	2008-2016: Managed Floating
Colombia	Managed Floating
Indonesia	Starting 2005 De facto crawling band +/-2 to 5% range.
Mexico	2000-2008: De facto moving band that is narrower than or equal to +/-5%
	2009-2016 Managed Floating.
Peru	Starting from 2002. De facto crawling band +/-2%. US dollar
Philippines	Starting from 2002. De facto crawling band +/-2%. US dollar
South Africa	2000-2016 Freely floating

Advanced Economies

Australia	2000-2016: Freely floating
Canada	2003-Onward: Freely Floating
Japan	2000-2016: Freely Floating
South Korea	2000-2003: De facto moving band that is narrower than or equal to +/-5%
	2004-2009 Managed Floating
	2010-2016: De facto moving band that is narrower than or equal to +/-5%

classifications from Ilzetzki et al. [2017]. Evidence suggests that Peru has the tightest exchange rate regime (with a de facto moving band of less than 2%), with Indonesia being a close second (de facto moving band with periods below 2% and other periods below 5%). Additionally, as commented in Section 4, both the Central Banks of Peru and Indonesia, and the economic literature have highlighted or studied these countries as case studies of foreign exchange rate intervention policies, see Rossini et al. [2013, 2019], Castillo et al. [2021] for the case of Peru and Warjiyo [2013] for the case of Indonesia. While South Korea also presents a de facto narrow band the Central Bank of Korea publicly denies interventions. As commented by Ryoo et al. [2013], the Korean Central Bank does not carry out FX interventions directly and only does it sporadically through private banks. Consequently, in order to construct the sub-sample between countries which employ tight exchange rate regimes and the rest of the sample I only consider Peru and the "Peru & Indonesia" group.

Second, I carried out a sample partition exercise according to Emerging Market's commodity dependence. The first two columns of Table 5 presents data on the share of commodity goods in countries' total export baskets as constructed by the UNCTAD's "The State of Commodity Dependence" report. All countries in the sample export commodity goods, with Peru showing the greatest share of commodity goods in total exports (89% and 88% for the 2009-2010 and 2014-2015 periods), and Mexico showing the lowest share of commodity goods in total exports (25% and 19% for the 2009-2010 and 2014-2015 periods).

I classify the countries in the Emerging Market economies sample into "High Com-

Table 5: Classification of Countries according to Commodity Dependence

Emerging Markets	Share of Commodity Goods in Total Exports		Classification
	2009-2010	2014-2015	
Brazil	63	63	High Commodity Dependence
Chile	88	86	High Commodity Dependence
Colombia	76	81	High Commodity Dependence
Indonesia	62	58	Low Commodity Dependence
Mexico	25	19	Low Commodity Dependence
Peru	89	88	High Commodity Dependence
South Africa	54	55	Low Commodity Dependence

modity Dependence" and "Low Commodity Dependence" according to whether they are on the top/bottom half of share of commodity goods in total exports. I follow this approach as I only seek to explore commodity goods as a potential source of heterogeneity. It is clear that there are other potential sample partitions. Additionally, there are other exercises to test commodity exports as potential sources of heterogeneity on the impact of spillovers of US interest rates. I leave these exercises for future research.

B Model Details

In this section of the appendix I provide additional details on the panel SVAR model and the identification strategy described in Section 2. Section B.1 presents details on the panel SVAR model while Section B.2 presents additional technical details on the recovery of structural shocks.

B.1 Panel SVAR Model

In this section of the appendix I provide additional details on the estimation of the Structural VAR model presented in Section 2.2. The model described by Equation 1 is estimated using Bayesian methods. In order to carry out the estimation of this model I first re-write the model. In particular, the model can be reformulated in compact form as

$$\underbrace{\begin{pmatrix} y'_{1,t} \\ y'_{2,t} \\ \vdots \\ y'_{N,t} \end{pmatrix}}_{Y_t,\quad N\times n} = \underbrace{\begin{pmatrix} y'_{1,t-1} \cdots y'_{1,t-p} \\ y'_{2,t-1} \cdots y'_{2,t-p} \\ \vdots \ddots \vdots \\ y'_{N,t-1} \cdots y'_{N,t-p} \end{pmatrix}}_{\mathcal{B},\quad N\times np} \underbrace{\begin{pmatrix} (A^1)' \\ (A^2)' \\ \vdots \\ (A^N)' \end{pmatrix}}_{X_t,\quad np\times n} + \underbrace{\begin{pmatrix} \epsilon'_{1,t} \\ \epsilon'_{2,t} \\ \vdots \\ \epsilon'_{N,t} \end{pmatrix}}_{\mathcal{E}_t,\quad N\times n} \tag{4}$$

or

$$Y_t = X_t \mathcal{B} + \mathcal{E}_t \tag{5}$$

Even more, the model can be written in vectorised form by stacking over the T time periods

$$\underbrace{vec\,(Y)}_{NnT\times 1} = \underbrace{(I_n \otimes X)}_{NnT\times nnp} \underbrace{vec\,(\mathcal{B})}_{nnp\times 1} + \underbrace{vec\,(\mathcal{E})}_{NnT\times 1} \tag{6}$$

or

$$y = \bar{X}\beta + \epsilon \tag{7}$$

where $\epsilon \sim \mathcal{N}\left(0, \bar{\Sigma}\right)$, with $\bar{\Sigma} = \Sigma_c \otimes I_{NT}$.

The model described above is just a conventional VAR model. Thus, the traditional Normal-Wishart identification strategy is carried out to estimate it. The likelihood function is given by

$$f\left(y|\bar{X}\right) \propto |\bar{\Sigma}|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\left(y - \bar{X}\beta\right)' \bar{\Sigma}^{-1}\left(y - \bar{X}\beta\right)\right) \tag{8}$$

As for the Normal-Wishart, the prior of β is assumed to be multivariate normal and the prior for Σ_c is inverse Wishart. For further details, see Dieppe et al. [2016]. All of the panel SVAR model computations are carried out using the BEAR Toolbox version 5.1.

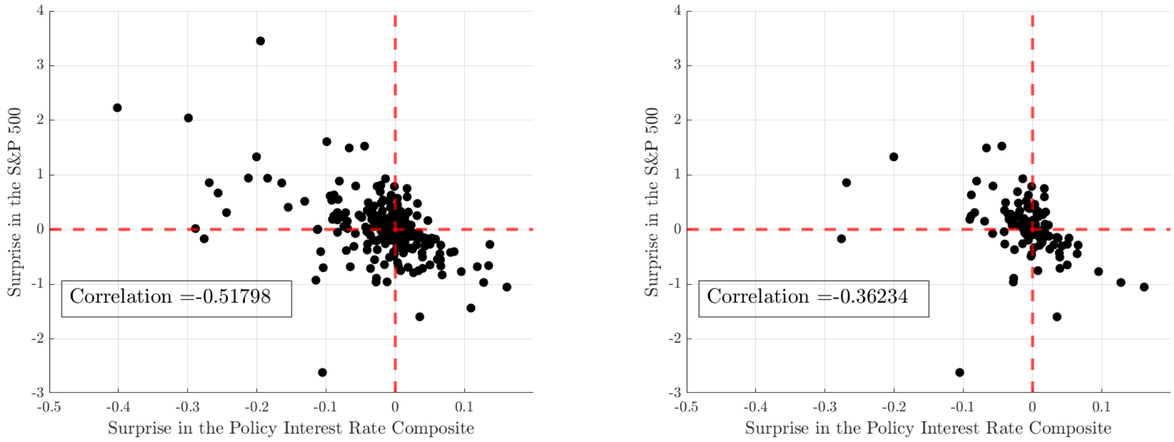
B.2 Identification Strategy & Shock Recovery

In this section of the appendix, I present additional details on the sign-restriction identification strategy presented in Section 2.3 which recovers the two FOMC structural shocks. As stated in Section 2.3, this identification strategy follows Jarociński and Karadi [2020] and Jarocinski [2020].

