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

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ABSTRACT

We quantify the role of global production linkages in explaining spillovers of U.S. monetary policy shocks on country-sector stock returns. We estimate a structural spatial autoregression (SAR) model that is consistent with an open-economy production network framework. Using the SAR model, we decompose the total impact of U.S. monetary policy on global stock returns into direct and network effects. Nearly 70% of the total impact is due to the network effect of global production linkages. Empirical counterfactuals show that shutting down global production linkages halves the total impact of U.S. monetary policy shocks.

THE RECENT ERA OF GLOBALIZATION witnessed (i) increased correlation of stock market returns across countries (Dutt and Mihov (2013) and Jach (2017)), and (ii) greater cross-country trade integration as firms' production chains spread across the world (Johnson and Noguera (2017)). While prior research has examined how *financial* integration affects 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

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production network plays an important role in the transmission of U.S. monetary policy shocks to world stock markets.

The conceptual framework delivers an empirical specification in which the international shock transmission pattern follows a spatial autoregression (SAR) process. To conduct this analysis, we construct a novel data set 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 1 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, the two-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 United Kingdom and the euro area.

We build our conceptual framework on a minimum of assumptions, offering an open-economy extension to the work of Ozdagli and Weber (2017). The framework can also be derived using a static multicountry multisector production model that follows the standard closed-economy setup (e.g., Acemoglu et al. (2012), Herskovic (2018), Richmond (2019)). Unlike many canonical macronetwork models, our framework allows for firm profits, which drive stock returns.[1] To generate monetary nonneutrality, we assume preset wages and allow money to be introduced in different ways, for instance, via cash-in-advance constraints, as in many recent macronetwork models (La'O and Tahbaz-Salehi (2020), Ozdagli and Weber (2017), Rubbo (2022)).[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

[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 (CRS) technology in a monopolistic competition setting (e.g., Bigio and La'O (2020)), or with decreasing returns to scale (DRS) 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).

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 firm 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 effect 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 IO data and Thompson Reuters Eikon for stock market information. WIOD provides domestic and global IO linkages for 56 sectors across 43 countries and the "rest of the world" aggregate annually for 2000 to 2014. From Eikon, we obtain firm-level stock prices, market capitalization, and firms' sector classification. Using 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 data set contains monthly country-sector stock returns and annual IO 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 to 2009 followed by the period of unconventional monetary policy, we limit our baseline analysis to 2000 to 2007. Our results are robust to other periods, however.

Before turning to the impact of U.S. monetary policy shocks, we use the raw stock market and IO 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 holds even if we exclude same-country cross-sector correlations from the analysis. This empirical regularity suggests that international IO 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)), with spatial distance represented by the coefficients in the global IO matrix. The SAR specification that 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* SAR. Second, we estimate country-sector specific coefficients, which is possible thanks to the time dimension in our panel setting. We estimate this

[3] Because IO 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 vary the weighting matrix for different time periods in our empirical analysis. We find that results are not sensitive to these changes.

heterogeneous-coefficient panel SAR model using the maximum likelihood methodology of Aquaro, Bailey, and Pesaran (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, Akcigit, and Kerr (2016) study that shows that the network-based shock propagation can be larger than a direct effect, as well as similar to what Ozdagli and Weber (2017) find for the response of U.S. stock returns to U.S. monetary policy shocks. Both studies focus only on the United States 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 shocks 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 effect of U.S. monetary policy shocks on global stock returns by half.

Our results are robust. They are not sensitive to the specific choice of time period or the year in which the IO matrix is sampled. This result suggests 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, with stock returns expressed 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 United KIngdom and the euro area. We find that there are no individual countries or sectors in which the spillover effects are concentrated. Furthermore, we rule out the possibility 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) the VIX, (ii) the two-year U.S. Treasury rate, and (iii) the broad U.S. dollar index.

A large literature in international macroeconomics 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 hence are more likely to identify reactions to monetary policy shocks. Our paper also differs 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, Kurz, and Tesar (2008), Bems, Johnson, and Yi (2010), Johnson (2014), Eaton et al. (2016), and Auer, Levchenko, and Sauré (2019), among others, model and quantify international shock transmission through input trade. Baqaee and Farhi (2019b) and Huo, Levchenko, and Pandalai-Nayar (2020) develop theoretical and quantitative treatments of the international input network model. Boehm, Flaaen, and Pandalai-Nayar (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, Levchenko, and Mejean (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 or on 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, Vega, and Wongswan (2010), Miranda-Agrippino and Rey (2020), among many others, provide evidence that 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).

Less attention has been devoted to cross-border monetary policy spillovers through real channels, such as IO 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 affects 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 real linkages across sectors play an important role in domestic shock transmission (see, among others, Foerster, Sarte, and Watson (2011), Acemoglu et al. (2012), Atalay (2017), Grassi (2017), Baqaee and Farhi (2019a)). Pasten, Schoenle, and Weber (2020) study the transmission of monetary policy in a production economy, while recent theoretical work on optimal monetary policy examines the impact of IO linkages on policy setting in a closed economy (La'O and Tahbaz-Salehi (2020), Rubbo (2022)), as well as in a small open-economy setting (Wei and

[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. Furthermore, 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, Loualiche, and Sauvagnat (2019).

Xie (2020)). Ozdagli and Weber (2017), to which our paper is most closely related, shows that IO linkages are quantitatively important for monetary policy transmission to stock returns in the United States,[6] while Herskovic (2018) and Richmond (2019) nest IO 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, Hodrick, and Zhang (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.

The paper is organized as follows. We present a stylized conceptual framework of global production model cross-country monetary policy shock transmission in Section I, which motivates the empirical model outlined in Section II. We then describe our data in Section III, before presenting our empirical results in Section IV. Section V concludes.

I. 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. Three main ingredients are 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; and 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 multicountry multisector IO model that allows monetary policy to have an impact on the real economy. Internet Appendix IA.I presents a simple multicountry multisector production model that embeds cash-in-advance constraints and sticky wages.[7]

[6] Moreover, Alfaro, García-Santana, and Moral-Benito (2021) and Bigio and La'O (2020) show the importance of production linkages in transmitting sectoral shocks to the aggregate economy.

[7] The Internet Appendix may be found in the online version of this article.

A. 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 consists 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 two second subscripts the importing (destination) country-sector, thank is, $x_{mi,nj}$ denotes goods produced in country m and 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 intermediate 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

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

where l_{nj} is the labor used by firms in sector nj, $\{x_{mi,nj}\}$ is the set representing quantities of intermediate goods used, and z_{nj} is a Hicks-neutral technology parameter. The function $F_{nj}(\cdot)$ allows for CRS or DRS production. Note that we assume a representative firm in each country-sector and thus drop any firm-specific notation.

B. Market Clearing

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

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

where p_{mi} is the price received by producers of good mi per unit of output. This condition is standard and holds 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 the 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.[8] The second term of the equation captures expenditure on intermediate inputs, where $\omega_{mi,nj}$ is the IO coefficient for country-sector nj purchases of the intermediate good from country-sector mi needed to produce a unit of output

[8] Internet Appendix IA.I provides a model that yields a structure akin to (2) and demonstrates how changes in modeling assumptions impact the derivation of the expenditure system.

of good nj,

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

We assume that the law of one price holds across goods in a given sector i, such that $p_{mi,n} = p_{mi}$.[9] Furthermore, 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 as

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

where $\boldsymbol{R}$ is the $NJ \times 1$ vector of country-sector sales, $\boldsymbol{C}$ captures the $NJ \times 1$ vector of final goods' expenditures, and $\boldsymbol{\Omega}$ is the $NJ \times NJ$ global IO matrix. Note that this expenditure system holds regardless of the underlying economic model, and is captured in the data by national accounting and world IO data.

