Journey to the (North, South, East, and) West: Global Spillovers of Chinese Monetary Policy

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Abstract

We evaluate the role production linkages play in the global transmission of Chinese monetary policy shocks through global stock returns. Using a heterogeneous spatial autoregression (SAR) with identified Chinese monetary policy shocks, we explore how shocks propagate upstream and downstream through a supply-chain channel of monetary policy. We highlight that the type of monetary policy shock matters: Target shocks transmit primarily through supply-chains and Path shocks operate through an additional non-network financial spillover component. On average, firms connected to the Chinese production network show negative country-industry level annualized equity returns in response to contractionary monetary policy. Across the three weighting matrices, network magnitude shares for Target shocks range between 74.33–93.44% upstream and 93.61–97.38% downstream. For Path shocks, shares range between 52.13–57.05% and 48.38–50.54%. Combined, this suggests a role for supply-chain transmission of monetary policy shocks. Additionally, we find that compared with US monetary policy shocks, Chinese shocks do not move global risk measures, with Path responses consistent with expectations or information effects. Our results underscore the role global supply-chains play in China's increasing influence on global markets.

JEL Classification

E5, F3, F4

Keywords

Monetary Policy; Spatial Econometrics; Spillovers; Trade; Spatial Autoregression; High-Frequency Identification; Chinese Economy; Production Networks; Supply Chains

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1 Introduction

Since the 2008 Financial Crisis, the effects of monetary policy have been a topic of debate in both policy and academic circles. We typically think about monetary policy conducted by the major central banks as having broad spillovers across global financial markets. For example, Miranda-Agrippino and Rey (2020b) finds that global financial conditions and asset prices co-move with US monetary policy shocks — the global financial cycle is directly affected by US monetary policy. The vast majority of papers focus on the financial spillovers of US and EU monetary policy shocks, with little focus on China.

Despite being the world's second-largest economy and being heavily connected to global supply-chains, the global implications of Chinese monetary policy are not well studied. China's international financial integration remains relatively limited despite its expansive and direct linkages to the global economy through its heavy participation in supply-chains. Strict capital controls, a managed exchange rate, limits on trading volume, and restrictions on asset classes available to foreign investors, among other regulations, reduce China's financial linkages with the rest of the world. While slowly changing, these limitations complicate how we typically think about cross-border monetary policy transmission. The standard channels are less likely to apply. In the seeming absence of these channels through which monetary policy transmits, one key question arises: How does Chinese monetary policy propagate globally?

We quantify the role production networks play in the global transmission of Chinese monetary policy shocks to global stock returns. In particular, we emphasize the role supply-chains play in the global transmission of Chinese monetary policy shocks. Due to China's strong links with many global trading partners, understanding how Chinese monetary policy affects countries along its immediate periphery, as well as around the world, gives us further insight into how monetary policy transmits across borders and how small-open economies respond to these shocks.

A key feature of our approach is to emphasize that the *type* of monetary policy shock matters when characterizing the spillover effects globally. Using the Shieh (2024) high-frequency monetary policy factors, we introduce Target and Path shocks into our analysis to separately identify how surprise changes to the current monetary policy stance (Target) may differ from surprise changes to beliefs about the future path of monetary policy (Path) in the global propagation of Chinese monetary policy shocks. Specifically, Target shocks directly modify the financing conditions that Chinese firms face, whereas Path shocks can act as either expectations or information shocks that reveal information about the current state of the economy or alter beliefs about future policy direction. These shocks behave differently and the inclusion of these different shocks allows us to assess the existence of both supply-chain and financial spillovers.

We make the case that due to China's outsized importance in global manufacturing, global production linkages are the primary propagation mechanism of Chinese monetary policy shocks. More specifically, we recontextualize Chinese monetary policy shocks as supply and demand shocks to global firms up and downstream of China. For firms upstream of China, we hypothesize a standard demand shock story in response to domestic Target Chinese shocks, while firms downstream of China face supply shocks — in either case, the domestic Chinese shocks

affect global markets through the global value chains. We allow for Chinese monetary policy to transmit through financial linkages and the results suggest that a financial spillovers pathway is possible through Path rather than Target.[1] However, we argue that because the relative exposure to global financial markets is much smaller than that of the US, as well as other structural limitations to Chinese financial linkages globally, spillovers through supply-chains are likely to play the dominant role in the transmission of Chinese shocks, with any potential financial channels playing a much smaller role.

We empirically assess our hypothesis by estimating a heterogeneous-coefficient spatial autoregression (hereafter, heterogeneous SAR) on annualized equity returns across 11 economies and 7 industries identified using the high-frequency Target and Path shocks updated from Shieh (2024). When Chinese Target shocks propagate upstream, that is, when contractionary Target monetary policy shocks materialize as negative demand shocks, foreign firms that are *upstream* of Chinese firms are affected due to decreased demand for intermediate goods by Chinese firms, resulting in negative stock returns. A 1SD contractionary Chinese Target shock is associated with a network-mediated average reduction between 0.71–0.89pp in equity returns across country-industry pairs. These indirect effects translate to network magnitude shares of roughly 74.33–93.44%. That is, the input-output linkages play a statistically significant role in the upstream transmission of Chinese monetary policy shocks. A 1SD contractionary Path shock generates a network-mediated reduction between 1.14–1.25pp in equity returns, with network magnitude shares of roughly 52.13–57.05%. Path shocks also have significant direct effects, in line with recent evidence of financial spillovers (Ma et al. 2026). The smaller network magnitude share relative to Target suggests that Path shocks operate through a combination of financial and supply-chain effects.

Consistent with this interpretation, we find that Chinese monetary policy shocks do not behave in a manner consistent with a Fed-style global risk channel. We find that VIX does not have a persistent response to Chinese shocks and no Fed-like drop in the Miranda-Agrippino and Rey (2020b) global factor. Instead, Path shocks are associated with an increase in the global factor, suggesting a response more consistent with non-risk financial components, such as information or expectations shocks.

Similarly, when Chinese monetary policy propagates as a negative supply shock, Chinese firms produce fewer intermediates in response to tighter domestic monetary policy and, as a result, export fewer intermediates to firms *downstream* that rely on Chinese intermediates, resulting in negative stock returns. A 1SD contractionary Target shock is associated with a network-mediated reduction between 0.98–1.02pp in equity returns, with network magnitude shares between 93.61–97.38%. A 1SD contractionary Path shock is associated with a network-mediated reduction of 1.06–1.11pp in equity returns, with network magnitude shares between

[1] Some literature suggests that there may be growing financial spillovers of Chinese monetary policy shocks, like in Ma et al. (2026). We discuss this a little more in the review of the literature. Possible financial channels of monetary policy transmitting include financial offshoring by domestic Chinese investors into offshore tax havens as discussed in Clayton et al. (2023), a bank-risk-like channel, since Chinese banks in 2021 constituted about 7.5% of global cross-border bank lending, with their primary customers coming from emerging markets and developing economies (Cerutti et al. 2021), and the expansion of The Belt and Road Initiative presenting a scenario in which increasing financial linkages from China to the developing economies may facilitate cross-border spillovers. While we find evidence for some potential financial spillovers, we argue these are secondary to production linkage spillovers. These all present interesting avenues for future research.

48.38–50.54%. The indirect Target effect is larger in magnitude downstream than upstream, while Path effects retains significance similar to the upstream case. Like in the upstream case, equity responses are heterogeneous across country-industries, suggesting that some country-industries downstream of China may be more (or less) reliant on Chinese intermediate goods.

The main point of comparison is with US monetary policy spillovers through production networks. Our results, relative to Di Giovanni and Hale (2022), show that trade-linkage shares are larger than in US monetary policy spillovers — underscoring the importance of supply-chains in the transmission of Chinese monetary policy shocks. Overall, the results highlight the role of production linkages and provide another pathway that explains how Chinese monetary policy transmits globally, which depends on a firm's location along the supply-chain. Surprise changes to Chinese policy result in spillovers throughout the global production network.

We complement our equity results with suggestive real-side transmission evidence. We find that contractionary Chinese monetary policy shocks lower Chinese industrial production. Existing evidence from Miranda-Agrippino et al. (2020) and Miranda-Agrippino et al. (2026) find that global commodity prices decrease after Chinese monetary policy shocks, taken alongside the reduction in industrial production, is suggestive of our upstream negative demand shock channel. Additionally, producer prices increase in Japan, South Korea, and Germany following a contractionary Chinese shock, consistent with a negative supply shock following a decrease in Chinese output. While we cannot separately identify supply and demand effects at the aggregate level, when taken together, provide additional context to our empirical estimates in the heterogeneous SAR and connect our equity responses to real economy.

We have three primary contributions to the rich literature examining the drivers of global asset prices and characterize China's importance and influence on global financial markets. First, we quantify an international transmission channel for Chinese monetary policy through supply-chains. Second, we distinguish between and characterize how Target and Path monetary policy shocks systematically differ in their global transmission, and third, we are able to analyze the directionality of production networks in the propagation of Chinese monetary policy shocks by separately examining upstream and downstream propagation.

Examining country-industry equity returns, we provide novel evidence of the supply-chain channel by linking Chinese monetary policy shock propagation with input-output linkages. Our results are broadly consistent with the macro results discussed in the literature but provide micro evidence showing the importance of supply-chains in the propagation of Chinese monetary policy shocks. To our knowledge, this is the first paper that examines the transmission of monetary policy shocks through both upstream and downstream firms and directly examines the role supply-chains and production networks play in the international transmission of Chinese monetary policy.

Canonical explanations for international monetary policy spillovers revolve around the exchange rate channel (e.g. Mundell (1963)) or financial markets (e.g. Miranda-Agrippino and Rey (2020a) and Miranda-Agrippino and Rey (2020b)) and is not as well understood as standard domestic channels of transmission. The literature typically focuses on US monetary policy, highlighting the Fed's outsized influence on global asset markets and financial intermediaries. One set of papers finds that US monetary policy transmits powerfully across borders

and drives movements in international asset prices and international financial markets (see, among others, Obstfeld (2015), Park and Um (2016), Rey (2016), Miranda-Agrippino and Rey (2020a), Miranda-Agrippino and Rey (2020b), Lin and Niu (2021)). Other papers highlight a banking channel in the transmission of US monetary policy (see, among others, Bruno and Shin (2015), Buch et al. (2018), and Bräuning and Ivashina (2020)), emphasizing the degree to which the Fed influences global financial intermediation. Our paper, however, is one of the first to examine China's influence on global markets by linking movements in global asset prices with global supply-chains and Chinese monetary policy shocks — providing an alternative channel for policy transmission that accounts for China's institutional context.

Our paper contributes to a small but growing literature highlighting the role trade and global value chains play in transmitting Chinese monetary policy. A majority of these studies (e.g. Kozluk and Mehrotra (2009), Johansson (2012), Huang et al. (2014), Vespignani (2015), Cho and Kim (2021), Beirne et al. (2023), and Chen et al. (2023)) focus on the regional transmission of Chinese shocks to asset markets and trade.[2] Our paper diverges from these and examines the global transmission of Chinese shocks by connecting asset price movements to production network linkages — unifying the global transmission of Chinese monetary policy as a supply-chain transmission channel. Three studies closely relate to this paper and evaluate the global impact of Chinese monetary policy, with complementary results. Ma et al. (2026) examines the global financial spillovers of Chinese monetary policy, with estimates broadly in line with what we find for the effects not associated with production linkages. In other words, we view their results as synergistic with ours, finding that while small (but growing) financial spillovers exist, most of the effect can be characterized through alternative channels. Miranda-Agrippino et al. (2020) and Miranda-Agrippino et al. (2026) find that Chinese monetary policy broadly transmits through global commodities markets and value chains, unlike US monetary policy. Our results complement these findings and provide deeper evidence that not only characterizes how value chains transmit Chinese monetary policy shocks but also quantifies the importance of these supply-chain linkages as a channel of international monetary policy transmission to international financial markets.

Our paper is also one of a few papers in the growing literature examining the identification of Chinese monetary policy shocks, with our approach continuing in the tradition of high-frequency identification of monetary policy shocks. Closely related to our approach are Kamber and Mohanty (2018) and Das and Song (2023), who rely on policy surprises to interest rate swaps on the 7-Day Repo Rate as an instrument for monetary policy shocks. Shieh (2024) extends this by extracting Target and Path factors from these surprises, which we adopt and refine, as our measure of policy shocks. Other work examines alternative derivative products as instruments to measure Chinese monetary policy. He et al. (2024) examines the usage of Negotiable Certificates of Deposit (NCDs) as their instrument, Liu et al. (2025) uses Chinese Treasury Futures to identify PBOC shocks, and Gürkaynak et al. (2026) relies on copper futures to identify shocks. Our approach allows for disentangling short-term policy surprises against surprise changes to the expected future monetary policy stance, uniquely allowing us

[2] There is also recent work showing that Chinese macro announcements affect global financial markets (Gutierrez et al. 2026).

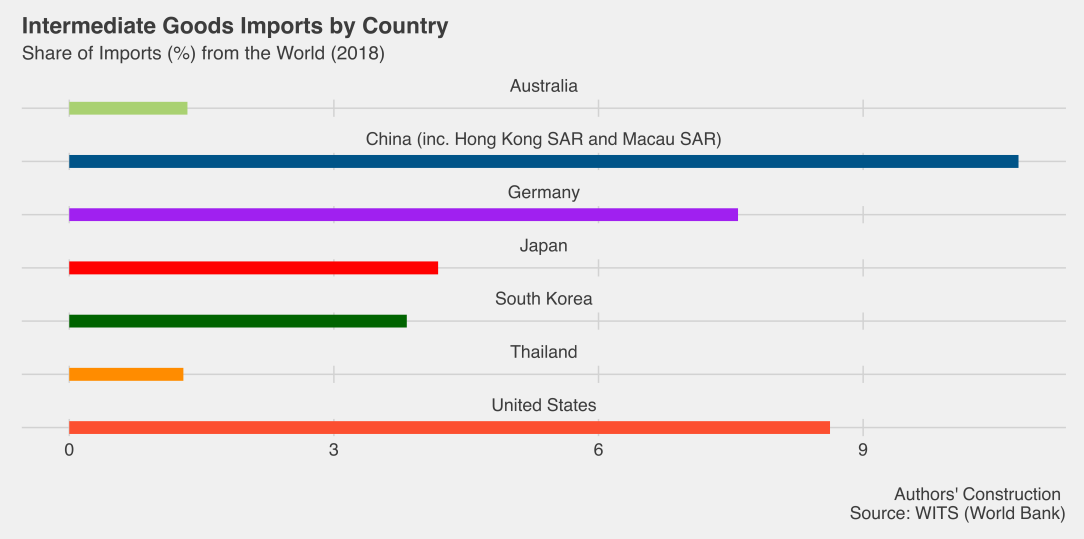
to comment on how different monetary policy shocks matter in their global transmission.

One of the highlights of our approach is our ability to connect asset price movements with supply-chain connections in both an upstream and downstream capacity (i.e., we look at the middle of the supply-chain rather than just the ends. In other words, we can examine "center-out" effects versus "outer-in" ones). Specifically, we leverage input-output linkages to and from China. The usage of input-output linkages in macroeconomic analysis is not new. Methodologically, we are closely related to the work done in Di Giovanni and Hale (2022), where they examine the propagation of US monetary policy shocks through global value chains, focusing on the upstream propagation of those shocks. We differ mainly by studying China, which is more exposed to global markets through trade, as opposed to financial linkages, but also by directly evaluating both upstream and downstream propagation of policy shocks from the middle of a value chain as opposed to the ends. Our results are complementary, highlighting the role supply-chains play in monetary policy transmission, especially for China. Following Acemoglu et al. (2016), we can evaluate how macroeconomic shocks propagate up and downstream through an input-output network. The role supply-chains and production networks play in the transmission of monetary policy shocks has only been a recent area of economic inquiry (see, among others, Gong et al. (2016), Ozdagli and Weber (2017), Todorova (2018), Bräuning and Sheremirov (2019), Wei and Xie (2020), La'O and Tahbaz-Salehi (2022), Rubbo (2023)). These studies emphasize the viability of monetary policy transmission through these input-output linkages. However, these studies focus on the transmission of US and EU monetary policy shocks globally through these linkages. Our paper would be the first to use global production networks in the analysis of monetary policy shocks that originate from China.

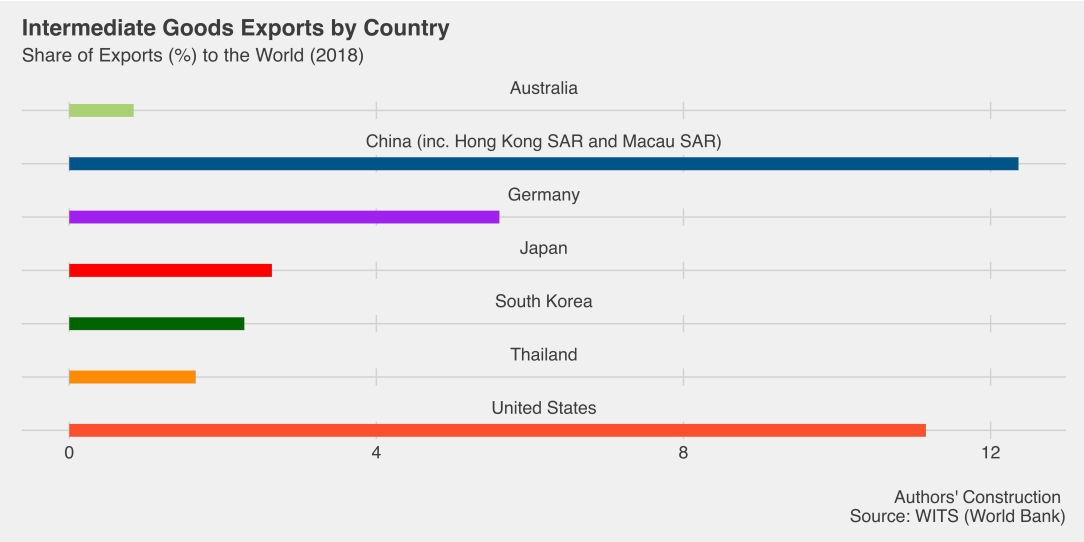
The remainder of the paper is organized as follows. Section 2 discusses the empirical framework and issues of identification. Section 3 details the data utilized in this study, with specific emphasis on how the novel panel data was created, as well as the industry-level matching done to match input-output data with stock return data. Section 4 discusses the empirical upstream and downstream impacts of Chinese monetary policy shocks. Section 5 examines a few robustness checks and Section 6 concludes.

2 Empirical Framework

We begin by discussing and contextualizing how Chinese monetary policy transmits along global supply-chains. China's unique position in global supply-chains plays a prominent role in the propagation of a Chinese monetary policy shock. Figure 1a and Figure 1b show China's dominance in intermediate goods trade in 2018. Since China both exports and imports the largest share of global intermediate goods, other countries are dependent on either exporting intermediate goods for Chinese firms to use (as is the case of Australia) or receiving Chinese exports of intermediate goods for their own final goods production (as is the case of South Korea).



(a) Intermediate Goods Imports



(b) Intermediate Goods Exports

2.1 Channels and Propagation of a Chinese Monetary Policy Shock

Because China is less exposed to global financial markets than to trade, Chinese monetary policy should have more limited spillover avenues through the standard financial channels. Thus, we hypothesize that the most likely suspect is through a supply-chain channel. Shocks either propagate upstream or downstream in the supply-chain. What that means, in a more intuitive sense, is that firms up or downstream of China are affected by Chinese monetary policy spillovers either as a materialization of supply shocks or demand shocks. We motivate this analysis using a simple partial equilibrium model modified from Di Giovanni and Hale (2022) and show that the spatial spillover of Chinese monetary policy shocks can be linked to country-industry level input-output linkages in a production function. Specifically, we can show the effect of these linkages in the firms' problem and characterize the effect of the Chinese monetary policy in both an upstream and downstream context. To be clear, we present this simple model as a way of motivating our empirical strategy, rather than explicitly solving for quantity and prices. We formalize this with the following:

A Partial Equilibrium Model

From the perspective of countries up and downstream from China, we assume that there are M countries (belonging to a continuum $\in \Theta$) and N products. Among these M countries, H is the home country and country $F = \Theta - \{H\}$ are the foreign countries. More specifically, we focus on China, which we denote as F_{PRC}. The firm uses a nested Cobb-Douglas production function to produce their output. The nested production function is represented as follows

$$\hat{Y}_H^i = A_H \left[\left(L_H^i \right)^{\alpha_{iH}} \left(K_H^i \right)^{1-\alpha_{iH}} \right]^{\beta_{iH}} \left[\prod_{j=1}^{M} \prod_{l=1}^{N} m_{j\to H, l\to i}^{\gamma_{jH}^{li}} \right]^{1-\beta_{iH}} \tag{1}$$

Here, the subscripts (H, j) are countries and the superscripts (i, l) are the products. The first part of the production function is the composite of the labor and capital and the second part is the composite of the intermediate goods. $\hat{Y}_H^i$ is the output of product i in country H. L_H^i and K_H^i are the labor and capital demand. $m_{j\to H, l\to i}^{\gamma_{jH}^{li}}$ is the demand of the intermediate goods where γ_{jH}^{li} represents global input-output linkages. A_H is the firm specific productivity. (1-β_{iH}) is the share of intermediate goods and α_{iH} is the labor share in country H and sector i within the labor-capital share. The marginal cost of the firm in country H is MC_H^i, given by

$$MC_H^i = \Omega \left[\left(w_t \right)^{\alpha_{iH}} \left(R_t \right)^{1-\alpha_{iH}} \right]^{\beta_{iH}} \left[\prod_{j=1}^{M} \prod_{l=1}^{N} \left(p_{j\to H}^{l\to i} \right)^{\gamma_{jH}^{li}} \right]^{1-\beta_{iH}} \tag{2}$$

where w_t is the wage rate, R_t is the rental rate of capital, $\left(p_{j\to H}^{l\to i} \right)$ is price of the intermediate goods and Ω is a constant.

The output of the firms can be intermediate goods or final goods and the demand of $\hat{Y}_H^i$ depends on the domestic and foreign demand i.e. at market clearing, $\hat{Y}_H^i = \hat{Y}_{HH}^i + \hat{Y}_{HF}^i$ where HH and HF represent the domestic demand and foreign demand of the home-produced goods. Assuming no trade frictions, at equilibrium,

$$\begin{aligned} P_{Ht}^i C_{HH,t}^i + \sum_{F\in\Theta-\{H\}} P_{Ft}^i C_{HF,t}^i &= P_{Ht}^i \hat{Y}_{Ht}^i \quad \text{(For Final Goods)} \\ \hat{Y}_{H,t}^i = \underbrace{\sum_{l=1}^{N} \gamma_{HH}^{il} m_{H,t}^{i\to l}}_{\text{Domestic demand}} &+ \underbrace{\sum_{j=1, j\neq H}^{M} \sum_{l=1}^{N} \gamma_{Hj}^{il} m_{H\to j}^{i\to l}}_{\text{Foreign demand}} \quad \text{(For Intermediate Goods)} \end{aligned} \tag{3}$$

Here, $C_{HH,t}^i$ is the consumption of the home produced goods in country H, $C_{HF,t}^i$ is the export demand of home goods in country F.

The monetary policy spillover happens through the input-output linkages i.e. γ_{jH}^{li}. For the final goods, a contractionary monetary policy shock in a foreign country, say China (F_{PRC}), reduces $C_{HF_{PRC},t}^i$ — reducing the total demand of product i and home country production decreases. Assuming efficient markets, changes in home country production are taken as changes to country-industry stock returns.

The contractionary Chinese monetary policy shocks also reduce the demand for intermedi-

ate goods in China (F_{PRC}), which in turn reduces the demand for intermediate goods from the home country H (i.e. $m^{i \to l}_{H \to F_{PRC}}$ moderates). This is the upstream story, where a contractionary Chinese monetary policy shock realizes as a *negative Chinese demand shock* for both domestic Chinese and non-Chinese intermediate goods, which should materialize as negative country-industry stock returns.

On the downstream side, contractionary Chinese monetary policy reduces supply of the intermediate goods from China due to tighter financing conditions yielding higher marginal costs of producing intermediate goods in China.[3] In other words, $m^{l \to i}_{F_{PRC} \to H}$ decreases as Chinese firms produce less intermediate goods due to elevated marginal cost, with a spillover effect of reduced intermediate exports. This is effectively a *negative Chinese supply shock* that results in lower supply of intermediate goods faced by Home firms reliant on these inputs. Lower supply of intermediate goods is reflected through higher Home firm marginal costs. For example, we can use the Covid-19 supply-chain disruptions as evidence of this behavior. Meier and Pinto (2024) show that sectors with high exposure to Chinese intermediate goods imports saw larger declines in output and show evidence of resulting higher input and output prices.[4] As a result, we argue that Chinese intermediates have a lower elasticity of substitution relative to other suppliers resulting in higher production bottlenecks, delays, and inefficient input substitution when faced with a negative supply shock from China, culminating in lower output and higher effective marginal costs. As marginal cost MC^i_H increases, the resulting Home goods markup increases, resulting in lower output as domestic demand falls. This too should materialize as negative stock returns. Notice that in either case, if the input-output connections are stronger, the effect is more severe. That is, when $\gamma^{il}_{HF_{PRC}}$ is high, we should expect a larger effect from a Chinese monetary policy shock.

With the upstream and downstream propagation channels in mind, the empirical strategy is straightforward. The goal is to connect Chinese monetary policy shocks with production linkages between China and countries along its supply-chain. Using identified Chinese monetary policy shocks, we estimate a spatial autoregression by examining the effects of those shocks on industry-level stock returns across multiple countries over time. We proxy production and output changes as changes to industry stock returns. We justify this primarily for two reasons: (1) assuming efficient markets, stock returns reflect beliefs about future discounted cash flows, so if domestic monetary policy shocks affect cross-border industry output, then cross-border industry stock returns will react to the shock. (2) stock returns do not have the lead/lag problem when compared to using output data. Since the shocks occur at the daily frequency (then aggregated to monthly), output at the industry level at the monthly frequency may suffer from lags due to the nature of production contracts. Since stock prices reflect changes to expected future discounted cash flows, the reaction time of stock prices will be faster than a real-side variable in response to a shock at the monthly frequency.

[3] Existing studies suggest that China was able to increase the trade surplus by maintaining low export prices which helped to maintain export competitiveness in international market (Al-Haschimi et al. (2024)). This suggests that the Chinese manufacturers are expected to maintain the producer prices even if they are facing higher marginal costs due to tightening monetary policy. However, the supply of the intermediate goods is likely to get impacted as the manufacturers' margin gets thinned out.

[4] More generally, Finck et al. (2026) find in Swedish microdata that supply-chain shocks have persistent inflationary effects.

2.2 Identification of Chinese Monetary Policy Shocks

Identification of Chinese monetary policy shocks poses an interesting challenge. First, Chinese monetary policy uses multiple levers to enact its statutory goals. More challenging is the fact that there is a mix of both price and quantity-based tools over the sample (e.g., changing interest rates versus reserve requirement changes). Thus, quantifying the effects of both types of levers is a unique exercise. For example, on 06/28/2015, the PBOC announced a reduction in the reserve requirement and the benchmark lending rate by 50bps and 25bps, respectively. Disentangling this change in a quantity tool (reserve requirement) and a price tool (lending rate) is difficult. Instead, we recognize that these actions represent expansionary monetary policy and abstract away from the specific tool used. As a result, we shift focus to capturing only the unanticipated effect of this change in the policy stance on this specific announcement date.

Second, as has been pointed out in the literature surrounding monetary policy shock identification, potential endogeneity can be introduced when dealing with financial variables on the left-hand side. Namely, asset prices and monetary policy may have simultaneity – asset prices may respond to monetary policy, and monetary policy shocks may have already incorporated asset prices (e.g., Rigobon and Sack (2003), Bernanke and Kuttner (2004), Gertler and Karadi (2015), etc.). Due to this limitation, slower frequency measures of monetary policy (quarterly measures of monetary policy stance, M2, etc.) do not sufficiently identify monetary policy shocks when evaluating changes to equity returns.

To address these problems, we use the Chinese monetary policy factors introduced in Shieh (2024), following the methodology proposed in Gürkaynak et al. (2005) for surprise US monetary policy shocks. The Shieh (2024) Chinese monetary policy factors, like its Gürkaynak et al. (2005) analog for the United States, extracts latent factors from a set of asset price changes that bracket Chinese monetary policy announcements. Following Kamber and Mohanty (2018), Das and Song (2023), and Shieh (2024), the Chinese monetary policy stance is proxied by a commonly used market rate, the 7-Day Repo Rate. The underlying asset instrument set is five tenors of the interest rate swaps (IRS) on the 7-Day Repo rate. While not exactly like Fed Funds Futures, these are the closest approximations in the Chinese market that allow for some measure of market expectations of policy stance.

