Stock Market Spillovers Via the Global Production Network: Transmission of U.S. Monetary Policy

Julian di Giovanni
Galina Hale

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Stock Market Spillovers via the Global Production Network: Transmission of U.S. Monetary Policy*

Julian di Giovanni
Federal Reserve Bank of New York
ICREA-Universitat Pompeu Fabra
Barcelona GSE, CREI and CEPR

Galina Hale
University of California Santa Cruz
Federal Reserve Bank of San Francisco
CEPR

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Abstract

We quantify the role of global production linkages in explaining spillovers of U.S. monetary policy shocks to stock returns of 54 sectors in 26 countries. We first present a conceptual framework based on a standard open-economy production network model that delivers a spillover pattern consistent with a spatial autoregression (SAR) process. We then use the SAR model to decompose the overall impact of U.S. monetary policy on stock returns into a direct and a network effect. We find that up to 80% of the total impact of U.S. monetary policy shocks on average country-sector stock returns are due to the network effect of global production linkages. We further show that U.S. monetary policy shocks have a direct impact predominantly on U.S. sectors and then propagate to the rest of the world through the global production network. Our results are robust to controlling for correlates of the global financial cycle, foreign monetary policy shocks, and to changes in variable definitions and empirical specifications.

Keywords: Global production network, asset prices, monetary policy shocks

JEL Codes: G15, F10 , F36

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1 Introduction

The recent era of globalization witnessed (i) greater cross-country trade integration as firms' production chains have spread across the world (Johnson and Noguera, 2017), and (ii) stock market returns becoming more correlated across countries (Dutt and Mihov, 2013). While research has predominantly focused on how *financial* integration impacts the propagation of shocks across international financial markets (e.g., via a global financial cycle, Rey, 2013), *real* integration also influences these cross-border spillovers. In this paper, we analyze how the global production network impacts the transmission of U.S. monetary policy shocks to world stock markets.

To guide our empirical work, we present a conceptual framework that lays out necessary conditions for monetary policy shocks to transmit across countries via the global production network. In our setting, demand shocks induced by changes in monetary policy propagate upstream from customers to suppliers. The framework delivers an empirical specification where the international shock transmission pattern follows a spatial autoregression (SAR) process. We construct a novel dataset that combines production linkages information from the World Input-Output Database (WIOD, Timmer et al., 2015) with firm-level stock returns worldwide. Using these data, we document a positive relationship between the intensity of production linkages and stock market comovements at the country-sector level. We then use a panel SAR to quantify the role of the global production network in transmitting U.S. monetary policy shocks across international stock markets.

Using monthly stock return data at the country-sector level, we find that the propagation of U.S. monetary policy shocks through the global production network is statistically significant and accounts for most of the total impact. Specifically, average monthly stock returns increase by 0.12 percentage points in response to a one percentage point expansionary surprise in the U.S. monetary policy rate, with nearly 80% of this stock return increase due to the spillovers via global production linkages. U.S. monetary shocks' direct impact affects the domestic sectors and then spills over from the U.S. to foreign markets most prominently as the shocks to U.S. sectors' demand propagates upstream to their foreign suppliers. This finding is robust to controlling for other variables that may drive a common financial cycle across markets, such as the VIX, 2-year Treasury rate, and the broad U.S. dollar index. It is also robust to different time periods, different definitions of stock returns and monetary policy shocks, and to controlling for monetary policy shocks in the U.K. and the euro area.

The conceptual framework requires minimal assumptions and can be derived using a static multi-country multi-sector production model that follows the standard closed-economy setup (e.g., Acemoglu et al., 2012). Unlike many canonical macro-network models, however, our framework allows for firm profits, which in turn drive stock returns.[1] To generate monetary non-neutrality,

[1] For the purpose of our empirical work, we do not need to take a stand on the precise changes in the canonical model in order to generate profits. In particular, recent work in the literature has motivated firm profits by assuming

we assume pre-set wages and allow for the possibility of money to be introduced in different ways, for instance, via cash-in-advance constraints, as in many recent macro-network models (La'O and Tahbaz-Salehi, 2020; Ozdagli and Weber, 2020; Rubbo, 2020).

This conceptual framework delivers the result that firms in all countries will be affected by a monetary shock in a given country. The relative magnitude of the shock's impact is proportional to a firm's production linkages with the rest of the world, which captures the importance of intermediate products in the firm's production function. Unlike models that focus on technology shocks, which generally propagate downstream from supplier to customer via changes in marginal costs, our framework focuses on shocks to the monetary policy that will propagate upstream from customer to supplier given changes in customers' demand induced by the monetary policy shock. This change in demand in turn impacts firms profits and thus equity returns. We take the global input-output (IO) matrix as given, both in the model and in our empirical analysis. We view this assumption as realistic given that we are studying a short-run impact of a demand-side shock and the level of aggregation (country-sector) that we use in our empirical analysis. Robustness tests show that our empirical results are consistent with this assumption.

To conduct our regression analysis, we make use of the 2016 version of WIOD for input-output data and Thompson Reuters Eikon for stock market information. WIOD provides domestic and global input-output linkages for 56 sectors across 43 countries and the "rest of the world" aggregate annually for 2000–14. From Eikon we obtain firm-level stock prices, market capitalization, and firms' sector classification. Using the market capitalization as a weight, we construct our own country-sector stock market indexes by aggregating firm-level information to the same industrial sector level as WIOD for 26 of the countries available in WIOD.[2] The final merged dataset contains monthly country-sector stock returns and annual input-output matrices.[3] Our baseline analysis uses the 30-minute window U.S. monetary policy shock measure calculated from Federal Funds futures data by Jarociński and Karadi (2020). Because of the global trade collapse in 2008–09 followed by the period of unconventional monetary policy, we limit our baseline analysis to 2000–07. However, our results are robust to other periods.

Using the raw stock market and input-output data, we show that country-sector cells that are more closely connected in the global production network also have more correlated stock returns. This observation remains true even if we exclude same-country cross-sector correlations from the analysis. This empirical regularity suggests that international input-output linkages may provide

constant returns to scale technology in a monopolistic competition setting (e.g., Bigio and La'O, 2019), or with decreasing returns to scale technology in a competitive market setting (e.g., Ozdagli and Weber, 2020).

[2] We have to start from the firm-level data because there is no one-to-one correspondence between WIOD sector definitions and any of the standard classifications that could be matched to Eikon. The 26 countries in our final sample cover a majority of world production and trade. See Appendix B for details.

[3] While the IO matrices only exist up to 2014, we further extend stock returns data through 2016 given the availability of these data and our baseline monetary policy shock variable. This approach works since we keep fixed the IO matrix for a pre-determined year for the empirical analysis.

an important channel of shock transmission across global stock markets.

The theoretical framework delivers a SAR structure for our empirical analysis (LeSage and Pace, 2009), where spatial distance is represented by the coefficients in the global IO matrix. The SAR specification we use, however, is different from a standard one in two ways. First, in addition to a spatial dimension (country-sector in our case) we have a time dimension.[4] Thus, we have a *panel* spatial autoregression. Second, we estimate country-sector specific coefficients, which is possible thanks to the time dimension in our panel setting. We estimate this heterogeneous-coefficient panel SAR model using the maximum likelihood methodology in Aquaro et al. (2019), and approximate standard errors using a wild bootstrap procedure.

We find that production networks play a primary role in transmitting U.S. monetary policy shocks across global stock returns. This finding is consistent with the Acemoglu et al. (2016) study that shows that the network-based shock propagation can be larger than a direct effect, as well as being similar to what Ozdagli and Weber (2020) find for the response of U.S. stock returns to monetary policy shocks. Both of these studies focus only on the U.S. in a closed-economy setting, while ours incorporates global production linkages. By separating the estimates for sectors in the U.S. from those of foreign sectors, we show that foreign stock returns respond to U.S. monetary policy shocks mostly through the network of customer-supplier linkages, while the magnitude of the direct impact of the U.S monetary policy on foreign stock returns is small and only marginally statistically significant. Even for the U.S. stock returns the network impact of U.S monetary policy shock plays a greater role than the direct impact.

Our results are not sensitive to the choice of a specific time period. We also show that the year in which the IO matrix is sampled does not affect the result, suggesting very limited, if any, endogenous response of global supply chains to monetary shocks. This result justifies the assumption of an exogenous trade structure in our theoretical framework. Our results are also robust to adjusting the input-output weighting matrix by a measure of trade costs. We further show that our results are robust to replacing nominal stock returns in local currency with real stock returns or with stock returns expressed in U.S. dollar, to other definitions of monetary policy shocks, and to controlling for monetary policy shocks in the U.K. and the euro area.

We extend our results by exploring the impact of three global financial cycle correlates: (i) VIX, (ii) 2-year Treasury rate, and (iii) broad U.S. dollar index. All three variables, whether included individually or together, have a statistically significant direct and network effects on stock returns worldwide. We find that including the VIX in our spatial autoregression reduces the direct effects of monetary policy shocks on foreign stock returns, while not impacting the direct effect on U.S.

[4]Because input-output coefficients do not change much over time, we use a static, beginning-of-period IO matrix. We are implicitly assuming that market participants react on the intensive margin of production networks, rather than to the expected changes in production linkages. This assumption is arguably more justifiable at the sector than the firm level. However, trade patterns have changed over time, so we also experiment by varying the weighting matrix for different time periods in our empirical analysis and find that results are not sensitive to these changes.

domestic returns. Interestingly, the size of the direct and network effects of the VIX is slightly larger for foreign stock returns than for the U.S. sectors. This is consistent with robust evidence in the literature of the global nature of the VIX shocks. Furthermore, the 2-year Treasury rate and the broad U.S. dollar index do not affect the impact of the U.S. monetary policy shocks.

We explore the cross-country and cross-sector heterogeneity of our estimates of monetary policy shock spillovers. We find that there are no individual countries or sectors in which the spillover effects are concentrated. We do not find a strong correlation between the size of international spillovers and countries' size, financial openness, current account, or other country characteristics. Similarly, we do not find strong correlation between spillover differences across sectors and sector-specific characteristics such as reliance on external finance.

Our finding of the quantitative importance of the global production network in international transmission of U.S. monetary policy shocks to global stock returns at the sector level contributes to several strands of the literature. The first is the growing literature on the international transmission of shocks through production linkages. For example, Burstein et al. (2008), Bems et al. (2010), Johnson (2014), and Eaton et al. (2016), Auer et al. (2019), among others, model and quantify international shock transmission through input trade. Baqaee and Farhi (2019b) and Huo et al. (2020) develop theoretical and quantitative treatments of the international input network model. Boehm et al. (2019) and Carvalho et al. (2016) use a case study of the Tōhoku earthquake to provide evidence of real shock transmission through global and domestic supply chains, while di Giovanni et al. (2018) show the importance of firms' international trade linkages in driving cross-country GDP comovement. None of these studies focus on the transmission of monetary policy shocks, nor stock markets' comovement.

Our paper also contributes to broader literature on international spillovers of U.S. monetary policy by documenting and quantifying the importance of real linkages. Miranda-Agrippino and Rey (2020), among many others, provide evidence which shows that U.S. monetary policy shocks induce comovements in international asset returns. Most analysis of the spillover channels focuses on bank lending and, more generally, global bank activity – see, among others, Cetorelli and Goldberg (2012); Bruno and Shin (2015b); Buch et al. (2019) and a survey by Claessens (2017). Another large group of papers study, more generally, the impact of U.S monetary policy on international capital flows – see, among others, Forbes and Warnock (2012); Bruno and Shin (2015a); Avdjiev and Hale (2019).

Much less attention has been devoted to cross-border monetary policy spillovers through real channels, such as input-output linkages.[5] Yet we know that real linkages across sectors play an

[5]Notable exceptions are Brooks and Del Negro (2006), who demonstrate that sensitivity of stock returns to global shocks is related to firms' foreign sales; Todorova (2018), who analyzes the network effect on monetary policy transmission in the European Union; Bräuning and Sheremirov (2019) study the transmission of U.S. monetary policy shocks on countries' output via financial and trade linkages, but do not study the production network; and Chang et

important role in domestic shock transmission (see, among others, Foerster et al., 2011; Acemoglu et al., 2012; Atalay, 2017; Grassi, 2017; Baqaee and Farhi, 2019a). Pasten et al. (2019) study the transmision of monetary policy in a production economy, while recent theoretical work on optimal monetary policy has examined the impact of input-output linkages in setting policy in a closed economy (La'O and Tahbaz-Salehi, 2020; Rubbo, 2020), as well as a small open-economy setting (Wei and Xie, 2020). Finally, a recent paper by Ozdagli and Weber (2020), to which our paper is most closely related, shows that input-output linkages are quantitatively important for monetary policy transmission to stock returns in the United States.[6]

We bridge the gap between these strands of the literature by showing the importance of real linkages in the international transmission of monetary policy shocks across asset markets. Our paper adds to this literature by showing, on the global scale, the importance of the trade channel in transmitting the U.S. monetary policy shocks, and providing a quantitative estimate of its contribution as well as transmission pattern. That is, we show how U.S. monetary policy directly impacts domestic stock returns and spills over to the rest of the world via the global production network.

We present a stylized conceptual framework of global production model cross-country monetary policy shock transmission in Section 2, which motivates the empirical model outlined in Section 3. We then describe our data in Section 4, before presenting our empirical results in Section 5. Section 6 concludes.

2 Conceptual Framework

We provide a conceptual framework to motivate our estimation strategy for studying the transmission of U.S. monetary policy shocks to stock returns internationally via production linkages. There are three main ingredients required to produce such shock transmission: first, firm's production technology or the economy's market structure must allow for positive profits in equilibrium, which in turn are reflected in stock returns; second, shocks in one country can be transmitted to firms (and their profits) in other countries; third, monetary shocks have real effects. A wide variety of theoretical frameworks can deliver each of these ingredients and they can be readily combined into a simple static multi-country multi-sector input-output model, which allows for monetary policy to have an impact on the real economy.

Technology and market structure. To model international dependence at the sector level, we introduce international trade in intermediate goods. To fix notation, assume that the world

al. (2020) who study how the transmission of shocks via countries' (aggregate) trade networks impacts asset prices using information from the sovereign CDS market.

[6]Moreover, Bigio and La'O (2019) and Alfaro et al. (2020) show the importance of production linkages in transmitting sectoral shocks and financial frictions to the aggregate economy.

economy is comprised of N countries and J sectors. Countries are denoted by m and n, and sectors by i and j. The notation follows the convention that for trade between any two country-sectors, the first two subscripts always denote exporting (source) country-sector, and the second subscript the importing (destination) country-sector – i.e., $x_{mi,nj}$ denotes goods produced in country m sector i that are used as intermediate inputs by sector j in country n.

A firm in a given sector produces using labor and a set of intermediates goods, which are potentially sourced from all countries and sectors, including its own. Output for a firm in country-sector nj, y_{nj}, can then be written as

$$y_{nj} = z_{nj} F_{nj} \left(l_{nj,}, \{x_{mi,nj}\} \right), \tag{1}$$

where l_{nj} is labor used by firms in sector nj, $\{x_{mi,nj}\}$ is the set representing quantities of intermediate goods used, z_{nj} is a Hicks-neutral technology parameter. $F_{nj}(\cdot)$ may allow for constant returns to scale (CRS) or decreasing returns to scale (DRS) production. Note that we have assumed a representative firm in each country-sector and thus have dropped any firm-specific notation.