C. Deviations from Steady State and Stock Returns

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

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

where $(I - \boldsymbol{\Omega})^{-1}$ is the $NJ \times NJ$ Leontief inverse of the IO matrix. Second, for any variable x, define the log deviation from steady state $\widehat{x} = \log(x) - \log(\bar{x})$ so that $x = \bar{x}\exp(\widehat{x}) \approx \bar{x}(1 + \widehat{x})$, where $\bar{x}$ is the steady-state value of x. Then, holding $\boldsymbol{\Omega}$ fixed,[10] we can express (4) in terms of deviations from steady state,

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

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: $\boldsymbol{\phi}_R = \left(\frac{\bar{C}_{11}}{\bar{R}_{11}}, \ldots, \frac{\bar{C}_{NJ}}{\bar{R}_{NJ}}\right)'$.

We need to deviate either from perfect competition or from firm CRS production technology to generate positive profits in equilibrium. One standard setup

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

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

in the macronetworks literature allows for CRS technology under monopolistic competition, where firms produce unique varieties and set prices with constant markups (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

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

where $\boldsymbol{\pi}$ is an $NJ \times 1$ 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: $\boldsymbol{\phi}_{\pi} = (\frac{\bar{C}_{11}}{\bar{\pi}_{11}}, \ldots, \frac{\bar{C}_{NJ}}{\bar{\pi}_{NJ}})'$.

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 by q_{nj}, 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 propagate across country-sectors' stock returns via the global production network:

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

D. Monetary Policy Shocks

The real effect of monetary policy has been subject to extensive analysis (see, for example, Woodford (2004) and Gali (2015) for textbook treatments). To generate a real effect, some form of price rigidity is built into the model.[11] In the case of a multicountry 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 predict that deviations in expenditures on final consumption $\mathcal{C}$ in country n around its steady state

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

are proportional to the monetary policy shock in country n, $\widehat{M}_n$,

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

where $\phi_n \geq 0$ depends on steady-state values and the elasticity of consumption growth with respect to changes in monetary policy.[12] Alternatively, if we allow for heterogeneity in sector-level consumption, $\mathcal{C}_{nj}$, responses, we can write (8) at the country-sector level as

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

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,

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

where $\boldsymbol{\beta}$ is an $NJ \times N$ 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 $\widehat{\boldsymbol{M}}$ is an $N \times 1$ vector of countries' monetary policy shocks.

Focusing on shocks to the U.S. monetary policy only, the element $\mathcal{M}_{US}$ in equation (10) gives

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

where $\boldsymbol{\beta}_{US}$ is an $NJ \times 1$ submatrix of $\boldsymbol{\beta}$ containing U.S.-specific elements. We present a simple model in Internet Appendix IA.I that embeds cash-in-advance constraints in an open-economy IO model to arrive at equations (10) and (11).

E. 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 potential impacts of monetary policy shocks on country-sectors' equity returns other than the transmission of demand shocks via global production linkages. A key channel of the monetary policy effect to consider is its impact on the stochastic discount factor (SDF) and risk-taking behavior, and thus on 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 effect 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 formally introducing portfolio decisions into

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

our conceptual framework is beyond the scope of this paper,[13] 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.

II. Regression Framework

The previous section's framework predicts that a monetary policy shock affects all stock returns in an amount proportional to their IO distance from the source of the shock. The empirical counterpart to this propagation pattern is a SAR (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

$$\widehat{\boldsymbol{q}}_t = \left(I - \mathbf{W}\text{diag}(\boldsymbol{\rho})'\right)^{-1} \boldsymbol{\beta} \widehat{M}_{US,t}, \tag{12}$$

where $\widehat{\boldsymbol{q}}_t$ is an $NJ \times 1$ vector of stock returns $\widehat{q}_{mi,t}$ for each t.[14] The subscript t represents the year-month in which a U.S. monetary policy shock occurs,[15] I is an $NJ \times NJ$ identity matrix, $\mathbf{W}$ is the $NJ \times NJ$ empirical global IO matrix, and $\widehat{\boldsymbol{M}}_{US,t}$ is the U.S. monetary policy shock at time t. This shock measure does not vary across sectors and comes from only one country, and thus the regression that 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, and thus replace it with an $NJ \times 1$ vector $\boldsymbol{\beta}$. Second, we add a set of country-sector-specific "resistance" coefficients to the network transmission mechanism. An $NJ \times 1$ vector $\boldsymbol{\rho}$ – diag($\boldsymbol{\rho}$) indicates an $NJ \times NJ$ diagonal matrix containing the vector $\boldsymbol{\rho}$ on the diagonal and zeros off-diagonal. The heterogeneous panel SAR setting allows

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

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

[15] Federal Open Market Committee (FOMC) announcements do not occur every month, and occasionally occur multiple times within a month. We include in our sample only months with FOMC announcements, but the results are robust to including all months. For months with multiple announcements, we aggregate announcements by adding up monetary policy shock measures.

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.[16]

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 I and Internet Appendix IA.I, where households' preferences for different goods or different competitive structures in different sectors, for example, lead to heterogeneous responses to the 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 $\mathbf{W}$).[17] 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.[18] It is worth emphasizing that identification of the effects of U.S. monetary policy shocks on stock returns comes entirely from the time-series variation, as the shocks do not vary by country-sector.

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

$$\widehat{\boldsymbol{q}}_t = \boldsymbol{\alpha} + \left(I - \mathbf{W}\mathrm{diag}(\boldsymbol{\rho})'\right)^{-1} \boldsymbol{\beta} \widehat{M}_{US,t} + \boldsymbol{\varepsilon}_t, \tag{13}$$

where $\boldsymbol{\varepsilon}_t = \left(I - \mathbf{W}\mathrm{diag}(\boldsymbol{\rho})'\right)^{-1} \boldsymbol{u}_t$ is the $NJ \times 1$ vector of errors $\forall t$, with the elements of $\boldsymbol{u}_t$ assumed to be independently identically distributed. Because of the complex structure of our model, instead of computing analytical standard errors, as suggested for the heterogeneous panel SAR of Aquaro, Bailey, and Pesaran (2021), we use a wild bootstrap to construct standard errors that are robust to heteroskedasticity introduced by the structure of heterogeneous SARs in equation (13). We describe the bootstrap procedure in detail below.

[16] For completeness, we also report estimates where coefficients $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ are constrained to be the same across all country-sector pairs. See Internet Appendix Table IA.III.

[17] 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, Ji, and Martin (2003), Fama and French (2012)).

[18] 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)).

A. Measuring Network Effects

The SAR model allows us to decompose the *total* marginal effect of the U.S. monetary policy on equity returns into *direct* and *network* (*indirect*) effects. 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 $\widehat{M}_{US,t}$ on stock returns $\widehat{q}_{mi,t}$. Instead, applying equation (12), the $NJ \times 1$ vector of total marginal effects is given by

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

where $\boldsymbol{\rho}$ and $\boldsymbol{\beta}$ are the estimated vectors of parameters. Specifically, for each country-sector cell, the total marginal effect of a U.S. monetary policy shock includes a direct impact as well as the sum of all indirect effects resulting from linkages expressed in the IO matrix $\mathbf{W}$. The $\boldsymbol{\rho}$-weighted Leontief inverse matrix, $(I - \mathbf{W}\,\mathrm{diag}(\boldsymbol{\rho})')^{-1}$, is an infinite sum of all immediate and indirect production linkages of all lengths. For example, consider an easing in the U.S. monetary policy that raises consumption demand for all goods in the United States, including Apple's iPhone. Conditional on U.S. consumers' preferences, Apple's revenues, profits, and stock price will rise. Furthermore, 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, with the size of these increases 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 such spillovers, as well as the initial impact on Apple.

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

Our baseline approach follows Acemoglu, Akcigit, and Kerr (2016) and performs the 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 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.[19] All effects intermediated by production linkages are included in the network effect.[20]

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

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

Alternatively, we may follow the textbook approach of LeSage and Pace (2009), and decompose the **Total** effect for each *mi* into direct and network effects according to

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

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

where $\mathbf{Direct}_{LP}$ and $\mathbf{Network}_{LP}$ are $NJ \times 1$ vectors. The key feature 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 country-sectors' returns back to themselves, and thus will 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 rather 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.

B. Reporting and Standard Errors

Results are reported as simple average values of $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, and **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 U.S. sectors to compute the U.S.-only direct and network effects.