The Target and Path factor approach differs from a surprise-only measure of monetary policy, as seen in Kamber and Mohanty (2018). Gürkaynak et al. (2005), Bauer and Swanson (2020), and Swanson (2021) argue that monetary policy is likely multi-dimensional, so a single surprise measure may not fully reflect surprise changes to the policy stance. This is particularly relevant to Chinese monetary policy, as the policy framework itself is opaque, complex, and not as well understood. Reducing Chinese policy into purely a surprise-only measure may potentially oversimplify the effect of Chinese policy shocks by aggregating the effect of surprises with beliefs about the future policy stance. Additionally, this approach allows us to be agnostic about the specific policy lever and instead looks at unanticipated changes to the policy stance in the short term.[5] Since we can distinguish between surprise short-term changes

[5] If a specific policy lever was of interest, then using Kamber and Mohanty (2018) could be appropriate. However, we note that using a singular surprise measure of surprises may aggregate both contractionary and expan-

to the stance (Target) versus surprise changes to the expected future path of policy (Path), we argue that we have sufficient measures of surprises to the monetary policy, measuring both stance changes and beliefs about the future.

While other high-frequency approaches to identifying Chinese monetary policy shocks exist, ours has the longest usable sample while retaining two dimensions of monetary policy shocks. For example, He et al. (2024) and Liu et al. (2025) do excellent work using NCDs and Treasury Futures. Respectively, their estimation samples range between 2015-2021 and 2017-2019, which is too short for our heterogeneous spatial autoregression. Gürkaynak et al. (2026) is the first to take advantage of copper futures and has a similar sample range to our approach. However, they only examine the first principal component. While useful as a singular monetary policy shock, our approach allows us to examine the differential effects between Target and Path shock transmission globally and comment on whether or not shock-type matters.

We briefly discuss this choice of instrument set and why we decided to focus on utilizing swaps that reference the 7-Day Repo Rate. 7-Day Repo IRS are the most liquid swap-type derivatives in the Chinese market with ample time coverage (market operations commenced in 2006). While SHIBOR 3M was also introduced during a similar time frame, the volume of transactions is heavily weighted in favor of IRS using 7-Day Repo. Table 1 shows the state of the 7-Day Repo vs SHIBOR 3M IRS market in December of 2023. From this table alone, we can see that swaps that reference the 7-Day Repo represent the most liquid and traded derivatives. Due to data limitations from ChinaMoney and the China Foreign Exchange Trade System (CFETS), we do not have a time series measure of these volumes since 2006 and can only verify through a few sources. First, Kamber and Mohanty (2018) and Das and Song (2023) both report similar levels of liquidity between the various tenors of the swaps between SHIBOR and 7-Day Repo, with 7-Day Repo being the dominant and most liquid of the two. Second, Chen (2008) notes that in 2007, 7-Day Repo swaps accounted for about 79% of the trading value of the swaps. Given the consistency in the rank ordering of 7-Day Repo IRS vs SHIBOR IRS, we take this as prima facie evidence that swaps that reference 7-Day Repo are the most liquid, most suitable, and sufficient for the high-frequency identification of PBOC shocks.

sionary effects. For example, Shieh (2024) notes that on the June 28th, 2015 cut in the lending rate and the reserve requirement, the Kamber and Mohanty (2018) surprise-only measure shows a nominally expansionary shock. However, the Shieh (2024) decompositions show that the Target shock is expansionary while Path is contractionary. Therefore, the effect of a single surprise shock could be contaminated by different components (surprise policy versus expected future policy) of a policy announcement if not controlled for.

Reference rate	Term	Fixed rate (%)	Nominal principal (RMB 100 million)	Deals (count)
FR007	1M	2.5560	1162.00	485
	3M	2.3286	1633.00	839
	6M	2.1827	1415.00	847
	9M	2.1371	1238.90	667
	1Y	2.1070	9838.26	8095
	2Y	2.1345	1524.80	1539
	3Y	2.2060	204.49	209
	4Y	2.2951	394.91	375
	5Y	2.3928	3922.70	9560
	7Y	2.4530	6.00	6
SHIBOR 3M	6M	2.5109	301.50	163
	9M	2.4282	164.00	120
	1Y	2.3776	995.00	1062
	2Y	2.3923	58.50	65
	3Y	2.4710	33.50	46
	4Y	2.5342	19.50	21
	5Y	2.6555	132.90	387
	7Y	2.7281	0.80	4
	10Y	2.8008	0.60	3

Table 1: Interest Rate Swaps Market Liquidity for Dec. 2023

Notes: The table reports monthly interest-rate-swap trading by reference rate and maturity. Nominal principal is reported in RMB 100 million. Fixed-rate entries are percentages; deals are transaction counts. Source: China Foreign Exchange Trade System (CFETS), ChinaMoney.

Additionally, we do not include 3-month SHIBOR swaps in the static factor model used to extract Target and Path factors, despite the existence of these contracts, for several reasons. First, consistently available pricing data from major providers begin only around 2011, for reasons that are unclear.[6] Moreover, SHIBOR swap pricing coverage across different swap tenors do not have similar start dates. In a static factor model, this creates an estimation problem, since adding instruments later in the sample changes the composition of the instrument set over time. Because the factors are estimated from the available instrument set at each date t, a time-varying instrument set would risk confounding changes in the latent monetary policy factors with changes in instrument availability. In that case, the estimated factors would vary not only with time but also with the composition of the instrument set. Since 7-day Repo swaps are sufficiently liquid, we prioritize a longer and more consistently observed sample over a marginally larger but time-varying instrument set.

Ultimately, our instrument set includes five tenors of the swaps that reference the 7-Day Repo Rate. Specifically, we look at the 3m, 6m, 9m, 1Y, and 2Y swaps. We do not include the 1m tenor due to coverage issues similar to SHIBOR swaps. Since we prioritized a longer sample, the 1m would require us to truncate since the pricing data for these swaps did not start until 2010. We also note that while the 5Y tenor has similar liquidity in terms of deal counts to the

[6] In our case, Bloomberg has inconsistent coverage of SHIBOR swap pricing starting in 2011, despite the existence of the SHIBOR swap market since roughly 2006.

1Y, we do not go beyond 2Y. Since longer term maturities tend to weight inflation and growth expectations, term premia, and other risks a little heavier than changes to monetary policy stance, this complicates the interpretation as pure monetary policy shocks once we extract our factors as it might push more weight into the longer end of the yield curve during factor estimation. Since our goal is to estimate orthogonal measures of short term surprises and surprises to the near-term expected path of monetary policy, we only include up to the 2Y tenor.

Chinese monetary policy announcements are compiled starting from 2006 and ending in 2019. There are 212 announcements in this time period.[7] Our set of policy announcements includes changes to the reserve requirement, various lending rates (loan prime rate, benchmark lending rate, etc.), foreign exchange interventions and policy shifts, quarterly monetary policy reports, window guidance, various other liquidity management programs like the Medium Term Lending Facility, and open market operations. The full announcement set in Appendix A.1 details the various policy announcements, their dates, and associated notes. Compared with the original Shieh (2024) sample of 167, we add 45 additional announcements that were discovered upon a re-reading of additional PBOC documents found only on the Chinese-language version of the website, covering the same types of announcements. We note that compared with the original Shieh (2024) factors, the magnitudes and signs of the shocks remain highly correlated. Table 2 shows a selected sampling of various policy announcements.

Date	RR	LR	FX	MPR	Other	Comments
06/28/15	-0.5	-0.25				Changes in Percentage Points
10/01/16			X			RMB Added to IMF SDR Basket
01/13/17					X	Liquidity Injection Through TLF
07/15/19					X	MLF operation
08/09/19				X	X	Q2 2019 MPR, CBS

Table 2: Example Announcement Dates

Notes: RR is the reserve requirement, LR is the lending rate encompassing the loan prime rate and benchmark lending rate, FX are changes to the foreign exchange, MPR is the PBOC Monetary Policy Report, Other represents other policy or regulatory changes, TLF is Temporary Liquidity Facility, MLF is Medium Term Lending Facility, IMF SDR is the IMF's Special Drawing Right, and CBS are central bank bills swap operations.

On these announcement dates, a modified version of the algorithm used to create the set of surprises from Kamber and Mohanty (2018) is used. Shieh (2024) uses the following set of surprises from five interest rate swaps that use the 7-Day Repo Rate as reference rate: $X = (\Delta S_7^3, \Delta S_7^6, \Delta S_7^9, \Delta S_7^{12}, \Delta S_7^{24})$, where ΔS_7^τ gives the surprise change in the IRS on the 7-Day Repo Rate at monthly tenor τ. For example, ΔS_7^{12} is the surprise change on the One-Year IRS on the 7-Day Repo. The construction of these surprises is standard, where we take the change in the daily closing prices of each specific asset that bracket the announcement date. Appendix A.2 provides a more detailed exposition of the Shieh (2024) approach.

We assume that there are latent factors that explain Chinese monetary policy during announcement dates that can be explained using this set of surprises. We estimate the following

[7] There are actually 214 announcements but we drop the 2/18/2011 and 3/18/2011 announcements due to a wide discrepancy in the IRS pricing that suggests a possible data error with the pricing provider.

factor model:

$$\underset{T\times n}{X} = \underset{T\times k}{F} \quad \underset{k\times n}{\lambda} + \underset{T\times n}{\eta} \tag{4}$$

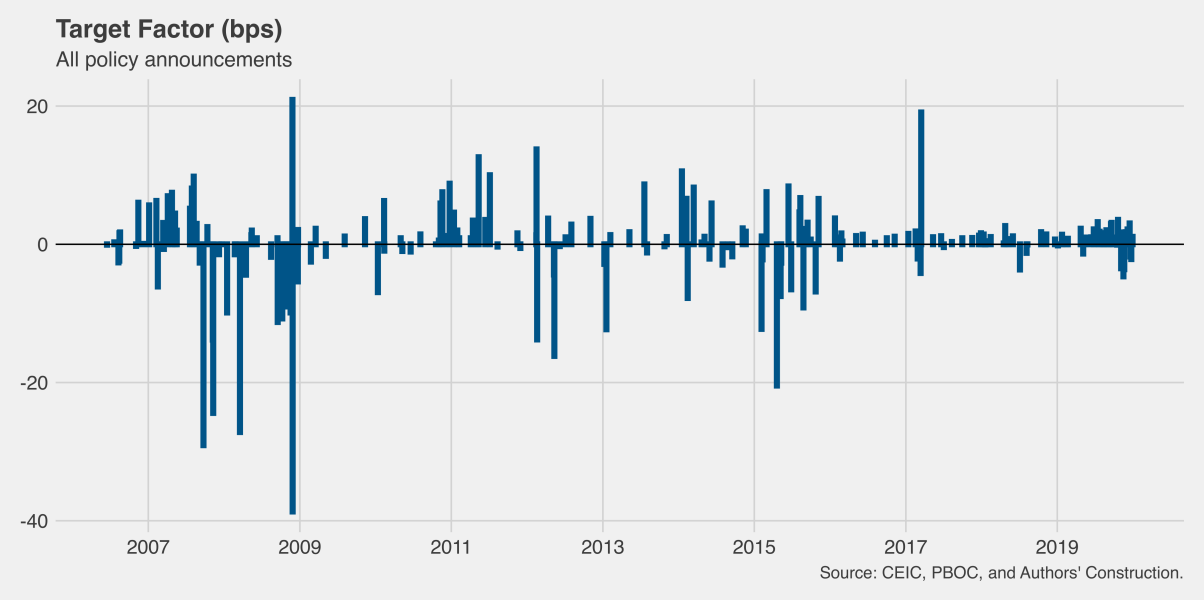
Where X is a matrix corresponding to the number of PBOC announcements, T, and IRS products, n. Each element in X corresponds with the change in the closing price of an IRS on the day of a PBOC announcement with the preceding closing price. F is a matrix of unobserved factors ($k < n$), λ is the matrix mapping those factors to IRS surprises, and η is a matrix of white noise disturbances.

We run a Cragg and Donald (1997) matrix rank test and confirm that two factors are sufficient to explain the variation in our underlying asset prices on announcement dates. Appendix A.3 reports these results. Two factors, F_1 and F_2, are extracted using principal components (PCA). These two factors explain roughly 82% of the variation in instrument set surprises.[8] We also report the variation explained by factors (up to 5) in Appendix A.3. Due to the way the factor rotation is conducted, by construction, the factors will be orthogonal to each other. By themselves, F_1 and F_2 do not have a structural interpretation, so we rotate these into Z_1 and Z_2 such that these factors are orthogonal and Z_2 does not have an impact on the 3m IRS on the 7-Day Repo. Z_1 is then re-scaled so that a 0.01 change in Z_1 corresponds with a surprise of 1bp to the 3 month 7-Day Repo IRS. Z_2 is then re-scaled so that the effect of a 0.01 change in Z_2 is equivalent to a 1bp surprise to the 1-Year 7-Day Repo IRS. An increase in either Z_1 or Z_2 represents a contractionary monetary policy shock. Z_1 and Z_2 are the Target and Path factors, respectively, where Z_1 measures the actual surprise component to the interest rate swap and Z_2 measures information from announcements, aside from the surprise component to the IRS that affects the expected future path of monetary policy out to twelve months. We confirm that our rotation was properly done by reporting a diagnostic regression that shows that Target loads onto the shorter end of the yield curve, with a unit effect on the 3-month tenor while Path loads more on the longer end with a unit effect on the 1-year tenor. We present more detail on the rotation process in Appendix A.2 and report the diagnostic results in Appendix A.3.

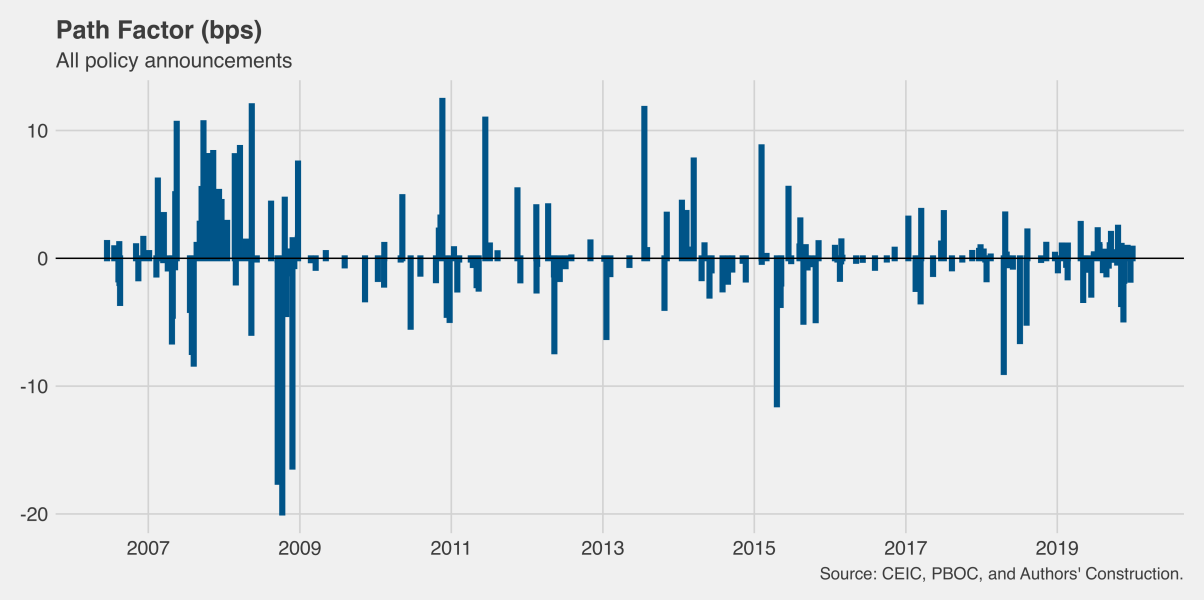
In our empirical analysis, we scale to 1SD shocks rather than 1pp shocks for two reasons. First, our monetary policy factors track the overall policy stance by extracting principal components from changes to 7-Day Repo swaps. These market-based surprises are analogous to Fed Funds Futures, but their mapping to policy levers differs: Fed Funds Futures track beliefs about a single policy rate, whereas 7-Day Repo swaps reflect Chinese monetary conditions across a relatively large set of policy instruments. The factors are therefore policy-lever agnostic but not stance agnostic. Although our Chinese factors are scaled such that 0.01 in the factor corresponds to 1bp and normalized to either the 3m IRS or the 1Y IRS, they represent generalized contractionary or expansionary policy rather than 1:1 movements in a particular policy-rate instrument. Second, a 1pp innovation in either latent factor would be large relative to

[8] We note that since our underlying instrument set only broadly tracks Chinese monetary policy stance, rather than a specific policy instrument, the extracted factors should explain less of the variation in these surprises than say in the case of the Fed, where Target/Path should explain more since they are more closely tracking Fed Funds movements.

its observed distribution, whereas a 1SD innovation represents an empirically relevant shock. Standard-deviation scaling therefore provides a more useful within-sample metric without requiring us to interpret the magnitude of or assign a value to a particular policy lever. Within sample, a 1SD Target shock translates to roughly 4.9bps and a 1SD Path shock translates to roughly 3.5bps. Figure 2 shows the Target and Path from 2006 through 2019.



(a) Estimated Target Factor



(b) Estimated Path Factor

Figure 2: Chinese Monetary Policy Factors

Notes: Estimated using PCA on IRS surprises during the sample period spanning June 2006 to December 2019 on policy announcement dates. Units are in basis points (bps). Positive values indicate contractionary monetary policy and negative values indicate expansionary policy.

2.3 Robustness to Simultaneous Non-PBOC Announcements

One concern with high-frequency Chinese monetary policy shocks is the simultaneity of fiscal policy announcements made by the Chinese central government through the State Council (the Chinese government's executive organ). This concern is investigated and evaluated in Das and Song (2023), who find evidence of monetary-fiscal coordination. Relatedly, simultaneous monetary policy announcements from the Bank of Japan (BOJ) may affect Chinese financial market expectations and subsequently, the pricing of our 7-Day Repo IRS. To account for potential contamination from these announcements, we first purge from our PBOC announcement set any dates that overlap with BOJ monetary policy announcements. The BOJ announcement set comes from Kubota and Shintani (2022). We also recognize that other important global central banks (The Fed, BOE, and the ECB) also affect the 7-Day Repo IRS, but due to timing assumptions around market open/close in China relative to announcements by these other central banks, we opted to only purge BOJ announcements since these occur during market open in China.

For the State Council, we do a modified version of the approach undertaken in Das and Song (2023). Rather than do an English-language keyword search for fiscal policy terms on the State Council website, we do a text search using simple keyword matching and classification of the archived communiqués released by the State Council after a policy meeting and categorize these into either *monetary*, *fiscal*, or *joint monetary and fiscal* communiqués in the original Chinese. We used the post-meeting communiqué date as opposed to the meeting date since the communiqué date is effectively when policy is announced.[9] The keyword matching rules and terms (along with their English-language equivalents) we used are shown in Supplemental Appendix B.1. We then find the dates that overlap with PBOC announcements for communiqués related to either *fiscal* or *joint* to isolate the potential effects of a fiscal policy shock contamination. Table 3 summarizes the announcement overlaps. After purging both BOJ and State Council announcements, we are left with 173 PBOC announcements. Appendix A.4 reports the specific dates that overlap, along with the meeting types.

[9] We also expanded our text search into archived Politburo post-meeting communiqués using four categories: *General Policy*, *Political Event*, *Economic Related*, and *Economic Specific*. However, no Politburo post-meeting communiqués related to economic policy, both specific and in general, overlapped with PBOC announcements. We include Politburo overlaps (0) in Table 3 for completeness.

Overlap Category	Count	Share of PBOC
PBOC announcement dates	212	100.0%
Politburo only	0	0%
State Council only	30	14.2%
BOJ only	8	3.8%
State Council w/ BOJ	1	0.5%
Any State Council or BOJ overlap	39	18.4%
Non-overlapping PBOC announcement dates	173	81.6%

Table 3: Simultaneous Non-PBOC Announcements on PBOC Announcement Dates

Notes: The table reports PBOC announcement dates that overlap with economic policy Politburo communiqués, fiscal-policy State Council communiqués, and BOJ monetary policy announcements. State Council overlaps use the dates of communiqués classified as either fiscal or joint monetary/fiscal announcements. Shares are computed relative to the 212 PBOC announcement dates used to construct the monetary policy shocks. The clean sample excludes the 39 PBOC announcements purged due to overlapping with either the BOJ or State Council.

From here, we repeat the PCA estimation of Equation 4 to generate our purged sample Target and Path factors and report in Supplemental Appendix B.2 the Cragg and Donald (1997) matrix rank test, PCA Factor contribution, and the diagnostic regressions; all of which are similar to the non-purged sample.

2.4 Heterogeneous-Coefficient Panel Spatial Autoregression

We now introduce the econometric model that allows us to connect country-industry pairs outside of China with industries within China and evaluate the effect of Chinese monetary policy shock. Let N be the total number of countries, with $m, n \in [1; N]$ being specific countries. Further, let J be the total number of sectors with the individual sectors denoted as $i, j \in [1; J]$ Consider the following panel spatial autoregression, taken from the regression framework in Di Giovanni and Hale (2022):

$$\hat{\boldsymbol{\pi}}_t = (\mathbf{I} - \text{diag}(\boldsymbol{\rho})\mathbf{W})^{-1}\mathbf{B}^{MP}\mathbf{Z_t} + \boldsymbol{\Gamma}\mathbf{X}_t + \boldsymbol{\alpha} + \boldsymbol{\epsilon}_t \tag{5}$$

$\hat{\boldsymbol{\pi}}_t$ is a $NJ \times 1$ vector of the annualized monthly industry-level equity returns $\hat{\pi}_{mi,t}$ by country for each month t. $\boldsymbol{I}$ is an identity matrix of dimension $NJ \times NJ$ and $\boldsymbol{W}$ is a $NJ \times NJ$ empirical global input-output matrix. This empirical input-output matrix is fixed over time (a specific input-output table for a specific year). $\mathbf{B}^{MP} = [\,\boldsymbol{\beta}^{Target} \quad \boldsymbol{\beta}^{Path}\,]$ are the estimates for each type of shock. $\mathbf{Z}_t \equiv \begin{bmatrix} Z_t^{Target} \\ Z_t^{Path} \end{bmatrix}$ are the surprise Chinese monetary policy shocks measured by the Target and Path Factors from Shieh (2024) at month t.[10] $\boldsymbol{X_t}$ is a vector of controls that includes each country's central bank policy rate, the nominal effective exchange rate, VIX, and the Wu and Xia (2015) Shadow rate for US monetary policy. These do not vary by sector and only by

[10] Target/Path only vary over time, as it is a measure of Chinese monetary policy only. We aggregate the daily factors into monthly ones by summing the daily estimate of the Target/Path factors by month. Since there are days and months without a policy announcement, there are months where the Target or Path factor are 0.

country to control for specific aggregate country-level monetary policy, exchange rate effects, as well as global effects of US monetary policy. We also include country-industry level fixed effects that do not vary over time, denoted by the vector $\boldsymbol{\alpha}$. We include country-specific measures of network transmission, where vector $\boldsymbol{\rho}$ is heterogeneous and governs network transmission. diag($\boldsymbol{\rho}$) is a $NJ \times NJ$ diagonal matrix that has zeros on the off-diagonal and the elements of $\boldsymbol{\rho}$ on the diagonal, allowing for the spatial autoregressive parameter to vary by country-industry pair.

The empirical exercise is to then estimate a vector of country-industry spatial autoregressive correlations, ρ_{mi}, as well as the elements in $\boldsymbol{B^{MP}}$, as our parameters of interest. This heterogeneous SAR allows $\boldsymbol{\rho}$ to vary by country-industry rather than imposing the fixed $\boldsymbol{\rho}$ of a traditional homogeneous SAR. We are not specifically estimating any dynamics in this setup – just the average elasticities of country-industry returns in response to contractionary monetary policy shocks, as well as the spatial correlations between country-industries. To be clear, ρ_{mi} measures the degree of passthrough of monetary policy through the production linkage for each country-industry, where $\rho_{mi} = 0, \forall m, i$ would suggest there is no passthrough through the production linkages and $\rho_{mi} = 1 \forall m, i$ would be complete passthrough. Notice that ρ_{mi} varies by country-industry, allowing us to investigate any heterogeneity in the passthrough of monetary policy shocks by country and by industry. Similarly, our $\boldsymbol{B^{MP}}$ estimate also varies by country and industry. The heterogeneous SAR approach allows for a richer empirical evaluation when compared to a standard homogeneous SAR, as it allows for the passthrough of the shock to vary by country-industry pair. We also note here that a limitation of this approach is that we cannot fully disentangle the effects of a downstream shock by controlling for an upstream response (and vice versa). Similarly, since a country may be simultaneously hit with both a downstream and upstream shock, our results could simply be an average effect for a country-industry that is particularly plugged into Chinese supply-chains. We estimate the heterogeneous SAR following Aquaro et al. (2020) using quasi-maximum likelihood (QML), with Standard errors wild bootstrapped at the observation level using the continuous multipliers of Mammen (1993).

Decomposition of Effects

The primary benefit of utilizing a spatial econometric approach is the ability to decompose the shock effects into total, direct, and indirect (network) effects. In other words, we can quantify exactly how much a Chinese monetary policy shock is directly responsible for changes to stock returns, as well as quantify how much of the measured effect is due to the shock propagating through input-output linkages (the network effect). Following Acemoglu et al. (2016), the decomposition can be written as:

$$\textbf{Total Effect} \equiv (\mathbf{I} - \text{diag}(\boldsymbol{\rho})\mathbf{W})^{-1}\mathbf{B}^{MP} \tag{6}$$

$$\textbf{Direct Effect} \equiv \mathbf{B}^{MP} \tag{7}$$

$$\textbf{Network Effect} \equiv \textbf{Total Effect} - \textbf{Direct Effect} \tag{8}$$

The total effect is the combined effect of the direct effect of Chinese monetary policy shocks

on equity returns, captured by $\boldsymbol{B^{MP}}$, as well as the indirect effect of the immediate and indirect production linkages captured by the Leontief inverse matrix that is weighted by $\boldsymbol{\rho}$. This indirect effect is the supply-chain spillover, capturing all the linkages that propagate the monetary policy shocks. As a matter of interpretation, the direct effect of a shock represents the measured effect of equity prices in response to a shock *without* network propagation. The indirect or network effect is the effect of the shock on equity prices *that rely on the network structure*. In other words, how do equity prices respond to monetary policy shocks that propagate throughout the production network. Since we use both Target and Path shocks, we can investigate different channels — our supply-chain hypothesis and any standard asset pricing/financial valuation channel as a result of monetary policy. Target shocks would then be interpreted as the reaction of equity prices to *surprise changes in the Chinese monetary policy stance* while Path would be how equity prices respond to *changes in expected future path of Chinese monetary policy*. The indirect effects should capture the relative role that the production network plays for each type of shock. For example, the supply-chain hypothesis should see indirect effects being larger than direct effects since the production network plays a larger role.

Given this framework, we can also extract the higher order effects throughout the network by expanding the Leontief inverse in Equation 5:

$$\begin{aligned}
\hat{\pi}_t &= \left(\mathbf{I} - \text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^{-1}\mathbf{B}^{MP}\mathbf{Z}_t \\
&= \left[\mathbf{I} + \text{diag}(\boldsymbol{\rho})\mathbf{W} + \left(\text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^2 + \left(\text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^3 + \cdots\right]\mathbf{B}^{MP}\mathbf{Z}_t \\
&= \left[\mathbf{I} + \text{diag}(\boldsymbol{\rho})\mathbf{W} + \left(\text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^2 + \cdots\right]\left(\boldsymbol{\beta}^{Target}\, Z_t^{Target} + \boldsymbol{\beta}^{Path}\, Z_t^{Path}\right) \\
&= \sum_{k=0}^{\infty}\left(\text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^k\boldsymbol{\beta}^{Target}\, Z_t^{Target} \;+\; \sum_{k=0}^{\infty}\left(\text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^k\boldsymbol{\beta}^{Path}\, Z_t^{Path},
\end{aligned} \tag{9}$$

These higher order effects measure the shocks' persistence across the network, measuring how much of the input-output network structure propagates the shock beyond the first order linkages as the network distance increases. Put differently, we examine the spillover of the shocks beyond the direct linkages and measure the effect of the shocks on indirect linkages throughout the network. We can extract higher order effects beyond $k > 1$, where k denotes the order of network propagation. For example, the second-order effect is given by $\left(\text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^2 \times \boldsymbol{\beta}^{Target}\, Z_t^{Target}$ and $\left(\text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^2 \times \boldsymbol{\beta}^{Path}\, Z_t^{Path}$ where $k = 2$. We report up to degree 5.[11]

We note that the LeSage and Pace (2009) textbook decomposition can be used, where the direct effect also accounts for a round-trip of the monetary policy shock to each country-industry return back to itself.[12] This may be less realistic, as this round-tripping may be a different stage in the production chain. We follow the Di Giovanni and Hale (2022) approach and use only the Acemoglu et al. (2016) decomposition, but note that the LeSage and Pace (2009) approach provides qualitatively similar effects. We report the LeSage and Pace (2009) decomposition in

[11] We could report even higher order effects, however, the effects $\to 0$ as we approach the n-th order.