Market clearing. We can express the goods market clearing conditions for every country-sector mi in terms of expenditures, $R_{mi} = p_{mi} y_{mi}$, as

$$R_{mi} = \underbrace{\mathcal{C}_{mi}}_{\substack{\text{Final goods}\\ \text{expenditure on } mi\\ \text{across } N \text{ countries}}} + \underbrace{\sum_{j=1}^{J} \sum_{n=1}^{N} \omega_{mi,nj} R_{nj}}_{\substack{\text{Intermediate input}\\ \text{expenditure}}}, \tag{2}$$

where p_{mi} is the price received by producers of good mi per unit of output. This condition is standard and will hold regardless of the underlying economic model. The first term of (2) captures expenditures on goods produced by country-sector mi that are used for final consumption both domestically and abroad. This term can be expressed as a function of underlying parameters of a model, such as households' preferences and their share of income. However, since we ultimately link movements in final goods' expenditure to exogenous changes in monetary policy, we omit these details to avoid introducing unneeded notation.[7] The second term of the equation captures expenditure on intermediate inputs, where $\omega_{mi,nj}$ is the input-output coefficient for country-sector nj purchases of the intermediate good from country-sector mi needed to produce a unit of sales of good nj:

$$\omega_{mi,nj} = \frac{p_{mi,n} x_{mi,nj}}{p_{nj} y_{nj}},$$

and we assume that the law of one price holds across goods in a given sector i, possibly with iceberg transports costs, $\tau_{mi,n} \geq 1$, such that $p_{mi,n} = \tau_{mi,n} p_{mi}$.[8]

[7] Appendix A provides a model that yields a structure akin to (2), and demonstrates how changes in modeling assumptions will impact the derivation of the expenditure system.

[8] We did not explicitly specify the numéraire, but one may think of all prices as being expressed in one country's currency and therefore incorporating exchange rates.

Stacking (2) over country-sector cells, we can express the expenditure system in matrix form:

$$\mathbf{R} = \boldsymbol{\mathcal{C}} + \boldsymbol{\Omega}\mathbf{R}, \tag{3}$$

where $\mathbf{R}$ is the vector of country-sector sales, $\boldsymbol{\mathcal{C}}$ captures the vector of final goods' expenditures, and $\boldsymbol{\Omega}$ is the global input-output matrix. Note that this expenditure system holds regardless of the underlying economic model, and is measured in the data by national accounting and world input-output data.

Deviations from steady-state and stock returns. We are ultimately interested in studying how monetary policy shocks impact stock returns given the world input-output network, and study deviations from a steady-state. First, re-arranging (3), we express revenues as a function of final goods expenditures:

$$\mathbf{R} = (I - \boldsymbol{\Omega})^{-1}\boldsymbol{\mathcal{C}}, \tag{4}$$

where $(I - \boldsymbol{\Omega})^{-1}$ is the Leontief inverse of the input-output matrix. Second, for any variable x, define the log deviation from steady-state $\widehat{x} = \log(x) - \log(\bar{x})$ so that $x = \bar{x}\exp(\widehat{x}) \approx \bar{x}(1 + \widehat{x})$, where $\bar{x}$ is the steady-state value of x. Then, holding $\boldsymbol{\Omega}$ fixed,[9] we can express (4) in terms of deviations from steady-state as:

$$\widehat{\mathbf{R}} = (I - \boldsymbol{\Omega})^{-1}\widehat{\boldsymbol{\mathcal{C}}}. \tag{5}$$

Expenditure to profit and stock returns. Next, to link changes in expenditure (or firm revenue) to changes in stock returns, we assume that market efficiency translates changes in profits to stock returns. To generate positive profits in equilibrium, we need to either deviate from perfect competition or from firm CRS production technology. One standard setup in the macro-networks literature allows for CRS technology under monopolistic competition, where firms produce unique varieties and set prices with a constant mark-ups (e.g., Bigio and La'O, 2019). Alternatively, one can assume that firms to produce with DRS in a competitive market structure as in Ozdagli and Weber (2020).

To a first-order, changes in firm profits are proportional to changes in firm revenues around the steady-state: $\widehat{\pi}_{nj} \approx \widehat{R}_{nj}$. In particular, in a monopolistic competitive market where firms have CRS technology, or in a competitive equilibrium where firms have DRS technology, profits will be a constant multiple of revenues, where the constant is a function of underlying model parameters. To ease notation, we assume that firm profits change one-for-one with firm revenues, so that Equation (5) yields

$$\widehat{\boldsymbol{\pi}} = (I - \boldsymbol{\Omega})^{-1}\widehat{\boldsymbol{\mathcal{C}}}, \tag{6}$$

[9] Holding $\boldsymbol{\Omega}$ fixed implicitly assumes Cobb-Douglas production. However, given the static nature of the model and how our empirical estimation strategy, this assumption is not strong and the same results will follow for a more general CES production structure.

where $\boldsymbol{\pi}$ is a vector of nj profits. Thus, shocks to the consumption of final goods will translate upstream via the global input-output network, impacting profits and thus stock returns both at home and abroad.

Monetary policy shocks. The real impact of monetary policy has been subject to vast study (see, for example Woodford, 2004; Gali, 2015, for textbook treatments). To generate a real effect, some form of price rigidity is built into the model. In the case of a multi-country framework, assuming wage rigidity across countries helps simplify the model solution. Money can then be introduced into the model via different channels, such as cash-in-advance constraints, money in the utility function, or interest rate rules. Such models will predict that deviations in expenditures on final consumption $\mathcal{C}$ in country n around its steady-state are proportional to the monetary policy shock in country n, $\widehat{\mathcal{M}}_n$:

$$\widehat{\mathcal{C}}_n = \beta_n \widehat{\mathcal{M}}_n, \tag{7}$$

where β_n depends on preferences and other parameters in the model.

Writing (7) for N countries in vector form, and combining it with (6), we can express stock returns (changes in profits) as a function of monetary policy shocks:

$$\widehat{\boldsymbol{\pi}} = (I - \boldsymbol{\Omega})^{-1} \boldsymbol{\beta} \widehat{\boldsymbol{\mathcal{M}}}, \tag{8}$$

or, considering only shocks to U.S. monetary policy, $\mathcal{M}_{US}$:

$$\widehat{\boldsymbol{\pi}} = (I - \boldsymbol{\Omega})^{-1} \boldsymbol{\beta} \widehat{\mathcal{M}}_{US}. \tag{9}$$

We present a simple model in Appendix A, which embeds cash-in-advance constraints in an open-economy input-output model to arrive at equations like (8) and (9).

3 Regression Framework

Under the efficient markets hypothesis, stock returns reflect expected changes in profits. Thus, the model predicts that a monetary policy shock affects all stock returns in the amount proportional to their input-output distance from the source of the shock. The empirical counterpart to this propagation pattern is a spatial autoregression.

Specifically, holding the parameters of the model fixed, the empirical counterpart of Equation (9) for a given country-sector observation is

$$\widehat{\pi}_{mi,t} = (I - \rho\, \mathbf{W})^{-1}\, \beta_{mi}\, \widehat{\mathcal{M}}_{US,t}, \tag{10}$$

where the subscript t is for the year-month in which a monetary policy shock occurs,[10] $\mathbf{W}$ is the empirical global input-output matrix, and ρ and β_{mi} are coefficients that will be estimated.

[10]FOMC announcements do not occur every month, and at times multiple times within a month. We only include in our sample months with FOMC announcements, but the results are robust to including all months. For months with multiple announcements, we aggregate all announcement by adding up measures of monetary policy shock.

Theoretically, β_{mi} can be derived from the parameters of a specific model, but in practice these cannot be measured directly. Moreover, the estimate of β_{mi} can be affected by factors that are outside of the model, such as financial openness, level of financial developments, sector's dependence on external financing, and institutional factors. Such factors may also add resistance to the shock transmission through the production network. While equation (9) predicts the pass-through of monetary policy shocks to stock returns to be perfect ($\rho = 1$), this need not be the case in practice, which is why we let the data determine the empirical estimate of ρ.

Equation (10) is a representation of a spatial autoregressive process, and can be written in the following vector form:

$$\widehat{\boldsymbol{\pi}}_t = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \rho\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t,$$

or, adding an error term,

$$\widehat{\boldsymbol{\pi}}_t = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \rho\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \boldsymbol{\varepsilon}_t, \tag{11}$$

where ρ is the spatial autoregressive coefficient, and $\boldsymbol{\beta}$ is a vector of β_{mi}'s.

To take into account that barriers to shock propagation may vary across sectors and countries, we extend the SAR model to allow for heterogeneity in the autoregressive coefficient. In particular, like $\boldsymbol{\beta}$, we can allow ρ to vary at the mi level:

$$\widehat{\boldsymbol{\pi}}_t = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\mathbf{W}\,\widehat{\boldsymbol{\pi}}_t + \boldsymbol{\varepsilon}_t, \tag{12}$$

where $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ are $NJ \times 1$ vectors of the coefficients we estimate and $\boldsymbol{\varepsilon}$ is the $NJ \times 1$ vector of error terms. The time dimension of our data allows us to estimate individual parameters for every country-sector pair. Finally, the regression model also includes a set of country-sector specific intercepts.

Additional Controls. The panel SAR model (12) can be extended to include additional controls:

$$\widehat{\boldsymbol{\pi}}_t = \boldsymbol{\beta}_1\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\beta}_2\,\mathbf{X}_t + \boldsymbol{\rho}\mathbf{W}\,\widehat{\boldsymbol{\pi}}_t + \boldsymbol{\varepsilon}_t, \tag{13}$$

where $\mathbf{X}_t$ is matrix of additional independent variables. This specification assumes that additional shocks may also impact stock returns both directly and indirectly via the global input-output matrix. We use this specification to examine the robustness of results by including variables related to the global financial cycle that have been found to both correlate with U.S. monetary policy shocks and drive global asset prices.

Inference. Because of the recursive nature of the spacial autoregression model, the coefficient $\boldsymbol{\beta}$ vector is not equal to the marginal impact of the monetary shock $\widehat{\mathcal{M}}_{US,t}$ on stock returns $\widehat{\pi}_{mi,t}$. Instead, from (10), the $NJ \times 1$ vector of marginal effects is given by

$$\textbf{Total} \equiv (\mathbf{I} - \boldsymbol{\rho}\mathbf{W})^{-1}\boldsymbol{\beta}. \tag{14}$$

Following LeSage and Pace (2009), this marginal effect for each mi can be decomposed into a direct effect of the shock and the network effect as

$$\mathbf{Direct} \equiv \mathrm{diag}(\mathbf{I} - \boldsymbol{\rho}\mathbf{W})^{-1}\boldsymbol{\beta}, \tag{15}$$

$$\mathbf{Network} \equiv \mathbf{Total} - \mathbf{Direct}, \tag{16}$$

where **Direct** and **Network** are $NJ \times 1$ vectors. Our primary object of interest is the share of **Network** in **Total**.

Reporting and standard errors. We present our results by reporting simple average values of $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, **Direct** and **Network** effects across all country-sectors. We also examine the cross-country transmission of monetary policy shocks by splitting the effects into domestic and international components. Specifically, we compute *international* direct and network effects as simple averages of the elements of **Direct** and **Network** across all the non-U.S. country-sectors. We take simple averages of the elements of **Direct** and **Network** over only U.S. sectors in order to compute the U.S.-only direct and network effects.

We compute standard errors for each element of $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, **Direct**, and **Network** as well as their overall, international, and U.S. average values using a wild bootstrap procedure proposed by Mammen (1993). To do so, for each iteration k of the 500 repetitions we replace our dependent variable with a synthetic one that is equal to the fitted values from the main estimation plus a random perturbation ν of the fitted error term:

$$\widehat{\pi}^k_{mi,t} = \widehat{\beta}_{mi}\,\widehat{\mathcal{M}}_{US,t} + \widehat{\rho}_{mi}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \nu^k_{mi,t}\,\varepsilon_{mi,t}.$$

We use a continuous distribution from which we draw perturbations

$$\nu^k_{mi,t} = \frac{u^k_{mi,t}}{\sqrt{2}} + \frac{1}{2}\left[(v^k_{mi,t})^2 - 1\right],$$

where u and v are drawn from independent standard normal distributions. We then estimate our regression model replacing true dependent variable with synthetic one and retain estimation results. Standard deviations of each estimated parameter across 500 repetitions are reported as standard errors.

4 Data

We source data from two main datasets: the global production network data are from the World Input-Output Database (WIOD), and the stock market information is from the Thompson-Reuters Eikon database (TREI). The WIOD provides annual data for input-output linkages across 56 sectors and 43 countries and a rest of the world aggregate for 1996–2014. For our analysis, we limit the data to 26 countries with active stock markets and 54 sectors that are connected to each others.[11]

From TREI, we obtain end-of-period monthly stock prices, stock market capitalization, and industrial classification for individual companies. We then construct our own stock return indexes for the same sector definitions as used in WIOD, using stock market capitalization of the firm as a weight. This is not straightforward, given that the TREI sector classification uses Thomson-Reuters Business Classification (TRBC), while the World Input-Output Tables are constructed under International Standard Industrial Classification (ISIC) Revision 4. Fortunately, in addition to TRBC, TREI also reports North American Industry Classification System (NAICS) 2007 sector codes for each firm, which we use to create a crosswalk to ISIC Rev. 4. This then allows us to aggregate firms' stock market indices into WIOD-based sectors.[12] For each of the resulting country-sector cells we construct monthly stock returns as a log change in weighted average of stock prices of all firms in that country-sector cell.

Table A1 presents cross-country sector coverage of monthly returns for the months where there are monetary surprise shocks over 2000–16. Given cross-country differences in size, industrial specialization patterns, and stock market depth we see that larger countries (e.g., the United States) have a larger coverage of sectors, while some countries only cover a few sectors (e.g., Portugal and Russia). These differences motivate a flexible empirical approach, where we allow for country-sector fixed effects as well as country-sector specific coefficients for the effect of the monetary policy shock variable.

4.1 Input-Output Coefficient Construction

The construction of the global input-output matrix using WIOD data is standard and follows from the literature. We denote countries as $m, n \in [1; N]$ and sectors as $i, j \in [1; J]$. WIOD provides information of output produced in a given country-sector and where it flows to; both geographical and what sector of the economy (including government and households). We first use this information to build a matrix $\mathbf{W}$, which is $NJ \times NJ$, where each element $\mathsf{w}_{mi,nj}$ represents the use of inputs from country m sector i as a share of total output of sector j in country n:

$$\mathsf{w}_{mi,nj} = \frac{Sales_{mi \to nj}}{Sales_{nj}}.$$

In network terminology, $\mathbf{W}$ is the adjacency matrix that gives us direct linkages between each pair of country-sector cells. Because by construction $\mathsf{w}_{mi,nj} \in [0; 1]$ and $\mathsf{w}_{mi,nj} \neq \mathsf{w}_{nj,mi}$, the network is weighted and directed. Note that we use all countries and sectors when constructing the adjacency

[11] The remaining two sectors, household production ("T" in WIOD codes) and extraterritorial organization ("U") are not sufficiently connected to the rest of the network.

[12] Even with these data, there is not always 1-to-1 correspondence between the TREI and WIOD codes, and we rectify such instances in a variety of ways as described in Appendix B.

matrix, but only exploit the sub-matrix where we have stock returns in the estimation below. This requires a re-normalization of the matrix for estimation purposes, but all preliminary statistics are based on manipulating the adjacency matrix without this re-normalization.

