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

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Job Market Paper†
First Version: July 2022
This Version: November 2023

Abstract

Does Chinese monetary policy matter on a global stage? This study evaluates how Chinese monetary policy shocks are transmitted globally. We examine the role production linkages play in the global transmission of Chinese monetary policy shocks to global stock returns. Using a high-frequency measure of Chinese monetary policy shocks, we evaluate how Chinese monetary policy shocks propagate upstream and downstream through supply chains using a heterogeneous coefficient spatial autoregression (SAR) model. Three findings emerge. First, firms on both ends of the Chinese production network show negative country-industry level equity returns in response to a contractionary monetary policy shock. Second, approximately 70-78% of the observed equity responses to Chinese monetary policy shocks can be attributed to the network effect of firms being connected across global supply chains. Third, we attribute the observed heterogeneity in the equity responses across countries and industries to a country's degree of home-bias, which we demonstrate by simulating a standard small-open economy model with supply chain integration. We show that supply chains are a key channel for the global transmission of Chinese monetary policy.

JEL Classification

E5, F3, F4

Keywords

Monetary Policy; Spatial Econometrics; Spillovers; Trade; SAR; High-Frequency Identification; Chinese Economy; production networks; supply chains

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†We would like to thank Galina Hale, Eric Swanson, Chenyue Hu, Alonso Villacorta, Falk Braeuning, Jose Fillat, and the UCSC Macro Workshop participants for their extremely helpful comments and suggestions throughout the life-cycle of this paper. Part of this paper was completed while Harrison Shieh was a Dissertation Fellow at the Boston Fed. The views of this paper do not necessarily reflect those of FRB Boston or the Federal Reserve System, as well as the Reserve Bank of India. All errors ours and ours alone.

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, as 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 monetary policy shocks, and only recently has there been a literature that examines the role production linkages play in the transmission of monetary policy.

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 typical channels – the exchange rate, risk-taking, and credit channels, etc. – 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 matter on the global stage?

In this paper, we characterize how Chinese monetary policy transmits worldwide. In particular, we emphasize the role that supply chains play in the global transmission of Chinese monetary policy shocks. Due to China's strong links (and growing soft-power influence) 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, as well as how small-open economies respond to these shocks. Furthermore, having a more complex understanding of the role supply chains play in the transmission of monetary policy may help guide the design of optimal trade and monetary policy in small-open economies.

Supply chains are increasingly in the public consciousness. China's centrality in global supply chains — more precisely, global reliance on Chinese manufacturing — was thrust into the public spotlight during the coronavirus pandemic, where a prolonged Chinese lockdown was felt globally as China-reliant supply chains struggled to keep up with increased global demand due to limited supply. This is further highlighted by the current geopolitical tensions between China and the West, where calls for "decoupling" and "de-risking" underscore the outsized importance China plays in global supply chains.

Similarly, Chinese monetary policy has received greater scrutiny. The People's Bank of China (PBOC) has continually faced challenges related to Chinese financial market stability and slowing economic growth. In an attempt to project confidence (and mimicking other central banks), the PBOC has increased the frequency in which it communicates its policy goals, despite a strong state-level institutional bias towards secrecy during periods deemed sensitive to the central government. This behavior by the PBOC raises important questions about whether or not Chinese monetary policy is effective and whether or not global markets "care".

We start by hypothesizing a global transmission channel for Chinese monetary policy. Consider, for a moment, the various channels in which US monetary policy can transmit worldwide. These channels generally revolve around financial linkages — that is, US monetary policy works its way globally through banks and asset prices. A US monetary policy shock will inevitably have cross-border implications due to the strength of the financial linkages of the US financial system and the rest of the world. The classic adage holds true: "When the United States sneezes, the rest of the world catches a cold."

This conclusion is not as obvious in the case of China. The typical channels through which US monetary policy transmits across borders are generally not applicable — China does not enjoy the level of financial integration the United States does. Despite this, policy transmission coming from China need not primarily work their way through financial linkages. We make the case that due to China's outsized importance in global manufacturing, production linkages propagate the effects of Chinese monetary policy shocks. More specifically, we recontextualize Chinese monetary policy shocks as both supply and demand shocks, conditional on where a firm lies on the supply chain. To be clear, we do not rule out the possibility that Chinese monetary policy may transmit through some financial linkages.[1] For example, 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). The expansion of The Belt and Road Initiative also presents a scenario in which increasing financial linkages from China to the developing economies may facilitate cross-border spillovers. 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 a larger role in the transmission of Chinese shocks.

With that context, we empirically assess our hypothesis by estimating a heterogeneous coefficient spatial autoregression (SAR) on equity returns across 11 economies and 7 industries identified using a high-frequency surprise Chinese monetary policy shock. We construct an identified monetary policy measure, a Target Factor, which measures surprise changes to the Chinese policy stance. When Chinese monetary policy shocks propagate upstream, that is, when contractionary Chinese 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. The SAR results show that a 1pp contractionary Chinese monetary policy shock results in a roughly 20bp decline in equity returns (on average across country-industry pairs), and roughly 70% of the total effect of a surprise contractionary monetary policy shock can be attributed to a propagation as a result of firms being connected to the Chinese production network. That is, the input-output linkages play a statistically significant role in the upstream transmission of Chinese monetary policy shocks. We also find heterogeneous equity responses across country-industry pairs,

[1] In fact, some literature suggests some financial spillovers of Chinese monetary policy shocks exist. I discuss this a little more in the review of the literature. We also do not investigate the possibility of monetary policy transmitting through financial offshoring by domestic Chinese investors into offshore tax havens as discussed in Clayton et al. (2023). This could be an interesting avenue for future research.

with evidence suggesting that there is some degree of substitution for input goods from source countries. This may be conditional on the number of customers the source country may have outside of China. The individual upstream equity returns point estimates can be interpreted as a measure of how entrenched an industry is as suppliers to Chinese firms.

Contractionary Chinese monetary policy materializes as a negative supply shock for firms downstream of China. 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. Like the upstream case, these downstream firms reduce their output, resulting in negative stock returns. The results show that a 1pp contractionary Chinese monetary policy shock yields a roughly 17bp decline in equity returns (on average across country-industry pairs). Nearly 78% of the total effect can be attributed to network effects, suggesting that production linkages downstream of China are also important when transmitting realizations of tighter Chinese monetary policy. 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. Like the upstream analog, the equity point estimates can be interpreted as the degree of reliance of a downstream firm on Chinese suppliers.

We argue that the observed heterogeneity in equity responses can be explained by a country's degree of home-bias. We examine the role home-bias plays in a slightly modified small-open economy (SOE) model with supply chain integration following Wei and Xie (2020). The highlight of this model is that we can match the equity responses that we observe in the SAR by modulating the degree of home-bias a SOE has in the production of intermediate goods. We calibrate our model to two of China's main trading partners — South Korea and Japan. The simulation results show that the degree of exposure to Chinese supply chains (measured by home-bias) affects the amount of intermediate goods produced by the SOE. When looking at South Korea and Japan, the simulation results match the equity responses of the spatial autoregression. South Korea, having relatively less home-bias than Japan, has a more negative intermediate goods output response than Japan, in line with the more negative equity responses South Korea has, relative to Japan, in both the upstream and downstream cases. We argue that the observed heterogeneity in the data can be explained by a country's relative degree of home-bias.

Overall, the results show the importance of production linkages and provides a 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. Simulation results show that the degree of exposure to the supply chain affects the intermediate goods production output response in response to supply and demand shocks.

Our primary contribution is to the growing literature examining spillovers of Chinese monetary policy, where we provide novel results that link Chinese monetary policy shock propagation through production networks by examining the responses of country-industry equity returns. Our results are broadly consistent with the macro results discussed in the literature but provide micro evidence showing supply chains' importance in the propagation of Chinese monetary policy shocks. To our knowledge, no existing paper directly examines the role supply chains and production networks play in the transmission of Chinese monetary policy.

There are a few studies closely related to this paper, where a few key themes emerge: trade and global value chains appear to be important in the transmission of Chinese monetary policy shocks, with evidence of real and some financial spillovers. Miranda-Agrippino et al. (2020) and Huang et al. (2014) argue that Chinese monetary policy transmits primarily through international trade and global value chains, echoing papers that study the regional transmission of Chinese policy shocks. However, unlike our approach, this set of papers does not examine the role production linkages play in the transmission of Chinese policy shocks. Our results highlight the role global value chains play in this transmission by quantifying the contribution of production networks to the transmission to global equity returns. Johansson (2012) find that expansionary Chinese monetary policy has a short-lived but significant effect on equities in South East Asia, qualitatively mirroring our empirical results. Beirne et al. (2023) argues that Chinese monetary policy shocks have more persistent effects on Asian economies when compared to the United States. Cho and Kim (2021) and Chen et al. (2023) argue that the standard expenditure shifting channel (that is, contractionary monetary policy domestically should increase foreign production) is the main transmission channel. Cho and Kim (2021) finds that East Asian countries reduce their exports to China and increase their imports from China in response to an expansionary monetary policy shock. and Chen et al. (2023) finds similar effects for countries engaged in China's Belt and Road Initiative. We find limited evidence of this effect and argue that our characterization of upstream demand shock and downstream supply shock is the dominant channel of monetary policy transmission. Vespignani (2015), examining Chinese monetary policy shocks into the Eurozone, find that expansionary Chinese monetary policy increases commodity prices and has real effects on Euro area inflation and growth. Similarly, Kozluk and Mehrotra (2009) examines the effect of Chinese monetary policy shocks on surrounding SE Asian countries and finds that expansionary Chinese monetary policy caused an increase in GDP and inflation for China's neighbors. Our paper would be the first to specifically quantify the role that supply chains play in the propagation of Chinese monetary policy, as well as contextualize how these spillovers occur across borders.

At a more macro level, this paper fits into broader literature examining the international transmission of monetary policy. Set against the backdrop of the Fed's unconventional monetary policy in response to the 2008 Financial Crisis, the vast majority of the empirical literature documenting the transmission channel of monetary policy focuses on the transmission of US monetary policy. One set of papers examines the relationship between US monetary policy and asset prices, with Rey (2016), Miranda-Agrippino and Rey (2020a), and Miranda-Agrippino and Rey (2020b) (among others) finding that US monetary policy transmits powerfully across borders and induces co-movements in international asset prices and other international financial variables. Another set of papers emphasizes the role banks play in the international spillovers of monetary policy, with Bruno and Shin (2015) emphasizing the role that bank leverage plays in cross-border transmission of US monetary policy and Buch et al. (2018) providing additional evidence for the transmission of policy through the international bank lending channel, as well as the portfolio channel. Specific to emerging market economies (EMEs), US monetary policy appears to also transmit through the bank lending channel (Bräuning and Ivashina 2020). Miyajima et al. (2014) find that unconventional US monetary policy led to an increase in Asian domestic long-term bond yields, consistent with the conclusions of Obstfeld (2015). In a related paper, Park and Um (2016) find that Asian financial markets are vulnerable to US monetary policy. Due to strict capital controls in China, it is hypothesized that Chinese financial markets have less exposure to international transmission of monetary policy. However, a recent paper by Lin and Niu (2021) finds that unconventional US monetary policy had an effect on the Chinese yield curve, implying that there is some growing exposure by Chinese financial markets to the global factor discussed in Miranda-Agrippino and Rey (2020b).

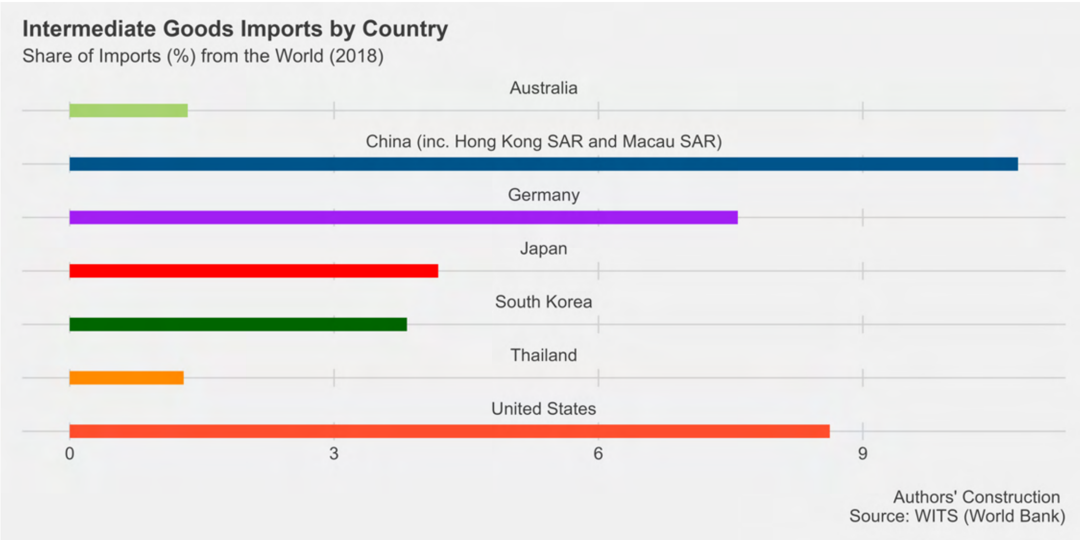
This paper also contributes to the literature related to the usage of production networks in macroeconomic analysis, as well as the importance of supply chains in examining policy spillovers. Acemoglu et al. (2016) discusses how input-output linkages, as well as geographic linkages, can be used to analyze how various policy shocks can transmit through these input-output linkages. A set of papers examine theoretically, in both closed-economy and open-economy settings, the importance of supply chains and production networks in the design of policy (see, among others, Rubbo (2023), La'O and Tahbaz-Salehi (2022), Wei and Xie (2020), and Gong et al. (2016)). Four studies are closely related to this study, examining cross-border input-output linkages and monetary policy, focusing on the US and the Eurozone: Ozdagli and Weber (2017), using stock returns in the US, examines the role production networks play in the transmission of US monetary policy and find that production linkages play a role in the domestic transmission of monetary policy. Bräuning and Sheremirov (2019) examine the effects of US monetary policy spillovers on global output utilizing production linkage data and find a sizable spillover from US monetary policy shocks, primarily through trade linkages. Di Giovanni and Hale (2022) evaluates the effect of US monetary policy shocks on foreign stock returns through global production networks. In contrast, Todorova (2018) looks at the effect of ECB shocks on EU periphery stock returns. The last two papers find that stock market returns react due to network effects from monetary policy shocks — underscoring the importance of production networks in the transmission of policy. To that end, the burgeoning literature on the role of production networks in the transmission of monetary policy, along with the conclusions of Miranda-Agrippino et al. (2020) and Huang et al. (2014), motivate the study of Chinese monetary policy transmission through global supply chains. To our knowledge, we would be the first paper using global production networks in the analysis of macroeconomic shocks for China.

The paper is organized as follows. Section 2 discusses the empirical framework — we examine the hypothesized transmission channel, as well as detail the identification of Chinese monetary policy shocks and discuss the spatial econometric method used in this paper. 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 builds a simple small-open economy model motivated by the empirical results that model the Chinese spillovers in a modal small-open economy. Section 6 concludes.

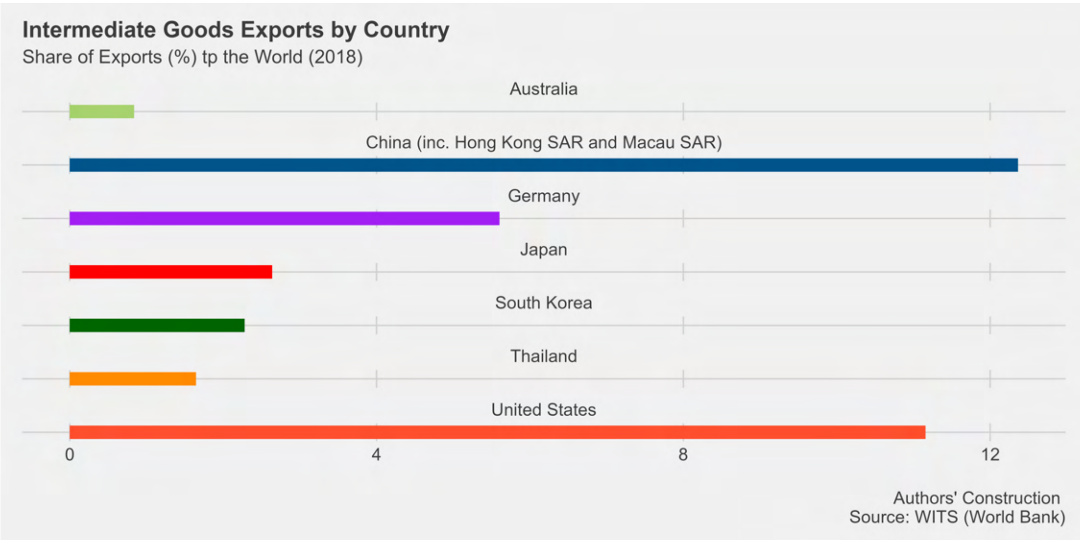
2 Empirical Framework

Before we fully present the empirical framework, it is useful to have a broader discussion about how Chinese monetary policy may propagate across borders. Specifically, we discuss and contextualize how Chinese monetary policy transmits along global supply chains.

2.1 Channels and Propagation of a Chinese Monetary Policy Shock



(a) Intermediate Goods Imports



(b) Intermediate Goods Exports

First, we note China's unique position in global supply chains and that this position 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). More importantly, because China is relatively less exposed to global financial markets, Chinese monetary policy has limited avenues (if any) of global transmission. The most likely suspect is through a trade-type channel. More specifically, 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. Notice that we recontextualize domestic monetary policy shocks into cross-border supply and demand shocks rather than direct responses to Chinese monetary policy shocks. We illustrate these propagation channels more concretely by example.