Given the time dimension of our panel is short (66 periods in the benchmark) relative to the spatial dimension (an unbalanced panel of 26 countries and 54 sectors with a total of 671 country-sector cells), and our shocks only vary over time, one may be concerned that the analytical standard errors proposed by Aquaro, Bailey, and Pesaran (2021) are unreliable in our setting. We therefore employ a bootstrap approach to compute standard errors. In a standard bootstrap approach, one uses random subsamples of the data to reestimate a model. This is not an option for our setup, however, because estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ in the panel SAR strongly depend on the ordering of $\mathbf{W}$ and because $\widehat{\boldsymbol{M}}_{US,t}$ does not vary across country-sector cells. Thus, for our model the best approach is a wild bootstrap, in which random perturbations are added to the dependent variable by multiplying residuals by a random variable drawn from a specific distribution.[21]

We compute standard errors using the wild bootstrap procedure with continuous distribution proposed by Mammen (1993). This procedure allows for heteroskedasticity. In addition, we allow for cross-sectional correlation of errors by implementing a cluster version of this procedure, that is, we draw random variables for the size T vector and repeat the same perturbation for all country-sector cells within a given 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,

$$\widehat{\boldsymbol{q}}_t^z = \boldsymbol{a} + \left(I - \mathbf{W}\text{diag}(\boldsymbol{r})'\right)^{-1}\boldsymbol{b}\widehat{M}_{US,t} + \nu_t^z \circ \boldsymbol{e}_t,$$

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

We use a continuous distribution from which we draw 500 perturbations for each period. We then repeat the step for each element $\nu_{mi,t}^z$ of each vector ν_t^z,

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

where ξ and υ are drawn from independent standard normal distributions. We next estimate our SAR model replacing the true dependent variable with a synthetic one and retain the estimation results. Standard deviations of each estimated parameter across 500 repetitions are reported as standard errors.

III. Data

We source data from two main data sets: the global production network data come from the WIOD, and the stock market data come from the Thompson-Reuters Eikon database (TREI). WIOD provides annual data for IO linkages across 56 sectors and 43 countries as well as a rest of the world aggregate for 2000 to 2014.[22] For our analysis, we limit the data to 26 countries with active stock markets and 54 sectors that are connected to each other.[23]

From TREI, we obtain end-of-period monthly stock prices, stock market capitalization, and industrial classification for individual companies for the

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

[22] 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 in sectoral classification makes it impossible to merge the two sets of tables.

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

period 2000 to 2016.[24] We then construct our own stock return indexes for sectors as determined in WIOD, using a firm's stock market capitalization as a weight. This is not straightforward, given that the TREI sector classification uses the Thomson-Reuters Business Classification (TRBC), while WIOD's 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 Revision 4. This allows us to aggregate firms' stock market indices into WIOD-based sectors.[25] For each of the resulting country-sector cells, we construct monthly stock returns as the log change in the 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 of our analysis.[26]

Table AI presents cross-country sector coverage of monthly returns for the months in which there are monetary surprise shocks over 2000 to 2016. Given cross-country differences in size, sectoral specialization patterns, and stock market depth, we see that larger countries (e.g., the United States) have larger coverage of sectors, while some countries cover only a few sectors (e.g., Portugal and Russia). Furthermore, as Table AII shows, there is heterogeneity in the coverage of stock returns across the sectoral dimension. These differences motivate a flexible empirical approach. Accordingly, we allow for country-sector fixed effects as well as country-sector-specific coefficients for the effect of the monetary policy shock variable.

A. Input-Output Coefficient Construction

The construction of the global IO matrix using WIOD data is standard and follows the literature. We denote countries as $m, n \in [1; N]$ and sectors as $i, j \in [1; J]$. WIOD provides information on output produced in a given country-sector and where it flows to, in terms of both geographical destination and destination sector of the economy (including government and households). We first use this information to build an $NJ \times NJ$ matrix $\mathbf{W}$, where each element $w_{mi,nj}$ represents the use of inputs from country m sector i as a share of the total output of sector j in country n,[27]

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

[24] We are constrained to starting the sample period in 2000 to capture the largest sample of country-sector stock returns.

[25] Even with these data, there is not always a one-to-one correspondence between the TREI and WIOD codes. We rectify such instances in a variety of ways as described in Internet Appendix IA.II.

[26] 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 a recent discussion of the complex relationship between exchange rates and stock prices, see Karolyi and Wu (2021).

[27] Note that this is analogous to $\omega_{mi,nj}$ in the conceptual framework.

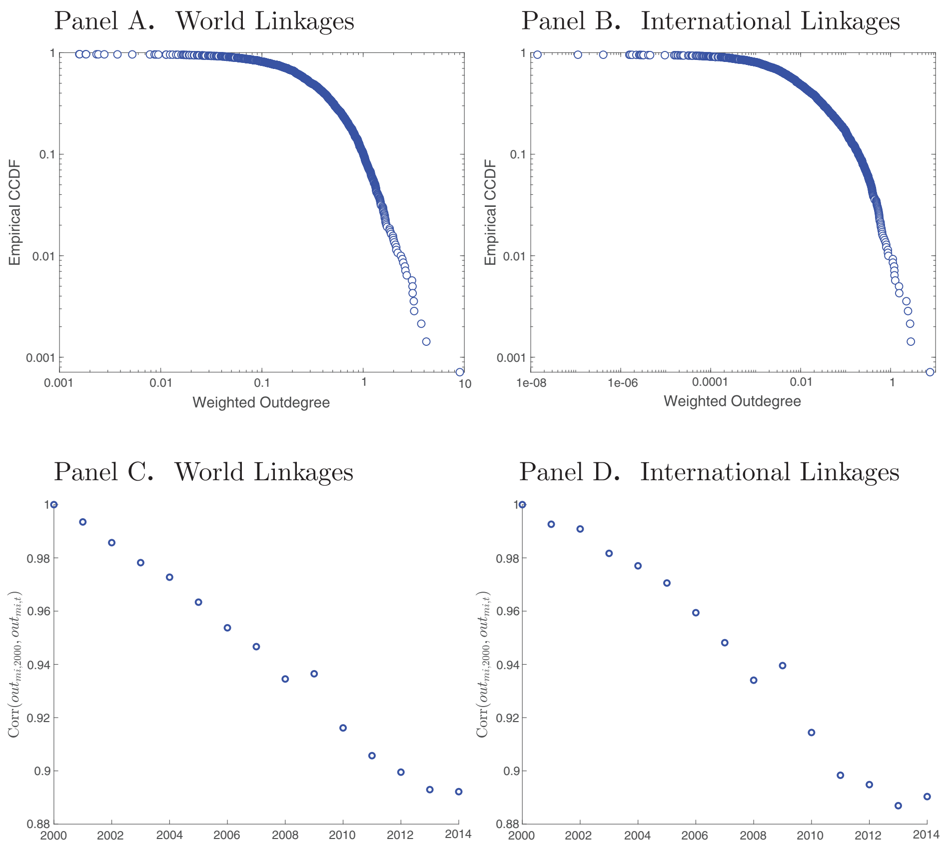

Figure 1. Distribution of weighted outdegree for WIOD. The first row of this figure plots the countercumulative distribution function (CCDF) of the weighted outdegree using the average of the WIOD annual database over 2000 to 2014. The second row plots changes in the distribution of country-sector weighted 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 2000. The panels representing World Linkages are based on the full WIOD table, while the panels for International Linkages use internationally connected country-sector cells only (i.e., we omit domestic-only linkages across sectors) in constructing the weighted outdegree measure. (Color figure can be viewed at wileyonlinelibrary.com)

In network terminology, **W** is the adjacency matrix that gives us direct linkages between each pair of country-sector cells. Because by construction $w_{mi,nj} \in [0;1]$ and $w_{mi,nj} \neq w_{nj,mi}$, the network is weighted and directed. Note that we use all countries and sectors when constructing the adjacency matrix, but only exploit the submatrix where we have stock returns in the estimation below. This requires a renormalization of the matrix for estimation purposes, but all preliminary statistics are based on manipulating the adjacency matrix without this renormalization.