The identification strategy introduced by Jarocinski [2020] exploit the high-frequency surprises of multiple financial instruments to recover two distinct FOMC shocks: a pure monetary policy (MP) shock and information disclosure (ID) shock. In particular, the authors impose sign restrictions conditions on the co-movement of the high-frequency surprises of interest rates and the S&P 500 around FOMC meetings. This co-movement is informative as standard theory unambiguously predicts that a monetary policy tightening shock should lead to lower stock market valuation. This is because a monetary policy tightening decreases the present value of future dividends by increasing the discount rate and by deteriorating present and future firm's profits and dividends. Thus, MP shocks are identified as those innovations that produce a negative co-movement between these high-frequency financial variables. On the contrary, innovations generating a positive co-movement between interest rates and the S&P 500 correspond to ID shocks.

Figure 7 presents a scatter plot of the high-frequency surprises of interest rates and the S&P 500 around FOMC meetings. The co-movement of these high-frequency surprises is

Figure 7: Scatter Plot of Interest Rate & S&P 500 Surprises around FOMC Meetings



(a) 1990 - 2018

(b) 2004 - 2016

Note: The left panel presents data for the period 1990-2018, in line with the sample constructed by Jarocinski [2020]. The right panel presents data for the period 2004-2016, the sample for the empirical exercises in Section 3. The high-frequency changes of the Policy Interest Rate Composite and the S&P 500 are computed using 30-minute windows around FOMC meetings. Each black filled circle represents a different FOMC meeting.

remarkably different across FOMC meetings. Although a majority of FOMC meetings exhibit a negative co-movement between the interest rates and S&P 500 surprises, a significant share of observations exhibit a positive co-movement. The authors' way to account for the positive co-movement is to attribute it to a shock that occurs systematically at the same time the FOMC announces its policy decisions, but that is different from a standard monetary policy shock. In particular, this additional shock is the disclosure of the FOMC's information about the present and future state of the US economy. Hence, by combining both the high-frequency surprises and imposing sign-restriction in their co-movements, the authors separately identify two structural FOMC shocks: a pure US monetary policy (MP) shock (which exhibits a negative co-movement between the interest rates and S&P high-frequency surprises) and an information disclosure (ID) shock (which exhibits a positive co-movement between the interest rates and S&P high-frequency surprises).

The high frequency surprise in the policy interest rate, i^{Total}, can be decomposed as

$$i^{\text{Total}} = i^{\text{MP}} + i^{\text{ID}} \tag{9}$$

where i^{MP} is negatively correlated with the high frequency surprise of the $S\&P500$ "s", and i^{ID} is positively correlated with the "s". As shown by Jarocinski [2020], the sign restriction recovery of the structural shocks must satisfy the following decomposition

$$M = UC \tag{10}$$

where $U'U$ is a diagonal matrix, C takes the form of

$$C = \begin{pmatrix} 1 & c^{MP} < 0 \\ 1 & c^{ID} > 0 \end{pmatrix} \tag{11}$$

where $M = (i^{Total}, s)$ is a $T \times 2$ matrix with i^{Total} in the first column, s in the second; $U = (i^{\text{MP}}, i^{\text{ID}})$ is a $T \times 2$ matrix with i^{MP} in the first column and i^{ID} in the second column; and T denoting the time length of the sample. By construction, i^{MP} and i^{ID} are mutually orthogonal. Matrix C captures how i^{MP} and i^{ID} translates into financial market surprises.

The decomposition in 11 is not unique. In terms of Jarocinski [2020] there is a range of rotations of matrices U and C that satisfy the sign restrictions $c^{MP} < 0$ and $c^{ID} > 0$.

The matrices U and C are computed as

$$U = QPD \tag{12}$$

$$C = D^{-1}P'R \tag{13}$$

where the matrices Q, P, D, R are obtained in three steps.

1. Decompose matrix $M = UC$ into two orthogonal components using a QR decomposition such that

$$M = QR \tag{14}$$

$$Q'Q = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \tag{15}$$

$$R = \begin{pmatrix} r_{1,1} > 0 & r_{1,2} \\ 0 & r_{2,2} > 0 \end{pmatrix} \tag{16}$$

2. Rotate these orthogonal components using the rotation matrix

$$P = \begin{pmatrix} \cos(\alpha) & \sin(\alpha) \\ -\sin(\alpha) & \cos(\alpha) \end{pmatrix} \tag{17}$$

   To satisfy the sign restrictions use any angle α in the following range

$$\alpha \in \left((1-w) \times \arctan \frac{r_{1,2}}{r_{2,2}}, \frac{w \times \pi}{2} \right) \qquad \text{if } r_{1,2} > 0$$
$$\alpha \in \left(0, w \times \arctan \frac{-r_{2,2}}{r_{1,2}} \right) \qquad \text{if } r_{1,2} \leq 0$$

   where w is weight, between 0 and 1, scaling the rotation angle. Setting $w = 0.5$ implies the median rotation angle, assumption used under the benchmark specification

3. Re-scale the resulting orthogonal components with a diagonal matrix D to ensure that they add up to the interest rate surprises i^{Total}. It is straightforward to show that

$$D = \begin{pmatrix} r_{1,1}\cos(\alpha) & 0 \\ 0 & r_{1,1}\sin(\alpha) \end{pmatrix} \tag{18}$$

Figures 8 and 9 present the time series of the high frequency surprise of the interest rate and of the two recovered structural for my benchmark specification, respectively.

Figure 8: High-Frequency Financial Surprises around FOMC Meetings

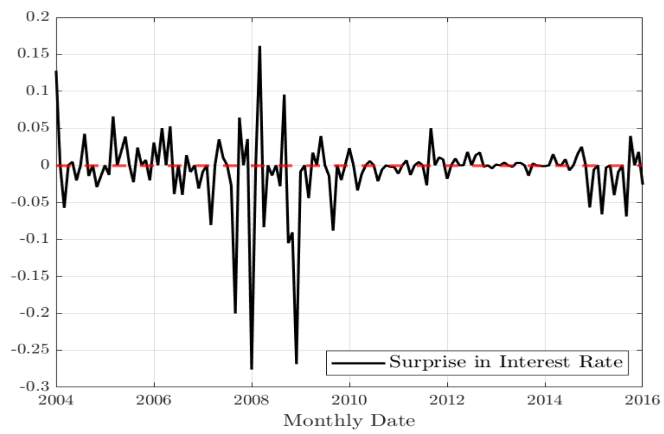
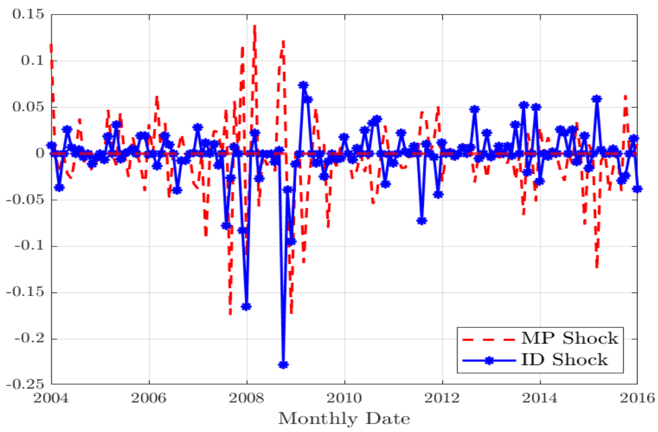


Figure 9: Structural FOMC Shocks



The first robustness check in Section 4 which proposes an alternative approach to deal with the non-uniqueness problem of sign-restriction identification follows the approach of Jarocinski [2020]. In Jarocinski [2020], the angle of rotation α of matrix P is pinned down following these steps

1. Construct "poor man's sign restrictions" shocks such that

$$\begin{aligned} i^{\text{Total}} &= i^{MP} \quad \& \quad i^{\text{ID}} = 0 \qquad \text{if } i^{Total} \times s \leq 0 \\ i^{\text{Total}} &= i^{ID} \quad \& \quad i^{\text{MP}} = 0 \qquad \text{if } i^{Total} \times s > 0 \end{aligned}$$

In the data, Jarocinski [2020] finds that the poor man's monetary policy shocks account for 88% of the variance of the Federal Reserve's total interest rate surprises, i.e,

$$\frac{var\left(i^{\text{MP}}\right)}{var\left(i^{\text{MP}}\right)} = 0.88$$

To pin down the decomposition, Jarocinski [2020] impose that, as in the "poor man's sign restrictions" case, $var\left(i^{\text{MP}}\right)/var\left(i^{\text{MP}}\right) = 0.88$. Additionally, Jarocinski [2020] shows that the angle α can meets this condition can be recovered as

$$\alpha = \arccos\sqrt{\frac{var\left(i^{\text{MP}}\right)}{var\left(i^{\text{MP}}\right)}} \tag{19}$$

In particular, the α that meets this condition is set equal to $\alpha = 0.8702$.