Upstream Shocks

In the upstream case, consider the following scenario involving the Chinese tech conglomerate Xiaomi. Xiaomi has upstream suppliers located in the United States and in Taiwan, separated by degrees.[2] Xiaomi's phone manufacturing division relies on a first-degree supplier of SoC processors. In this case, this is US-based Qualcomm. Qualcomm's own first-degree (and, in this specific context, Xiaomi's second-degree) supplier is TSMC in Taiwan, which manufactures the chipsets used by Qualcomm to produce the SoC processors that Xiaomi utilizes in its phones. A domestic Chinese monetary policy shock materializes upstream as a demand shock since Chinese firms are now faced with higher costs of external finance[3] scale back their import orders of intermediate inputs from Qualcomm, who in turn has to scale back orders from TSMC due to reduced demand from the source: Xiaomi. This demand shock materialization reflects as reduced outputs (and negative profits, as a proxy for this) for TSMC, Qualcomm, and Xiaomi. Notice that the degree of connectedness in the supply chain can be measured. How important these interconnections are can be directly measured in the empirical exercise. Figure 2 is a visual representation of this demand-shock channel.

[2] We define degrees in this context as the "closeness" of the supplier to the end customer. For example, a first-degree supplier directly supplies customer, whereas a second (or higher) degree supplier either supplies the first-degree supplier or the good that is provided is acquired through non-direct means by the customer.

[3] This could be explained as an interest-rate channel or credit-channel story. Other papers have evaluated domestic Chinese monetary policy shocks in Chinese financial markets. Shieh (2022) 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).

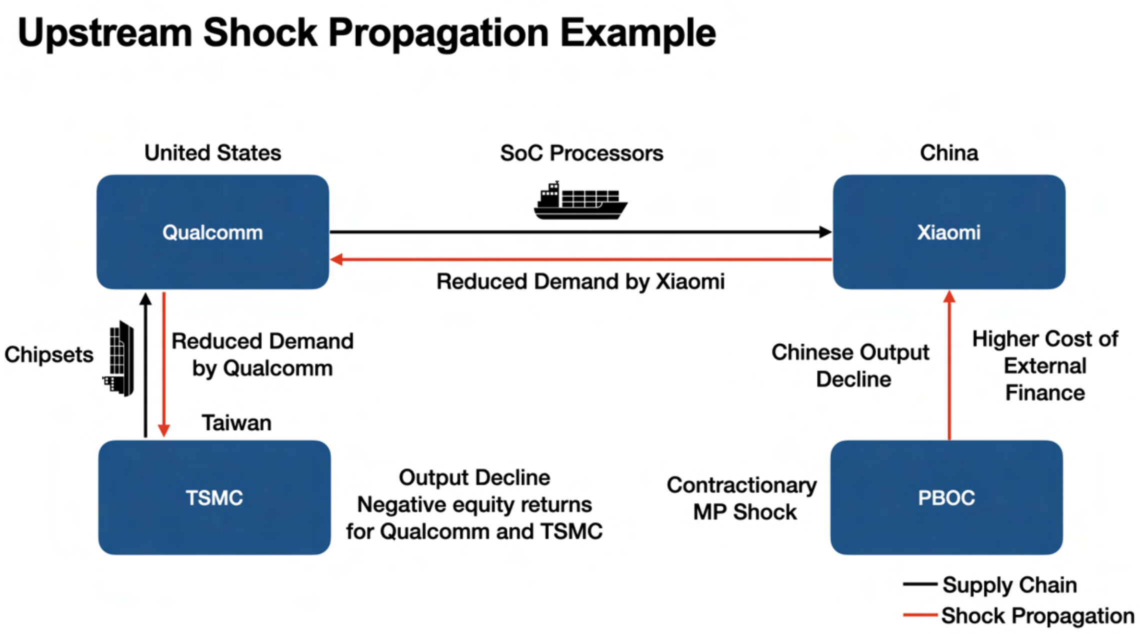


Figure 2: Simplified Upstream Shock Propagation

Notes: Chinese monetary policy shock materializes as a standard credit channel (or interest rate channel) for domestic firms but as a demand shock for upstream suppliers.

Downstream Shocks

The downstream shock case is similar but treats China as upstream of other country-industries. In other words, the monetary policy shock materializes as a supply shock to firms downstream of Chinese intermediate-goods-providing firms. This can be easily illustrated using EV vehicle batteries. China is home to one of the largest cobalt finishing companies in the world, Huayou Cobalt. Downstream of Huayou is South Korea's Samsung SDI, which purchases processed cobalt for use in its EV battery-making division. In this case, Samsung SDI and Huayou Cobalt's relationship is that of a first-degree supplier – Huayou directly supplies Samsung. Germany's BMW utilizes Samsung SDI batteries in a host of EVs. Since Huayou does not directly sell cobalt to BMW, this relationship can be characterized as second-degree. Notice again that a domestic Chinese monetary policy shock may not necessarily directly affect BMW, but, as a spillover consequence of affecting suppliers upstream of BMW, may have an effect as a result of a shock. In this case, since China is upstream of these firms, this can be characterized as a supply shock as the supply of Chinese intermediates is affected in response to a tightening of domestic Chinese monetary policy. Figure 3 is a visual representation of this supply-shock channel.

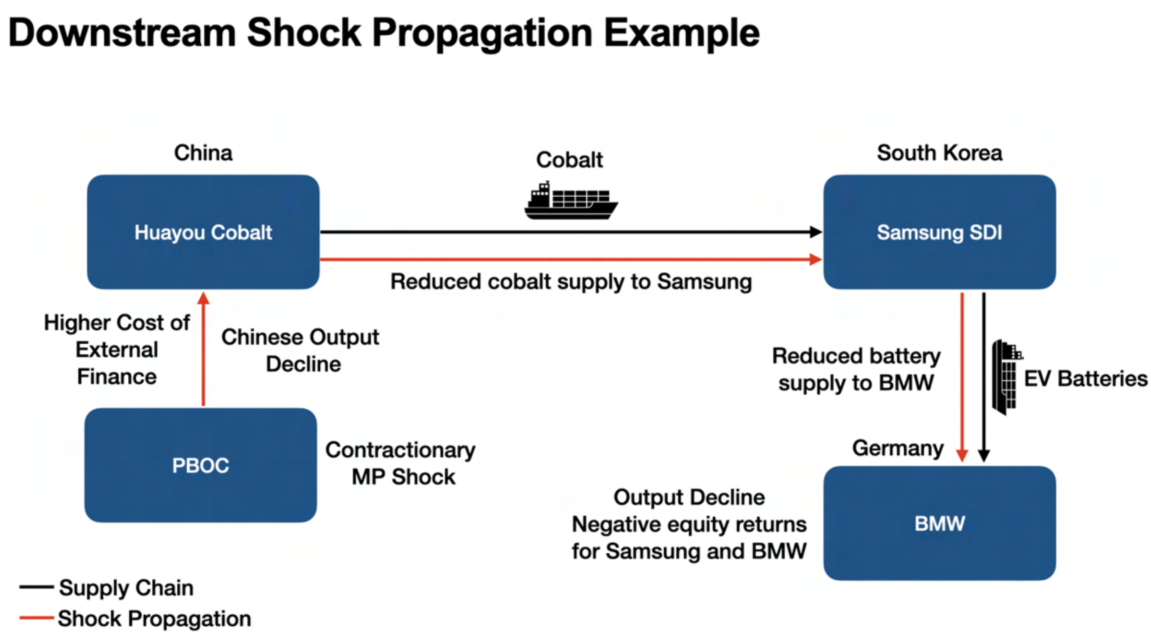


Figure 3: Simplified Downstream Shock Propagation

Notes: Chinese monetary policy shock materializes as a standard credit channel (or interest rate channel) for domestic firms but as a supply shock for downstream firms that rely on Chinese intermediate goods.

It should be made clear, however, that these examples are stylized in the sense that in a single country, firms can be both up and downstream of China, so the transmission of the Chinese monetary policy shock can hit a country as both a supply and a demand shock, depending on the relative degree of upstream or downstreamness.

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 justify the usage of stock returns as the dependent variable primarily due to two primary reasons: (1) assuming efficient markets, stock returns reflect beliefs about future discounted cash flows, so if monetary policy shocks affect industry output, then 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 a monthly frequency, 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.

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 poses is an unique exercise. For example, on 06/28/2015, the PBOC announced a reduction in the reserve requirement and the lending rate by 0.50pp and 0.25pp, 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 being 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 Target Factor introduced in Shieh (2022), which follows the methodology proposed in Gürkaynak et al. (2005) for surprise US monetary policy shocks. The Shieh (2022) 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. The Target factor measures the unanticipated changes to the current Chinese monetary policy stance. This can be best considered a monetary policy "surprise" shock. While the Shieh (2022) paper also extracts a Path Factor, which measures changes to the expected future stance of policy, we only use the Target Factor since we are only interested in the effects of an identified shock to the existing policy stance.[4]

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. We can also distinguish between surprise short-term changes to the stance versus surprise changes to the expected future path of policy. More precisely, the Shieh (2022) factors take advantage of high-frequency pricing changes on policy announcement dates to Chinese financial derivatives that use a commonly used proxy for the Chinese monetary policy stance, the 7-Day Repo rate. This factor approach differs from a surprise-only measure of monetary policy, as seen in Kamber and Mohanty (2018) and Shieh (2021). 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

[4] The empirical results are broadly robust to including the Path factor in Shieh (2022), as well as a single policy-news-like factor for China that is similar in construction to the Nakamura and Steinsson (2018) policy news shock measure. Path is omitted in the analysis as it adds unnecessary dimensionality to interpreting the shocks. We only need a single identified measure of Chinese monetary policy to measure the broad effects of these shocks globally. Additionally, it is unclear whether or not global financial markets are directly reacting to surprise changes in domestic beliefs about the expected path of future policy. Rather, it is more plausible that global markets react to changes in the domestic Chinese response (real or financial) to changes in future expected policy stance.

oversimplify the effect of Chinese policy shocks by aggregating the effect of surprises with beliefs about the future policy stance.

Chinese monetary policy announcements are compiled starting from 2006 and ending in 2019. There are 167 announcements in this time period. Various types of policy announcements are captured, reflecting different policy levers at the disposal of the People's Bank of China, as well as analogs of FOMC statements and other press releases. Table 1 shows a selected sampling of various policy announcements.

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

Table 1: Example Announcement Dates

Notes: Taken from Shieh (2021). RR is the reserve requirement, LR is the lending rate, FX are changes to the foreign exchange, MPR is the PBOC Monetary Policy Report, OMO is open market operations, Other represents other policy or regulatory changes, TLF is Term Liquidity 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 (2022) uses the following set of surprises using 5 interest rate swap (IRS) tenors referencing the 7-Day Repo 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 systematic construction of these daily changes to the interest rate swap prices that bracket the announcement date can be summarized as follows:

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, I 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 I take the difference in closing price between the next available trading day and the preceding trading day prior to the non-trading day.

Next, 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 factor model:

$$\underset{T\times n}{X} = \underset{T\times k}{F} \underset{k\times n}{\lambda} + \underset{T\times n}{\eta} \tag{1}$$

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 a matrix of factor loadings, and η is a matrix of white noise disturbances.

Two factors, F_1 and F_2, are extracted using principal components (PCA). It should be noted that while we are only interested in the first factor, F_1 (which captures surprise changes to the current monetary policy stance), we extract two factors to disentangle the effects of a *change in the current monetary policy stance* and *a change in beliefs about the future monetary policy stance*. Due to the way the factor rotation is conducted, by construction, the factors will be orthogonal to each other. In principle, it is possible to just extract a singular factor, but this would effectively average the Target and Path effects. In fact, a singular factor would be more analogous to the Nakamura and Steinsson (2018) policy news shock. To have the "purest" measure of a shock to the current monetary policy stance, we focus on just the Target Factor. 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. Appendix A provides additional details on the rotation of the factors. For a complete description of the construction and additional analysis, please refer to Shieh (2022). Figure 4 shows the Target factor from 2006 through 2019.

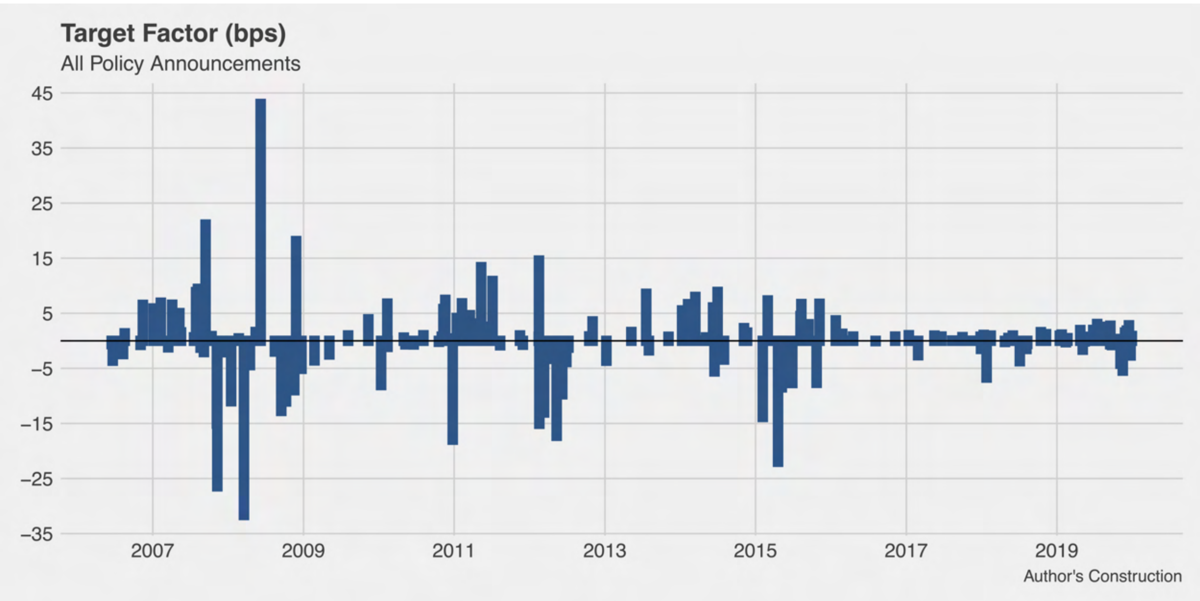


Figure 4: Estimated Target Factor

Notes: Estimated using PCA on IRS surprises during 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. Details on the construction can be found in Shieh (2022)

2.3 Heterogeneous Coefficient Panel SAR

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):

$$\hat{\boldsymbol{\pi}}_t = (\boldsymbol{I} - \text{diag}(\boldsymbol{\rho})\boldsymbol{W})^{-1}\boldsymbol{\beta}^{\boldsymbol{MP}} Target_t + \boldsymbol{\Gamma}\mathbf{X}_t + \boldsymbol{\alpha} + \boldsymbol{\epsilon}_t \tag{2}$$

$\hat{\boldsymbol{\pi}}_t$ is a $NJ \times 1$ vector of the average annualized industry-level equity returns $\hat{\pi}_{mi,t}$ by country for each month-year 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). $Target_t$ are the surprise Chinese monetary policy shocks measured by the Target Factor from Shieh (2022) at time t[5] Since there are, while $\boldsymbol{X_t}$ is a vector of controls that includes each country's central bank policy rate, the real 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 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 $\boldsymbol{\rho} - diag(\boldsymbol{\rho})$ is a $NJ \times 1$ indicates a $NJ \times NJ$ diagonal matrix that has zeros on the off-diagonal and $\boldsymbol{\rho}$ on the diagonal.

The empirical exercise is to then estimate a vector of country-industry spatial autoregressive correlations, ρ_{mi}, as well as β^{MP}_{mi}, as our parameters of interest. This SAR is heterogeneous since it allows $\boldsymbol{\rho}$ to vary by country-industry rather than in the traditional fixed $\boldsymbol{\rho}$ homogeneous coefficient 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 β^{MP}_{mi} 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. This spatial autoregression (Equation 2) can be justified theoretically using a simple production economy, as shown in Ozdagli and Weber (2017), Todorova (2018), and Di Giovanni and Hale (2022), and presented in Appendix B. We estimate the SAR following Aquaro et al. (2020).

[5] Target only varies 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 factor by month. Since there are days and months without a policy announcement, there are months where the Target factor is 0.

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:

$$\begin{aligned}\textbf{Total Effect} &\equiv (\boldsymbol{I} - diag(\boldsymbol{\rho W})^{-1})\boldsymbol{\beta^{MP}} \\ \textbf{Direct Effect} &\equiv \boldsymbol{\beta^{MP}} \\ \textbf{Network Effect} &\equiv \textbf{Total Effect} - \textbf{Direct Effect}\end{aligned}$$

The total effect is the combined effect of the direct effect of a Chinese monetary policy shock on equity returns, captured by $\boldsymbol{\beta^{MP}}$, 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 mechanism described in Subsection 2.1, capturing all the linkages that propagate the monetary policy shock. 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.[6] This may be less realistic, as this round-tripping may be a different stage in the production chain. We follow Di Giovanni and Hale (2022) approach and use only the Acemoglu et al. (2016), but note that the LeSage and Pace (2009) provides a larger direct effect with the overall results. In either case, the decompositions provide qualitatively similar effects. We report the LeSage and Pace (2009) decomposition in Appendix D.

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

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

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. For reasons that will be explained in Subsection 3.2, we collapse the 35 ISIC industries in the MRIOT into 7 GICS supersectors for the creation of the weighting matrix. Table 7 in Appendix C 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 country-industry usage of goods supplied by another country-industry cell. Let the 11 countries in the sample be denoted $m, n \in [1; N]$ and industrial sectors $i, j \in [1; J]$. Thus, the weighting matrix W is simply an $NJ \times NJ$ matrix where each element, $w_{mi,nj}$, are the inputs from country m and sector i as a share of the total output of sector j in country n:

$$w_{mi,nj} = \frac{Sales_{mi \to nj}}{Sales_{nj}} \tag{3}$$

It should be immediately obvious that this is simply the fraction of the value of a particular input in a specific country-industry mi relative to the row-sum of outputs in country-industry nj. This formulation, then, assumes an upstream propagation of the Chinese monetary policy shocks, given the functional form of the SAR regression in Equation 2. 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 supply from country-industry pairs from another country-industry pair. Thus, we repeat the exercise as in the upstream case but transpose the MRIO table and then row-normalize such that the sum of each row equals 1. The downstream W is then an $NJ \times NJ$ matrix, such that:

$$W^{Down} = W^T$$

where each element, $w_{mi,nj} \in W^{Downstream}$ is a share of the inputs that country-sector mi supplies country-sector nj relative to the overall output supplied to country-sector nj.