The top row of Figure 1 presents the empirical countercumulative distribution function (CCDF) of the weighted outdegree of **W** for WIOD data, where we use the average IO coefficients over the 2000 to 2014 sample period. The weighted outdegree for a given country-sector pair mi is defined as

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

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, if skewed that would imply the potential for shocks to propagate and amplify across the production network (Acemoglu et al. (2012)). Panel A plots the distribution using all possible IO linkages in the world including both domestic and international linkages in computing the weighted outdegree, while Panel B exploits international linkages only. As can be seen in both panels, the distributions are highly 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 IO tables from the Bureau of Economic Analysis. In comparing Panels A and B, it is worth noting that the x-axes of the two plots employ two different scales. In particular, the international weighted-outdegree measures tend to be smaller on average than those using the full world IO table (which includes domestic linkages) as several country-sector cells are not used as intermediate inputs (or in very tiny amounts) abroad.

Panels C and D of Figure 1 examine how the outdegree distributions have changed over time. Specifically, we calculate the correlation of the out_{mi} measures for each year with those for 2000. As can be seen, both for world linkages in Panel C and international linkages in D, the correlation has been decreasing over time, indicating a "reshuffling" 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 monetary policy shocks propagate heterogeneously across country-sectors via the global production network, which further motivates our choice of estimating a heterogeneous panel SAR as the baseline.

We next present the distribution of 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 United States, 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, 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.[28] Panel A includes all country-sector pairs of the world that are in our sample of 26 countries and

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

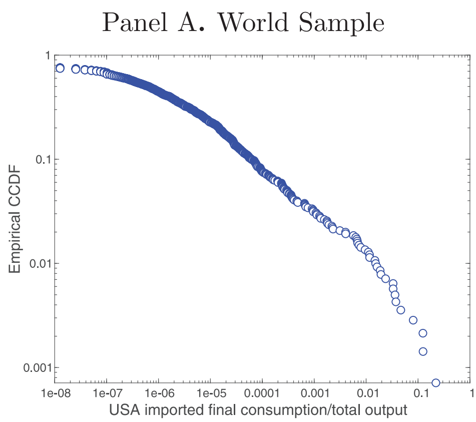

Figure 2. Closeness to U.S. consumers. This figure presents the distribution of a country-sector's sales of final consumption goods to the United States relative to the country-sector's total output using 2000 data from WIOD. Panel A presents the distribution for all country-sector cells in the 26 countries and 54 sectors in our full sample, while Panel B omits U.S. country-sector cells to construct the international sample. (Color figure can be viewed at wileyonlinelibrary.com)

54 sectors, and thus it includes U.S. own consumption of final goods produced domestically. Panel B omits the U.S. country-sector pairs. As can be seen, there is substantial heterogeneity across country-sector pairs, but the distribution is not as skewed as the world IO matrix. The cross-sectional heterogeneity in $c_{nj,USA}$ allows us to test whether the effect of U.S. monetary policy shocks on stock returns in country-sectors that are "closer" to the United States are driven relatively more by the **Direct** than the **Network** share, as one would expect from the structural model written down in Internet Appendix IA.I.

B. Returns Data

We next explore our data and show that there is a relationship between stock return correlations and IO linkages. As described previously, a unit of observation in our data is the monthly stock return in country m and sector i. We express all returns in U.S. dollars for consistency 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 of the 1,404 possible country-sector cells for each month from January 2000 through December 2016.[29] Figure 3 presents the distribution of pairwise correlations between each possible pair of the 671 time series of stock returns. We find that most correlations are positive and that the mass of the distribution is between 0 and 0.5.[30]

[29] Recall that we have a maximum of 54 sectors and 26 countries. The number of country-sectors is further restricted to ensure that **W** has full rank for estimation purposes, even if stock return data may exist for some of the omitted country-sectors.

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

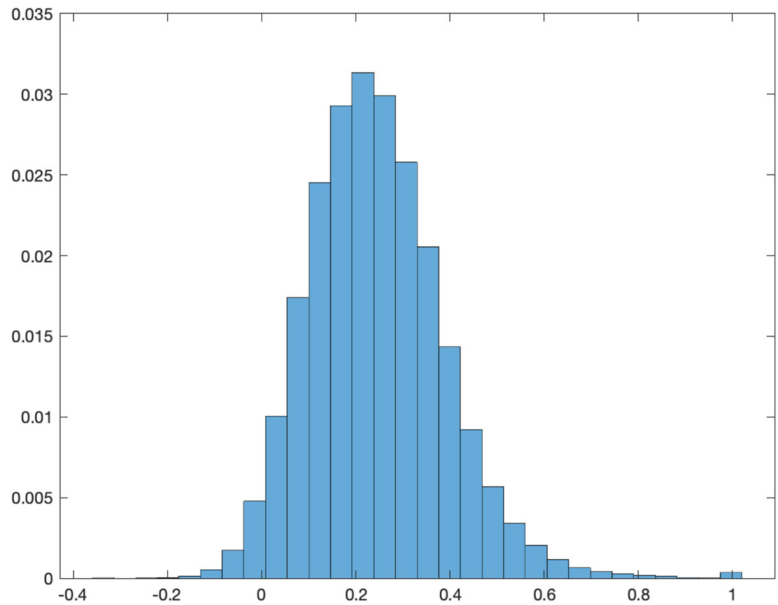

Figure 3. Correlation of stock returns over the entire sample. This figure plots the distribution of pairwise correlations of annualized U.S. dollar monthly stock returns over 2000 to 2016 across 26 countries and 54 sectors. (Color figure can be viewed at wileyonlinelibrary.com)

B.1. Returns and the IO Network

Our main goal is to shed light on 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. For illustrative purposes, we replace $\mathrm{w}_{mi,nj} < 0.05$ with zero, and the rest of the cells with one, 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 $mi \rightarrow nj$ and $nj \rightarrow mi$ path lengths). Even though the diameter, that is the longest distance of the IO network, averaged over time is 23, we plot distances only up to eight because for 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 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 see that pairs most closely connected through IO linkages exhibit the highest correlation of stock returns (correlation coefficient of 0.39). The larger is the distance, the

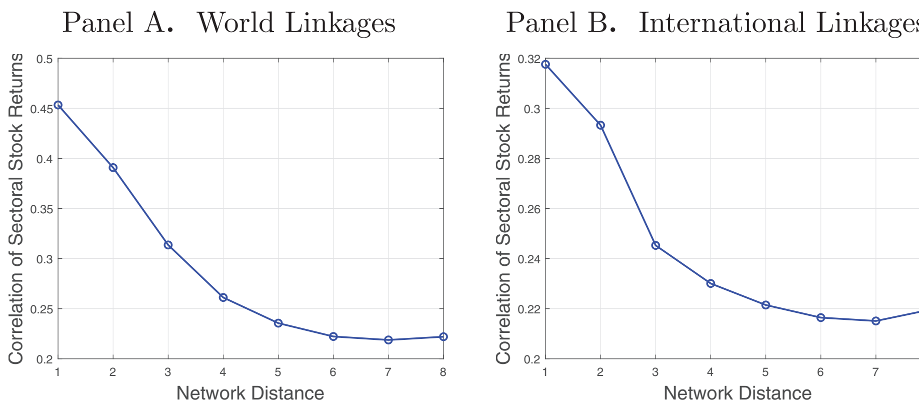

Figure 4. WIOD network distance of supply linkages and the correlation of stock returns. This figure plots correlations of U.S. dollar annualized monthly stock returns over the 2000 to 2016 period across 26 countries and 54 sectors on the *y*-axis, across network distance bins based on the direct bilateral supply linkage using the average of the WIOD annual database over the 2000 to 2014 period. The elements of the IO matrix are defined as country-sector *mi*'s usage of country-sector *nj*'s good as an intermediate goods divided by *mi*'s gross output. Panel A is based on the full WIOD table, while Panel B extracts the correlation and distance variable for internationally connected country-sector cells only (i.e., we omit domestic-only linkages across sectors). (Color figure can be viewed at wileyonlinelibrary.com)

lower is the correlation. This correlation tapers out just below 0.17 for any distance over four. Panel B shows that a similar pattern holds when we exclude all domestic sector pairs from the analysis, with the highest average correlation equal to 0.23. This finding alleviates the concern that our results are driven entirely by domestic IO 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 at a greater distance from each other in the global production network.