In Section 4 I carry out three robustness checks. The two additional robustness checks replace the benchmark assumption of using the median rotation angle and instead use the 75^{th} and 25^{th} percentile assumptions. These different rotation angles imply setting the weight w equal to 0.75 and 0.25, respectively. Figures 15a and 15b in Appendix D present the results of these robustness checks.

C Alternative Strategies that Control for Information Effects

In this section, I show that the main results of this paper are also present when estimating the spillovers of a pure US monetary policy shock using alternative identification strategies which control for possible information effects around FOMC meetings. This result strengthens the argument that recent atypical international dynamics found when following the standard high-frequency identification strategy of US monetary policy shock, such as the expansion of industrial output, can be attributed to the systematic disclosure of information around FOMC meetings.

I consider two alternative identification strategies: the one proposed by Miranda-Agrippino and Ricco [2021] and the one presented by Bauer and Swanson [2022]. These two alternative identification strategies control for information effects of the Federal Reserve's monetary policy through different approaches to that followed by Jarociński and Karadi [2020]. First, Miranda-Agrippino and Ricco [2021] define US monetary policy shocks as exogenous shifts in the policy instrument that surprise market participants, are unforecastable, and are not due to the central bank's systematic response to its own assessment of the macroeconomic outlook. To this end, the authors construct an instrument constructed by regressing the high-frequency market surprises in the fourth federal fund future onto a set of Greenbook forecasts for output, inflation and unemployment. Through this instrument, the authors can control for the signalling effect of monetary policy, i.e., the Federal Reserve responding to expected changes in macroeconomic and financial variables. Unlike Jarociński and Karadi [2020], this approach controls for the Federal Reserve's own information set which may or may not reflect or include the financial market's information.[21]

Second, Bauer and Swanson [2022] define US monetary policy shocks as exogenous shifts in policy interest rates that are purged of any response of the Federal Reserve to macroeconomic news. To do so, the authors identify US monetary policy shocks by orthogonalizing the high-frequency surprises of the first component of four Eurodollar futures contracts of key macroeconomic or financial information available prior to the FOMC meeting.[22] The authors argue these approach purges the interest rate surprises of the "Fed Response to News" channel, in which incoming, publicly available economic news causes both the Fed to change

[21]The time series on the US monetary policy shocks under the two alternative identification strategies is sourced directly from the authors' websites. For the case of Miranda-Agrippino and Ricco [2021] the shocks can be recovered from `https://github.com/GRicco/info-policy-surprises`. This time series is only available up until December 2015. Thus, when estimating the model under this identification strategy the relevant sample is January 2004 to December 2015. For the case of Bauer and Swanson [2022] the shocks can be recovered from `https://www.michaeldbauer.com/publication/mps/`.

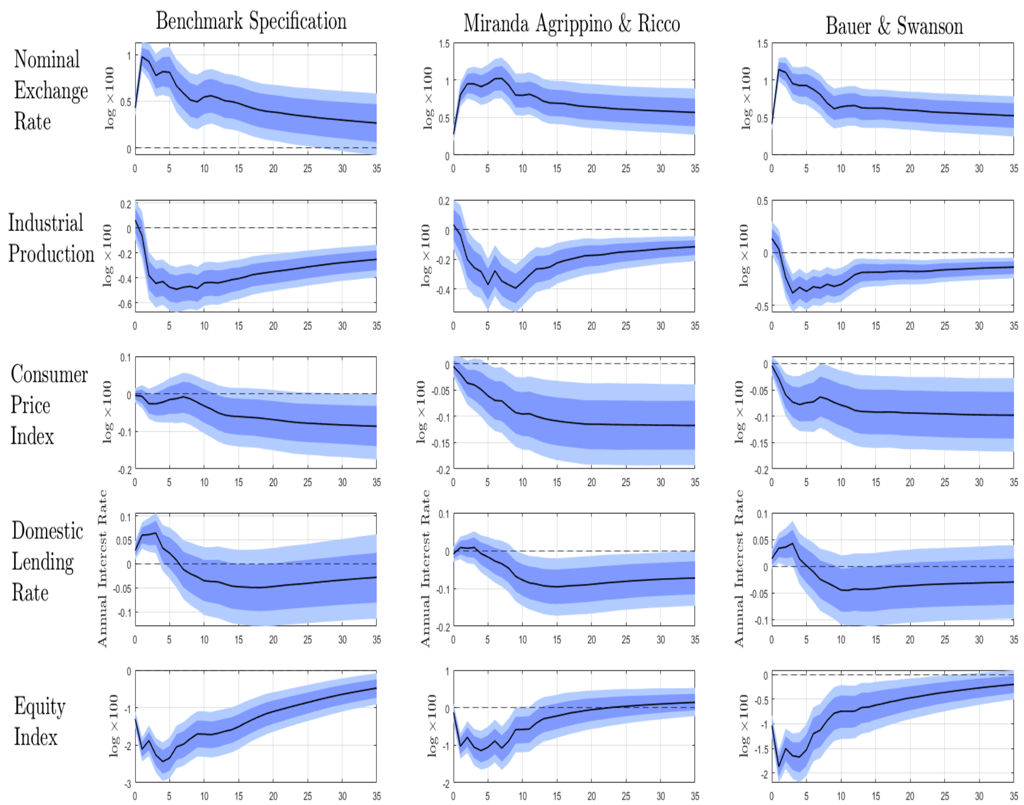
[22]Note that both the surprise in the Fed Funds Futures used by Miranda-Agrippino and Ricco [2021] and the Eurodollar future contracts used by Bauer and Swanson [2022] are part of the policy interest rate composite used to construct the FOMC shocks in Section 3.

monetary policy and the private sector to revise its forecasts. It is noteworthy to state that this identification strategy is based on a previous paper, Bauer and Swanson [2020], which argues that the "Fed Information Effect", as presented by Jarocinski [2020], is not quantitatively important. Furthermore, the authors argue that a plausible explanation to this effect is the "Fed Response to News" channel. However, as stressed by Jarocinski [2020] the theoretical models presented in Bauer and Swanson [2020, 2022] still predict a negative correlation between interest rate surprises and stock price surprises. Furthermore, even as the overall correlation between the high-frequency surprises between interest rates and the S&P 500 is negative, to the extent that some variants of the "Fed Response to News" channel generates a positive correlation between these financial surprises, one can interpret the ID shock as a proxy for this effect too (see Jarocinski [2020]).

Figure 10 compares the impulse response functions of a MP shock under the benchmark specifications, with the impulse response functions of a US monetary policy shock under the two alternative identification strategies.[23] The resulting impulse response functions are qualitatively in line with the main results presented in Section 3. All three specifications of a US monetary policy shock leads to a nominal exchange rate depreciation, a hump-shaped fall in industrial production, a drop in the consumer price index, a mild increase in lending rates and a persistent drop in the equity index. Quantitatively the results are also significantly close across the three identification strategies. While the two alternative identification strategies predict a greater and more significant reduction in the consumer price index, the benchmark specification predicts a greater increase in domestic lending rates and a larger and more persistent drop in the equity index. In summary, the robustness check in which two alternative identification strategies which control for the disclosure of information by the Federal Reserve around FOMC meetings lead to similar qualitatively and quantitatively results to our benchmark results leads to two main conclusions. First, by controlling for the disclosure of information around FOMC meetings, a pure US monetary policy shock leads to negative spillovers over a panel of countries, consistent with the older and conventional view. The second conclusion is that the systematic disclosure of information about the state of the US economy during FOMC announcements leads to recent atypical dynamics, such as those presented by Ilzetzki and Jin [2021] and the ones presented in Section 3 under the "Standard HFI" strategy. Once the ID shocks are taking into account, whether interpreted as the "Fed Information Effect" or the "Fed Response to News" channel, any atypical dynamics disappear.