Figure 1 presents the empirical counter cumulative distribution function (CCDF) of the weighted outdegree of $\mathbf{W}$ for WIOD data, where we use the average input-output coefficients over the sample period 2000–14. The weighted outdegree for a given country-sector pair mi is defined as

$$out_{mi} = \sum_{n=1}^{N} \sum_{j=1}^{J} \mathsf{w}_{mi,nj},$$

and measures how important a given country-sector's inputs are for production use across all possible country-sector pairs. It is informative to look at this distribution, since a skewed one implies the potential for shocks to propagate and amplify across the production network (Acemoglu et al., 2012). Panel (a) plots the distribution using all possible input-output linkages in the world including both domestic and international linkages in computing the weighted outdegree, while panel (b) exploits only the international linkages. As can be seen in both figures, the distributions are very skewed. The curves were fitted using a Pareto distribution and as can be seen the slopes of the tail are steep, implying that the distributions are fat-tailed. This finding is along the lines of what Carvalho (2014) shows for the U.S. economy using detailed input-output tables from the BEA. In comparing panels (a) and (b), it is worth noting that the x-axis of the two figures are on two different scales. In particular, the international weighted-outdegree measures tend to be smaller on average than those using the full world input-output table (which includes domestic linkages) as several country-sector cells are not used as intermediate inputs (or in very tiny amounts) abroad.

Trade Costs. We construct a matrix of trade costs using the methodology of Head and Ries (2001), which relies on observed trade flows. In particular, the index is constructed based on total trade, intermediate and final consumption goods, for a given sector between two countries. The Head-Reis index is a bilateral measure that imposes symmetry in trade costs between countries. Specifically, we define bilateral iceberg trade costs of good i between countries m and n as

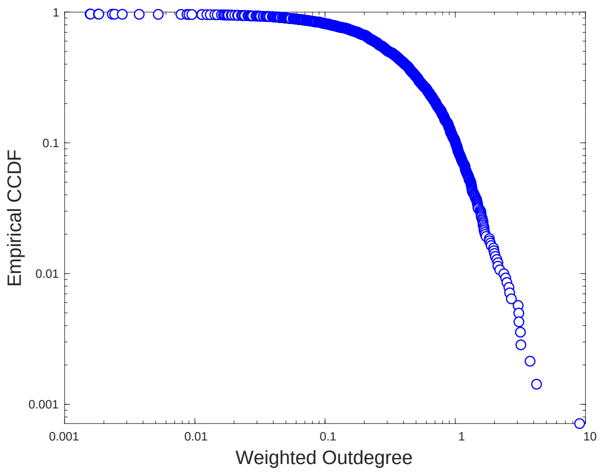
$$\tau_{mi,n} = \sqrt{\frac{X_{mi,n} \times X_{ni,m}}{X_{mi,m} \times X_{ni,n}}},$$

where $X_{mi,n}$ is m's exports to n of good i, and $X_{mi,m}$ is m's internal trade of good i. The same definitions hold for exports from country n.

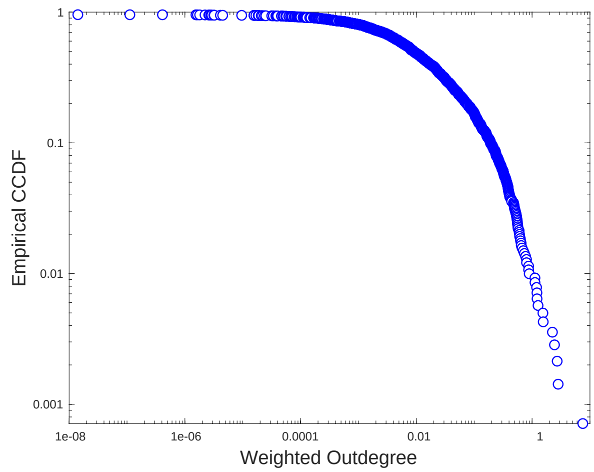
We calculate $\tau_{mi,n}$ for every country-sector pair in WIOD and create trade cost matrix τ, which we adjust the input-output matrix ($\mathbf{W}$) by to create the final weighting matrix for the spatial autoregressions.[13] We use the WIOD trade data for the sample period in constructing both the $\boldsymbol{\tau}$

[13] See the matrix definitions after (A.8) in Appendix A for the scaling equation.

Figure 1. Distribution of Weighted Outdegree for WIOD



(a) World Linkages



(b) International Linkages

Notes: This figure plots the counter cumulative distribution function of the weighted outdegree using the average of the WIOD annual database over 2000–14. The panel with World Linkages is based on the full WIOD table, while the International Linkages panel uses only internationally connected country-sector cells (i.e., we omit the domestic-only linkages across sectors) in constructing the weighted outdegree measure.

and $\mathbf{W}$ matrices. Further, note that to eliminate some outliers in $\boldsymbol{\tau}$, we winsorize the final sample matrix at the one percent level. Note that unlike the $\mathbf{W}$ matrix, $\boldsymbol{\tau}$ is not a directed matrix as its elements are symmetric between country pairs for a given sector.

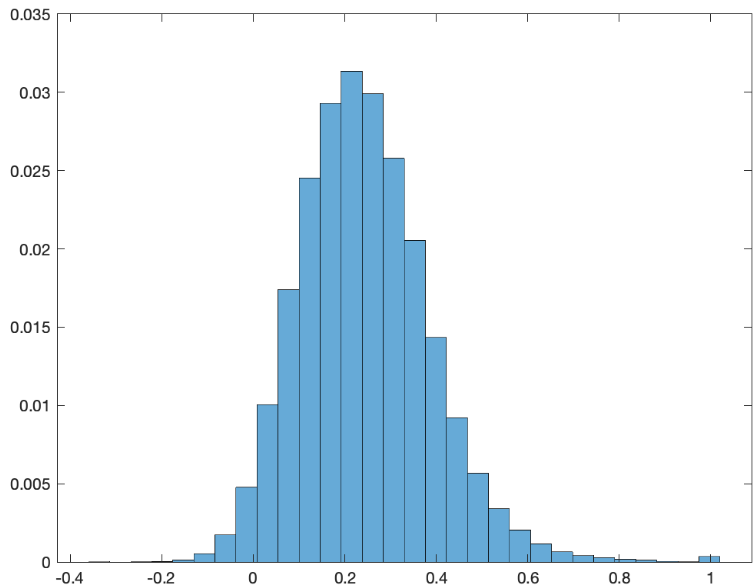
4.2 Returns Data

We next explore our data and show that there is a relationship between stock return correlations and input-output linkages. As described previously, a unit of observation in our data is monthly stock returns in country m and sector i. Because not all sectors are present in all countries, we have stock indexes for 671 out of possible 1404 country-sector cells for each month from January 2000 through December 2016.[14] Figure 2 presents the distribution of pairwise correlations between each possible pair of the 671 time series of stock returns. We can see that most correlations are positive and that the mass of the distribution is between 0 and 0.5.

Returns and the Input-Output Network. Our main goal is to explore whether stock market correlations are associated with production linkages. To do so, we first compute a measure of distance between each pair of country-sector cells. The concept of distance is better defined for

[14] Recall that we have potentially a maximum of 54 sectors and 26 countries. The number of possible country-sectors is further restricted to insure that $\mathbf{W}$ is full rank for estimation purposes, even if stock returns data may exist for some of these country-sectors.

Figure 2. Correlation of Stock Returns over the Entire Sample



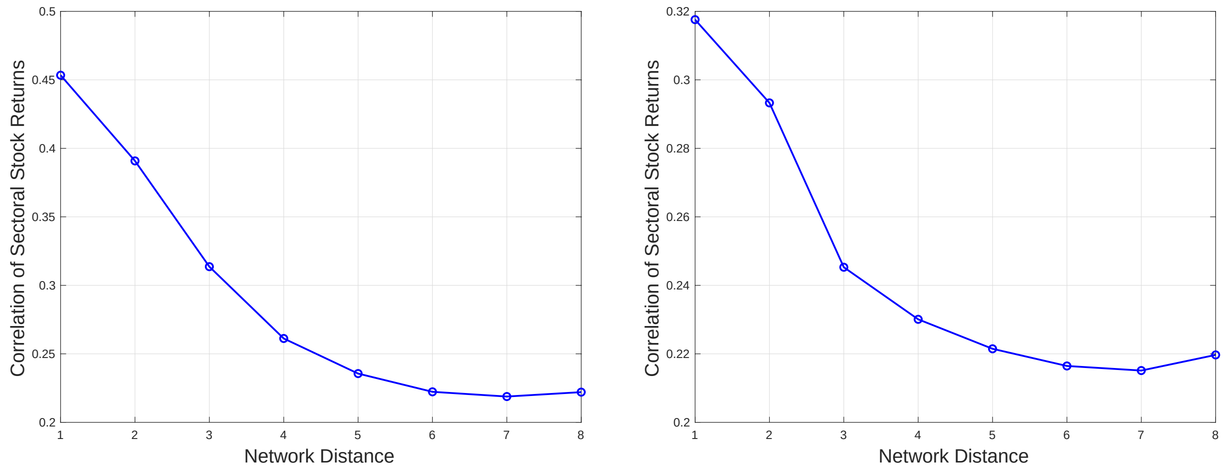
Notes: This figure plots the distribution of pairwise correlations of monthly stock returns over 2000–16 across 26 countries and 54 sectors.

binary networks. Thus, for illustrative purposes, we replace $\mathsf{w}_{mi,nj} < 0.05$ with 0, and the rest of the cells with 1, converting our network into a binary one. In a such a network, the distance between two cells is defined as the length of the shortest path (geodesic) between them.

We use this concept of distance for each pair of country-sector cells and compare it to the correlation of stock returns for this pair of country-sector cells. Figure 3 plots this relationship, where we compute the average directional distance between any two country-sector cells (i.e., the average distance from $mi \rightarrow nj$ and $nj \rightarrow mi$). Even though the diameter, the longest distance, of the input-output network averaged over time is 23, we only plot distances up to 8 because for any distances longer than that the decline in stock price correlation levels off. The figure shows the average stock price correlation for all country-sector cell pairs that are at a given distance from each other in the network.

In panel (a), which uses the full set of country-sector cells, we can see that pairs most closely connected through input-output linkages exhibit the highest correlation of stock returns (correlation coefficient of 0.45). The larger is the distance, the lower is the correlation. We can see that it tapers out just below 0.25 for any distance over 4. Panel (b) shows that a similar pattern holds when we exclude all domestic sector pairs from the analysis. This finding alleviates a concern that our results are driven entirely by domestic input-output linkages and stock return correlations. We can see that even excluding domestic linkages, the country-sector cells that are most highly connected

Figure 3. WIOD Network Distance and Correlation of Stock Returns: Supplier Linkages



(a) World Linkages **(b)** International Linkages

Notes: This figure plots correlations of monthly stock returns over 2000–16 across 26 countries and 54 sectors on the y-axis, across network distance bins based on the direct bilateral supply linkage using the average of the WIOD annual database over 2000–14. The elements of IO matrix are defined as country-sector mi's usage of country-sector nj's good as an intermediate divided by mi's gross output. The panel with World Linkages is based on the full WIOD table, while the International Linkages panel extracts the correlation and distance variable for only internationally connected country-sector cells (i.e., we omit the domestic-only linkages across sectors).

exhibit a strong correlation of stock returns (correlation coefficient of 0.33).

These two figures provide *prima facie* evidence that two sectors that rely more heavily on each other for the supply of inputs in productions also have more strongly correlated stock returns. However, these bilateral correlations may be driven by numerous transmission channels or shocks, and are silent on how shocks are transmitted via the overall network.

4.3 Monetary Policy Shocks and Global Financial Cycle Correlates

Our baseline measure of U.S. monetary policy shocks is sourced from Jarociński and Karadi (2020). They construct a measure of an interest rate surprise as the change in the 3-month Federal Funds future rate, which they interpret as the expected federal funds rate following the next policy meeting. The change in the futures rate is calculated in the 30-minute window around the time of the Federal Open Market Committee (FOMC) press release, which is 2 p.m. East Coast time on the day of a regular FOMC meeting.[15]

We explore the robustness of our regression results to including other correlates of the global financial cycle, namely the VIX, 2-year U.S. Treasury rate, and broad U.S. dollar index. The VIX is obtained from Federal Reserve Economic Data (FRED). The 2-year Treasury rate and broad U.S.

[15]This measure of monetary surprise shocks is common in the literature, and follows the work of Gertler and Karadi (2015). Note that we aggregate shocks within months for the (infrequent) months where there are multiple announcements.

dollar index are obtained from the Board of Governors of the Federal Reserve (series H.15 and H.10, respectively). We take the monthly log difference of the VIX and broad U.S. dollar index and the monthly first difference of the 2-year Treasury rate before including them in the regressions below. The VIX and dollar index are common variables used to capture the global financial cycle (e.g., Bruno and Shin, 2015a; Miranda-Agrippino and Rey, 2020), while changes in the 2-year Treasury rate captures the overall change in monetary policy stance as well as the cost of funding.[16]

Given potential contemporaneous monetary policy shocks across countries, we check the robustness of our results by including ECB and Bank of England monetary policy shocks constructed by Cieslak and Schrimpf (2019). To best match the definition we use for the U.S. monetary policy shock, we use the series that are not decomposed into monetary and non-monetary news. We include these shocks along with the U.S. monetary policy shock vector in order to control for potential foreign monetary responses to U.S. monetary policy, and which would be picked up in the network contribution if omitted. Finally, we also exploit U.S. monetary policy shocks from Nakamura and Steinsson (2018), Bu et al. (2019), and Ozdagli and Weber (2020) for further robustness checks.

5 Empirical Results

5.1 Linear Regression Results

To establish a baseline, we estimate a simple linear regression that ignores any spatial network effects:

$$\widehat{\pi}_{mi,t} = \alpha + \beta^{LS}\widehat{\mathcal{M}}_{US,t} + \varepsilon_{mi,t}, \tag{17}$$

where α represents either a constant or different sets of fixed effects.

The results of the estimation for the Jarociński and Karadi (2020) shock for 2000–07 sample period are reported in Table 1.[17] The simple OLS estimate in column (1) implies that a one percentage point surprise in the monetary policy shock results in a 0.1 percentage points rise in the average country-sector monthly stock return. The standard errors increase substantially when we cluster them at the monthly (t) level, as reported in column (2), which should be expected given that the monetary policy shock is being repeated for each country-sector return in a given time period of the panel. The magnitude of the effect does not change much whether we control for country, sector, or country-sector fixed effects (column (3)). We use the (most restrictive) country-sector fixed effect specification as our baseline for the linear regression, and thus only report these

[16] The 2-year Treasury rate is a more convenient measure than the Federal Funds rate because it never reached the zero lower bound and because it is highly correlated with the "shadow" Federal Funds Rate, such as the one proposed by Wu and Xia (2016), while at the same time being a more transparent measure.

[17] The results for other monetary shock measures and other time periods are nearly identical and can be obtained from the authors upon request. The exception is including 2008, which lowers the magnitude of the effect. Because the dependent variable is the stock return, including lagged dependent variable in these regression does not alter the results.

