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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 across countries and sectors using a newly constructed dataset. Our estimation strategy is based on a standard open-economy production network model that delivers a spillover pattern consistent with a spatial autoregression (SAR) process. We use the SAR model to decompose the overall impact of U.S. monetary policy on global stock returns into a direct and a network effect. We find that nearly 70% of the total impact of U.S. monetary policy shocks on country-sector stock returns are due to the network effect of global production linkages. Empirical counterfactuals show that shutting down global production linkages would reduce the total global impact of U.S. monetary policy shocks by half. Our results are robust to changes in the definitions of stock returns and monetary policy shocks, to controlling for correlates of the global financial cycle, foreign monetary policy shocks, and to alternative empirical specifications.

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1 Introduction

The recent era of globalization witnessed (i) stock market returns becoming more correlated across countries (Dutt and Mihov, 2013; Jach, 2017), and (ii) greater cross-country trade integration as firms' production chains have spread across the world (Johnson and Noguera, 2017). While research has predominantly focused on how *financial* integration impacts the propagation of shocks across international financial markets and the resulting impact on asset prices (e.g., via a global financial cycle, Rey, 2013), *real* integration also influences these cross-border spillovers. In this paper, we show that the global production network plays an important role in 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. To fix ideas of the mechanisms at work, consider an easing in U.S. monetary policy. The expansionary shock to U.S. monetary policy initially increases consumer demand in the U.S., which in turn leads to increased demand for both domestic and foreign final goods. This will directly impact domestic and foreign stock prices. Next, given the global production network, the initial demand shock will propagate across countries as firms increase demand for intermediate inputs along international supply chains. Thus, global production linkages lead to an increase in both U.S. and global demand, which increase global equity returns.

The conceptual framework delivers an empirical specification where the international shock transmission pattern follows a spatial autoregression (SAR) process. To conduct this analysis, 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, which we aggregate to the country-sector level. We first exploit these data to document an unconditional positive correlation between the intensity of production linkages and stock market returns at the country-sector level. We then merge these data with U.S. monetary policy shocks and use a panel SAR to quantify the importance of the global production network in amplifying the transmission of U.S. monetary policy shocks to both domestic and foreign stock markets.

Our baseline SAR estimation shows that the bulk of the response of global stock returns to U.S. monetary policy shocks is due to global production linkages. Specifically, the average country-sector annualized U.S. dollar monthly stock return increases by 2.7 percentage points in response to a one percentage point expansionary surprise in the U.S. monetary policy rate, with approximately 70% of this stock return increase due to spillovers via global production linkages. This finding is robust to conditioning on other variables that may drive a common financial cycle across markets, such as the VIX, 2-year U.S. Treasury rate, and the broad U.S. dollar index. Our main result 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.

We build our conceptual framework based on a minimal assumptions. The framework can also be derived using a static multi-country multi-sector production model that follows the standard closed-economy setup (e.g., Acemoglu et al., 2012; Herskovic, 2018; Richmond, 2019). Unlike many canonical macro-network models, our framework allows for firm profits, which in turn drive stock returns.[1] To generate monetary non-neutrality, 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, 2017; Rubbo, 2020).[2]

This 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. Standard models with technological shocks generally have shocks propagating downstream from supplier to customer via changes in marginal costs. Our framework differs in that it focuses on how shocks to monetary policy propagate upstream from customer to supplier given changes in customers' demand induced by the monetary policy shock. This change in demand 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. The final merged dataset contains monthly country-sector stock returns and annual input-output matrices. 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

[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 constant returns to scale technology in a monopolistic competition setting (e.g., Bigio and La'O, 2020), or with decreasing returns to scale technology in a competitive market setting (e.g., Ozdagli and Weber, 2017).

[2] In this framework without dynamics or investments we are abstracting from other channels of monetary policy transmission summarized in Ozdagli and Velikov (2020).

the period of unconventional monetary policy, we limit our baseline analysis to 2000–07. However, our results are robust to other periods.

Before turning to examining the impact of U.S. monetary policy shocks, we use the raw stock market and input-output data to 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 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 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.[3] 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. (2021), and approximate standard errors using a wild bootstrap procedure.

We find that production networks play a crucial 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 (2017) find for the response of U.S. stock returns to U.S. 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 U.S. sectors from those of foreign sectors, we show that foreign stock returns respond to U.S. monetary policy shocks primarily through the network of customer-supplier linkages. Similar to the finding of Ozdagli and Weber (2017), the network impact of U.S monetary policy shock on U.S. returns plays a greater role than the direct impact. Computing empirical counterfactuals, we show that shutting down global production linkages would reduce the total impact of U.S. monetary policy shocks on global stock returns by half.

Our results are robust. They are not sensitive to the choice of a specific time period or the year in which the IO matrix is sampled. This result suggests very limited, if any, endogenous response of global supply chains to U.S. monetary policy shocks and thus justifies the assumption of an exogenous trade structure in our theoretical framework. We further show that our results are robust to replacing nominal U.S. dollar stock returns with excess returns, stock returns expressed

[3] 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.

in local currency, and with real stock returns. Our results are also robust to using other definitions of monetary policy shocks, and to controlling for monetary policy shocks in the U.K. and the euro area. We find that there are no individual countries or sectors in which the spillover effects are concentrated. Further, we are able to rule out that the heterogeneity of estimates across countries and sectors is explained by alternative transmission channels. We also present a placebo analysis to rule out spurious effects that may be present given the recursive nature of the SAR model. Finally, our results are robust to conditioning stock returns on global financial cycle correlates: (i) VIX, (ii) 2-year U.S. Treasury rate, and (iii) broad U.S. dollar index.

There is a large literature in international macroeconomics that studies the transmission of shocks and business cycle comovement. We provide novel evidence on the spillovers of monetary shocks and the role of production networks as a conduit for this transmission by analyzing assets return responses at the country-sector level. This approach differs from the majority of the literature that focuses on output comovements, and has the advantage that asset returns are observable at a higher frequency than national accounts data, and therefore are more likely to identify reactions to monetary policy shocks. We also differ from the international real business cycle literature that typically studies the transmission of real shocks via trade linkages by examining the impact of nominal shocks. 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. (2021) 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. Wongswan (2006); Ehrmann and Fratzscher (2009); Ammer et al. (2010); 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 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. Bräuning and Sheremirov (2019) study the transmission of

U.S. monetary policy shocks on countries' output via financial and trade linkages, and Chang et al. (2020) study how the transmission of shocks via countries trade linkages impacts asset prices using information from the sovereign CDS market. The latter two papers differ from our work in that they focus on total bilateral trade linkages, and thus cannot measure transmission via international production linkages.[4,5]

There is also a growing literature that shows how real linkages across sectors play an 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. (2017) 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). Ozdagli and Weber (2017), 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] while Herskovic (2018) and Richmond (2019) nest input-output structures into standard asset pricing models.

Finally, our paper contributes to a strand of international finance literature that focuses on the relative importance of country and sector characteristics in international asset pricing (see, for instance, Griffin and Stulz, 2001; Bekaert et al., 2009; Lewis, 2011). Our results highlight that the size and location of country-sector production linkages are key characteristics to consider for better understanding the cross-section response of global asset prices to monetary policy shocks.

We bridge these different strands of the literature by showing the importance of real linkages in the international transmission of monetary policy shocks across asset markets. Our main contribution is to show, on a global scale, the importance of the intermediate trade channel in transmitting U.S. monetary policy shocks across asset markets, and providing a quantitative estimate of its contribution as well as transmission pattern on asset prices. 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.

[4]In particular, these trade flows include trade in both final consumption and intermediate goods, and are measured in gross output and not value added, which implies potential overstating trade linkages. Further, gross output trade need not be strongly correlated with intermediates trade. These are well-known problems, and are discussed in Johnson and Noguera (2017), among others.

[5]Other papers that study how trade globalization affects asset prices include Brooks and Del Negro (2006) and Barrot et al. (2019).

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

2 Conceptual Framework

This section provides 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, to have predictions for stock returns, a firm's production technology or the economy's market structure must allow for positive profits in equilibrium; second, shocks in one country can be transmitted to firms (and their profits) in other countries; third, monetary shocks must 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. Appendix A presents a simple multi-country multi-sector production model, which embeds cash-in-advance constraints and sticky wages.

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 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 output 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, such that $p_{mi,n} = p_{mi}$.[8] Further, as we are working with a cross-country expenditure system, all prices should be expressed in a common currency. We set the currency to be the U.S. dollar, and take this currency choice into account by transforming all countries stock returns to U.S. dollar returns in our empirical work below.

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

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

where $\mathbf{R}$ is the $NJ \times 1$ vector of country-sector sales, $\boldsymbol{\mathcal{C}}$ captures the $NJ \times 1$ vector of final goods' expenditures, and $\boldsymbol{\Omega}$ is the $NJ \times NJ$ 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

[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] The appendix model allows for iceberg trade costs across countries. These costs are not crucial for the derivation of the model nor for econometric estimation, and we thus assume that they are set to zero for the remainder of the paper to keep notation to a minimum.

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:

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

where $(I-\mathbf{\Omega})^{-1}$ is the $NJ \times NJ$ 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 $\mathbf{\Omega}$ fixed,[9] we can express (4) in terms of deviations from steady-state as

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

where $\circ$ represents the Hadamard product, and $\boldsymbol{\phi}_R$ is the $NJ \times 1$ vector containing the steady-state consumption-to-revenue ratio in each country-sector: $\boldsymbol{\phi}_R = \left(\frac{\bar{\mathcal{C}}_{11}}{\bar{R}_{11}}, \ldots, \frac{\bar{\mathcal{C}}_{NJ}}{\bar{R}_{NJ}}\right)'$.

We need to either deviate from perfect competition or from firm CRS production technology in order to generate positive profits in equilibrium. 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, 2020). Alternatively, one can assume that firms produce with DRS in a competitive market structure as in Ozdagli and Weber (2017).

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

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

where $\boldsymbol{\pi}$ is a $NJ \times 1$ vector of nj profits, and $\boldsymbol{\phi}_\pi$ is the $NJ \times 1$ vector containing the steady-state consumption-to-profit ratio in each country-sector: $\boldsymbol{\phi}_\pi = \left(\frac{\bar{\mathcal{C}}_{11}}{\bar{\pi}_{11}}, \ldots, \frac{\bar{\mathcal{C}}_{NJ}}{\bar{\pi}_{NJ}}\right)'$.

In the above framework, domestic households are assumed to fully own domestic firms and thus have claim to all profits. If we explicitly account for equity ownership, and abstract from any uncertainty or financial market frictions, innovations to firms' profits pass one-for-one into domestic stock returns. Specifically, denoting the stock price for a firm in country-sector nj as q_{nj}, then the stock return around steady-state is $\widehat{q}_{nj}$, which is identical to the change in profits around the steady state: $\widehat{q}_{nj} = \widehat{\pi}_{nj}$, or in vector-form across all country-sector cells: $\widehat{\boldsymbol{q}} = \widehat{\boldsymbol{\pi}}$, where $\widehat{\boldsymbol{q}}$ is the $NJ \times 1$ vector $(\widehat{q}_{11}, \ldots, \widehat{q}_{NJ})'$. Therefore, following Equation (6), demand shocks will propagate

[9] Holding $\mathbf{\Omega}$ 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.

across country-sectors' stock returns via the global production network:

$$\widehat{\boldsymbol{q}} = (I - \boldsymbol{\Omega})^{-1} \boldsymbol{\phi}_{\pi} \circ \widehat{\boldsymbol{\mathcal{C}}}. \tag{7}$$

Monetary Policy Shocks

The real effect of monetary policy has been subject to extensive analysis (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.[10] 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, $\widehat{\mathcal{M}}_n$:

$$\widehat{\mathcal{C}}_n = \phi_n \widehat{\mathcal{M}}_n, \tag{8}$$

where $\phi_n \geq 0$ depends on steady-state values and the elasticity of consumption growth with respect to changes in monetary policy.[11] Or, if we allow for heterogeneity in sector-level consumption, $\mathcal{C}_{nj}$, responses, we can write (8) at the country-sector level as

$$\widehat{\mathcal{C}}_{nj} = \phi_{nj} \widehat{\mathcal{M}}_n, \tag{9}$$

where $\phi_{nj} \geq 0$ differs from ϕ_n given households' consumption preferences for country-sector goods.

Writing (9) for NJ country-sector cells in vector form, and combining it with (7), we express stock returns as a function of monetary policy shocks:

$$\widehat{\boldsymbol{q}} = (I - \boldsymbol{\Omega})^{-1} \boldsymbol{\beta} \widehat{\boldsymbol{\mathcal{M}}}, \tag{10}$$

where $\boldsymbol{\beta}$ is a $NJ \times N$ matrix that combines the elements of the vector $\boldsymbol{\phi}_{\pi}$ and the elements of the $NJ \times 1$ vector of elements $\{\phi_{nj}\}$, and $\widehat{\boldsymbol{\mathcal{M}}}$ is $N \times 1$ vector of countries' monetary policy shocks.

Considering only shocks to U.S. monetary policy, the element $\mathcal{M}_{US}$, Equation (10) gives

$$\widehat{\boldsymbol{q}} = (I - \boldsymbol{\Omega})^{-1} \boldsymbol{\beta}_{US} \widehat{\mathcal{M}}_{US}, \tag{11}$$

where $\boldsymbol{\beta}_{US}$ is a $NJ \times 1$ sub-matrix of $\boldsymbol{\beta}$ containing U.S.-specific elements. 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 (10) and (11).

[10] Gorodnichenko and Weber (2016) show that price rigidities are an important determinant of the extent to which stock returns respond to monetary policy shocks.

[11] In the cash-in-advance model presented in Appendix A, changes in the money supply map one-to-one to changes in consumption, so that $\phi_n = 1$.

Risk and Asset Pricing

The above framework does not account for uncertainty. In particular, we have not taken a stand on households' risk aversion nor their intertemporal consumption decisions. Doing so opens the door to other potential impacts of monetary policy shocks on country-sectors' equity returns, besides the transmission of demand shocks via global production linkages. A key channel of monetary policy effect to consider is its impact on the stochastic discount factor (SDF) and risk-taking behavior; thus the pricing of firms' payouts (profits in our framework) by investors.

In the international context, movements in investors' risk-taking behavior lie at the heart of the impact of U.S. monetary policy on cross-country asset returns via the global financial cycle (Bruno and Shin, 2015a; Miranda-Agrippino and Rey, 2020). While it is beyond the scope of this paper to formally introduce portfolio decisions into our conceptual framework,[12] our empirical setup must still control for other variables that are correlated with U.S. monetary policy shocks and that may impact the pricing of firms' profits via changes in the SDF. In particular, changes in the variables that affect the SDF, such as changes in global risk aversion, may impact equity returns regardless of the production linkages. To obtain an unbiased estimate of the "demand channel" impact of monetary policy shocks on equity returns highlighted in our conceptual framework, we must therefore control for movements in SDF covariates that may be correlated with monetary policy shocks.