[23] Under the two alternative shocks I set the vector m_t of structural shocks as solely containing the US monetary policy shock of either identification strategy. Note that the methodology presented by Bauer and Swanson [2022] expands the set of monetary policy announcements to include speeches by the Fed Chair, which essentially duplicates the number of announcements in their dataset. This leads to multiple announcements and high-frequency surprises within a month. In order to construct a monthly time series of shocks to introduce into vector m_t I take the simple average of all shocks within the same month.

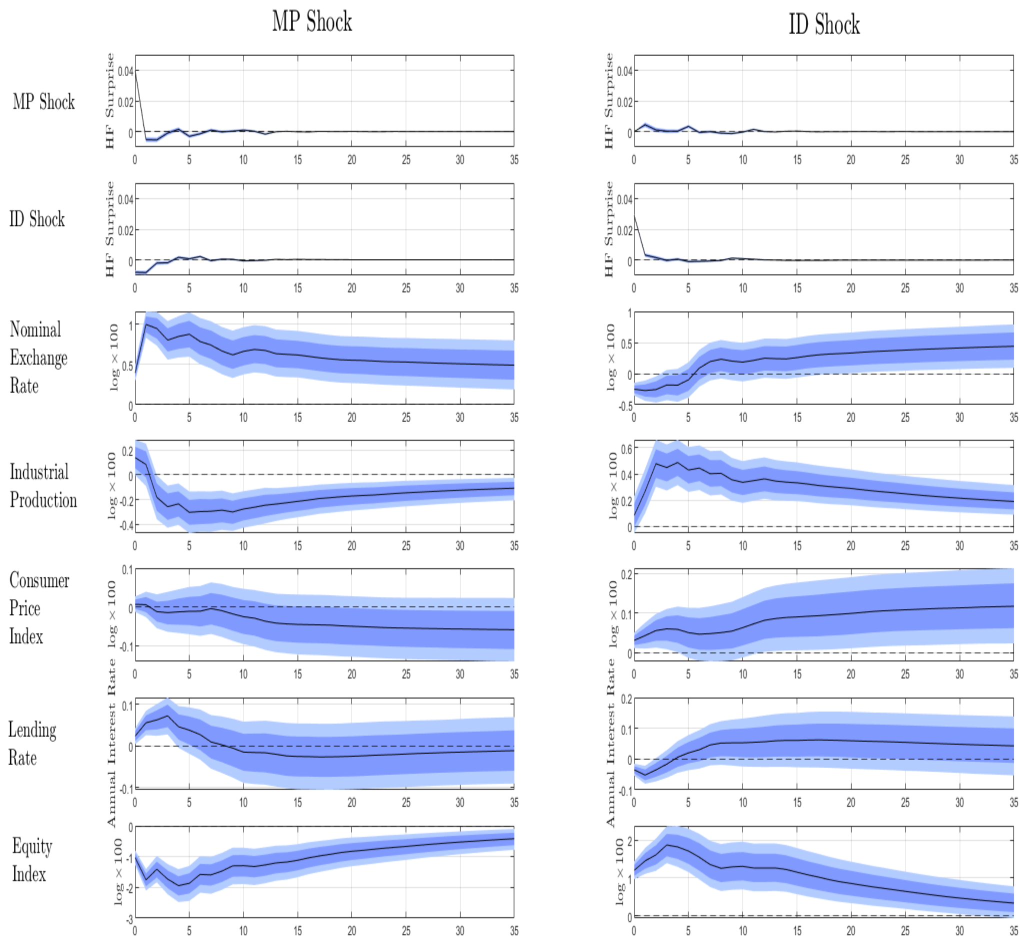
Figure 10: Impulse Response to One-Standard-Deviation Shock
Benchmark Specification



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock under the benchmark specification, the middle column presents the results for the ID or "Information Disclosure" shock, and the last column presents the results for the interest rate composite high frequency surprise or "Standard HFI". In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

D Additional Results

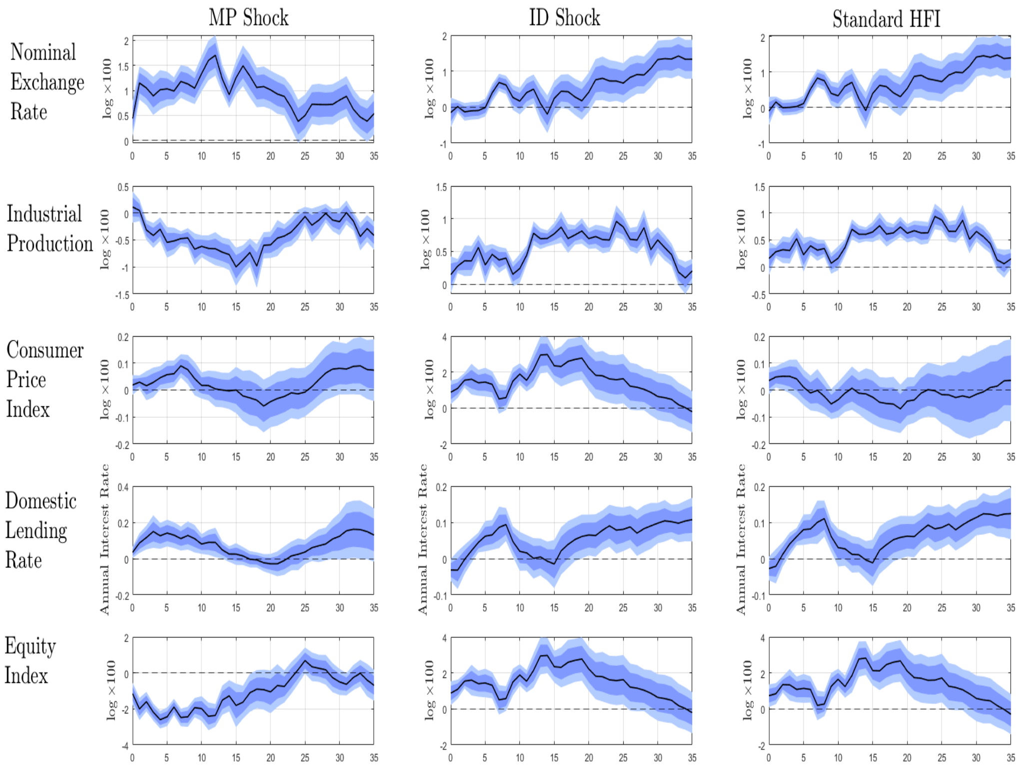
Figure 11: Impulse Response to One-Standard-Deviation Shock
Benchmark Specification



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 14 sub-figures ordered in seven rows and two columns. Every row represents a different variable: (i) the MP structural FOMC shock, (ii) the ID structural FOMC shock, (iii) nominal exchange rate, (iv) industrial production index, (v) consumer price index, (vi) lending rate, (vii) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock, the last or right column presents the results for the ID shock. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