Table 1. Linear Regression Estimation Results, Full Sample

$\widehat{\pi}_{mi,t} = \alpha + \beta^{LS}\widehat{\mathcal{M}}_{US,t} + \varepsilon_{mi,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
MP shock	-0.102***	-0.102**	-0.103**	-0.083***	-0.098***	-0.136***
(β^{LS})	(0.008)	(0.044)	(0.044)	(0.011)	(0.009)	(0.049)
Constant	0.010***	0.010**	0.010*	0.010***	0.010***	0.010*
	(0.000)	(0.005)	(0.005)	(0.001)	(0.001)	(0.005)
Estimator	OLS	OLS	LS	Random coeffs	Mean Group	LS - country
Fixed effects	None	None	*mi*	Random	*mi*	*m*
St. errors	Regular	Clustered on t		Conventional	Group-specific	Clustered on t

Notes: This table reports coefficients from linear regressions where the dependent variable $\widehat{\pi}_{mi,t}$ is the country-sector monthly stock return (country average in column (6)) over 2000–07 in month with FOMC announcements, and the independent variable $\widehat{\mathcal{M}}_{US,t}$ is the measure of the monetary policy shock taken from Jarociński and Karadi (2020). There are 49,667 observations in columns (1)-(5), and 1,716 observations in column (6). Standard errors are in parentheses with *, **, and *** denoting coefficients significantly different from zero at the 1, 5 and 10% levels, respectively.

regression results.

Keeping in mind that our conceptual framework allows for U.S. monetary policy shocks to have heterogeneous effects across country-sector pairs, we allow for heterogeneous values of β for each mi in our estimation procedure. This is possible because of the time dimension of our data. First, we estimate a random coefficients model with β's varying across country-sector panels. We find that the coefficient estimate declines slightly, as shown in column (4). Second, we use a Mean Group estimator (Pesaran and Smith, 1995) with groups defined as country-sector pairs. In this case, the average β is nearly identical to the OLS estimate, as seen in column (5).

Finally, we aggregate stock returns at the country level and estimate a country fixed effects linear regression, reported in column (6). We find that the coefficient for this country-time panel specification is slightly larger (in absolute value) than the estimated coefficient based on country-sector level data.

Table 2 reports the same sets of regressions, splitting the sample into all foreign countries (Panel A) and only the United States (Panel B). The overall point estimate for the international sample is similar to the baseline estimates using the whole sample of Table 1. However, the point estimates for the United States (Panel B) are substantially larger. The estimated coefficient for the fixed effect specification in column (3) implies that a one percentage point surprise in monetary loosening is associated with a 0.17 percentage point increase in the average monthly return across

Table 2. Linear Regression Estimation Results, International and United States Sub-Samples

$\widehat{\pi}_{mi,t} = \alpha + \beta^{LS}\widehat{\mathcal{M}}_{US,t} + \varepsilon_{mi,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
				Panel A. Excluding the United States		
MP shock	-0.097***	-0.097**	-0.134**	-0.076***	-0.092***	-0.134***
(β^{LS})	(0.008)	(0.045)	(0.045)	(0.012)	(0.010)	(0.050)
Constant	0.010***	0.010**	0.010*	0.010***	0.010***	0.010*
	(0.000)	(0.005)	(0.005)	(0.001)	(0.001)	(0.005)
				Panel B. United States only		
MP shock	-0.171***	-0.171***	-0.171***	-0.156***	-0.179***	-0.173***
(β^{LS})	(0.019)	(0.040)	(0.040)	(0.029)	(0.023)	(0.039)
Constant	0.007***	0.007	0.007*	0.007***	0.007***	0.005
	(0.001)	(0.004)	(0.004)	(0.001)	(0.001)	(0.004)
Estimator	OLS	OLS	LS	Random coeffs	Mean Group	LS - country
Fixed effects	None	None	mi	Random	mi	m
St. errors	Regular	Clustered on t		Conventional	Group-specific	Clustered on t

Notes: This table reports coefficients from linear regressions where the dependent variable $\widehat{\pi}_{mi,t}$ is the country-sector monthly stock return (country average in column (6)) over 2000–07 in month with FOMC announcements, and the independent variable $\widehat{\mathcal{M}}_{US,t}$ is the measure of the monetary policy shock taken from Jarociński and Karadi (2020). Panel A includes all countries but the United States (25 countries in total, 46,357 observations in columns (1)-(5), 1,650 observations in column (6)), and Panel B includes only the United States (3,310 observations in columns (1)-(5), 66 observations in column (6)). Country×sector level fixed effects are included in all specifications. Robust standard errors clustered at the monthly level are in parentheses with *, **, and *** denoting coefficients significantly different from zero at the 1, 5 and 10% levels, respectively.

U.S. sectors.[18]

The linear regressions do not allow for the network structure and therefore β^{LS} combines both direct and network effects. We therefore next turn to the spatial autoregression setup to be able to measure these two effects separately.

5.2 SAR Results

We now allow for network effects by estimating a spatial autoregression model (SAR). Effectively, this estimation strategy removes the restriction, imposed by the linear regression framework, of

[18]Note that this point estimate is substantially smaller than the implied impact in Ozdagli and Weber (2020), as well as other event-type studies on the impact of U.S. monetary policy shocks on stock returns. We believe this is due to higher level of aggregation in our data (fewer industries) and further attenuation due to our use of monthly frequency data, rather than looking at the returns around the 30-minute window of the FOMC announcement.

Table 3. Spatial Autoregression Panel Estimation Results

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

	Avg. β (1)	Avg. ρ (2)	Avg. **Direct** (3)	Avg. **Network** (4)	**Network/Total** (5)
			Panel A. Weighting Matrix without Trade Costs		
Full sample	-0.019	0.748***	-0.026*	-0.093***	78%***
	(0.021)	(0.179)	(0.020)	(0.018)	(0.197)
International	-0.016	0.746***	-0.023	-0.091***	80%***
	(0.020)	(0.179)	(0.019)	(0.020)	(0.084)
USA	-0.056*	0.768***	-0.066**	-0.122***	65%***
	(0.035)	(0.212)	(0.033)	(0.035)	(0.047)
			Panel B. Weighting Matrix with Trade Costs		
Full sample	-0.027*	0.675***	-0.035**	-0.053***	60%***
	(0.020)	(0.157)	(0.020)	(0.012)	(0.164)
International	-0.023	0.681***	-0.031*	-0.052***	62%***
	(0.020)	(0.158)	(0.019)	(0.020)	(0.045)
USA	-0.080***	0.600***	-0.087***	-0.065**	42%***
	(0.034)	(0.154)	(0.034)	(0.034)	(0.008)

Notes: This table reports results from heterogeneous coefficient spatial panel autoregressions where the dependent variable is the country-sector monthly stock return over 2000–07 over month with FOMC announcements, and the independent variable is the measure of the monetary policy shock taken from Jarociński and Karadi (2020). There are 44,286 observations total comprised of 671 country-sectors over 66 months. In Panel B autoregressive weighting matrix $\mathbf{W}$ is replaced with the one that sets all trade costs τ to 1. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions and *, **, and *** denote coefficients significantly different from zero at the 1, 5 and 10% levels, respectively.

independent panels, i.e. $\rho = 0$ in Equation (11).

The baseline results of the estimation of the heterogeneous coefficients SAR model (Equation (12)) are presented in Table 3. We allow for country-sector fixed effects following Elhorst (2014). We estimate the regression with maximum likelihood following Aquaro et al. (2019), and bootstrap standard errors for all parameters as well as for the decompositions, using a wild panel bootstrap with 500 repetitions.

Panel A of Table 3 shows the average values of $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, **Direct**, **Network**, and the share of **Network** in **Total** across country-sectors. We report averages across all country-sectors, for country-sectors outside of the U.S., and for the U.S. sectors only. The full distribution of these estimates are reported in Figure A1. In addition to our baseline, we estimate an alternative specification which accounts for trade costs τ. Effectively, the second specification weighs the input-output matrix by trade costs. This second specification is reported in Panel B.

We find that for the full sample, about 20% of the average total effect is due to the direct impact of the U.S. monetary policy shock while the rest is due to the production network shock transmission. This is due to a high coefficient of shock propagation ρ, which is on average 0.75. Interestingly, the average ρ is less than one, the value implied by our conceptual framework, due to unmodelled resistance to the transmission of shocks across international stock markets via the global production network.

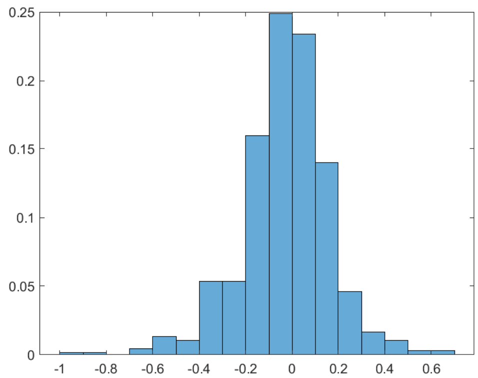
Computing averages for foreign country-sectors and for the U.S. sectors separately, we can see the pattern of transmission of U.S. monetary policy shocks to stock returns globally. We see a much larger (2.5 times) direct effect of U.S monetary policy shock on U.S. sectors, which is expected. This direct effect is then propagated through the production network, both globally and domestically. The share of the production network effect for U.S. sectors is 65%, while for foreign country-sectors it is 80%. In fact, the direct effect of U.S. monetary policy shocks on stock returns in foreign countries is not statistically significant. These results are very intuitive and show that production linkages are very important in transmitting demand shocks at the sector level.[19]

Panel B shows that allowing for trade costs τ lowers the autoregressive coefficient and increases the direct effect overall as well as for international and U.S. subsamples. That is, not accounting explicitly for trade cost may exaggerate the share of shock transmission that is due to the global production network on average as shown in panel A. By looking at the distribution of direct and network effects across country-sectors for both sets of estimates reported in panels A and B, as shown in Figure 4, we can see that the amplification of the network effect in the model without trade costs is due to a larger proportion of country-sectors with negative network effects.

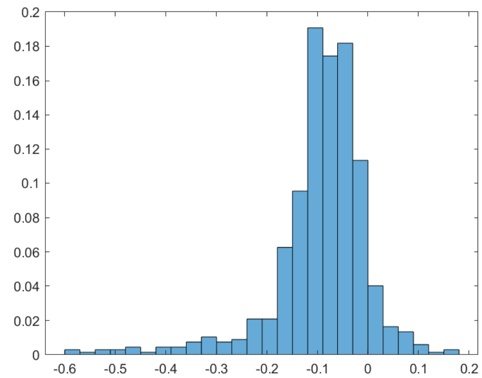
We conjecture that there are two potential reasons that the network effects decline when including trade costs in the spatial weighting matrix. First, the trade costs place greater weights on countries that have larger bilateral trade in a given sector with respect to their total output – i.e., a measure of bilateral sectoral integration. This integration may not match up to how intensely intermediate goods are used for total production, and may therefore dampen the input-output weights. Second, the trade costs are symmetric for a given sector, while the input-output weights are asymmetric. Therefore, introducing the trade costs may create some noise, which would attenuate the estimated impact of the production network. Keeping these potential biases in mind, we proceed with our analysis relying on the model without trade costs.

[19]We will show that the direct effect on foreign sectors declines further when we explicitly allow for other financial shocks to affect foreign stock returns.

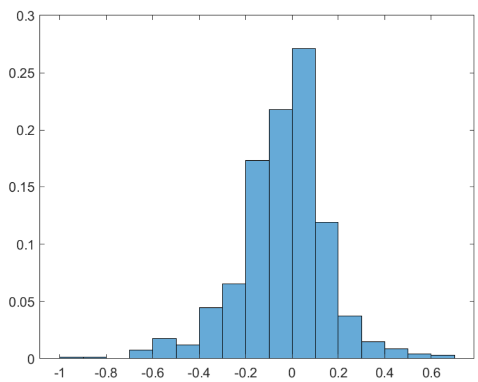
Figure 4. Distribution of Direct and Network Effects across Country-Sectors



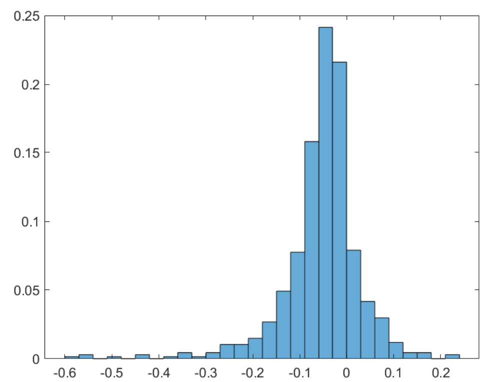
(a) Direct, no trade costs



(b) Network, no trade costs



(c) Direct, trade costs



(d) Network, trade costs

Notes: This figure plots the distribution of **Direct** and **Network** across *mi* from the estimation of equation $\widehat{\boldsymbol{\pi}}_t = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \boldsymbol{\varepsilon_t}$ for 2000–07, using Jarociński and Karadi (2020) monetary policy shocks for $\widehat{\mathcal{M}}_{US}$. The averages of these distributions are reported in Table 3.

5.3 Sensitivity to Time Period

So far we have limited our analysis to the 2000–07 time period. Our baseline estimates are through 2007 for three reasons: first, this period includes a full cycle of monetary policy actions but excludes the effective lower bound period; second, this period ends well prior to the Great Trade Collapse that occurred during the Global Financial Crisis in 2008:H2–2009:H1; third, this period does not include the dramatic decline in global stock prices that followed the collapse of Lehmann Brothers. In our baseline analysis, as in our model, we take the global production network as given, and therefore we use the input-output coefficients from 2000. It is possible, however, that a rapid increase in trade globalization and the lengthening of global supply chains in the early 2000s may affect our results. Therefore, we want to explore the evolution of our results as we vary the time

Table 4. Spatial Autoregression Panel Estimation Results: Variation over time

Time period	Observations	Year for **W**	Share of network effect		
			Full sample	International	United States
2000–07	44,286	Average 2000–07	77%	79%	63%
			(0.190)	(0.020)	(0.013)
2000–16	92,598	2000	84%	89%	61%
			(0.358)	(0.237)	(0.134)
2000–16	92,598	Average 2000–16	87%	93%	60%
			(0.377)	(0.254)	(0.175)
2000–07,09-16	87,230	2000	80%	82%	67%
			(0.218)	(0.130)	(0.156)

Notes: This table reports networks shares calculated from heterogeneous coefficient spatial panel autoregressions where the dependent variable is the country-sector monthly stock return over 2000–07 over month with FOMC announcements, and the independent variable is the measure of the monetary policy shock taken from Jarociński and Karadi (2020). Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions. All network shares are significant at the 1% level. Full regression results are reported in Table A3.

period and the year from which we sample matrix **W**.

Table 4 reports just the share of network effect across different variations of the sample for our baseline regression reported in Panel A of Table 3. A full set of estimates is reported in Table A3. We can see that replacing **W** measured in 2000 with the average **W** for 2000–07 does not change the results. This is not surprising given that elements of **W** are driven by production technologies and a trade structure that do not change very quickly. Next we extend our time period through 2016.[20] We can see that the share of the network effect increases dramatically in this extended sample, especially for foreign sectors. However, we can tell that this is driven by the coincidence of monetary policy shocks, stock market crashes, and the global trade collapse in 2008 – once we exclude 2008 from the sample, our results become very similar to the baseline. Furthermore, in this extended sample, using average **W** instead of **W** for 2000 does not make much difference.

5.4 The Global Financial Cycle and Foreign Monetary Policy Shocks

We next explore the robustness of the global production network demand channel of U.S. monetary policy shocks by controlling for two potentially important sources of transmission, which if omitted may lead to estimation biases of our baseline direct and network effects. In particular, if these omitted shocks are correlated with U.S. monetary policy shocks and have a direct effect on global

[20]While WIOD is only available through 2014, we gather information on all other variables through the end of 2016. To compute average **W** for 2000–16 we simply assume that the WIOD for 2015 and 2016 would be the same as the average 2000–14 WIOD matrix.

stock returns, our estimates of the impact of U.S. monetary policy shocks would spuriously attribute some of their effect to propagation through the production network. Two main sources of such shocks are or particular concern: the global financial cycle and foreign monetary policy shocks.