3 Regression Framework

The previous section's framework 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 (LeSage and Pace, 2009).

Specifically, holding the parameters of the model ($\boldsymbol{\beta}$ and $\boldsymbol{\Omega}$) fixed, the empirical counterpart of Equation (11) for a given country-sector observation is

$$\widehat{\boldsymbol{q}}_t = (I - \mathrm{diag}(\boldsymbol{\rho})\, \mathbf{W})^{-1}\, \boldsymbol{\beta}\, \widehat{\mathcal{M}}_{US,t}, \tag{12}$$

where $\widehat{\boldsymbol{q}}_t$ is a $NJ \times 1$ vector of stock returns $\widehat{q}_{mi,t}$ for each t.[13] The subscript t represents the year-month in which a U.S. monetary policy shock occurs,[14] I is a $NJ \times NJ$ identity matrix, $\mathbf{W}$ is the $NJ \times NJ$ empirical global input-output matrix, and $\widehat{\mathcal{M}}_{US,t}$ is the U.S. monetary policy shock at

[12] For papers that embed a basic production network framework into asset pricing models, see for example, Herskovic (2018) in a closed-economy setting, and Richmond (2019) for a multi-country setting.

[13] To see how the SAR setting is analogous to a traditional autoregression, it helps to rewrite Equation (12) as $\widehat{\boldsymbol{q}}_t = \boldsymbol{\beta}\, \widehat{\mathcal{M}}_{US,t} + \mathrm{diag}(\boldsymbol{\rho})\, \mathbf{W} \widehat{\boldsymbol{q}}_t$.

[14] 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.

time t. This shock measure does not vary across sectors and only emanates from one country, and thus the regression we run differs from the literature that analyses the propagation of idiosyncratic shocks across production networks.

In writing Equation (12) we make two important modifications to the model prediction (Equation (11)). First, instead of a constant parameter β, we allow the shock impact to vary by country and sector, thus replacing it with a $NJ \times 1$ vector $\boldsymbol{\beta}$. Second, we add a set of country-sector specific "resistance" coefficients to the network transmission mechanism, a $NJ \times 1$ vector $\boldsymbol{\rho}$ – $\text{diag}(\boldsymbol{\rho})$ indicates a $NJ \times NJ$ diagonal matrix containing the vector $\boldsymbol{\rho}$ on the diagonal and zeros off diagonal. The heterogeneous panel SAR setting allows for estimation of country-sector specific estimates of the coefficients β_{mi} and ρ_{mi} of the vectors $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$, thanks to the time dimension of our data.[15]

We allow for country-sector heterogeneity in our estimated coefficients on theoretical and empirical grounds. Theoretically, β_{mi} is determined from the parameters of a specific model, such as the one outlined Section 2 and Appendix A, where households' preferences for different goods or different competitive structures in different sectors, for example, lead to heterogeneous responses to U.S. monetary policy shocks across countries and sectors. In practice, these β's cannot be measured directly and are therefore estimated. Equation (11) assumes that the spatial pass-through of monetary policy shocks to stock returns is perfect ($\rho_{mi} = 1\, \forall\, m, i$). This need not be the case in practice due to factors outside our conceptual framework, such as asset market frictions, which may add resistance to the shock transmission through the production network (i.e., through $\mathbf{W}$).[16] For this reason we let the data determine the empirical estimate of $\boldsymbol{\rho}$, again allowing for heterogeneity in this potential resistance across country-sector cells.[17]

Our static model abstracts from any steady-state differences across countries and sectors. While most of them would not affect our analysis of a temporary monetary policy shock effect on stock returns, there is one important exception. If countries or sectors differ in their steady-state growth rates of stock prices, we might erroneously assign these differences to the heterogeneous impact of the monetary policy shock. Thus, we absorb any country- or sector-level heterogeneity in baseline stock returns by adding a $NJ \times 1$ vector $\boldsymbol{\alpha}$ of country-sector specific intercepts (fixed effects) to Equation (12). We also add an error term to arrive at the following estimation equation

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \text{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t, \tag{13}$$

where $\forall\, t$ the $NJ \times 1$ vector of errors $\boldsymbol{\varepsilon}_t = (I - \text{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\mathbf{u}_t$, where the elements of $\mathbf{u}_t$ are assumed to be independently identically distributed. Because of the complex structure of our

[15] For completeness we also report estimates where coefficients $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ are constrained to be the same across all country-sector pairs in Appendix C.

[16] For example, it is well established that momentum plays an important role in pricing stocks globally but is not generally correlated with macroeconomic shocks (Griffin et al., 2003; Fama and French, 2012).

[17] Heterogeneity of ρ_{mi} may also be due to financial frictions, such as the liquidity premium, which may vary across countries and sectors (Amihud et al., 2015).

model, instead of computing analytical standard errors, suggested for the heterogeneous panel SAR by Aquaro et al. (2021), we use a wild bootstrap to construct standard errors that are robust to heteroschedasticity introduced by the structure of heterogeneous SAR in Equation (13). We describe the bootstrap procedure in detail later in this section.

Measuring Network Effects

The spatial autoregressive model allows us to decompose the *total* marginal effect of U.S. monetary policy on equity returns into a *direct* and *network* (*indirect*) effect. In particular, in contrast with linear regression models, the coefficient vector $\boldsymbol{\beta}$ is not equal to the total marginal effect of the U.S. monetary shock $\widehat{\mathcal{M}}_{US,t}$ on stock returns $\widehat{q}_{mi,t}$. Instead, applying Equation (12), the $NJ \times 1$ vector of total marginal effects is given by

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

where $\boldsymbol{\rho}$ and $\boldsymbol{\beta}$ are the estimated vectors of parameters. Specifically, for each country-sector cell, the total marginal effect of U.S. monetary policy shock includes a direct impact as well as the sum of all indirect effects resulting from linkages expressed in the input-output matrix $\mathbf{W}$. The $\boldsymbol{\rho}$-weighted Leontief inverse matrix, $(I - \text{diag}(\boldsymbol{\rho})\mathbf{W})^{-1}$, is an infinite sum of all immediate and indirect production linkages of all lengths. For example, consider an easing in U.S. monetary policy that raises consumption demand for all goods in the U.S., including Apple's iPhone. Conditional on U.S. consumers' preferences, Apple's revenues, profits and stock price will rise. Further, to meet the increased U.S. demand for iPhones, there will be increased demand for firms assembling iPhones in China, as well for firms in Germany and Korea supplying components to assembly firms in China, as the initial demand shock propagates up Apple's global production chain. As a result, we would also expect to see stock prices rising for the Chinese, German, and Korean suppliers that are part of this production chain, and the size of these increases will be proportional to the importance of the firms' goods in the production of the iPhone. The **Total** effect of the U.S. monetary policy shock accounts for all of such spillovers, as well as the initial impact on Apple.

There are a number of ways to decompose the **Total** effect in order to extract the contribution of the global production network in transmitting U.S. monetary policy across equity markets.

Our baseline approach follows Acemoglu et al. (2016) and performs the following decomposition:

$$\textbf{Direct}_{AAK} \equiv \boldsymbol{\beta}, \tag{15}$$

$$\textbf{Network}_{AAK} \equiv \textbf{Total} - \textbf{Direct}_{AAK}, \tag{16}$$

where the direct measures are simply equal to the estimated vector of coefficients $\boldsymbol{\beta}$, reflecting only the immediate impact of U.S. monetary policy shocks on stock returns of each country-sector cell.[18]

[18] This corresponds to the pure final demand effect of the U.S. monetary policy shock as derived in the model.

All effects intermediated by production linkages included in the network effect.[19]

Alternatively, we may follow the textbook approach of LeSage and Pace (2009), where the **Total** effect for each mi can be decomposed into a direct and network effects as

$$\mathbf{Direct}_{LP} \equiv \text{diag}\left[(I - \text{diag}(\boldsymbol{\rho})\mathbf{W})^{-1}\right]\boldsymbol{\beta}, \tag{17}$$

$$\mathbf{Network}_{LP} \equiv \mathbf{Total} - \mathbf{Direct}_{LP}, \tag{18}$$

where $\mathbf{Direct}_{LP}$ and $\mathbf{Network}_{LP}$ are $NJ \times 1$ vectors. The key aspect of this decomposition is that in addition to the immediate impact of the shock on the country-sector cell, $\mathbf{Direct}_{LP}$ includes round-trip (indirect) transmission of the shock to each country-sectors' returns back to themselves, and will thus be larger than $\mathbf{Direct}_{AAK}$. We find that this measure is less appropriate for the analysis of the network effects at the sector level, because round-trip transmission to the same country-sector cell likely reflects a different step in the production chain and therefore would not be attributed to a direct effect in a more disaggregated network.

Our primary object of interest is not the absolute size but the share of the **Network** effect in the **Total** effect. We calculate this share for each country-sector when we estimate the heterogeneous SAR model, and present the mean value across country-sector estimates along with corresponding standard errors.

Reporting and Standard Errors

Results are reported as simple average values of $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, **Direct** and **Network** effects across all country-sectors. We also examine the *cross-country* transmission of U.S. monetary policy shocks by splitting the effects into domestic and international components. Specifically, the *international* direct and network effects are computed 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.

Given the time dimension of our panel is short (66 time periods in the benchmark) relative to the spatial dimension (an unbalanced panel of 26 countries and 54 sectors with the total of 671 country-sector cells), and our shocks only vary over time, we are concerned that the analytical standard errors proposed by Aquaro et al. (2021) are unreliable in our setting. Thus, we turn to a bootstrap approach to compute standard errors. In a standard bootstrap approach one uses random subsamples of the data to re-estimated a model. This, however, is not an option for our set-up, because estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ in the panel SAR strongly depend on the ordering of $\mathbf{W}$ and because $\widehat{\mathcal{M}}_{US,t}$ does not vary across country-sector cells. Thus, for our model the best approach is a

[19] Given that we are working at the sector level, the $\mathbf{Direct}_{AAK}$ will include spillover effects across firms within the same sector in the same country.

wild bootstrap, in which random perturbations are added to the dependent variable by multiplying residuals by a random variable drawn from a specific distribution.[20]

We compute standard errors using the wild bootstrap procedure with continuous distribution proposed by Mammen (1993). This procedure allows for heteroschedasticity, and in addition we allow for cross-section correlation of errors by implementing a cluster version of this procedure; i.e., we draw random variables for the size T vector and repeat the same perturbation for all country-sector cells within a given time period. We bootstrap standard errors for each element of $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, **Direct**, **Network**, and the share of **Network** in **Total**, as well as for their overall, international, and U.S. average values. To do so, for each iteration z 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 $\nu_{mi,t}$ of the residuals:

$$\widehat{\boldsymbol{q}}_t^z = \mathbf{a} + (I - \text{diag}(\mathbf{r})\,\mathbf{W})^{-1}\,\mathbf{b}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\nu}_{\boldsymbol{t}}^{\boldsymbol{z}} \circ \mathbf{e}_t,$$

where $NJ \times 1$ vectors $\mathbf{a}$, $\mathbf{b}$, and $\mathbf{r}$ are estimates of $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\rho}$, respectively, and $\mathbf{e}_t$ is a $NJ \times 1$ vector of estimated residuals for each t.

We use a continuous distribution from which we draw 500 perturbations for each time period, and then repeat for each element $\nu_{mi,t}^z$ of each vector $\boldsymbol{\nu}_{\boldsymbol{t}}^{\boldsymbol{z}}$:

$$\nu_{mi,t}^z = \frac{\xi_t^z}{\sqrt{2}} + \frac{1}{2}\left[(v_t^z)^2 - 1\right], \quad \forall m \forall i,$$

where ξ and v are drawn from independent standard normal distributions. We then estimate our SAR model replacing the true dependent variable with a 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 2000–14.[21] For our analysis, we limit the data to 26 countries with active stock markets and 54 sectors that are connected to each others.[22]

[20] In contrast with the standard residual bootstrap, a wild bootstrap allows for heteroschedasticity (Davidson and Flachaire, 2008) and is frequently used in heteroschedastic models as well as models with multiple equations.

[21] This current WIOD database, which has a higher level of disaggregation only begins in 2000, while the older version begins in 1995, but a change of sectoral classification makes it impossible to merge the two sets of tables.

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

From TREI, we obtain end-of-period monthly stock prices, stock market capitalization, and industrial classification for individual companies from 2000–16.[23] 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.[24] 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. We then multiply these returns by month-on-month exchange rate changes vis-à-vis the U.S. dollar, and annualize the monthly U.S. dollar returns for all our analysis.[25]

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, sectoral 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:[26]

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

[23]We are constrained to starting the sample period in 2000 in order to capture large sample of country-sectors stock returns.

[24]Even with these data, there is not always a 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.

[25]We confirm that our results are robust to using domestic currency returns as well as real returns. We do not explicitly study the effects of exchange rate changes. For the recent discussion of complex relationship between exchange rates and stock prices, see Karolyi and Wu (2020).

[26]Note that it is analogous to $\omega_{mi,nj}$ in conceptual framework.

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 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.

The top row of 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

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

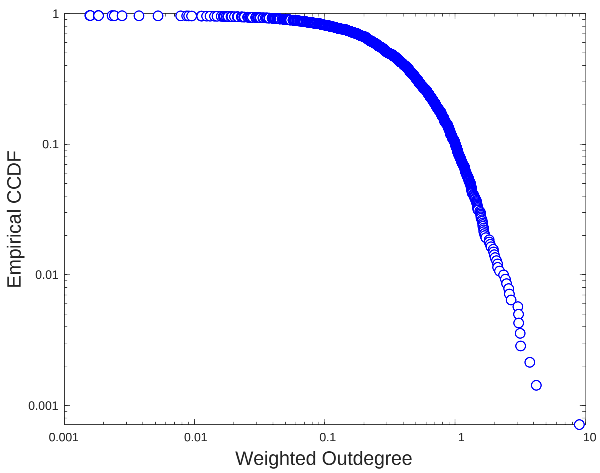
and measures how important a given country-sector's inputs are for production use across all possible country-sector pairs. It is informative to look at this distribution, since a skewed one implies the potential for shocks to propagate and amplify across the production network (Acemoglu et al., 2012). 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 it 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 Bureau of Economic Analysis. 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.

Next, panels (c) and (d) examine how the outdegree distributions have changed over time. Specifically, we calculate the correlation of the out_{mi} measures for each year with those of 2000. As can be seen, both for world linkages in panel (c) and international linkages in (d), the correlation has been falling over time, indicating a "re-shuffling" of the global production network. However, the change in correlation has been relatively small, indicating that the cross-country cross-sector distribution of the importance of key suppliers has not changed dramatically over our sample period.