[12] The LeSage and Pace (2009) decomposition treats the direct effect slightly differently, where **Direct Effect** $\equiv \text{diag}\left[\left(\mathbf{I} - \text{diag}(\boldsymbol{\rho})\mathbf{W}\right)^{-1}\right]\mathbf{B}^{MP}$. Notice here that the direct effect explicitly includes the round-tripping effect.

Supplemental Appendix B.4.

3 Data

The data follows recent work that match sector-level stock market data with input-output connections by country-industry pairs. Di Giovanni and Hale (2022) and Todorova (2018) both approach the data similarly, where global production network data is gathered from the World Input-Output Database (WIOD) and sectoral equities data is from Bloomberg. Due to the availability of stock return data and country-industry level coverage, this paper departs slightly in the construction of the empirical input-output matrix, as well as the stock returns data. As we detail the construction of the data, we will note where we differ from the literature and the implications of the departure.

3.1 Empirical Input-Output Matrix Construction

The weighting matrix W is created using a global input-output matrix (MRIOT) provided by the Asian Development Bank (ADB). The ADB's MRIOT follows the methodology used in the construction of the World Input-Output Database (WIOD) used in Di Giovanni and Hale (2022) and Todorova (2018). The benefit of using the ADB's MRIOT is that, unlike WIOD, a few more Asian economies are represented in the sample, allowing for more relevant production linkages as they pertain to China. The MRIOT coverage spans from 2009 to 2019 at an annual frequency. For this study, 11 countries, including China, are used. Industries are classified according to the International Standard Industrial Classification System (ISIC) revision 4. We discuss further below why we collapsed the 35 ISIC industries in the MRIOT into 7 GICS supersectors for the creation of the weighting matrix. Table 13 in Appendix A.5 details the sample countries being analyzed.

Upstream and Downstream

To create the weighting matrix, we use the MRIO table and take advantage of the data structure to compute production linkages. Looking at the cells in the MRIO table row-wise allows for analysis of how goods supplied by a particular country-industry are used by other country-industries. Let A_t denote the raw input-output matrix in year t, where $(A_t)_{mi,nj} = Sales_{mi \to nj,t}$. Thus, the upstream weighting matrix $\mathbf{W}_t^{Up}$ is obtained by row-normalizing the raw flow matrix, where each element gives the value of intermediate goods supplied by country m and sector i and used by country n and sector j, as a share of the total value supplied by country-industry mi to all country-industries within the sample:

$$(\mathbf{W}_t^{Up})_{mi,nj} = \frac{Sales_{mi \to nj,t}}{\sum_{n',j'} Sales_{mi \to n'j',t}}. \tag{10}$$

This is simply the fraction of the value of inputs supplied by country-industry mi to country-industry nj relative to the row-sum of intermediate outputs supplied by country-industry mi. This formulation, then, assumes an upstream propagation of the Chinese monetary policy

shocks, given the functional form of the heterogeneous SAR regression in Equation 5. In other words, with this particular construction of W, this formulation assumes that monetary policy shocks travel from customer to supplier through the production network.

To analyze downstream propagation, the MRIO table columns show inputs supplied to each country-industry pair by other country-industry pairs. Thus, we repeat the exercise as in the upstream case but transpose the raw MRIO table and then row-normalize such that the sum of each row equals 1. Writing $\mathcal{R}(A)$ for row-normalization of a matrix A, the directional weighting matrices are

$$\mathbf{W}_t^{Up} = \mathcal{R}(A_t), \qquad \mathbf{W}_t^{Down} = \mathcal{R}(A_t').$$

Thus, the downstream weights are

$$(\mathbf{W}_t^{Down})_{mi,nj} = \frac{Sales_{nj \to mi,t}}{\sum_{n',j'} Sales_{n'j' \to mi,t}}. \tag{11}$$

where each element, $(\mathbf{W}_t^{Down})_{mi,nj}$, is a share of the inputs that country-sector nj supplies country-sector mi relative to the overall intermediate inputs supplied to country-sector mi within the sample. With this construction, monetary policy shocks travel from supplier to customer through the production network. We apply these procedures to the 2009 and 2019 raw flow matrices.[13]

3.2 Industry-Level Concordance and Stock Returns Data

One of the challenges with our returns data is to map the industries in the input-output table to industry-level equity returns. We detail the concordance procedure below.

Industry-Level Matching

While the MRIOT utilizes the ISIC rev. 4 industry-level classification, the industry-level sub-indices for each country's primary equities index use differing classifications. For example, Germany's DAX index has 18 sector-level indices that can aggregate into 8 supersectors using the ISIC rev. 4 categorization. In contrast, South Korea's KOSPI index has 19 subsector-level indices that follow the GICS industry classification system. On top of this, to complicate matters a bit further, industry-level coverage within each country's respective equities market varies — certain industries are either heavily concentrated or lacking representation, depending on the country in question. Taiwan, as an example, has more sector-level representation for industries related to electronic parts related to manufacturing and sales (think computer chips and associated products) when compared with Thailand, which has more agri-business-related industry exposure. In Appendix A.5, Table 14 shows the full ISIC categorization found in the MRIOT, and Table 15 shows the GICS sector classification.

[13] For the average weighting matrix, we first compute the element-by-element arithmetic average of the annual raw input-output flow matrices, $\bar{A} = \frac{1}{11}\sum_{t=2009}^{2019} A_t$. We then set $\bar{A}^{Up} = \bar{A}$ and $\bar{A}^{Down} = \bar{A}'$ and row-normalize each directional matrix: $(\mathbf{W}_{2009-2019}^{Avg,d})_{mi,nj} = \bar{A}^d_{mi,nj} / \sum_{n',j'} \bar{A}^d_{mi,n'j'}$, where $d \in \{Up, Down\}$. Therefore, we average the raw flows before normalization, rather than averaging the annual row-normalized weighting matrices.

One solution is to create a custom index for each country based on the 35 ISIC classification — in effect, taking the universe of available firms listed on the stock market and then creating 35 indices after matching these firms to the ISIC classifications. However, a limitation to this approach is coverage. Due to the variety of concentration of specific industries for specific countries, there may be situations where some of the custom industry level indices are sparsely populated while others are densely filled with firms. Additionally, some industries in some countries may simply not exist, thus limiting the ability to examine industry-level effects by country. Thus, the solution here is to aggregate the industries to simplify the problem.

Since the vast majority of the stock indices in the sample follow the GICS classification (specifically, the sector level classifications), the challenge is to then aggregate the 35 ISIC *industry* categories into the equivalent 11 GICS *sector* classifications. To further simplify the GICS sector classifications, we drop three GICS sectors (Energy, Utilities, and Real Estate) since these sectors have very limited coverage in some of the countries in the sample, as well as not being as useful in this paper's analysis, since these three sectors are unlikely to be important in cross-border production linkages. Additionally, we combine the GICS sectors Information Tech with Communications Services, as some countries classify firms into these two groups somewhat interchangeably. As a result, we are left with 7 GICS sectors that need to be matched with 35 ISIC industries. This process is relatively straightforward — ISIC industry-level classifications, for the most part, have analogs in the GICS industry classifications, which then can be aggregated into the GICS sectors. Table 16 in Appendix A.5 shows the final matching between the ISIC categories in the MRIOT with the 7 GICS sectors.

Input-Output Connections

With these collapsed and aggregated sectors, examining the strength of intermediate goods trade connections is relatively straightforward. Figure 3 and Figure 4 show the upstream and downstream chord diagrams highlighting these sector and country-level linkages for the 11 countries sampled in this paper. Note here that the strongest upstream linkages for China are intermediate goods connections in material and industrials. By far, these connections make up the largest share for China in an upstream sense. As such, there should be an expectation that these sectors should be important in the passthrough of domestic Chinese monetary policy shocks upstream throughout the production network. Looking at the downstream angle, materials, and industrials make up the strongest connections and share of intermediate goods sent downstream from China. As a result, these two sectors should have a relatively high degree of passthrough from a domestic policy shock.

Stock Returns Data

Stock returns data construction is standard and covers the period from January 2009 through December 2019. From each country's main index, we use the monthly GICS sector-level index price.[14] Returns are calculated as the monthly log changes to the end-of-month closing index

[14] Germany's DAX index follows the ICB categorization – specifically, ICB Supersectors. To the best of our ability, we matched the ICB supersectors with the GICS sectors. There is not an exact 1:1 match, so there may be some minor overlap between industry classifications.

price and then annualized.[15] To keep the amount of GICS sectors consistent with the empirical W matrix, we do not include energy, utilities, and real estate indices for each country. For the aggregation of IT and communication services, we calculate the equity index as the market cap weighted average of the end-of-month index prices for each country before calculating returns.[16] Due to the wide range of countries and industries, we also winsorize the returns at the 1% level to eliminate any large outliers in returns. Appendix A.6 shows the distribution of monthly returns for the full sample, as well as the winsorized returns.

[15] More concretely, our annualized monthly sectoral returns are calculated as $\pi_{mi,t} = 12 \times 100 \times \Big(\log(x_{mi,t}) - \log(x_{mi,t-1})\Big)$ where $x_{mi,t}$ is the monthly closing index price of industry i in country m corresponding to the GICS sub-index in the respective country's main stock exchange index.

[16] However, for China and India, due to incomplete market cap data, we use a simple average (equal weights) to calculate the index value before calculating returns.

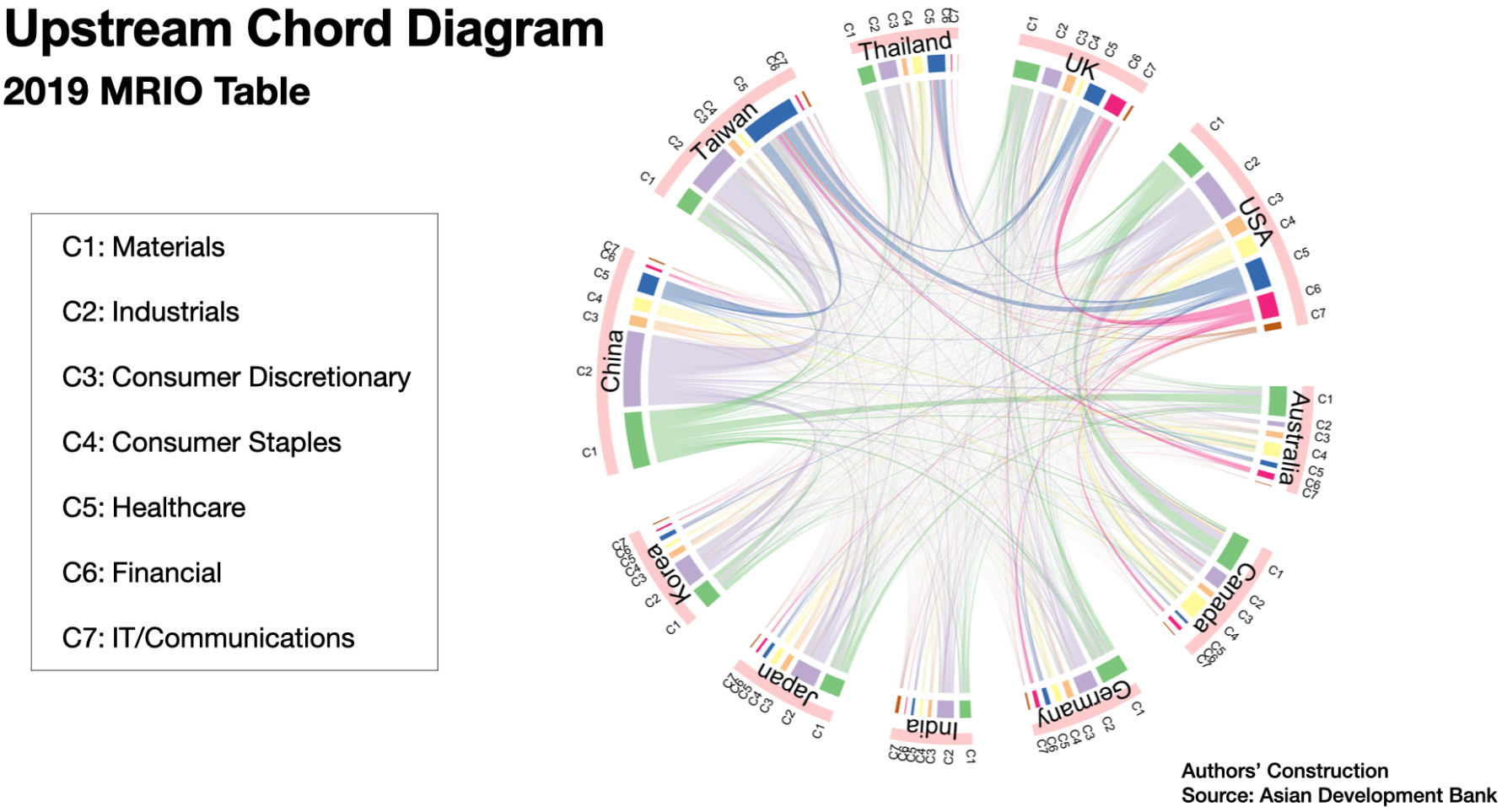


Figure 3: Upstream Chord diagram of 11 countries and 7 industries.

Notes: Upstream Chord diagram with industries collapsed following the concordance process outlined in Section 3.2 and constructed using the 2019 ADB MRIO Table. Thickness represents strength of linkage.

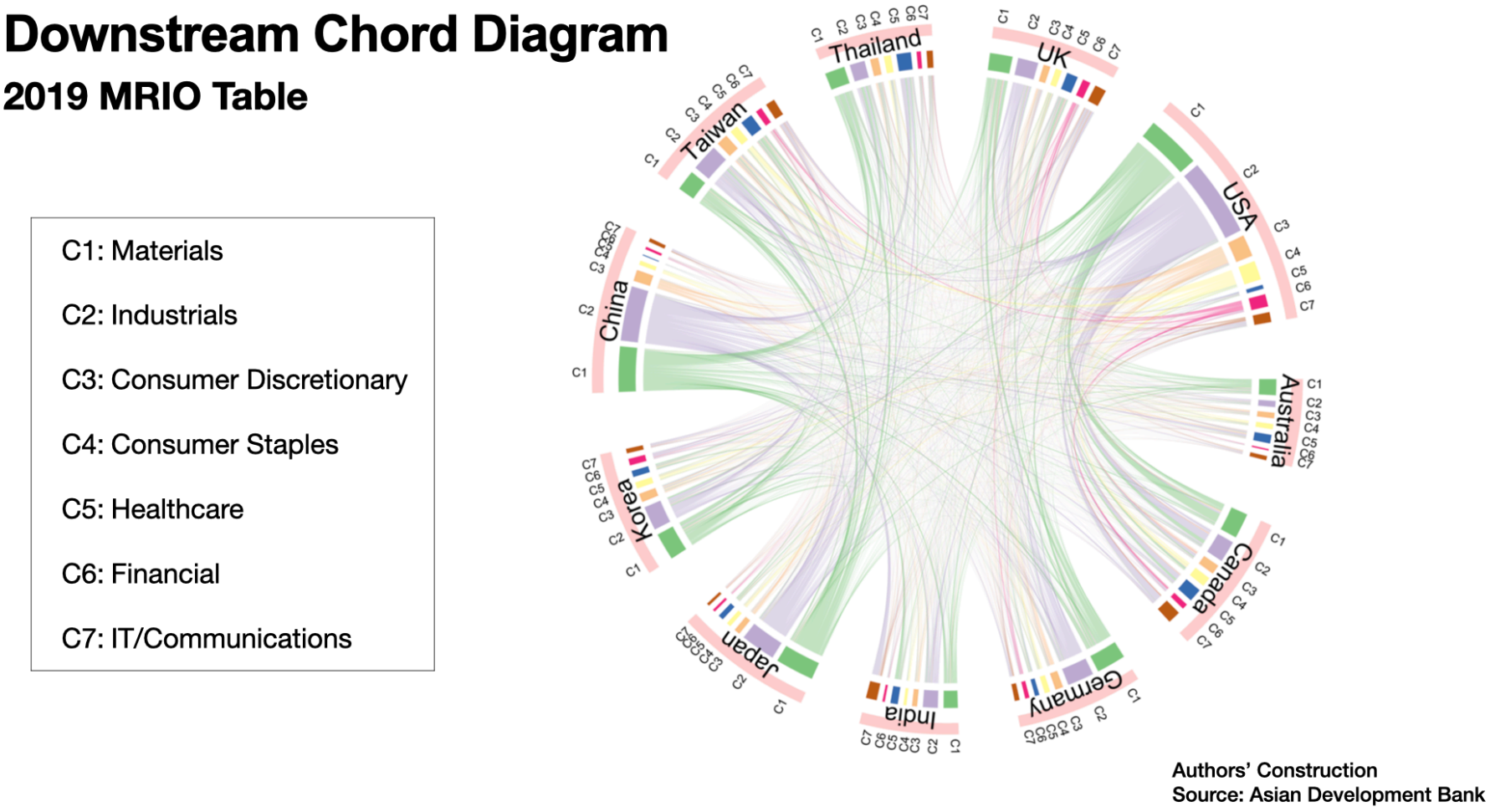


Figure 4: Downstream Chord diagram of 11 countries and 7 industries.

Notes: Downstream Chord diagram with industries collapsed following the concordance process outlined in Section 3.2 and constructed using the 2019 ADB MRIO Table. Thickness represents strength of linkage.

4 Results and Discussion

Before explaining our results, we briefly map the empirical exercises to the channel described in Subsection 2.1. We build our case in four steps. First, since our supply-chain channel relies on Chinese monetary policy changing domestic output as a source of cross-border transmission, we verify that contractionary Chinese monetary policy shocks reduce domestic Chinese output. Second, we establish a baseline response of global equities to Chinese monetary policy while shutting down network linkages, and show that country-level aggregation obscures the effects of shock transmission, directly motivating our heterogeneous SAR approach. Third, we present the core heterogeneous SAR results that evaluate our supply-chain channel of monetary policy transmission, considering both upstream and downstream propagation. Finally, we conduct two complementary assessments where we benchmark the financial spillovers against Fed spillovers, and we link the heterogeneous SAR results to suggestive real-side evidence through commodity-price and foreign producer-price responses.

We begin by confirming that there is evidence of domestic policy transmission into the real sector. That is, we show that Chinese monetary policy shocks affect domestic production as a necessary component to our hypothesized transmission mechanism. To proxy real activity at the monthly level, we source monthly YoY growth of Industrial Production from CEIC. Due to missing January and February values that are common in Chinese data due to Chinese New Year, we interpolate the missing values using cubic spline following the method prescribed in Fernald et al. (2014). We estimate the following standard local projection:

$$y^{IP}_{t+h} = \alpha_h + \mathbf{B}^{MP}_h \mathbf{Z}_t + \mathbf{\Gamma}_h \mathbf{X}_t + \varepsilon_{t+h}, \qquad h = 0, \ldots, H \tag{12}$$

Where $\mathbf{Z}_t \equiv \begin{bmatrix} Z^{Target}_t \\ Z^{Path}_t \end{bmatrix}$ and $\mathbf{X}_t$ is a vector of controls that includes lagged y^{IP}, Target, Path, CPI, and global commodity prices. We estimate Equation 12 using 6 lags (6 months) with HAC standard errors between 2009M1 and 2019M12.

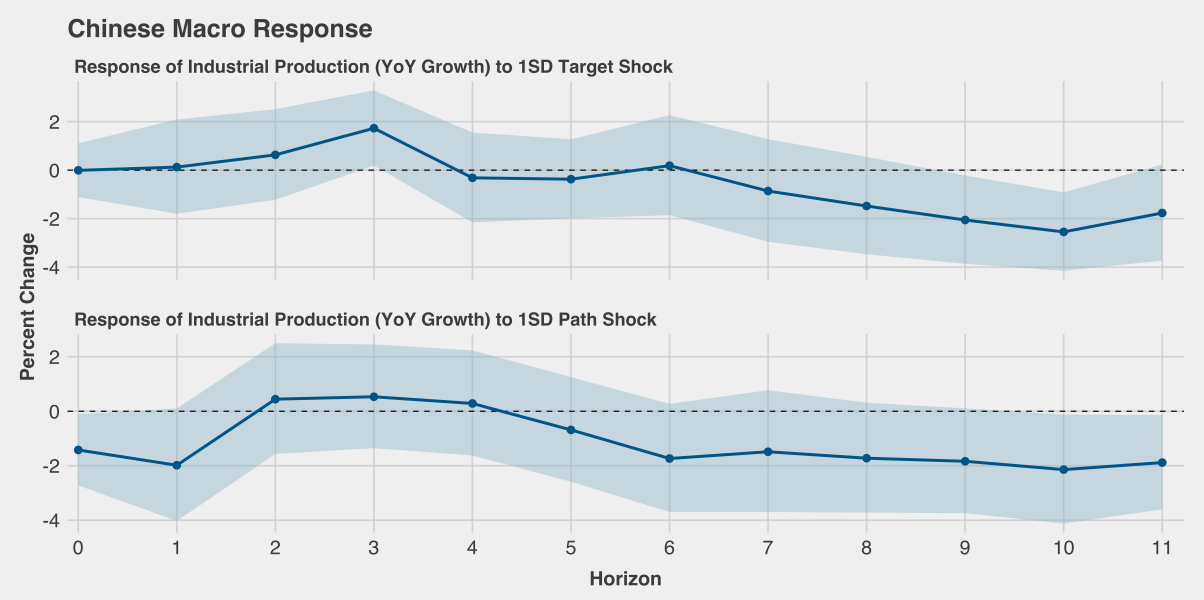


Figure 5: Response of Industrial Production to a Contractionary MP Shock

Notes: Local projection estimated for sample period 2009M1 to 2019M12 with 6 lags (6 months) and shown with 90% HAC error bands. Point estimates represent the percent change in the YoY growth rate of monthly Chinese industrial production in response to a 1SD increase in either Target or Path.

Figure 5 suggests that a tightening of Chinese monetary policy has a contractionary effect on Chinese industrial production, with some persistence out to about a year. Although there are some minor differences between Target and Path responses, this suggests that industrial production does respond to tighter Chinese monetary policy shocks in a manner consistent with the domestic component of our upstream/downstream propagation discussion. That is, tighter policy is linked with a reduction in real Chinese activity, which can materialize upstream foreign firms facing reduced Chinese demand and/or downstream foreign firms facing constrained Chinese intermediate-goods supply.[17] Our simple analysis here is not meant to represent a detailed analysis of domestic transmission or isolate upstream/downstream real activity.[18] Rather, we show suggestive evidence that firms along the supply chain can potentially be affected by changes to real Chinese economic activity as a result of tight Chinese monetary policy.

4.1 Baseline Cross-Country Equity Analysis

We now turn our attention to the propagation of the shocks up and downstream by examining the cross-border equity responses. First, we estimate a baseline regression that assumes

[17] The real side response could suggest tighter policy leads to output decline as a result of an interest rate channel or external finance constraints. We do not take a particular stance on the interest rate channel in China, as our supply-chain mechanism is specific to spillovers outside of China. We note that other papers have evaluated domestic Chinese monetary policy shocks on Chinese financial markets. Shieh (2024) finds that in response to Chinese monetary policy tightening, interbank rates and treasuries yields increase across the yield curve. Various studies have also examined the interest rate channel for China, see, among others, Chen et al. (2007), Porter and Xu (2009), Porter and Cassola (2011), He et al. (2013), Fernald et al. (2014), Chen et al. (2016), and Fu and Ho (2022).

[18] Aside from data limitations, it is unclear whether or not high-frequency identified shocks are sufficient to separately identify supply and demand effects in a real sense, thus necessitating using financial proxies with our SAR model.

that production linkages do not matter — specifically, we measure the total effect of Chinese policy shocks on global equity returns. This provides a first-pass estimation on the relationship between industry-level returns across countries and Chinese monetary policy shocks. In this panel setup, we explicitly assume that $\rho = 0$ in Equation 5, and therefore estimate the following regression:

$$\widehat{\pi_{mi,t}} = \beta_0 + \beta_1^{MP} Target_t + \beta_2^{MP} Path_t + \mathbf{\Gamma X}_{mi,t} + \epsilon_t \tag{13}$$

Table 4 shows the results of the baseline regression. For robustness, Equation 13 was estimated a few ways: Pooled, country level, country-industry level fixed effects, and mean group.[19]

Stock Returns	**(1)**	**(2)**	**(3)**	**(4)**
	Pooled	FE	FE	Mean Group
Target Factor	-0.933	-0.715	-0.715	-0.650
	(0.772)	(0.765)	(0.769)	(0.534)
Path Factor	-2.215***	-2.157***	-2.157***	-2.033***
	(0.720)	(0.722)	(0.728)	(0.473)
Fixed Effects	×	m	mi	×
Observations	10,164	10,164	10,164	10,164

Bootstrapped Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Baseline Regression Results ($\rho = 0$)

Notes: Baseline estimation for sample period 2009M1 to 2019M12 for 11 countries (m) and 7 industries (i) (77 country-industry specific returns). Returns have been winsorized at the 1% level and annualized. The coefficients represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Regressions include each country's domestic policy rate, nominal effective exchange rate, VIX, and the Wu-Xia Shadow Rate as controls. Constant and controls omitted for ease of exposition. Standard Errors bootstrapped 1000 times.

Across the different estimators, the standard errors and coefficients are very stable, indicating that the restrictiveness of the estimator type has a negligible effect on the results. Consistent with Shieh (2024), Path shocks appear to matter in the baseline more than Target. Target shocks are generally associated with negative returns, although they are insignificant. Compared with Path, the Target effect sizes are much smaller. With Path, we see a 1SD contractionary shock leads to a decrease in average stock returns by roughly 2.2pp. At the minimum, global markets are reacting to some component of Chinese monetary policy. These baseline results are roughly complementary to Ma et al. (2026), where they find a growing spillover to global markets from Chinese monetary policy shocks. Further below we contextualize the possibility of financial spillovers by examining whether or not Chinese monetary policy shocks behave like Fed shocks and have spillovers through the global-risk channel.

[19] For more on the mean group estimator, see Pesaran et al. (1999).

The baseline results provide evidence of global spillovers of Chinese monetary policy across different sectors. It is also possible that, due to the relatively limited financial linkages of Chinese monetary policy, there is a limited reflection of a Chinese policy shock in global equity prices, hence the insignificant Target effects. This differs from the case of Fed shocks, which, given the literature on the financial spillovers of US monetary policy shocks, play a role in global equity responses. We provide the following estimates as a descriptive benchmark against studies that examine high-frequency monetary policy shocks on stock returns, with the caveat that the shock units are not directly comparable across studies.[20] For example, using similar network estimation, in response to a contractionary US monetary policy shock, Di Giovanni and Hale (2022) find a roughly 2.5pp decrease in global equity returns, while Todorova (2018) finds a roughly 3.5pp decline in Eurozone stocks in response to a 1pp tightening of ECB policy.

However, the analysis here does not consider network linkages (recall that this is assuming $\rho = 0$) and only provides insight into the total effect of monetary policy shocks on equity returns. To decompose the effects of the Chinese policy shocks and to evaluate the contribution of network linkages, we estimate the heterogeneous SAR described in Equation 5. Before presenting the country-industry estimates, we use a country-level aggregation to benchmark how much information is lost when industry-level exposure is aggregated.

Aggregation to the Country Level

We estimate a modified version of Equation 5 using country-averaged annualized monthly country-industry returns and collapse our $NJ \times NJ$ raw input-output matrix into an $N \times N$ country-level matrix.[21] Therefore the spatial variation in this modification is at the country rather than country-industry level.

The country-level estimates corroborate the existence of network transmission. When compared with the baseline results in Table 4, the results suggest that shocks transmit between countries within the network. The indirect Target effects are statistically significant, while Path retains significance for both Target and Path. We report the complete direct and network effects in Supplemental Appendix B.3 and summarize them with the other robustness exercises in Table 7. This level of aggregation, however, has its limits. First, the results are not a substitute for a country-industry specification. The results could simply be a result of a single country-level return and network coefficient averaging out, suppressing variation in industry exposure to Chinese supply chains. The country-industry level of analysis is therefore necessary for identifying the cross-industry heterogeneity and directional patterns central to our mechanism.

[20] The shocks are not 1:1 comparisons and should not be intended as such. Di Giovanni and Hale (2022) use the Jarociński and Karadi (2020) shock, while Todorova (2018) constructs ECB Target and Path factors following Gürkaynak et al. (2005); ter Ellen et al. (2020) uses a similar decomposition to study ECB spillovers. These 1pp innovations are not directly comparable to Chinese Target or Path, which reflect a broader set of policy levers. Contractionary or expansionary Chinese Target/Path should be taken to be generalized contractionary or expansionary monetary policy shocks, rather than mappings onto a particular policy tool.

[21] We collapse the raw $NJ \times NJ$ sales matrix by summing industry rows and columns within each country before applying the direction-specific transpose and row normalization. Equity returns are aggregated to the country level by averaging monthly returns across industries.

4.2 Upstream Propagation

We now assume that monetary policy shocks travel upstream across country-industries. Recall from the earlier discussion that in this scenario, firms that provide Chinese firms with intermediate goods (as such, these are directly upstream of Chinese firms) are hit with a demand shock that stems from domestic Chinese firms reacting to a more financially constrained domestic environment due to contractionary monetary policy. Since we do not explicitly close off a financial spillovers channel, we can also explore the standard financial spillovers channel and compare with the supply-chain channel. Given the results, we highlight the importance of the supply-chain channel for Chinese monetary policy shocks through Target, but also find global financial market spillovers through Path.