These two panels provide prima facie evidence that two sectors that rely more heavily on each other for the supply of inputs in production 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.

C. Monetary Policy Shocks and Global Financial Cycle Correlates

Our baseline measure of the U.S. monetary policy shocks comes from Jarociński and Karadi (2020). The authors capture an interest rate surprise as the change in the three-month Federal Funds futures 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 FOMC press release, which is 2 p.m. East Coast time on the day of a regular FOMC meeting.[31]

We explore the robustness of our regression results to conditioning on other correlates of the global financial cycle, namely, the VIX, two-year U.S. Treasury rate, and the broad U.S. dollar index. The VIX is obtained from Federal Reserve Economic Data (FRED). The two-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 two-year U.S. Treasury rate before including them in the regressions below. The VIX and dollar index are commonly used to capture the global financial cycle (e.g., Bruno and Shin (2015a), Miranda-Agrippino and Rey (2020)), while changes in the two-year U.S. Treasury rate capture the overall change in the U.S. monetary policy stance as well as the cost of funding.[32] Moreover, the unique role of 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 European Central Bank (ECB) and Bank of England (BOE) 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 nonmonetary news. We include these shocks along with the U.S. monetary policy shock vector to control for potential foreign monetary responses to the U.S. monetary policy, and which would be picked up in the network contribution if omitted. Finally, we also exploit the U.S. monetary policy shocks from Nakamura and Steinsson (2018), Bu, Rogers, and Wu (2021), and Ozdagli and Weber (2017) as further robustness checks.

IV. 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 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.

[31] 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 in which there exist multiple announcements.

[32] The two-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 that proposed by Wu and Xia (2016), while at the same time is a more transparent measure.

Table I

Least-Squares Regression Estimation: Full Sample

This table reports coefficients from linear regressions in which the dependent variable $\widehat{q}_{mi,t}$ is the annualized U.S. dollar country-sector monthly stock return in columns (1) to (5) and the country market return in column (6), over 2000 to 2007 in months with FOMC announcements, and the independent variable $\widehat{M}_{US,t}$ is the measure of the U.S. monetary policy shock taken from Jarociński and Karadi (2020). There are 49,667 observations in columns (1) to (5), and 1,716 observations in column (6). Standard errors are in parentheses. All coefficients are significant at the 5% confidence level or better.

$\widehat{q}_{mi,t} = \alpha + \beta^{LS}\widehat{M}_{US,t} + \varepsilon_{mi,t}$						
	(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)
Adjusted R^2	0.0033	0.0033	0.0482			0.0646
Wald χ^2				58.65	90.54	
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*

Finally, we show that our baseline direct and network effects are not driven by specific countries or sectors.

A. 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.[33] Effectively, this estimation strategy imposes the restriction of spatially uncorrelated country-sector cells in the SAR framework of (13); that is, setting $\rho = 0$. As a result, the network and direct effects are captured in the estimate β^{LS}.

Results of the estimation using the Jarociński and Karadi (2020) monetary policy shock series for the 2000 to 2007 sample period are reported in Table I. The simple OLS estimate in column (1) implies that a 1 percentage point surprise in monetary policy easing results in a 2.7 percentage point increase in the average country-sector monthly stock return.[34] Column (2) shows that the standard errors increase substantially when we cluster them

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

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

at the monthly (t) level, which should be expected because the monetary policy shock is repeated for each country-sector return in a given time period of the panel and the strong factor structure in panels of stock returns. The magnitude of the effect does not change much when 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.

Given that our conceptual framework allows the 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, in column (4) we estimate a random coefficients model with β's varying across country-sector panels. We find that the average coefficient estimate declines slightly. Second, in column (5) we use a Mean Group estimator (Pesaran and Smith (1995)) with groups defined as country-sector pairs. In this case, the average β is somewhat larger (in absolute value) than the random-coefficient estimate, 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. These results are reported in column (6). We find that the coefficient in 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. Furthermore, the point estimate is in line with other estimates in 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 apparent in the first four weeks following the announcement (Bernanke and Kuttber (2005), Cieslak, Morse, and Vissing-Jorgensen (2019)) and with at least three to four days delay even for U.S. firms (Chava and Hsu (2019)).[36]

Table II reports least-squares regression results where we split the sample into all foreign countries (Panel A) and the United States only (Panel B). The overall point estimates for the international sample in Panel A are somewhat smaller than the baseline estimates using the full sample of Table I for the country-setor returns in columns (1) to (5), with the impact of a 1 percentage point innovation in the 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

[35] Using hourly returns, Ammer, Vega, and Wongswan (2010) that is about twice as large as ours, for both domestic and foreign stock returns. In a much longer sample, Miranda-Agrippino and Rey (2020) find 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 United States, the United Kingdom, and German stock indexes.

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

Table II
Least-Squares Regression Estimation: International and U.S. Subsamples

This table reports coefficients from linear regressions in which the dependent variable $\widehat{q}_{mi,t}$ is the annualized U.S. dollar country-sector monthly stock return in columns (1) to (5) and the country market return in column (6), over 2000 to 2007 in months with FOMC announcements, and the independent variable $\widehat{M}_{US,t}$ 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) to (5), 1,650 observations in column (6)), and Panel B includes the United States only (3,310 observations in columns (1) to (5), 66 observations in column (6)). Standard errors are in parentheses. All coefficients are significant at the 10% confidence level or better.

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

	(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)
Adjusted R^2	0.0029	0.0029	0.0457			0.0616
Wald χ^2				47.11	74.07	
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)
Adjusted R^2	0.0325	0.0328	0.047			0.1476
Wald χ^2				25.18	37.01	
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

reported in Table I. 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 a 1 percentage point change in the U.S. monetary policy increasing the average sector return by approximately four percentage points in columns (1) to (5), and by 3 percentage points in looking at the overall market return in column (6). The magnitude of this effect is consistent with prior literature (e.g., Ehrmann and Fratzscher (2004), Bernanke and Kuttber (2005), Ozdagli and Weber (2017)).

Note that the linear regressions do not allow us to condition on the network structure and thus β^{LS} combines both direct and network effects. We next turn to the SAR analysis which allows us to measure these two effects separately.

Table III

Heterogeneous Spatial Autoregression Panel Estimation: Baseline Specification and Decompositions

This table reports results from heterogeneous coefficient panel SARs (equation (13)) in which the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000 to 2007 in 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 for of 671 country-sectors over 66 months. LP09 and AAK16 refer to the decomposition methodologies in LeSage and Pace (2009) and Acemoglu, Akcigit, and Kerr (2016), respectively. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions. All coefficients are significant at the 1% confidence level.

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

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)	
United States	−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)
United States	−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)
United States	−1.988	−2.313	0.538
	(0.224)	(0.386)	(0.065)

B. Heterogeneous SAR Results

We now allow for network effects by estimating a SAR model. We first present results of the heterogeneous-coefficients SAR model in Table III, where we allow for country-sector fixed effects following Elhorst (2014).[37] We estimate the regression with maximum likelihood following Aquaro, Bailey, and Pesaran

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

(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, Akcigit, and Kerr (2016) direct and network decompositions. We present the Acemoglu, Akcigit, and Kerr (2016) decomposition only for additional results 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 III shows the average values of $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$. We report averages across all country-sectors, for country-sectors outside of the United States, and for U.S. sectors only. The full distribution of these estimates is reported in Internet Appendix Figure IA.1. 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 above. 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 United States, and for U.S. sectors only. The full distribution of direct and network effects is presented in Figure 5.[38]

The first point to note is that the sum of the estimated **Direct** and **Network** effects, that is, the **Total** effect, lines up with the least-squares estimates of Table I as we would expect. Turning to our primary 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 to transmission through the production network using our preferred decomposition method of Acemoglu, Akcigit, and Kerr (2016). In fact, as we can see in Figure 5 the network effect is negative for a larger subset of country-sector cells than the direct effect. This result follows from the high estimated coefficient on shock propagation, ρ, which is 0.63 on average. Interestingly, this average ρ is less than one, the value implied by our conceptual framework, due to unmodeled resistance to the transmission of shocks across international stock markets via the global production network. The network effect also explains over half of the total effect if we use the LeSage and Pace (2009) decomposition, which shows the robust importance of global production networks in transmitting the U.S. monetary policy shocks in our baseline estimation.