Figure 12: Local Projection Impulse Response Functions

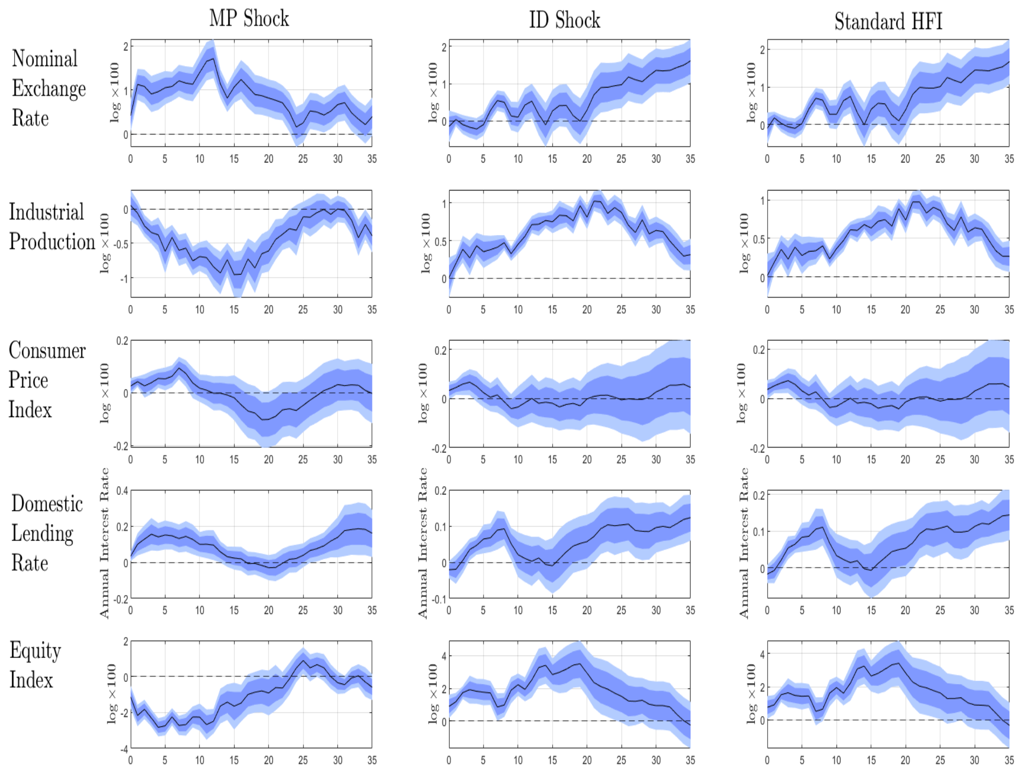
F.E. + Time Trend Specification



Note: The black solid line represents the point estimate of coefficient for either one of the two FOMC shocks, or the high-frequency surprise of the policy interest rate composite. The dark shaded area represents a 68% confidence intervals, and the light shaded are represents the 90% confidence intervals. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock, the middle column presents the results for the ID or "Information Disclosure" shock, and the last column presents the results for the interest rate composite high frequency surprise or "Standard HFI". In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure. For each shock, I standardize the coefficients such that they represent the dynamics of a one-standard deviation shock.

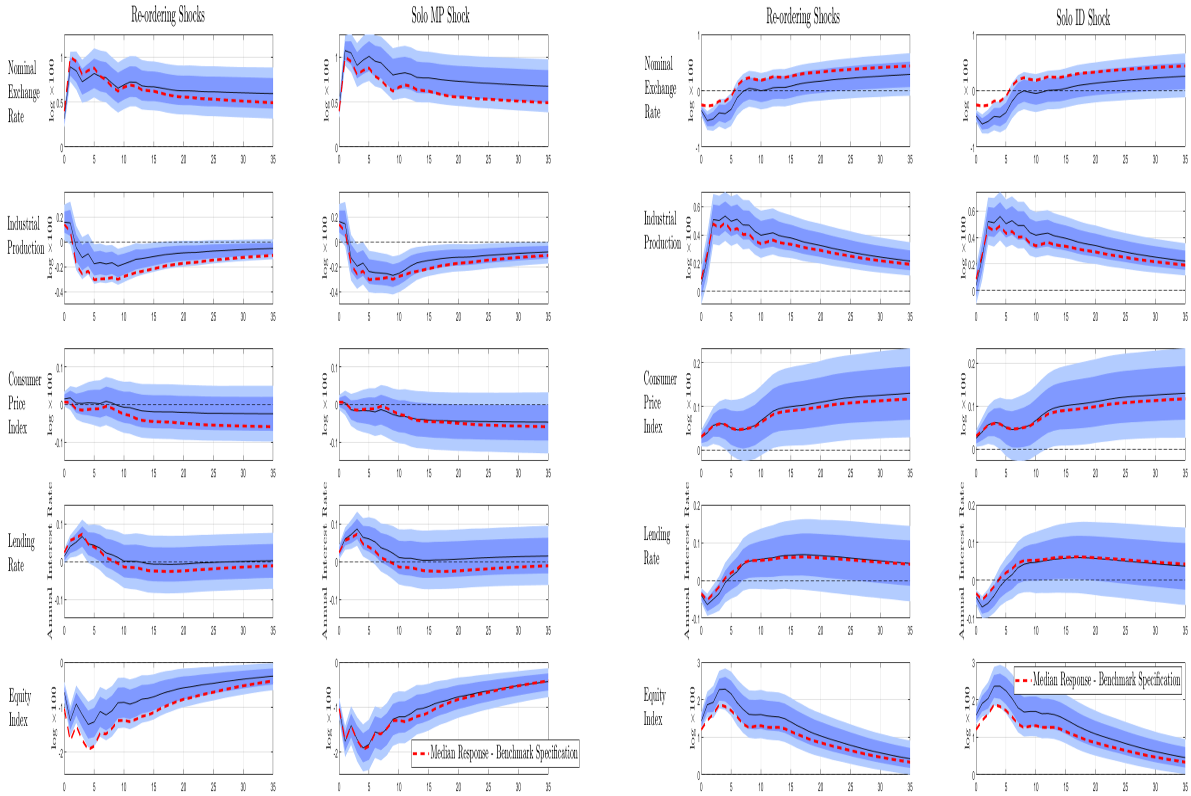
Figure 13: Local Projection Impulse Response Functions

Month-Country F.E. Specification



Note: The black solid line represents the point estimate of coefficient for either one of the two FOMC shocks, or the high-frequency surprise of the policy interest rate composite. The dark shaded area represents a 68% confidence intervals, and the light shaded are represents the 90% confidence intervals. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the MP or "Pure US Monetary Policy" shock, the middle column presents the results for the ID or "Information Disclosure" shock, and the last column presents the results for the interest rate composite high frequency surprise or "Standard HFI". In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure. For each shock, I standardize the coefficients such that they represent the dynamics of a one-standard deviation shock.