Table 5 reports the results of estimating Equation 5, as well as the effect decompositions. Column (1) constructs the empirical weighting matrix (W) using the 2009 input/output data for the input/output connections. Column (2) uses 2019 input/output data, and Column (3) looks at the average input/output data between 2009 and 2019. Supplemental Appendix B.4 reports the LeSage and Pace (2009) style decompositions, as well as the distributions of the indirect and direct Target and path effects. The alternative decomposition yields qualitatively similar results.

Stock Returns (Upstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
Average ρ	0.666***	0.672***	0.670***
	(0.085)	(0.086)	(0.084)
Direct Target Effect	-0.244	-0.062	-0.165
	(0.393)	(0.399)	(0.394)
Indirect Target Effect	-0.706**	-0.889***	-0.784***
	(0.299)	(0.304)	(0.292)
Network Magnitude Share (%)	74.33***	93.44***	82.58***
	(18.2)	(15.0)	(16.0)
Direct Path Effect	-0.943**	-1.050**	-1.004**
	(0.439)	(0.453)	(0.443)
Indirect Path Effect	-1.252***	-1.144***	-1.191***
	(0.302)	(0.323)	(0.304)
Network Magnitude Share (%)	57.05***	52.13***	54.26***
	(14.0)	(14.1)	(13.9)
Fixed Effects	*mi*	*mi*	*mi*
Observations	10,164	10,164	10,164

Wild Bootstrapped Standard Errors in Parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Heterogeneous SAR Regression Results (Upstream)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming upstream propagation. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constants and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|\text{Indirect}|/(|\text{Direct}| + |\text{Indirect}|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Direct versus Network Effects

First, notice that the passthrough measure, ρ, is statistically significant and shows that the upstream production linkages matter. In fact, across all three weighting years, the degree of passthrough is consistent and high, averaging roughly 0.67. Compared to existing studies

that examine the upstream propagation of monetary policy shocks, the point estimates are numerically in line with those of the United States and differ from the Eurozone. In Di Giovanni and Hale (2022), the full sample ρ estimates are ≈ 0.632. In comparison with Europe, Todorova (2018) estimates a ρ of roughly 0.43 and statistically significant. This suggests that there are differences between how US, EU, and Chinese shocks propagate through production networks. While we cannot directly compare our ρ estimates against these other estimates directly due to differences in estimation, sample, and granularity, they do help us establish the role production networks play in the international transmission of monetary policy shocks. One explanation for the variation in the estimates could be varying degrees of transmission frictions, however, the ρ estimates cannot directly establish or test this explanation.

Comparing this with the scenario in which we allow for $\rho = 0$ (Table 4), we see a few interesting results. Recall that the baseline results from Table 4 reveal that the *average* Target shock is not statistically significant. However, once we allow for input-output linkages to matter, we see the indirect effect of Target to be statistically significant and negative. Specifically, a 1SD contractionary Target shock is associated with a 0.71–0.89pp decrease on average in equity returns through the production network. Moreover, the network magnitude share ranges from 74.33% to 93.44% across the three weighting matrices. Since the indirect effect measures how the equity returns react to the shock accounting for the network linkages, we see that Target shocks predominately matter *through the production linkages*. In other words, Target shocks rely on the production network to propagate. Our supply-chain propagation story argues that tighter Chinese policy shocks act as negative demand shocks to upstream firms — this is unlikely to be a present discounting effect as a result of interest rate changes. Rather, it is a negative demand shock from Chinese firms reducing orders due to tighter credit conditions that propagate upstream to suppliers connected to Chinese customers. Since the indirect effect dominates the direct effect, we argue that Target-style shocks primarily propagate through supply-chains rather than a financial channel.

For Path shocks, the Table 5 suggests a slightly more nuanced story. First, entirely consistent with Shieh (2024), Path shocks matter — global equity prices are directly responding to Path shocks. Second, since Path shocks are in some sense expectations modifiers, the standard financial spillovers channel can show up. Rather than changes to the current monetary policy (and by extension, current financing conditions), Path represents market expectations of future monetary policy path (and as a result, future financing conditions).

This complicates the analysis in a few ways. Path could also be measuring the information content of the PBOC policy announcement. But suppose that a Chinese firm interprets Path as an information shock, then it is entirely possible that the reported effect can be due to either: (1) Chinese firms believing future credit to be tighter since policy announcements reveal some information about the current state of the economy. This in turn might act as a negative demand shock as firms infer from PBOC policy that the economy doing worse than it is.[22] Or (2), equity prices can respond to expected higher interest rates in the future, causing present value to decline, yielding negative returns. In the first case, that type of shock could

[22] This need not be an information shock. A very simple Path interpretation would be policy is expected to be tighter in the future, so expected future demand which propagate upstream to suppliers.

be supply-chain mediated, whereas the second case would be a standard financial spillovers story. While our empirical setup does not allow us to directly disentangle these two channels, we can infer which channel matters more given the point estimates.

Unlike the Target shock, Path shocks matter in both a direct and indirect sense. A 1SD Path shock yields a direct effect of a 0.94–1.05pp decline in global equity returns, whereas the indirect effect is a 1.14–1.25pp decline. With network magnitude shares of 52.13–57.05% across the three weighting matrices, Path shocks are less network-mediated than Target shocks. Since the direct effect is also statistically significant, we interpret this as Path shocks operating through both a supply-chain channel and a possible financial channel, with a smaller network magnitude share and a greater relative role for the non-network component than for Target shocks. This result is complementary to the results shown in Ma et al. (2026), who find a nascent financial spillovers of Chinese policy shocks globally. Our results here show that direct equity responses do exist, but the *type* of monetary policy shock matters — Path shocks open up the possibility of a financial spillovers channel, whereas Target shocks have more limited financial market spillovers and rely more on supply-chain network propagation.

Since the network effects are large and significant for both Target and Path shocks, a natural question is: How much does the network structure matter in the propagation of these shocks? Since this paper's hypothesis is that the supply-chain channel is the primary propagation mechanism for Chinese monetary policy shocks, higher order effects should reveal some persistence across the network distance. In other words, the shocks should not only have first-order effects on China's trading partners but also spillover effects across country-industries connected to these trading partners. Figure 6 and Figure 7 show the persistence of the Target and Path shocks up to degree 5.

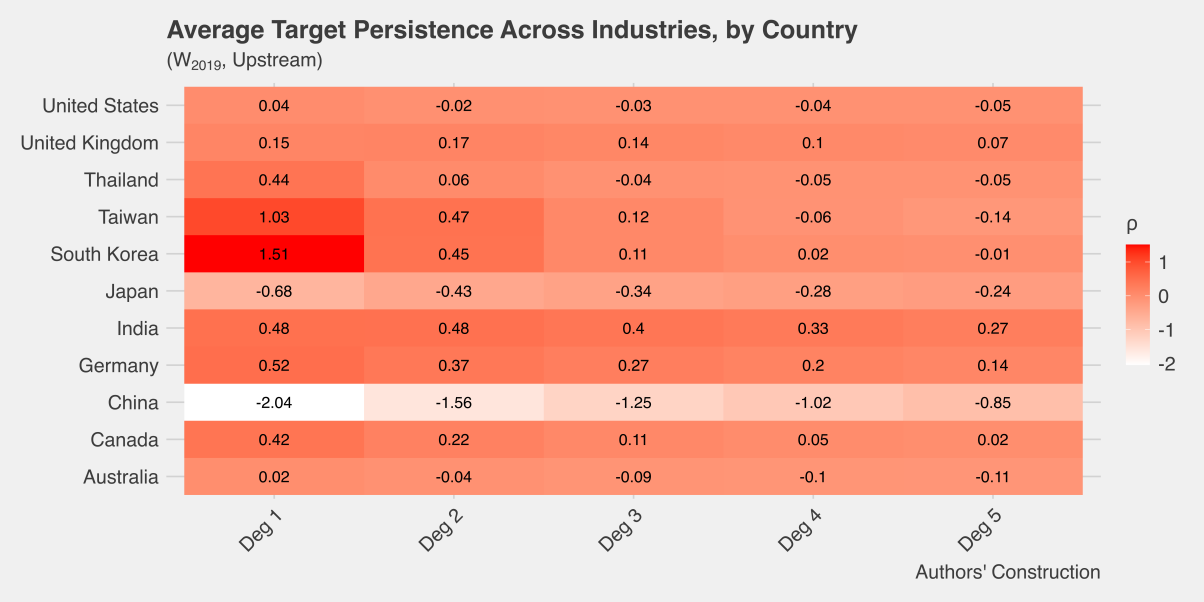


Figure 6: Heat Map of Higher Order Effects (Target Shock)

Notes: Higher order effects heat map up to degree 5 ($K \in [1,5]$) using W^{2019} weighting matrix following the decomposition shown in Equation 9. Results calculated using the $\boldsymbol{\rho}$ and β^{Target} estimates from Column (2) of Table 5.

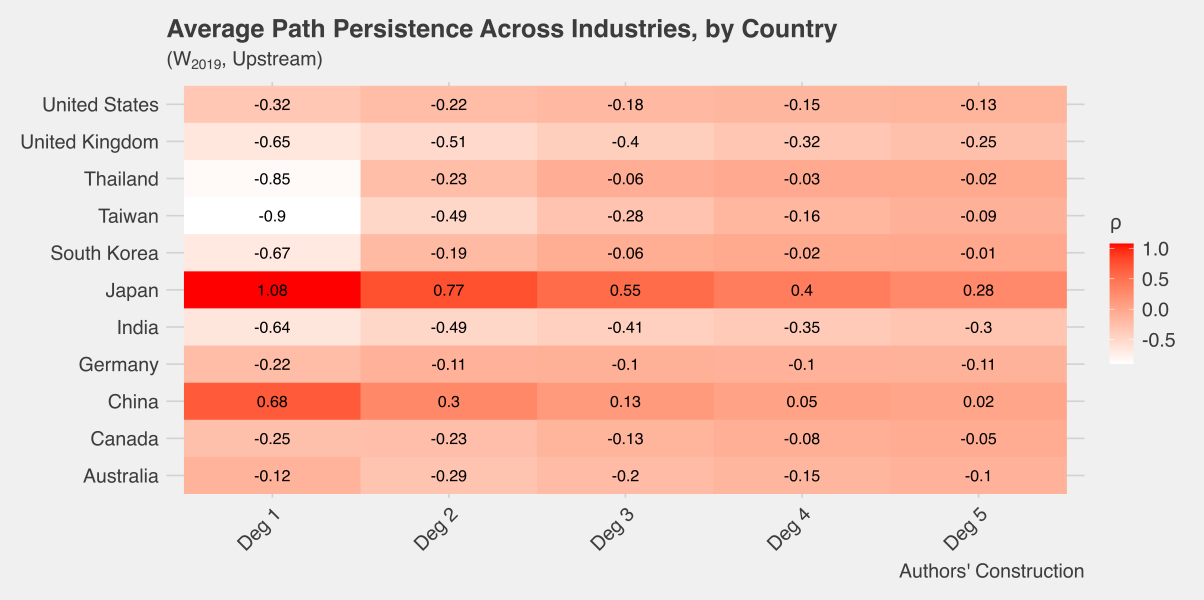


Figure 7: Heat Map of Higher Order Effects (Path Shock)

Notes: Higher order effects heat map up to degree 5 ($K \in [1,5]$) using W^{2019} weighting matrix following the decomposition shown in Equation 9. Results calculated using the $\boldsymbol{\rho}$ and β^{Path} estimates from Column (2) of Table 5.

With both shocks, we observe that first-order connections have the largest effects (as expected), but also that the effects decay as the degree order increases. This is entirely consistent and what we expect the shock to do as network distance increases. The shocks move through multiple layers of input-output linkages. Put plainly, Target and Path not only affect the immediate trading partner, but also other countries and industries connected to that trading partner indirectly connected to China. This suggests that the global transmission of Chinese monetary policy shocks is better explained using supply-chain matters rather than purely bilateral linkages.

Upstream Heterogeneity

A few studies in the literature suggest that expenditure shifting in the aggregate is observed in response to Chinese monetary policy shocks (e.g., Chen et al. (2023), Cho and Kim (2021), etc.). We provide two clarifications: first, in our set up, expenditure shifting shows up as some country-industry pairs benefiting and others hurting as result of the negative demand shock. For example, if the Chinese MP shock causes Firm A to be negatively affected due to reduced Chinese demand, Firm A may decide to find an alternative customer in Firm B outside of China. This benefits Firm B and may show as positive equity returns. Second, this would be captured by $\rho_{mi} < 0$ in the heterogeneous SAR: equity responses move inversely to their network neighbors. More concretely, $\rho_{mi} < 0$ can be interpreted as network substitutability whereas $\rho_{mi} > 0$ is network amplification. So while we cannot directly measure textbook expenditure shifting in a general equilibrium sense, we can infer from our heterogeneous SAR possible substitution occurring in our country-industry pairs. To investigate this possibility, Figure 8 shows how $\boldsymbol{\rho}$ varies by country-industry.

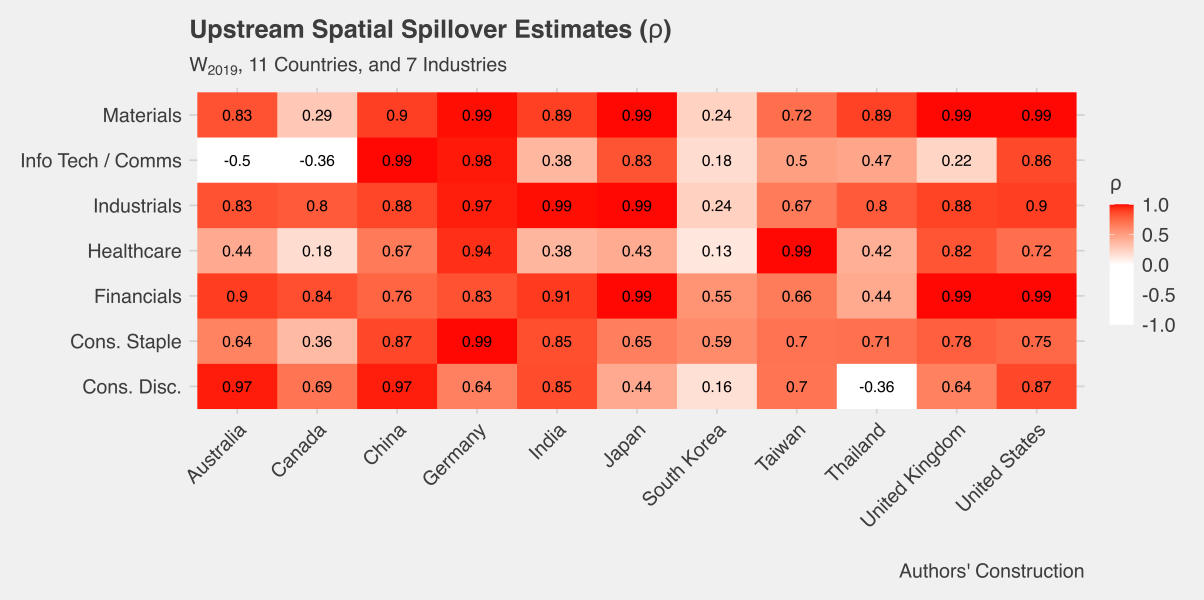


Figure 8: Heat Map of Passthrough Parameter, ρ

Notes: Heat Map of ρ across countries and industries using Upstream W^{2019} as weighting matrix. Results calculated using the $\boldsymbol{\rho}$ estimates from Column (2) of Table 5. ρ_{mi} estimated following Equation 5. $\rho_{mi} > 0$ indicates network amplification and $\rho_{mi} < 0$ indicates network substitutability.

Only a few country-industry pairs exhibit the expenditure shifting (in a network sense) behavior, with the majority of the pairs show a positive ρ, implying that the shock has network amplification. In other words, the input-output linkages help propagate the Chinese monetary policy shocks. The degree of amplification varies by country. For example, South Korea has a relatively lower degree of amplification than Japan. This suggests is that in response to Chinese monetary policy shocks, the reliance of the shock transmission on the network structure is relatively weaker. This is not a statement about raw bilateral trade flows between China and South Korea, rather, this reveals how exposed South Korean firms are to China-exposed production networks as a means of monetary policy shock transmission.

There could be a few explanations for this. It could be that Korean firms are relatively more insulated compared with say, German firms. It could also imply that Korean firms have an easier time substituting away from Chinese customers. For example, the Korean healthcare sector has $\rho = 0.13$, which is a low level of amplification. This could imply that in response to Chinese shocks, Korean healthcare firms are less reliant on Chinese customers and can easily shift away to either domestic or other foreign customers.

We further explore this concept of network entrenchment by examining the country-level indirect effects. We measure a country's level of entrenchment as the degree in which its equity returns respond to Chinese monetary policy shocks through network amplification. In our model, this is characterized by relatively high $\boldsymbol{\rho}$ values combined with negative indirect equity returns that are amplified through the network as a result of a tightening of monetary policy. In some sense, this can be interpreted as upstream firms with larger constraints on their ability to substitute away from customers exposed to negative Chinese demand shocks. We explore this further by looking at the indirect Target and Path effects. Figure 9 and Figure 10 show the

country-level indirect effects.

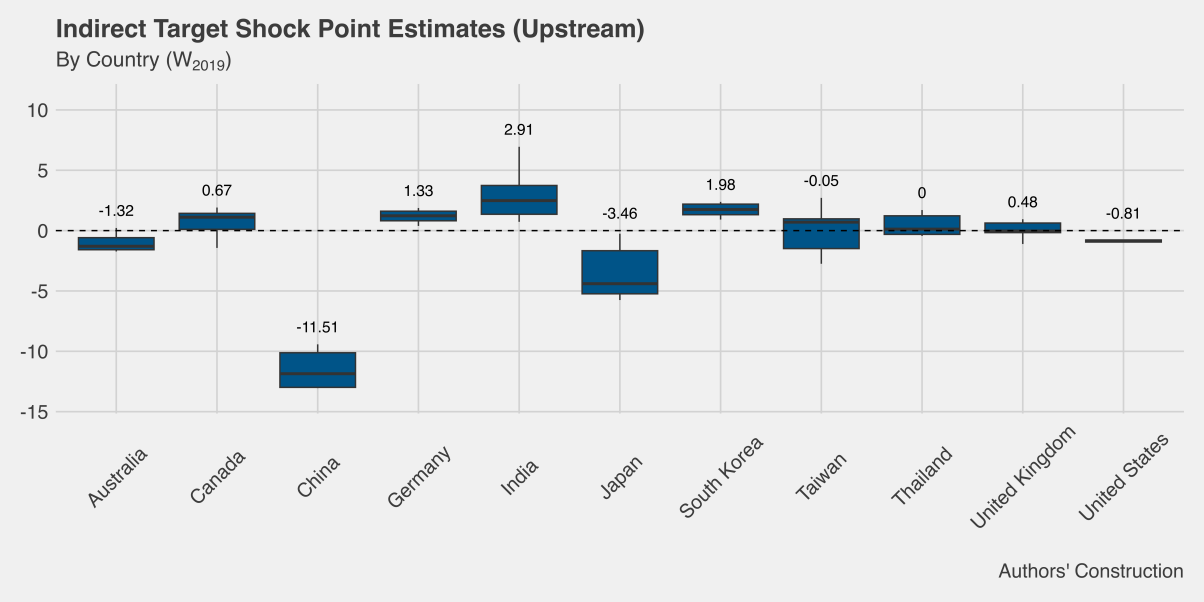


Figure 9: Indirect Target Shock Point Estimates (Upstream)

Notes: Box plot of Indirect Target shock point estimates using W^{2019} weighting matrix showing the IQR spanning the 25th-75th percentiles. Black bars represent the median response, while the labeled values represent the mean response. Results calculated using the β^{Target} estimates from Column (2) of Table 5 estimated following Equation 5.

Recall from Table 5 that Indirect Target effects are significant while Direct Target effects are not, suggesting that Target shocks only primarily operate through production linkages. From the point estimates, we see a couple of reassuring patterns. First, China has the largest negative indirect equity returns and the largest amplification values. We would expect Chinese monetary policy shocks to be amplified the strongest from firms at the enter of the production network. Second, we also expect non-uniform effects in the production network — a country's reliance on China along the production chain depends on its network position and its ability to substitute and this is captured by the estimated indirect effects.

If we examine, for example, the South Korean case and the Japan case, the mechanism is much more suggestive. South Korea has low amplification and a mean indirect Target effect of 1.98pp, compared with -3.46pp for Japan. This implies that South Korea is relatively more resilient to Chinese monetary policy shocks that present itself as negative demand shocks and that Korean firms, relative to Japanese firms, have an easier ability to substitute away from Chinese-exposed customers to less-exposed alternative customers. Whereas Japan is more network entrenched, as shown by the higher ρ and negative indirect Target effects.

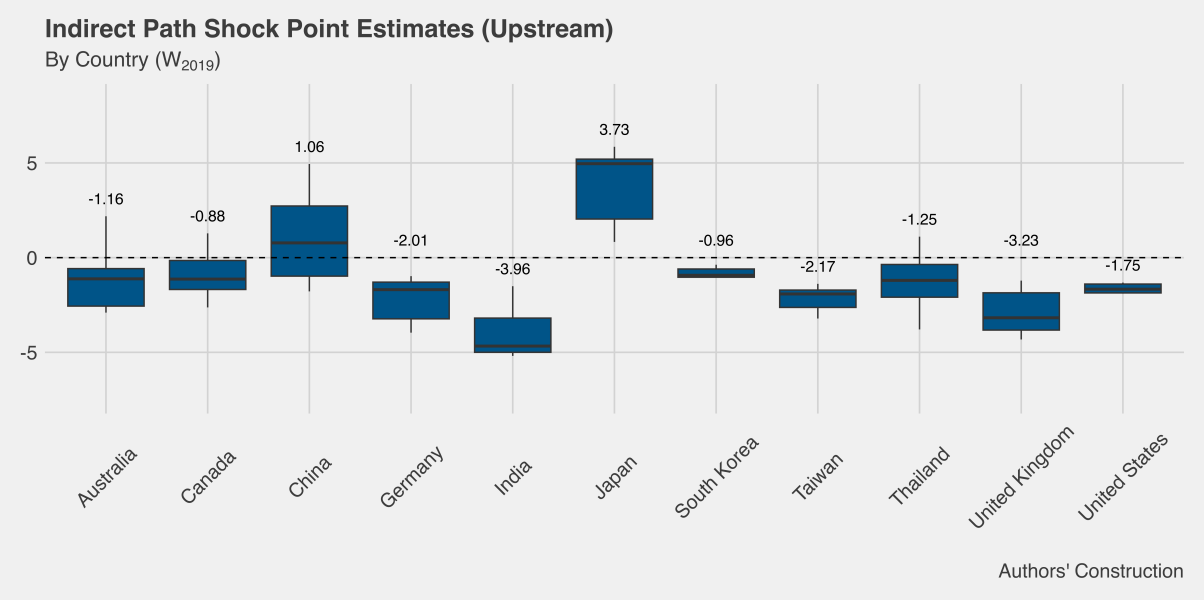


Figure 10: Indirect Path Shock Point Estimates (Upstream)

Notes: Box plot of Indirect Path shock point estimates using W^{2019} weighting matrix showing the IQR spanning the 25th-75th percentiles. Black bars represent the median response, while the labeled values represent the mean response. Results calculated using the β^{Path} estimates from Column (2) of Table 5 estimated following Equation 5.

With Path, network linkages matter, but not as starkly as with Target shocks. The results potentially reveal Path shocks act like expectations or information shocks. Since Path shocks are shocks to beliefs about future monetary policy, the network propagation of Path shocks leans more towards valuation/discounting effects rather than negative demand effects due to a surprise chance to the current stance. The indirect Path shock effects on China show positive returns, suggesting the classic information shock where a contractionary monetary policy shock signals that the economy is *doing better* than previously expected, causing firms expectations to be more optimistic, yielding positive returns. Interestingly, countries that are more network entrenched and exposed to Chinese production networks are more likely to mirror the response of Chinese firms to Path shocks.

This mechanism can explain the sign reversal in South Korea and Japan in response to Path shocks, as well as highlight the degree of entrenchment for both countries. The mean upstream indirect Path effects are -0.96pp for South Korea, 3.73pp for Japan, and 1.06pp for China. Japanese firms appear to be more entrenched within Chinese production networks, so information shocks cause a positive co-movement with Chinese firms in the same direction — they are responding to an information shock that is being amplified throughout the network. In contrast, Korean firms have a negative co-movement, suggesting that they are responding less to an information shock but more to expected future demand conditions as a result of tightening of Chinese policy in a global sense.

4.3 Downstream Propagation

When looking at the downstream propagation, we assume that monetary policy shocks act as negative supply shocks (rather than upstream negative demand shocks). Chinese firms

supply intermediate goods to firms downstream. Once again, we do not explicitly close off a financial spillover and allow for that possibility by examining both direct and indirect effects of two different types of monetary policy shocks. Similar to the upstream case, the results highlight the importance of global supply-chains in the amplification of Chinese monetary policy shocks, with the network-mediated Target response being larger in magnitude in the downstream case. We discuss the implications of this further below. Table 6 shows the point estimates from three heterogeneous SAR estimations with differing W weights. Supplemental Appendix B.5 reports the LeSage and Pace (2009) style decompositions, as well the distributions of the indirect and direct Target and path effects. The alternative decomposition yields qualitatively similar results.

Stock Returns (Downstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
Average ρ	0.647***	0.651***	0.649***
	(0.082)	(0.093)	(0.094)
Direct Target Effect	0.068	0.026	0.070
	(0.447)	(0.446)	(0.447)
Indirect Target Effect	-1.019***	-0.977***	-1.022***
	(0.290)	(0.314)	(0.333)
Network Magnitude Share (%)	93.75***	97.38***	93.61***
	(14.2)	(14.9)	(15.2)
Direct Path Effect	-1.133**	-1.086**	-1.122**
	(0.493)	(0.531)	(0.527)
Indirect Path Effect	-1.062***	-1.110***	-1.071***
	(0.359)	(0.396)	(0.381)
Network Magnitude Share (%)	48.38***	50.54***	48.82***
	(16.1)	(17.9)	(17.4)
Fixed Effects	*mi*	*mi*	*mi*
Observations	10,164	10,164	10,164

Wild Bootstrapped Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Heterogeneous SAR Regression Results (Downstream)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming downstream propagation. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constant and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|\text{Indirect}|/(|\text{Direct}| + |\text{Indirect}|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Direct versus Network Effects

Similar to the upstream case, the degree of network passthrough and amplification is high and similar in magnitude. This confirms that the downstream production network is similarly

important to the upstream case. We highlight a few differences in the point estimates from the upstream case.

First, Target shocks remain similarly network-centric but even more than the upstream case. The network magnitude share ranges from 93.61% to 97.38% across the three weighting matrices, suggesting that this is primarily a supply-chain channel rather than a financial spillover.[23] A 1SD increase in Target is associated with a 0.98–1.02pp decline in equity returns through the production network, on average across country-industry pairs. Compared with upstream Target shocks, the network-mediated decline in equity returns is generally larger in share downstream.

Second, the Path shock looks very similar to the upstream case, where both Direct and Indirect effects matter. Unlike Target shocks, which represent changes to current external financing conditions, Path operates through expectations about the future. A 1SD Path shock yields a direct effect of a 1.09–1.13pp decline in global equity returns, whereas the indirect effect is a 1.06–1.11pp decline. With network magnitude shares of 48.38–50.54%, the direct and indirect effects are similar in magnitude. Since both effects are statistically significant, we interpret this as Path shocks operating through both a supply-chain channel and a possible financial channel.

We argue that the asymmetric responses from Target and Path shocks reinforce our story of China's importance in the global supply-chain. The overall downstream responses further highlight China as a supplier of intermediates to firms downstream. Tighter financing conditions propagate downstream through the network, with Target shocks associated with a 0.98–1.02pp network-mediated decline in equity returns downstream, compared with a 0.71–0.89pp decline upstream. But more importantly, we show that Target shocks work their way primarily through supply-chain linkages, whereas Path shocks propagate through some combination of channels. For brevity, we report the higher order effects of Target and Path shocks in Appendix A.7, as the results are qualitatively similar to the upstream case.

Downstream Heterogeneity

Using our entrenchment definition from the upstream heterogeneity analysis, we can examine how network entrenched some country-industry pairs are in the downstream sense. At first pass, Figure 11 is not too qualitatively different from Figure 8 in that downstream shocks have a high degree of passthrough and amplification. Once again, the Chinese estimates are reassuring — Chinese industries "feel" the Target and Path shocks more than other country-industry pairs.