Computing averages for foreign country-sectors and for U.S. sectors separately allows us to see the pattern of transmission of the U.S. monetary policy shocks to stock returns globally. We find a larger direct effect of U.S monetary policy shocks on U.S. sectors than foreign sectors, which is expected.

[38] Note that heterogeneity of the total effects consists of both heterogeneity of the IO coefficients and heterogeneity of the impact and propagation coefficients, β and ρ. Figure IA.1 shows that the impact and propagation coefficients vary substantially across sectors. To check whether this distribution is related to the importance of a given sector-cell in the production network, we compute the eigenvector centrality of each country-sector in the IO network, following Richmond (2019). We find that total effect is uncorrelated with the eigenvector centrality measure (the correlation coefficient is -0.02), pointing to the importance of allowing for variation in SAR coefficients.

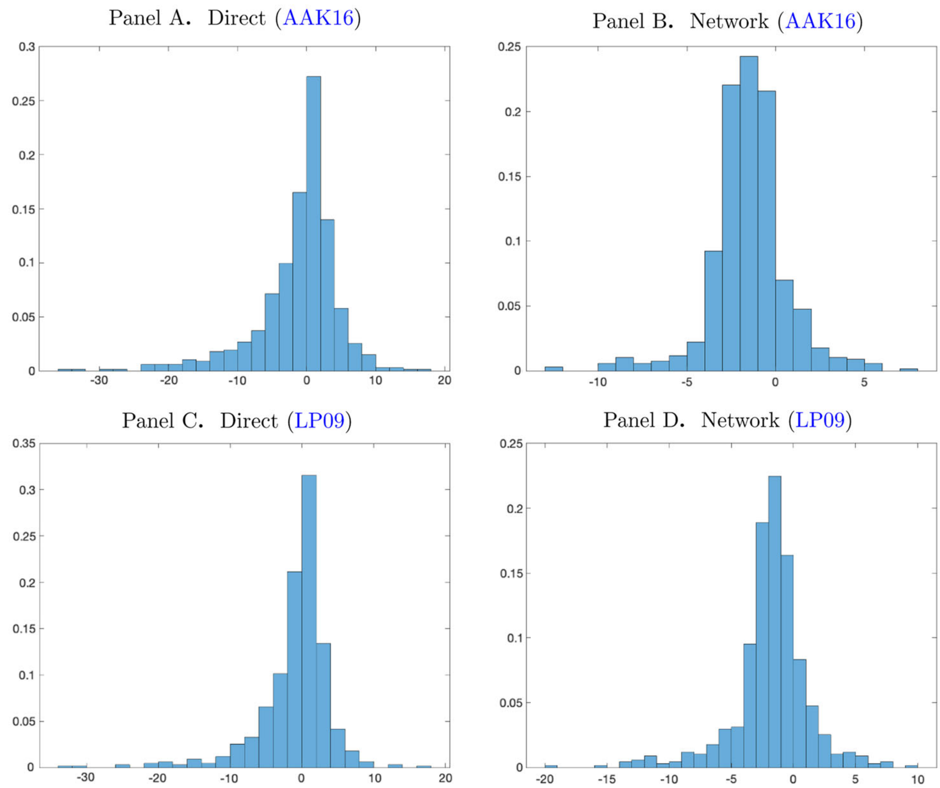

Figure 5. Distribution of direct and network effects across country-sectors. This figure plots the distribution of **Direct** and **Network** across *mi* from the estimation of equation (13) for 2000 to 2007, using Jarociński and Karadi (2020) monetary policy shocks for $\widehat{M}_{US}$. The averages of these distributions are reported in Table III. (Color figure can be viewed at wileyonlinelibrary.com)

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 intuitive and show that production linkages are important in transmitting demand shocks across sectors and, even more so, across countries. We establish robustness of these findings below.

C. Closeness to Final Consumers and Gravity Forces

In this section, we explore how the structural model presented in Internet Appendix IA.I maps into our empirical estimates. In particular, the simple theoretical framework in Internet Appendix IA.I includes a "gravity force" by

[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.

Table IV

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 United States 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" versus "high" groups, where the threshold for the cutoff of each bin is the (i) mean, (ii) median, or (iii) 90th percentile (P90) of the consumption-to-output share observed in 2000. Panel A includes all country-sector cells, while Panel B omits U.S. country-sector cells. All numbers are based on our baseline estimates and bootstrapping used to construct Table III.

	Panel A: Full Sample				Panel B: 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)

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 Internet Appendix equation (IA.10), country n's 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 continues to hold in a model without trade costs 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 IV presents the results using the full sample in Panel A and restricting estimates to the international sample in Panel B. As in our main tables, we calculate the means of the country-sector decomposition using our baseline point

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

estimates and construct confidence intervals based on the clustered wild bootstrapping procedure (from Table III). Comparing the "low" and "high" groups, 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 final goods consumption in the United States 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 U.S. 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 in Panel B—indeed, the opposite pattern holds when focusing on the U.S. sample 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 picking up not only the role of intermediate trade linkages between the country and the United States, 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 United States, these other forces may still dominate the impact of the overall transmission of a U.S. monetary policy shock.

D. 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 so, we compute two "autarkic" decompositions using two counterfactual intermediate goods trade (production linkage) regimes.[41]

The first decomposition shuts down trade in intermediate goods across all countries. As such, the **W** matrix is now block-diagonal, where we have renormalized 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 by $\mathbf{W}_{AUT1}$. This renormalization ensures that a country-sector's overall intermediate input-to-output ratio is the same as in the data. For the second decomposition, we assume that intermediate trade is shut down across all countries *except* for the shipment of intermediates to the United States. Therefore, **W** is block-diagonal except for the entries that correspond to shipments to the United States. We again renormalize 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 by $\mathbf{W}_{AUT2}$.

Given these new synthetic IO matrices, we define two new measures of the counterfactual **Total** effect of the U.S. monetary policy on cross-country-sector

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

Table V

Total Impact of the U.S. Monetary Policy Shocks: Baseline versus Autarkic Scenario Empirical Counterfactuals

This table presents the **Total** impact of monetary policy shocks for our baseline estimation along with two empirical autarky counterfactuals: (i) Autarky$_1$ assumes no intermediate goods trade across any countries, and (ii) Autarky$_2$ only allows the United States to source intermediate 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 1% 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)

stock returns, using the estimated $\boldsymbol{\rho}$'s and $\boldsymbol{\beta}$'s from our baseline estimation:

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

$$\mathbf{Total}_{AUT2} = \left(I - \mathrm{diag}(\boldsymbol{\rho})\mathbf{W}_{AUT2}\right)^{-1}\boldsymbol{\beta}.$$

We then compare our baseline **Total** effect to the different counterfactual values. Comparing these differentials allows us to measure spillovers under different intermediate goods trade regime counterfactuals. We present the results in Table V. The results are quite striking—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.

E. Robustness Checks

We conduct a number of robustness checks of our main result. First, we test for sensitivity of our findings to the sample period and to the choice of timing at which the IO matrix is sampled. We then return to the benchmark sample period and test for sensitivity of our result to alternative definitions of stock returns and the U.S. monetary policy shocks. We further test for potential effects of monetary policy shocks emanating from other countries (namely, the United Kingdom 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**

Thus far we have limited our analysis to the 2000 to 2007 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

Table VI

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

This table reports network shares calculated from heterogeneous coefficient panel SARs (equation (13)) where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over periods indicated in the first column in months 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 Internet Appendix Table IA.IV.