Figure 14: Robustness Check under Alternative Shock Ordering
All variables

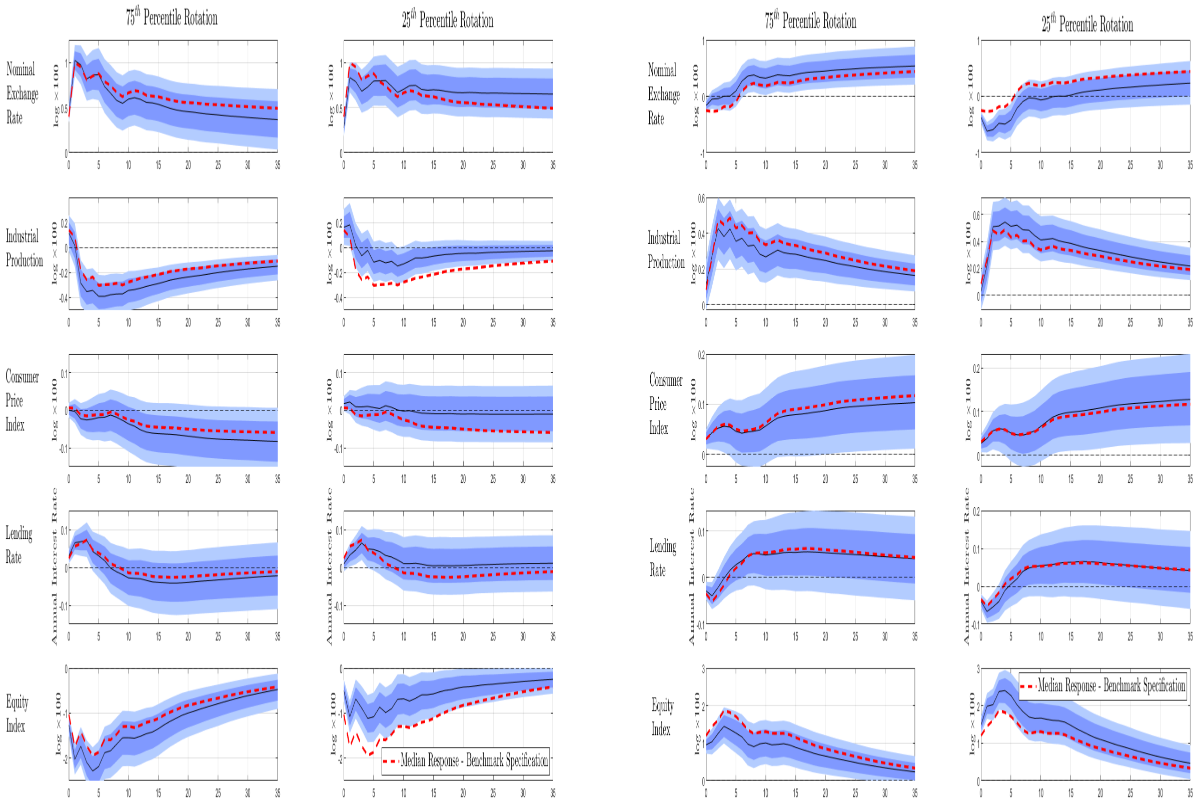


(a) MP Shock (b) ID Shock

Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The dashed red line presents the median response of the benchmark specifications presented in Figure 1. Each figure is comprised of 6 sub-figures ordered in three rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) equity index. The first column presents the results when ordering the ID shock first and the MP shock second, and the second column presents the dynamics for a specification with m_t containing only the MP or the ID shock. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

Figure 15: Robustness Check under Alternative Sign Restriction Rotations

All Variables

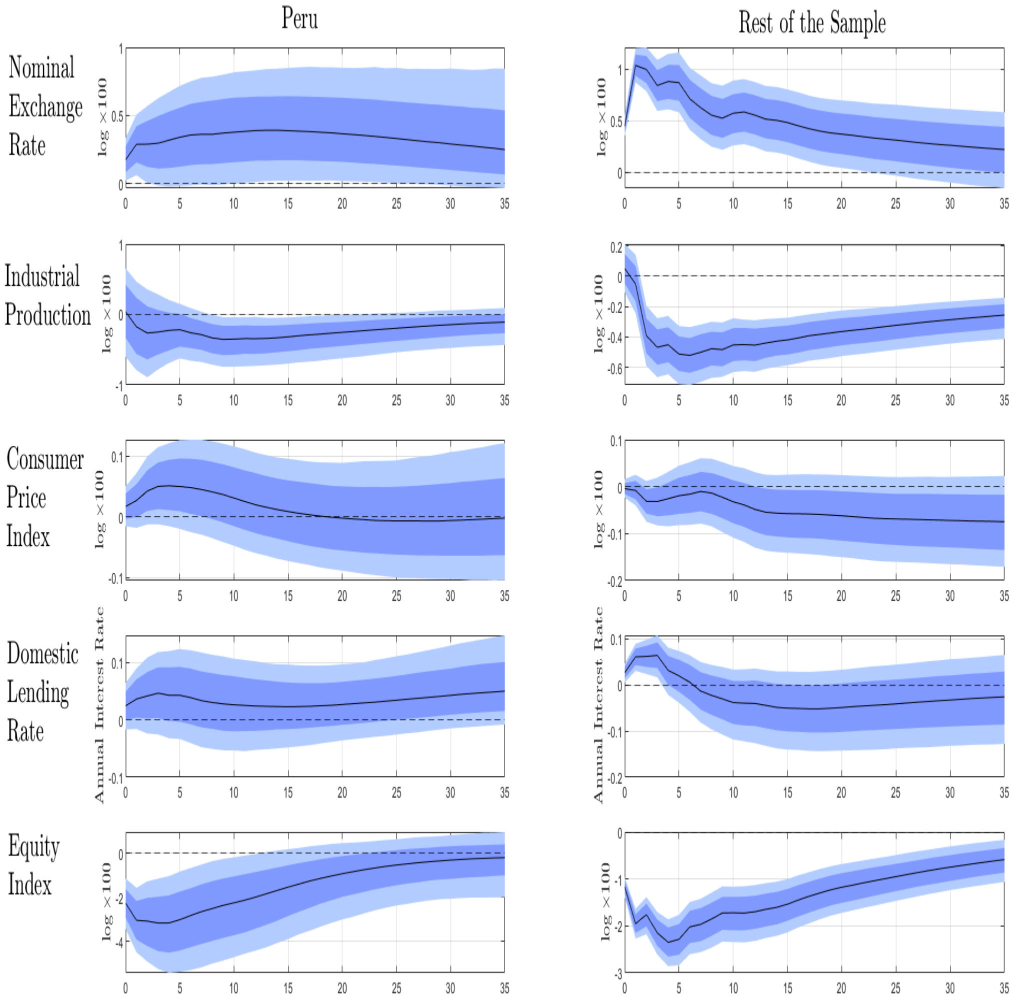


(a) MP Shock (b) ID Shock

Note: The left and right panel present the results for the MP and ID shock, respectively. The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The dashed red line presents the median response of the benchmark specifications presented in Figure 1. The figure is comprised of 10 sub-figures ordered in three rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for the 75 percentile rotation while the last column presents the results of the 25 percentile rotation. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

Figure 16: IRF to One-Standard-Deviation MP Shock

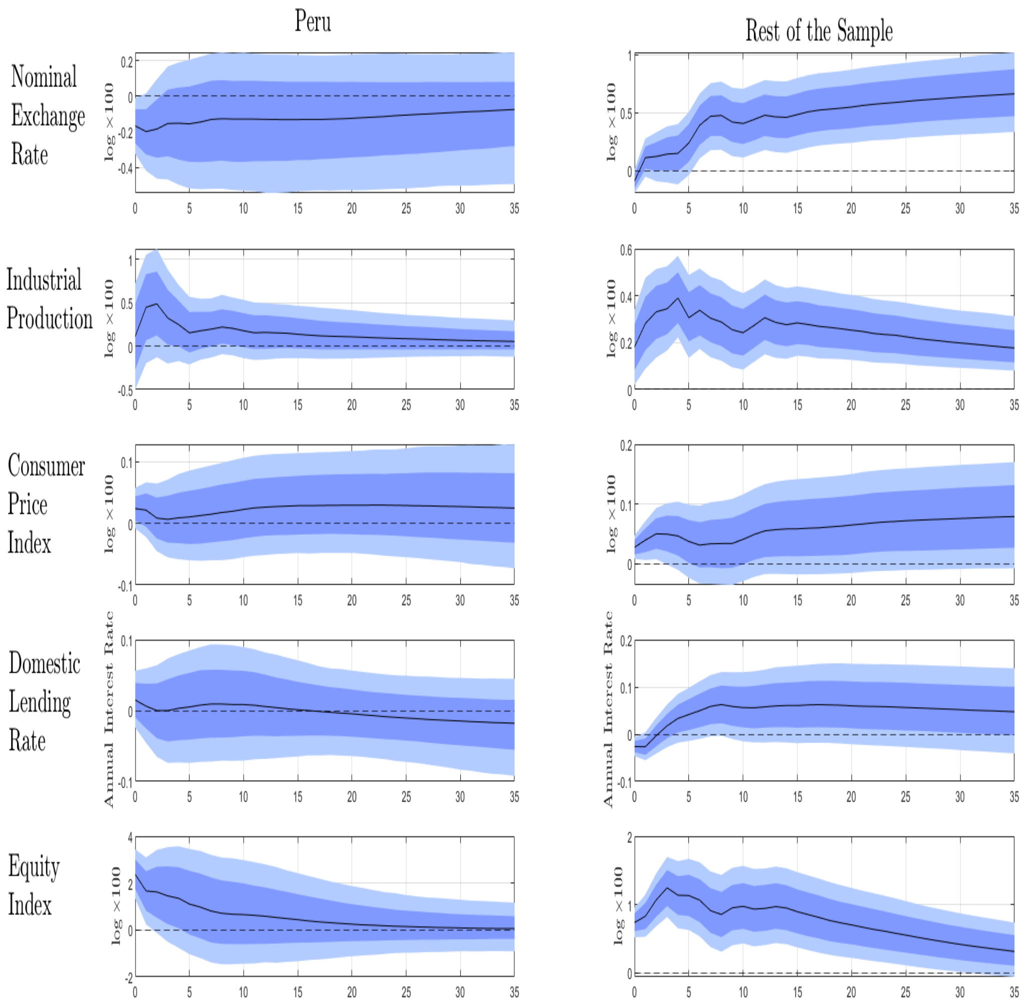
Exchange Rate Regimes - Peru



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for Peru, the middle column presents the results for a sample of both Advanced and Emerging Market economies except Peru, the third or right column presents the results for a sample of Emerging Market economies except Peru. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