5.4.1 The Global Financial Cycle

There is clear evidence in the literature that global stock prices respond to a global financial cycle (Miranda-Agrippino and Rey, 2020). Some movements of the global financial cycle are due to changes in U.S. monetary policy, while others are market driven. Here we show the robustness of our results to controlling for such shocks. In our analysis we focus on three variables that are not highly correlated with each other and are easily available: changes in the VIX, the U.S. 2-year Treasury rate, and the broad U.S. dollar Index. We conduct both LS and SAR analysis and include these variables one at a time and then all together.

LS Results

Table 5 shows the results of the fixed effects least-square regressions for the full sample as well as for subsamples of foreign country-sectors and for the U.S. only. In the interest of space we only present the results with all three additional control variables included for the subsamples – the results do not vary much if we include them individually.[21]

The VIX has been shown to be highly correlated with the global financial cycle and is therefore likely to affect global stock returns given changes in risk aversion and the behavior of financial intermediaries. To the extent that some movements in the VIX are correlated with U.S. monetary policy shocks, our baseline regressions may be attributing some of the effect of the VIX to the demand-channel effect of the monetary policy shock that the input-output network captures. Indeed, when we include the VIX in the regression, we find that the impact of the monetary policy shock is smaller than in the baseline and is no longer statistically significant for the full sample in columns (1) and (4), nor for foreign country-sectors in column (5). The effect of monetary policy shock does remain significant for the U.S. sectors of column (6). Consistent with the literature, increases in the VIX lower stock market returns worldwide, and by about the same amount in the U.S. and in foreign countries. We are able to further explore the varying results on the impact of the U.S. monetary policy shock when we include the VIX via the SAR analysis below, which will allow us to better unpack the potential channels at play in the international transmission of the policy shock.

Monetary policy can affect stock returns through surprises but it may also have an effect through the level of interest rates, which would not be necessarily reflected in monetary policy shocks. This second effect is likely to be reflected in capital flows (Avdjiev and Hale, 2019). According to the

[21] The full set of regressions is available upon request.

Table 5. Least-Squares Panel Estimation Results: Other Shocks

$\widehat{\pi}_{mi,t} = \beta^{LS}_{MP}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\beta}^{LS}_{X}\,\mathbf{X}_t + \varepsilon_{mi,t}$

	Full Sample				International	United States
	(1)	(2)	(3)	(4)	(5)	(6)
MP shock	-0.061	-0.117**	-0.107**	-0.076	-0.070	-0.152***
	(0.046)	(0.046)	(0.044)	(0.047)	(0.048)	(0.040)
VIX	-0.162***			-0.146***	-0.148***	-0.123***
	(0.037)			(0.036)	(0.036)	(0.031)
T2y		0.146*		0.091*	0.090*	0.113***
		(0.077)		(0.047)	(0.049)	(0.035)
USD			-0.546	-0.338	-0.332	-0.417
			(0.363)	(0.290)	(0.297)	(0.281)
R^2	0.060	0.030	0.02	0.070	0.070	0.14
Observations	49,667				46,357	3,310

Notes: This table reports coefficients from linear regressions where the dependent variable $\widehat{\pi}_{mi,t}$ is the country-sector monthly stock return over 2000–07 in month with FOMC announcements.The independent variables include the measure of the monetary policy shock taken from Jarociński and Karadi (2020) (MP shock), the monthly changes in the VIX index (VIX); the 2-year Treasury rate (T2y), and the broad U.S. dollar index (USD). Robust clustered standard errors are in parentheses with *, **, and *** denoting coefficients significantly different from zero at the 1, 5 and 10% levels, respectively.

authors, an increase in the policy rate during the lending boom is likely to increase capital flows worldwide, which would imply increases in stock returns globally. Indeed, we find that an increase in the 2-year Treasury rate increases stock returns during our sample period of 2000–07 as seen in columns (2) and (4)-(6), which corresponds to a lending boom. Controlling for the 2-year Treasury rate, however, does not change much the impact of the monetary policy shock relative to the baseline across any of the specifications.

In our baseline analysis we assumed away the explicit effect of exchange rates. Given that the value of the dollar can be affected by monetary policy shocks (Inoue and Rossi, 2019), we want to separate the impact of monetary policy surprises that is orthogonal to exchange rate changes from the reaction to the change in the value of the dollar. To do so, we control for the broad U.S. dollar index in columns (3)-(6). We find that the value of the dollar does not have an effect on global stock returns and that controlling for the dollar index does not change our baseline results in any specification.[22] Combining the three additional control variables produces results that are similar to the regression with the VIX only, showing, consistent with the literature, that the VIX is the dominant correlate of the global financial cycle when it comes to explaining movements in global

[22] The results are very similar if we instead control for each country's bilateral exchange rate vis-à-vis the U.S. dollar.

stock returns.

SAR Results

The least-square analysis does not allow us to separate the direct impact from the effect of the global production chain. Thus, we include these additional control variables in our baseline spatial autoregression. The results of this analysis are reported in Table 6. In the interest of space, we only show the decomposition into foreign and U.S. sectors for the regression that includes all three controls at once. We also only report the average country-sector $\boldsymbol{\rho}$, **Direct**, and **Network** estimates.[23]

If correlates of the global financial cycle have a direct effect on stock market returns across countries, as previous research has shown, our baseline estimation might be incorrectly attributing these to the propagation of monetary policy shocks through production network. In terms of estimation, this would be reflected in the spacial autoregression coefficient ρ being upwards biased. When we include the VIX as a control in the regressions (columns (1) and (4)-(6)) we find a slight decline in ρ relative to the baseline, but the difference is not statistically significant. Controlling for the 2-year Treasury rate and broad U.S. dollar index does not alter the estimate of ρ relative to the baseline. It is important to note that we estimate only one spacial autoregression coefficient ρ for each country-sector for all exogenous variables, which then implies that the "resistance" in the transmission of all shocks through the production network is the same, and therefore differences in the share of the network effect are driven by the differences in the estimated β's for each exogenous variable.

When we control for the VIX in column (1), we find that both direct and network effects of monetary policy shocks are reduced and that the network share of the impact of the VIX is roughly two thirds of the total. The decline in the overall impact of the U.S. monetary shock matches the least-square estimates in Table 5, while the **Network** contribution is still significant and large (82%) as in our baseline estimates of Table 3. Interestingly, the changes in the VIX have both direct and network effects, with the **Network** contribution roughly equal to 60% of the total effect for all countries. Controlling for the 2-year Treasury rate and broad U.S. dollar index, in columns (2) and (3) respectively, does not alter our baseline results, even though both the direct and network effects of these controls are statistically significant with the effects going in the same direction as in the linear regression. Similarly to our findings for the VIX, the network effect contributes to roughly two-thirds of the total effect for both the 2-year Treasure rate and dollar index. Notably, the quantitative impact of the U.S. monetary policy shocks are similar to our baseline estimates, indicating that the impacts of 2-year Treasury rate and dollar index are uncorrelated with the impact of U.S. monetary policy surprises.

[23]Full regression results are available in Tables A4, A5, and A6.

Table 6. Spatial Autoregression Panel Estimation Results: Other Shocks

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}_{MP}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\beta}_X\,\mathbf{X}_t + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

	Full Sample				International	United States
	(1)	(2)	(3)	(4)	(5)	(6)
Average ρ	0.712***	0.737***	0.748***	0.706***	0.705***	0.720***
	(0.162)	(0.161)	(0.196)	(0.182)	(0.183)	(0.204)
Direct effect of MP	-0.013	-0.031*	-0.026	-0.018*	-0.014	-0.067***
	(0.010)	(0.019)	(0.021)	(0.012)	(0.012)	(0.023)
Network effect of MP	-0.059***	-0.099***	-0.094***	-0.064***	-0.063***	-0.081***
	(0.014)	(0.020)	(0.020)	(0.017)	(0.013)	(0.025)
Direct effect of VIX	-0.060**			-0.056***	-0.058***	-0.038***
	(0.030)			(0.023)	(0.023)	(0.024)
Network effect of VIX	-0.091***			-0.080***	-0.081***	-0.073***
	(0.015)			(0.016)	(0.025)	(0.025)
Direct effect of T2y		0.045*		0.028**	0.027**	0.039***
		(0.030)		(0.018)	(0.017)	(0.023)
Network effect of T2y		0.086***		0.044***	0.043***	0.060***
		(0.029)		(0.017)	(0.018)	(0.025)
Direct effect of USD			-0.146**	-0.086*	-0.082*	-0.145***
			(0.081)	(0.062)	(0.063)	(0.096)
Network effect of USD			-0.248***	-0.097*	-0.101*	-0.054*
			(0.080)	(0.075)	(0.068)	(0.102)

Notes: This table reports direct and network effects from heterogeneous coefficient spatial panel autoregressions where the dependent variable is the country-sector monthly stock return over 2000–07 over month with FOMC announcements, and the independent variable is the measure of the monetary policy shock taken from Jarociński and Karadi (2020). There are 44,286 observations total comprised of 671 country-sectors over 66 months. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions and *, **, and *** denote coefficients significantly different from zero at the 1, 5 and 10% levels, respectively. Full regression results are reported in Table A4-Table A6.

Next, we combine all global financial sector variables with the U.S. monetary policy shock and provide the decomposition into direct and network effects in column (4) for all countries, along with decompositions for the international and U.S. samples of country-sectors in columns (5) and (6), respectively. As in our baseline case, we continue to find that for foreign country-sectors most of the monetary policy shock transmission is due to the production network, while for the U.S. sectors the role of the direct effect is larger. The impact and decompositions of the VIX effect is similar to when it is included on its own in column (1), while the inclusion of the VIX decreases the overall effects of the 2-year Treasury rate and U.S. dollar index relatively to what we find if we include them alone in columns (2) and (3), respectively. In contrast to the U.S. monetary policy shock, the direct effect of the VIX is larger for foreign sectors than for the U.S. sectors, confirming the findings in the literature that the VIX is an important correlate of the global financial cycle (Rey, 2013).

These estimates show that both U.S. monetary policy and other financial shocks propagate through the global production network. To understand the intuition behind this finding, remember that our distance matrix reflects upstream production linkages, from final demand to suppliers of intermediate goods. Our conceptual framework highlights the fact that monetary policy shocks lead to changes in final demand that propagate upstream through demand for intermediate goods. Similarly, shocks to uncertainty that are reflected in VIX are likely to lead to a change in investment demand (Bloom et al., 2018), which in turn will also lead to a change in the demand for intermediate goods and thus also propagate upsteam along global production linkages.

Overall, we find that, while there is some contamination of our baseline results that arises from omitting correlates of the global financial cycle, especially the VIX, our description of the pattern and quantitative relevance of the monetary policy shock transmission through the global production network remains unchanged: U.S. monetary policy shocks have a direct impact predominantly on the U.S. stock returns, which then spread via production linkages internationally.

5.4.2 Foreign Monetary Policy Shocks

We further control for foreign monetary policy shocks in case they occur in reaction to or in concert with the U.S. monetary policy surprises. This coincidence of monetary policy actions could lead to an upward bias in the contribution of the network effect, which would capture the direct impact of a country's domestic monetary policy change rather than the spillover from U.S. monetary policy. In particular, we are able to control for ECB and Bank of England (BOE) monetary policy shocks using measures constructed by Cieslak and Schrimpf (2019). Controlling for these shocks has implications for both euro countries and the UK, but also for countries that have deeper production linkages with these nations than the U.S., thus potentially impacting our baseline measure of the international network effect of U.S. monetary policy shocks along several dimensions.

Table 7 presents these regression results, where like above we estimate the same resistance vector ($\boldsymbol{\rho}$) for all potential monetary policy shocks. Looking at direct and network effects of U.S. monetary policy in the second and third rows, we see that our main results on the importance of the international network effect of U.S. monetary policy remain unchanged, while notably the direct effect is now (marginally) significant. Meanwhile, monetary surprises of the ECB do not appear to have an impact on global stock prices, except marginally via the network (though in the opposite direction as expected) after controlling for U.S. MP shocks, and the BOE shocks only show up via the direct channel, where the sign is as expected for the international sample but goes in the opposite direction for the U.S. sample of sectors.

Table 7. Summary Regression Results for Foreign Monetary Policy Shocks

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}_{MP}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\beta}_X\,\mathbf{X}_t + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

		Full Sample		International	United States
	(1)	(2)	(3)	(4)	(5)
Average ρ	0.749***	0.747***	0.748***	0.746***	0.770***
	(0.169)	(0.168)	(0.174)	(0.174)	(0.204)
Direct effect of U.S. MP	-0.026*	-0.026*	-0.026*	-0.023*	-0.065***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.028)
Network effect of U.S. MP	-0.094***	-0.093***	-0.094***	-0.092***	-0.123***
	(0.019)	(0.019)	(0.021)	(0.018)	(0.030)
Direct effect of ECB MP	0.005		0.002	0.002	0.002
	(0.010)		(0.012)	(0.013)	(0.011)
Network effect of ECB MP	0.025*		0.026*	0.028	0.007
	(0.016)		(0.016)	(0.013)	(0.011)
Direct effect of BOE MP		-0.017*	-0.017	-0.020**	0.026**
		(0.013)	(0.014)	(0.015)	(0.013)
Network effect of BOE MP		-0.001	0.007	0.006	0.026**
		(0.012)	(0.014)	(0.015)	(0.013)

Notes: This table reports direct and network effects calculated from heterogeneous coefficient spatial panel autoregressions where the dependent variable is the country-sector monthly stock return over 2000–07 over month with FOMC announcements, and the independent variables are measures of the monetary policy shocks. There are 44,286 observations total comprised of 671 country-sectors over 66 months. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions. This table presents summary regression results. Full regression results are available upon request.

5.5 Additional Robustness Tests

We perform additional tests to check the robustness of our results to alternative measures of stock returns and U.S. monetary policy shocks. As a baseline for our robustness tests we take the set of SAR results reported in Panel A of Table 3. In the interest of space, we report only the share of the network effect in Table 8, with the full regression results reported in Table A7.

We begin by replacing nominal stock returns in local currency with either real stock returns or with stock returns expressed in U.S. dollars. To do so, we use last quarter's inflation rate for each observation in our sample in order to avoid incorporating any response of inflation to monetary policy shocks into our returns data. We compute real returns as $\widehat{r\pi}_{mi,t} = (1+\widehat{\pi}_{mi,t})/(1+infl_{m,t-1})-1$, where $\widehat{r\pi}_{mi,t}$ is the real stock return, and $infl_{m,t-1}$ is the inflation rate. We compute U.S. dollar returns by subtracting currency depreciation against the U.S. dollar from nominal returns in local currency. The results are reported in the top two rows of Table 8. We find that the share of the network effect of monetary policy increases slightly compared to our baseline results across all subsamples, but the differences are not large or statistically significant.