3.2 Industry-Level Concordance and Stock Returns Data

Industry-Level Matching

While the MRIOT utilizes the ISIC rev. 4 industry-level classification, the industry-level subindices 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 C, Table 8 shows the full ISIC categorization found in the MRIOT, and Table 9 shows the GICS sector classification.

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 not simply 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 10 in Appendix C 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 5 shows 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.

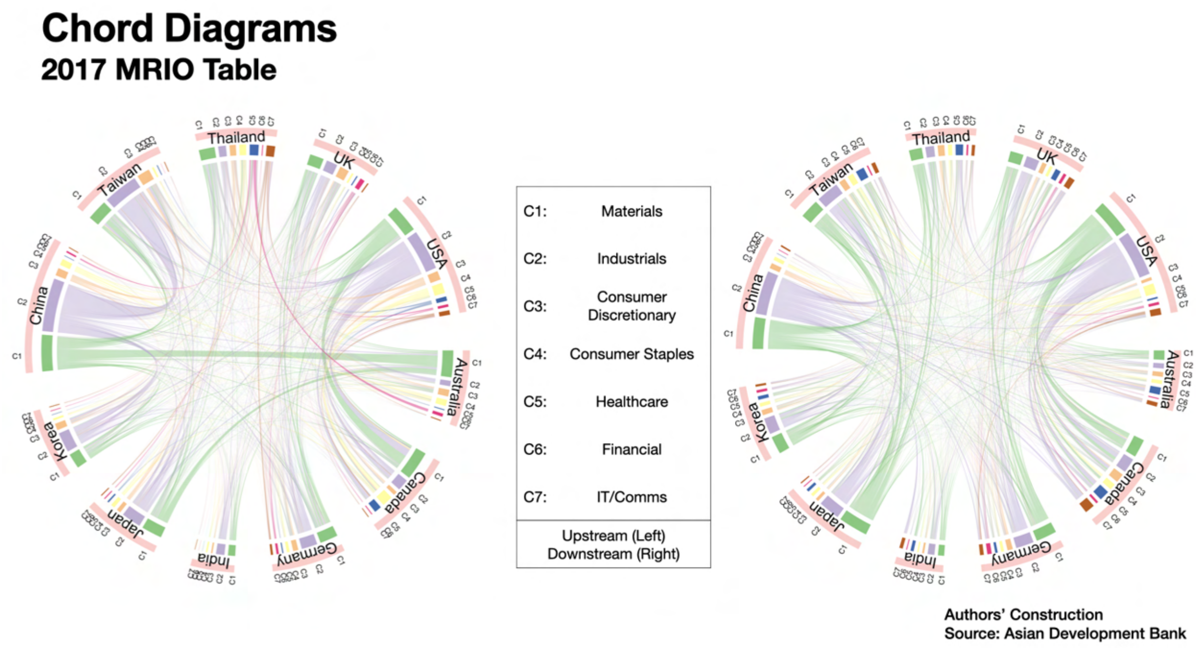


Figure 5: Chord diagram of 11 countries and 7 industries.

Notes: Industries collapsed following the concordance process outlined in Subsection 3.2 and constructed using the 2017 ADB MRIO Table.

Stock Returns Data

Stock returns data construction is standard and covers the period from January 2009 through December 2019. For each country's main index, we use the monthly GICS sector-level index price.[7] Returns are calculated as the monthly log changes to the end-of-month closing index price and then annualized. 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.[8] 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 Figure 12 and Figure 13 show the distribution of monthly returns for the full sample, as well as the winsorized returns.

4 Results and Discussion

[7] 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.

[8] However, for China and India, due to incomplete market cap data, we use a simple average (equal weights) instead.

4.1 Baseline Estimation

We first estimate a baseline regression that assumes that production linkages do not matter. This provides a first-pass estimation on the relationship between industry-level returns across countries and Chinese monetary policy shocks. Notice that in this panel set up, we explicitly assume that $\rho = 0$ in Equation 2, thus I estimate the following regression:

$$\widehat{\pi_{mi,t}} = \beta_0 + \beta_1^{MP} Target_t + \mathbf{\Gamma X}_{mi,t} + \epsilon_t \tag{4}$$

Table 2 shows the results of the baseline regression. For robustness, Equation 4 was estimated 5 ways: Pooled, country level fixed effects, country-industry level fixed effects, mean group, and random coefficients.[9]

Stock Returns	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	OLS	FE	FE	Mean Group	Rnd Coef
Target Factor	-0.560***	-0.543***	-0.543***	-0.378***	-0.430***
	(0.143)	(0.143)	(0.143)	(0.095)	(0.127)
Fixed Effects	$\times$	m	mi	$\times$	$\times$
Bootstrap + Robust SE	✓	✓	✓	$\times$	Bstrp
Observations	10,164	10,164	10,164	10,164	10,164

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

Table 2: 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. The coefficients represent the percentage point change in the annualized average stock returns in response to a 1 percentage point surprise increase. Constant and controls omitted for ease of exposition.

Notice that with the 5 different regression specifications, the standard errors and coefficients are very stable, indicating that the restrictiveness of the estimator type has a negligible effect on the results. The baseline results show that surprise shocks to the monetary policy stance are associated with a decrease in stock returns. Specifically, a 1pp increase in the Target Factor leads to a decrease in average stock returns by 0.56pp, suggesting that global markets react to surprise changes to the current Chinese monetary policy stance. The magnitudes shown here are smaller than typical studies that examine high-frequency monetary policy shocks on stock returns. This could be explained by using a monthly aggregation level of the policy shock when compared to the typical intra-day high-frequency literature (e.g., Gürkaynak et al. (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Altavilla et al. (2019), Miranda-Agrippino and Nenova (2022), etc.). While the Target factor is generated using daily windows

[9] For more on the mean group estimator, see Pesaran et al. (1999). For more on the random coefficients estimator, see Swamy (1970).

bracketing the policy announcement date, the shocks are then aggregated from daily factors into monthly ones, which could potentially introduce attenuation bias. This phenomenon has been seen in similar studies using monthly aggregated high-frequency shocks (see, among others, Di Giovanni and Hale (2022), ter Ellen et al. (2020), Todorova (2018), etc.). The baseline results provide evidence of global spillovers of Chinese monetary policy across different sectors.

Additionally, it is also possible that given the relatively limited[10] financial spillovers of Chinese monetary policy, there is a limited reflection of a Chinese policy shock on global equities prices. This differs from the case of Fed shocks, which, given the literature on the financial spillovers of US monetary policy shocks, plays a role in global equity responses. For example, in response to a contractionary US monetary policy shocks, Di Giovanni and Hale (2022) find a roughly 2.5pp decrease in global equity returns, while Todorova (2018) find a roughly 3.5pp decline in Eurozone stocks in response to a 1pp tightening of ECB policy. Both of these responses are roughly an order of magnitude higher than the Chinese response. Two possible cases could potentially explain results in the context of Chinese shocks. First, since financial linkages are relatively smaller, Chinese monetary policy may contribute less to changes in global equity prices. Second, global equities markets may have a difficult time processing Chinese shocks, so the equity responses may be relatively muted due to an inability to fully incorporate information stemming from Chinese shocks. As a result, the global point estimates are smaller. Overall, our point estimates align with lower-frequency studies of Chinese monetary policy and equity responses. Johansson (2012) examines the equity responses to Chinese monetary policy in a set of foreign equities markets, with the impulse responses showing significant but modest responses.

However, the analysis here does not consider network linkages (recall that this is assuming $\rho = 0$) and only provides a "gut-check" into whether or not our monetary policy shocks yield an intuitive stock market reaction. To decompose the effects of the Chinese policy shocks and to evaluate the contribution of network linkages, we estimate the heterogenous SAR described in Equation 2. First, we examine the upstream propagation of Chinese policy shocks.

4.2 Upstream Propagation

In this first setup, we assume that monetary policy shocks travel upstream. 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. We argue that the empirical results highlight the importance of supply chains for the transmission of Chinese monetary policy shocks. We find that the results are complementary to the broad results in the existing literature.

Table 3 reports the main effect of the Target shocks. Regression (1) constructs the empirical weighting matrix (W) using the 2009 input/output data for the input/output connections. Regression (2) uses 2019 input/output data, and regression (3) looks at the average input/output data between 2009 and 2019.

[10] But not non-existent.

Stock Returns (Upstream)	(1) W_{2009}	(2) W_{2019}	(3) $W^{Avg}_{2009-2019}$
Average ρ	0.66***	0.66***	0.67***
	(0.019)	(0.014)	(0.017)
Average Target Factor	-0.202***	-0.184***	-0.196**
	(0.078)	(0.084)	(0.077)
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 3: 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 factor represent the percentage point change in the average annualized stock returns in response to a 1 percentage point surprise increase. Country and Industry level distributions of β^{MP} can be found in Appendix Appendix D. Constant and controls omitted for ease of exposition. Standard Errors Wild bootstrapped using 1000 iterations.

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 0.66. Second, stock returns decline by roughly 20pp (annualized) in response to a 1pp contractionary Chinese shock. This, taken with the magnitude and significance of ρ suggests that firms upstream of Chinese firms are affected by Chinese monetary policy but that the shock itself propagates through the production network that these firms are embedded in.

Examining the average ρ further, compared to existing studies that examine the upstream propagation of monetary policy shocks, the results here suggest an even higher degree of passthrough than the United States and the Eurozone. In Di Giovanni and Hale (2022), the ρ estimates are only slightly lower than the China results shown here ($\rho_{US} \approx 0.632$ versus $\rho_{China} = 0.66$), which is intuitive — the world's first and second largest economies have highly embedded production networks, so policy propagation through those networks should be particularly strong. In comparison with Europe, Todorova (2018) estimates a ρ_{EU} of roughly 0.43 and statistically significant. So, while the propagation of ECB shocks through the EU production networks is statistically significant, the role of the production network is arguably stronger in the China and the US cases. Why might this be the case? Structurally, the Eurozone, while sharing a common market and monetary policy, is still made up of sovereign states, each capable of devising and implementing its own industrial policies. The relatively smaller degree of passthrough could be due to differences in industrial policies across the Eurozone. In contrast, China is a singular sovereign made up of several provinces, which, like the United States, can have some varying degrees of different industrial policy. However, they are still subject to national-level industrial policy. Arguably, this structural difference could explain why the EU passthrough is smaller than the US and China.

Upstream Heterogeneity

A potential dynamic that the average responses in Table 3 can miss is differential effects across countries and industries. 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.). To investigate this possibility, Figure 6 shows the heatmap of β^{MP} point estimates by country-industry pairs. Distributions by industry and by country, separately, can be found in Appendix D.

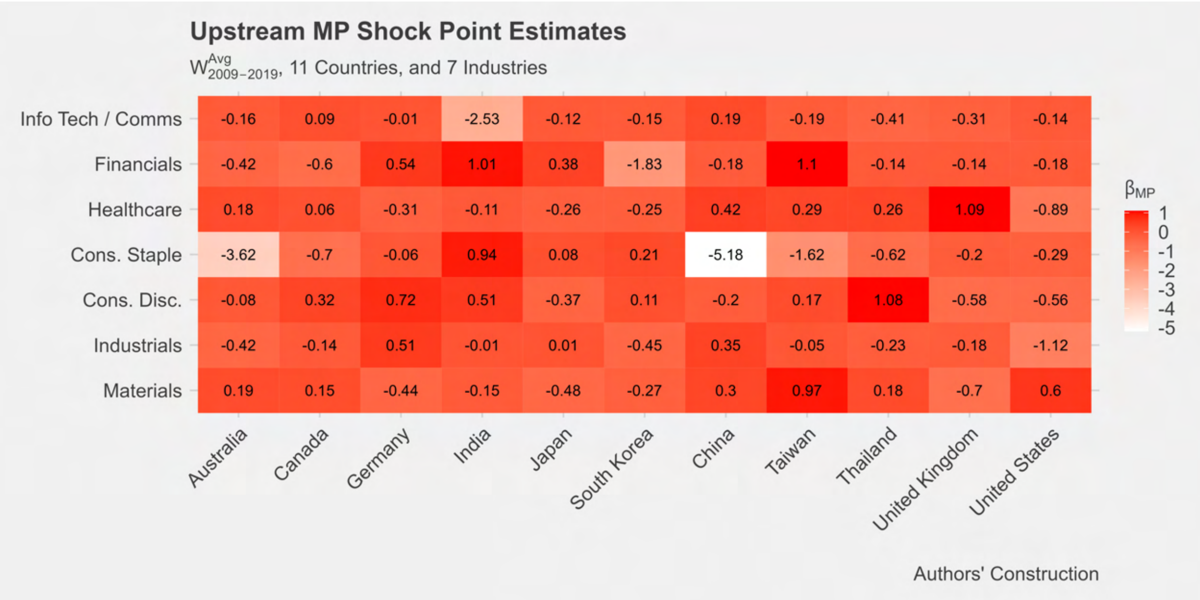


Figure 6: Heatmap of β^{MP} Estimate

Notes: Distribution of β^{MP} using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 3

We see mixed evidence supporting the expenditure switching story. In the expenditure switching story, a contractionary domestic monetary policy shock in China should increase output in non-Chinese economies. Suppose this channel dominates the demand shock story, that is, Chinese firms demand fewer foreign intermediates due to tighter Chinese policy. In this case, we should see positive equity responses since the foreign trade balance position improves, and these firms produce more to export to China. Specific to East Asia, Cho and Kim (2021) finds that intermediate goods imports from East Asian countries to China decrease and exports from China increase in response to expansionary monetary policy. If we isolate the three non-Chinese East Asian economies in these results, we see (on average) negative returns for South Korea and Japan, whereas Taiwan has a positive equity response. This suggests that South Korea and Japan are not engaging in meaningful expenditure shifting, as firms in these countries are expecting lower future profits in response to a contractionary Chinese shock.

For Taiwan, the average positive equity response is indicative that there is some expenditure shifting occurring for Taiwanese firms upstream of China. Expanding this into the rest of the sample, we see that Canada and India have, on average, positive equity returns in response to contractionary Chinese monetary policy shocks, which could also indicate a degree of expenditure shifting occurring. Overall, our results provide more limited evidence of expenditure shifting, in contrast to Chen et al. (2023) and Cho and Kim (2021), who find that this channel is a key transmission channel for Chinese monetary policy.

We argue, instead, that although there could be some evidence of expenditure shifting that varies by country and by industry, the few positive equity responses that we observe can be explained by the ability of an upstream firm to find alternative customers to make up for lowered Chinese demand. That is, the equity responses could potentially be conditional on the degree of ease with which an upstream firm can find an alternative customer in response to lowered Chinese demand. For example, intermediate goods related to Consumer Staples and Materials from Taiwan may have an easier time substituting away from Chinese customers when demand declines. Contractionary Chinese monetary policy then has the effect of increasing equity returns for these specific country-industry pairs since those firms can easily find business elsewhere. Of course, this substitution effect only occurs if the supplier is less entrenched in the Chinese supply chains. Given the data, however, we cannot provide a more concrete measure of how reliant upstream (or downstream) industries are on Chinese firms. Our second-best approximation, then, is these β^{MP} estimates in response to a negative demand shock from China — an entrenched industry/firm, unable to substitute alternative customers, should see negative equity returns due to lowered demand.

We also examine the heterogeneiety in the degree of policy transmission through production networks. Figure 7 and Figure 8 break down the distribution of the ρ estimates by country and by industry, respectively.

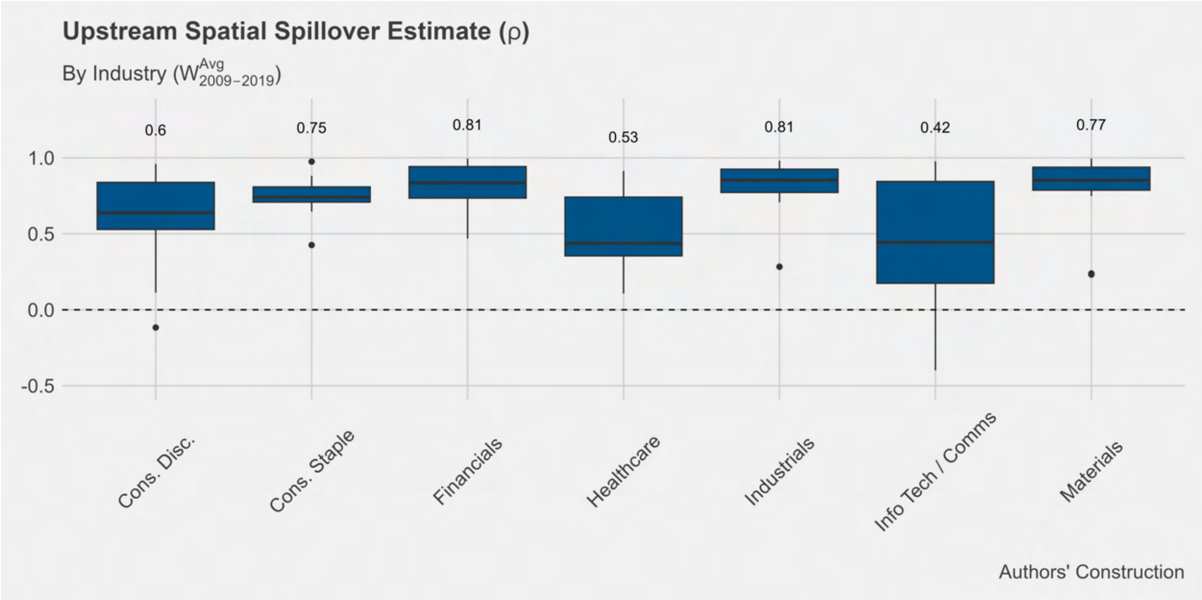


Figure 7: Box Plot of Passthrough Parameter, ρ, by Industry

Notes: Distribution of ρ by industry using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 3

Across industries, the passthrough of the shock is relatively high, with higher variability in consumer discretionary, healthcare, and IT/Communications. This could be due to the relative size of these sectors — intermediate goods categorized in the healthcare sector are smaller than intermediate goods traded in materials. As such, there is a bit more noise when tracing the degree of policy shocks through these industries. Moreover, as predicted, consumer materials and consumer discretionary both have a high degree of passthrough, which is in line with the upstream propagation story since these two industries represent the larger share of Chinese upstream intermediate goods trade sectors. In any case, the upstream spillover estimates are high across the board, suggesting that upstream propagation throughout the network does not vary wildly across industry.