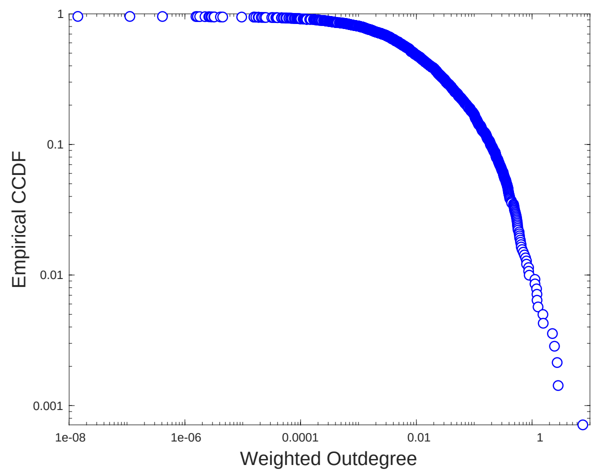
Overall, the skewness of the upstream linkages points to *a priori* evidence that the monetary policy shocks will propagate heterogeneously across different country-sectors via the global production network, which further motivates our choice of estimating a heterogeneous panel SAR as the baseline.

Figure 1. Distribution of Weighted Outdegree for WIOD

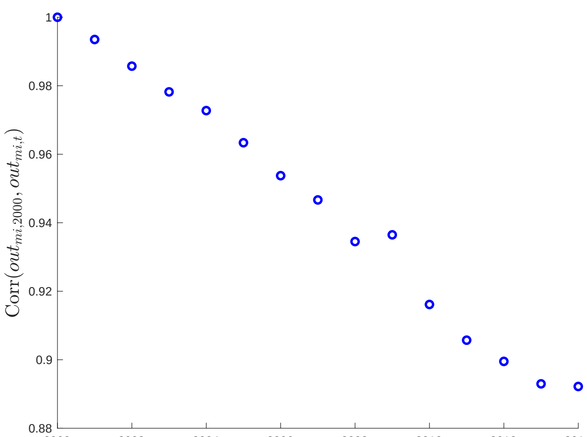
The first row of this figure plots the counter cumulative distribution function of the weighted outdegree using the average of the WIOD annual database over 2000–14. The second row of the figure plots changes in the distribution of country-sector weighted outdegrees, where the change is measured as the correlation of the vector of each year's country-sector outdegree measures with the vector of these measures for the year 2000. The panels with World Linkages are based on the full WIOD table, while the International Linkages panels use only internationally connected country-sector cells (i.e., we omit the domestic-only linkages across sectors) in constructing the weighted outdegree measure.



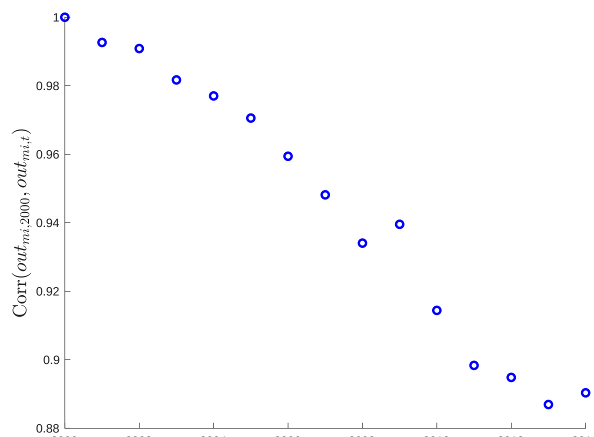
(a) World Linkages



(b) International Linkages



(c) World Linkages

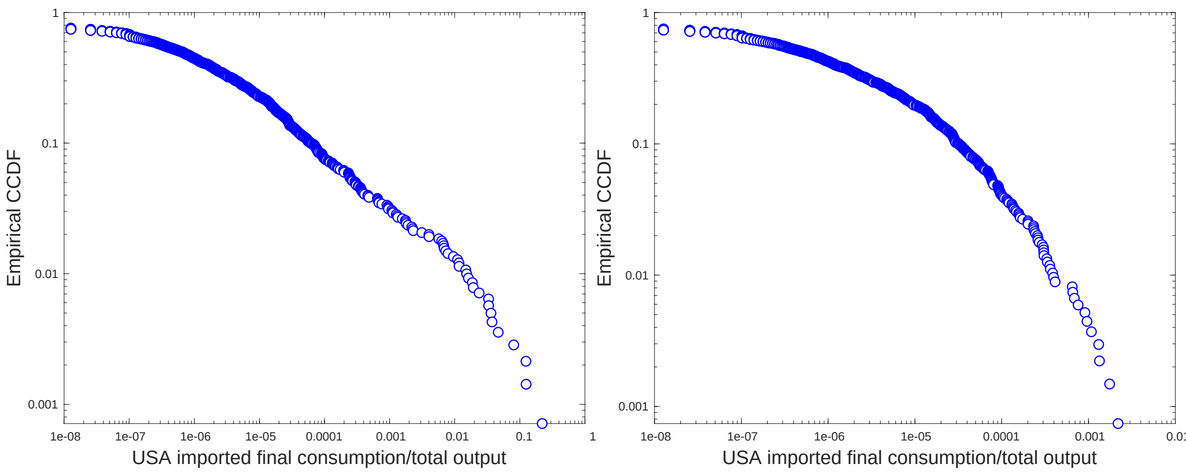


(d) International Linkages

Next, we present the distribution of the U.S. consumption of country-sectors' final goods in Figure 2. Given that we are studying the effects of a demand shock emanating from the U.S., we plot the distribution of U.S. imports of a given country-sector's final consumption goods relative to total output of the good produced by that country-sector – using the notation from our framework,

Figure 2. Closeness to U.S. Consumers

This figure presents the distribution of a country-sector's sales of final consumption goods to the U.S. relative to the country-sector's total output using 2000 data source from WIOD. Panel (a) presents the distribution for all country-sector cells in the 26 countries and 54 sectors sample, while panel (b) drops U.S. country-sector cells for the international sample.



(a) World Sample

(b) International Sample

this would correspond to $c_{nj,USA}$, U.S. consumption of goods produced by sector j in country n. We use this measure to compare the estimated effects and "closeness to final consumers" in the United States.[27] Panel (a) includes all the country-sector pairs of the world that are in our sample of 26 countries and 54 sectors, thus it also includes U.S. own consumption of final goods produced domestically. Panel (b) drops the U.S. country-sector pairs. As it can be seen in the plots, there is substantial heterogeneity across country-sector pairs, but the distribution is not as skewed as the world input-output matrix. The cross-sectional heterogeneity in $c_{nj,USA}$ allows us to test whether the impact of U.S. monetary policy shocks on stock returns country-sectors that are "closer" to the U.S. are driven relatively more by the **Direct** than the **Network** share, as one would expect from the structural model written down in Appendix A.

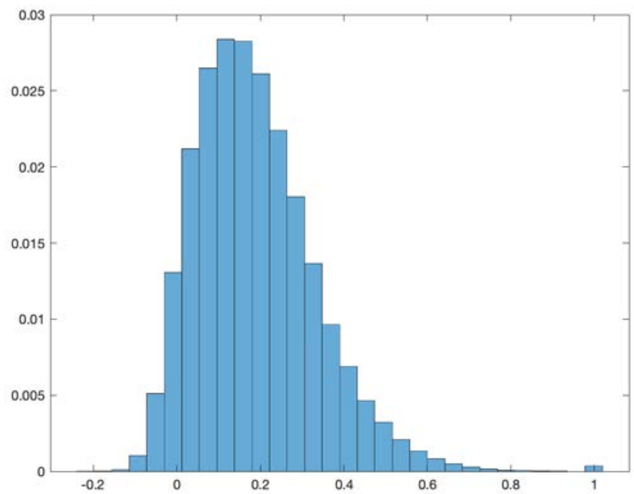
4.2 Returns Data

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. We express all returns in U.S. dollars to remain consistent with our conceptual framework, and we also annualize the returns. Given that not all sectors are present in all countries, we have stock indexes for 671 out of possible 1404 country-sector cells for

[27]This measure is motivated by, but is different from the one used in Ozdagli and Weber (2017).

Figure 3. Correlation of Stock Returns over the Entire Sample

This figure plots the distribution of pairwise correlations of annualized U.S. dollar monthly stock returns over 2000–16 across 26 countries and 54 sectors.



each month from January 2000 through December 2016.[28] Figure 3 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.[29]

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 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 such a network, the distance between two cells is defined as the length of the shortest path (geodesic) between them.

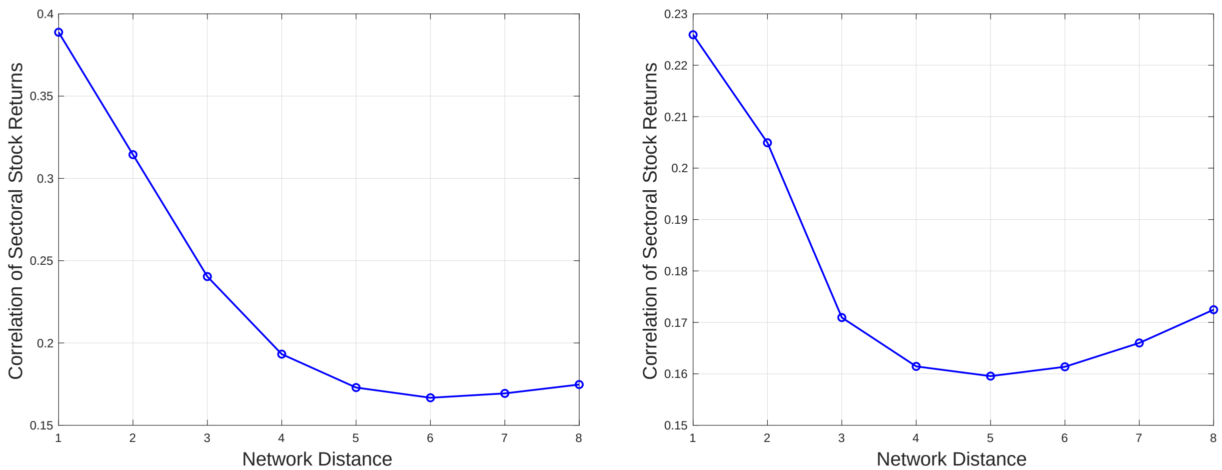
We use this concept of distance for each pair of country-sector cells and compare it to the correlation of stock returns for this pair of country-sector cells. Figure 4 plots this relationship, where we compute the average directional distance between any two country-sector cells (i.e., the average of $mi \to nj$ and $nj \to mi$ path lengths). 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

[28] 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.

[29] We obtain a similar distribution for local-currency returns.

Figure 4. WIOD Network Distance of Supply Linkages and the Correlation of Stock Returns

This figure plots correlations of U.S. dollar annualized 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 the 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).



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

any distances longer than that the decline in stock price correlation levels off. The figure's vertical axis shows the average stock price correlation for all country-sector cell pairs that are at a given distance from each other in the network, shown on the horizontal axis.

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 0.39). The larger is the distance, the lower is the correlation. We can see that it tapers out just below 0.17 for any distance over 4. Panel (b) shows that a similar pattern holds when we exclude all domestic sector pairs from the analysis, with highest average correlation of 0.23. 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 exhibit a stronger correlation of stock returns than those country-sector cells at a greater distance from each other in the global production network.

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 highly 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.[30]

We explore the robustness of our regression results to conditioning on 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 U.S. Treasury rate and broad U.S. 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 U.S. 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 U.S. Treasury rate captures the overall change in U.S. monetary policy stance as well as the cost of funding.[31] Moreover, the unique role of the U.S. dollar as an international currency make it especially important to control for the exchange rate channel of the U.S. monetary policy shock transmission, which is another reason to include the dollar index as a potential omitted variable.

Given potential contemporaneous monetary policy shocks across countries, we check the robustness of our results by including the 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. (2021), and Ozdagli and Weber (2017) for further robustness checks.

5 Empirical Results

We present our results starting with the baseline least-squares regression to give an idea of the overall effect of U.S. monetary policy shocks on global stock returns. We proceed with a spatial

[30]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.

[31]The 2-year U.S. 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.

autoregression (SAR) to identify the portion of the effect that is due to production network linkages, and to provide ample evidence of the robustness of our benchmark SAR specification. In particular, we condition stock returns on the drivers of the global financial cycle and show that our benchmark results are only minimally affected by this change in specification. Finally, we show that our baseline direct and network effects are not driven by specific countries or sectors.

5.1 Linear Regression Results

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

$$\widehat{q}_{mi,t} = \alpha + \beta^{LS}\widehat{\mathcal{M}}_{US,t} + \varepsilon_{mi,t}, \tag{19}$$

where α represents either a constant or different sets of fixed effects.[32] Effectively, this estimation strategy imposes the restriction of spatially uncorrelated country-sector cells in the SAR framework of (13); i.e., setting $\rho = 0$. As a result, the network and direct effects are captured in the estimate β^{LS}.

The results of the estimation use the Jarociński and Karadi (2020) monetary policy shock series for 2000–07 sample period are reported in Table 1.[33] The simple OLS estimate in column (1) implies that a one percentage point surprise in monetary policy easing results in a 2.7 percentage points rise in the average country-sector monthly stock return.[34] 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 and because of the strong factor structure in panels of stock return. 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.

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 estimation strategy 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 avearge 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 column (5). In this case, the average β is somewhat larger than

[32] We cannot include time fixed effects in the regression because monetary policy shocks vary only over time,

[33] 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. Furthermore, because the dependent variable is the stock return, including a lagged dependent variable in these regression does not alter the results.

[34] Unless stated otherwise, all our results are in terms of annualized U.S. dollar monthly returns, as discussed above in Section 4.

Table 1. Least-Squares Regression Estimation: Full Sample

This table reports coefficients from linear regressions where the dependent variable $\widehat{q}_{mi,t}$ is the annualized U.S. dollar country-sector monthly stock return in columns (1)-(5) and the country market return in column (6), over 2000–07 in months with FOMC announcements, and the independent variable $\widehat{\mathcal{M}}_{US,t}$ is the measure of the U.S. 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. All coefficients are significant at (at least) the 5% confidence level.

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

	(1)	(2)	(3)	(4)	(5)	(6)
MP shock	-2.669	-2.669	-2.74	-2.454	-2.533	-3.110
	(0.208)	(1.303)	(1.311)	(0.320)	(0.266)	(1.046)
Constant	0.993	0.993	0.992	0.893	1.013	0.526
	(0.013)	(0.090)	(0.091)	(0.029)	(0.026)	(0.086)
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

the random-coefficient estimate (in absolute value), but still smaller (in absolute value) than the least-squares estimates.