Next, we consider three alternative measures of monetary policy shocks those proposed by (Bu

Table 8. Spatial Autoregression Panel Estimation Results, Robustness

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

Specification	Share of network effect		
	Full sample	International	United States
Real returns, JK shock	80%	83%	65%
	(0.216)	(0.096)	(0.013)
USD returns, JK shock	82%	84%	63%
	(0.215)	(0.158)	(0.048)
Nominal returns, BRW shock	78%	77%	85%
	(0.268)	(0.215)	(0.275)
Nominal returns, OW shock	71%	71%	67%
	(0.158)	(0.014)	(0.014)
Nominal returns, NS shock	76%	76%	71%
	(0.197)	(0.129)	(0.099)

Notes: This table reports the network shares calculated from heterogeneous coefficient spatial panel autoregressions where the dependent variable is the country-sector monthly stock return over 2000–07 over month with FOMC announcements, and the independent variable is a measure of the monetary policy shock. The first row uses real equity returns and the 'JK' monetary policy shock from Jarociński and Karadi (2020). Rows two to four use nominal returns but use a different measure of the monetary policy shock taken from: 'BRW' (Bu et al., 2019), 'OW' (Ozdagli and Weber, 2020), and 'NS' (Nakamura and Steinsson, 2018). There are 44,286 observations total comprised of 671 country-sectors over 66 months. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions. All network shares are significant at the 1% level. Full regression results are reported in Table A7.

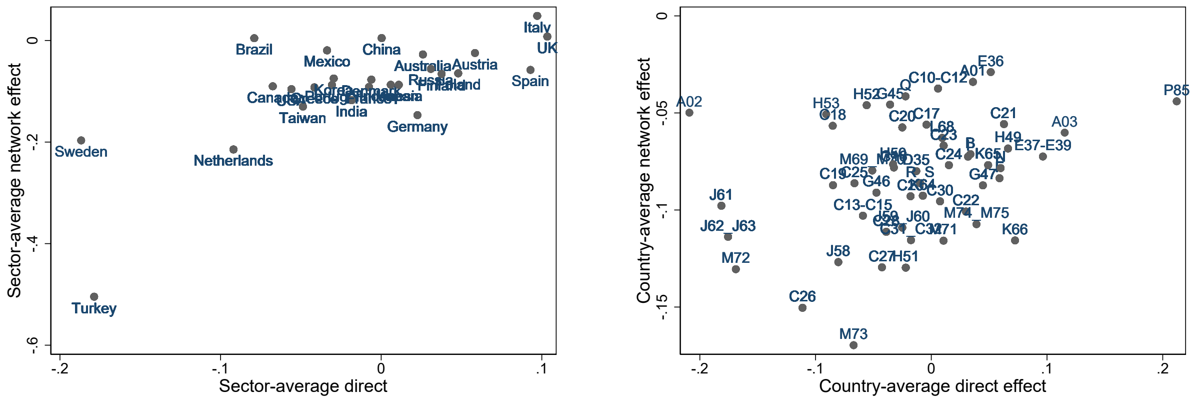
et al., 2019; Ozdagli and Weber, 2020; Nakamura and Steinsson, 2018, 'BRW', 'OW', and 'NS', respectively). We find that the share of the network effect for the U.S. sectors is slightly larger if we use BRW shocks, but qualitatively our results are very similar to the baseline. Furthermore, the 67% network share using the 'OW' shock series corresponds to the lower bound found in Ozdagli and Weber (2020), who use a different frequency of stock returns as well as a U.S. input-output table with a higher degree of sectoral disaggregation.

5.6 Heterogeneity of Estimates

We next explore drivers of the observed heterogeneity in the importance of network effects across countries and sectors. Our approach is to analyze the country-sector cross-section of the decomposition of the total effect into direct and network components. We observe that large direct and network effects are not concentrated in specific sectors nor specific countries. Figure 5 plots the average network effect against the average direct effect, panel (a) computes the average across sectors within countries, and panel (b) computes averages across countries within sectors.

We consider sectoral financial external dependence, an important source of sectoral heterogeneity, which may impact the estimated contribution of the network on the total effect of monetary

Figure 5. Distribution of Direct and Network Effects across Countries and Sectors



(a) Distribution across countries, sector averages

(b) Distribution across sectors, country averages

Notes: This figure plots averages of **Direct** and **Network** across i, plotted for each m and averages across m plotted for each i from the estimation of equation $\widehat{\boldsymbol{\pi}}_t = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \boldsymbol{\varepsilon}_t$ for 2000–07, using Jarociński and Karadi (2020) monetary policy shocks for $\widehat{\mathcal{M}}_{US}$. The overall averages of these distributions are reported in Table 3.

policy. To study this issue, we correlate the network effects to a measure of sectoral financial external dependence based on the extension of Rajan and Zingales (1998) to non-manufacturing sectors and computed for 2002–06 by Catão et al. (2009). We find a correlation of almost zero between the network effect and financial dependence across sectors.

Analyzing heterogeneity across countries along several dimensions, we do not find any significant correlation of either the total, direct, or network effects with country size, financial openness, current account, or other variables we considered. We also compared the average direct and network effects for 16 advanced and 10 emerging economies samples and find that both the direct and network effects are very similar for these two country groups.

6 Conclusion

In this paper we quantitatively evaluate the propagation of the U.S. monetary policy shocks to stock returns worldwide through the global production network. Basing our analysis on a simple conceptual framework, which can be derived from a canonical multi-country multi-sector production network model, we estimate a spatial autoregression in a panel setting that allows for coefficients to vary across countries and sectors. The conceptual framework predicts that country-sectors which are more closely linked to the U.S. via supply linkages will be more affected by U.S. monetary policy shocks.

We find a very robust and quantitatively important role of the production network – nearly 80% of the total estimated impact of U.S. monetary policy shocks on global stock returns is due to production linkages. Among U.S. sectors, the share of the network effect is smaller and the magnitude of the direct effect is substantially larger than for foreign sectors. Our findings thus suggest that U.S. monetary policy shocks directly affect predominantly domestic stock returns and the resulting changes in stock returns propagate globally via production linkages. The pattern we uncover is not affected by allowing for the financial channel of U.S. monetary policy shock transmission studied in the the global financial cycle literature. These findings contribute to the growing literature on the spillovers of the U.S. monetary policy internationally by documenting and quantifying the role of real linkages in global transmission of financial shocks.

While our analysis focuses on the transmission of demand shocks along the global production network, other general equilibrium features of the transmission mechanism of monetary policy shocks, such as the impact of associated exchange rate movements – propagated both upstream and downstream – may play an important role. Examining such issues will require enriching both the current conceptual and empirical frameworks, which we leave for future work.

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Appendix A Theoretical Framework

In this section we provide a model to illustrate the conceptual framework for studying the transmission of U.S. monetary policy shocks to stock returns internationally via production linkages. The core model is based on the static closed-economy model of sectoral linkages of Acemoglu et al. (2012). In addition, we incorporate three features in order to study the impact of monetary policy shocks on stock returns, as in Ozdagli and Weber (2020): (i) firms produce with decreasing returns to scale and face fixed costs of production, (ii) wages are preset and do not adjust given monetary shocks, and (iii) consumers have cash-in-advance constraints.

We take the technology and trade structure as fixed since we are studying the short run. We make two further assumptions to solve the model analytically. First, we assume that trade is balanced across countries. Second, we assume that prices in a given sector are equal across countries after adjusting for an iceberg trade cost, which varies at the sector and country-pair level.

The world is comprised of N countries and J sectors. Countries are denoted by m and n, and sectors by i and j. The notation follows the convention that for trade between any two country-sectors, the first two subscripts always denote exporting (source) country-sector, and the second subscript the importing (destination) country-sector.

A.1 Model Setup

Households. There is a representative household in each country n, which consumes a bundle of goods across all sectors i produced across countries m, and supplies labor in country n, l_n. Its maximization problem is

$$\max_{\{c_{mi,n}\},l_n} \sum_{i=1}^{J}\sum_{m=1}^{N} b_{mi,n}\log c_{mi,n} - l_n$$
$$\text{s.t.}$$
$$\sum_{i=1}^{J}\sum_{m=1}^{N} p_{mi,n}c_{mi,n} = w_n l_n + \pi_n + f_n,$$

where $b_{mi,n}$ is a preference parameter for which we assume $\sum_{i=1}^{J}\sum_{m=1}^{N} b_{mi,n} = 1$. Besides wage income, the domestic household's income includes aggregate profits, π_n and aggregate fixed costs, f_n, which firms must pay to produce. Note that in writing the budget constraint we assume balanced trade. Note that aggregate labor supply, profits, and fixed costs are additive across sectors: $l_n = \sum_{j=1}^{J} l_{nj}$, $\pi_n = \sum_{j=1}^{J}\pi_{nj}$, $f_n = \sum_{j=1}^{J} f_{nj}$. Maximization yields the standard first-order conditions, and the consumption-labor trade off: $b_{mi,n}w_n = p_{mi,n}c_{mi,n}\ \forall\ mi, n$.

Technology. There are $j = 1, \ldots, J$ sectors in each country $n = 1, \ldots, N$. Firms in country-sector nj have the following Cobb-Douglas production function:

$$y_{nj} = z_{nj} l_{nj}^{\alpha_{nj}} X_{nj}^{\lambda_{nj}}, \tag{A.1}$$

where z_{nj} is a Hicks-neutral technology term, l_{nj} is labor, X_{nj} is a composite intermediate good, and $\alpha_{nj} + \lambda_{nj} < 1$ implying decreasing returns to scale. Given our focus on monetary policy shocks, we simplify notation by assuming that $z_{nj} = 1\ \forall\ nj$.

The composite intermediate good is a Cobb-Douglas aggregate of intermediate goods sourced both domestically and abroad from all sectors. Specifically:

$$X_{nj} = \prod_{i=1}^{J}\prod_{m=1}^{N} x_{mi,nj}^{\omega_{mi,nj}}, \tag{A.2}$$

where $x_{mi,nj}$ is the amount of sector i's good produced in country m used by country-sector nj in final production, and $\omega_{mi,nj}$ is the associated input-output coefficient for country-sector nj usage of the intermediate good from country-sector mi in the aggregate intermediate good, where $\sum_{i=1}^{J}\sum_{m=1}^{N}\omega_{mi,nj} = 1$.[24]

[24] We have also solved the model assuming a CES production structure in labor and the aggregate intermediate good, as well as as CES aggregator underlying intermediate goods. The main results needed to motivate the empirical approach setup do not change qualitatively. The model solution is available upon request.

Given a competitive market structure with wages preset and prices taken as given by each firm, profit maximization for country-sector nj is

$$\max_{l_{nj},\{x_{mi,nj}\}} \; p_{nj}y_{nj} - \sum_{i=1}^{J}\sum_{m=1}^{N} p_{mi,n}x_{mi,nj} - w_n l_{nj} - f_{nj} \quad \text{s.t. (A.1), (A.2),}$$

where p_{nj} is the price of the good produced by sector j in country n, $\{p_{mi,n}\}$ is a vector of prices of goods sold in country n, w_n is the wage in country n, and f_{nj} is a fixed cost of production.[25] We do not model these costs but they may include access to credit or bureaucratic costs, for example. Further, we do not differentiate between fixed costs of production and fixed costs of accessing foreign markets, as is common in the international trade literature.

Solving the firm's maximization problem we can write profits as

$$\pi_{nj} = (1 - \lambda_{nj} - \alpha_{nj})R_{nj} - f_{nj}, \tag{A.3}$$

where total revenue $R_{nj} = p_{nj}y_{nj}$.

Goods Market Clearing. Global goods market clearing condition for any good mi is given by

$$y_{mi} = \sum_{n=1}^{N} c_{mi,n} + \sum_{j=1}^{J}\sum_{n=1}^{N} x_{mi,nj}, \tag{A.4}$$

where the first term capture final consumption of good mi across n destination countries, and the second term captures intermediate consumption across nj country-sector destinations. To simplify the market clearing condition we first use the household first-order condition, $\frac{b_{mi,n}}{c_{mi,n}} = \theta p_{mi,n}$ (θ is the Lagrange multiplier), and its budget constraint to express consumption as

$$c_{mi,n} = \frac{b_{mi,n}\sum_{j=1}^{J}(1-\lambda_{nj})p_{nj}y_{nj}}{p_{mi,n}}. \tag{A.5}$$

Combining this term and the firm's first-order condition, $\lambda_{nj}\omega_{mi,nj}R_{nj} = p_{mi,n}x_{mi,nj}$, the market clearing condition is

$$y_{mi} = \sum_{j=1}^{J}\sum_{n=1}^{N} \frac{b_{mi,n}(1-\lambda_{nj})R_{nj}}{p_{mi,n}} + \sum_{j=1}^{J}\sum_{n=1}^{N} \frac{\lambda_{nj}\omega_{mi,nj}R_{nj}}{p_{mi,n}}. \tag{A.6}$$

Next, multiplying (A.6) by p_{mi}, and assuming iceberg trade costs $\tau_{mi,n}$ that vary by sector and country pair ($p_{mi,n} = \tau_{mi,n}p_{mi}$, where $\tau_{mi,n} \geq 1$),[26] we express revenues in country-sector mi as:

$$R_{mi} = \sum_{j=1}^{J}\sum_{n=1}^{N} \frac{b_{mi,n}(1-\lambda_{nj})}{\tau_{mi,n}}R_{nj} + \sum_{j=1}^{J}\sum_{n=1}^{N} \frac{\lambda_{nj}\omega_{mi,nj}}{\tau_{mi,n}}R_{nj}. \tag{A.7}$$

[25] These fixed costs are needed given pre-set wages in order to satisfy the firm-entry condition in steady state.

[26] Note that $\tau_{mi,n}$ may differ depending on the direction of trade; i.e., $\tau_{mi,n}$ need not equal $\tau_{ni,m}$. However, given our empirical definition of trade costs described in Section 4.1, the constructed trade costs are in fact symmetric and are equal to one for trade within the same country.

The above equation characterizes a recursive relationship between sectors' revenues across countries, as well as the the role of different parameters in the model. Note that we are implicitly assuming that these revenues are denominated in a common currency. While we do not incorporate the exchange rate explicitly in this framework, we address this issue in our regression analysis.

Stacking (A.7) across country-sectors leads to a matrix formulation of the global system of country-sector revenues:

$$(I - \widetilde{\mathbf{\Omega}}\mathbf{\Lambda})\mathbf{R} = \sum_{j=1}^{J}\sum_{n=1}^{N} \frac{b_{mi,n}(1-\lambda_{nj})}{\tau_{mi,n}} R_{nj}, \tag{A.8}$$

where

$$\begin{aligned}
&\mathbf{R} \equiv (R_{11}, \ldots, R_{NJ})', && NJ \times 1, \\
&\mathbf{\Lambda} \equiv \operatorname{diag}\left(\{\lambda_{nj}\}\right), && NJ \times NJ, \\
&\widetilde{\mathbf{\Omega}} \equiv \tilde{\boldsymbol{\tau}} \circ \mathbf{\Omega}, && NJ \times NJ, \\
&\mathbf{\Omega} \equiv \begin{pmatrix} \omega_{11,11} & \cdots & \omega_{11,NJ} \\ \vdots & \ddots & \vdots \\ \omega_{NJ,11} & \cdots & \omega_{NJ,NJ} \end{pmatrix}, && NJ \times NJ, \\
&\tilde{\boldsymbol{\tau}} \equiv \begin{pmatrix} \left(\frac{1}{\tau_{11,1}}\right) \circ 1_{1\times J} & \cdots & \left(\frac{1}{\tau_{11,N}}\right) \circ 1_{1\times J} \\ \vdots & \ddots & \vdots \\ \left(\frac{1}{\tau_{NJ,1}}\right) \circ 1_{1\times J} & \cdots & \left(\frac{1}{\tau_{NJ,N}}\right) \circ 1_{1\times J} \end{pmatrix}, && NJ \times NJ,
\end{aligned}$$

where $\circ$ represents the Hadamard product, and $\mathbf{\Omega}$ is the global input-output matrix, where each element of the matrix, $\omega_{mi,nj}$, is the associated input-output coefficient for country-sector nj usage of the intermediate good from country-sector mi in nj's aggregate output.