We again expect there to be differences in ρ across country-industries, depending on how entrenched these pairs are with others in Chinese-linked production networks. This time, however, rather than the ease in which firms can find an alternative customer to send intermediates too, downstream firms must find alternative suppliers. In this case, a high degree of entrenchment would indicate firms are much more reliant on Chinese intermediates so the network

[23] Network magnitude shares are calculated using the absolute values of the Direct and Indirect effects in all cases. Because these effects have opposite signs here, the statistic is a magnitude-based comparison rather than an additive decomposition. The raw Indirect point estimate is larger in magnitude than the Direct point estimate, so the qualitative interpretation that the network effect dominates still holds.

would have a larger amplification of Chinese policy shocks, combined with negative indirect equity returns.

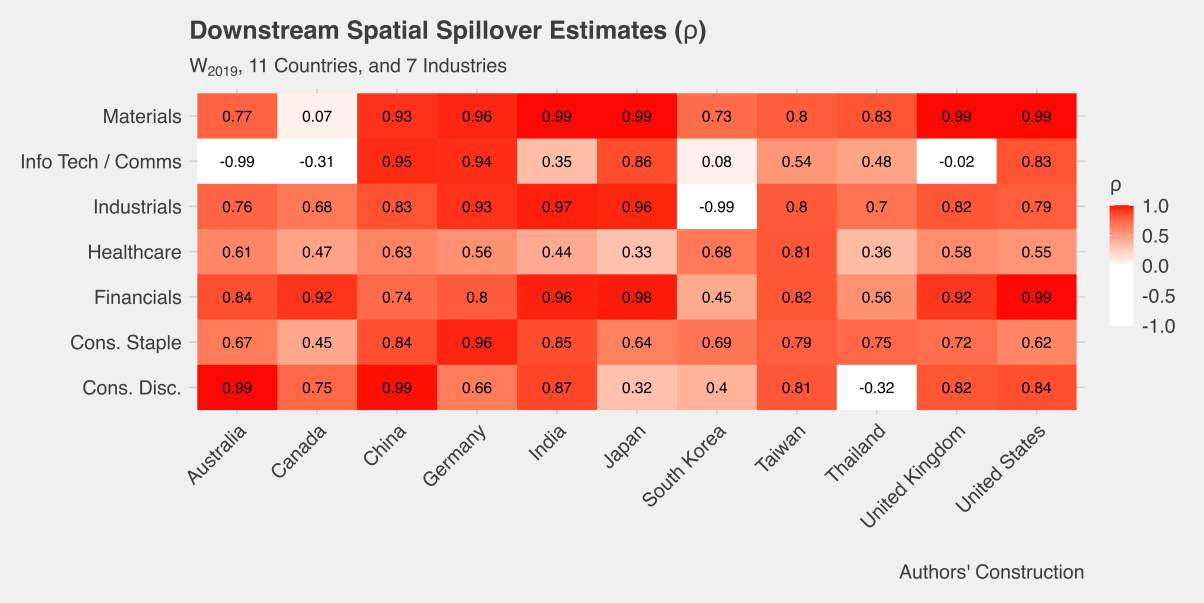


Figure 11: Heat Map of Passthrough Parameter, ρ

Notes: Heat Map of ρ across countries and industries using Downstream W^{2019} as weighting matrix. Results calculated using the $\boldsymbol{\rho}$ estimates from Column (2) of Table 6. $\rho_{mi} > 0$ indicates network amplification and $\rho_{mi} < 0$ indicates network substitutability.

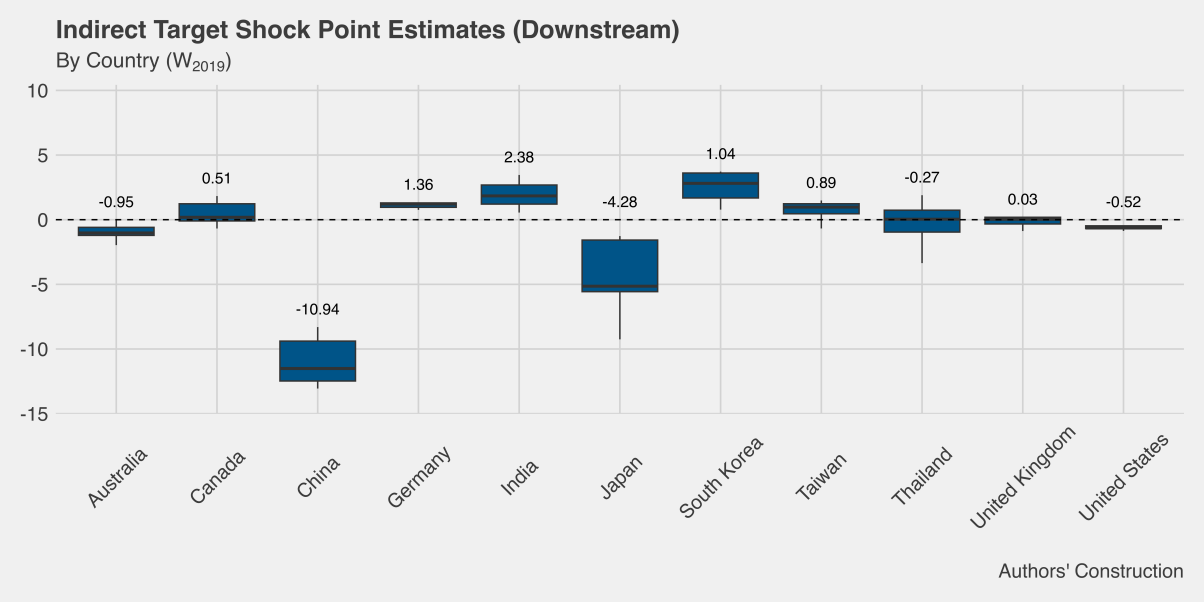


Figure 12: Indirect Target Shock Point Estimates (Downstream)

Notes: Box plot of Indirect Target shock point estimates using W^{2019} weighting matrix showing the IQR spanning the 25th-75th percentiles. Black bars represent the median response, while the labeled values represent the mean response. Results calculated using the β^{Target} estimates from Column (2) of Table 6 estimated following Equation 5.

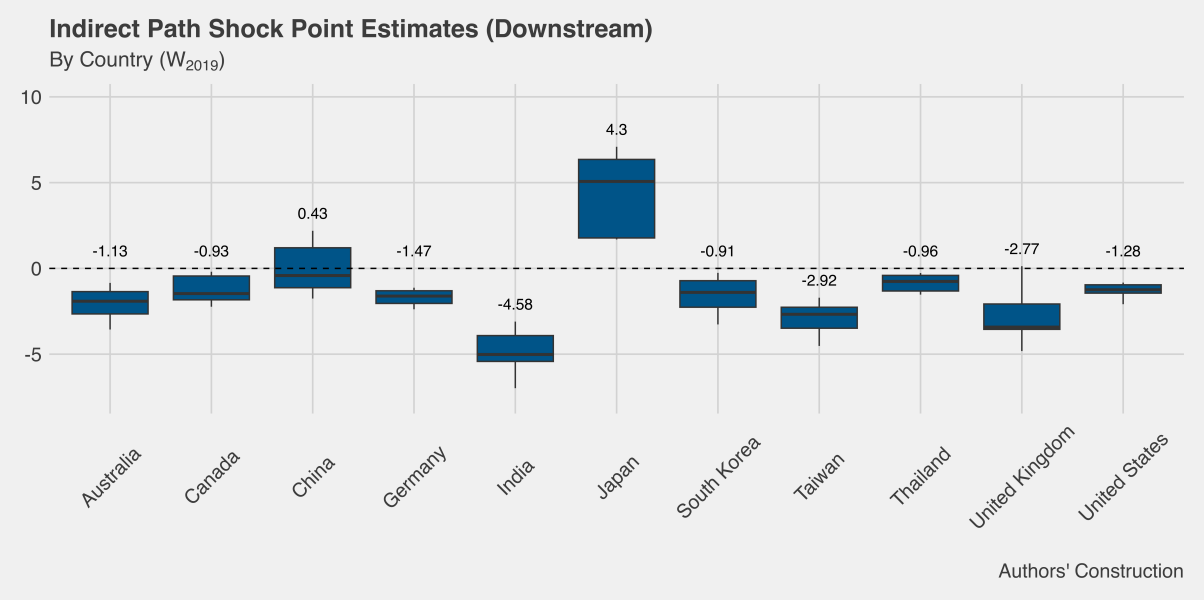


Figure 13: Indirect Path Shock Point Estimates (Downstream)

Notes: Box plot of Indirect Path shock point estimates using W^{2019} weighting matrix showing the IQR spanning the 25th-75th percentiles. Black bars represent the median response, while the labeled values represent the mean response. Results calculated using the β^{Path} estimates from Column (2) of Table 6 estimated following Equation 5.

The downstream country-level results largely mirror the upstream pattern rather than depart from it. Figure 11 shows that downstream passthrough is generally high but heterogeneous across industries. For Target shocks, the mean indirect effects in Figure 12 are 1.04pp for South Korea, −4.28pp for Japan, and −10.94pp for China. The positive Korean response, compared with the negative Japanese response, is consistent with our conjecture that Korean firms may have greater flexibility to substitute away from Chinese intermediate-input suppliers, whereas the larger Japanese response suggests less substitutability and deeper entrenchment in their China-linked production networks. Since we cannot directly observe supplier switching, we view this as more suggestive evidence of this behavior rather than causal.

Path shocks show a larger contrast. Japan's downstream Path indirect effect in Figure 13 is positive, reversing the sign of its Target response but matching the positive Chinese response, while South Korea's mean Path effect is −0.91pp, compared with 4.30pp for Japan and 0.43pp for China. This Target/Path sign pattern also appears in the upstream results, indicating that Japanese firms' valuations are more persistently linked to China on both sides of the production network. The negative Japanese Target effect is consistent with disruption transmitted through current Chinese financing conditions and intermediate-input linkages. By contrast, the positive Japanese Path effect is more consistent with an information or valuation channel, through which news about future Chinese policy and economic conditions is reflected by Chinese and Japanese equities. The downstream evidence provides additional evidence that Target shocks operate primarily through supply-chain linkages, whereas Path shocks combine supply-chain transmission with financial spillovers.

4.4 Benchmarking Financial Spillovers

Due to our earlier results showing significant direct Path effects, we evaluate the possibility that PBOC shocks resemble a Fed-style global risk channel. Miranda-Agrippino and Rey (2020b) argue that the Fed drives global risk cycles, affecting global asset prices. Given the size of the Chinese economy, there is a possibility that Chinese shocks may behave similarly. To address this, we first examine whether or not PBOC shocks affect global risk aversion by running standard local projections on VIX. We first estimate a daily local projection to check for persistent effects after a PBOC shock, following the method prescribed in Shieh (2024). We estimate:

$$\Delta R_{t+h} = \alpha_h + \mathbf{B}_h^{MP}\mathbf{Z}_t + \mathbf{\Gamma}_h\mathbf{X}_t + \varepsilon_{t+h}, \qquad h = 0, \ldots, H \tag{14}$$

where ΔR_{t+h} denotes the daily change relative to the closing VIX value on the day prior to a PBOC announcement and $\mathbf{X}_t$ is a lagged control vector of Fed Target and Path shocks.[24] We set $H = 15$, which is the median number of days between PBOC announcements and following Swanson (2021), estimate this LP with 0 lags since ΔR_{t+h} measures a daily difference. Figure 14 presents the response of our daily VIX LP.

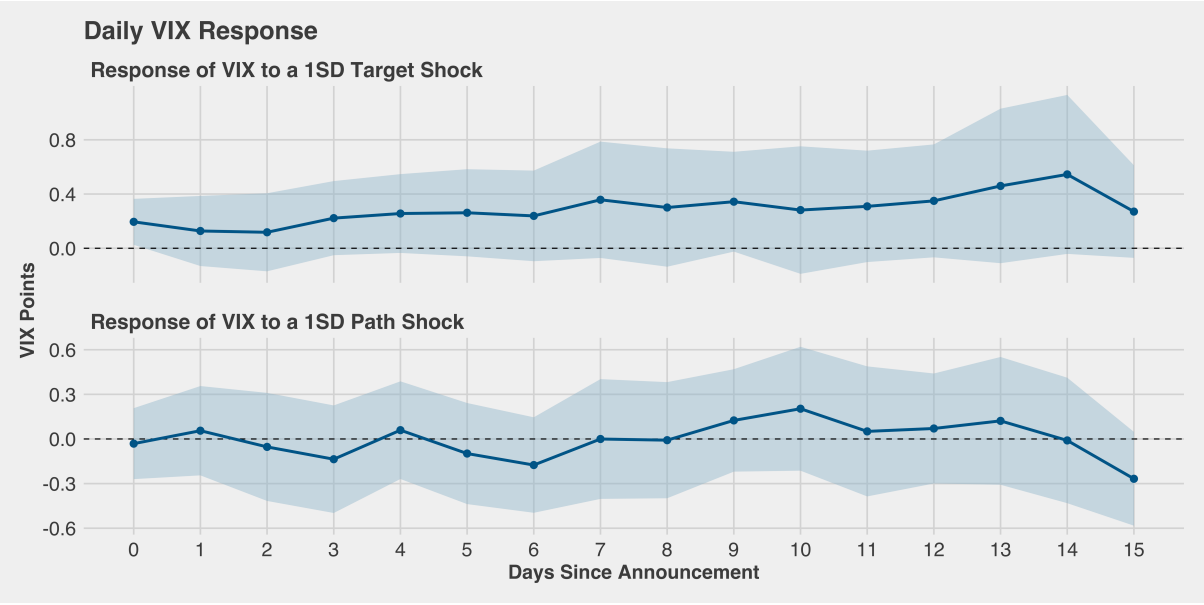


Figure 14: Daily VIX IRFs in Response to a Target or Path Shock

Notes: Local projection estimated for sample period 2009M1 to 2019M12 estimated on 0 lags and presented with 90% HAC Standard Errors. Horizon is set as the median days between PBOC announcements. Point estimates represent the change in VIX Points in response to a contractionary 1SD increase in either Target or Path.

In the immediate period after a Chinese monetary policy announcement, VIX does not robustly respond to either Target or Path with persistence. This suggests that PBOC shocks do not resemble the Fed-style global risk shock along this dimension. The equity results in

[24] Specifically, let t denote a PBOC announcement date and X_s the closing value on day s. We calculate $\Delta R_{t+h} = X_{t+h} - X_{t-1}$, holding the pre-announcement closing value X_{t-1} fixed for each day after the announcement up to, but not including, the next announcement. If $t + h$ falls on a weekend or trading holiday, we use the most recent available closing value, provided that $t + h$ is not the date of the next announcement.

the heterogeneous SAR instead may indicate what we had suggested previously, that Path shocks are more consistent alternatives such as information effects, expectations about future demand, or valuation effects. We further confirm this by estimating a monthly local projection and evaluating the response of VIX while controlling for US monetary policy shocks. The result holds at the monthly level, where we do not find any robust movements in VIX in response to Target or Path shocks. We show the impulse responses in Appendix A.8.

We then assess how PBOC shocks affect the Global Factor estimated in Miranda-Agrippino and Rey (2020b) by estimating a monthly local projection similar to Equation 12 and controlling for US Target and Path shocks. Figure 15 presents the results:

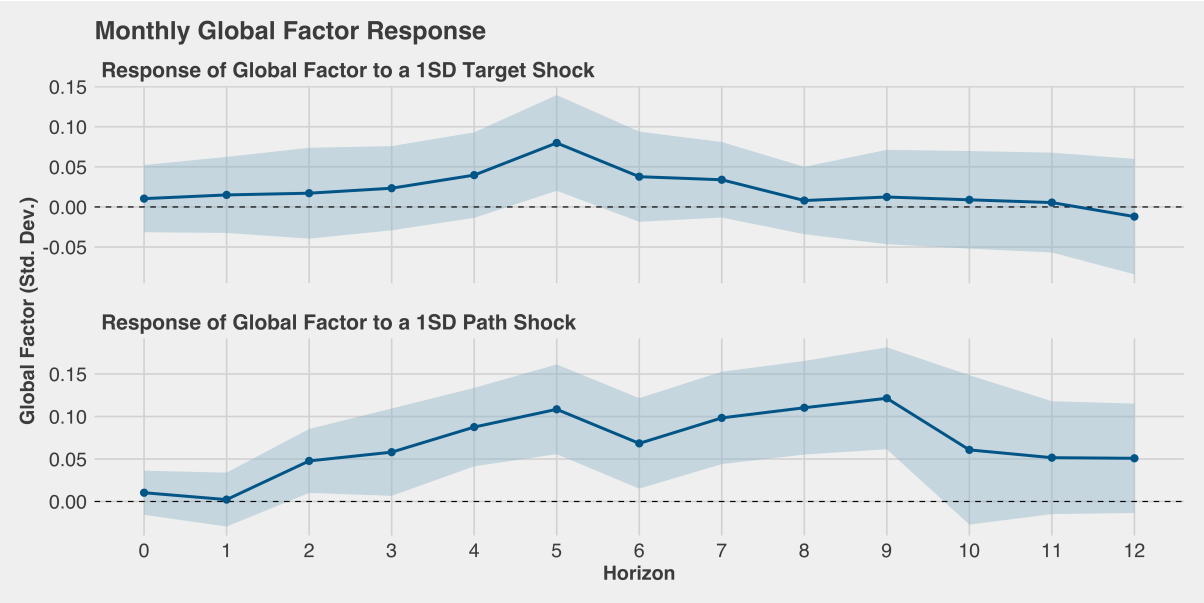


Figure 15: Monthly Miranda-Agrippino and Rey (2020b) Global Factor IRFs in Response to a Target or Path Shock

Notes: Local projection estimated for sample period 2009M1 to 2019M12 estimated on 6 lags (6 months) and presented with 90% HAC Standard Errors. Point estimates represent the change in standard deviations of the Miranda-Agrippino and Rey (2020b) Global Factor in response to a contractionary 1SD increase in either Target or Path.

Unlike the results in Miranda-Agrippino and Rey (2020b), who find that Fed shocks reduce the Global Factor, we see that Chinese monetary policy shocks do not behave similarly. Specifically, Target seems to have no robust effect on the Global Factor, while a contractionary 1SD Path shock *increases* the Global Factor. Taken together with the VIX results, we argue that PBOC shocks are not consistent with a Fed-style risk channel. The results are more suggestive of a non-risk financial component, although we cannot separately identify whether the component reflects information, expectations, or valuation effects. This highlights that the *type of shock* matters for the transmission of Chinese monetary policy.

4.5 Suggestive Evidence on Real-Side Transmission

We attempt to connect our heterogeneous SAR results with macro evidence of the supply-chain channel. We note that our results are suggestive, given the nature of trade flows and pricing data at the aggregate level. Since aggregate flows are (1) highly volatile at the monthly level

and (2) aggregate away industry or firm level heterogeneity, it is difficult to provide direct evidence of the transmission through standard macro variables. In either case, we cannot properly identify an upstream negative demand shock as separate from a negative supply shock, given countries lie both up and downstream of each other. Moreover, it would be difficult to disentangle pricing, quantity, and exchange rate effects in a partial equilibrium sense given the data. While we cannot separately identify upstream demand and downstream supply shocks within countries in the aggregate, we attempt to triangulate our supply chain effects.

For the upstream case, we rely on complementary evidence from Miranda-Agrippino et al. (2020). They find that commodity prices contract significantly, with some delay, after a contractionary Chinese monetary policy shock and interpret this response as reflecting weaker Chinese demand for raw materials and intermediate production goods. This response is in line with our upstream mechanism, where tighter Chinese monetary policy reduces demand for inputs supplied by foreign firms. We do not interpret their results as directly identifying the upstream component of our shocks. Rather, taken together with the contraction in Chinese industrial production shown in Figure 5 and our finding that the upstream Target responses are primarily supply chain linked, the commodity-price response provides suggestive evidence that is consistent with an upstream demand channel.

For the downstream case, since our downstream hypothesis hinges on pricing pressure, we present pricing evidence by examining changes to the Producer Price Index (PPI) for manufacturing activity in a subset of our countries. Since our SAR results show downstream network effects to be larger, we expect this to be more informative of the supply chain channel. We estimate a local projection similar to Equation 12 on YoY PPI growth with 3 lags, while controlling for CNY/USD exchange rate, the Wu-Xia US Shadow Rate, and global oil prices.

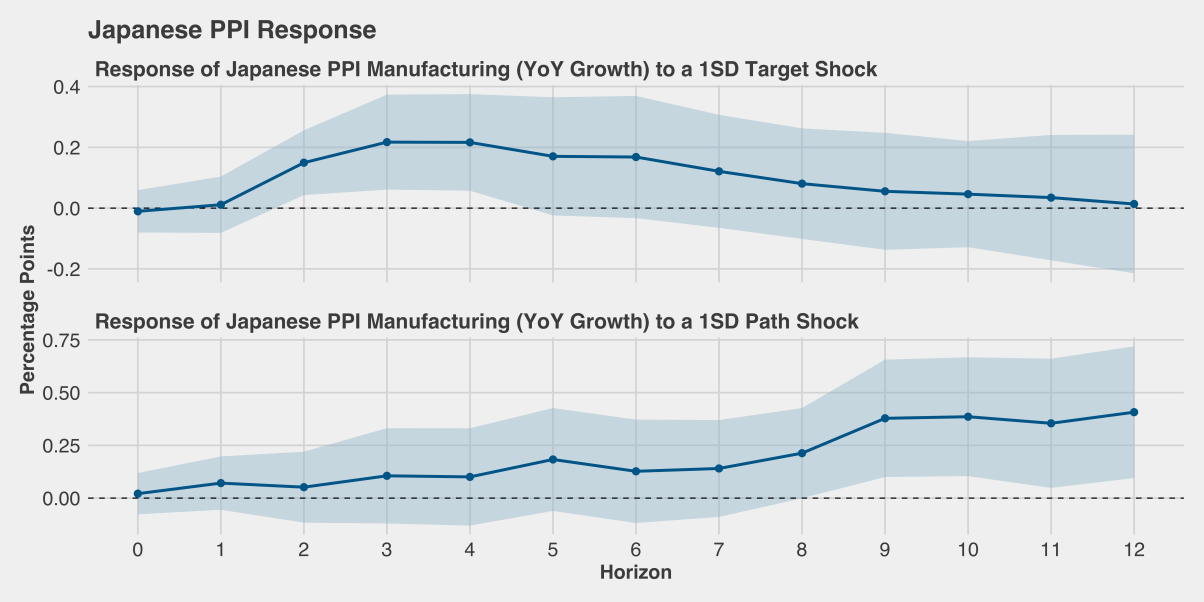


Figure 16: Monthly Japanese PPI (Manufacturing) IRFs in Response to a Target or Path Shock

Notes: Local projection estimated for sample period 2009M1 to 2019M12 estimated with 3 lags (3 months) and presented with 90% HAC Standard Errors. Point estimates represent the percentage-point change in the YoY growth rate of manufacturing PPI in response to a contractionary 1SD increase in either Target or Path.

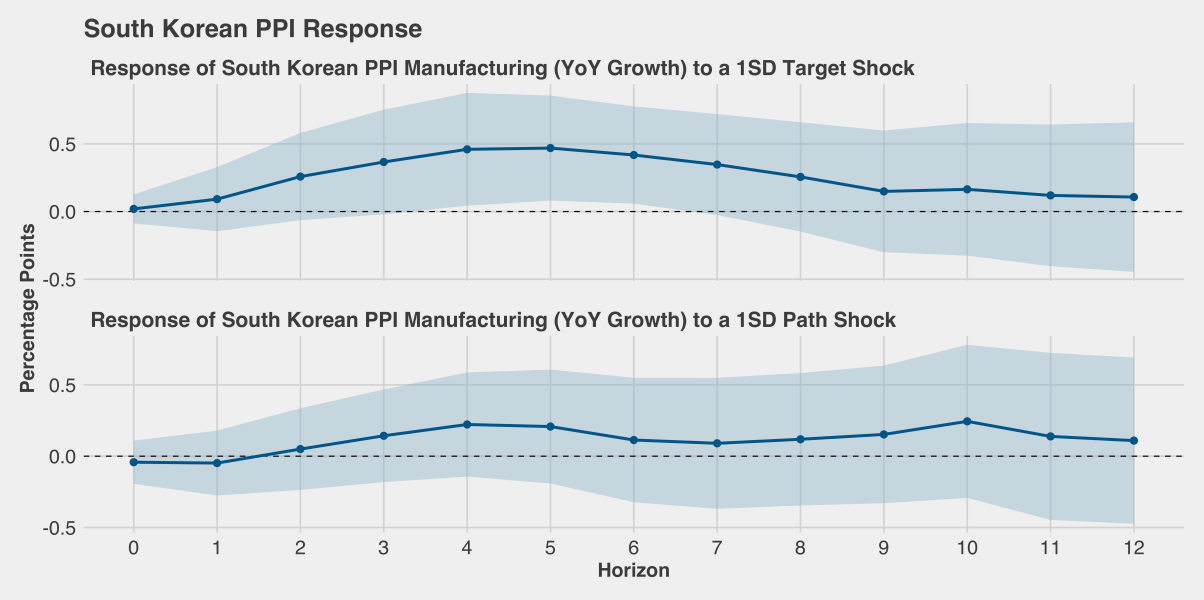


Figure 17: Monthly South Korean PPI (Manufacturing) IRFs in Response to a Target or Path Shock

Notes: Local projection estimated for sample period 2009M1 to 2019M12 estimated with 3 lags (3 months) and presented with 90% HAC Standard Errors. Point estimates represent the percentage-point change in the YoY growth rate of manufacturing PPI in response to a contractionary 1SD increase in either Target or Path.

In response to a Chinese monetary policy shock, we note that Target shows an increase in PPI for both Japan and South Korea (Figure 16 and Figure 17), suggesting upward pricing pressure after a Chinese shock. The observed upward PPI pressure appears roughly 2 months after a Target shock and in the case of Japan, around 8 months after a Path shock, whereas the Chinese industrial production responses occur at roughly 8 months for both Target and Path. Since Target and Path capture different dimensions of policy shocks and our local projections do not identify the precise timing differences and response ordering of output and prices, we cannot establish a strict temporal chain capturing our supply-chain mechanism. Rather, we view the results as suggestive of output and pricing effects emerging at different time horizons.

Linking these results with the domestic real transmission shown in Figure 5 provides suggestive evidence of our supply-chain channel, as we expect there to be downstream pricing pressure after a contractionary Chinese monetary policy shock. Since Path can encompass additional channels outside of our supply-chain channel, we view the weaker Path results relative to Target as consistent with our overall heterogeneous SAR results. Thus, the aggregate industrial production, commodity price, and producer price responses to Chinese shocks provide suggestive, real-side evidence of the supply-chain mechanism that is consistent with the equity results. We show the German PPI results in Appendix A.9, which, while more imprecise, generally show the same pattern.

5 Robustness

Robustness to Simultaneous Announcements

Since our heterogeneous SAR examines equity returns, there may be some concern about the effect of other macroeconomic announcements affecting these returns. Using our purged measure of PBOC shocks discussed in Subsection 2.3, we re-estimate our heterogeneous SAR. The results are presented in Appendix A.10 and show that our original estimates remain similar after excluding overlapping announcements by either concurrent Chinese fiscal policy shocks or Japanese monetary policy announcements. In both the upstream and downstream cases, the passthrough remains high and the network magnitude shares are qualitatively similar to the non-purged shocks. This suggests that our results are not necessarily being driven by same-day Japanese monetary policy or Chinese fiscal policy shocks.

2009–2015 Stability Sample

Trade frictions may play a role in driving our results. Specifically, changes in Chinese export-control policy and US–China trade policy during our sample period are potential concerns with our results. To avoid large-scale trade disruptions that occurred after 2017, we estimate a subsample starting in January of 2009 and ending in December of 2015.[25] We view our subsample as informative because of Chinese export controls. Since 2009, China imposed export controls on strategic materials related to rare-earths and other raw materials. These were relatively tighter during the period between 2009 and 2015, with China settling a WTO dispute and relaxing these restrictions during 2015 (The World Trade Organization 2015). This subsample provides a stability exercise, due to the relatively stable nature of Chinese export controls between 2009 and 2015, as well as avoid any large-scale shocks to the global trading environment in the full sample. We re-estimate our heterogeneous SAR on the 2009-2015 period. We report the results in Appendix A.11. Broadly, our passthrough measure ρ remains similar to the full sample, as are the Target and Path network magnitude shares. This suggests that our original estimates are not solely a feature of changes to either Chinese export policy or US trade policy. We note that our exercise cannot assess the independent effects of different export-control or trade-policy regimes. Table 7 shows the headline results for both robustness exercises.

[25] While the Trump Administration did not impose large-scale tariff policy changes until late 2017, we do not include 2016 to control for possible anticipatory effects due to increasingly aggressive trade policy rhetoric from the Obama administration, as well as the 2016 US presidential candidates during the election cycle.