Figure 17: IRF to One-Standard-Deviation CBI Shock

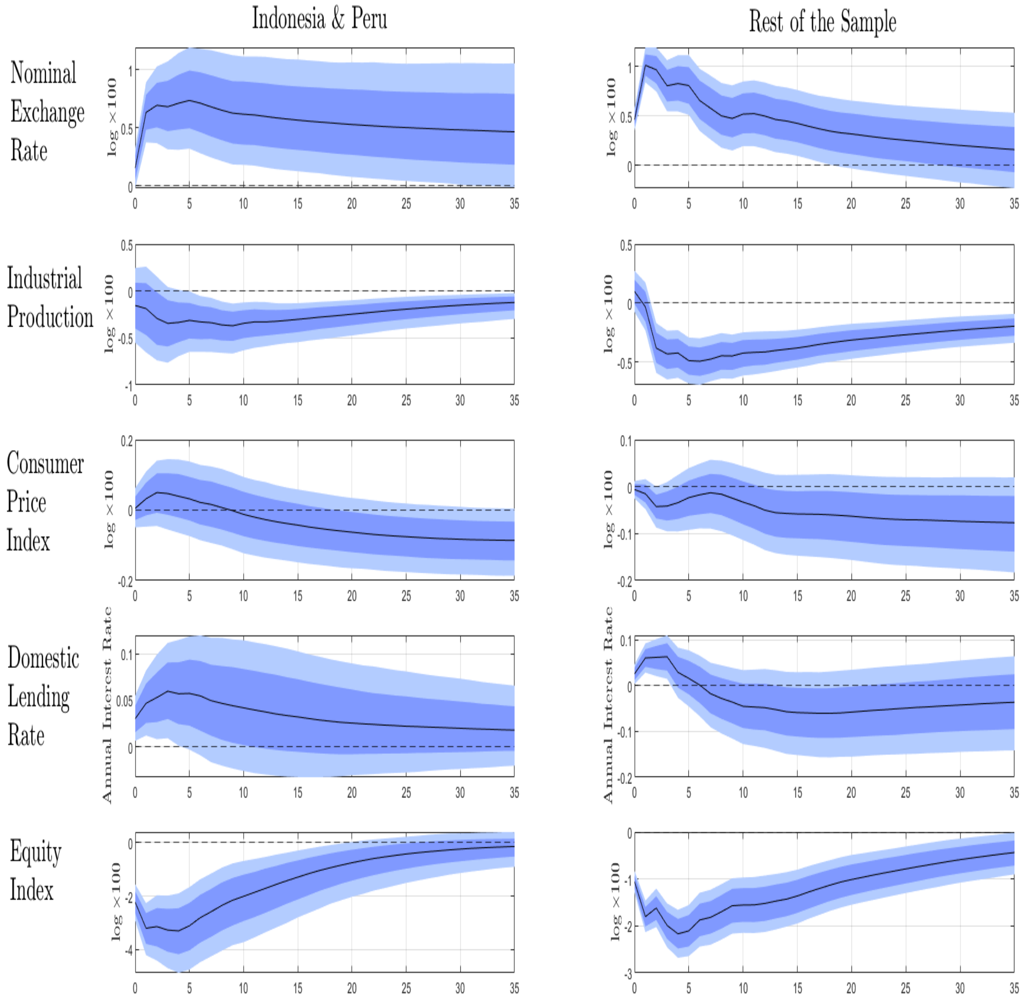
Exchange Rate Regimes - Peru



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for Peru, the middle column presents the results for a sample of both Advanced and Emerging Market economies except Peru, the third or right column presents the results for a sample of Emerging Market economies except Peru. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

Figure 18: IRF to One-Standard-Deviation MP Shock

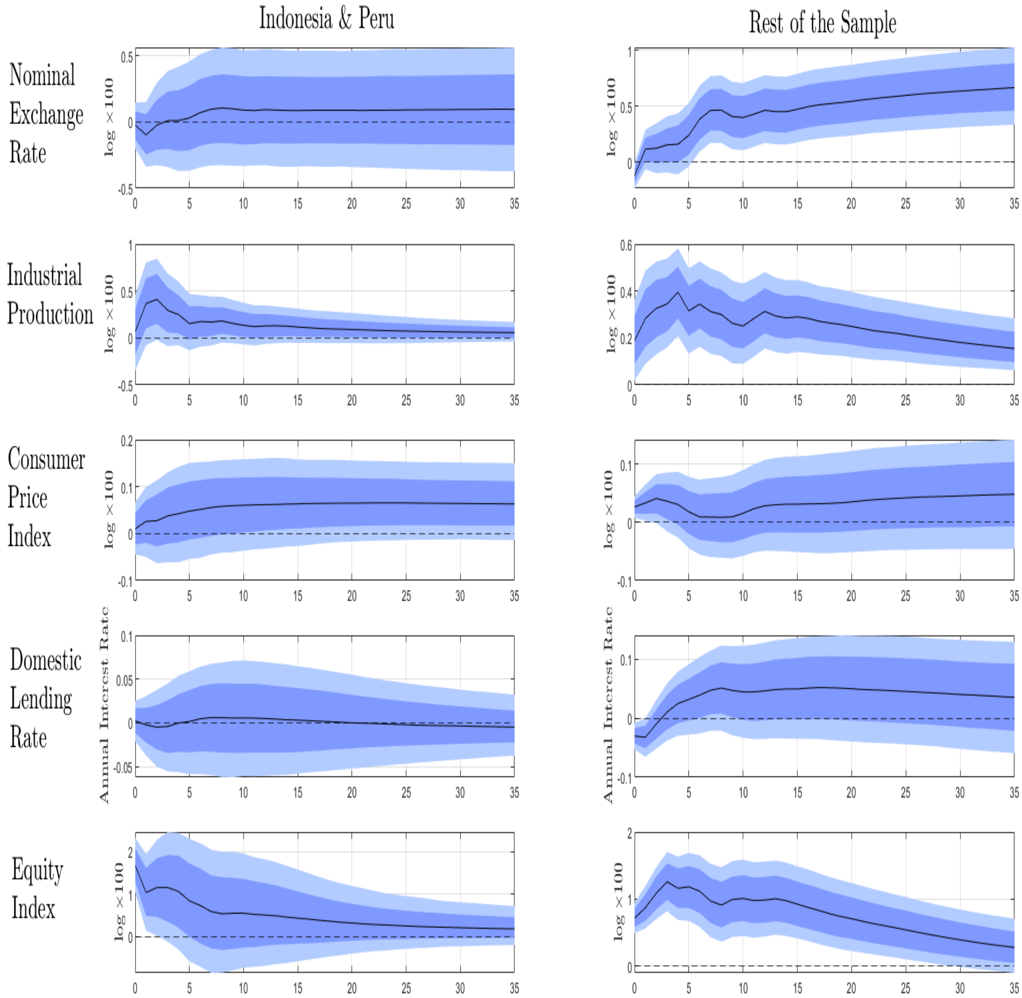
Exchange Rate Regimes - P & I



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for a sample of Peru and Indonesia, the middle column presents the results for a sample of both Advanced and Emerging Market economies except Peru and Indonesia, the third or right column presents the results for a sample of Emerging Market economies except Peru and Indonesia. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