Money Supply. We introduce money by assuming that consumers face a cash-in-advance constraint as in Ozdagli and Weber (2020); they justify this approach by assuming that firms enter into trade credit relationships, and thus there is no such constraint in the trade of intermediate goods.[27] Specifically, for a given economy n total final consumption is given by

$$\sum_{i=1}^{J}\sum_{m=1}^{N} p_{mi,n}c_{mi,n} = \sum_{i=1}^{J}\sum_{m=1}^{N} b_{mi,n} \sum_{j=1}^{J}(1-\lambda_{nj})R_{nj} = \mathcal{M}_n,$$

where $\mathcal{M}_n$ is the domestic money supply in country n and we again see the result of our assumption of balanced trade. Recalling that $\sum_{i=1}^{J}\sum_{m=1}^{N} b_{mi,n} = 1$, we re-write the cash-in-advance constraints

[27]This assumption may be more tenuous in the open-economy context given potential frictions in international trade credit. Given the differences in these frictions across sectors and countries, they are partly incorporated in our iceberg trade costs (Antràs and Foley, 2015; Niepmann and Schmidt-Eisenlohr, 2017; Caballero et al., 2018). The remaining part, not reflected in the model, gives us heterogeneity across countries and sectors in our regression analysis.

for country n as

$$\sum_{j=1}^{J}(1-\lambda_{nj})R_{nj} = \mathcal{M}_n. \tag{A.9}$$

Next, substitute (A.9) into (A.8) to arrive at

$$(I - \widetilde{\mathbf{\Omega}}\mathbf{\Lambda})\mathbf{R} = \tilde{\boldsymbol{b}}\boldsymbol{\mathcal{M}}, \tag{A.10}$$

where $\tilde{\boldsymbol{b}}$ is a $NJ \times N$ matrix composed of elements $\{\tilde{b}_{mi,n}\}$, where $\tilde{b}_{mi,n} \equiv \frac{b_{mi,n}}{\tau_{mi,n}}$, and $\boldsymbol{\mathcal{M}} \equiv (\mathcal{M}_1, \ldots, \mathcal{M}_N)'$.

A.2 Network Effects of Money Shocks on Global Stock Returns

To determine the impact of money shocks on global stock returns we will examine deviations of firm profits around their deterministic steady state and only consider a shock to the money supply of one country n (the U.S.).[28]

In particular, for any variable x, define the log deviation from steady-state $\widehat{x} = \log(x) - \log(\bar{x})$ so that $x = \bar{x}\exp(\widehat{x}) \approx \bar{x}(1 + \widehat{x})$, where $\bar{x}$ is the steady-state value of x. Further define $\boldsymbol{\pi}$ to be a $NJ \times 1$ vector composed of elements $\{\pi_{mi}\}$, $\boldsymbol{\lambda}$ to be a $NJ \times 1$ vector composed of elements $\{\lambda_{mi}\}$, $\boldsymbol{\alpha}$ to be a $NJ \times 1$ vector composed of elements $\{\alpha_{mi}\}$, and $\mathbf{f}$ to be a $NJ \times 1$ vector composed of elements $\{f_{mi}\}$. Stacking country-sector profits in (A.3):

$$\boldsymbol{\pi} = (\mathbf{1} - \boldsymbol{\lambda} - \boldsymbol{\alpha}) \circ \mathbf{R} - \mathbf{f}. \tag{A.11}$$

Log-linearizing (A.11) and using (A.10), we arrive at

$$\widehat{\boldsymbol{\pi}} = \left(I - \widetilde{\mathbf{\Omega}}\mathbf{\Lambda}\right)^{-1} \boldsymbol{\beta}\widehat{\boldsymbol{\mathcal{M}}}, \tag{A.12}$$

where $\boldsymbol{\beta} \equiv \mathrm{diag}\left(\left\{\frac{(1-\lambda_{nj})\bar{\mathcal{M}}_n}{\bar{\pi}_{nj}}\tilde{b}_{mi,n}\right\}\right)$ is a $NJ \times N$ matrix.

Allowing for shocks only to the U.S. monetary supply, write (A.12) as

$$\widehat{\boldsymbol{\pi}} = \left(I - \widetilde{\mathbf{\Omega}}\mathbf{\Lambda}\right)^{-1} \boldsymbol{\beta}_{US}\widehat{\mathcal{M}}_{US}, \tag{A.13}$$

where $\boldsymbol{\beta}_{US} \equiv \mathrm{diag}\left(\left\{\frac{(1-\lambda_{US\,j})\bar{\mathcal{M}}_{US}}{\bar{\pi}_{US\,j}}\tilde{b}_{mi,US}\right\}\right)$ is a $NJ \times 1$ vector.

Appendix B Linking sector classifications

TREIs data are available under Thomson Reuters Business Classification(TRBC), but the World Input-Output Tables (WIOT) have been constructed under ISIC Revision 4.

We take advantage of the fact that TREI reports both 10-digit TRBC activity codes and 6-digit NAICS 2007 codes for all equity prices. With this information one can use a concordance from

[28] In equating stock returns with changes in profits, we apply the efficient market hypothesis.

NAICS 2007 to ISIC Rev. 4 to match each firm's information to WIOT codes. In the next step, one can use the firm-level information from TREI data to construct alternative sector-specific stock price indices that are consistent with WIOT sector definitions.

However, a mapping from NAICS2007 to WIOT16 codes (2-digit ISIC Rev 4) is not perfect, as there can be many-to-many correspondences between NAICS 2007 and ISIC Rev. 4 codes. The following figure shows an example of a possible 'rear' overlapping of NAICS2007 sectors (3-digit code) in a WIOT2016 code.

wiot16code	wiot16 description	naics07_3d	naics07_3d_name	naics07_2d	naics07_2d_name
B	Mining and quarrying	211	Oil and Gas Extraction	21	Mining, Quarrying, and Oil and Gas Extraction
B	Mining and quarrying	212	Mining (except Oil and Gas)	21	Mining, Quarrying, and Oil and Gas Extraction
B	Mining and quarrying	213	Support Activities for Mining	21	Mining, Quarrying, and Oil and Gas Extraction
B	Mining and quarrying	311	Food Manufacturing	31-33	Manufacturing

In this example, the WIOT2016 Code B (Mining and quarrying) besides mining and oil sectors, it also contains the NAICS2007-Food Manufacturing sector. This occurs because the NAICS2007 sector "311942-Spice and Extract Manufacturing" from the Food Manufacturing includes the "mining and processing of table salt" activity, that is classified as a Mining activity in ISIC Rev. 4.

B.1 A reduced version of the NAICS 2007 to ISIC Rev. 4 correspondence

To limit similar occurrences as in the one in the previous example, a new version of the NAICS 2007 to ISIC Rev. 4 correspondence is constructed. The objective is to reduce the number of very different 4-digit ISIC Rev. 4 sectors per each 6-digit NAICS 2007 sector. With that in mind, the next steps were followed:

1. Work only on the set of 6-digit NAICS 2007 codes that (i) have more than one 2-digit ISIC Rev. 4 sector, and/or (ii) have more than one WIOT16 sector .

2. For a single 6-digit NAICS 2007 code, compute the frequency of its corresponding multiple 4-digit ISIC Rev. 4 sectors. When possible, the following principles were taken into consideration to assign one single NAICS 2007 code to a single 2-digit sector, the predominant sector.

3. Frequency criteria: If a 2-digit ISIC Rev. 4 sector represents more than 60 percent of the 6-digit NAICS 2007 sector in consideration, it is the called the predominant sector.

Example: The following example shows the corresponding multiple ISIC Rev. 4 codes for the single 6-digit NAICS 2007 sector "Paper (except Newsprint) Mill":

naics2007	naics2007_name	type_match	isic4	isic4_name
322121	Paper (except Newsprint) Mills	keep	1709	Manufacture of other articles of paper and paperboard
		keep	1701	Manufacture of pulp, paper and paperboard
		keep	1702	Manufacture of corrugated paper and paperboard and of containers of paper and paperboard
		delete	~~2399~~	~~Manufacture of other non-metallic mineral products n.e.c. (tar paper made in paper mills)~~

The frequency of the 2-digit ISIC Rev. 4 sector "17-Manufacture of paper and paper products" is 75 percent and it is the predominant sector. The other 2-digit ISIC Rev. 4 sector, "23- Manufacture of other non-metallic mineral products", is not predominant and its deleted from the concordance. Note that for this sector its 2-digit ISIC Rev. 4 meaning is very different from the 3-digit NAICS 2007 meaning too ("322-Paper Manufacturing").

Closest sector criteria: When the frequency criteria is not sufficient, the predominant sector is chosen by a comparison of meanings between the single 6-digit NAICS 2007 code and its corresponding 4-digit ISIC Rev. 4 codes. Then, the ISIC Rev. 4 sector with the closest meaning to the NAICS 2007 sector is selected as the predominant sector. The meaning of aggregate codes (3-digit NAICS 2007 and 2-digit ISIC Rev. 4) helped also to decide, when the comparison of 6-digit NAICS and 4-digits ISIC Rev. 4 meanings were not clear enough to reach a decision.

Example: The following example shows the corresponding multiple 4-digit ISIC Rev. 4 codes for the single 6-digit NAICS 2007 sector "Carbon and Graphite Product Manufacturing"

naics2007		isic4		naics2007_3digit	isic4_2digit
335991	Carbon and Graphite Product Manufacturing	~~2790~~	~~Manufacture of other electrical equipment~~	Electrical Equipment, Appliance, and Component Manufacturing	~~Manufacture of electrical equipment~~
		2399	Manufacture of other non-metallic mineral products n.e.c.	Electrical Equipment, Appliance, and Component Manufacturing	Manufacture of other non-metallic mineral products

Although by frequency the two 4-digit (and 2-digit) ISIC Rev. 4 sectors are equally representative for this NAICS 2007 code, their sector meanings are different. In fact, the 6-digit NAICS 2007 "335991-Carbon and Graphite Product Manufacturing" is closest to the 4-digit ISIC Rev. 4 "2399-Manufacture of other non-metallic mineral products n.e.c." than to the 4-digit ISIC Rev. 4 "2790-Manufacture of other electrical equipment" sector. Then, the 2-digit ISIC Rev. 4 "27-Manufacture of electrical equipment" is denominated the predominant sector.

There was only one exception, NAICS 2007 "337920-Blind and Shade Manufacturing". As it can be observed below, none of the previous criteria worked; and it was hard coded arbitrarily based on its 3-digit NAICS 2007 meaning, "Furniture and Related Product Manufacturing", to the 2-digit ISIC Rev. 4 "3100-Manufacture of furniture" sector.

naics2007		isic4	isic4_name	naics2007_3digit	isic4_2digit
337920	Blind and Shade Manufacturing	1392	Manufacture of made-up textile articles, except apparel	Furniture and Related Product Manufacturing	"Manufacture of textiles"
		1629	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials		"Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials"
		2220	Manufacture of plastics products		"Manufacture of rubber and plastics products"
		2593	Manufacture of cutlery, hand tools and general hardware		"Manufacture of fabricated metal products, except machinery and equipment"
		2599	Manufacture of other fabricated metal products n.e.c.		"Manufacture of fabricated metal products, except machinery and equipment"

Once this new NAICS 2007 to ISIC Rev. 4 concordance was finished, it was easy to go from NAICS 2007 to WIOT16. In the final NAICS 2007-WIOT16 concordance:

- 1020 correspondences were tagged based on the official NAICS 2007-ISIC Rev. 4 concordance.
- 37 correspondences were tagged based on the frequency criteria.
- 122 correspondences were tagged based on the closest sector criteria.
- 1 correspondence was arbitrarily hard coded.

Table A1 presents cross-country sector coverage of monthly returns for the months where there are monetary surprise shocks over 2000–14. Given cross-country differences in size, industrial specialization patterns, and stock market depth we see that larger countries (e.g., the United States) have a larger coverage of sectors, while some countries only cover a few sectors (e.g., Portugal and Russia). These differences motivate a flexible empirical approach, where we allow for country-sector fixed effects as well as country-sector specific coefficients for the effect of monetary policy surprise variable.

Table A2 presents coverage of of monthly returns for the months where there are monetary surprise shocks along the sector dimension. This table shows how the distribution of sector returns varies across countries. For example, all countries have returns for the 'Construction,' 'Telecommunication,' and 'Financial service activities, except insurance and pension funding' sectors. Meanwhile, sectors like 'Forestry and logging,' 'Fishing and aquaculture,' and 'Repair and installation of machinery and equipment' have sparse stock returns coverage across countries.

Table A1. Monthly Country Stock Return Coverage for Months with Monetary Surprise Shocks

Country	No. Industries	Observations
Australia	38	5,893
Austria	15	2,477
Brazil	17	3,781
Canada	38	5,803
China	47	6,735
Germany	28	4,841
Denmark	17	2,525
Spain	24	3,783
Finland	22	3,410
France	38	5,542
United Kingdom	40	5,954
Greece	10	1,943
Indonesia	18	3,220
India	40	5,690
Italy	22	4,370
Japan	45	6,706
Korea	34	6,108
Mexico	14	2,401
Netherlands	20	2,895
Poland	17	3,266
Portugal	8	1,209
Russia	5	1,419
Sweden	29	4,584
Turkey	21	3,887
Taiwan	29	4,675
United States	50	6,982

Notes: This table presents information on the number of sectors and observation of monthly sector returns per country for dates where there are monetary surprise shocks (FOMC meetings or off-cycle meetings) over 2000–16. The data are constructed by merging stock returns data from TREI with the WIOD classification of sectors.