Specification	Sample	Direction	Avg. ρ	Target Network Magnitude Share	Path Network Magnitude Share
Original Estimation	2009–2019	Upstream	0.666–0.672	74.3–93.4%	52.1–57.0%
	2009–2019	Downstream	0.647–0.651	93.7–97.4%	48.4–50.5%
Purged PBOC Shocks	2009–2019	Upstream	0.666–0.671	67.3–73.8%	52.7–54.7%
	2009–2019	Downstream	0.647–0.650	75.5–77.9%	44.3–49.1%
Stability Sample	2009–2015	Upstream	0.671–0.671	73.2–82.3%	59.4–61.8%
	2009–2015	Downstream	0.651–0.653	96.5–99.4%	57.8–58.4%
Country-Level Aggregation	2009–2019	Upstream	0.846–0.879	80.3–91.4%	75.6–82.6%
	2009–2019	Downstream	0.881–0.892	97.1–97.6%	82.8–83.7%

Table 7: Original Estimation and Robustness Exercises

Notes: Table compares the original estimates with the purged-shock, short-sample, and country-level exercises. For compactness and consistent comparison, entries report ranges across the two endpoint input-output matrices: W_{2009} and W_{2019} for the 2009–2019 sample, and W_{2009} and W_{2015} for the 2009–2015 sample. The complete tables additionally report estimates using the corresponding average W matrix. The purged-shock exercise re-estimates Target and Path after excluding PBOC announcements that overlap with BOJ announcements and State Council fiscal or joint monetary/fiscal communiqués. The short-sample exercise retains the original shocks and estimates the model over 2009–2015. The country-level exercise aggregates the 77 country-industry returns and weighting matrix to 11 countries. Network magnitude shares are calculated as $|Indirect|/(|Direct| + |Indirect|) \times 100$ *using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.*

6 Conclusion

We examine how Chinese monetary policy shocks propagate globally through production linkages; specifically, we evaluate whether surprise changes to the existing policy stance and surprise changes to the beliefs about the future stance have any global implications. Using a simple and tractable spatial econometric model, we decompose the effects of these shocks into total, direct, and network effects. We highlight two important results. First, the *type* of monetary policy shock matters when thinking about how Chinese monetary policy shocks transmit globally. Target shocks, or changes to the current policy stance, primarily operate and propagate through a supply-chain channel. Path shocks, or changes to the expected future policy stance, operate through a combination of a supply-chain channel with some financial spillovers. Path shocks exhibit behavior that suggests a possible information effect. Our financial benchmarking exercises reinforce a distinction between PBOC and Fed shocks — namely, Chinese shocks do not exhibit the same behavior as Fed-like global risk shocks. Second, Target shocks generate a network-mediated reduction in equity returns between 0.71–0.89pp upstream and 0.98–1.02pp downstream. Path shocks generate indirect declines of 1.14–1.25pp upstream and 1.06–1.11pp downstream, alongside significant direct declines of 0.94–1.05pp and 1.09–1.13pp, respectively. The sign and magnitude of individual country-industry responses depend on their positions in China-linked supply-chains. Chinese monetary policy shocks still act as negative demand (for upstream suppliers) and negative supply shocks (for downstream customers) and that network propagation of these shocks is important. The heterogeneous results across the production network country-industry pairs are suggestive of the degree of entrenchment firms have relative to Chinese-linked supply-chains.

More specifically, we characterize the transmission as supply and demand shocks originating from China. Target network magnitude shares range between 74.33–93.44% upstream and 93.61–97.38% downstream. We show expenditure shifting (in a network sense) exists in

that some country-industry pairs shift away from China as either a customer or a supplier in response to these shocks. We then link and contextualize our empirical results with suggestive real-side evidence of this supply-chain channel by examining domestic Chinese industrial production contracting after tighter monetary policy as well as increased pricing pressure on Japan and South Korea in response to Target shocks. This is broadly in line with our conjecture that Target shocks primarily operate through the supply-chain channel. Overall, our results are qualitatively in line with the hypothesis presented in Miranda-Agrippino et al. (2020) and Huang et al. (2014): global value chains are the avenue through which Chinese monetary policy primarily transmits worldwide.

Our overall results suggest that a Chinese Target monetary policy shock, while acting in a standard way in the domestic environment (tighter financial conditions in the Mainland), materializes differently depending on the direction of the production chain. In the upstream case, the shock appears to materialize as a demand shock, where Chinese firms demand fewer foreign intermediates as a direct consequence of tighter financing conditions post-shock. In the downstream case, the shock materializes as a supply shock, where Chinese firms supply fewer intermediates to export to foreign firms. Both of these scenarios result in lower expected profits for foreign firms — presenting as negative equity returns. In contrast, Path shocks introduce financial spillovers that are modulated by supply-chain spillovers. Path shocks are consistent with information shocks, resulting in more valuation/discounting asset pricing effects rather than purely demand or supply effects.

Our results show that production linkages matter and serve as the vehicle for the global propagation of Chinese monetary policy. The recent international experience with the massive supply-chain interruptions due to Coronavirus highlights the importance of production linkages between countries. Because of China's relative centrality in supply-chains, understanding how Chinese monetary policy transmits through these linkages is essential due to the relative lack of understanding of how Chinese monetary policy operates. Moreover, in light of the recent geopolitical push to "de-risk" or even decouple from China, having an increased understanding of the global spillovers of Chinese monetary policy is a critical piece of the puzzle in fully understanding the ramifications of future manufacturing and trade policy. In a different vein, for countries reliant on the Chinese supply-chain, either as suppliers or end-users, there may be implications for the conduct of their own monetary policy when faced with Chinese monetary policy shocks propagating up and down the supply-chain. There are a few caveats with this study. First, industries are collapsed into 7 large sectors, from the initial 35 ISIC sectors. This aggregation eliminates some potential variation that can be observed by industry. Second, regardless of the level of sectoral aggregation, the equities data cannot provide any meaningful distinction between intermediate and final goods trade. At best, this study relies on the relative volume of import and export of intermediate goods to justify the shock propagation story. Future work could disaggregate the industry classifications to be more granular and examine if there are differences in the shock propagation that vary by more specific sectors, as well as explore implications for optimal monetary policy for countries both upstream and downstream in the Chinese supply-chain.

Appendix A

A.1 Chinese Monetary Policy Announcements

Table 8 reports the set of monetary policy announcements used for our factor estimation encompassing June 2006 to December 2019. The two reserve-requirement announcements on 02/18/11 and 03/18/11 are retained here for completeness but are excluded from the factor estimation in the main text because of the pricing discrepancy noted in the main text.

#	Date	Type	Notes
2006			
1	06/16/06	RR	Increase
2	07/21/06	RR	Increase
3	08/10/06	MPR	Q2 MPR
4	08/14/06	RR	Increase
5	08/15/06	WG	
6	08/18/06	LR	Increase
7	11/03/06	RR, WG	RR Increase
8	11/14/06	MPR	Q3 MPR
9	12/08/06	WG	
2007			
10	01/05/07	RR	Increase
11	02/09/07	MPR	Q4 2006
12	02/16/07	RR	Increase
13	03/14/07	WG	
14	03/17/07	LR	Increase
15	04/05/07	RR	Increase
16	04/25/07	RR	Increase
17	04/29/07	RR	Increase
18	05/10/07	MPR	
19	05/11/07	WG	
20	05/18/07	RR, LR, FX	RR Increase; Float Expansion; LR Increase
21	07/21/07	LR	Increase
22	07/30/07	RR, FX	RR Increase
23	08/08/07	MPR	
24	08/22/07	LR	Increase
25	09/06/07	RR	Increase
26	09/15/07	LR	Increase
27	09/24/07	WG	
28	10/13/07	RR	Increase
29	11/08/07	MPR	
30	11/10/07	RR	Increase
31	12/08/07	RR	Increase
32	12/20/07	LR, Other	LR Increase; Rural loans program in Xinjiang
2008			
33	01/16/08	RR	Increase
34	02/22/08	MPR	
35	02/27/08	WG	
36	03/18/08	RR	Increase
37	04/16/08	RR	Increase
38	05/12/08	RR	Increase
39	05/14/08	MPR	

Table 8 – continued from previous page

#	Date	Type	Notes
40	06/07/08	RR	Increase
41	08/15/08	MPR	
42	09/15/08	RR	Decrease
43	09/16/08	LR	Decrease
44	10/08/08	RR	Decrease
45	10/09/08	LR	Decrease
46	10/20/08	WG	
47	10/27/08	LR, Other	Mortgage Rate Decrease
48	10/30/08	RR	LR Decrease
49	11/17/08	MPR	
50	11/26/08	RR	Decrease
51	11/27/08	LR	Decrease
52	12/05/08	WG	
53	12/22/08	RR	Decrease
54	12/23/08	LR	Decrease
2009			
55	02/23/09	MPR	Q4 2008
56	03/18/09	WG	
57	05/06/09	MPR	Q1 2009
58	08/05/09	MPR	Q2 2009
59	11/11/09	MPR	Q3 2009
2010			
60	01/12/10	RR	Increase
61	02/11/10	MPR	Q4 2009
62	02/12/10	RR	Increase
63	05/02/10	RR	Increase
64	05/10/10	MPR	Q1 2010
65	06/19/10	FX	Reform RMB FX Mechanism
66	08/05/10	MPR	Q2 2010
67	10/19/10	LR	Increase
68	11/02/10	MPR	Q3 2010
69	11/10/10	RR	Increase
70	11/19/10	RR	Increase
71	12/10/10	RR	Increase
72	12/24/10	LR	Increase
2011			
73	01/14/11	RR	Increase
74	01/30/11	MPR	Q4 2010
75	02/08/11	LR	Increase
76	02/18/11	RR	Increase
77	03/18/11	RR	Increase
78	04/05/11	LR	Increase
79	04/15/11	RR	Increase
80	05/03/11	MPR	Q1 2011
81	05/13/11	RR	Increase
82	06/14/11	RR	Increase
83	07/06/11	LR	Increase
84	08/12/11	MPR	Q2 2011
85	11/16/11	MPR	Q3 2011
86	11/30/11	RR	Decrease

Table 8 – continued from previous page

#	Date	Type	Notes
2012			
87	02/15/12	MPR	Q4 2011
88	02/16/12	RR	Differentiated RR changes for agricultural institutions
89	02/19/12	RR	Decrease
90	04/12/12	FX	Expand floating range of RMB to USD
91	05/10/12	MPR	Q1 2012
92	05/12/12	RR	Decrease
93	06/07/12	RR	Decrease
94	07/05/12	RR	Decrease
95	08/02/12	MPR	Q2 2012
96	11/02/12	MPR	Q3 2012
2013			
97	01/08/13	Other	Standing Lending Facility (SLF) Establishment
98	01/18/13	Other	Short-Term Liquidity Operations (SLO) Establishment
99	02/06/13	MPR	Q4 2012
100	05/09/13	MPR	Q1 2013
101	07/20/13	LR	Lending rate Liberalization
102	08/02/13	MPR	Q2 2013
103	10/25/13	Other	LBR Launched (loan base rate)
104	11/05/13	MPR	Q3 2013
2014			
105	01/17/14	Other	SLF operations Pilot
106	02/08/14	MPR	Q4 2013
107	02/14/14	WG	
108	03/15/14	FX	RMB/USD band expanded
109	04/22/14	RR	Decrease
110	05/06/14	MPR	Q1 2014
111	05/30/14	Other	Use Won currency swap to support trade financing
112	06/09/14	RR	Decrease
113	08/01/14	MPR	Q2 2014
114	08/27/14	WG, Other	
115	09/17/14	Other	Established Medium-Term Lending (MLF) facility
116	11/06/14	MPR, FX	Q3 2014 and FX facilitation for RMB Qualified Domestic Institutional Investor (RMB QDII)
117	11/21/14	LR	Decrease
2015			
118	02/05/15	RR	Decrease
119	02/06/15	Other	SLF promoted to nationwide
120	02/10/15	MPR	Q4 2014
121	03/01/15	LR	Decrease
122	04/20/15	RR	Decrease
123	05/08/15	MPR	Q1 2015
124	05/11/15	LR	Decrease
125	06/15/15	Other	Monetary Policy Committee (MPC) composition adjusted
126	06/28/15	RR, LR	RR Decrease; LR Decrease
127	08/07/15	MPR	Q2 2015
128	08/11/15	FX	CNY/USD Parity rate quote mechanism
129	08/26/15	LR	Decrease
130	09/06/15	RR	Decrease
131	09/15/15	Other	Deposit reserve system change

Table 8 – continued from previous page

#	Date	Type	Notes
132	09/30/15	FX	Foreign central banks allowed to participate in forex
133	10/24/15	LR	Decrease
134	11/07/15	MPR	Q3 2015
2016			
135	01/25/16	RR	Implemented normal reserve requirement for overseas banks
136	02/06/16	MPR	Q4 2015
137	02/18/16	OMO	Est. Open Market Operations (OMO) mechanism
138	02/24/16	Other	Open RFQII for interbank bond market access
139	02/25/16	RR	Dynamic adjustment for targeted decreases
140	03/01/16	RR	Decrease
141	05/06/16	MPR	Q1 2016 MPR
142	06/07/16	FX, Other	Opened RFQII to US and RMB Clearing w/ Fed
143	08/05/16	MPR	Q2 2016
144	10/01/16	FX	RMB inclusion into IMF SDR Basket
145	11/08/16	MPR	Q3 2016
2017			
146	01/13/17	Other	Temporary Liquidity Facility (TLF) injections
147	02/17/17	MPR	Q4 2016
148	02/27/17	RR	Dynamic adjustment
149	03/13/17	WG	
150	03/16/17	Other	MPC composition adjusted
151	05/12/17	MPR	Q1 2017 MPR
152	06/20/17	Other	Treasury bond market support operations; improvement of yield curve
153	07/03/17	WG, Other	Stock Connect Opened
154	08/11/17	MPR	Q2 2017 MPR
155	09/30/17	RR	Targeted decrease
156	11/17/17		Q3 2017 MPR
157	12/20/17	WG	
158	12/27/17	FX, Other	CFETS allowed to introduce overseas banks to participate in regional interbank forex
159	12/29/17	Other	Establishment of Contingency Reserve Arrangement (CRA)
2018			
160	01/11/18	Other	Natl Banks used CRA w/ 30 day term
161	01/19/18	WG	
162	01/25/18	RR	Targeted decrease for inclusive finance
163	02/14/18	MPR	Q4 2017
164	04/18/18	WG	
165	04/25/18	RR	Decrease
166	05/02/18	FX	RMB Cross border payment system active
167	05/11/18	MPR	Q1 2018
168	06/01/18	Other	MLF expansion
169	07/05/18	RR	Decrease
170	08/06/18	FX	Adjusted forex risk reserve ratio
171	08/10/18	MPR	Q2 2018
172	10/15/18	RR	Decrease
173	11/09/18	MPR	Q3 2018
174	12/21/18	Other	Add Term medium term lending facility (TMLF)
2019			
175	01/04/19	RR	Decrease

Table 8 – continued from previous page

#	Date	Type	Notes
176	01/23/19	Other	TMLF operation
177	01/24/19	Other	CBS (central bank bill swap) facility created
178	01/25/19	RR, Other	Conducted dynamic assessment of targeted RR
179	02/13/19	Other	Issuance of central bank bills in HK
180	02/20/19	OMO, Other	CBS operation implemented
181	02/21/19	MPR	Q4 2018
182	04/24/19	Other	TMLF operation
183	05/06/19	RR	Decrease
184	05/15/19	OMO	Cbill issuance
185	05/17/19	MPR	Q1 2019
186	06/14/19	WG, Other	
187	06/26/19	Other	Issue more Cbills
188	06/27/19	OMO, Other	CBS operation implemented
189	07/15/19	Other	MLF operation
190	07/23/19	Other	MLF Operation
191	07/24/19	WG	
192	08/09/19	MPR, Other	CBS operation and Q2 2019 report
193	08/14/19	Other	Cbill issuance
194	08/15/19	Other	MLF operation
195	08/20/19	LR	Announced LPR
196	08/26/19	Other	MLF operation
197	09/06/19	RR	Decrease
198	09/11/19	Other	CVS operation
199	09/17/19	Other	MLF Operation
200	09/20/19	LR	Announced LPR
201	09/26/19	Other	Cbill Issuance
202	10/17/19	Other	CBS operation
203	10/21/19	LR	Announced LPR
204	11/05/19	Other	MLF operation
205	11/07/19	Other	Cbill issuance
206	11/15/19	Other	MLF operation
207	11/16/19	MPR	Q3 2019
208	11/20/19	LR	LPR announce
209	11/27/19	Other	CBS operation
210	12/06/19	Other	MLF operation
211	12/16/19	Other	MLF operation
212	12/20/19	LR, Other	Cbill issuance; LPR announce
213	12/24/19	Other	CBS operation
214	12/30/19	Other	SLF interest rate decrease

Table 8. Full PBOC Announcement Set, 2006–2019

Notes: We report the sample of PBOC announcement dates used to construct the high-frequency shock spanning June 2006 through December 2019. The # column gives the chronological count of announcements in the full sample. RR is the reserve requirement, LR is the lending rate and encompasses changes to the benchmark lending rate and the loan prime rate, FX are changes to the foreign exchange system, including Forex market related actions, MPR is the PBOC Monetary Policy Report, OMO is open market operations, WG is window guidance, and Other represents other policy or regulatory changes. The 02/18/11 and 03/18/11 reserve-requirement announcements are retained for completeness but excluded from the factor estimation because of the pricing discrepancy discussed in the text.

A.2 Construction of High Frequency Measure of Chinese Monetary Policy

The monetary policy factors were created following Shieh (2024). We provide a semi-detailed summary of the factor rotation process here, leaving out the additional analysis done in Shieh (2024). For a more detailed discussion, please refer to the original paper.

Surprise Construction Algorithm

1. Take the difference between the closing price on the day of the announcement and the day prior to the announcement.
2. If the announcement was over the weekend, we take the difference in closing price between the following Monday and the preceding Friday.
3. If the announcement falls on a non-trading day (holidays, etc.), then we take the difference in closing price between the next available trading day and the preceding trading day prior to the non-trading day.

A.3 Cragg and Donald (1997) Matrix Rank Test, Factor Rotation, Interpretation, and Diagnostic Regressions

H_0: Number of Factors Equals	Wald Statistic	χ^2 Degrees of Freedom	P-Value	Number of Observations
0	44.62	10	0.00	212
1	19.87	5	0.00	212
2	0.15	1	0.69	212

Table 9: Results from a Cragg and Donald (1997) Matrix Rank Test.

Notes: The null hypothesis tests k_0 number of factors that can explain X against the alternative of $k > k_0$. At H_0 : Factors $= 2$, we fail to reject, suggesting that 2 factors are sufficient. Sample is from June 2006 to December 2019 on PBOC policy announcement dates. $X = (\Delta S_7^3, \Delta S_7^6, \Delta S_7^9, \Delta S_7^{12}, \Delta S_7^{24})$, where S_7 is the interest rate swap on the 7-Day Repo Rate and the superscript denotes the monthly tenor of the IRS. We use the 3m, 6m, 9m, 1Y, and 2Y tenors.

The results shown in Table 9 suggest that 2 factors can sufficiently explain the underlying variation in the movements of interest rate swaps on PBOC announcement dates since we fail to reject at $k = 2$. From here, we detail the case where we extract two factors using PCA and then rotate into a Target and a Path factor. If we were to extract a single factor and rotate, this singular factor would be in principle closer to the Nakamura and Steinsson (2018) policy news shock factor — which is somewhat of an average of the Target and Path factors. Because we want to disentangle the effect of a surprise monetary policy shock with changes to long-run expected monetary policy shocks, we extract both factors and rotate them so that they are

orthogonal to each other. Consider a 212×2 matrix: [26]

$$Z = FU \tag{A.1}$$

Where U:

$$U = \begin{bmatrix} \xi_1 & \eta_1 \\ \xi_2 & \eta_2 \end{bmatrix}$$

We impose the following identifying restrictions on U:

1. $Z_1 \perp Z_2$. That is, the new factors are orthogonal to each other, where

$$E[Z_1 Z_2] = \xi_1 \eta_1 + \xi_2 \eta_2 = 0 \tag{A.2}$$

2. The columns of U are normalized to unit variance.

3. Z_2 has no effect on the 3m IRS on the 7-Day Repo rate, which is our short term policy surprise.

4. Let λ_1 and λ_2 denote the estimated responses of the 3m IRS factor regression on F_1 and F_2. Then

$$F_1 = \frac{\eta_2 Z_1 - \xi_1 Z_2}{\xi_1 \eta_2 - \xi_2 \eta_1} \tag{A.3}$$

$$F_2 = \frac{\xi_1 Z_2 - \eta_1 Z_1}{\xi_1 \eta_2 - \xi_2 \eta_1} \tag{A.4}$$

   Which implies

$$\lambda_2 \xi_1 - \lambda_1 \xi_2 = 0 \tag{A.5}$$

Using these restrictions, it is trivial to solve for the matrix U. As described in the main text, the rotated factors are then rescaled such that a 0.01 change in Z_1 corresponds with a surprise of 1bp to the 3 month IRS (ΔS_7^3) while Z_2 is rescaled so that a 0.01 change is equivalent to a 1bp surprise to the 1 Year IRS (Δ_7^{12}). Z_1 and Z_2 are now the target and path factors, respectively. To verify the rotated factors were constructed correctly, we estimate the following regression of the interest rate swaps on factors:

$$\Delta S_{t,7}^j = \beta_0 + \beta_1 Z_{1,t} + \beta_2 Z_{2,t} + \epsilon_t \tag{A.6}$$

Where j is the IRS tenor and t is the announcement date. Again, the interest rate swap data brackets a PBOC announcement at time t. Following Gürkaynak et al. (2005), the standard errors are bootstrapped due to the factors being generated. Table 10 shows the variation explained by each principal component. The first two components explain 81.96 percent of the

[26] 212 PBOC announcements and 2 latent factors. As discussed in the main text, 45 additional announcements were added to the original Shieh (2024) set.

total variation, consistent with the two-factor specification suggested by the Cragg and Donald (1997) matrix rank test. Table 11 shows the diagnostic results of the Z_1 and Z_2 factors.

Component	Variance Explained	Cumulative Variance Explained
PC1	67.33	67.33
PC2	14.63	81.96
PC3	7.47	89.43
PC4	6.79	96.22
PC5	3.78	100.00

Table 10: Variance Explained by Principal Components.

Notes: This table reports the share of variation in X explained by each principal component and the cumulative share explained by the first j components. $X = (\Delta S_7^3, \Delta S_7^6, \Delta S_7^9, \Delta S_7^{12}, \Delta S_7^{24})$, where S_7 is the interest rate swap on the 7-Day Repo Rate and the superscript denotes the monthly tenor of the IRS. We use the 3m, 6m, 9m, 1Y, and 2Y tenors.

Interest Rate Swap	Target (Z_1)	Path (Z_2)	R^2
3m 7-Day IRS	1.000***	0.00	0.826
	(0.079)	(0.095)	
6m 7-Day IRS	1.060***	0.368***	0.749
	(0.154)	(0.126)	
9m 7-Day IRS	0.739***	0.729***	0.831
	(0.064)	(0.087)	
1Y 7-Day IRS	0.781***	1.000***	0.793
	(0.122)	(0.099)	
2Y 7-Day IRS	0.261***	1.435***	0.900
	(0.069)	(0.070)	

1000 bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Diagnostic regression results of factors on the various IRS products.

Notes: Estimated using the same sample period as in the main analysis. Standard errors are based on 1000 bootstrap replications. There were 212 PBOC announcements between June 2006 and December 2019. Coefficients represent the percentage point change in interest rates in response to a contractionary Target or Path shock (1pp surprise increase). Note we use 1pp shocks here for benchmarking reasons. Constants omitted for ease of exposition.

A.4 Event-Level Overlaps Used in the Purged-Shock Sample

Date	Overlap Source	Overlap Type	PBOC Type
2007-12-20	BOJ	Monetary policy	LR, Other
2008-04-16	State Council	Joint Monetary/Fiscal	RR
2008-11-26	State Council	Joint Monetary/Fiscal	RR
2009-03-18	BOJ	Monetary policy	WG
2009-05-06	State Council	Joint Monetary/Fiscal	MPR
2010-05-10	BOJ	Monetary policy	MPR
2010-10-19	State Council	Fiscal	LR
2010-11-10	State Council	Fiscal	RR
2011-06-14	BOJ	Monetary policy	RR
2011-07-06	State Council	Fiscal	LR
2011-11-16	State Council and BOJ	Fiscal; Monetary policy	MPR
2011-11-30	State Council	Fiscal	RR
2012-02-15	State Council	Joint Monetary/Fiscal	MPR
2013-02-06	State Council	Joint Monetary/Fiscal	MPR
2014-05-30	State Council	Joint Monetary/Fiscal	Other
2014-08-27	State Council	Fiscal	WG, Other
2014-09-17	State Council	Joint Monetary/Fiscal	Other
2015-02-06	State Council	Fiscal	Other
2015-08-07	BOJ	Monetary policy	MPR
2015-08-26	State Council	Fiscal	LR
2015-09-15	BOJ	Monetary policy	Other
2016-02-24	State Council	Fiscal	Other
2017-03-16	BOJ	Monetary policy	Other
2018-04-18	State Council	Fiscal	WG
2018-04-25	State Council	Joint Monetary/Fiscal	RR
2018-05-02	State Council	Fiscal	FX
2018-11-09	State Council	Joint Monetary/Fiscal	MPR
2019-01-23	BOJ	Monetary policy	Other
2019-02-20	State Council	Fiscal	OMO, Other
2019-05-06	State Council	Fiscal	RR
2019-05-15	State Council	Joint Monetary/Fiscal	OMO
2019-06-26	State Council	Joint Monetary/Fiscal	Other
2019-07-24	State Council	Joint Monetary/Fiscal	WG
2019-09-11	State Council	Fiscal	Other
2019-09-26	State Council	Joint Monetary/Fiscal	Other
2019-11-07	State Council	Joint Monetary/Fiscal	Other
2019-11-20	State Council	Fiscal	LR
2019-11-27	State Council	Joint Monetary/Fiscal	Other
2019-12-30	State Council	Fiscal	Other

Table 12: PBOC Announcement Dates with Simultaneous Non-PBOC Policy Announcements

Notes: The table lists PBOC announcement dates removed from the purged-shock robustness sample because they coincide with fiscal-policy State Council communiqués or BOJ monetary policy announcements. State Council classifications use communiqué dates and retain fiscal and joint monetary/fiscal announcements. BOJ announcements come from Kubota and Shintani (2022). The PBOC Type column uses the same announcement-type classification as the full PBOC announcement chronology in Appendix A.1. The 39 dates in this table correspond to the union of 31 State Council overlaps and 9 BOJ overlaps, with one date overlapping both sources.

A.5 Data Appendix

Countries and Equities Indices

Country	Index	Notes
Australia	ASX	
Canada	TSE	
China	SHSE	
Germany	DAX	DAX subindex is ICB supersector not GICS.
India	BSE	
Japan	TPX	
South Korea	KOSPI	
Taiwan	TWSE	
Thailand	SET	
United Kingdom	FTSE	
United States	S&P 500	

Table 13: Countries and Stock Exchanges

Notes: $N = 11$ economies in sample. Coverage includes China's largest trading partners. Industry level stock returns collected from industry-indices for each country on the above stock exchanges from Bloomberg Terminal. Returns are calculated as $\pi_{mi,t} = 12 \times 100 \times \Big(\log(x_{mi,t}) - \log(x_{mi,t-1}) \Big)$ where $x_{mi,t}$ is the closing index price of industry i in country m corresponding to the GICS sub-index in the respective country's main stock exchange index.

ISIC Industry Classification

Industry (I/O)	ADB Code	ISIC Code
Agriculture, hunting, forestry, and fishing	c1	A01 - A03
Mining and quarrying	c2	B
Food, beverages, and tobacco	c3	C10 - C12
Textiles and textile products	c4	C13, C14
Leather, leather products, and footwear	c5	C15
Wood and products of wood and cork	c6	C16
Pulp, paper, paper products, printing, and publishing	c7	C17,C18
Coke, refined petroleum, and nuclear fuel	c8	C19
Chemicals and chemical products	c9	C20
Rubber and plastics	c10	C22
Other nonmetallic minerals	c11	C23
Basic metals and fabricated metal	c12	C24, C25
Machinery, nec	c13	C28
Electrical and optical equipment	c14	C26
Transport equipment	c15	C29,C30
Manufacturing, nec; recycling	c16	E
Electricity, gas, and water supply	c17	D35,E36
Construction	c18	F41 - F43
Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel	c19	G45
Wholesale trade and commission trade, except of motor vehicles and motorcycles	c20	G46
Retail trade, except of motor vehicles and motorcycles; repair of household goods	c21	G47
Hotels and restaurants	c22	I55, I56
Inland transport	c23	H49
Water transport	c24	H50
Air transport	c25	H51
Other supporting and auxiliary transport activities; activities of travel agencies	c26	H52
Post and telecommunications	c27	J61, H53
Financial intermediation	c28	K64-K66
Real estate activities	c29	L68
Renting of M&Eq and other business activities	c30	N
Public administration and defense; compulsory social security	c31	O
Education	c32	P
Health and social work	c33	Q
Other community, social, and personal services	c34	S
Private households with employed persons	c35	T

Table 14: ADB MRIO Industries

Notes: ISIC rev. 4 industry classification with the ADB MRIOT code, as well as the ISIC Codes range. Source: ADB MRIOT Tables. These 35 industries are collapsed into the 7 GICS sectors used in the empirical W following the concordance in Table 16.