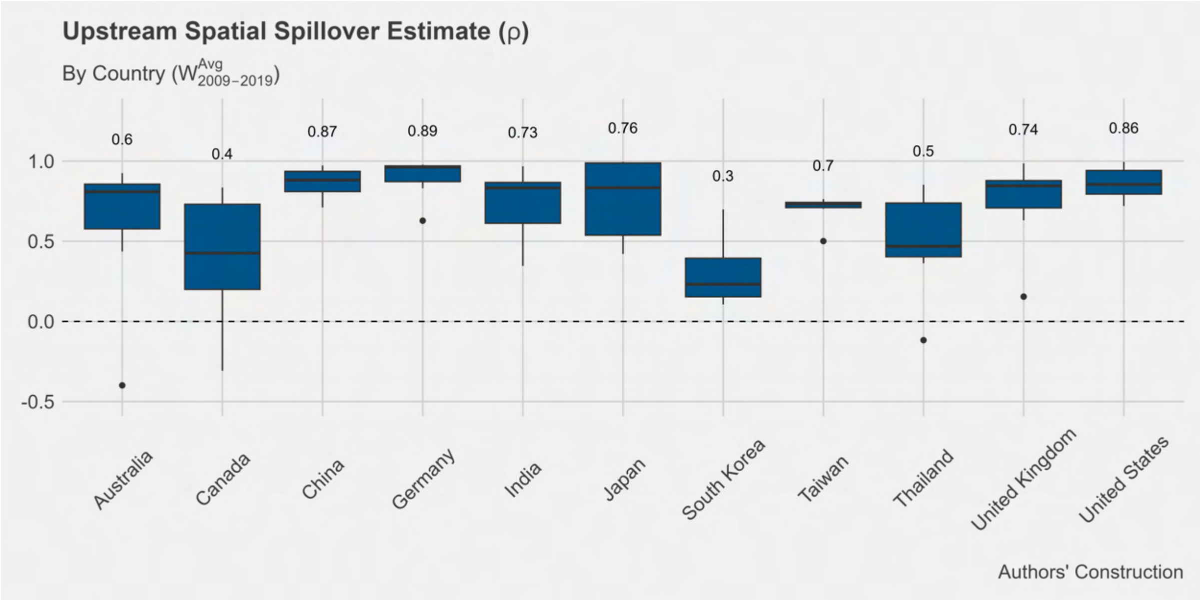


Figure 8: Box Plot of Passthrough Parameter, ρ, by Country

Notes: Distribution of ρ by country using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 3

When compared to industry, the country-level heterogeneity in the passthrough measure is more variable, with some countries having a relatively low level of passthrough (South Korea with $\rho = 0.30$) while others have very high levels of passthrough (Germany with $\rho = 0.89$). The degree of this passthrough would depend on exactly how connected these specific countries are (across all industries) to China (or at least, to a Chinese monetary policy shock). Noticeably, South Korea has the smallest average degree of passthrough despite being within extremely close geographic proximity to each other, as well as China being South Korea's largest trading partner. Looking at the heatmap in Appendix D, notice that what brings down the South Korean ρ average is a relatively low passthrough in Consumer Discretionary and Financials. This makes sense, as these industries are probably less connected cross-border between China and South Korea (both upstream and downstream), especially for intermediates, so Chinese monetary policy shocks have a smaller passthrough effect on intermediates related to these two categories, as opposed to the higher passthrough for industrials, materials, and info tech/ communications intermediates.

Direct versus Network Effects

The average β^{MP} reveals that equity returns respond to Chinese monetary policy shocks. However, the results from Table 3 alone do not differentiate between the effect size as a result of a direct effect from the shock or the indirect effect as a result of the firms being in a production network. Table 4 decomposes this effect into direct and network effects and provides the share of the contribution the network effect has on the total effect of the shock.

Stock Returns (Upstream)	**(1)**	**(2)**	**(3)**
Acemoglu et al. (2016) Decomposition	W_{2009}	W_{2019}	$W^{Avg}_{2009-2019}$
Avg. Target Direct Effect	-0.202***	-0.184**	-0.196***
	(0.075)	(0.075)	(0.074)
Avg. Target Network Effect	-0.448***	-0.484***	-0.455***
	(0.078)	(0.084)	(0.077)
Network Share (%)	68.91***	72.51***	69.91***
	(0.050)	(0.071)	(0.053)

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

Table 4: Heterogeneous SAR Effect Decomposition (Upstream)

Notes: Heterogeneous SAR Effect Decomposition of point estimates in Table 3. Standard Errors Wild bootstrapped using 1000 iterations.

The decompositions here suggest that the network effect drives a majority of the effect size shown in the SAR results — that is, the equity responses seen in the regression results are reliant on the monetary policy shock moving throughout the production network. While the direct effect of the shock itself is important, the indirect effect of the shock is the primary driver of the shock — specifically, it is the connection of firms upstream of China that is important in the transmission of Chinese policy. These propagation linkages appear to increase over time, with the network share increasing about 4pp over a decade, with an average of about 70% network share when averaging the weighting matrix over a decade. This suggests some degree of "entrenchment" of upstream firms within the Chinese production chain and that monetary policy shocks affect upstream firms in a relatively consistent manner over a decade (2009-2019). Similar to Di Giovanni and Hale (2022), production linkages are an important component in the transmission of monetary policy shocks. Interestingly, we find that the network effect for the Chinese shock is larger than the US shock examined in Di Giovanni and Hale (2022), who find that the United States has a network effect of roughly 66%. This makes sense, given China has a larger share of global intermediate goods import demand than the United States.

The importance of the production network in the propagation of Chinese monetary policy shocks, as shown in these results, compliment the argument presented in Miranda-Agrippino et al. (2020) and Huang et al. (2014) — Chinese monetary policy primarily transmits through global value chains and international trade. We find limited evidence of the expenditure shifting channel in the upstream scenario. How do the upstream results fit into the demand shock story? Recall that in the upstream case, the assumption is that firms upstream of China are hit with a negative demand shock due to a contractionary domestic Chinese monetary policy shock. Namely, the argument is that foreign firms who provide Chinese domestic firms with intermediate goods would export less due to reduced Chinese demand — this should be reflected as negative equity returns. If this hypothesis were to hold, then the linkages between these upstream firms (more importantly, being able to empirically link these sectors with China) should show evidence of 1) the propagation of the policy shock through these linkages and 2) negative equity returns. With respect to the importance of the linkages, the SAR results show that there is a high degree of passthrough throughout the production network. The effect of these Chinese monetary policy shocks yields negative returns (on average) across country-industries. However, more importantly, the effect of this shock is primarily driven by the production linkages rather than the direct effect of the Chinese shock. The empirical upstream results confirm that Chinese policy shocks travel from China to its upstream suppliers and support the upstream demand shock hypothesis.

4.3 Downstream Propagation

Repeating the exercise for the downstream case, Table 5 shows the point estimate from three SAR estimations with differing W weights.

Stock Returns (Downstream)	**(1)** W_{2009}	**(2)** W_{2019}	**(3)** $W^{Avg}_{2009-2019}$
Average ρ	0.65***	0.65***	0.65***
	(0.014)	(0.014)	(0.013)
Average Target Factor	-0.171*	-0.168*	-0.170*
	(0.089)	(0.091)	(0.089)
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 (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 upstream propagation. Three different empirical W are chosen, — 2010, 2017, and an average of input/output coefficients between 2009 and 2019. Returns have been winsorized at the 1% level. The coefficients for the Target factor represent the percentage point change in the average annualized stock returns in response to a 1 percentage point surprise increase. Constant and controls omitted for ease of exposition. Standard Errors Wild bootstrapped using 1000 iterations.

The results are broadly similar to the upstream case — a high degree of monetary policy shock passthrough that is very statistically significant ($\rho \approx 0.65$ across the board), and the effect of a 1pp increase in the Target Factor is a roughly 17bp decrease in equity returns that is also statistically very significant. The equity responses are marginally different from the upstream case (a differential of roughly 3bp), suggesting that regardless of where firms lie on the production chain vis-à-vis China, Chinese monetary policy shocks flow both up and downstream. A limitation of this type of analysis, however, is the inability to disentangle re-imports and re-exports throughout the global value chain. That is, because the MRIO table weights by gross values of imports and exports of intermediate goods, there is not a straightforward way to account for the possibility that a downstream and upstream firm are the same but are importing an intermediate good from China for use in the production of another intermediate good that is then exported to China. The results do, however, suggest that both upstream and downstream production linkages do matter on average in the transmission of Chinese monetary policy shocks globally.

Downstream Heterogeneity

Figure 9 shows the heatmap for the 77 country-industry pairs' equity elasticities in response to a contractionary Chinese monetary policy shock. Similar to the upstream scenario, we find limited evidence of expenditure shifting. While some country-industry pairs show positive equity returns, the average results are mainly negative. The interpretation is similar to the upstream case — for industries that exhibit positive returns, we conjecture that this represents the degree of ease with which a firm can find a different supplier outside of Chinese intermediate goods exporting firms. The point estimates thus represent the degree of reliance of a downstream firm on Chinese intermediates.

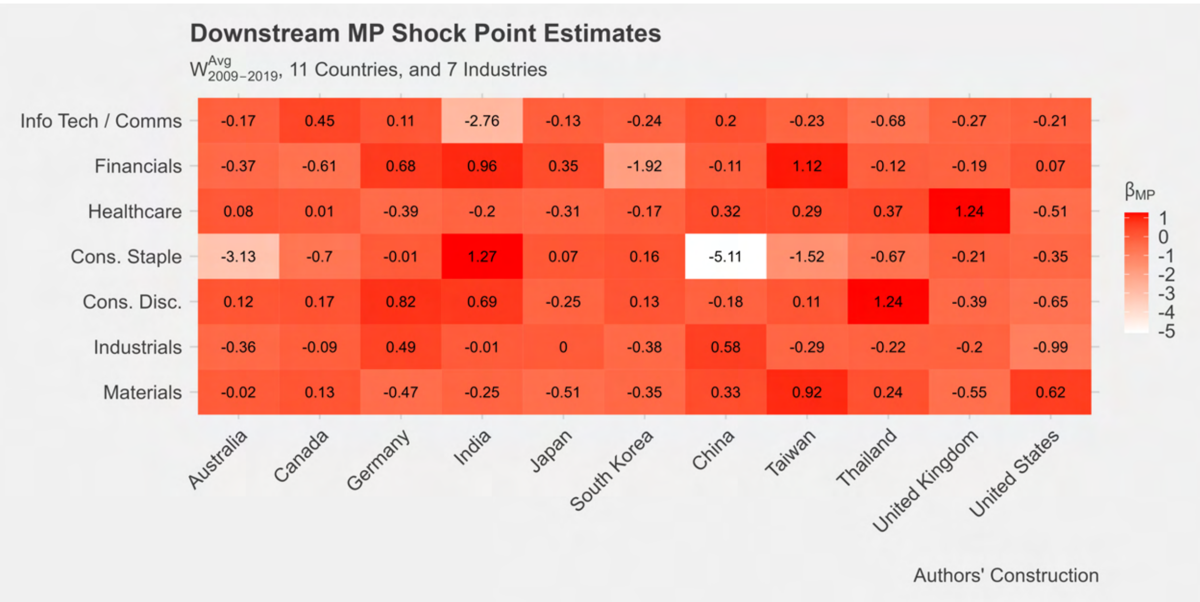


Figure 9: Heatmap of β^{MP} Estimate

Notes: Distribution of β^{MP} using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 5

Similar to the upstream case, the heterogeneity of the shock passthrough across countries and industries is relatively similar. Figure 20 and Figure 21 show the country and industry level distribution of the ρ point estimates. While Appendix Subsection D.5 presents the heatmap by country-industry. Because the results are broadly similar, the logic is similar to the upstream case, with the difference being the transmission is downstream. Once again, South Korea shows the smallest degree of monetary policy passthrough, mostly driven by the same industries in the upstream case — Financials and Consumer Discretionary. This suggests that in either the up or downstream case, South Korean firms that export and import intermediate goods in the financial and consumer discretionary sectors either have higher trade barriers (which would dampen policy passthrough) or are less connected than other sectors of the economy in a cross-border sense.

Direct versus Network Effects

Table 6 examines the decomposition of the total effect of the Chinese monetary policy shock, assuming a downstream propagation of the shock. The results are very similar to the upstream case, with the network effect being the dominant driver of the effect of Chinese monetary policy shocks — notice, however, two things. Here, the network effects account for roughly 78% of the total effect of the shock, which is about 8pp higher than in the upstream case. This could be explained as differences in the amount of "stops" goods have to make along the production chain, indicating that there may be more stops in the downstream case when compared to the upstream case – increasing the contribution of the network to the propagation of the shock. Alternatively, our sample can be more connected downstream of China, which would explain the significantly larger network share. Second, the network shares are relatively stable across time — suggesting the relative importance of China as an intermediate goods supplier has been consistent between 2009 and 2019. Contrast this with the upstream case, which saw the network share increase, suggests that the number of upstream connections (in other words, Chinese firms being connected to more upstream suppliers) may be increasing. Overall, the downstream results generally mirror those of the upstream results, suggesting that firms all along the Chinese supply chain are affected by Chinese monetary policy shocks — in fact, these sectoral and country-level linkages are primarily propagating the monetary policy shock.

Stock Returns (Downstream) Acemoglu et al. (2016) Decomposition	**(1)** W_{2009}	**(2)** W_{2019}	**(3)** $W^{Avg}_{2009-2019}$
Avg. Target Direct Effect	-0.171**	-0.168**	-0.170**
	(0.076)	(0.078)	(0.076)
Avg. Target Network Effect	-0.588***	-0.639***	-0.596***
	(0.089)	(0.091)	(0.089)
Network Share (%)	77.46***	79.20***	77.80***
	(0.081)	(0.090)	(0.086)

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

Table 6: Heterogeneous SAR Effect Decomposition (Downstream)

Notes: Heterogeneous SAR Effect Decomposition of point estimates in Table 5. Standard Errors Wild bootstrapped using 1000 iterations.

Recall that the downstream shock assumes Chinese monetary policy shocks materialize as supply shocks. As the domestic financing situation becomes tighter due to contractionary monetary policy shocks, Chinese firms reduce their output – including intermediate goods. Global firms in this specific supply chain reliant on Chinese intermediates are immediately affected by a reduction in Chinese intermediates, reducing their output; this is a supply shock. And like the upstream scenario, this reduction in supply reflects as negative equity returns due to reduced output (and by extension, profits). The downstream results provide evidence of this — production linkages matter in the downstream propagation of the monetary policy shock across all countries and industries in the sample, equity returns are negative in response to contractionary Chinese monetary policy, and the network effect of these shocks are the primary driver (roughly 78%) of the total effect.

The SAR results suggest that Chinese monetary policy propagates into global value chains both as an upstream demand shock and a downstream supply shock — specifically, the linkages between China and other countries contribute the most to the transmission of Chinese monetary policy shocks worldwide. Although the existing literature finds some evidence of expenditure shifting as the primary transmission channel of Chinese monetary policy shocks, our analysis finds that the transmission of Chinese shocks is primarily through supply chain linkages. In both the upstream and downstream transmission, between 70 and 78% of the estimated impact of these Chinese monetary policy shocks can be attributed to these linkages. These results provide micro-evidence and are consistent with the aggregate results found in Miranda-Agrippino et al. (2020). The empirical results here provide a clearer picture of the nature of cross-border Chinese monetary policy spillovers.

5 A SOE Model with Chinese Spillovers

Using these empirical results, we show that a slight modification to the small-open economy model presented in Wei and Xie (2020) provides results that match the empirical results. The model is purely illustrative of the mechanism we highlight in the empirical results. Specifically, we show that negative supply and negative demand shocks have differing effects depending on the degree of exposure the SOE has to China. We highlight that the degree of home-bias can generate impulse responses of intermediate goods output that match the heterogeneous equity results in Section 4. Since we only introduce additional shocks at the firm level, we only include the relevant equations at the firm level and the equilibrium conditions. The household block, risk-sharing condition, and the firm's pricing problem will be relegated to Appendix E. The complete derivations can be found in Wei and Xie (2020).

5.1 Model Environment

Consider a New Keynesian model of a modal small-open economy (SOE). Households are infinitely lived and maximize their utility, subject to a budget constraint. Firms produce intermediate goods and final goods in a two-stage setup. At each stage of production, firms face a Calvo pricing environment with producer currency pricing (i.e., pricing is set (and is sticky) in the home currency of the exporter).[11] The SOE's monetary policy follows a standard Taylor rule. Our main departure from Wei and Xie (2020) model is the inclusion of an exogenous supply and exogenous demand shock for intermediate goods that originate from contractionary Chinese monetary policy. We abstract away from China proper and treat China as entirely exogenous. We assume that domestic Chinese monetary policy behaves in a standard manner, given the existing empirical literature. As a result, a contractionary Chinese monetary policy shock increases the cost of domestic external finance, reducing 1) the demand for foreign intermediate goods and 2) the supply of intermediate goods to export. We model these as exogenous supply and demand shocks to the SOE. For the SOE, monetary policy follows a standard Taylor-Rule. For notational purposes, variables with an asterisk, $(\cdot)^*$, denote Chinese variables in the Chinese currency, Renminbi (RMB). What we emphasize in this model is the role economic openness and home-bias plays in generating heterogeneous output reactions in response to Chinese monetary policy shocks.