Finally, to compare our findings with existing country-level analysis, we aggregate the individual firm stock returns to the country level and estimate a country fixed effects linear regression, which is 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, but with larger standard errors. Further, the point estimate is in line with other estimates from the literature (e.g., Ehrmann and Fratzscher, 2009).[35] The use of monthly returns is justified by findings that most of the equity premium resulting from changes in the U.S. monetary policy is reflected in the first four weeks following the announcement (Bernanke and Kuttber, 2005; Cieslak et al., 2019) and with at least 3-4 days delay even for U.S. firms (Chava and Hsu, 2019).[36]

Table 2 reports least-squares regression results where we split the sample into all foreign countries (Panel A) and only the United States (Panel B). The overall point estimates for the international sample in Panel A are somewhat smaller than the baseline estimates using the whole sample

[35] Ammer et al. (2010), using hourly returns, find the effect that is about twice as large as ours, for both domestic and foreign stock returns. Miranda-Agrippino and Rey (2020) find, in a much longer sample, an impulse response that is also about twice as large as ours for the effect of the increase in the federal funds rate on the U.S., U.K., and German stock indexes.

[36] Moreover, at least for the cases when monetary policy shocks do not fall on the first day of the month, using monthly returns side steps the 24 hour pre-announcement drift in the response of U.S. stock returns to FOMC scheduled announcements documented by Lucca and Moench (2015).

Table 2. Least-Squares Regression Estimation: International and United States Sub-Samples

This table reports coefficients from linear regressions where the dependent variable $\widehat{q}_{mi,t}$ is the annualized U.S. dollar country-sector monthly stock return in columns (1)-(5) and the country market return in column (6), over 2000–07 in months with FOMC announcements, and the independent variable $\widehat{\mathcal{M}}_{US,t}$ is the measure of the U.S. monetary policy shock taken from Jarociński and Karadi (2020). Panel A includes all countries except 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)). Standard errors are in parentheses. All coefficients are significant at (at least) the 10% confidence level.

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

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Excluding the United States			
MP shock	-2.553	-2.553	-2.625	-2.322	-2.405	-3.114
	(0.221)	(1.378)	(1.386)	(0.338)	(0.279)	(1.080)
Constant	1.035	1.035	1.034	0.932	1.054	0.542
	(0.014)	(0.094)	(0.094)	(0.030)	(0.027)	(0.088)
			Panel B. United States only			
MP shock	-4.308	-4.308	-4.308	-4.068	-4.418	-2.990
	(0.407)	(0.702)	(0.709)	(0.811)	(0.726)	(0.594)
Constant	0.411	0.411	0.411	0.371	0.414	0.142
	(0.026)	(0.074)	(0.074)	(0.037)	(0.030)	(0.054)
Estimator	OLS	OLS	LS	Random coeffs	Mean Group	LS - country
Fixed effects	None	None	*mi*	Random	*mi*	*mi*
Standard errors	Regular	Clustered on t		Conventional	Group-specific	Clustered on t

of Table 1 for the country-setor returns in columns (1)-(5), with the impact of a one percentage point innovation in U.S. monetary policy moving foreign country-sector returns by approximately 2.5 percentage points. Turning to the country-level returns in column (6), the point estimate is also similar to the estimate reported in Table 1. Turning to Panel B and the results for the United States, we see that the point estimates are larger (in absolute value) than the pooled sample's estimates across all specifications, with an estimated impact of a one percentage point change in U.S. monetary policy impacting the average sector return by approximately four percentage points across columns (1)-(5), and three percentage points in looking at the overall market return in column (6). This magnitude of the effect is consistent with the literature (e.g., Ehrmann and Fratzscher, 2004; Bernanke and Kuttber, 2005; Ozdagli and Weber, 2017).

The linear regressions do not allow to condition on 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 Heterogeneous SAR Results

We now allow for network effects by estimating a spatial autoregression model. We first present results of the heterogeneous coefficients SAR model in Table 3, where we allow for country-sector fixed effects following Elhorst (2014).[37] We estimate the regression with maximum likelihood following Aquaro et al. (2021), and bootstrap standard errors for all parameters as well as for the decompositions, using a wild panel bootstrap with 500 repetitions. Our baseline estimation table presents both the LeSage and Pace (2009) and Acemoglu et al. (2016) direct and network decompositions. We then present only the Acemoglu et al. (2016) decomposition for additional results in order to save space, and because this methodology omits the own-sector round-trip effect when calculating the direct effect of the transmission of U.S. monetary policy shocks to global stock markets.

Panel A of Table 3 shows the average values of $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$. We report averages across all country-sectors, for country-sectors outside of the U.S., and for U.S. sectors only. The full distribution of these estimates are reported in Figure A1. The number of observations corresponds to the number of country-sector cells that contribute to each average. In Panel B, we report **Direct**, **Network**, and the share of **Network** in **Total** across country-sectors using the two approaches discussed previously. Because the decomposition is conducted at the country-sector level, we report the averages of **Direct**, **Network**, and the share of **Network** in **Total** for all country-sectors, for country-sectors outside of the U.S., and for U.S. sectors only. The full distribution of direct and network effects is reported in Figure 5.[38]

The first point to note is that the sum of the estimated **Direct** and **Network** effects – i.e., the **Total** effect – line up with the least-squares estimates of Table 1 as we would expect. Turning to our headline result, we find that for the full sample, nearly 70% of the average total effect of the U.S. monetary policy shock on global stock returns is due to the transmission through production network using our preferred decomposition method Acemoglu et al. (2016). In fact, we can see from Figure 5 that network effect is negative for a larger subset of country-sector cells than the direct effect. This results from the high estimated coefficient of shock propagation, ρ, which is on average 0.63. Interestingly, this average ρ is less than one, the value implied by our conceptual framework,

[37] See Table A3 for results using a homogeneous SAR model. Results in this estimation generally match up with our baseline heterogeneous estimates.

[38] Note that heterogeneity of the total effects is comprised of both heterogeneity of the input-output coefficients, and heterogeneity of the impact and propagation coefficients, β and ρ. Figure A1 shows that the impact and propagation coefficients do vary substantially across sectors. To check whether this distribution is related to the importance of a given sector-cell in the production network, we computed the eigenvector centrality of each country-sector in the input-output network, following Richmond (2019). We find that total effect is, in fact, uncorrelated with the eigenvector centrality measure (the correlation coefficient is -0.02), pointing to the importance of allowing for variation in SAR coefficients.

Table 3. Heterogeneous Spatial Autoregression Panel Estimation: Baseline Specification and Decompositions

This table reports results from heterogeneous coefficient spatial panel autoregressions (Equation (13)) where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000–07 over months with FOMC announcements, and the independent variable is the measure of the U.S. monetary policy shock taken from Jarociński and Karadi (2020). There are 44,286 total observations comprised of 671 country-sectors over 66 months. LP09 and AAK16 refer to the decomposition methodologies in LeSage and Pace (2009) and Acemoglu et al. (2016), respectively. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions. All coefficients are significant at the 1% confidence level.

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \mathrm{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t$$

Panel A. Coefficient Estimates

	Average β	Average ρ	Observations
Full sample	-0.907	0.632	44,286
	(0.094)	(0.028)	
International	-0.828	0.635	40,986
	(0.101)	(0.029)	
USA	-1.871	0.585	3,300
	(0.271)	(0.044)	

Panel B. Total Effect Decomposition

	Avg. **Direct**	Avg. **Network**	**Network/Total**
Decomposition 1 (AAK16)			
Full Sample	-0.907	-1.808	0.666
	(0.274)	(0.317)	(0.064)
International	-0.828	-1.757	0.680
	(0.101)	(0.322)	(0.068)
USA	-1.871	-2.430	0.565
	(0.271)	(0.442)	(0.080)
Decomposition 2 (LP09)			
Full Sample	-1.214	-1.501	0.553
	(0.082)	(0.094)	(0.059)
International	-1.151	-1.435	0.555
	(0.087)	(0.275)	(0.063)
USA	-1.988	-2.313	0.538
	(0.224)	(0.386)	(0.065)

due to unmodelled resistance to the transmission of shocks across international stock markets via the global production network. Further, the network effect also explains over half of the total effect if we use the LeSage and Pace (2009) decomposition, and shows the robust importance of global production networks in transmitting U.S. monetary policy shocks in our baseline estimation.

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 larger direct effect of U.S monetary policy shock on U.S. sectors that foreign sectors, which is expected. In terms of transmission via production networks, the share of the network effect for U.S. sectors is 57%,[39] while for foreign country-sectors it is larger, at 68%. These results are very intuitive and show that production linkages are very important in transmitting demand shocks across sectors, and, even more so, across countries. In what follows we establish robustness of these findings.

5.3 Closeness to Final Consumers and Gravity Forces

We explore how the structural model presented in Appendix A maps into our empirical estimates. In particular, the simple theoretical framework in Appendix A includes a "gravity force" by incorporating iceberg trade costs. Doing so implies that the measure of the direct effect, $\boldsymbol{\beta}$, is a function of two underlying parameters related to final consumption (import) decisions in a given country-sector: (i) preferences, and (ii) trade costs. Crucially, as seen in equations (A.10), country n' final goods consumption of good i from country m and the estimated direct effect of the U.S. monetary policy shocks should be positively correlated with the preference parameter and negatively correlated with trade costs. While we do not have empirical estimates of preferences, we can still examine how the direct effects for country-sectors vary relative to observed final goods imports to the United States. This point holds true in a model without trade costs as well and maps nicely into the notion of "closeness to final consumers."[40] We therefore calculate the relative difference between the share of the direct (and network) effects in two groups of country-sectors, defined as "low" and "high" total U.S. final goods consumption of a country-sector's good – using the notation from our framework, this would correspond to $c_{nj,USA}$ – relative to the country-sector's total output (as we do not have a clean measure of profits). This analysis is based on three cutoffs of the consumption-to-output ratio: (i) mean, (ii) median, and (iii) 90th percentile.

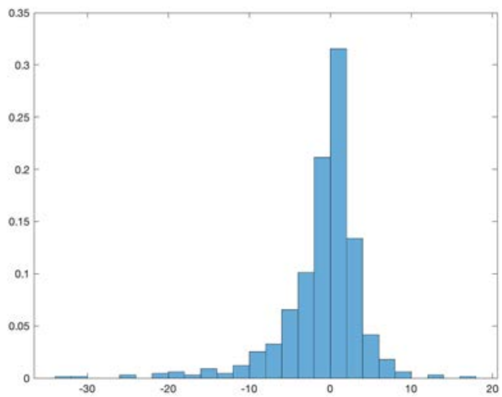
Table 4 presents the results using the full sample in panel A while restricting estimates to the international sample in panel B. Like our main tables, we calculate the means of the country-sector decomposition using our baseline point estimates and construct confidence intervals based on the clustered wild bootstrapping procedure (from Table 3). Comparing the "low" and "high" groups,

[39] Ozdagli and Weber (2017) find a nearly identical magnitude for the network effect and a smaller magnitude for the direct effect using the same methodology (with a different measure of monetary policy shocks) in a longer sample with more disaggregated U.S. sectoral data.

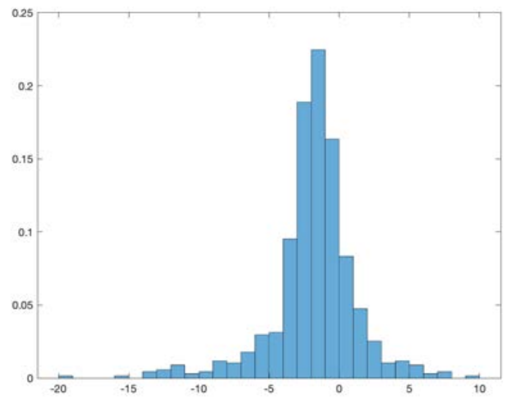
[40] See Ozdagli and Weber (2017) for another way of defining this concept.

Figure 5. Distribution of Direct and Network Effects across Country-Sectors

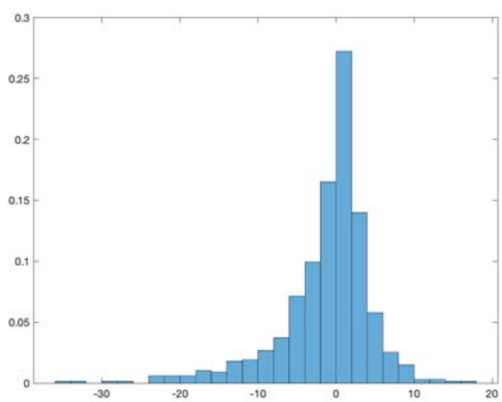
This figure plots the distribution of **Direct** and **Network** across mi from the estimation of equation Equation (13) for 2000–07, using Jarociński and Karadi (2020) monetary policy shocks for $\widehat{\mathcal{M}}_{US}$. The averages of these distributions are reported in Table 3.



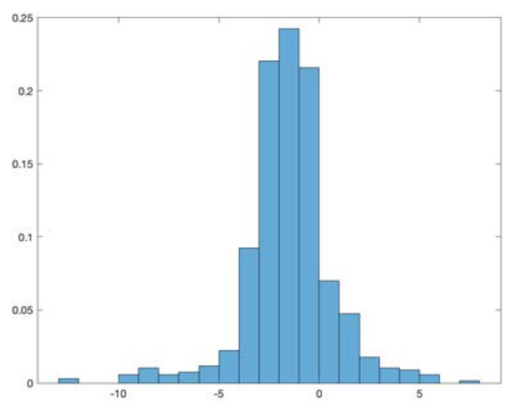
(a) Direct (AAK16)



(b) Network (AAK16)



(c) Direct (LP09)



(d) Network (LP09)

we see that the direct share of the total effect is always significantly larger for the country-sector cells that are "closer" to the United States' as measured by the U.S.'s final goods consumption relative to the country-sector's output. This finding maps to the structural model, where $\boldsymbol{\beta}_{US}$ is increasing with respect to the steady-state ratio of the United States' consumption of a country-sector's goods relative to the country-sector's profits. It is also worth noting that unlike in the closed-economy analysis of Ozdagli and Weber (2017), the network share is still larger than the direct share across both low and high groups. This is particularly noteworthy for the International sample of panel B – indeed, the opposite pattern holds when looking only at the U.S. sample

Table 4. Comparing effects by United States' consumption to country-sector output ratio

This table compares the direct and network shares of the total impact of U.S. monetary policy spillovers across country-sector cells by splitting the shares across two bins based on the ranking of a country-sector's sales of final consumption goods to the U.S. relative to the country-sector's total output. We take the average across the country-sectors' shares in each bin based on averages within "low"/"high" groups, where the threshold for the cutoff of each bin is either the (i) mean, (ii) median, or (iii) ninetieth percentile (P90) of the consumption-to-output share observed in 2000. Panel A includes all country-sector cells, while panel B drops U.S. country-sector cells.All numbers are based on our baseline estimates and bootstrapping used to construct Table 3 of the main text.