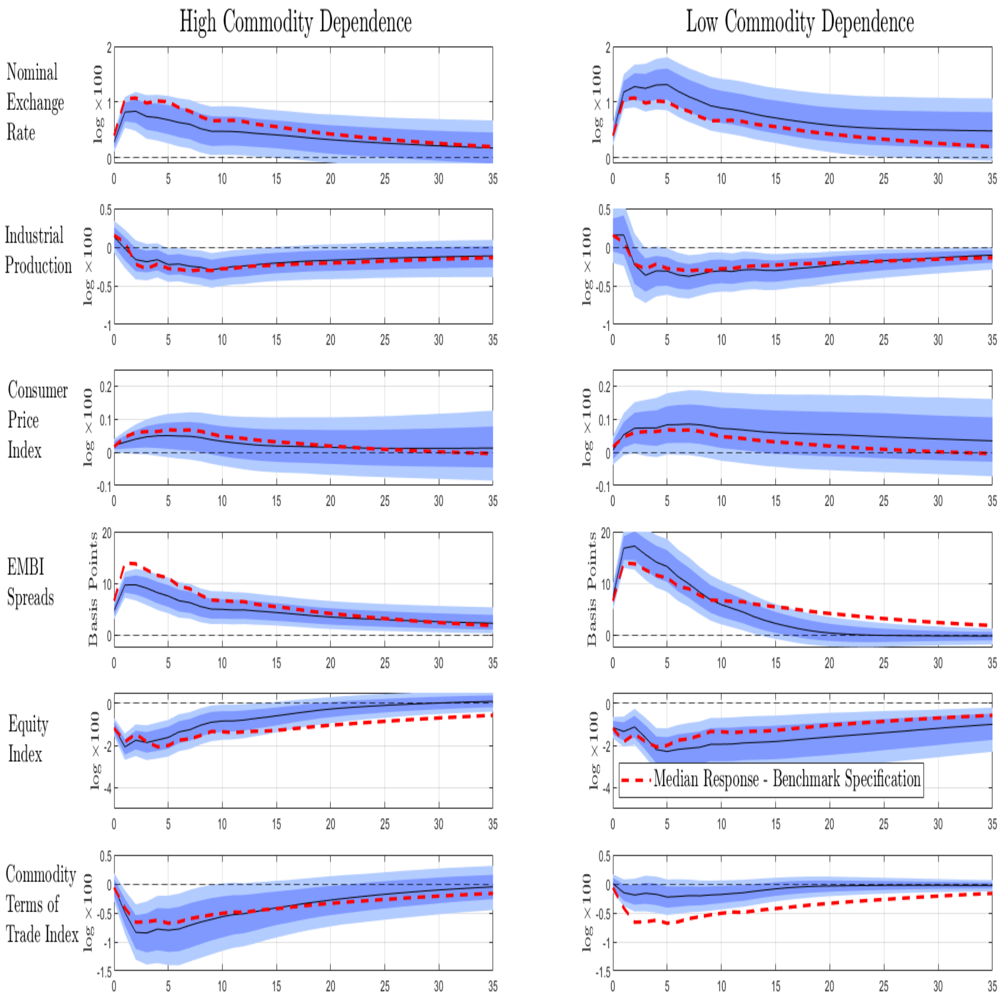
Figure 19: IRF to One-Standard-Deviation ID Shock

Exchange Rate Regimes - P & I



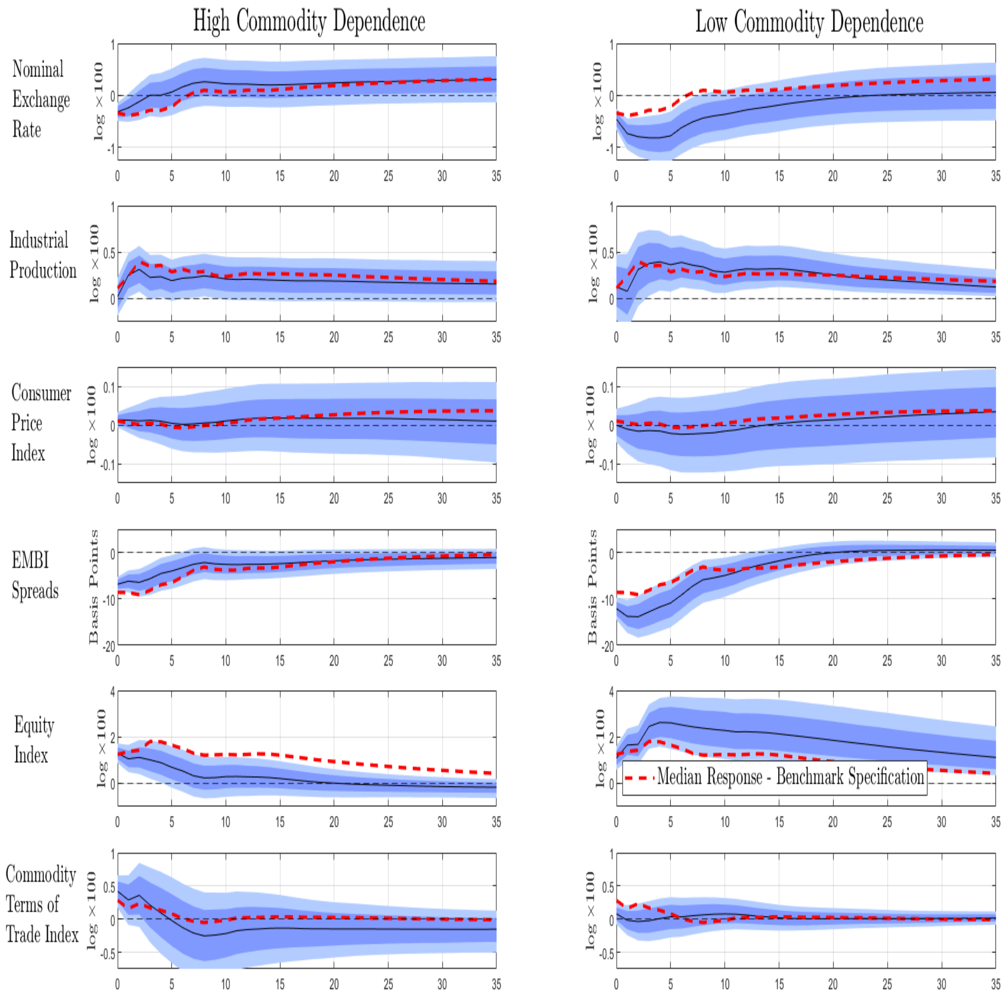
Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The figure is comprised of 15 sub-figures ordered in five rows and three columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production index, (iii) consumer price index, (iv) lending rate, (v) equity index. The first column presents the results for a sample of Peru and Indonesia, the middle column presents the results for a sample of both Advanced and Emerging Market economies except Peru and Indonesia, the third or right column presents the results for a sample of Emerging Market economies except Peru and Indonesia. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

Figure 20: IRF to One-Standard-Deviation MP Shock
Commodity Dependence



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The dashed red line represents the median response under the Emerging Market variable specification estimated only for Emerging Market economies (see Figure 6). The figure is comprised of 12 sub-figures ordered in 6 rows and two columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production, (iii) consumer price index, (iv) EMBI spreads, (v) equity index, (vi) Commodity Terms of Trade Index. The first or left column presents the results for the sub-sample of Emerging Markets considered "High-Commodity Dependence": Brazil, Chile, Colombia and Peru. The second or right column presents the results for the sub-sample of Emerging Markets considered "Low-Commodity Dependence": Indonesia, Mexico and South Africa. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.

Figure 21: IRF to One-Standard-Deviation ID Shock
Commodity Dependence



Note: The black solid line represents the median impulse response function. The dark shaded area represents the 16 and 84 percentiles. The light shaded are represents the 5 and 95 percentiles. The dashed red line represents the median response under the Emerging Market variable specification estimated only for Emerging Market economies (see Figure 6). The figure is comprised of 12 sub-figures ordered in 6 rows and two columns. Every row represents a different variable: (i) nominal exchange rate, (ii) industrial production, (iii) consumer price index, (iv) EMBI spreads, (v) equity index, (vi) Commodity Terms of Trade Index. The first or left column presents the results for the sub-sample of Emerging Markets considered “High-Commodity Dependence”: Brazil, Chile, Colombia and Peru. The second or right column presents the results for the sub-sample of Emerging Markets considered “Low-Commodity Dependence”: Indonesia, Mexico and South Africa. In the text, when referring to Panel (i, j), i refers to the row and j to the column of the figure.