5.2 Firms

Similar to Gong et al. (2016), Wei and Xie (2020) introduce N-stage production and trade in intermediate goods in the model. To keep the math tractable (and to get analytical expression), we will reduce this to a two-stage production process ($N = 2$). For the production of final goods, each final good requires 2-stages of production, where a domestic firms produce a unit continuum of differentiated outputs exhibiting constant returns to scale. In the first stage, intermediate output is either sold at home or exported abroad and is created by domestic labor. The production function for good $u \in [0, 1]$ is:

$$\underbrace{Y_{1H}(u)}_{\text{For Domestic Use}} + \underbrace{Y_{1H}^{X}(u)}_{\text{For Export}} = A_1 L_1(u) \tag{5}$$

A_1 is the first stage productivity and $L_1(u)$ is domestic labor used to produce good u. Output from the first stage that is sold domestically is: $Y_{1H} = \left[\int_0^1 Y_{1H}(u)^{\frac{\theta-1}{\theta}} du\right]^{\frac{\theta}{1-\theta}}$ with price $P_{1H} = \left[\int_0^1 P_{1H}(u)^{1-\theta} du\right]^{\frac{1}{1-\theta}}$. We can define the Chinese demand for this output as (at stage 1, but it is also applicable to stage 2):

$$Y_{1H}^{Xd}(u) = \left(\frac{P_{1H}(u)}{P_{1H}}\right)^{-\theta} \frac{Y_{1H}^{*} P_{1H}^{*} \mathcal{E}_t}{P_{1H}} \tag{6}$$

Y_{1H}^{*} is the exogenous Chinese demand for this good and we assume that it follows an $AR(1)$ process: $y_{1H,t}^{*} = \rho_1 y_{1H,t-1} + \epsilon_{1,t}$ where $y_{1H,t}^{*} = \ln Y_{1H}^{*}$ and $\rho_1 \in (0, 1)$. $\epsilon_{1,t}$ is distributed normally and i.i.d. (i.e., $\epsilon_1 \sim N(0, \sigma^2_{y_{1H}^*})$). We treat this as an exogenous Chinese import demand shock. The SOE produced goods in RMB is denoted as P_{1H}^{*}. When a domestic contractionary monetary policy shock occurs, changes to the amount of the SOE's stage 1 intermediate goods being exported are caused by an exogenous change in Chinese demand for these goods.

[11] We have a planned extension that brings in a flexible implementation of the three currency pricing paradigms (local currency, producer currency, and dominant currency), as derived in Gopinath et al. (2020).

For stage 2, the process is broken into two-steps. In the first step, the firm uses intermediate goods, from both domestic and Chinese sources, to produce a bundle of intermediate goods. In the second step, it uses this bundle of intermediate goods to produce a final good. The bundle of intermediate goods used in step one is a bundle of two composites — domestic produced intermediates from stage 1 and Chinese intermediate goods exported in the Chinese equivalent of stage 1.

$$\bar{Y}_2 = \Theta \bar{Y}_{1H}^{\gamma} \bar{Y}_{1F}^{1-\gamma} \tag{7}$$

$$\bar{Y}_{1H} = \left[\int_0^1 Y_{(1)H}(j)^{\frac{\theta-1}{\theta}} dj \right]^{\frac{\theta}{\theta-1}} \tag{8}$$

A stage 2 firm then purchases the domestically produced $Y_{1H}(j)$ amount of good j from stage 1, while $\bar{Y}_{1F}$ is the amount of intermediates purchased by the SOE from China that is produced in the Chinese equivalent of stage 1. The supply of Chinese intermediates is perfectly elastic in price and the SOE's firms are price takers when purchasing Chinese intermediates.

The stage 2 aggregate price index for inputs is then: $\bar{P}_2 = \bar{P}_{1H}^{\gamma} \bar{P}_{1F}^{1-\gamma}$. Note that $\bar{P}_{1H} = \left[\int_0^1 P_{1H}(u)^{1-\theta} du \right]^{\frac{1}{1-\theta}}$ and $\bar{P}_{1F} = T_t \mathscr{E}_t P_{1F}^*$. The price of Chinese produced intermediate goods in stage 1, priced in RMB, is P_{1F}^*. Departing from Wei and Xei (2020), we introduce our downstream supply shock here. Specifically, when contractionary Chinese monetary policy constrains the amount of exportable Chinese intermediate goods, the price of these intermediate goods increase. To simulate this, we introduce the downstream shock as an $AR(1)$ process of the unit cost of Chinese intermediate goods: $p_{1F,t} = \rho_1 p_{1F,t-1} + \epsilon_{2,t}$ where $p_{1F,t} = \ln(P_{1F}^*)$ and $\rho_2 \in (0, 1)$. $\epsilon_{2,t}$ is distributed normally and i.i.d. (i.e., $\epsilon_2 \sim N(0, \sigma_{P_{1F}}^2)$).[12]

Stage 2's second step sees the firm create a good using the first step's intermediate good composite, along with some labor. This production function is therefore:

$$Y_{2H}(u) + Y_{2H}^X(u) = \Theta^* A_2 \bar{Y}_2(u)^{\phi} L_2(u)^{1-\phi} \tag{9}$$

Where we define the normalization parameter, $\Theta^* = \left[(1-\phi)^{1-\phi} \phi^{\phi} \right]^{-1}$. From the SOE's perspective, $Y_{2H}^X(u)$ is the amount of this good that is being exported to China and has a demand function similar to the Stage 1 Chinese demand expression. Domestic demand for stages 1 and 2 ($n \in [1, 2]$)is:

$$Y_{nH}(u) = \left(\frac{P_{nH}(u)}{P_{nH}} \right)^{-\theta} \frac{\bar{Y}_{nH} \bar{P}_{nH}}{P_{nH}} \tag{10}$$

Further, we define the steady state share of goods sold at home in both stage 1 and 2 as:

5.3 Market Clearing

Given exogenous monetary policy, tariffs, Chinese demand, Chinese prices, the following conditions must hold:

[12] Here, we focus on the transmission of monetary policy shocks through intermediate goods trade. The demand shocks of final goods are not considered in this paper.

1. The representative household maximizes its utility, given prices and wages
2. Firms in each stage maximize their profits, given intermediate input good prices, wages, and all output prices except their own.
3. Intertemporal trade balance condition holds
4. The labor market clears and all goods markets clear for both stages, where:

$$L_t = \sum_{n=1}^{N} L_t^d, \quad Y_{nH} = Y_{nH}^d, \quad Y_{nH}^X = Y_{nH}^{Xd}$$

$$\bar{a}_1 = \frac{Y_{1H}^d}{Y_{1H}^d + Y_{1H}^X} \tag{11}$$

$$\bar{a}_2 = \frac{Y_{2H}^d}{Y_{2H}^d + Y_{2H}^X} \tag{12}$$

We note that, in additional to the home-bias parameter γ, $\bar{a}_1$ and $\bar{a}_2$ also measure the degree of economic openness in the model, with $\bar{a}_{n=1,2} \to 1$ describes an economy with less economic openness.

Since the steady state, flex price, and sticky price equilibria remain unchanged from the original paper, we forgo the derivations. These equilibria derivations can be found in Wei and Xie (2020).

5.4 The Role of Chinese Monetary Policy Shocks

We assume that Chinese monetary does not directly affect the SOE. Instead, Chinese monetary policy affects both the Chinese demand for the SOE's intermediate goods and the supply Chinese firms provide the SOE. In other words, Chinese monetary policy works domestically, but the spillover effect is through intermediate goods trade, and the strength of the transmission is governed by a country's degree of home-bias and economic openness. The model abstracts away from domestic Chinese monetary policy since we do not model this process within China. We assume that Chinese domestic transmission works in a standard way and in line with the empirical literature on Chinese monetary policy transmission (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), Fu and Ho (2022), and Shieh (2022)). As such, our two shock processes assume that the existence of the domestic transmission works and materializes as upstream negative demand shocks and downstream negative supply shocks.

5.5 Calibrating the Model

Since we want to simulate results that mirror two of China's main trading partners, we calibrate the model to some basic South Korean and Japanese data. Unless otherwise stated, all the other parameters are taken from Wei and Xie (2020). South Korea has roughly a 40% import share (relative to GDP), so we set $\gamma = 0.6$, which implies that South Korea has a modest amount of home-bias. Similarly, using the Trade in Value Added (TiVA) data from the World Trade Organization, we set $\bar{a}_1 = \bar{a}_2 = 0.50$. South Korea uses roughly 50% of its intermediate goods imports in its exports, which gives us a proxy measure of the amount of home-bias at each production stage. For Japan, the data suggests a higher degree of home-bias. We set $\gamma = 0.8$, implying a 20% import share of GDP, as well as setting $\bar{a}_1 = \bar{a}_2 = 0.8$, implying 20% of foreign intermediates are used for export. Comparing the South Korean calibration to the Japanese one, South Korea has less home-bias in production than Japan. We also set our shock persistence to 0.66 and the shock standard deviation to 1. All other parameters are standard in the open-economy literature.

Parameter Values: South Korean Case

	Parameter	Value	**Comments**
Discount Rate	β	0.99	4% interest rate in a quarterly model
Intertemporal Elasticity of Substitution	σ	2	Corsetti et al. (2010)
Share of Home Traded Goods (Home-Bias)	γ	0.60	Implies Import Share of 40% of GDP
Elasticity of Substitution (Consumption)	θ	6	Gong et al. (2016); Galí and Monacelli (2008)
Share of Intermediate Goods in Production	ϕ	0.60	Wei and Xie (2020)
Share of Goods Selling to Domestic Market	$\bar{a}_1, \bar{a}_2$	0.50	Implies 50% Foreign Intermediates used for Export
Calvo Parameter	α_1, α_2	0.85	Implies average duration of wage contract of 1.5 years
Persistency of Chinese Supply Shock	ρ_1	0.66	
Standard Deviation of Chinese Supply Shock	$\sigma^2_{P_{1F}}$	1	
Persistency of Chinese Demand Shock	ρ_2	0.66	
Standard Deviation of Chinese Demand Shock	$\sigma^2_{y^*_{2H}}$	1	

Parameter Values: Japanese Case

	Parameter	Value	**Comments**
Discount Rate	β	0.99	4% interest rate in a quarterly model
Intertemporal Elasticity of Substitution	σ	2	Corsetti et al. (2010)
Share of Home Traded Goods (Home-Bias)	γ	0.80	Implies Import Share of 20% of GDP
Elasticity of Substitution (Consumption)	θ	6	Gong et al. (2016); Galí and Monacelli (2008)
Share of Intermediate Goods in Production	ϕ	0.60	Wei and Xie (2020)
Share of Goods Selling to Domestic Market	$\bar{a}_1, \bar{a}_2$	0.80	Implies 20% Foreign Intermediates used for Export
Calvo Parameter	α_1, α_2	0.85	Implies average duration of wage contract of 1.5 years
Persistency of Chinese Supply Shock	ρ_1	0.66	
Standard Deviation of Chinese Supply Shock	$\sigma^2_{P_{1F}}$	1	
Persistency of Chinese Demand Shock	ρ_2	0.66	
Standard Deviation of Chinese Demand Shock	$\sigma^2_{y^*_{2H}}$	1	

5.6 Simulation Results

In response to a negative supply and negative supply shock, both South Korean and Japanese intermediate goods production decreases. Figure 10 and Figure 11 shows the generalized decrease in output but also the heterogeneous responses by country. These results are complementary to the empirical results from the SAR. Recall that the direct effect of the upstream and downstream shocks was negative equity returns, but the magnitude of the responses varied across countries. In Figure 10, we observe that South Korea, with relatively less home-bias, has a more pronounced reduction in intermediate goods output in response to a negative Chinese demand shock. Japan, which is exposed but less so than South Korea, also has a reduction in intermediate goods output. This tracks with both intuition and the empirical results. Intuitively, since South Korea is more connected to China by virtue of being more "open", we see that the reduction in intermediate goods output is higher than that of Japan. The downstream simulation results, shown in Figure 11, have a similar result. South Korea (relative to Japan), which is more exposed to Chinese suppliers, has a larger intermediate goods output response from a negative Chinese supply shock. In the SAR results, South Korea has a larger negative equity response than Japan. In the country-specific equity response breakdowns shown in Figure 15 and Figure 22 in Appendix D, we observe that South Korea has more negative equity returns than Japan in both the upstream and downstream shock scenarios.

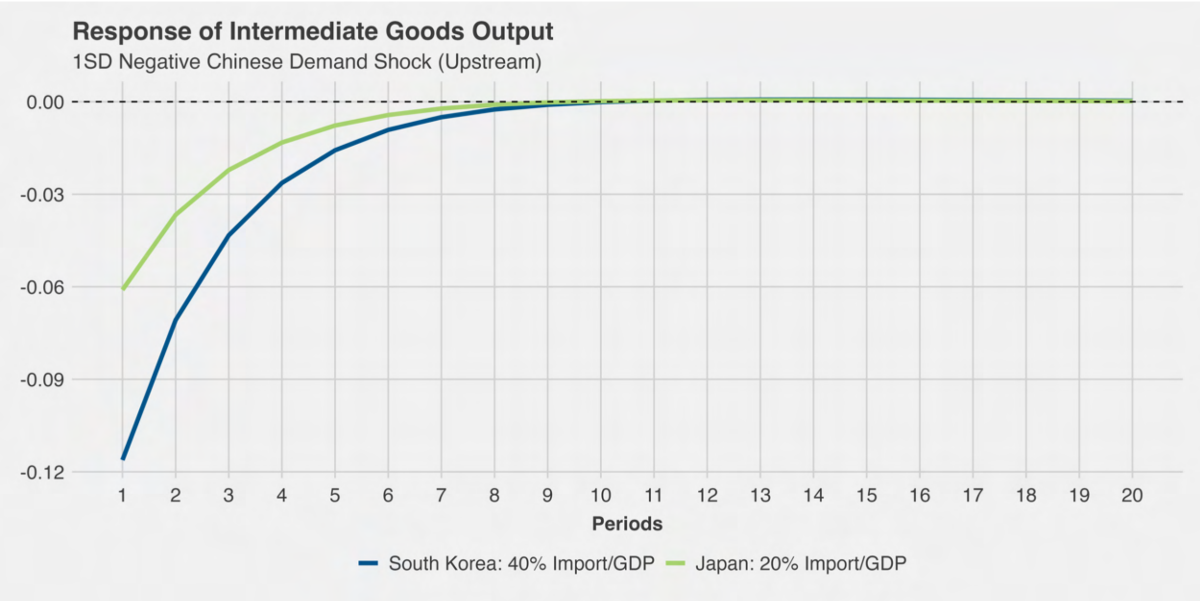


Figure 10: Intermediate goods output IRF

Notes: IRF response units are percent deviations from steady state.

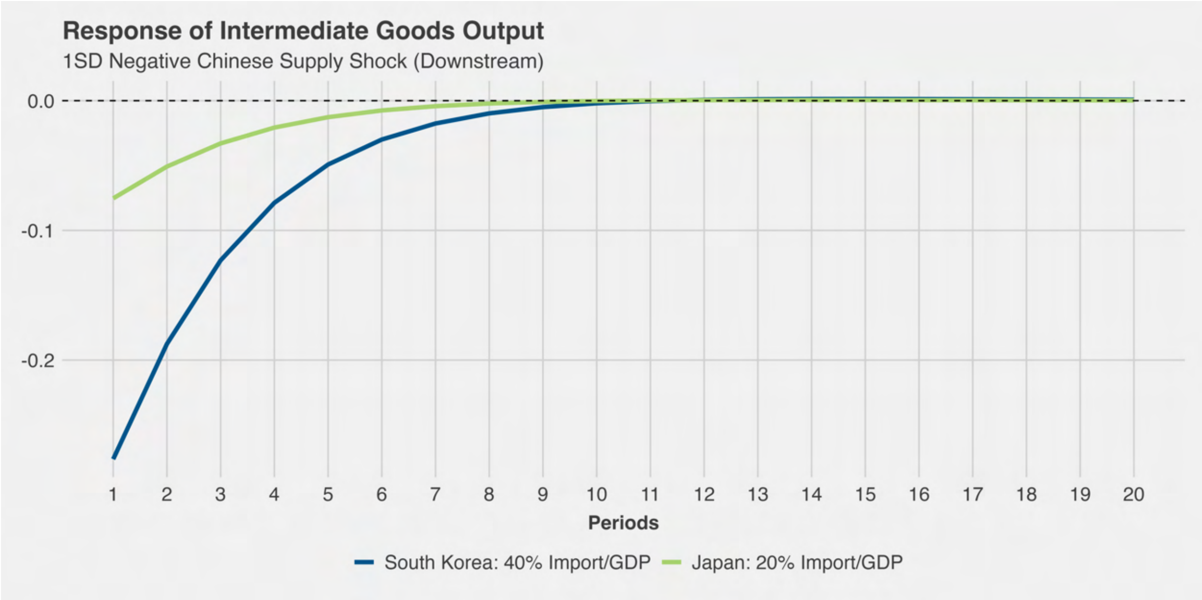


Figure 11: Intermediate goods output IRF

Notes: IRF response units are percent deviations from steady state.

Overall, we argue that in a standard SOE model with a supply chain component, we can easily capture the heterogeneous transmission of Chinese shocks throughout the supply chain through the degree of home-bias. In countries with more home-bias, the effects of a China shock are less pronounced due to lower exposure to supply chains that connect with China — these countries are more "isolated" from China shocks. In countries more exposed, the spillover is more pronounced due to higher exposure to foreign inputs.