	Panel A. Full Sample				**Panel A.** International Sample			
	Direct/Total		**Network/Total**		**Direct/Total**		**Network/Total**	
	Low	High	Low	High	Low	High	Low	High
Cutoff definition:								
Mean	0.328	0.412	0.672	0.588	0.299	0.465	0.701	0.535
	(0.019)	(0.024)	(0.025)	(0.021)	(0.018)	(0.017)	(0.025)	(0.050)
Median	0.240	0.401	0.760	0.599	0.212	0.396	0.788	0.604
	(0.019)	(0.020)	(0.025)	(0.025)	(0.019)	(0.019)	(0.025)	(0.026)
P90	0.308	0.512	0.692	0.488	0.309	0.468	0.692	0.532
	(0.019)	(0.026)	(0.025)	(0.013)	(0.018)	(0.015)	(0.025)	(0.030)

of country-sectors, which we omit for brevity. This finding does not necessarily run counter to the gravity intuition. The network impact in a given foreign economy is not only picking up the role of intermediate trade linkages between the country and the U.S., but also linkages with other countries and, importantly, within the foreign economy itself. Therefore, even if the country-sector is a relatively large exporter of final consumption goods to the U.S., these other forces may still dominate the impact of the overall transmission of a U.S. monetary policy shock.

5.4 Empirical Counterfactual Trade Regimes

We next examine what our baseline SAR estimates imply about the role of intermediate goods trade in the transmission of U.S. monetary policy shocks relative to the other trade forces at work in the model. To do this, we compute two "autarkic" decompositions using two different counterfactual intermediate goods trade (production linkages) regimes.[41]

The first decomposition shuts down trade in intermediate goods across all countries. As such, the $\mathbf{W}$ matrix is now block diagonal, where we have re-normalized all domestic elements to assume that intermediate goods previously imported from a foreign country-sector, are now sourced from the corresponding domestic sector. We denote this matrix as $\mathbf{W}_{AUT1}$. This re-normalization ensures

[41] Note that we must maintain trade in final goods in order for the SAR model to be identified in the open economy.

Table 5. Total Impact of U.S. Monetary Policy Shocks: Baseline vs. Autarkic Scenario Empirical Counterfactuals

This table presents the **Total** impact of monetary policy shocks for our baseline estimation along with two empirical autarky couternfactuals: (i) Autarky$_1$ assumes no intermediate input goods trade across any countries, and (ii) Autarky$_2$ only allows for the U.S. to source intermeidate inputs from abroad. We present the mean and bootstrapped standard errors of our estimates for the full and international samples of country-sectors. All estimates are statistically significant at the one percent level.

	Total	**Total**$_{AUT1}$	**Total**$_{AUT2}$
Full Sample	-2.716	-1.221	-1.211
	(0.435)	(0.202)	(0.193)
International	-2.580	-1.091	-1.109
	(0.443)	(0.211)	(0.197)

that a country-sector's overall intermediate inputs-to-output ratio is the same as in the data. For the second decomposition, we assume that the intermediate trade is shut down across all countries *except* for the shipment of intermediates to the United States. Therefore, the **W** is block diagonal, except for the entries that correspond to shipments to the United States. We again re-normalize all entries where needed such that a country-sector's overall intermediate-to-output ratio does not differ from what we observe in the WIOD data. We denote this matrix as $\mathbf{W}_{AUT2}$.

Given these new synthetic input-output matrices, we then defined two new measures of the counterfactual **Total** effect of U.S. monetary policy on cross-country-sector stock returns, using the estimated $\boldsymbol{\rho}$s and $\boldsymbol{\beta}$s from our baseline estimation:

$$\mathbf{Total}_{AUT1} = (I - \text{diag}(\boldsymbol{\rho})\mathbf{W}_{AUT1})^{-1}\boldsymbol{\beta}$$
$$\mathbf{Total}_{AUT2} = (I - \text{diag}(\boldsymbol{\rho})\mathbf{W}_{AUT2})^{-1}\boldsymbol{\beta}$$

We then compare our baseline **Total** effect to the different counterfactual values. Comparing these differentials allow us to measure spillovers under different intermediate goods trade regime counterfactuals. We present these results in Table 5. The results are quite striking, where the autarkic effects are half of the baseline value. This shows that cross-border production linkages are at least as important for the global transmission of U.S. monetary policy shocks as within-country linkages.

5.5 Robustness Checks

We conduct a number of robustness check for our main result. First, we test for sensitivity of our findings to the sample time period and to the choice of timing at which the input-output matrix is sampled. We then return to the benchmark sample period and test for sensitivity of our result to definitions of stock returns and U.S. monetary policy shocks. We test for potential effects of monetary policy shocks emanating from other countries (namely, the U.K. and the euro area). Finally, we evaluate whether any specific sectors or countries are particularly influential for our results.

Sensitivity to Time Period and Definition of W

So far we have limited our analysis to the 2000–07 time period. Our baseline estimates are based on this period 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 Lehman 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 period and the year from which we sample the matrix $\mathbf{W}$.

Table 6 reports a variety of robustness checks based on different definitions of $\mathbf{W}$ and sample period coverage. For compactness, we just report the share of network effect across different variations of the sample for our baseline regression reported in Panel A of Table 3; the full set of estimates is reported in Table A4. First, we can see that replacing $\mathbf{W}$ measured in 2000 with the average $\mathbf{W}$ for 2000–07 does not change the results. This is not surprising given that elements of $\mathbf{W}$ are driven by production technologies and a trade structure that does not change very quickly, as observed in Figure 1. Second, we extend our time period through 2016.[42] We can see that the share of the network effect increases somewhat in this extended sample, not surprisingly given that increasing trend in cross-country trade integration and lengthening of global supply chains resumed following the Great Trade Collapse. However, even in this extended sample, using the average $\mathbf{W}$ instead of $\mathbf{W}$ for 2000 does not make much difference.

These results not only show the stability of our findings over time, but also support the assumption made in the model on the exogeneity of production linkages. At least in the studies of temporary monetary shocks, it seems to be safe to assume that technological coefficients of input-output linkages as well as trade patterns do not respond rapidly and can be taken as given.

Alternative Measures of Shocks and Returns

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

Table 6. Heterogeneous Spatial Autoregression Panel Estimation: Varying Sample Period and Weighting Matrix

This table reports networks shares calculated from heterogeneous coefficient spatial panel autoregressions (Equation (13)) where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over time periods indicated in the first column over month with FOMC announcements, and the independent variable is the measure of the U.S. 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 A4.

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \mathrm{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t$$

Time period	Year for $\mathbf{W}$	Share of network effect		
		Full sample	International	USA
2000-07	Avg. 2000-07	0.668	0.679	0.588
		(0.056)	(0.060)	(0.068)
2000-16	2000	0.748	0.758	0.661
		(0.056)	(0.059)	(0.034)
2000-16	Avg. 2000-16	0.765	0.772	0.707
		(0.050)	(0.054)	(0.032)
2000-07,09-16	2000	0.723	0.734	0.625
		(0.051)	(0.054)	(0.041)
2000-07,09-16	Avg. 2000-16	0.747	0.756	0.670
		(0.052)	(0.055)	(0.043)
2000-08,10-16	2000	0.743	0.748	0.693
		(0.044)	(0.046)	(0.059)
2000-08,10-16	Avg. 2000-16	0.759	0.762	0.737
		(0.062)	(0.064)	(0.073)

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 7, with the full regression results reported in Table A5.

We begin by replacing stock returns, which are measured in terms of U.S. dollars, with excess returns measured as a difference between annualized monthly USD nominal stock returns and a change in the 2-year U.S. Treasury rate during the same month, which proxies for the global risk-free rate. We also replace nominal stock returns expressed in U.S. dollars with nominal stock returns expressed in domestic currency as well as with real stock returns. To compute real stock returns, we start with domestic-currency nominal returns and adjust them with domestic inflation rate. We use last quarter's inflation rate for each observation in our sample in order to avoid incorporating any response of inflation to U.S. monetary policy shocks into our returns data. We compute real

Table 7. Heterogeneous Spatial Autoregression Panel Estimation: Robustness to Returns and Shock Measures

This table reports the network shares calculated from heterogeneous coefficient spatial panel autoregressions (Equation (13)) where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000–07 over months with FOMC announcements, and the independent variable is a measure of the U.S. monetary policy shock. The first row uses the nominal USD stock returns net of the 2-year U.S. Treasury rate. The second row uses nominal domestic currency stock returns. The third row uses real equity returns. All first three rows use the 'JK' monetary policy shock from Jarociński and Karadi (2020). Rows three to six use USD nominal returns but use a different measure of the monetary policy shock taken from: 'BRW' (Bu et al., 2021), 'OW' (Ozdagli and Weber, 2017), and 'NS' (Nakamura and Steinsson, 2018). There are 44,286 total observations 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 A5.

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \mathrm{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t$$

	Share of network effect		
Specification	Full sample	International	USA
Excess returns	0.799	0.813	0.693
	(0.107)	(0.119)	(0.046)
Domestic currency returns	0.678	0.684	0.629
	(0.060)	(0.062)	(0.074)
Real domestic currency returns	0.665	0.675	0.594
	(0.084)	(0.087)	(0.082)
USD returns, OW shock	0.663	0.668	0.606
	(0.050)	(0.052)	(0.103)
USD returns, NS shock	0.672	0.678	0.612
	(0.060)	(0.063)	(0.074)
USD returns, BRW shock	0.609	0.606	0.655
	(0.102)	(0.104)	(0.122)

returns as $\widehat{rq}_{mi,t} = (1 + \widehat{q}^{DC}_{mi,t})/(1 + infl_{m,t-1}) - 1$, where $\widehat{rq}_{mi,t}$ is the real stock return, $\widehat{q}^{DC}_{mi,t}$ is nominal return in domestic currency, and $infl_{m,t-1}$ is the inflation rate.

The results are reported in the top three rows of Table 7. We find that across all subsamples the share of the network effect increases substantially when we consider excess returns, indicating that changes in the risk-free rate contribute to the direct effect of U.S. monetary policy shocks to global stock returns, lowering our baseline measure of the share of the network effect. Using domestic currency returns, real or nominal, produces estimates of the network effect share that are similar to our baseline results.

Next, we consider three alternative measures of U.S. monetary policy shocks proposed by Bu et al. (2021); Nakamura and Steinsson (2018); Ozdagli and Weber (2017) ('BRW', 'NS', and 'OW', respectively). We find that the share of the network effect for the U.S. sectors is slightly smaller if we use 'BRW' shocks, but qualitatively our results are very similar to the baseline. Furthermore, the 67% network share for the U.S. stock returns using the 'OW' shock series is similar to the lower bound found in Ozdagli and Weber (2017), who use longer time series, a different frequency of stock returns, and a U.S. input-output table with a higher degree of sectoral disaggregation.

Placebo Analysis

The use of sector-level stock returns in the recursive SAR structure has the potential to generate spurious results. In particular, there might be a mechanical relationship between the sector-level stock returns used as the left-hand side variable and the weighted-average (based on the global input-output matrix) of sector returns used as explanatory variables. To examine whether this is indeed the case, we conduct two placebo checks where we randomly sort the return vector or the weighting matrix, while keeping key properties of the global production network fixed.

In our first approach, we reshuffle the columns of $\mathbf{W}$ within each row, which implies that we reassign customers for a given supplier, both across countries and across industries. This permutation leaves the outdegree (or total sales) of each country-sector cell unchanged. However, this perturbation does alter the distribution of production linkages across countries and sectors. Alternatively, in the second approach, we keep the right-hand side of the estimation equation unchanged, but instead reshuffle stock returns *within* each time period. These stock returns are still subject to the same U.S. monetary policy shock as before, but their assignment to a particular country-sector is now randomly changed and they are therefore associated with a different row of the weighting matrix. We expect the first randomization to lead to a smaller share of the network effect compared to the benchmark regression, but still a positive share, because the relative role of a country-sector as a supplier to customers along the global production network is unchanged. The second randomization, however, should converge to a zero network effect because stock returns of a given country-sector are now disassociated from the country-sector's production coefficients.

We conducted 500 randomizations for each approach. Figure A2 reports the distribution of the average share of network effect for the perturbation of the weighting matrix $\mathbf{W}$ in panel (a), and the perturbation of the vector of returns $\mathbf{q}$ for each t in panel (b).[43] We can see that with the perturbation of $\mathbf{W}$, the share of the network effect is on average positive (the mean is 0.29), but substantially below the baseline value we find in the main estimation (which is 0.67). For the perturbation of stock returns within a given time period, the network share is closer to zero (the mean is 0.15), as expected.

Foreign Monetary Policy Shocks

We next control for foreign monetary policy shocks in case they occur in reaction to or in concert

[43] We winsorized the share of the network effect to exclude cases of large values that are due to small estimated total effect in the denominator.

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 effect of a foreign country's 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 with the U.S., thus potentially impacting our baseline measure of the international network effect of U.S. monetary policy shocks along several dimensions.

In particular, we operationalize Equation (10) in a panel SAR model. We do this by extending (13) to include foreign monetary policy shocks as additional controls:

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \mathrm{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\left(\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \sum_{k=1}^{K} \boldsymbol{\gamma}_k\,\widehat{\mathcal{M}}_{kt}\right) + \boldsymbol{\varepsilon}_t, \tag{20}$$

where each $\widehat{\mathcal{M}}_{kt}$ is a measure the monetary policy shocks of country k (like the U.S. monetary policy shock term), and $\boldsymbol{\gamma}_k$ is a $NJ \times 1$ vector of coefficients. We further assume that the error term follows the same structure as in the baseline regression model (13). This specification assumes that the additional foreign monetary policy shock variables may impact stock returns both directly and indirectly via the global input-output matrix.