GICS Sectors

GICS Sector	Sector Code	Notes
Energy	10	Dropped
Materials	15	
Industrials	20	
Consumer Discretionary	25	
Consumer Staples	30	
Healthcare	35	
Financials	40	
Information Tech	45	Combined w/ 50
Communication Services	50	Combined w/ 45
Utilities	55	Dropped
Real Estate	60	Dropped

Table 15: GICS Sectors

Notes: The table reports the specific GICS sectors used in this paper. Information Tech and Comm Services combined, while Energy, Utilities, and Real Estate dropped from sample. Source: MSCI/S&P Global Industry Classification Standard (GICS).

GICS and I/O Table Concordance

Materials	Industrials	ConsDisc	ConsStap	Health	Financials	IT/Comm
C2	C13	C4	C1	C33	C28	C27
C6	C14	C5	C3			
C7	C15	C19				
C9	C16	C20				
C10	C18	C21				
C11	C23	C22				
C12	C24					
	C25					
	C26					
	C30					

Table 16: Collapsed Industry Matches Used for Empirical W

Notes: Final concordance between ADB Industry categories (based on ISIC rev. 4) and GICS (reduced from 35 to 7 sectors). Dimensionally, since there are 11 countries and 7 industries, the full sample used in this paper is a 77×77 matrix of $NJ \times NJ$ country-industry cells.

A.6 Returns

Distribution of Returns

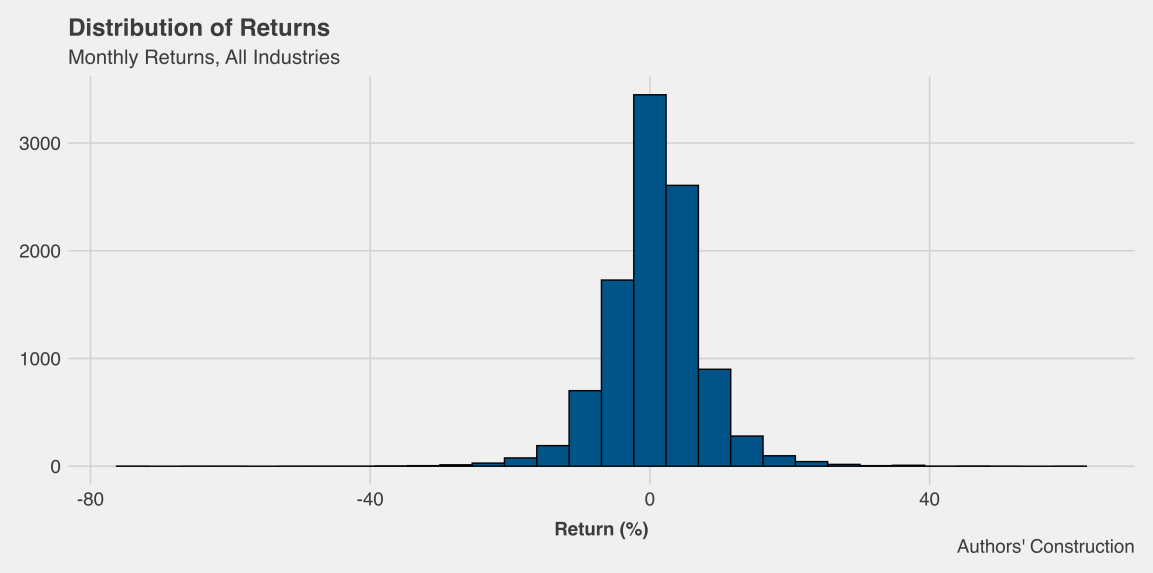


Figure 18: Distribution of Returns

Notes: Distribution of monthly returns from Jan 2009 to Dec 2019 encompassing all 7 GICS industries across 11 countries. Calculated as $\pi_{mi,t} = 100 \times \Big(\log(x_{mi,t}) - \log(x_{mi,t-1})\Big)$ where $x_{mi,t}$ is the closing index price of industry i in country m corresponding to the GICS sub-index in the respective country's main stock exchange index.

Distribution of Winsorized Returns

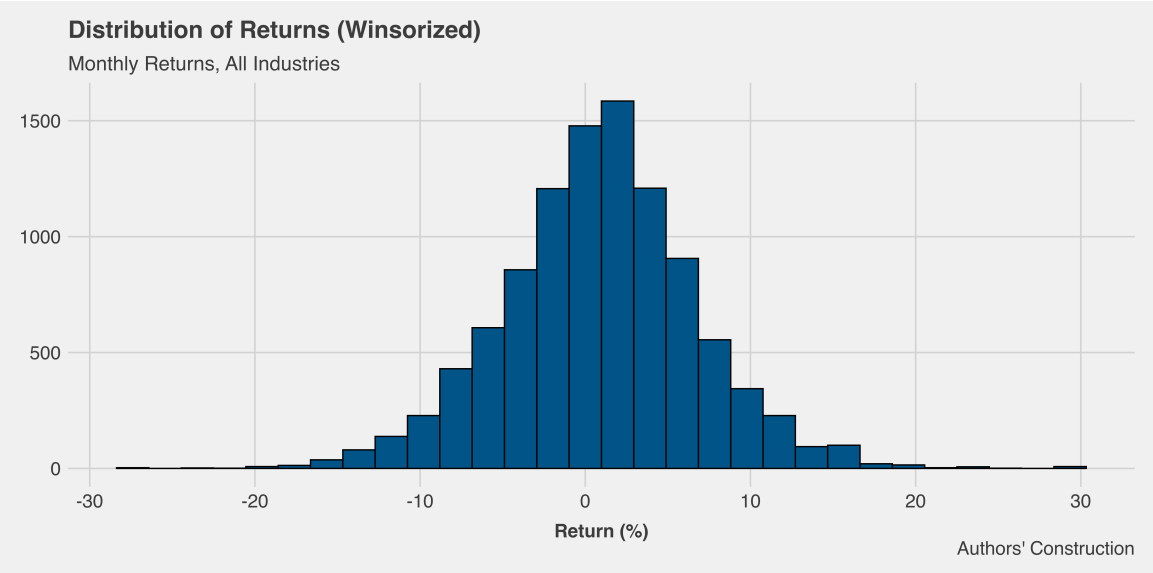


Figure 19: Distribution of Winsorized Returns

Notes: Distribution of Returns from Jan 2009 to Dec 2019 encompassing all 7 GICS industries. Calculated as $\pi_{mi,t} = 100 \times \Big(\log(x_{mi,t}) - \log(x_{mi,t-1})\Big)$ where $x_{mi,t}$ is the closing index price of industry i in country m corresponding to the GICS sub-index in the respective country's main stock exchange index. Returns are then winsorized at the 1% level.

A.7 Country-Industry Heterogeneous SAR: Downstream Persistence Heat Map

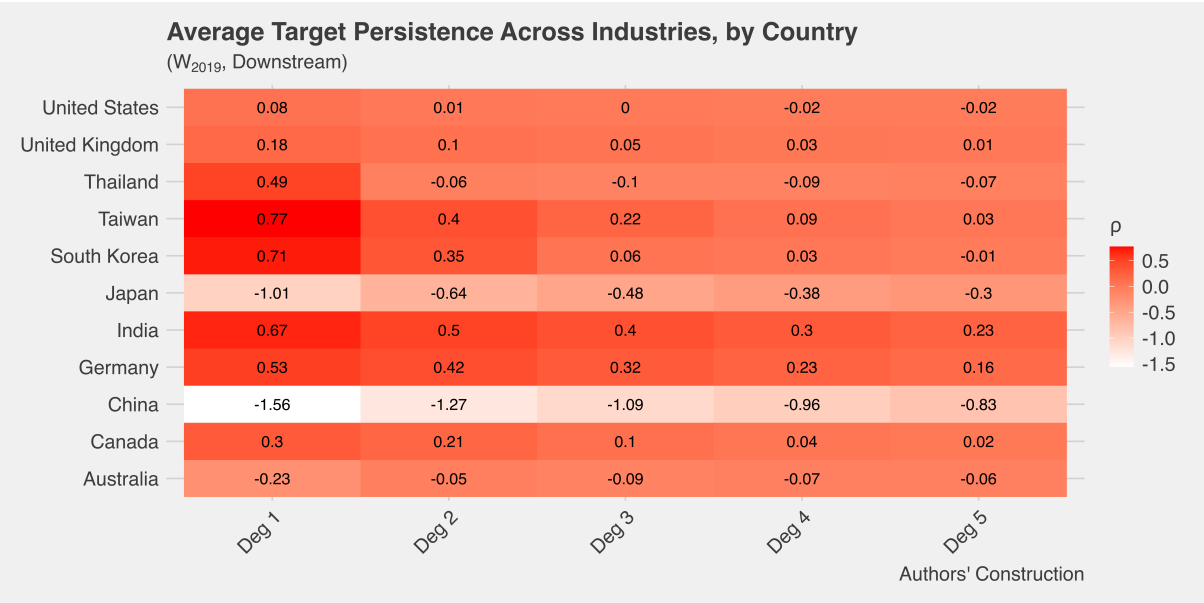


Figure 20: Heat Map of Higher Order Effects (Target Shock)

Notes: Higher order effects heat map up to degree 5 ($K \in [1,5]$) using W^{2019} weighting matrix following the decomposition shown in Equation 9. Results calculated using the $\boldsymbol{\rho}$ and β^{Target} estimates from Column (2) of Table 6.

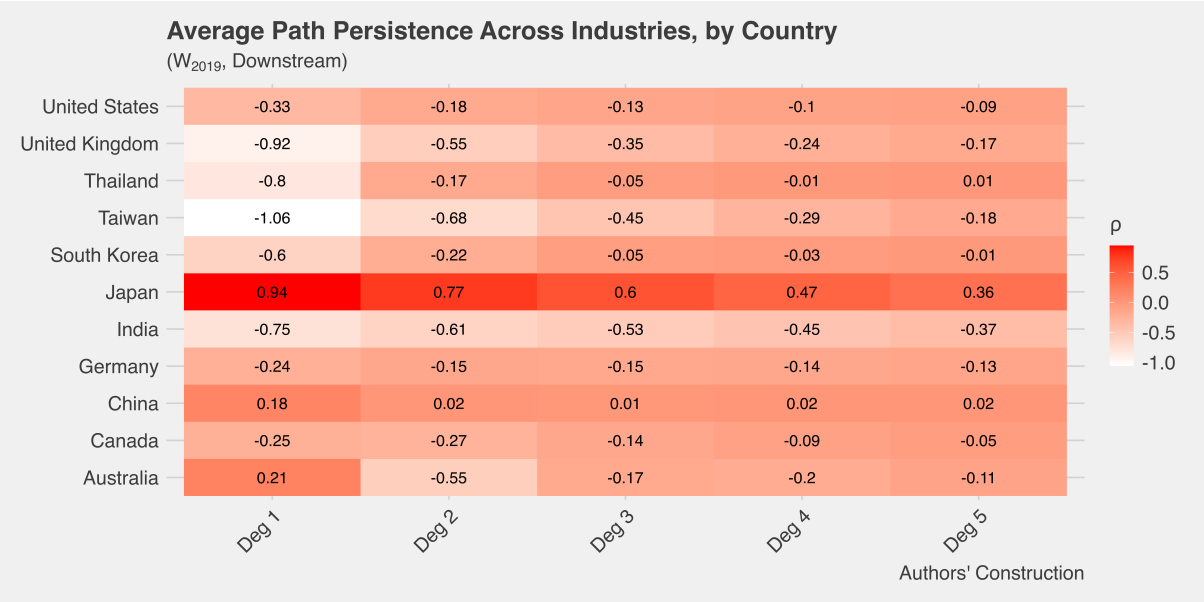


Figure 21: Heat Map of Higher Order Effects (Path Shock)

Notes: Higher order effects heat map up to degree 5 ($K \in [1,5]$) using W^{2019} weighting matrix following the decomposition shown in Equation 9. Results calculated using the $\boldsymbol{\rho}$ and β^{Path} estimates from Column (2) of Table 6.

A.8 Monthly VIX Local Projection

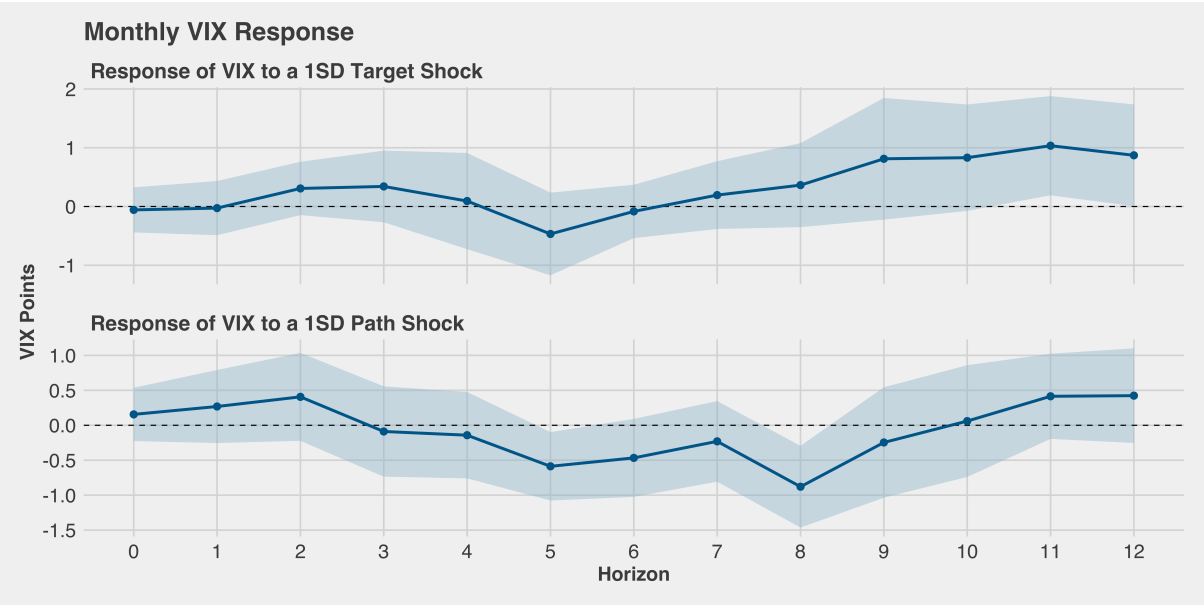


Figure 22: Monthly VIX IRFs in Response to a Target or Path Shock

Notes: Local projection estimated for sample period 2009M1 to 2019M12 on 6 lags (6 months) and presented with 90% HAC Standard Errors. Point estimates represent the change in VIX Points in response to a 1SD increase in either Target or Path.

A.9 German Manufacturing PPI Local Projection

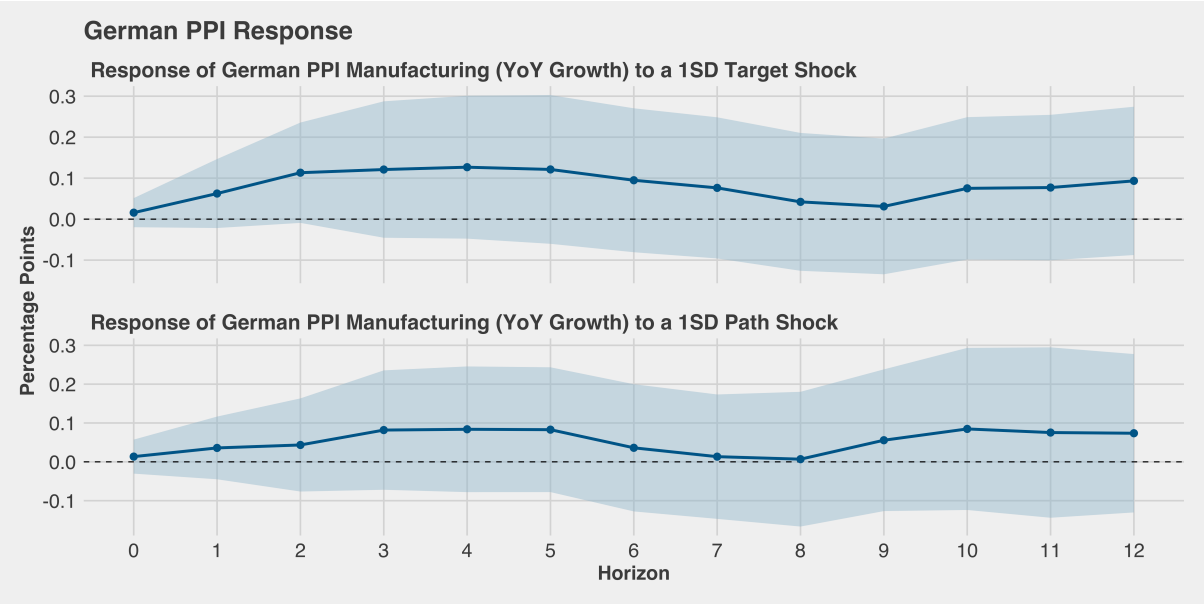


Figure 23: Monthly German PPI (Manufacturing) in Response to a Target or Path Shock

Notes: Local projection estimated for sample period 2009M1 to 2019M12 on 3 lags (3 months) and presented with 90% HAC Standard Errors. Point estimates represent the percentage-point change in the YoY growth rate of manufacturing PPI in response to a 1SD increase in either Target or Path.

A.10 Robustness: Heterogeneous SAR Results Using Purged PBOC Shocks

Stock Returns (Upstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
Average ρ	0.666***	0.671***	0.670***
	(0.090)	(0.087)	(0.083)
Direct Target Effect	-0.816**	-0.655*	-0.728**
	(0.369)	(0.384)	(0.365)
Indirect Target Effect	-1.682***	-1.841***	-1.768***
	(0.293)	(0.288)	(0.285)
Network Magnitude Share (%)	67.35***	73.76***	70.83***
	(10.4)	(11.0)	(10.4)
Direct Path Effect	-0.893**	-0.932**	-0.927**
	(0.426)	(0.437)	(0.426)
Indirect Path Effect	-1.079***	-1.040***	-1.045***
	(0.283)	(0.331)	(0.275)
Network Magnitude Share (%)	54.73***	52.72***	52.99***
	(14.4)	(15.1)	(13.9)
Fixed Effects	*mi*	*mi*	*mi*
Observations	10,164	10,164	10,164

Wild Bootstrapped Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Heterogeneous SAR Regression Results (Upstream w/ Purged PBOC Shocks)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming upstream propagation. Target and Path factors were estimated after purging PBOC policy announcements w/ same day overlaps with Bank of Japan monetary policy announcements, as well as same day policy communiqués by the Chinese State Council. There were 173 PBOC announcements post-purge to estimate Target and Path from. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constant and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|Indirect|/(|Direct| + |Indirect|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Stock Returns (Downstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
Average ρ	0.647***	0.650***	0.648***
	(0.088)	(0.092)	(0.095)
Direct Target Effect	-0.552	-0.611	-0.548
	(0.423)	(0.423)	(0.417)
Indirect Target Effect	-1.942***	-1.882***	-1.948***
	(0.261)	(0.250)	(0.289)
Network Magnitude Share (%)	77.87***	75.48***	78.03***
	(11.1)	(11.0)	(11.1)
Direct Path Effect	-1.098**	-1.004*	-1.068**
	(0.480)	(0.514)	(0.483)
Indirect Path Effect	-0.873***	-0.967***	-0.904***
	(0.308)	(0.358)	(0.347)
Network Magnitude Share (%)	44.30***	49.07***	45.82***
	(16.5)	(18.7)	(17.5)
Fixed Effects	*mi*	*mi*	*mi*
Observations	10,164	10,164	10,164

Wild Bootstrapped Standard Errors in Parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 18: Heterogeneous SAR Regression Results (Downstream w/ Purged PBOC Shocks)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming downstream propagation. Target and Path factors were estimated after purging PBOC policy announcement overlaps with the Bank of Japan monetary policy announcements, as well as simultaneous policy communiqués by the Chinese State Council. There were 173 PBOC announcements post-purge to estimate Target and Path from. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients across 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constant and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|Indirect|/(|Direct| + |Indirect|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

A.11 Robustness: Heterogeneous SAR Results (Stability Sample)

Stock Returns (Upstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2015}	$W^{Avg}_{2009-2015}$
Average ρ	0.671***	0.671***	0.672***
	(0.070)	(0.065)	(0.069)
Direct Target Effect	-0.310	-0.205	-0.245
	(0.532)	(0.536)	(0.536)
Indirect Target Effect	-0.849**	-0.954***	-0.912***
	(0.369)	(0.346)	(0.343)
Network Magnitude Share (%)	73.24***	82.29***	78.81***
	(17.6)	(15.8)	(15.9)
Direct Path Effect	-0.872	-0.927*	-0.893
	(0.549)	(0.544)	(0.558)
Indirect Path Effect	-1.410***	-1.356***	-1.391***
	(0.352)	(0.335)	(0.342)
Network Magnitude Share (%)	61.79***	59.39***	60.90***
	(16.4)	(16.0)	(16.4)
Fixed Effects	*mi*	*mi*	*mi*
Observations	6,468	6,468	6,468

Wild Bootstrapped Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Heterogeneous SAR Regression Results (Upstream, 2009–2015 Sample)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2015M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming upstream propagation. Three different empirical W are chosen — 2009, 2015, and an average of input/output coefficients between 2009 and 2015. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constant and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|Indirect|/(|Direct| + |Indirect|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Stock Returns (Downstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2015}	$W^{Avg}_{2009-2015}$
Average ρ	0.651***	0.653***	0.654***
	(0.085)	(0.087)	(0.084)
Direct Target Effect	-0.040	-0.007	-0.030
	(0.564)	(0.566)	(0.556)
Indirect Target Effect	-1.110***	-1.151***	-1.129***
	(0.391)	(0.395)	(0.394)
Network Magnitude Share (%)	96.52***	99.37***	97.44***
	(15.8)	(14.8)	(15.1)
Direct Path Effect	-0.967	-0.950	-0.939
	(0.614)	(0.626)	(0.606)
Indirect Path Effect	-1.325***	-1.333***	-1.344***
	(0.435)	(0.429)	(0.442)
Network Magnitude Share (%)	57.82***	58.41***	58.88***
	(19.0)	(19.1)	(18.7)
Fixed Effects	*mi*	*mi*	*mi*
Observations	6,468	6,468	6,468

Wild Bootstrapped Standard Errors in Parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 20: Heterogeneous SAR Regression Results (Downstream, 2009–2015 Sample)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2015M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming downstream propagation. Three different empirical W are chosen — 2009, 2015, and an average of input/output coefficients between 2009 and 2015. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constant and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|Indirect|/(|Direct| + |Indirect|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Appendix B (Online Supplement, Not For Publication)

B.1 Chinese Keyword Mapping for Monetary vs Fiscal vs Joint Policy State Council Announcements

Chinese Keywords for Monetary Policy

English keywords	Chinese keywords
Monetary policy	货币政策；稳健的货币政策；稳健货币政策
Money supply	货币供应量；货币供给；M2；广义货币
Credit supply	信贷供给；信贷投放；新增贷款；贷款投放；信贷支持；信贷结构；优化信贷结构
Lending / loans	贷款；放贷；贷款支持；信贷；融资支持；信贷直达
Reserve requirement ratio / RRR	存款准备金率；准备金率；降准；提高准备金率；差别化存款准备金率；定向降准
Interest rates	利率；贷款利率；存款利率；存贷款基准利率；降息；加息；利率水平
Policy rates	政策利率；公开市场操作利率；中期借贷便利利率
Loan prime rate / LPR	贷款市场报价利率；LPR
Re-lending	再贷款；支农再贷款；支小再贷款；专项再贷款
Re-discount	再贴现
Pledged supplemental lending / PSL	抵押补充贷款；PSL
Social financing / TSF	社会融资规模；社融；新增社会融资规模
Liquidity	流动性；流动性合理充裕
Open market operations	公开市场操作；逆回购；正回购
MLF / SLF	中期借贷便利；MLF；常备借贷便利；SLF
Interest rate corridor	利率走廊
Bond market financing	债券融资；信用债融资
Structural monetary policy	结构性货币政策工具；结构性货币政策
Carbon emission reduction facility	碳减排支持工具
Window guidance	窗口指导
Financing costs	融资成本；降低融资成本；综合融资成本；实体经济融资成本
Inclusive finance / SME lending	普惠金融；普惠小微贷款；小微企业贷款；中小微企业贷款；小微企业融资；数字普惠金融
Government-backed financing guarantee	政府性融资担保；政府性融资担保机构；融资担保费率；担保费率
Policy banks	政策性银行；政策性金融；国家开发银行；农业发展银行；进出口银行
Macroprudential policy	宏观审慎；宏观审慎管理；宏观审慎评估；MPA
Inflation / prices	通货膨胀；物价；物价总水平；CPI；PPI；居民消费价格；工业品出厂价格；价格稳定；价格总水平
Exchange rate	汇率；人民币汇率；人民币汇率基本稳定；外汇市场；人民币国际化；跨境人民币业务
Green finance	绿色金融；绿色信贷
Cross-cyclical / counter-cyclical	跨周期调节；逆周期调节
Macro-leverage ratio	宏观杠杆率
Monetary policy flexibility	松紧适度；灵活适度

Table 21: English to Chinese Monetary Policy Keyword Mapping.

Notes: State Council Communiqués are categorized as *Monetary* if they contain at least one keyword in Table 21 and no keywords in either Table 22 or Table 23. Source: State Council post-meeting communiqués released by Xinhua and The People's Daily, collected from their archives through the Internet Archive.

Chinese Keywords for Fiscal Policy

English keywords	Chinese keywords
Fiscal policy	财政；财政政策；积极的财政政策
Deficit-to-GDP / fiscal deficit	赤字率；财政赤字；预算赤字；基本赤字
Budget	一般公共预算；政府预算；预算安排；预算执行；国有资本经营预算
Fiscal spending / funds	财政支出；财政资金；财政补助；中央财政；地方财政；专项资金；基础设施投资；基建投资
Transfers	转移支付；一般性转移支付；专项转移支付
Fiscal sustainability	财政可持续性；财政空间
Government bonds	政府债券；国债；特别国债；超长期特别国债
Local government bonds	地方政府债券；地方政府债务；政府债务
Local government special bonds	地方政府专项债券；专项债券；专项债；新增专项债
Bond quotas / debt limits	专项债额度；新增专项债额度；债券额度；发债额度；债务限额
Local government debt restructuring	债务置换；存量债务置换；隐性债务；化债；化解债务风险；地方政府隐性债务
Land revenue	土地出让收入；国有土地使用权出让收入
Subsidies	补贴；财政补贴；财政补助；财政贴息
Tax exemptions / tax relief	减税；降费；减税降费；税费减免；税收减免；税收优惠；免税
Tax rebates	退税；留抵退税；出口退税
Value-added tax	增值税；增值税改革
Consumption tax	消费税
Property tax	房地产税
Income taxes	所得税；企业所得税；个人所得税
Social benefits / social protection	社会保障；社会保险；社保；社会福利；社会保护；民生保障；民生支出
Social assistance	社会救助；救助补助；困难群众；低保；最低生活保障
Pension / health / unemployment insurance	基本养老保险；养老保险；医疗保险；医保；失业保险；工伤保险；生育保险
Employment subsidies	就业补助；稳岗补贴
Fee cuts	收费；涉企收费；行政事业性收费；降低收费；取消收费；减免收费；降低费率；阶段性降低费率
Government funds	政府性基金；政府性基金预算
Fiscal risk	财政风险；或有负债
Government deposits	财政存款；国库存款
Fiscal federalism	事权与支出责任

Table 22: English to Chinese Fiscal Policy Keyword Mapping.

Notes: State Council Communiqués are categorized as *Fiscal* if they contain at least one keyword in Table 22 and no keywords in either Table 21 or Table 23. Source: State Council post-meeting communiqués released by Xinhua and The People's Daily, collected from their archives through the Internet Archive.

Chinese Keywords for Joint Monetary–Fiscal Policy

English keywords	Chinese keywords
Stabilize growth	稳增长
Economic stimulus	刺激经济
Policy coordination	政策协调；政策协调配合；财政货币政策联动
Special construction fund	专项建设基金

Table 23: English to Chinese Joint Monetary–Fiscal Policy Keyword Mapping.

Notes: State Council Communiqués are categorized as *Joint* if they contain at least one keyword in Table 23, or if they contain keywords from both Table 21 and Table 22. Source: State Council post-meeting communiqués released by Xinhua and The People's Daily, collected from their archives through the Internet Archive.

Source	Communiqué Type	Count
Politburo	General Policy	144
Politburo	Political Event	19
Politburo	Economic Related	40
Politburo	Economic Specific	53
Politburo	Total	256
State Council	Other/Neither	100
State Council	Monetary	21
State Council	Fiscal	265
State Council	Joint Monetary/Fiscal	291
State Council	Total	677

Table 24: Classification Counts for Politburo and State Council Communiqués

Notes: The table reports announcement classification counts by source and communiqué type. State Council counts are computed after deduplicating by communiqué date. Politburo classifications follow the political/economic-topic coding, while State Council classifications follow the monetary, fiscal, and joint monetary/fiscal keyword coding. The keyword mapping above details the State Council classification procedure.