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 have any global implications. Using a simple and tractable spatial econometric model to decompose the effects of these shocks into total, direct, and network effects, we find the following. First, Chinese monetary policy shocks matter and propagate through supply chains. We characterize this transmission as supply and demand shocks originating from China. We find that between 70 and 79% of the observed equity responses are due to input-output linkages between China and other countries. Second, we show limited evidence of expenditure shifting in response to a contractionary Chinese monetary policy shock, departing from other results in the literature. We instead argue that the few positive equity responses we observe measure the degree of substitutability in a particular country-industry — that is, how easily a country-industry can substitute away from China as either supplier or customer in response to negative supply or demand shocks. We then use a slightly modified SOE model with supply chain integration to show that the degree of home-biasedness (proxying for the degree of foreign exposure) affects the degree of transmission of these shocks, with impulse responses from two cases matching the empirical results in the SAR. Specifically, the heterogeneous equity responses we observe can be explained by a country's level of home-bias. 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 transmits worldwide.

The empirical results suggest that a Chinese monetary policy shock while acting in a standard way in the domestic environment (tighter financial conditions in the Mainland), materializes in different manners 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.

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 Construction of High Frequency Measure of Chinese Monetary Policy

The monetary policy factors were created in Shieh (2022). We provide a semi-detailed summary of the factor rotation process here, leaving out the additional analysis done in Shieh (2022). The algorithm in constructing the surprises, are in the main text. For a more detailed discussion, please refer to the original paper.

A.1 Factor Rotation and Interpretation

We detail the case where we extract two factors, the Target and Path factors using PCA and then rotate. If one were to just extract a single factor and rotate, this singular factor would be closer to in principle 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 167×2 matrix:[13]

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

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 orthogononal 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 be the known loadings for 3m IRS factors 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

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

[13] 167 PBOC announcements and 2 latent factors.

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.

The Target Factor, or Z_1 will be the monetary policy shock of choice in this study, as it measures the pure surprise change in the current monetary policy stance.

Appendix B An Estimable Production Model

Consider the following multi-country sectoral production model that allows for monetary policy to have a heterogeneous effect on stock prices. This simple model yields an equation similar to a spatial autoregression that can be estimated. The set up below follows most closely with Di Giovanni and Hale (2022), Todorova (2018), and Ozdagli and Weber (2017):

A Simple Production Economy

Let K by the number of countries in a production network, where there exists L industries. This implies that there are $N = K \times L$ country-industry pairs, where each industry produces a differentiated product that can be used as an intermediate good or as a final consumption good by households in the economy. Let i be a specific industry and π_i be that specific industry's profits. Industries maximize their profits by choosing homogenous labor ℓ and intermediate inputs x_{ij} from industries $j = 1, \cdots, N$, given wages ω and prices $\{p_i\}_{i=1}^{N}$. Industries also face a pre-determined fixed cost, f_i. Assume that each industry's production process follows Cobb-Douglas production. Industry i's objective is therefore:

$$\pi_i = \max p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - \omega \ell_i - f_i \tag{B.1}$$

$$y_i = \ell_i^{\lambda} \left(\prod_{j=1}^{N} x_{ij}^{w_{ij}} \right)^{\alpha} \tag{B.2}$$

Where industry i's output is y_i, λ and α are factor shares, and the share of inputs w_{ij} from industry j used in i's production satisfies $\sum_{j=1}^{N} w_{ij} = 1$.

The FOCs of this maximization problem yield:

$$\alpha w_{ij} R_i = p_j x_{ij} \tag{B.3}$$

$$\lambda R_i = \omega \ell_i \tag{B.4}$$

Where $R_i = p_i y_i$ is defined as revenue for i. Using (B.3) and (B.4), we get:

$$\pi_i = (1 - \lambda - \alpha) R_i - f_i \tag{B.5}$$

Households

Consumers maximize their utility subject to a budget constraint, where they consume N products using the income earned from their labor, profits, and transfers. In this set up, assume that fixed costs industries take on are transfers to households. Thus, the consumer's problem is:

$$\max \sum_{i=1}^{N} \log(c_i) \tag{B.6}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} p_i c_i = \omega \sum_{i=1}^{N} \ell_i + \sum_{i=1}^{N} \pi_i + \sum_{i=1}^{N} f_i \tag{B.7}$$

Using the household FOC and combining with (B.4) and (B.5):

$$c_i = \frac{\omega \sum_{i=1}^{N} l_i + \sum_{i=1}^{N} (\pi_i + f_i)}{N p_i} = \frac{(1-\alpha) \sum_{i=1}^{N} R_i}{N p_i} \tag{B.8}$$

The goods clearing condition (in terms of revenue) is thus:

$$y_i = c_i + \sum_{j=1}^{N=1} x_{ij} = \frac{(1-\alpha) \sum_{i=1}^{N} R_i}{N p_i} + \frac{\alpha \sum_{j=1}^{N} w_{ji} p_j y_j}{p_i} \tag{B.9}$$

$$\Longrightarrow \quad R_i = (1-\alpha) \frac{\sum_{i=1}^{N} R_i}{N} + \alpha \sum_{j=1}^{N} w_{ji} R_j \tag{B.10}$$

This goods clearing condition implies that household demand shocks can affect industry revenue and that shocks can propagate through production networks. Notice here that the size of industry j that buys intermediate goods from i (the R_j term), as well as the importance of industry i as a supplier to j, denoted as $\alpha \times w_{ji}$. Let $W \equiv [w_{ij}]$ be the matrix of intermediate shares and a $R \equiv (R_1, \cdots, R_N)'$ be a vector of revenues, which leads to:

$$\left(I - \alpha W'\right) R = (1-\alpha) \begin{pmatrix} \left(\sum_{i=1}^{N} R_i\right)/N \\ \vdots \\ \left(\sum_{i=1}^{N} R_i\right)/N \end{pmatrix}_{N \times 1} \tag{B.11}$$

Money Supply and Equilibrium

Assume that intermediate goods are purchased using trade credit and that consumers purchase goods using cash. Thus the money supply, M, will affect prices using the following cash-in-advance constraint:

$$\sum_{i=1}^{N} p_i c_i = (1-\alpha) \sum_{i=1}^{N} R_i = M \tag{B.12}$$

Combining (B.11) and (B.12) yields:

$$\left(I - \alpha W'\right) R = (1-\alpha) \begin{pmatrix} M/N \\ \vdots \\ M/N \end{pmatrix}_{N \times 1} = m \tag{B.13}$$

Let $\pi \equiv (\pi_1, \cdots, \pi_N)'$ and $f \equiv (f_1, \cdots, f_N)'$. Substituting (B.13) and (B.5) and log-linearizing, we get the following profit expression:

$$\pi = \left(I - \alpha W'\right)^{-1} (1 - \lambda - \alpha) m - f \tag{B.14}$$

$$\implies \bar{\pi}\hat{\pi} = \left(I - \alpha W'\right)^{-1} (1 - \lambda - \alpha) \bar{m} \widehat{M} \tag{B.15}$$

Define $\beta \equiv (\beta_1, \cdots, \beta_N)'$ with

$$\beta_i = \frac{(1 - \lambda - \alpha)\bar{m}}{\bar{\pi}_i} \tag{B.16}$$

Which implies:

$$\hat{\pi} = \left(I - \alpha W'\right)^{-1} \beta \widehat{M} \tag{B.17}$$

Which can be rewritten as the reaction of the deviation of net income as:

$$\hat{\pi} = \alpha \times W' \times \hat{\pi} + \beta \times \widehat{M} \tag{B.18}$$

Notice that equation (B.18) takes on the form of an estimable SAR, shown in Equation 2. An industry's net income reacts to changes in the money supply, $\hat{M}$, as well as how its own customers react to the shock $W' \times \hat{\pi}$. Changes to industry net income are taken as changes to the industry stock returns.

Appendix C Data Appendix

C.1 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 7: Countries and Stock Exchanges

Notes: $N = 11$ economies in sample. Industry level stock returns collected from industry-indices for each country on the above stock exchanges from Bloomberg Terminal. Returns calculated as log-difference in monthly index price and then annualized.

C.2 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 8: ADB MRIO Industries

Notes: ISIC industry classification with the ADB MRIOT code, as well as the ISIC Codes range.

C.3 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 9: GICS Sectors

Notes: Information Tech and Comm Services combined, while Energy, Utilities, and Real Estate dropped from sample.

C.4 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 10: 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.

C.5 Distribution of Returns

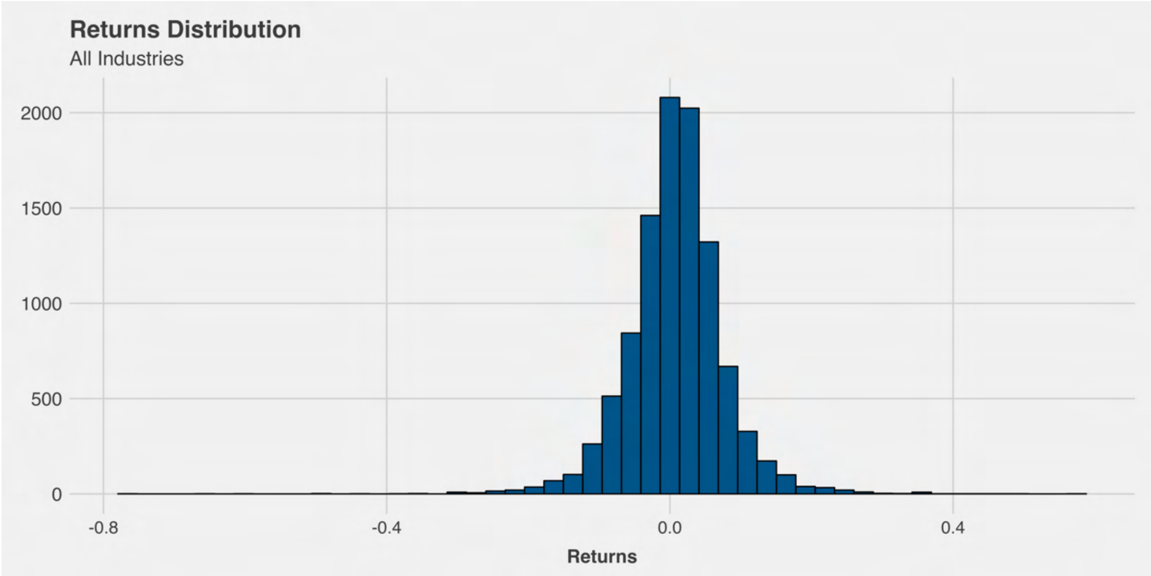


Figure 12: Distribution of Returns

Notes: Distribution of Returns from Jan 2009 to Dec 2019 encompassing all 7 GICS industries.

C.6 Distribution of Winsorized Returns

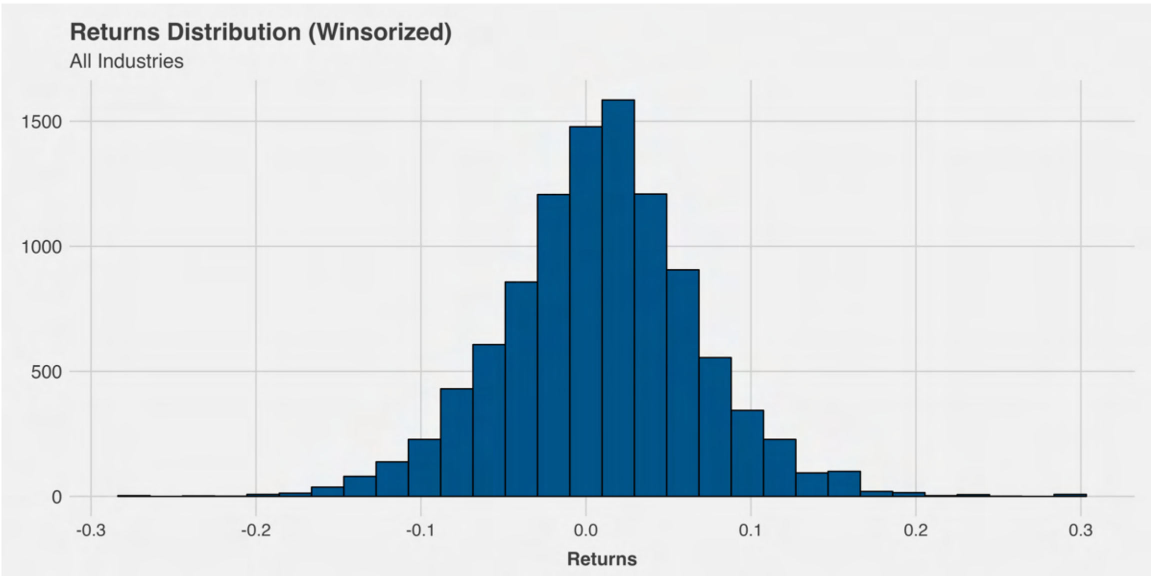


Figure 13: Distribution of Winsorized Returns

Notes: Distribution of Returns from Jan 2009 to Dec 2019 encompassing all 7 GICS industries winsorized at the 1% level.

Appendix D Additional SAR Results

D.1 Upstream ρ Heatmap

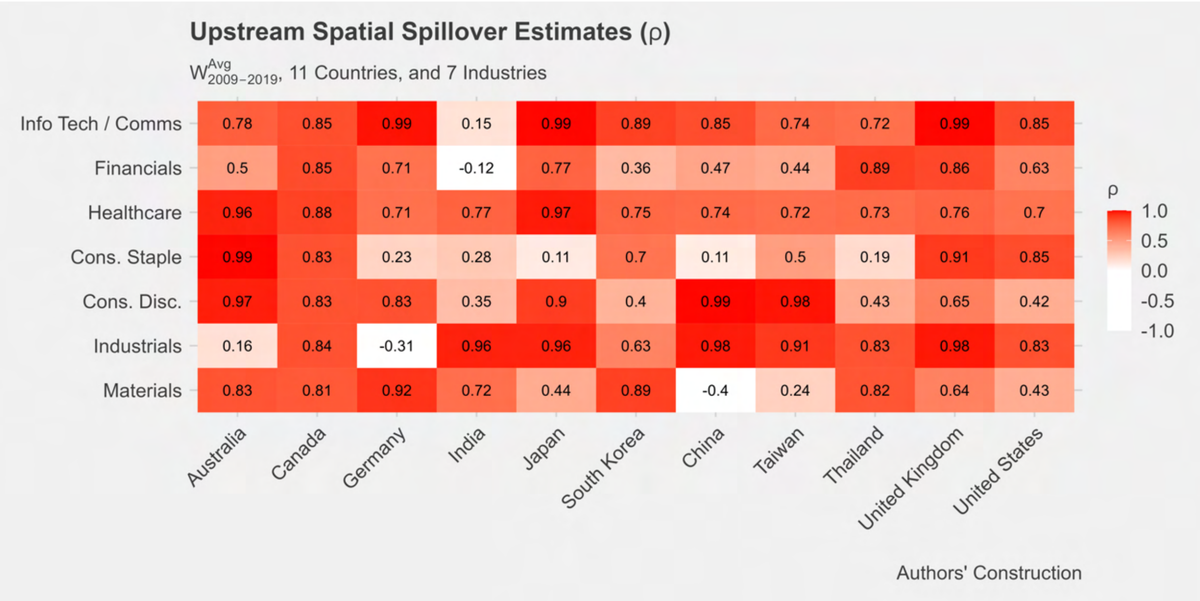


Figure 14: Heatmap of Passthrough Parameter, ρ

Notes: Distribution of ρ using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 3

D.2 Upstream β^{MP} Distributions

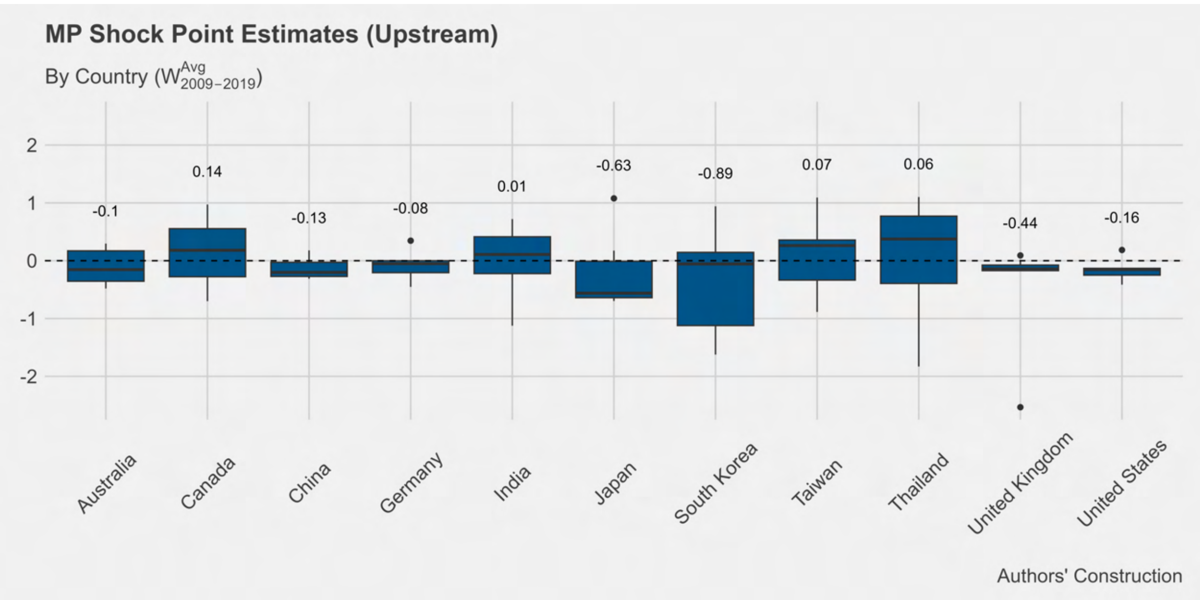


Figure 15: Distribution of β^{MP} Estimate by Country

Notes: Distribution of β^{MP} (by country) using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 3