Table 8 presents these regression results, where we report total effects of foreign monetary policy shocks alongside the decomposition of U.S. monetary policy shocks. Looking at the direct and network effects of U.S. monetary policy in the first two rows, we see that our main results on the importance of the international network effect of U.S. monetary policy remain unchanged. In particular, when including all foreign monetary policy shocks the network is share in columns (3)-(5) is 0.684, 0.699, 0.575, for the full, foreign, and U.S. country-sectors respectively. Meanwhile, BOE monetary surprises have a significant effect on global stock prices, outside of the U.S., but the magnitude of this effect is about six times smaller than those of the U.S. monetary policy shocks. ECB monetary surprises do not appear to have an impact on global stock prices – the point estimates are small in magnitude and are not statistically significant.[44]

Heterogeneity of Estimates

[44]This result persists if we extend our sample through 2016 and is consistent with the literature. For example, Rogers et al. (2014) study the Fed, BOE, ECB, and BOJ monetary policy shocks during and after the 2008-09 crisis. They find that the effect of ECB shocks on stock markets is almost never significant and is much smaller than the effect of other central banks' shocks, even in a narrow intra-day window. Focusing on unconventional policies post-crisis, they find, more generally, that "the effects of US monetary policy shocks on non-US yields are larger than the other way round." For the pre-crisis period (2000-2008), Hussain (2011) finds also in intra-day analysis that the effect of ECB shocks on French, German, UK, and Swiss stock index returns are substantially smaller than the effect of BOE shocks. For the UK index (FTSE100), in particular, the effect is nearly zero and not statistically significant. Similarly, Bredin et al. (2009) find the effect of the ECB monetary policy shocks on German and U.K. stock markets is insignificant.

Table 8. Heterogeneous Spatial Autoregression Panel Estimation: Summary Results for Foreign Monetary Policy Shocks

This table reports direct and network effects of U.S. monetary policy shocks and total effects of foreign monetary policy shocks. These are calculated from heterogeneous coefficient spatial panel autoregressions (Equation (13)) where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000–07 over months with FOMC announcements, and the independent variables are measures of the monetary policy shocks in the U.S. and other countries. There are 44,286 total observations 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.

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \text{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\left(\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \sum_{k=1}^{K} \boldsymbol{\gamma}_k\,\widehat{\mathcal{M}}_{kt}\right) + \boldsymbol{\varepsilon}_t$$

	Full Sample			International	United States
	(1)	(2)	(3)	(4)	(5)
Direct effect of US MP	-0.877	-0.889	-0.883	-0.804	-1.848
	(0.314)	(0.317)	(0.291)	(0.088)	(0.301)
Network effect of US MP	-1.974	-1.897	-1.912	-1.863	-2.501
	(0.347)	(0.357)	(0.328)	(0.333)	(0.474)
Total effect of BOE MP	-0.599		-0.572	-0.644	0.302
	(0.274)		(0.293)	(0.196)	(0.408)
Total effect of ECB MP		0.014	-0.118	-0.114	-0.165
		(0.247)	(0.243)	(0.190)	(0.381)

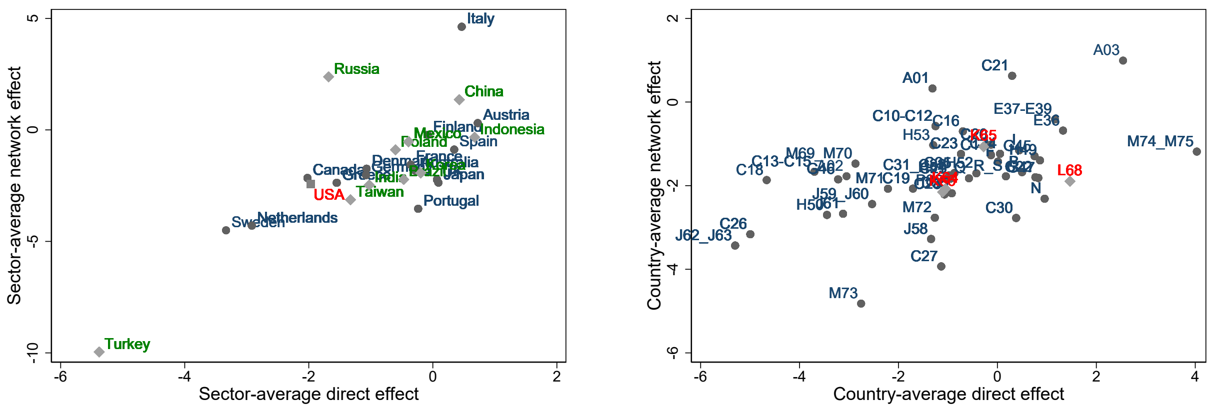
Before proceeding to analyze potential determinants of the heterogeneity of our estimates, we demonstrate that our results are not driven by the outliers. Figure 6 plots the average network effect against the average direct effect, where panel (a) computes the average across sectors within countries, and panel (b) computes averages across countries within sectors.

In panel (a), blue labels indicate advanced economies, green labels indicate emerging economies, and a red label is used for the U.S. We can see that the largest average direct and network effects are observed for Turkey, although the distance from the rest of the countries is not so large as to cause concern about undue influence of just one country on overall results. For the rest of the countries, we do not observe substantial differences between advanced and emerging economies. With the exception of Italy and Russia, we see a strong positive correlation between direct and network effects across countries. Finally, the U.S. does not stand out of the pack, with both direct and network effects tending to be larger than the average country-sector's, but within the distribution across other countries.

In panel (b) red labels indicate sectors that are related to finance and real estate and blue labels indicate all other sectors. We can see that there is a positive correlation between network and direct effects across sectors as well, but it is not as strong as across countries. There are no sectors that appear to be outliers.

Figure 6. Distribution of Direct and Network Effects across Countries and Sectors

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 (13) for 2000–07, using Jarociński and Karadi (2020) U.S. monetary policy shocks for $\widehat{\mathcal{M}}_{US}$, using *Decomposition 1 (AAK16)*. The overall averages of these distributions are reported in Table 3. In panel (a), blue labels are for advanced economies, green labels are for emerging economies, and the red label is for the USA. In panel (b), financial and real estate industries are labeled in red.



(a) Distribution across countries, sector averages

(b) Distribution across sectors, country averages

We next explore potential drivers of the observed heterogeneity in the estimated total effects and network shares across countries and sectors. Different variables are constructed at the country and sector levels that may be associated with the degree to which U.S. monetary policy shocks spillovers across countries and/or sectors. We focus on variables commonly used in the literature as well as those that may correlate with differences in production linkages, in order to rule out potential omitted variable bias in our estimates of the network share. Table A7 presents the definitions and sources of the variables we use in the regressions.

Two approaches are exploited to address heterogeneity. First, to estimate whether these variables can help explain the cross-section distribution of the total effect of U.S. monetary policy shocks on stock returns, we interact the explanatory variable with the monetary policy shock measure in our OLS panel analysis. Second, we regress shares of the network effect in the total effect for each country-sector cell estimated from our benchmark SAR specification on the explanatory variables in cross-section regressions.

All OLS interaction regressions are included in Table A8, where we include country×sector fixed effects in all specifications, with benchmark results reported in column (1) for convenience. All country or sector interaction variables are defined as 0/1 indicators for "low" or "high," where the cutoff is based on the median of the distribution of each variable.[45] Further, all data are based

[45]We also experimented with continuous variables, but results were qualitatively similar.

on the average of 2000-07 values, so we only rely on the cross-section variation in these variables for identification. We continue to use 0/1 indicators of high and low values for each variable in the analysis of the cross-section distribution of the network share of the total effect, and do not include any additional controls.[46] The results of these cross-section regressions are reported in Table A9.

Country size: looking at columns (2) and(3) of Table A8, we see that the coefficient on the interaction of country size and the monetary policy shock (MP) is negative, implying that larger countries may be more affected by an unexpected U.S. monetary policy loosening (or tightening). However, neither coefficient is significant. Further, the coefficient for the main effect of MP in column (2) is similar in magnitude to the baseline estimate of column (1), and remains significant. Turning to the cross-section heterogeneity regressions for the network share in Table A9, column (1), we find that the country size indicator variable has a coefficient of almost zero and is not statistically significant.

External debt: the literature, most recently Wiriadinata (2021), shows that the impact of U.S. monetary policy shocks is associated with a country's external debt. We investigate this channel by including countries' external debt as a share of GDP, from the World Bank World Development Indicators. First, in the panel regressions with interactions of Table A8, we see that the coefficients on the interaction of $Debt$ and MP in both columns (4) and (5) are positive, indicating that the transmission of U.S. monetary policy shock is in fact dampened in countries with larger external debt positions. However, neither of these coefficients are statistically significant, and the main effect of the monetary policy shock that is identified in column (4) where we exclude time effects is similar to the baseline estimate. The cross-section regression of the network share in Table A9 yields similar results as the interaction estimates. In particular, the coefficient on the Debt variable in column (2) is negative but is not statistically significant.

Financial frictions: we use a measure of external financial dependence by sector, using the Catão et al. (2009) update to the Rajan and Zingales (1998) methodology. We chose the Catão et al. (2009) measure because this metric covers sectors outside of manufacturing. Given that this Rajan-Zingales (RZ) measure only exploits differences across sectors, we also create a country-sector measure of financial frictions by interacting the RZ sectoral measure (expressed as a binary low/high indicator) with a low/high indicator of a country-level measure of financial frictions ($FinFric$). The FinFric indicated is based on a country's private credit-to-GDP ratio (sourced from the World Bank), which is a commonly used indicator of the level of financial development. We generate the FinFric indicator as one minus the indicator of financial development, so that "low/high" means a country has a low/high level of financial frictions. The coefficient on the double interaction of RZ with $FinFric$ and MP in our panel regression would then capture whether a sector that is

[46] Using continuous variables, including log of GDP to control for country size, or country and sector fixed effects, when possible, does not change the bottom line.

highly dependent on external financing situated in a high financial friction country (a “high/high” regime) is more/less affected by MP relative to other country-sectors.

Columns (6) and (7) of Table A8 present the regressions interacting financial development or the Rajan-Zingales measure with MP, respectively. We again omit time-varying fixed effects in order to estimate a coefficient on MP. Neither interaction coefficient is significant. Next, we include the double interaction term in column (8), where we now control for both country and sector time-varying fixed effects. The coefficient on the double-interaction term is negative, indicating that U.S. monetary policy may have a larger impact on stock returns in more financially dependent sectors in higher friction economies (less financially developed), but the coefficient is not significant. We also did not find significance when excluding time-varying fixed effects.

We next include measures of financial frictions ($FinFric$), financial dependence (RZ) and their interaction in our analysis of cross-section differences of the network share of the total effect using our baseline estimates in columns (3)-(5) of Table A9. We find that individually these variables have no effect on the share of the network in the total monetary policy shock propagation. The interaction effect is positive, suggesting that financially dependent sectors in countries with larger financial frictions experience more shock transmission through trade linkages. However, the difference between the groups of country-sectors is not statistically significant. Moreover, the R^2 is very low in all three regressions, indicating that these variables do not provide a good explanation for heterogeneity of our estimates of the network effect.

Financial openness: we construct a measure of financial openness of a country by a 0/1 indicator of high and low level of the ratio of the sum of total external assets and liabilities to GDP ($FinOpen$). As with financial frictions, we interact this country-level measure with the sector-level indicator of financial dependence. This interaction would then capture whether a sector that is highly dependent on external financing situated in a high financial openness country (a “high/high” regime) is more/less impacted relative to other country-sectors.

Column (9) in Table A8 includes the interaction of the country-level $FinOpen$ and MP without including any time effects in order to keep the coefficient on MP. The main effect remains negative and significant, while the interaction of $FinOpen$ and MP is insignificant. Next, column (10) includes the double interaction of the financial dependence and financial openness measures with MP. This specification includes both time-varying country and sector effects, so only the interaction coefficient can be identified. The coefficient is negative, indicating that sectors that are more dependent on external finance in more open (financially connected) economies are more affected by U.S. monetary policy shocks. However, the coefficient on this variable is insignificant.

Finally, turning to the cross-section heterogeneity regressions for the network share in Table A9, we find that financial openness does not explain the differences between countries (columns (6) and (7)). When we interact the country-level financial openness indicator with the sector-level financial dependence measure, we continue to find that there is no statistically significant difference between the share of network effects across the resulting four categories.

Price stickiness: we assemble measures of price rigidities from Pasten et al. (2017), which are based on detailed U.S. pricing data. We aggregate up (via simple averages) these measures to the WIOD sector-level. We prefer this measure to the one used by Zhang (2020) – who constructs a measure of price rigidity based on the Rauch (1999) classification – for two reasons. First, the Zhang (2020) measure only exploits information on tradeable sector goods and thus excludes several interesting sectors in the WIOD. Second, the Rauch (1999) classification is very coarse relative to the measures Pasten et al. (2017) create using detailed micro pricing data.

We interact the price stickiness measure ($PrSticky'$) with our baseline monetary policy shock variable in column (11) of Table A8, which excludes time fixed effects so that we can still identify a main effect of MP. As it can be seen, the coefficient on the price stickiness interaction terms is not significant. This result holds when controlling for country×time effects.[47] Column (8) of Table A9 shows that the distribution of the network share of the total effect of the U.S. monetary policy on stock returns across sectors is not explained by price stickiness: the coefficient is not statistically different from zero and the R^2 is very low.

Currency invoicing: a natural question to ask is whether U.S. monetary policy shock transmission is stronger for countries that rely more on the U.S. dollar for their trade invoicing. We collect data on the share of U.S. dollar invoicing of exports and imports by country from Boz et al. (2020). We first run simple interactions with the indicators of low/high export and import shares invoiced in U.S. dollars in columns (12) and (13) of Table A8.[48] As expected, the coefficients are negative, indicating that country-sector stock returns in economies with more dollarized trade are more sensitive to U.S. monetary policy shocks, but the estimated coefficients are not significant. Next, following the model of Zhang (2020), we interact these indicators with the price stickiness measure. These regressions are estimated with time-varying fixed effects in columns (14) and (15) of Table A8. The coefficients on the double interacted variables are negative, consistent with Zhang (2020). However, unlike that paper the coefficients are not significant.[49]

We include measures of dollar invoicing share in the analysis of the heterogeneity of the network share of the effect of U.S. monetary policy on stock returns across countries and sectors in columns (9) and (10) of Table A9. Regressions show that a higher share of dollar invoicing is associated with a higher share of the network in the shock transmission, but the differences are not statistically significant. We then interact these measures with the indicator of price stickiness, but still do not find statistically significant differences between country and sector groups (columns (11) and (12)).

[47] In the interest of space, this result is not reported but is available from the authors upon request.

[48] Note that the split of countries into "low" and "high" bins are identical for import and export shares, so the coefficients are identical, but we report both estimations for completeness.

[49] While we cannot pinpoint precisely why this is the case, it is worth noting that our sample is much broader, both across sectors and countries, than the data used in Zhang (2020).

Overall, both the analysis of variable interactions in the panel regressions and the cross-section regressions of Tables A8 and A9 generally deliver coefficient estimates with expected signs, but none of them are statistically significant. Thus, the heterogeneity of the estimated direct and network effects is not driven by variables that might capture alternative shock transmission channels.