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

		Share of Network Effect		
Time Period	Year for **W**	Full Sample	International	USA
2000 to 2007	Avg. 2000 to 2007	0.668	0.679	0.588
		(0.056)	(0.060)	(0.068)
2000 to 2016	2000	0.748	0.758	0.661
		(0.056)	(0.059)	(0.034)
2000 to 2016	Avg. 2000 to 2016	0.765	0.772	0.707
		(0.050)	(0.054)	(0.032)
2000 to 2007, 2009 to 2016	2000	0.723	0.734	0.625
		(0.051)	(0.054)	(0.041)
2000 to 2007, 2009 to 2016	Avg. 2000 to 2016	0.747	0.756	0.670
		(0.052)	(0.055)	(0.043)
2000 to 2008, 2010 to 2016	2000	0.743	0.748	0.693
		(0.044)	(0.046)	(0.059)
2000 to 2008, 2010 to 2016	Avg. 2000 to 2016	0.759	0.762	0.737
		(0.062)	(0.064)	(0.073)

that occurred during the Global Financial Crisis of 2008:H2 to 2009:H1; and 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 use the IO 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. We therefore want to explore the evolution of our results as we vary the time period and the year from which we sample the matrix **W**.

Table VI reports a variety of robustness checks based on different definitions of **W** and sample period coverage. For compactness, here we report the share of the network effect across different variations of the sample for our baseline regression reported in Panel A of Table III; the full set of estimates is reported in Table IA.IV. First, we can see that replacing **W** measured in 2000 with the average **W** over 2000 to 2007 does not change the results. This is not surprising given that elements of **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, which is not surprising given that the increasing trend in cross-country trade integration and the lengthening of global supply chains resumed following the Great Trade Collapse. However, even in this extended sample, using the average **W** instead of **W** for 2000 does not make much difference.

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

Alternative Measures of Shocks and Returns

We perform additional tests to check the robustness of our results to alternative measures of stock returns and the 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 III. In the interest of space, here we report only the share of the network effect in Table VII; the full regression results are reported in Table IA.V.

We begin by replacing stock returns, which are measured in terms of U.S. dollars, with excess returns measured as the difference between annualized monthly U.S. dollar index (USD) nominal stock returns and the change in the two-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 by the 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 the U.S. monetary policy shocks into our returns data. We compute real 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 the 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 VII. 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, reducing 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 the U.S. monetary policy shocks, namely, the measures proposed by Bu, Rogers, and Wu (2021), Nakamura and Steinsson (2018), and Ozdagli and Weber (2017) (BRW, NS, and

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

Table VII

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

This table reports the network shares calculated from heterogeneous coefficient panel SARs (equation (13)) in which the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000 to 2007 in months with FOMC announcements, and the independent variable is a measure of the U.S. monetary policy shock. The first row uses nominal USD stock returns net of the two-year U.S. Treasury rate. The second row uses nominal domestic currency stock returns. The third row uses real equity returns. The first three rows use the "JK" monetary policy shock from Jarociński and Karadi (2020). The last three rows use USD nominal returns but use a different measure of the monetary policy shock: "BRW" (Bu, Rogers, and Wu (2021)), "OW" (Ozdagli and Weber (2017)), and "NS" (Nakamura and Steinsson (2018)). There are 44,286 total observations for 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 Internet Appendix Table IA.V.

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

	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)

OW, respectively). We find that the share of the network effect for U.S. sectors is slightly smaller if we use BRW shocks, but the results are similar qualitatively to the baseline. Furthermore, the 67% network share for 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. IO 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 IO matrix) sector returns used as explanatory variables. To examine whether this is indeed the case, we conduct two placebo checks in which we randomly sort the return vector or the weighting matrix while keeping key properties of the global production network fixed.

Under the first approach, we reshuffle the columns of **W** within each row, which implies that we reassign customers for a given supplier, across both countries and industries. This permutation leaves the outdegree (or total sales) of each country-sector cell unchanged, but alters the distribution of production linkages across countries and sectors. Under 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 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 generate 500 random draws for each approach. Figure IA.2 shows the distribution of the average share of the network effect for the perturbation of the weighting matrix **W** in Panel A and the perturbation of the vector of returns **q** for each t in Panel B.[43] We find that for the perturbation of **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 (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 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 BOE monetary policy shocks using measures constructed by Cieslak and Schrimpf (2019). Controlling for these shocks has implications for both euro countries and the United Kingdom, but also for countries that have deeper production linkages with these nations than with the Untied States, thus potentially affecting our baseline measure of the international network effect of the U.S. monetary policy shocks along several dimensions.

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

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

Table VIII

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

This table reports direct and network effects of the U.S. monetary policy shocks and total effects of foreign monetary policy shocks. These are calculated from heterogeneous coefficient panel SARs (equation (13)) where the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000 to 2007 in months with FOMC announcements, and the independent variables are measures of the monetary policy shocks in the United States and other countries. There are 44,286 total observations for 671 country-sectors over 66 months. Standard errors (in parentheses) are obtained via wild bootstrap with 500 repetitions. This table presents summary regression results. All network shares are significant at the 1% level.

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

	Full Sample			International	United States
	(1)	(2)	(3)	(4)	(5)
Direct effect of U.S. MP	−0.877	−0.889	−0.883	−0.804	−1.848
	(0.314)	(0.317)	(0.291)	(0.088)	(0.301)
Network effect of U.S. 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)

controls,

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

where each $\widehat{M}_{kt}$ is a measure the monetary policy shocks of country k (like the U.S. monetary policy shock term), and $\boldsymbol{\gamma}_k$ is an $NJ \times 1$ 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 IO matrix.

Table VIII presents the 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 hold. In particular, when we include all foreign monetary policy shocks the network share in columns (3) to (5) is 0.684, 0.699, and 0.575 for the full, foreign, and U.S. country-sectors, respectively. BOE monetary surprises also significantly affect global stock prices although the magnitude of this effect is about six times smaller than that of the U.S. monetary policy shocks. In contrast, ECB monetary surprises do not appear to have an effect on global stock prices—the point estimates are small

Panel A. Distribution across countries, sector averages

Panel B. Distribution across sectors, country averages

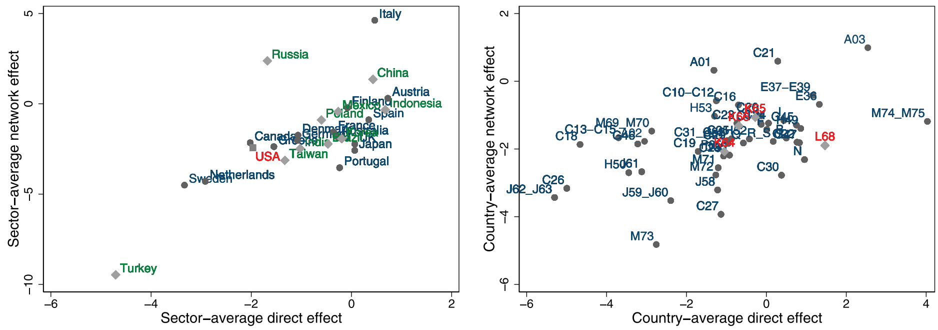

Figure 6. Distribution of direct and network effects across countries and sectors. This figure plots averages of **Direct** and **Network** across i plotted for each m and averages across m plotted for each i from the estimation of equation (13) for 2000 to 2007, using Jarociński and Karadi (2020) U.S. monetary policy shocks for $\widehat{M}_{US}$ and using *Decomposition 1* (AAK16). The overall averages of these distributions are reported in Table III. In Panel A, blue labels are for advanced economies, green labels are for emerging economies, and the red label is for the United States. In Panel B, financial and real estate industries are labeled in red. (Color figure can be viewed at wileyonlinelibrary.com)

in magnitude and are not statistically significant.[44] This result is consistent with the literature but is at odds with our simplified theoretical framework, which does not account for the special role the U.S. plays as the world's supplier of the reserve currency and dollar-denominated assets, above and beyond what the global production network can capture.