B.2 Cragg and Donald (1997) Matrix Rank Test, PCA Variance, and Diagnostic Regression on Purged Announcement Set

H_0: Number of Factors Equals	Wald Statistic	χ^2 Degrees of Freedom	P-Value	Number of Observations
0	41.50	10	0.000	173
1	15.05	5	0.010	173
2	0.23	1	0.633	173

Table 25: Results from a Cragg and Donald (1997) Matrix Rank Test Using the Purged Announcement Set.

Notes: The null hypothesis tests k_0 number of factors that can explain X against the alternative of $k > k_0$. At H_0 : Factors $= 2$, we fail to reject, suggesting that 2 factors are sufficient for the purged announcement set. The purged sample excludes PBOC announcement dates that overlap with BOJ monetary policy announcements or State Council communiqués classified as fiscal or joint monetary/fiscal. $X = (\Delta S_7^3, \Delta S_7^6, \Delta S_7^9, \Delta S_7^{12}, \Delta S_7^{24})$, where S_7 is the interest rate swap on the 7-Day Repo Rate and the superscript denotes the monthly tenor of the IRS. We use the 3m, 6m, 9m, 1Y, and 2Y tenors.

Component	Variance Explained	Cumulative Variance Explained
PC1	67.63	67.63
PC2	14.22	81.85
PC3	7.72	89.57
PC4	6.35	95.92
PC5	4.08	100.00

Table 26: Variance Explained by Principal Components Using the Purged Announcement Set.

Notes: This table reports the share of variation in X explained by each principal component and the cumulative share explained by the first j components in the purged announcement set. $X = (\Delta S_7^3, \Delta S_7^6, \Delta S_7^9, \Delta S_7^{12}, \Delta S_7^{24})$, where S_7 is the interest rate swap on the 7-Day Repo Rate and the superscript denotes the monthly tenor of the IRS. We use the 3m, 6m, 9m, 1Y, and 2Y tenors.

Interest Rate Swap	Target (Z_1)	Path (Z_2)	R^2
3m 7-Day IRS	1.000***	0.000	0.843
	(0.087)	(0.083)	
6m 7-Day IRS	1.054***	0.315**	0.742
	(0.169)	(0.136)	
9m 7-Day IRS	0.676***	0.674***	0.822
	(0.066)	(0.078)	
1Y 7-Day IRS	0.711***	1.000***	0.806
	(0.120)	(0.064)	
2Y 7-Day IRS	0.288***	1.173***	0.880
	(0.075)	(0.045)	

1000 bootstrapped standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 27: Diagnostic regression results of purged-sample factors on the various IRS products.

Notes: Estimated using the purged announcement set. Standard errors are based on 1000 bootstrap replications. There were 173 PBOC announcements in the diagnostic regression sample after purging overlapping BOJ monetary policy announcements and State Council communiqués classified as fiscal or joint monetary/fiscal. Coefficients represent the percentage point change in interest rates in response to a contractionary Target or Path shock (1pp surprise increase). We note that we use a 1pp shock for benchmarking reasons. Constants omitted for ease of exposition.

B.3 Country-Level Heterogeneous SAR Results

Stock Returns (Upstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
Average ρ	0.879***	0.846***	0.868***
	(0.007)	(0.010)	(0.008)
Direct Target Effect	0.100	0.304***	0.214**
	(0.094)	(0.110)	(0.092)
Indirect Target Effect	-1.058***	-1.244***	-1.109***
	(0.226)	(0.270)	(0.239)
Network Magnitude Share (%)	91.37***	80.34***	83.84***
	(6.5)	(7.3)	(6.7)
Direct Path Effect	-0.384***	-0.539***	-0.448***
	(0.057)	(0.086)	(0.064)
Indirect Path Effect	-1.824***	-1.671***	-1.792***
	(0.186)	(0.229)	(0.199)
Network Magnitude Share (%)	82.61***	75.60***	80.00***
	(1.8)	(3.1)	(2.2)
Fixed Effects	m	m	m
Observations	1,452	1,452	1,452

Wild Bootstrapped Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 28: Heterogeneous SAR Regression Results (Upstream, Country Level)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m), assuming upstream propagation at the country level. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across countries, measured as the percentage point change in annualized stock returns, in response to a one-standard-deviation surprise increase. Constant and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|Indirect|/(|Direct| + |Indirect|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Stock Returns (Downstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
Average ρ	0.892***	0.881***	0.887***
	(0.007)	(0.008)	(0.007)
Direct Target Effect	0.030	0.024	0.056
	(0.101)	(0.111)	(0.100)
Indirect Target Effect	-1.008***	-0.976***	-1.026***
	(0.198)	(0.218)	(0.212)
Network Magnitude Share (%)	97.14***	97.57***	94.83***
	(5.9)	(7.1)	(5.9)
Direct Path Effect	-0.354***	-0.378***	-0.372***
	(0.061)	(0.064)	(0.058)
Indirect Path Effect	-1.821***	-1.821***	-1.806***
	(0.160)	(0.185)	(0.172)
Network Magnitude Share (%)	83.73***	82.83***	82.92***
	(1.8)	(1.9)	(1.7)
Fixed Effects	m	m	m
Observations	1,452	1,452	1,452

Wild Bootstrapped Standard Errors in Parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 29: Heterogeneous SAR Regression Results (Downstream, Country Level)

Notes: Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m), assuming downstream propagation at the country level. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across countries, measured as the percentage point change in annualized stock returns, in response to a one-standard-deviation surprise increase. Constant and controls omitted for ease of exposition. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|Indirect|/(|Direct| + |Indirect|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

B.4 Additional Heterogeneous SAR Upstream Results

Alternative Decomposition of Total Effect (Upstream)

Stock Returns (Upstream)	**(1)**	**(2)**	**(3)**
LeSage and Pace (2009) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
ρ	0.666***	0.672***	0.670***
	(0.085)	(0.086)	(0.084)
Direct Target Effect	-0.373	-0.203	-0.328
	(0.388)	(0.388)	(0.390)
Indirect Target Effect	-0.577**	-0.749***	-0.621**
	(0.271)	(0.262)	(0.265)
Network Magnitude Share (%)	60.73***	78.70***	65.40***
	(18.2)	(14.9)	(17.3)
Direct Path Effect	-1.105***	-1.134***	-1.105***
	(0.423)	(0.419)	(0.420)
Indirect Path Effect	-1.091***	-1.060***	-1.089***
	(0.282)	(0.289)	(0.277)
Network Magnitude Share (%)	49.67***	48.32***	49.65***
	(12.9)	(12.4)	(12.5)
Fixed Effects	*mi*	*mi*	*mi*
Observations	10,164	10,164	10,164

Wild Bootstrapped Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 30: Heterogeneous SAR Regression Results (Upstream, Alternative Decomposition)

Notes: Upstream heterogeneous SAR results using alternative decomposition following the method discussed in LeSage and Pace (2009) after estimating Equation 5. Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming upstream propagation. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constant and controls omitted for ease of exposition. The results here are qualitatively similar to the Acemoglu et al. (2016) decomposition, with the only difference being in how the direct effect is calculated since it allows for a round-tripping effect. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|\text{Indirect}|/(|\text{Direct}| + |\text{Indirect}|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Upstream Indirect and Direct Effect Distributions

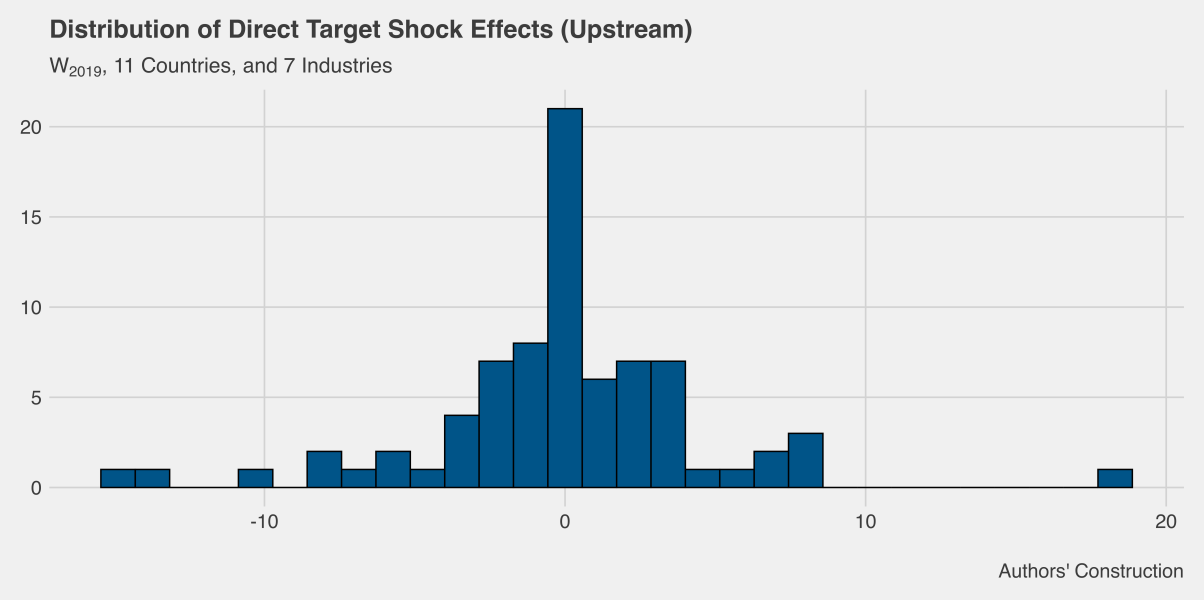


Figure 24: Distribution of Direct Target Shock Effect Estimates

Notes: Distribution of Direct Target effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 5, estimated using Equation 5.

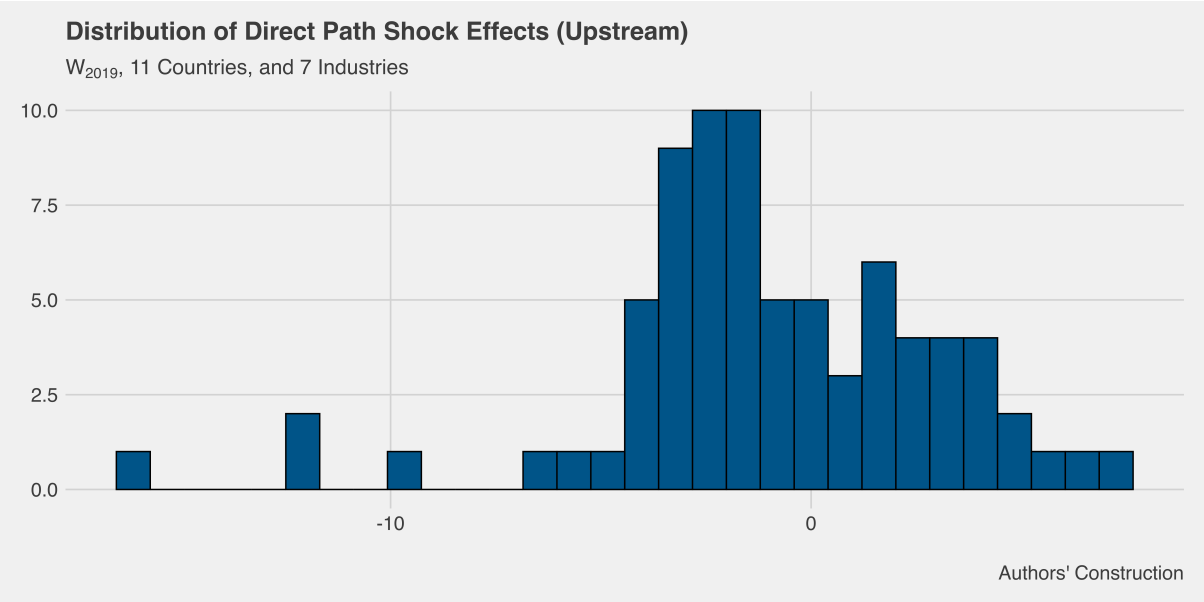


Figure 25: Distribution of Direct Path Shock Effect Estimates

Notes: Distribution of Direct Path effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 5, estimated using Equation 5.

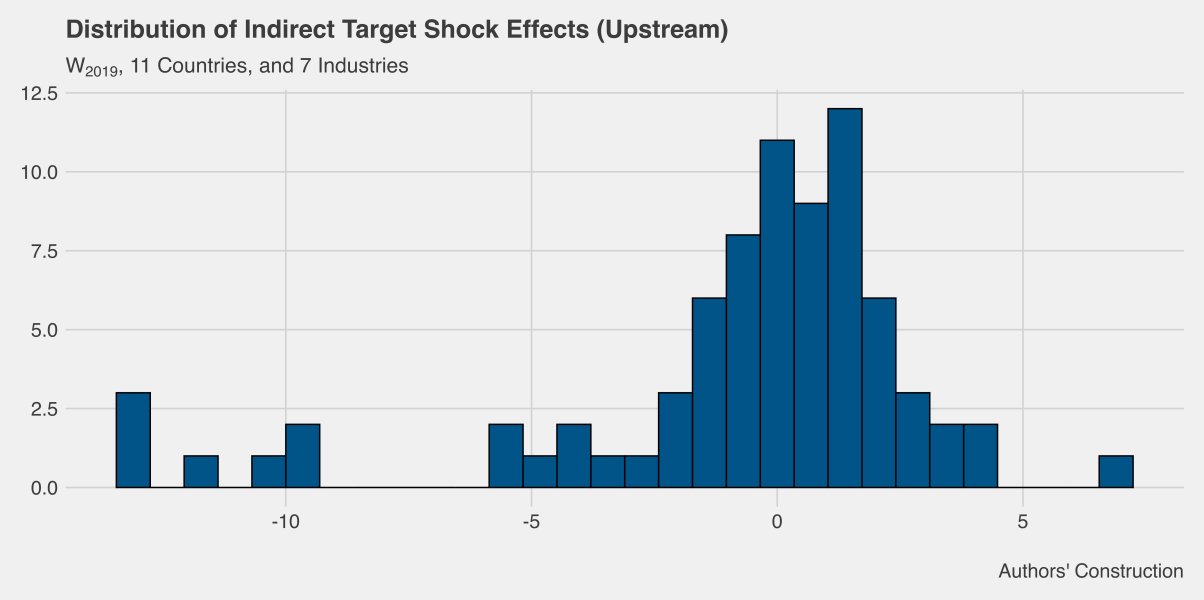


Figure 26: Distribution of Indirect Target Shock Effect Estimates

Notes: Distribution of Indirect Target effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 5, estimated using Equation 5.

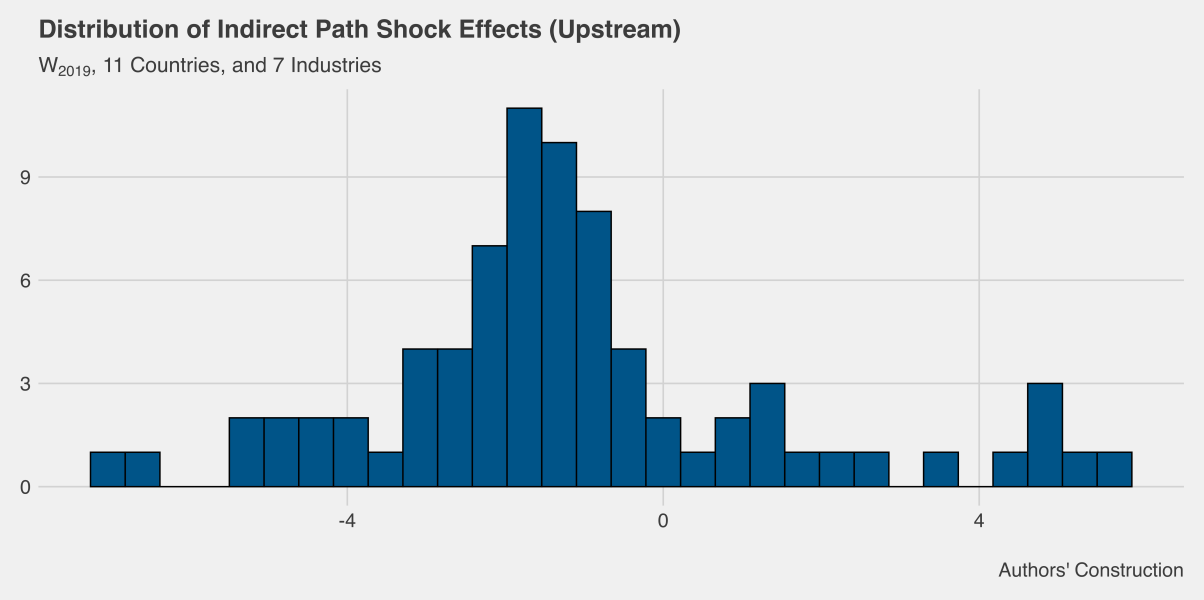


Figure 27: Distribution of Indirect Path Shock Effect Estimates

Notes: Distribution of Indirect Path effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 5, estimated using Equation 5.

B.5 Additional Heterogeneous SAR Downstream Results

Alternative Decomposition of Total Effect (Downstream)

Stock Returns (Downstream)	**(1)**	**(2)**	**(3)**
LeSage and Pace (2009) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
ρ	0.647***	0.651***	0.649***
	(0.082)	(0.093)	(0.094)
Direct Target Effect	-0.345	-0.392	-0.340
	(0.396)	(0.395)	(0.396)
Indirect Target Effect	-0.606**	-0.559**	-0.613**
	(0.251)	(0.273)	(0.271)
Network Magnitude Share (%)	63.76***	58.77***	64.31***
	(16.2)	(16.4)	(16.8)
Direct Path Effect	-1.184***	-1.069**	-1.135***
	(0.414)	(0.430)	(0.429)
Indirect Path Effect	-1.011***	-1.127***	-1.058***
	(0.276)	(0.302)	(0.291)
Network Magnitude Share (%)	46.07***	51.32***	48.24***
	(12.1)	(13.0)	(12.5)
Fixed Effects	*mi*	*mi*	*mi*
Observations	10,164	10,164	10,164

Wild Bootstrapped Standard Errors in Parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 31: Heterogeneous SAR Regression Results (Downstream, Alternative Decomposition)

Notes: Downstream heterogeneous SAR results using alternative decomposition following the method discussed in LeSage and Pace (2009) after estimating Equation 5. Heterogeneous SAR estimation for sample period 2009M1 to 2019M12 for 11 economies (m) and 7 industries (i) (77 country-industry specific returns), assuming downstream propagation. Three different empirical W are chosen — 2009, 2019, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target and Path factors represent the average equity response across country-industry pairs, measured as the percentage point change in annualized stock returns, in response to a 1SD surprise increase. Constant and controls omitted for ease of exposition. The results here are qualitatively similar to the Acemoglu et al. (2016) decomposition, with the only difference being in how the direct effect is calculated since it allows for a round-tripping effect. Standard Errors wild bootstrapped 1000 times at the observation level using the continuous multipliers of Mammen (1993). Network magnitude shares are calculated as $|\text{Indirect}|/(|\text{Direct}| + |\text{Indirect}|) \times 100$ using the absolute values of both effects. When the direct and indirect effects have opposite signs, this is a magnitude-based comparison rather than an additive decomposition.

Downstream Indirect and Direct Effect Distributions

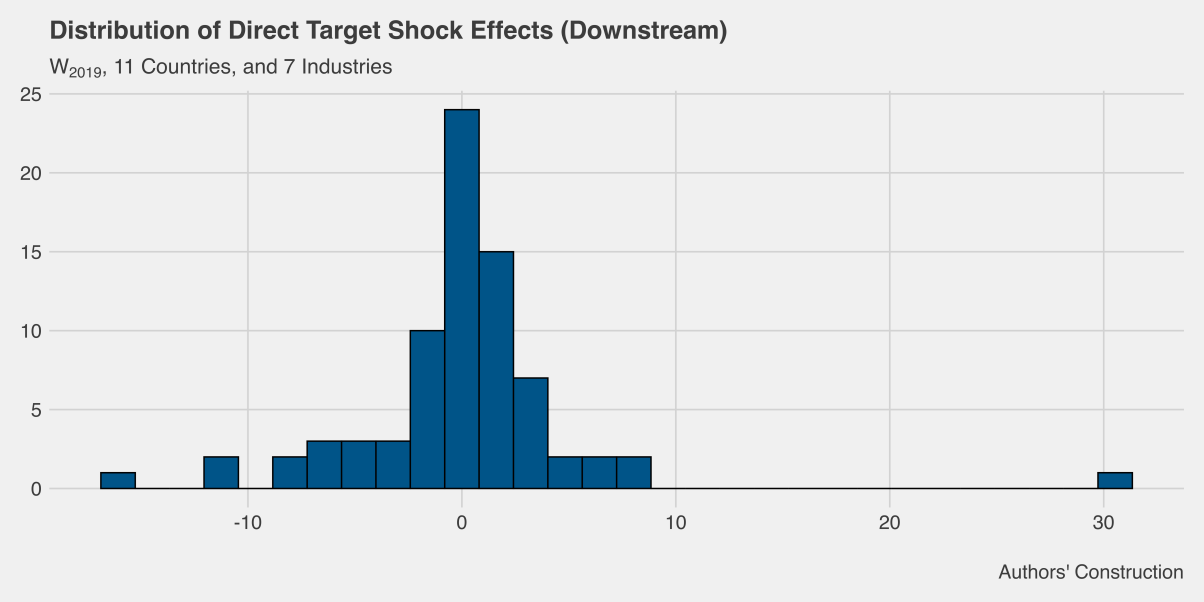


Figure 28: Distribution of Direct Target Shock Effect Estimates

Notes: Distribution of Direct Target effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 6, estimated using Equation 5.

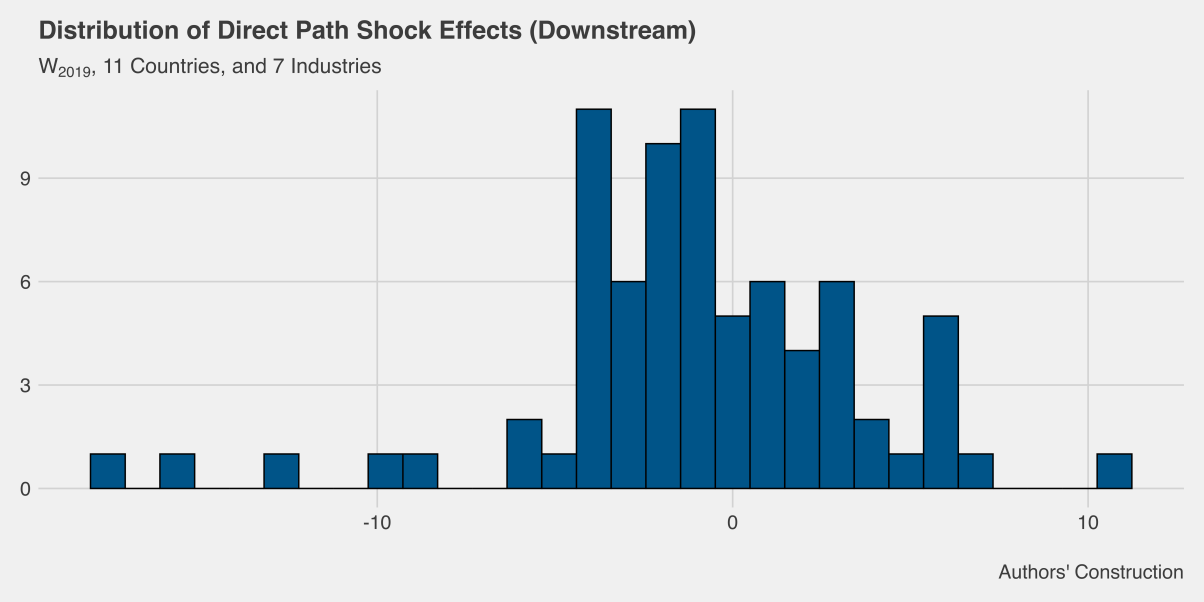


Figure 29: Distribution of Direct Path Shock Effect Estimates

Notes: Distribution of Direct Path effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 6, estimated using Equation 5.

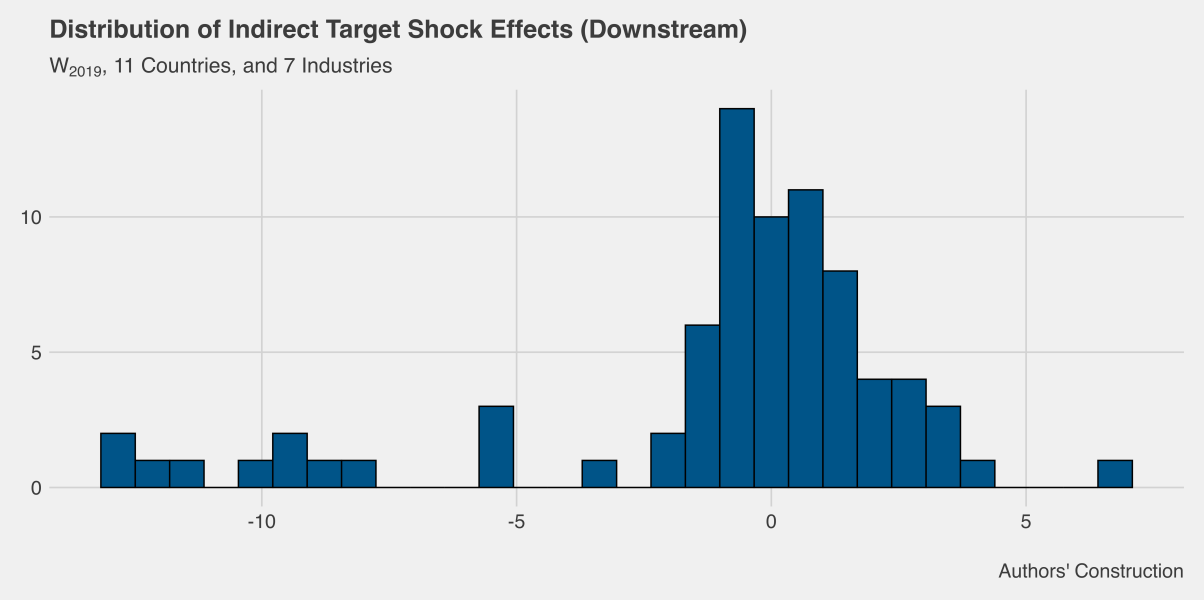


Figure 30: Distribution of Indirect Target Shock Effect Estimates

Notes: Distribution of Indirect Target effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 6, estimated using Equation 5.

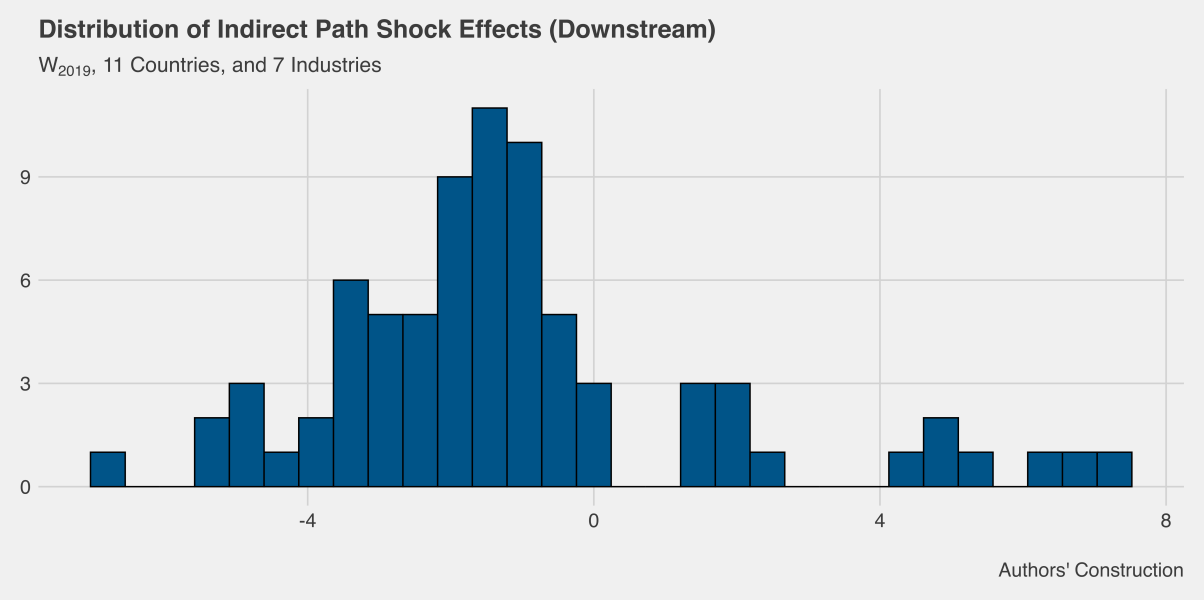


Figure 31: Distribution of Indirect Path Shock Effect Estimates

Notes: Distribution of Indirect Path effect estimates across countries and industries using W_{2019} as the weighting matrix. Results calculated from Column (2) in Table 6, estimated using Equation 5.

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