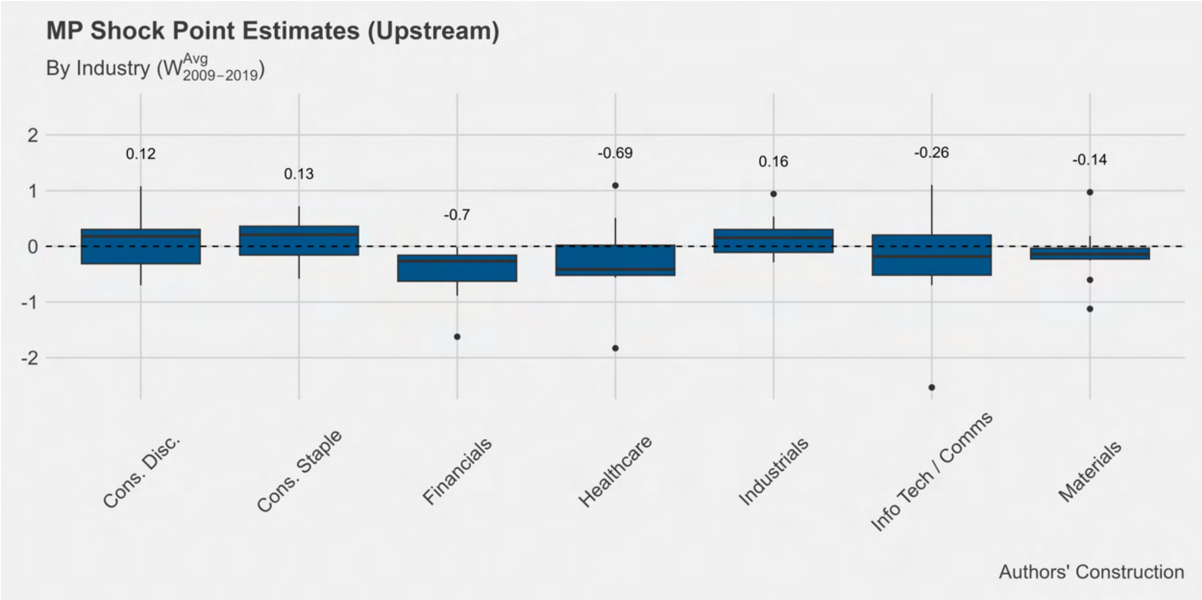


Figure 16: Distribution of β^{MP} Estimate by Industry

Notes: Distribution of β^{MP} (by industry) using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 3

D.3 LeSage and Pace (2009) Decomposition of Total Effect (Upstream)

Stock Returns (Upstream) LeSage and Pace (2009) Decomposition	**(1)** W_{2009}	**(2)** W_{2019}	**(3)** $W^{Avg}_{2009-2019}$
Avg. Target Direct Effect	-0.269***	-0.243***	-0.261***
	(0.075)	(0.075)	(0.074)
Avg. Target Network Effect	-0.381***	-0.425***	-0.391***
	(0.078)	(0.084)	(0.077)
Network Share (%)	58.63***	63.67***	59.96***
	(0.050)	(0.071)	(0.053)

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

Table 11: Heterogeneous SAR Effect Decomposition (Upstream)

Notes: Heterogeneous SAR Effect Decomposition of point estimates in Table 3. Standard Errors Wild bootstrapped using 1000 iterations.

D.4 Upstream Indirect and Direct Effect Distributions

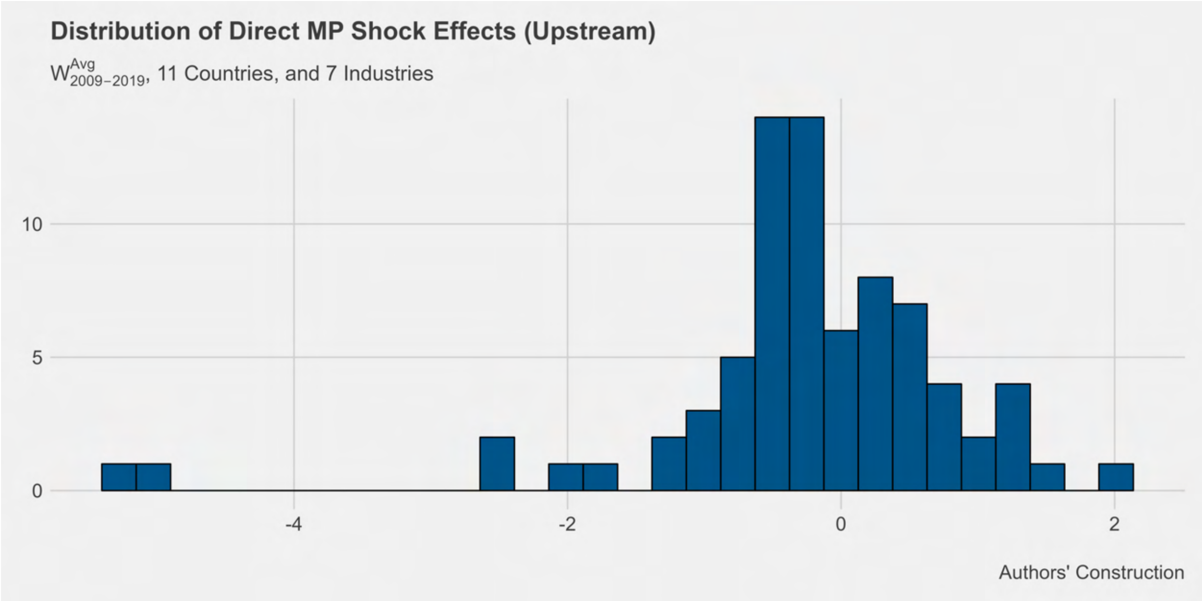


Figure 17: Distribution of Direct Effect Estimates

Notes: Distribution of Direct Effect Estimates using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 11

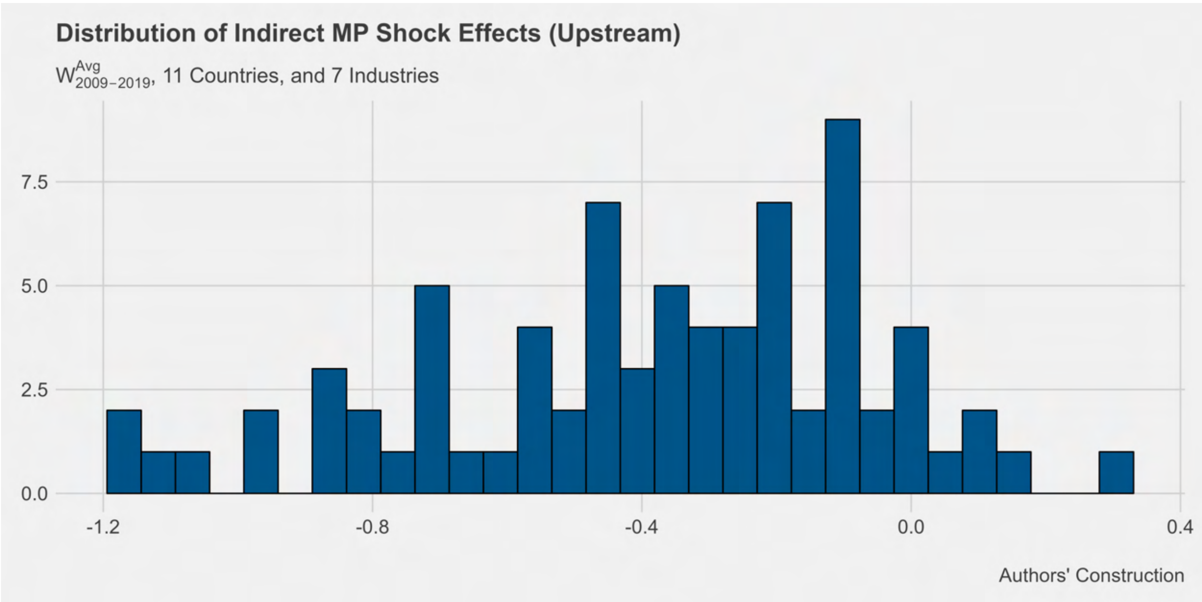


Figure 18: Distribution of Indirect Effect Estimates

Notes: Distribution of Indirect Effect Estimates using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 11

D.5 Downstream ρ Heatmap

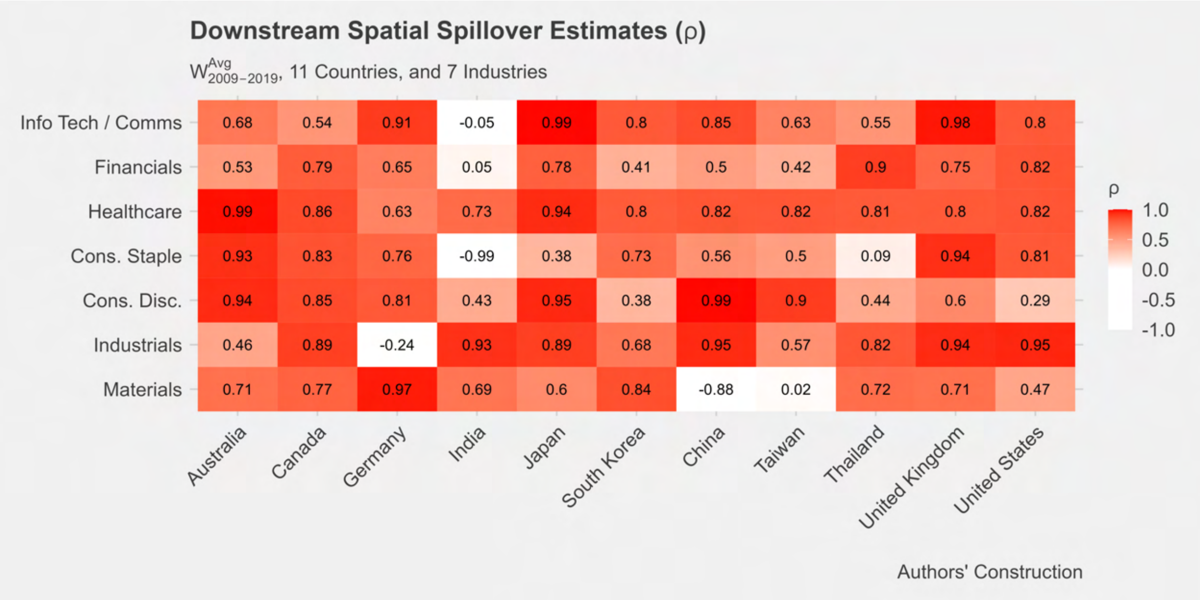


Figure 19: Heatmap of Passthrough Parameter, ρ

Notes: Distribution of ρ using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 3

D.6 Downstream ρ Distributions

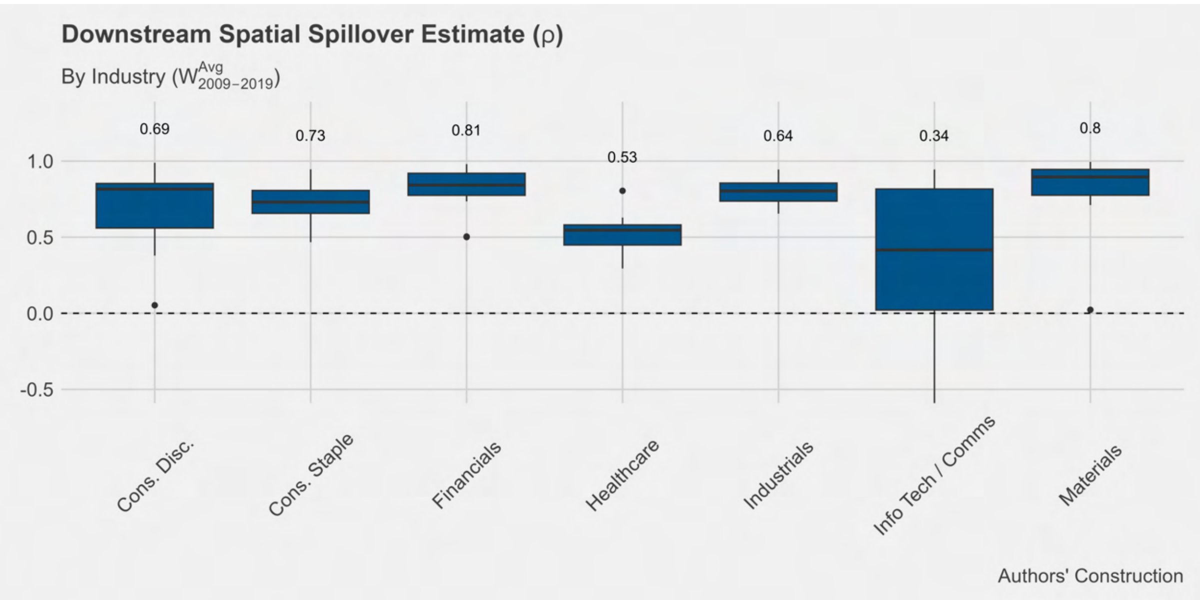


Figure 20: Box Plot of Passthrough Parameter, ρ, by Industry

Notes: Distribution of ρ by industry using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 5

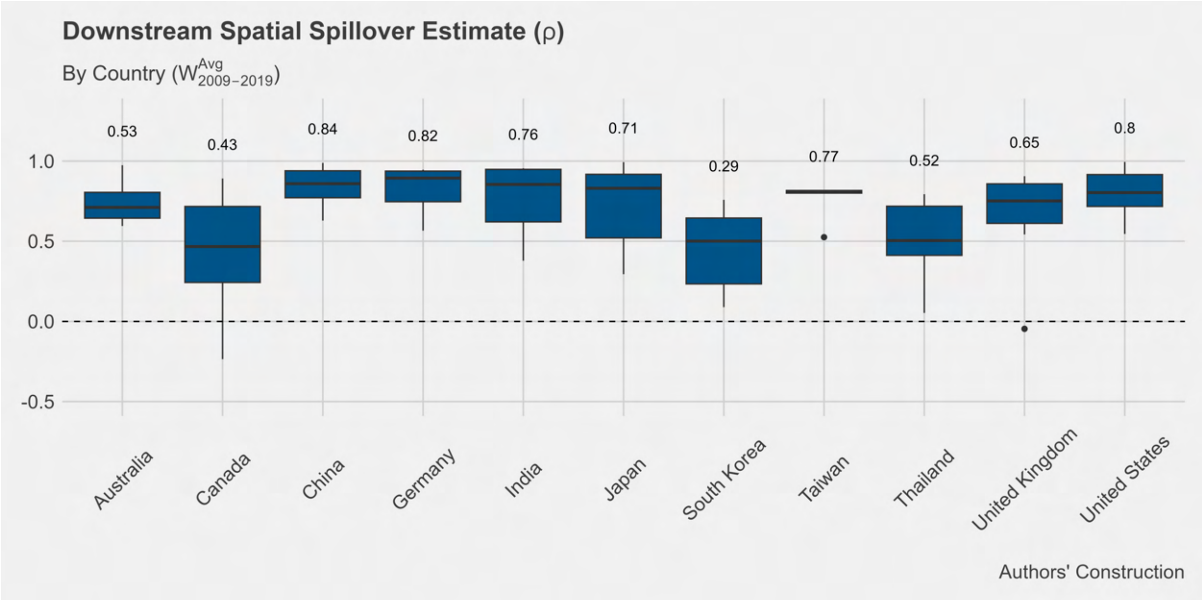


Figure 21: Box Plot of Passthrough Parameter, ρ, by Country

Notes: Distribution of ρ by country using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 5

D.7 Downstream β^{MP} Distributions

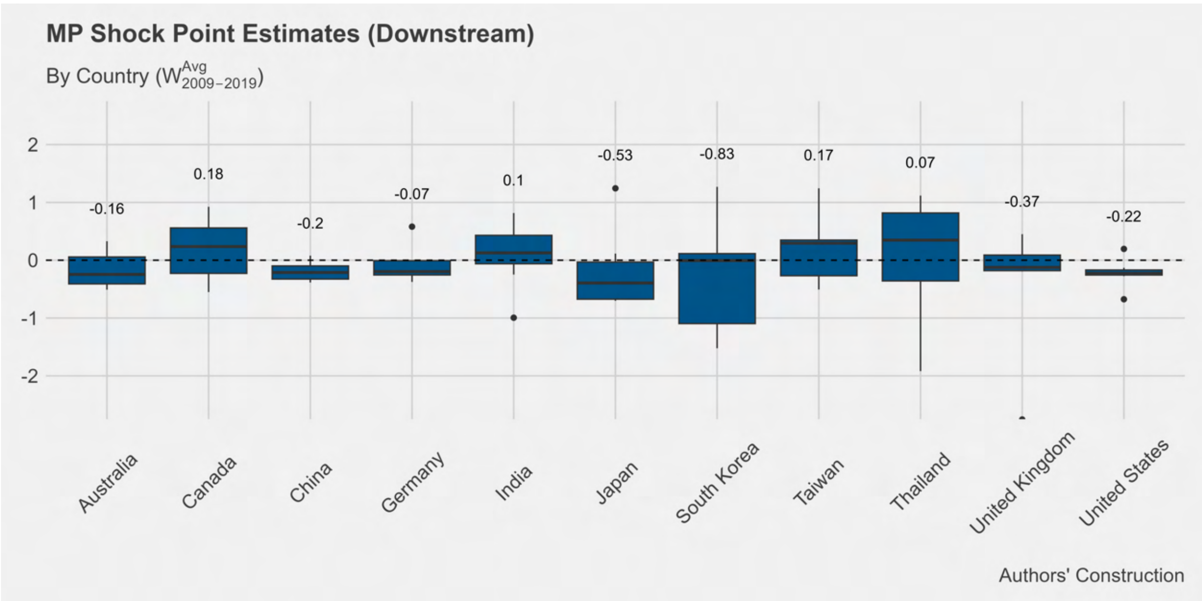


Figure 22: Distribution of β^{MP} Estimate by Country

Notes: Distribution of β^{MP} (by country) using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 5