Table A2. Monthly Sector Stock Return Coverage for Months with Monetary Surprise Shocks

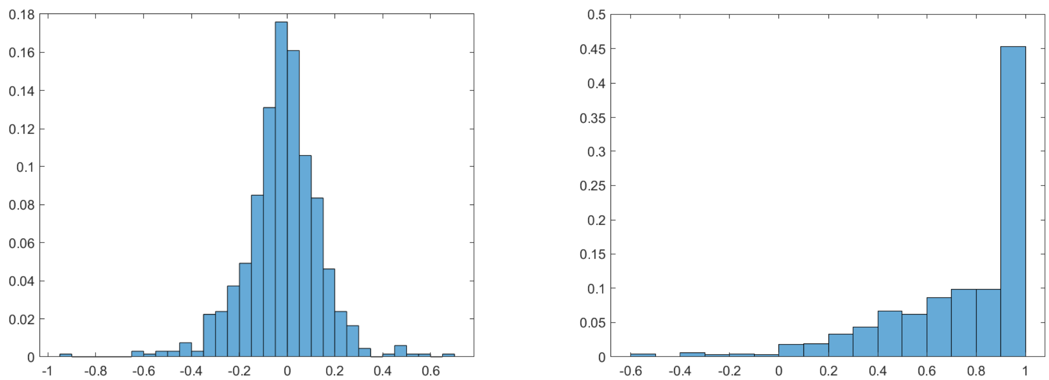
Industry	WIOD code	No. countries	Observations
Crop and animal production, hunting and related service activities	A01	13	1,614
Forestry and logging	A02	3	348
Fishing and aquaculture	A03	6	626
Mining and quarrying	B	19	2,593
Manufacture of food products, beverages and tobacco products	C10-C12	23	3,174
Manufacture of textiles, wearing apparel and leather products	C13-C15	16	2,167
Manufacture of wood and of products of wood and cork, etc	C16	10	1,196
Manufacture of paper and paper products	C17	19	2,504
Printing and reproduction of recorded media	C18	8	1,034
Manufacture of coke and refined petroleum products	C19	20	2,623
Manufacture of chemicals and chemical products	C20	25	3,251
Manufacture of basic pharmaceutical products and pharmaceutical preparations	C21	20	2,513
Manufacture of rubber and plastic products	C22	18	2,370
Manufacture of other non-metallic mineral products	C23	18	2,488
Manufacture of basic metals	C24	24	3,129
Manufacture of fabricated metal products, except machinery and equipment	C25	14	1,724
Manufacture of computer, electronic and optical products	C26	22	3,036
Manufacture of electrical equipment	C27	16	2,044
Manufacture of machinery and equipment n.e.c.	C28	19	2,519
Manufacture of motor vehicles, trailers and semi-trailers	C29	20	2,708
Manufacture of other transport equipment	C30	17	2,181
Manufacture of furniture; other manufacturing	C31-C32	17	2,219
Repair and installation of machinery and equipment	C33	1	84
Electricity, gas, steam and air conditioning supply	D35	22	2,874
Water collection, treatment and supply	E36	6	740
Sewerage; waste collection, treatment and disposal activities; etc	E37-E39	9	1,111
Construction	F	26	3,526
Wholesale and retail trade and repair of motor vehicles and motorcycles	G45	12	1,522
Wholesale trade, except of motor vehicles and motorcycles	G46	19	2,537
Retail trade, except of motor vehicles and motorcycles	G47	24	3,136
Land transport and transport via pipelines	H49	17	1,957
Water transport	H50	9	1,138
Air transport	H51	19	2,318
Warehousing and support activities for transportation	H52	19	2,245
Postal and courier activities	H53	8	796
Accommodation and food service activities	I	19	2,483
Publishing activities	J58	18	2,358
Motion picture, video and television programme production, etc	J59-J60	16	2,104
Telecommunications	J61	26	3,563
Computer programming, consultancy and related activities; info; etc	J62-J63	21	2,794
Financial service activities, except insurance and pension funding	K64	26	3,508
Insurance, reinsurance and pension funding, except compulsory social security	K65	21	2,613
Activities auxiliary to financial services and insurance activities	K66	22	2,491
Real estate activities	L68	23	2,930
Legal and accounting activities; activities of head offices; etc	M69-M70	10	1,036
Architectural and engineering activities; technical testing and analysis	M71	16	2,004
Scientific research and development	M72	13	1,575
Advertising and market research	M73	10	1,182
Other professional, scientific and technical activities; veterinary activities	M74-M75	7	848
Administrative and support service activities	N	18	2,248
Education	P85	7	831
Human health and social work activities	Q	13	1,445
Other service activities	R-S	17	2,037

Notes: This table presents information on the number of sectors and observation of monthly sector returns per sector for dates where there are monetary surprise shocks (FOMC meetings or off-cycle meetings) over 2000–16. The data are constructed by merging stock returns data from TREI with the WIOD classification of sectors.

Appendix C Full Regression Tables and Additional Charts

Here we report additional information about our baseline estimation as well as tables will full estimation results for all the tables in the paper.

Figure A1. Distribution of β and ρ across Country-Sectors



(a) β **(b)** ρ

Notes: This figure plots the distribution of β and ρ across mi from the estimation of equation $\widehat{\boldsymbol{\pi}}_t = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \boldsymbol{\varepsilon_t}$ for 2000–07, using Jarociński and Karadi (2020) monetary policy shocks for $\widehat{\mathcal{M}}_{US}$. The averages of these distributions are reported in Table 3.

Table A3. Full Regression Results for Different Time Periods and Weighting Matrices

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

	Avg. β (1)	Avg. ρ (2)	Avg. **Direct** (3)	Avg. **Network** (4)	**Network/Total** (5)
			Panel A. Full Sample		
2000–07, average W	-0.020	0.749***	-0.033**	-0.090***	77%***
	(0.020)	(0.173)	(0.019)	(0.018)	(0.190)
2000–16, 2000 W	-0.006	0.805***	-0.033***	-0.040***	84%***
	(0.011)	(0.198)	(0.011)	(0.016)	(0.358)
2000–16, average W	-0.005	0.810***	-0.033***	-0.041**	87%***
	(0.012)	(0.211)	(0.011)	(0.018)	(0.377)
2000–16, 2000 W, no 2008	-0.015	0.778***	-0.033**	-0.083***	80%***
	(0.020)	(0.197)	(0.019)	(0.018)	(0.218)
			Panel B. International Sample		
2000–07, average W	-0.017	0.748***	-0.023	-0.088***	79%***
	(0.020)	(0.176)	(0.019)	(0.020)	(0.020)
2000–16, 2000 W	-0.003	0.804***	-0.005	-0.037***	89%***
	(0.012)	(0.199)	(0.011)	(0.012)	(0.237)
2000–16, average W	-0.002	0.809***	-0.003	-0.039***	93%***
	(0.011)	(0.214)	(0.011)	(0.011)	(0.254)
2000–16, 2000 W, no 2008	-0.012	0.775***	-0.018	-0.080***	82%***
	(0.020)	(0.196)	(0.019)	(0.020)	(0.130)
			Panel C. USA Sample		
2000–07, average W	-0.058*	0.768***	-0.068**	-0.114***	63%***
	(0.037)	(0.170)	(0.035)	(0.037)	(0.013)
2000–16, 2000 W	-0.040**	0.822***	-0.046**	-0.071***	61%***
	(0.021)	(0.222)	(0.022)	(0.021)	(0.134)
2000–16, average W	-0.041	0.825***	-0.046*	-0.068**	60%***
	(0.032)	(0.233)	(0.031)	(0.032)	(0.175)
2000–16, 2000 W, no 2008	-0.047*	0.815***	-0.056**	-0.113***	67%***
	(0.033)	(0.228)	(0.031)	(0.033)	(0.156)

Notes: This table presents full regression results for the regressions reported in Table 4. See notes to Table 4.

Table A4. Full Regression Results with Additional Shocks: Full sample

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}_{MP}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\beta}_X\,\widehat{\mathbf{X}}_t + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

	(1)	(2)	(3)	(4)
Average ρ	0.712***	0.737***	0.748***	0.706***
	(0.162)	(0.161)	(0.196)	(0.182)
Monetary shock				
Average β_{MP}	-0.009	-0.023	-0.019	-0.013
	(0.011)	(0.020)	(0.022)	(0.013)
Direct effect of MP	-0.013	-0.031*	-0.026	-0.018*
	(0.010)	(0.019)	(0.021)	(0.012)
Network effect of MP	-0.059***	-0.099***	-0.094***	-0.064***
	(0.014)	(0.020)	(0.020)	(0.017)
Share of network effect (MP)	0.817***	0.762***	0.781***	0.785***
	(0.224)	(0.176)	(0.209)	(0.229)
VIX				
Average β_{VIX}	-0.051**			-0.048**
	(0.031)			(0.025)
Direct effect of VIX	-0.060**			-0.056***
	(0.030)			(0.023)
Network effect of VIX	-0.091***			-0.080***
	(0.015)			(0.016)
Share of network effect (VIX)	0.602***			0.587**
	(0.008)			(0.250)
2-year Treasury rate				
Average β_{T2y}		0.039*		0.025*
		(0.030)		(0.018)
Direct effect of T2y		0.045*		0.028**
		(0.029)		(0.017)
Network effect of T2y		0.086***		0.044***
		(0.016)		(0.015)
Share of network effect (T2y)		0.655***		0.614***
		(0.102)		(0.014)
USD Broad Index				
Average β_{USD}			-0.115*	-0.069
			(0.089)	(0.067)
Direct effect of USD			-0.146**	-0.086*
			(0.081)	(0.062)
Network effect of USD			-0.248***	-0.097*
			(0.080)	(0.075)
Share of network effect (USD)			0.629***	0.529***
			(0.021)	(0.008)

Notes: This table presents full regression results for the regressions reported in Table 6. See notes to Table 6.

Table A5. Full Regression Results with Additional Shocks: International

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}_{MP}\, \widehat{\mathcal{M}}_{US,t} + \boldsymbol{\beta}_X\, \widehat{\mathbf{X}}_t + \boldsymbol{\rho}\, \mathbf{W} \widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

	(1)	(2)	(3)	(4)
Average ρ	0.711***	0.736***	0.746***	0.705***
	(0.161)	(0.161)	(0.195)	(0.183)
Monetary shock				
Average β_{MP}	-0.005	-0.020	-0.016	-0.009
	(0.011)	(0.019)	(0.021)	(0.013)
Direct effect of MP	-0.010	-0.027*	-0.023	-0.014
	(0.010)	(0.019)	(0.020)	(0.012)
Network effect of MP	-0.058***	-0.096***	-0.092***	-0.063***
	(0.011)	(0.020)	(0.022)	(0.013)
Share of network effect (MP)	0.858***	0.778***	0.799***	0.822***
	(0.110)	(0.147)	(0.175)	(0.127)
VIX				
Average β_{VIX}	-0.052**			-0.049**
	(0.032)			(0.025)
Direct effect of VIX	-0.062**			-0.058***
	(0.030)			(0.023)
Network effect of VIX	-0.092***			-0.081***
	(0.032)			(0.025)
Share of network effect (VIX)	0.598***			0.583***
	(0.010)			(0.029)
2-year Treasury rate				
Average β_{T2y}		0.039*		0.025*
		(0.030)		(0.017)
Direct effect of T2y		0.045*		0.027**
		(0.029)		(0.017)
Network effect of T2y		0.084***		0.043***
		(0.030)		(0.018)
Share of network effect (T2y)		0.652***		0.615**
		(0.011)		(0.046)
USD Broad Index				
Average β_{USD}			-0.114*	-0.065
			(0.087)	(0.067)
Direct effect of USD			-0.145**	-0.082*
			(0.081)	(0.063)
Network effect of USD			-0.252***	-0.101*
			(0.088)	(0.068)
Share of network effect (USD)			0.635***	0.552***
			(0.102)	(0.012)

Notes: This table presents full regression results for the regressions reported in Table 6. See notes to Table 6.

Table A6. Full Regression Results with Additional Shocks: United States

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}_{MP}\, \widehat{\mathcal{M}}_{US,t} + \boldsymbol{\beta}_X\, \widehat{\mathbf{X}}_t + \boldsymbol{\rho}\, \mathbf{W} \widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

	(1)	(2)	(3)	(4)
Average ρ	0.735***	0.751***	0.764***	0.720***
	(0.199)	(0.194)	(0.236)	(0.204)
Monetary shock				
Average β_{MP}	-0.053***	-0.062**	-0.058*	-0.060***
	(0.023)	(0.032)	(0.041)	(0.025)
Direct effect of MP	-0.059***	-0.073***	-0.067**	-0.067***
	(0.021)	(0.031)	(0.038)	(0.023)
Network effect of MP	-0.076***	-0.129***	-0.121***	-0.081***
	(0.023)	(0.033)	(0.041)	(0.025)
Share of network effect (MP)	0.562***	0.640***	0.644***	0.547**
	(0.075)	(0.017)	(0.083)	(0.180)
VIX				
Average β_{VIX}	-0.039*			-0.035***
	(0.030)			(0.025)
Direct effect of VIX	-0.043*			-0.038***
	(0.030)			(0.024)
Network effect of VIX	-0.087***			-0.073***
	(0.030)			(0.025)
Share of network effect (VIX)	0.670***			0.656***
	(0.007)			(0.010)
2-year Treasury rate				
Average β_{T2y}		0.043*		0.034***
		(0.032)		(0.023)
Direct effect of T2y		0.048*		0.039***
		(0.031)		(0.023)
Network effect of T2y		0.105***		0.060***
		(0.032)		(0.025)
Share of network effect (T2y)		0.684***		0.604***
		(0.121)		(0.010)
USD Broad Index				
Average β_{USD}			-0.136	-0.128**
			(0.162)	(0.099)
Direct effect of USD			-0.161	-0.145***
			(0.152)	(0.096)
Network effect of USD			-0.198	-0.054*
			(0.164)	(0.102)
Share of network effect (USD)			0.551***	0.270***
			(0.053)	(0.075)

Notes: This table presents full regression results for the regressions reported in Table 6. See notes to Table 6.

Table A7. Full Regression Results for Different Monetary Policy Shocks and Real Returns

$\widehat{\pi}_{mi,t} = \boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\rho}\,\mathbf{W}\widehat{\boldsymbol{\pi}}_t + \varepsilon_{mi,t}$

	Avg. β (1)	Avg. ρ (2)	Avg. **Direct** (3)	Avg. **Network** (4)	**Network/Total** (5)
			Panel A. Full Sample		
Real returns	-0.015	0.749***	-0.021	-0.086***	80%***
	(0.022)	(0.182)	(0.020)	(0.017)	(0.216)
USD returns	-0.014	0.787***	-0.020	-0.087***	82%***
	(0.020)	(0.199)	(0.020)	(0.020)	(0.215)
Nom. returns, BRW shock	-0.017	0.748***	-0.019	-0.067***	78%***
	(0.025)	(0.184)	(0.025)	(0.018)	(0.268)
Nom. returns, OW shock	-0.032	0.747***	-0.041*	-0.102***	71%***
	(0.025)	(0.176)	(0.024)	(0.018)	(0.158)
Nom. returns, NS shock	-0.035	0.747***	-0.047	-0.146***	76%***
	(0.040)	(0.186)	(0.038)	(0.029)	(0.197)
			Panel B. International Sample		
Real returns	-0.011	0.747***	-0.017	-0.083***	83%***
	(0.021)	(0.182)	(0.020)	(0.021)	(0.096)
USD returns	-0.010	0.789***	-0.016	-0.084***	84%***
	(0.020)	(0.200)	(0.019)	(0.020)	(0.158)
Nom. returns, BRW shock	-0.017	0.746***	-0.019	-0.064***	77%***
	(0.025)	(0.183)	(0.024)	(0.025)	(0.215)
Nom. returns, OW shock	-0.031	0.745***	-0.040*	-0.101**	71%***
	(0.026)	(0.175)	(0.024)	(0.026)	(0.014)
Nom. returns, NS shock	-0.034	0.745***	-0.045	-0.145***	76%***
	(0.040)	(0.185)	(0.038)	(0.040)	(0.129)
			Panel C. United States Sample		
Real returns	-0.056**	0.784***	-0.066**	-0.121***	65%***
	(0.036)	(0.211)	(0.034)	(0.036)	(0.013)
USD returns	-0.059***	0.764***	-0.070**	-0.121***	63%***
	(0.035)	(0.222)	(0.034)	(0.035)	(0.048)
Nom. returns, BRW shock	-0.013	0.775***	-0.020	-0.112***	85%***
	(0.039)	(0.219)	(0.038)	(0.039)	(0.275)
Nom. returns, OW shock	-0.044**	0.769***	-0.052**	-0.105***	67%***
	(0.026)	(0.214)	(0.024)	(0.026)	(0.014)
Nom. returns, NS shock	-0.057	0.770***	-0.068*	-0.167***	71%***
	(0.048)	(0.224)	(0.045)	(0.048)	(0.099)

Notes: This table presents full regression results for the regressions reported in Table 8. See notes to Table 8.