5.6 The Global Financial Cycle

We next explore the robustness of the global production network demand channel of U.S. monetary policy shocks by controlling for global financial cycle variables, 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 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. In terms of estimation, this would be reflected in the spacial autoregression coefficients vector $\boldsymbol{\rho}$ being upwardly biased (in absolute value).

There is clear evidence in the literature that global stock prices respond to a global financial cycle (Chen, 2018; Bruno and Shin, 2015b; 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 2-year U.S. Treasury rate, and the broad U.S. dollar Index. We conduct both least squares and SAR analysis and include these variables one at a time and then all together.

Linear Regression Results

Table 9 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, for the subsamples we only present the results with all three additional control variables included – the results do not vary much if we include them individually.[50]

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 U.S. monetary policy shock that the input-output network captures. However, when we include the VIX in the regression, we find that the impact of the U.S. monetary policy shock is not statistically different from the baseline for the full sample as well as the subsamples. Consistent with the literature, increases in the VIX lower stock market returns worldwide, by

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

Table 9. Least-Squares Panel Estimation: Controlling for Global Financial Cycle Covariates

This table reports coefficients from linear regressions where the dependent variable $\widehat{q}$ is the country-sector annualized U.S. dollar monthly stock return over 2000–07 in month with FOMC announcements. The independent variables include the measure of the U.S. monetary policy shock taken from Jarociński and Karadi (2020) (MP shock), the monthly changes in the VIX index (VIX); the 2-year U.S. Treasury rate (T2y), and the broad U.S. dollar index (USD). Robust clustered standard errors are in parentheses. All coefficients on MP shock are statistically significant at the 1% confidence levels.

$$\widehat{q}_{mi,t} = \alpha_{mi} + \beta^{LS}_{MP}\,\widehat{\mathcal{M}}_{US,t} + \mathbf{X}_t\,\boldsymbol{\beta'}^{LS}_{X} + \varepsilon_{mi,t}$$

	Full Sample				International	United States
	(1)	(2)	(3)	(4)	(5)	(6)
MP shock	-3.320	-3.514	-3.184	-3.465	-3.339	-4.472
	(0.888)	(0.875)	(0.903)	(0.848)	(0.872)	(0.710)
Δ lnVIX	-0.018			-0.016	-0.016	-0.013
	(0.003)			(0.004)	(0.004)	(0.003)
ΔT2y		0.551		0.209	0.220	0.061
		(0.383)		(0.363)	(0.380)	(0.305)
Δ lnUSD			-0.476	-0.438	-0.443	-0.357
			(0.574)	(0.542)	(0.560)	(0.448)
R^2	0.075	0.069	0.067	0.076	0.074	0.08
Observations	49,667				46,357	3,310
Cty-sec FE	Yes	Yes	Yes	Yes	Yes	Yes

about the same amount in the U.S. and in foreign countries.

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 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 U.S. 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, however, the effect is not statistically significant. Controlling for the 2-year U.S. Treasury rate does not change much the impact of the U.S. monetary policy shock relative to the baseline.

In our baseline analysis we incorporated the effect of exchange rates into stock returns by expressing them in U.S. dollars. Given that the value of the dollar can be affected by U.S. monetary policy shocks (Inoue and Rossi, 2019), we want to separate the impact of U.S. 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 a statistically significant effect on global stock returns and that controlling for the dollar index does not change our baseline results.[51] This is not surprising given our previous robustness tests in which we found the results to be very similar whether we use USD-based or domestic currency-based stock returns.

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 stock returns.

Heterogeneous SAR Results

In order to condition on the global financial cycle in SAR setting, we conduct a two-step procedure. The two-step procedure allows for isolating the effect of global financial cycle covariates without imposing transmission of these shocks through production network. In the first step, we regress annualized monthly stock returns expressed in U.S. dollars on annualized monthly log changes in the VIX and the broad U.S. dollar index (USD), and the change in the 2-year U.S. Treasury rate (T2y):

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma_1}\, \Delta \ln \mathrm{VIX}_t + \boldsymbol{\gamma_2}\, \Delta \ln \mathrm{USD}_t + \boldsymbol{\gamma_3}\, \Delta \mathrm{T2y}_t + \boldsymbol{\varepsilon}_t. \tag{21}$$

The estimates for this regression using OLS, random coefficients, or Mean Group estimator (Pesaran and Smith, 1995) are reported in Table A10. For consistency with the rest of our analysis, we allow for the effects of global financial cycle covariates to vary by country and sector, thus, as a benchmark, we estimate regression Equation (21) using Mean Group estimator (Pesaran and Smith, 1995), which allows us to estimate a separate coefficient for each country-sector cell.[52]

Residuals from this regression represent the component of stock returns that is orthogonal to global financial cycle covariates:

$$\widehat{\boldsymbol{q}}_{\perp \mathbf{X},t} = \widehat{\boldsymbol{q}}_t - \boldsymbol{a} - \boldsymbol{c_1}\, \Delta \ln \mathrm{VIX}_t - \boldsymbol{c_2}\, \Delta \ln \mathrm{USD}_t - \boldsymbol{c_3}\, \Delta \mathrm{T2y}_t, \tag{22}$$

where $\boldsymbol{a}$ is the estimate for $\boldsymbol{\alpha}$ and $\boldsymbol{c_1}$- $\boldsymbol{c_3}$ are estimates for $\boldsymbol{\gamma_1}$- $\boldsymbol{\gamma_3}$.

We then use the component of stock returns that is orthogonal to global financial cycle covariates as our dependent variable in the SAR analysis as follows:

$$\widehat{\boldsymbol{q}}_{\perp \mathbf{X},t} = \boldsymbol{\alpha} + \left(I - \mathrm{diag}(\boldsymbol{\rho})\, \mathbf{W}\right)^{-1} \boldsymbol{\beta}\, \widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t. \tag{23}$$

The results are reported in Table 10.

Relative to our benchmark results in Table 3, *Decomposition 1 (AAK16)*, we find that both the direct and network effects are now slightly larger for foreign stock returns and slightly smaller for

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

[52] The results are nearly identical if we use instead OLS or random coefficient estimators. These results are available upon request.

Table 10. Heterogeneous Spatial Autoregression Panel Estimation: Conditioning on the Global Financial Cycle

This table reports direct and network effects from heterogeneous coefficient spatial panel autoregression (Equation (23)) where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000–07 over months with FOMC announcements, after conditioning for the changes in VIX, 2-year U.S. Treasury rate, and U.S. Broad dollar index. Conditioning is based on the mean-group estimator with first stage reported in Table A10. Independent variable is the measure of the U.S. 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. All coefficients are statistically significant at the 1% confidence level.

$$\widehat{\boldsymbol{q}}_{\perp \mathbf{X},t} = \boldsymbol{\alpha} + (I - \mathrm{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t$$

	Avg. β	Avg. ρ	Avg. **Direct**	Avg. **Network**	**Network/Total**
Full sample	-1.001	0.589	-1.001	-1.880	0.653
	(0.106)	(0.035)	(0.269)	(0.310)	(0.063)
International	-0.936	0.589	-0.936	-1.848	0.664
	(0.108)	(0.035)	(0.108)	(0.315)	(0.066)
United States	-1.796	0.581	-1.796	-2.274	0.559
	(0.304)	(0.055)	(0.304)	(0.428)	(0.092)

the U.S. stock returns. The share of the network effect is unchanged for the U.S. stock returns, but is slightly lower for foreign stock returns. This finding is consistent with our concern that some of the global financial cycle effect was reflected in the network effect in our benchmark specification. The difference between the network share in the benchmark results and in the results in Table 10 is negligible in magnitude and is not statistically significant. Combined with the findings from our least-square analysis that the total effect of U.S. monetary policy shock is robust to controlling for global financial cycle covariates, this SAR results confirm that any bias arising from not controlling for global financial cycle in our benchmark specification is minor.

6 Conclusion

In this paper we quantitatively evaluate the role of the global production network in the propagation of U.S. monetary policy shocks to stock returns at a sector level worldwide. 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

70% of the total estimated impact of U.S. monetary policy shocks on global stock returns is due to production linkages. This finding is not affected by conditioning on the financial channel of U.S. monetary policy shock transmission studied in the global financial cycle literature. Thus, in addition to providing a quantitative evidence of the importance of the global production network in transmitting asset market shocks, we 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 the global transmission of such shocks.

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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 (2017): (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. Note that the this assumption is not crucial for the derivation of the framework and can be easily relaxed to assume that the law of one price holds across countries. See Devereux et al. (2020) who study the cross-country propagation of fiscal shocks in a similar setup.

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 $j = 1,\dots,J$ sectors in each country $n = 1,\dots,N$. 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 $\sum_{i=1}^{J}\sum_{m=1}^{N}\omega_{mi,nj} = 1$.[53]

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.[54] 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

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

[53] 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.

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

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 $\tau_{mi,n} \geq 1$), we express revenues in country-sector mi as:

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

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:

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

where

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

where $\circ$ represents the Hadamard product, and $\boldsymbol{\Omega}$ 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 (2017); 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.[55] 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 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

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

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.).[56]

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

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

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

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

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

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

[55] 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.

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

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 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

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.

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

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

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.

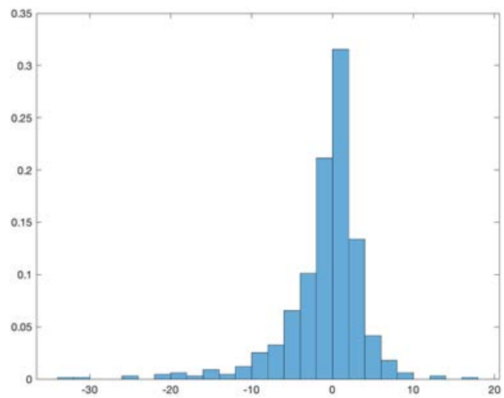
Industry	WIOD code	No. countries	Observations
Crop and animal production, hunting and related service activities	A01	13	1,614
Forestry and logging	A02	3	348
Fishing and aquaculture	A03	6	626
Mining and quarrying	B	19	2,593
Manufacture of food products, beverages and tobacco products	C10-C12	23	3,174
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

Appendix C Full Regression Tables and Additional Charts

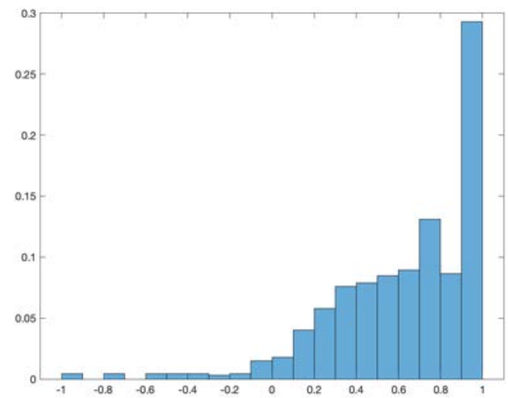
Here we report additional information about our baseline estimation as well as tables will full estimation results for all the tables in the paper.

Figure A1. Distributions of $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ across Country-Sectors

This figure plots the distribution of $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ across mi from the estimation of equation Equation (13) 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.



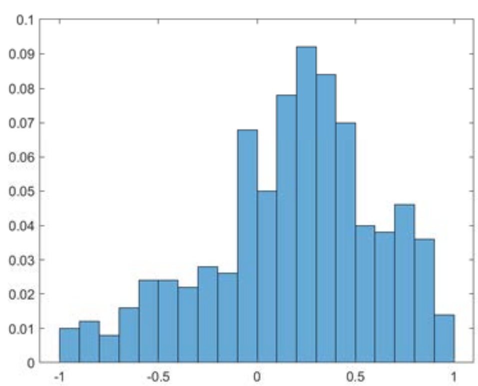
(a) β_{mi}



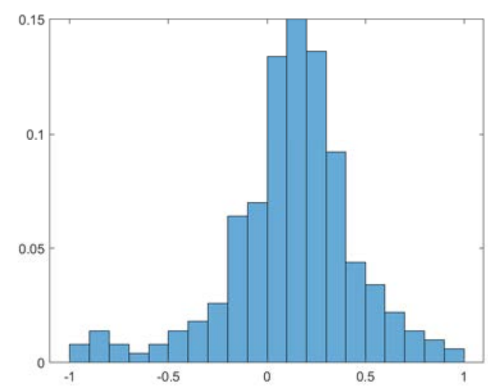
(b) ρ_{mi}

Figure A2. Placebo analysis

This figure plots the distribution of the share of the network effect across 500 randomizations of $\mathbf{W}$ in panel (a), and $\mathbf{q}$ in panel (b) for the benchmark SAR model reported in Table 3 in the paper.



(a) $\mathbf{W}$ randomization



(b) $\mathbf{q}$ randomization for each t

Table A3. Homogeneous Spatial Autoregression Panel Estimation: Baseline Specification

This table reports results from heterogeneous coefficient spatial panel autoregressions where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000–07 over months 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 total observations comprised of 671 country-sectors over 66 months. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions. All coefficients are significant at the 1% confidence level.