Heterogeneity of Estimates

Before analyzing potential determinants of the heterogeneity of our estimates, we demonstrate that our results are not driven by 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 United States. We find

[44] This result persists if we extend our sample through 2016 and is consistent with the literature. For example, Rogers, Scotti, and Wright (2014) study the Fed, BOE, ECB, and Bank of Japan (BOJ) monetary policy shocks during and after the 2008 to 2009 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 intraday window. Focusing on unconventional policies postcrisis, they find more generally that "the effects of U.S. monetary policy shocks on non-U.S. yields are larger than the other way round." For the precrisis period (2000 to 2008), Hussain (2011) also finds in intraday analysis that the effect of ECB shocks on French, German, the United Kingdom, and Swiss stock index returns are substantially smaller than the effect of BOE shocks. For the U.K. index (FTSE100), in particular, the effect is nearly zero and not statistically significant. Similarly, Bredin et al. (2009) find that the effect of ECB monetary policy shocks on German and U.K. stock markets is insignificant.

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 United States does not stand out of the pack, with both direct and network effects tending to be larger than that of the average country-sector, but within the distribution across other countries.

In Panel B, red labels indicate sectors related to finance and real estate and blue labels correspond to all other sectors. We find that the positive correlation between network and direct effects is positive across sectors as well, but it is not as strong as across countries. There are no sectors that appear to be outliers.

We next explore potential drivers of the observed heterogeneity in the estimated total effects and network shares across countries and sectors. To do so, we construct different variables at the country and sector levels that may be associated with the degree to which U.S. monetary policy shocks spillover 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, to rule out potential omitted variable bias in our estimates of the network share. Table IA.VII presents definitions and sources of the variables we use in these regressions.

We address heterogeneity using two approaches. First, to determine whether these variables can help explain the cross-sectional distribution of the total effect of the U.S. monetary policy shocks on stock returns, we interact the explanatory variable with the monetary policy shock measure in our OLS panel analysis. We conduct this analysis with and without time fixed effects. 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 (as of 2000) in cross-sectional regressions.

We present and discuss all regression results in Internet Appendix IA.III. Specifically, the variables we include in the regressions are: (i) country size, (ii) external debt, (iii) measures of financial frictions, (iv) financial openness, (v) price stickiness, and (vi) currency of trade invoicing. These regressions generally deliver coefficient estimates for country or sector characteristics with the expected signs, but none is statistically significant.

F. The Global Financial Cycle

We next explore the robustness of the global production network demand channel of the 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 the 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

Table IX

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

This table reports coefficients from linear regressions in which the dependent variable $\widehat{q}$ is the country-sector annualized U.S. dollar monthly stock return over 2000 to 2007 in months with FOMC announcements. The independent variables include the measure of the U.S. monetary policy shock taken from Jarociński and Karadi (2020) (MP shock), and the monthly change in the VIX index (VIX), the two-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% levels.

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

	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

spuriously attribute some of their effect to propagation through the production network. In terms of estimation, this would be reflected in the SAR 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 the 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 that are readily available: the monthly changes in the VIX, monthly changes in the two-year U.S. Treasury rate, and monthly changes in 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 IX presents 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 United States only. In the interest of space, for the subsamples we only present results with all three additional control variables included—the results do not change much if we include the additional controls individually.

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 IO 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 about the same amount in the United States and in other countries.

Monetary policy can affect stock returns through surprises, but it may also operate through the level of interest rates, which would not necessarily be reflected in monetary policy shocks. This second effect is likely to be seen, however, 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 an increase in stock returns globally. Indeed, we find that an increase in the two-year U.S. Treasury rate increases stock returns during our 2000 to 2007 sample period as seen in columns (2) and (4) to (6), which corresponds to a lending boom, although the effect is not statistically significant. This controlling for the two-year U.S. Treasury rate does not have much of an effect on the impact of U.S. monetary policy shocks relative to the baseline.

In our baseline analysis, we incorporate the effect of exchange rates on stock returns by expressing them in U.S. dollars. Given that the value of the dollar can be affected by the U.S. monetary policy shocks (Inoue and Rossi (2019)), we want to separate the effect of U.S. monetary policy surprises that is orthogonal to changes in the exchange rate from the reaction to the change in the value of the dollar. To do so, in columns (3) to (6) we control for the broad U.S. dollar index. 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.[45] This is not surprising given our previous robustness tests in which we find that the results are similar whether we use USD-based or domestic currency-based stock returns.

Including the three additional control variables simultaneously produces results that are similar to the regression with VIX only. Thus, consistent with the literature, we find 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

To condition on the global financial cycle in a SAR setting, we conduct a two-step procedure that allows us to isolate the effect of global financial cycle

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

covariates without imposing transmission of these shocks through the production network. In the first step, we regress annualized monthly stock returns expressed in U.S. dollars on the annualized monthly log changes in the VIX, the monthly log change in the broad USD, and the change in the two-year U.S. Treasury rate (T2y),

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

Estimates for this regression using Ordinary Least Squares (OLS), random coefficients, or mean group estimator (Pesaran and Smith (1995)) are reported in Panel B of Table X. For consistency with the rest of our analysis, we allow the effects of global financial cycle covariates to vary by country and sector, and thus as a benchmark we estimate regression equation (21) using the mean group estimator (Pesaran and Smith (1995)), which allows us to estimate a separate coefficient for each country-sector cell.[46]

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:

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

The results are reported in Table X.

Relative to our benchmark results in Table III, *Decomposition 1* (AAK16), we find that both the direct and network effects are now slightly larger for foreign stock returns and slightly smaller for the U.S. stock returns. The share of the network effect is unchanged for U.S. stock returns but 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 X is negligible in magnitude and not statistically significant. Together with the finding from our least-square analysis that the total effect of U.S. monetary policy shocks is robust to controlling for global financial cycle covariates, this SAR results confirm that any bias arising from not controlling for global financial cycles in our benchmark specification is minor.

[46] The results are nearly identical if we instead use OLS or random coefficient estimators.

Table X

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

This table reports direct and network effects from heterogeneous coefficient panel SARs (equation (23)) in which the dependent variable is the annualized U.S. dollar country-sector monthly stock return over 2000 to 2007 in months with FOMC announcements, after conditioning for changes in VIX, two-year U.S. Treasury rate, and U.S. broad dollar index. Conditioning is based on the mean-group estimator with the first stage reported in Panel B. The independent variable is the measure of the U.S. monetary policy shock taken from Jarociński and Karadi (2020). There are 44,286 observations total for 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% level.

Panel A: Second-Stage Regression

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

	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)

Panel B: First-Stage Regression

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

	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

V. 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 the sector-level worldwide. Basing our analysis on a simple conceptual framework that can be derived from a canonical multicountry multisector production network model, we estimate a SAR in a panel setting that allows coefficients to vary across countries and sectors. The conceptual framework predicts that country-sectors that are more closely linked to the United States via supply linkages will be more affected by the U.S. monetary policy shocks.

We find a 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 the U.S. monetary policy shock transmission studied in the global financial cycle literature. Thus, in addition to providing quantitative evidence on the importance of the global production network in transmitting asset market shocks, we contribute to the growing literature on the spillover of 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

Table AI

Monthly Country Stock Return Coverage for Months with Monetary Surprise Shocks

This table presents the number of sectors and the number of observations of monthly sector returns per country for dates when there are monetary surprise shocks (FOMC meetings or off-cycle meetings) over the 2000 to 2016 period. The data are constructed by merging stock returns data from TREI with the sectoral WIOD classification.

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

(*Continued*)

Table AI—*Continued*

Country	No. Industries	Observations
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 AII

Monthly Sector Stock Return Coverage for Months with Monetary Surprise Shocks

This table presents information on the number of sectors and the number of observations of monthly sector returns per sector for dates when there are monetary surprise shocks (FOMC meetings or off-cycle meetings) over the 2000 to 2016 period. The data are constructed by merging stock returns data from TREI with the WIOD sectoral classification.

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 nonmetallic 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

(*Continued*)

Table AII—*Continued*

Industry	WIOD Code	No. Countries	Observations
Manufacture of machinery and equipment n.e.c.	C28	19	2,519
Manufacture of motor vehicles, trailers, and semitrailers	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

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.