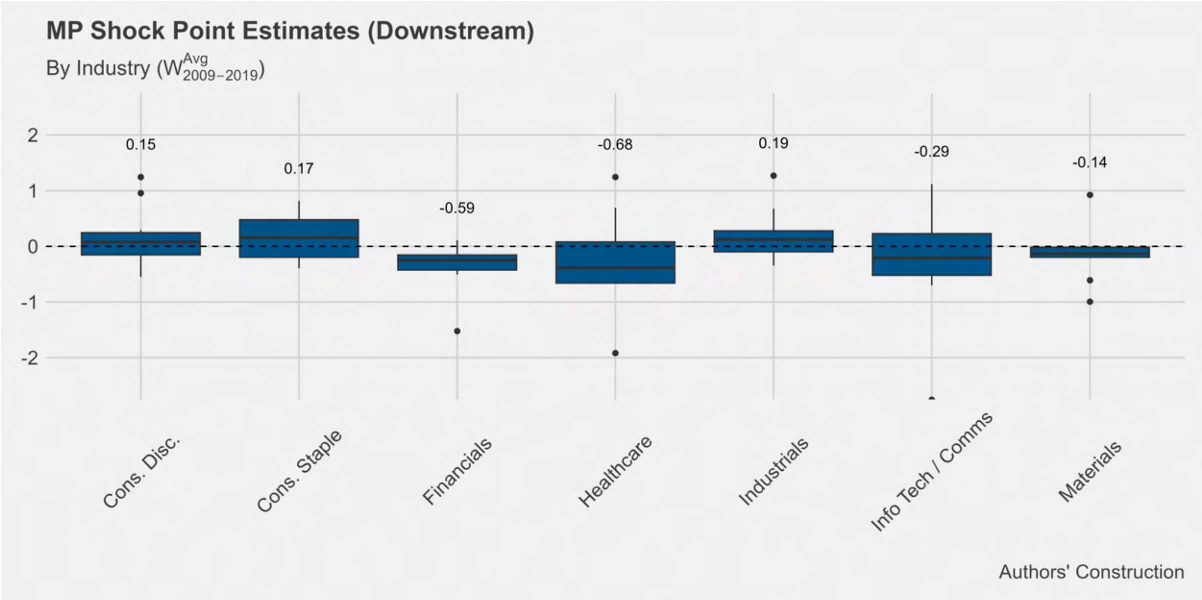


Figure 23: Distribution of β^{MP} Estimate by Industry

Notes: Distribution of β^{MP} (by industry) using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 5

D.8 LeSage and Pace (2009) Decomposition of Total Effect (Downstream)

Stock Returns (Downstream) LeSage and Pace (2009) Decomposition	**(1)** W_{2009}	**(2)** W_{2019}	**(3)** $W^{Avg}_{2009-2019}$
Avg. Target Direct Effect	-0.265***	-0.256***	-0.261***
	(0.076)	(0.078)	(0.076)
Avg. Target Network Effect	-0.494***	-0.551***	-0.504***
	(0.087)	(0.091)	(0.089)
Network Share (%)	65.01***	68.29***	65.93***
	(0.081)	(0.090)	(0.086)

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

Table 12: Heterogeneous SAR Effect Decomposition (Downstream)

Notes: Heterogeneous SAR Effect Decomposition of point estimates in Table 5. Standard Errors Wild bootstrapped using 1000 iterations.

D.9 Downstream Indirect and Direct Effect Distributions

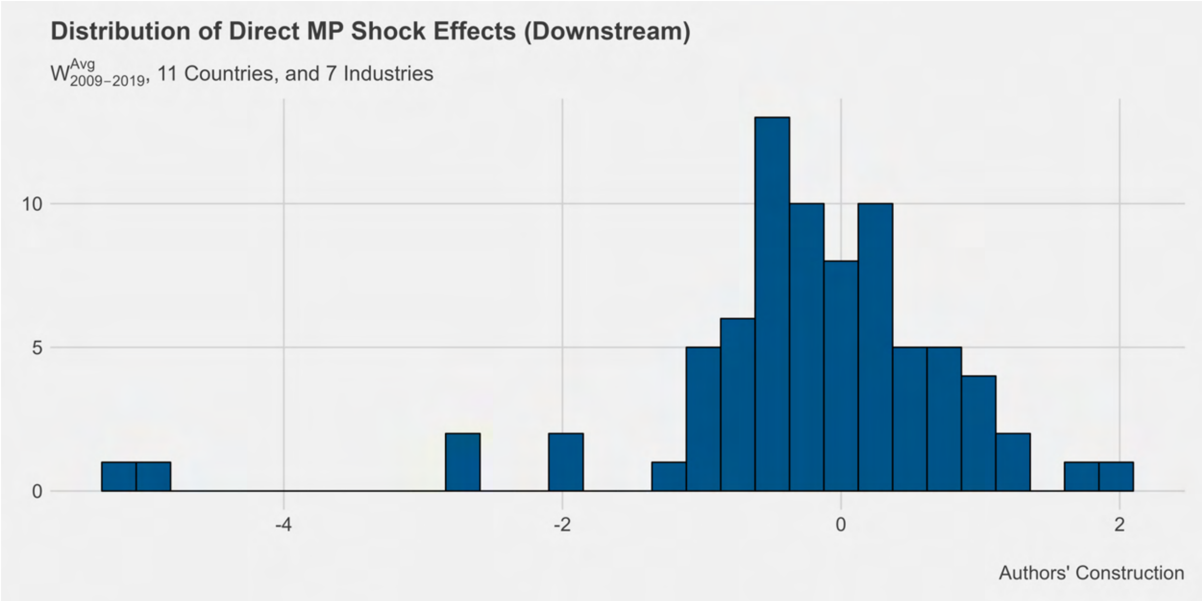


Figure 24: Distribution of Direct Effect Estimates

Notes: Distribution of Direct Effect Estimates using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 12

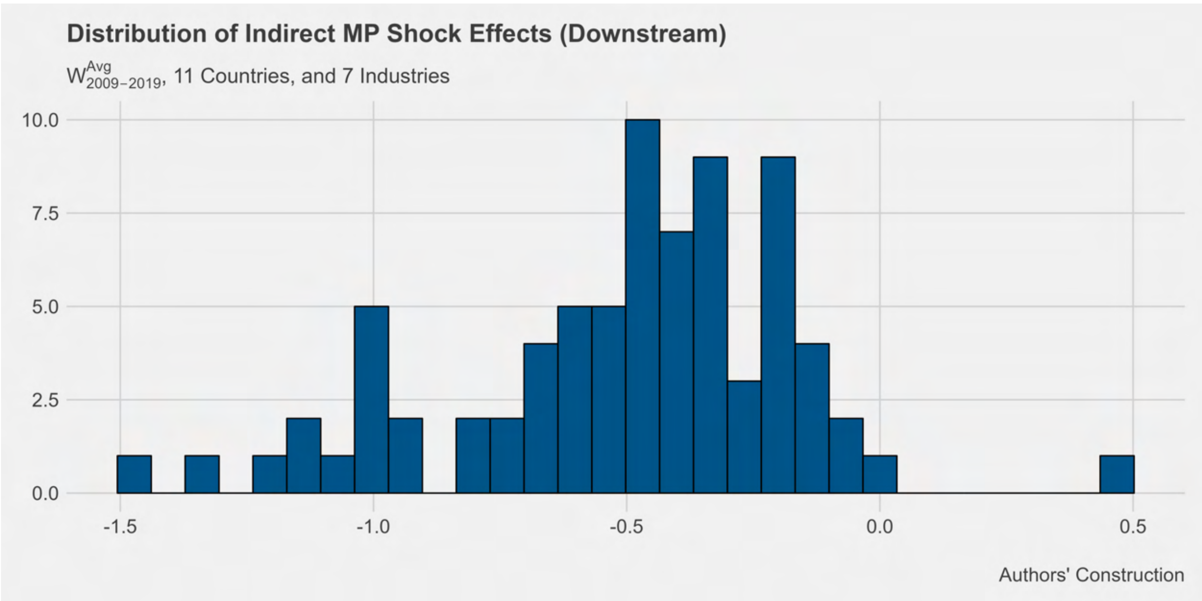


Figure 25: Distribution of Indirect Effect Estimates

Notes: Distribution of Indirect Effect Estimates using $W^{Avg}_{2009-2019}$ as weighting matrix. Results calculated from Column (2) in Table 12

Appendix E Wei and Xie (2020) Small-Open Economy Model with N-Stage Production

E.1 Households

Households consume a bundle of foreign and domestic final goods, provide labor to domestic intermediate goods firms, pay a lump-sum tax, and receive any profits that accrue from their ownership of home firms. We assume that financial markets are complete and that households have access to a set of domestic and international Arrow securities.

The representative household in the SOE has standard CRRA preferences:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t, L_t) = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{L_t^{1+\psi}}{1+\psi} \right\} \tag{E.1}$$

C_t is a composite of domestic and imported Chinese final goods:

$$C_t = \Theta \bar{Y}_{NH,t}^{\gamma} \bar{Y}_{NF,t}^{1-\gamma}$$

Where $\Theta = \left[\gamma^{\gamma}(1-\gamma)^{1-\gamma}\right]^{-1}$ is a normalization parameter, γ measures home-bias in home final goods consumption (i.e., $\gamma > 0.5$ indicates home-bias), and $\bar{Y}_{NH,t} = \left[\int_0^1 Y_{NH,t}(u)^{\frac{\theta-1}{\theta}} du\right]^{\frac{\theta}{\theta-1}}$ is a domestically produced bundle of differentiated final goods. $\bar{Y}_{NF,t}$ is the bundle of Chinese produced differentiated final goods.

After solving the household's expenditure minimization problem, we get the following household demand equations for final goods:

$$Y_{NH,t}^{d}(u) = \left[\frac{P_{NH,t}(u)}{\bar{P}_{NH,t}}\right]^{-\theta} \frac{\gamma P_t}{\bar{P}_{NH,t}} C_t \tag{E.2}$$

$$Y_{NF,t}^{d} = \frac{(1-\gamma)P_t}{\bar{P}_{NF,t}} C_t \tag{E.3}$$

where $P_t = \bar{P}_{NH,t}^{\gamma} \bar{P}_{NF,t}^{1-\gamma}$ is the aggregate price index for final consumption, $\bar{P}_{NH,t} = \left(\int_0^1 P_{NH,t}(\mu)^{1-\theta} d\mu\right)^{\frac{1}{1-\theta}}$ is the aggregate price index for domestically produced final goods, and the aggregate price index for Chinese produced final goods is given as: $\bar{P}_{NF,t} = T_t \mathscr{C}_t P_{NF,t}^{*}$. Define $\mathscr{C}$ is the price of RMB in terms of the SOE's currency, $P_{NF,t}^{*}$ as the exogenous Chinese price in RMB, and T_t is a uniform tariff on imports.

The representative household then maximizes Equation E.1 subject to the following period budget constraint:

$$P_t C_t(h) + \mathbb{E}_t(D_{t,t+1} B_{t+1}) \leq W_t L_t + \Pi_t + B_t \tag{E.4}$$

where P_t is home CPI, $D_{t,t+1}$ is the pricing kernel for a one-period ahead nominal payoff of the domestic household, B_{t+1} is the nominal payoff in period $t+1$ from a portfolio of Arrow securities held at the end of period t, W_t is wage from labor, L_t is labor, and Π_t are the aggregate profits that accrue from household ownership of home firms. We assume that these state contingent Arrow securities are tradeable between countries (complete financial markets).

The first order conditions are standard:

$$\text{Labor Leisure Choice:} \quad C_t^{\sigma} L_t^{\psi} = \frac{W_t}{P_t}$$

$$\text{Consumption Euler:} \quad 1 = \beta R_t \mathbb{E}_t \left[\frac{C_{t+1}(h)}{C_t(h)} \right]^{-\sigma} \frac{P_t}{P_{t+1}}$$

Where $R_t = \frac{1}{\mathbb{E}_t D_{t+1}}$ is the gross nominal return on a one-period arrow-security in home currency.

Risk Sharing Condition

Wei and Xie (2020) have a lengthy discussion regarding the timing assumption regarding the trade of the Arrow securities — before or after monetary policy is chosen. We take no explicit stance in that debate, since the timing assumptions should not affect our simulation results since we are not evaluating the SOE's optimal monetary policy. To that end, we follow the timing assumption made in Wei and Xie (2020). As such, if we equalize the intertemporal marginal rates of substitution between China and the SOE, we get:

$$\beta^t \frac{(C_t^*)^{-\sigma} / P_t^*}{(C_0^*)^{-\sigma} / P_0^*} \Lambda = \beta^t C_t^{-\sigma} \mathscr{E}_t P_t^{-1} \tag{E.5}$$

where Λ is the marginal utility of the household's initial debt holding. We get the following familiar risk-sharing condition:

$$C_t = \theta^* C_t^* Q_t^{1/\sigma} \tag{E.6}$$

Define the real exchange rate as $Q_t = \frac{\mathscr{E} P_t^*}{P_t}$. Notice that with the Wei and Xie (2020) timing assumption, $\theta^* = (\Lambda P_0^*)^{-1/\sigma} / C_0^*$ is invariant across monetary policies. Because we assume complete markets, the UIP condition holds: $i_t - i_t^* = \mathbb{E}_t(\Delta e_{t+1})$, where $e_t = \ln \mathscr{C}$.

E.2 Firm's Pricing Problem

The firm's pricing problem remains unchanged from the original paper, where at each stage of production, firms follow a Calvo pricing rule. The probability that firms at any particular stage adjusts their price is given as $1 - \alpha_n$, where $n \in [1, 2]$ is the stage of production. In period t the firm producing good u at stage n can set a new price $P_{nH}(u)$ in the SOE's currency for the product sold domestically and in China. The firm's pricing problem is thus:

$$\max_{P_{nH,t}(u)} E_t \Sigma_{k=t}^{\infty} \alpha_n^{k-t} D_{t,k} \left[(1+\tau) P_{nH,t}(u) - \Psi_{n,k}(u) \right] \left[\underbrace{Y_{nH,k}^{d}(u)}_{\text{Domestic Demand}} + \underbrace{Y_{nH,k}^{Xd}(u)}_{\text{Chinese Demand}} \right] \tag{E.7}$$

Distortions from monopolistic competition are corrected via a subsidy to firms, denote as τ. The nominal unit production cost for stage 2 is: $\Psi_{2,k}(u) = \bar{P}_{2,k}^{\phi} W_k^{1-\phi} / A_{2,k}$. The stage 1 nominal unit cost is: $\Psi_{1,k}(u) = W_k / A_{1,k}$ and $\bar{P}_{n.k}$ is the stage n price for the intermediate goods composite. The optimal pricing decision is therefore:

$$P^o_{nH,t}(u) = \frac{\mu}{1+\tau} \frac{E_t \Sigma_{\tau=t}^{\infty} \alpha_n^{\tau-t} D_{t,\tau} \Psi_{n,\tau}(u) \left[Y^d_{nH,\tau}(u) + Y^{Xd}_{nH,k}(u) \right]}{E_t \Sigma_{\tau=t}^{\infty} \alpha_n^{\tau-t} D_{t,\tau} \left[Y^d_{nH,\tau}(u) + Y^{Xd}_{nH,k}(u) \right]} \tag{E.8}$$

$\mu = \frac{\theta}{\theta-1}$ is familiar mark up cost, which is the same across both stages. For simplicity, the distortion subsidy is given as $\tau = \mu - 1$. The standard cost minimization problem at stage 2 gives us the period t factor demand functions:

$$\bar{Y}^d_{2,t} = \phi \frac{\Psi_{2,t}}{\bar{P}_{2,t}} \int_0^1 \left[Y^d_{2H,t}(u) + Y^{Xd}_{2H,t}(u) \right] du \tag{E.9}$$

$$L^d_{2,t} = (1-\phi) \frac{\Psi_{2,t}}{W_t} \int_0^1 \left[Y^d_{2H,t}(u) + Y^{Xd}_{2H,t}(u) \right] du \tag{E.10}$$

$$\bar{Y}^d_{1H,t} = \frac{\gamma \bar{P}_{2,t}}{\bar{P}_{1H,t}} \bar{Y}^d_{2,t} \tag{E.11}$$

$$\bar{Y}^d_{1F,t} = \frac{(1-\gamma)\bar{P}_{2,t}}{\bar{P}_{1F,t}} \bar{Y}^d_{2,t} \tag{E.12}$$

$$Y^d_{(1H,t}(u) = \left(\frac{P_{1H,t}(u)}{\bar{P}_{1H,t}} \right)^{-\theta} \bar{Y}^d_{1H,t} \tag{E.13}$$

The stage 1 firm has an easier pricing problem since labor is the only input. The pricing problem is:

$$P^o_{1H,t}(u) = \frac{E_t \Sigma_{\tau=t}^{\infty} \alpha_1^{\tau-t} D_{t,\tau} \Psi_{1,\tau}(u) \left[Y^d_{1,\tau}(u) + Y^{Xd}_{1H,k}(u) \right]}{E_t \Sigma_{\tau=t}^{\infty} \alpha_1^{\tau-t} D_{t,\tau} \left[Y^d_{1,\tau}(u) + Y^{Xd}_{1H,k}(u) \right]} \tag{E.14}$$

with $\Psi_{1,\tau}(u) = W_\tau / A_{1,\tau}$ being the unit production cost in stage 1. We only have labor demand, since it is the only factor of production in stage 1:

$$L^d_{1,t} = \frac{\Psi_{1,t}}{W_t} \int_0^1 \left[Y^d_{1H,t}(u) + Y^{Xd}_{1H,t}(u) \right] du \tag{E.15}$$

The aggregate price index for outputs in stages $n \in [1,2]$ is:

$$P_{nH,t} = \left[\alpha_n P^{1-\theta}_{nH,t-1} + (1-\alpha_n) \left(P^o_{nH,t} \right)^{1-\theta} \right]^{\frac{1}{1-\theta}} \tag{E.16}$$

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