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \rho\,\mathbf{W})^{-1}\,\beta\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t$$

Panel A. Coefficient Estimates

	Average β	Average ρ	Observations
No Fixed effects	-2.049	0.656	44,286
	(0.465)	(0.066)	
Fixed effects	-1.183	0.568	44,286
	(0.237)	(0.030)	

Panel B. Total Effect Decomposition

	Avg. **Direct**	Avg. **Network**	**Network/Total**
Decomposition 1 (AAK16)			
No Fixed effects	-2.049	-3.906	0.656
	(0.465)	(0.400)	(0.002)
Fixed effects	-1.183	-1.556	0.568
	(0.237)	(0.182)	(0.002)
Decomposition 2 (LP09)			
No Fixed effects	-2.649	-3.306	0.555
	(0.353)	(0.273)	(0.004)
Fixed effects	-1.454	-1.285	0.469
	(0.225)	(0.153)	(0.003)

Table A4. Heterogeneous Spatial Autoregression Panel Estimation: Varying Sample Period and Weighting Matrix

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

$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \mathrm{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t$

	Avg. β (1)	Avg. ρ (2)	Avg. **Direct** (3)	Avg. **Network** (4)	**Network/Total** (5)
			Panel A. Full Sample		
2000-2007, avg. W	-0.885	0.631	-0.885	-1.783	0.668
	(0.096)	(0.024)	(0.272)	(0.313)	(0.056)
2000-2016, 2000 W	-0.554	0.719	-0.554	-1.644	0.748
	(0.067)	(0.013)	(0.251)	(0.274)	(0.056)
2000-2016, avg. W	-0.500	0.728	-0.500	-1.628	0.765
	(0.055)	(0.015)	(0.242)	(0.260)	(0.050)
2000-2016, 2000 W, no 2008	-0.795	0.712	-0.795	-2.069	0.723
	(0.085)	(0.016)	(0.297)	(0.324)	(0.051)
2000-2016, avg. W, no 2008	-0.713	0.722	-0.713	-2.102	0.747
	(0.093)	(0.015)	(0.304)	(0.335)	(0.052)
2000-2016, 2000 W, no 2009	-0.658	0.696	-0.658	-1.902	0.743
	(0.065)	(0.013)	(0.225)	(0.246)	(0.044)
2000-2016, avg. W, no 2009	-0.603	0.706	-0.603	-1.902	0.759
	(0.068)	(0.023)	(0.293)	(0.315)	(0.062)
			Panel B. International Sample		
2000-2007, avg. W	-0.815	0.634	-0.815	-1.725	0.679
	(0.103)	(0.025)	(0.103)	(0.318)	(0.060)
2000-2016, 2000 W	-0.519	0.725	-0.519	-1.624	0.758
	(0.073)	(0.014)	(0.073)	(0.280)	(0.059)
2000-2016, avg. W	-0.472	0.734	-0.472	-1.593	0.772
	(0.060)	(0.015)	(0.060)	(0.265)	(0.054)
2000-2016, 2000 W, no 2008	-0.736	0.719	-0.736	-2.033	0.734
	(0.091)	(0.017)	(0.091)	(0.329)	(0.054)
2000-2016, avg. W, no 2008	-0.661	0.729	-0.661	-2.050	0.756
	(0.100)	(0.015)	(0.100)	(0.338)	(0.055)
2000-2016, 2000 W, no 2009	-0.633	0.700	-0.633	-1.879	0.748
	(0.070)	(0.014)	(0.070)	(0.247)	(0.046)
2000-2016, avg. W, no 2009	-0.584	0.709	-0.584	-1.865	0.762
	(0.071)	(0.023)	(0.072)	(0.313)	(0.064)
			Panel C. USA Sample		
2000-2007, avg. W	-1.744	0.603	-1.744	-2.489	0.588
	(0.277)	(0.046)	(0.277)	(0.491)	(0.068)
2000-2016, 2000 W	-0.972	0.639	-0.972	-1.893	0.661
	(0.080)	(0.013)	(0.080)	(0.222)	(0.034)
2000-2016, avg. W	-0.852	0.655	-0.852	-2.061	0.707
	(0.078)	(0.013)	(0.078)	(0.234)	(0.032)
2000-2016, 2000 W, no 2008	-1.504	0.624	-1.504	-2.509	0.625
	(0.135)	(0.020)	(0.136)	(0.299)	(0.041)
2000-2016, avg. W, no 2008	-1.348	0.640	-1.348	-2.730	0.670
	(0.128)	(0.019)	(0.129)	(0.336)	(0.043)
2000-2016, 2000 W, no 2009	-0.961	0.655	-0.961	-2.174	0.693
	(0.163)	(0.034)	(0.164)	(0.324)	(0.059)
2000-2016, avg. W, no 2009	-0.838	0.673	-0.838	-2.350	0.737
	(0.175)	(0.035)	(0.176)	(0.431)	(0.073)

Table A5. Heterogeneous Spatial Autoregression Panel Estimation: Robustness to Returns and Shock Measures

This table presents full regression results for the regressions reported in Table 7. See notes to Table 7.

$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + (I - \text{diag}(\boldsymbol{\rho})\,\mathbf{W})^{-1}\,\boldsymbol{\beta}\,\widehat{\mathcal{M}}_{US,t} + \boldsymbol{\varepsilon}_t$

	Avg. β (1)	Avg. ρ (2)	Avg. **Direct** (3)	Avg. **Network** (4)	**Network/Total** (5)
			Panel A. Full Sample		
Excess returns	-0.467	0.824	-0.467	-1.859	0.799
	(0.106)	(0.013)	(0.486)	(0.532)	(0.107)
Domestic currency returns	-1.018	0.595	-1.018	-2.147	0.678
	(0.112)	(0.043)	(0.365)	(0.408)	(0.060)
Real domestic currency returns	-0.926	0.605	-0.926	-1.841	0.665
	(0.103)	(0.065)	(0.383)	(0.428)	(0.084)
USD returns, OW shock	-1.053	0.635	-1.053	-2.070	0.663
	(0.073)	(0.033)	(0.252)	(0.282)	(0.050)
USD returns, NS shock	-1.446	0.634	-1.446	-2.963	0.672
	(0.116)	(0.036)	(0.452)	(0.507)	(0.060)
USD returns, BRW shock	-0.845	0.633	-0.845	-1.319	0.609
	(0.122)	(0.036)	(0.343)	(0.380)	(0.102)
			Panel B. International Sample		
Excess returns	-0.418	0.823	-0.418	-1.815	0.813
	(0.117)	(0.014)	(0.117)	(0.540)	(0.119)
Domestic currency returns	-0.970	0.594	-0.970	-2.100	0.684
	(0.113)	(0.044)	(0.113)	(0.408)	(0.062)
Real domestic currency returns	-0.853	0.602	-0.853	-1.776	0.675
	(0.098)	(0.066)	(0.098)	(0.419)	(0.087)
USD returns, OW shock	-1.033	0.639	-1.033	-2.077	0.668
	(0.076)	(0.034)	(0.076)	(0.287)	(0.052)
USD returns, NS shock	-1.405	0.638	-1.405	-2.954	0.678
	(0.125)	(0.037)	(0.125)	(0.516)	(0.063)
USD returns, BRW shock	-0.864	0.636	-0.864	-1.331	0.606
	(0.131)	(0.037)	(0.131)	(0.387)	(0.104)
			Panel C. United States Sample		
Excess returns	-1.064	0.834	-1.064	-2.403	0.693
	(0.111)	(0.008)	(0.111)	(0.463)	(0.046)
Domestic currency returns	-1.603	0.603	-1.603	-2.723	0.629
	(0.255)	(0.048)	(0.255)	(0.540)	(0.074)
Real domestic currency returns	-1.772	0.634	-1.772	-2.591	0.594
	(0.296)	(0.067)	(0.296)	(0.614)	(0.082)
USD returns, OW shock	-1.290	0.581	-1.290	-1.984	0.606
	(0.275)	(0.043)	(0.275)	(0.400)	(0.103)
USD returns, NS shock	-1.950	0.587	-1.950	-3.073	0.612
	(0.292)	(0.037)	(0.292)	(0.564)	(0.074)
USD returns, BRW shock	-0.620	0.593	-0.620	-1.179	0.655
	(0.177)	(0.044)	(0.177)	(0.371)	(0.122)

Table A6. Least-squares Regression Estimation: Controlling for Foreign Monetary Policy Shocks

This table reports the least-squares regression including foreign monetary shocks, where the dependent variable is the annualized U.S. dollar 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 total observations comprised of 671 country-sectors over 66 months. Robust clustered standard errors are in parenthesis. Country-sector fixed effects are included in all regression. The effect of the U.S. monetary polich shock (Fed shock) is significant at (at least) 10% confidence level in all regression.

$$\widehat{q}_{mi,t} = \alpha_{mi} + \beta^{LS}_{MP}\,\widehat{\mathcal{M}}_{US,t} + \mathbf{X}_t\,\boldsymbol{\beta'}^{LS}_{X} + \varepsilon_{mi,t}$$

	(1)	(2)	(4)
Panel A. Full sample			
Fed shock	-2.738	-2.741	-2.731
	(1.320)	(1.299)	(1.305)
ECB shock	-0.055		-0.756
	(1.430)		(1.537)
BOE shock		-0.691	-0.225
		(1.518)	(1.460)
R^2	0.060	0.060	0.060
Panel B. International sample			
Fed shock	-2.623	-2.625	-2.616
	(1.396)	(1.374)	(1.380)
ECB shock	-0.030		-0.826
	(1.472)		(1.592)
BOE shock		-0.763	-0.215
		(1.570)	(1.505)
R^2	0.060	0.060	0.060
Panel C. United States sample			
Fed shock	-4.290	-4.307	-4.292
	(0.728)	(0.720)	(0.733)
ECB shock	-0.396		0.222
	(1.136)		(1.031)
BOE shock		0.325	-0.347
		(1.030)	(1.148)
R^2	0.060	0.060	0.060

Table A7. Definitions and Sources of Additional Variables

This table presents definitions and sources of variables used in all regressions. The control variables, which vary at the country or sector level, are sourced as the average over 2000–07. The 0/1 ("low"/"high") dummies are defined based on whether a country (sector) variable's value is below/above the cross-section mean of the variable's distribution. Country variables are denoted by m and sector variables by i.

Variable	Definition	Source
MP_{US}	Baseline U.S. FFR monetary policy shock	Jarociński and Karadi (2020)
GDP_m	country 0/1 dummy log(GDP) bin	World Bank WDI
Debt_m	country 0/1 dummy foreign debt/GDP bin	World Bank WDI
$\mathrm{FinFric}_m$	country 0/1 dummy financial friction (1 − private credit/GDP) bin	World Bank WDI
$\mathrm{FinOpen}_m$	country 0/1 dummy financial openness (External assets + liabilities/GDP) bin	Lane and Milesi-Ferretti (2007)
RZ_i	sector 0/1 dummy financial dependence bin	Catão et al. (2009)
$\mathrm{PrSticky}_i$	sector 0/1 dummy price stickiness bin	Pasten et al. (2017)
$\mathrm{USDshIM}_m$	country 0/1 dummy U.S. dollar invoiced import share bin	Boz et al. (2020)
$\mathrm{USDshEX}_m$	country 0/1 dummy U.S. dollar invoiced export share bin	Boz et al. (2020)

Table A8. OLS Interaction Regressions of Total Effect

This table reports coefficients from linear regressions where the dependent variable $\widehat{q}_{mi,t}$ is the annualized U.S. dollar country-sector monthly stock return, over 2000–07 in months with FOMC announcements. All control variables are defined in Table A7. Robust standard errors, clustered at the time level, are in parentheses. Country variables are denoted by m and sector variables by i.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
MP shock	-2.740	-2.578		-2.885		-2.578	-3.275		-3.022		-3.599	-2.301	-2.301		
	(1.311)	(1.541)		(1.336)		(1.090)	(1.652)		(1.630)		(1.374)	(1.469)	(1.469)		
$\text{GDP}_m \times \text{MP}$		-0.257	-0.499												
		(0.731)	(0.762)												
$\text{Debt}_m \times \text{MP}$				0.380	0.134										
				(0.804)	(0.936)										
$\text{FinFric}_m \times \text{MP}$						0.155									
						(0.742)									
$\text{RZ}_i \times \text{MP}$							0.990								
							(0.673)								
$\text{FinFric}_m \times \text{RZ}_i \times \text{MP}$								-1.272							
								(1.300)							
$\text{FinOpen}_m \times \text{MP}$									0.576						
									(1.286)						
$\text{FinOpen}_m \times \text{RZ}_i \times \text{MP}$										-0.109					
										(0.831)					
$\text{PrSticky}_i \times \text{MP}$											1.431				
											(0.971)				
$\text{USDshIM}_m \times \text{MP}$												-1.644			
												(1.249)			
$\text{USDshEX}_m \times \text{MP}$													-1.644		
													(1.249)		
$\text{USDshIM}_m \times \text{PrSticky}_i \times \text{MP}$														-1.999	
														(2.078)	
$\text{USDshEX}_m \times \text{PrSticky}_i \times \text{MP}$															-1.999
															(2.078)
Country×sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector×time FE	No	No	Yes	No	Yes	No	No	Yes	No	Yes	No	No	No	Yes	Yes
Country×time FE	No	No	No	No	No	No	No	Yes	No	Yes	No	No	No	Yes	Yes
Observations	49,667	49,667	49,465	49,667	49,465	44,375	35,796	31,295	49,667	35,728	32,386	30,158	30,158	19,344	19,344
R-squared	0.064	0.064	0.199	0.064	0.199	0.067	0.064	0.341	0.064	0.345	0.059	0.068	0.068	0.366	0.366

Table A9. OLS Cross-section Regressions for Network/Total Effect

This table reports the least-squares regression of the estimated direct and network effect estimates obtained from the baseline regression equation reported in Table 3, using Acemoglu et al. (2016) decomposition. The unit of observation is country-sector cell, with 25 countries, 52 industries, 615 observations in all regressions. All control variables are defined in Table A7. Standard errors are in parentheses. Country variables are denoted by m and sector variables by i.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GDP_m	-0.087											
	(0.972)											
Debt_m		-0.963										
		(0.973)										
FinFric_m			0.922		-0.450							
			(1.061)		(2.062)							
RZ_i				-0.638	-2.970		1.152					
				(1.343)	(2.175)		(1.839)					
$\text{FinFric}_m \times \text{RZ}_i$					4.289							
					(2.950)							
FinOpen_m						-1.237	0.436					
						(0.972)	(1.873)					
$\text{FinOpen}_m \times \text{RZ}_i$							-3.778					
							(2.689)					
PrSticky_i								-0.904			-3.402	-3.96
								(1.485)			(3.555)	(3.527)
USDshIM_m									1.714		0.816	
									(1.656)		(3.447)	
USDshEX_m										2.155		0.636
										(1.655)		(3.439)
$\text{USDshIM}_m \times \text{PrSticky}_i$											3.929	
											(5.065)	
$\text{USDshEX}_m \times \text{PrSticky}_i$												5.243
												(5.055)
Observations	672	672	616	469	428	672	469	438	390	390	255	255
R-squared	0	0.001	0.001	0	0.008	0.002	0.007	0.001	0.003	0.004	0.008	0.011

Table A10. First-Stage Residual Regression Estimation: Controlling for Global Financial Variables

This table reports the least-squares regression of the annualized U.S. dollar country-sector monthly stock return over 2000–07 over monthd with FOMC announcements on log changes in VIX and the broad U.S. dollar index (USD), and changes in the 2-year U.S. Treasury rate (T2y). Standard errors are in parentheses and all coefficients are statistically significant at the 1% confidence level.

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + \boldsymbol{\gamma_1}\,\Delta \ln \mathrm{VIX}_t + \boldsymbol{\gamma_2}\,\Delta \ln \mathrm{USD}_t + \boldsymbol{\gamma_3}\,\Delta \mathrm{T2y}_t + \boldsymbol{\varepsilon}_t$$

	OLS (1)	RC (2)	MG (3)
Δ lnVIX	-0.057	-0.052	-0.057
	(0.019)	(0.004)	(0.003)
ΔT2y	0.037	0.065	0.035
	(0.395)	(0.079)	(0.064)
Δ lnUSD	-2.404	-2.376	-2.389
	(0.599)	(0.142)	(0.116)
Constant	1.087	0.983	1.105
	(0.078)	(0.030)	(0.028)
Observations	49,667	49,641	49,641
Adjusted R^2	0.023		
Wald χ^2		542.03	881.78