

Propagation of Macroeconomic Shocks through Input-Output and Geographic Networks in China*

Ergys Islamaj[†] Jinxin Wu[‡]

This version: September 2026

Abstract

Sector-specific shocks can propagate through input-output and geographic networks. We study this potential transmission in China using international, national, and interregional input-output tables, distinguishing direct industry exposure from indirect upstream and downstream exposure. China has the largest aggregate network exposure among the economies examined, approximately 50 percent of economic activity, with manufacturing accounting for a particularly large share. Interregional linkages also indicate substantial potential transmission across provinces. In an application to Chinese export demand, the estimates show positive own-industry and upstream patterns but no clear downstream response. The results provide suggestive evidence consistent with propagation from directly exposed industries to their domestic suppliers.

Keywords: Production networks; input-output linkages; regional networks; shock propagation; export demand; trade exposure; China.

JEL classification: D57, F14, R15, E32.

1 Introduction

Macroeconomic shocks can spread through input-output and geographic networks, leading to sizeable macroeconomic fluctuations. Demand-side shocks are more likely to spread to input-supplying industries, such as companies that supply raw materials for further processing; these are referred to as upstream industries (Acemoglu et al., 2016a). By contrast, supply-side shocks tend to spread to industries that purchase other firms' outputs for further processing or sale to consumers; these are referred to as downstream industries. This paper examines how sector-specific shocks may propagate through China's production networks. A network approach helps identify industries and regions that may be indirectly exposed even when they are not directly affected by the initial shock.

*The authors thank Francesca de Nicola, Elitza Mileva, Andy Mason, and Luan Zhao for useful comments. The views expressed in this paper are those of the authors and do not necessarily represent those of the World Bank Group, its Board of Executive Directors, or the governments they represent.

[†]World Bank. Email: eislamaj@worldbank.org.

[‡]Georgetown University. Email: jw2035@georgetown.edu.

The methodology distinguishes between the direct impact (the own effect) and the indirect impact (the network effect). Network effects are constructed using input-output tables. Each entry in an input-output table corresponds to sales of inputs between industries at a disaggregated level. The network effect for a downstream industry depends on the share of that industry’s sales to another downstream industry. This corresponds to the inputs supplied by an upstream sector that a downstream sector needs to produce one dollar of output. Under standard theoretical assumptions, downstream propagation effects depend directly on these input shares. Similarly, upstream propagation effects are a function of the sales of an upstream sector to a specific downstream sector.

We apply this methodology to the G7 economies and the seven largest emerging market economies. We then focus on China and examine estimates relating industry outcomes to direct and network-weighted export exposure. We report several findings. First, network linkages in large economies can be sizeable, ranging from 30 to 50 percent of the total economy. Second, manufacturing and services have the largest network exposure in advanced economies, whereas manufacturing is the dominant sector in emerging market economies. Third, manufacturing network linkages in China are larger than in any other economy in the sample. Fourth, shocks in China have the potential to propagate through sizeable regional networks. Finally, the empirical estimates exhibit positive own-industry and upstream associations, while downstream estimates are negative and imprecise. Given the demanding exclusion restriction, these estimates are presented as suggestive patterns rather than definitive causal evidence.

These results suggest that a better understanding of input-output linkages is necessary to capture the full impact of trade shocks on emerging markets, especially China. When shocks affect sectors with strong linkages to the rest of the economy, sectors that are not directly exposed may still experience a change in demand for their output. This can affect employment and investment, and the propagation may become larger as the economy diversifies and its production structure becomes more integrated.

Related literature and contribution . This paper relates first to the literature on production networks and aggregate fluctuations. A central insight of this literature is that idiosyncratic shocks need not wash out in the aggregate when production is concentrated or when sectors are connected through asymmetric input-output relationships (Gabaix, 2009; Carvalho, 2008; Acemoglu et al., 2012). Subsequent work shows that the aggregate consequences of microeconomic shocks depend on the structure of the production network, nonlinearities, and the ability of producers to substitute across inputs (Acemoglu et al., 2015; Baqaee and Farhi, 2018). Most closely related to the framework used here, Acemoglu et al. (2016a) distinguish the direction in which different shocks propagate: demand-side shocks travel primarily toward input suppliers, whereas supply-side shocks travel toward downstream customers. This distinction motivates the paper’s separate measures of own-industry, upstream, and downstream exposure.

A growing empirical literature documents propagation through observed supply relationships.

Using natural disasters as firm-level shocks, Barrot and Sauvagnat (2016) show that losses pass to customers, especially when inputs are difficult to replace. Carvalho et al. (2021) use the Great East Japan Earthquake to trace disruptions both upstream and downstream through firm-to-firm supply chains. In the trade literature, Autor et al. (2013) develop a shift-share design to isolate changes in Chinese import competition, while Acemoglu et al. (2016b) extend the analysis beyond directly exposed industries by incorporating input-output linkages. The present paper studies the complementary case of a positive foreign-demand shock to Chinese industries and asks whether its association with value added and employment extends to domestic suppliers and customers.

The paper also connects to work that uses input-output data to characterize China’s production structure. The international comparison draws on the World Input-Output Database, which harmonizes sectoral accounts across countries (Timmer et al., 2015, 2016). The national analysis is informed by efforts to construct consistent Chinese supply-use and input-output tables (Wu and Ito, 2015), while the regional analysis uses a multi-regional input-output system that maps economic interdependence across Chinese provinces (Mi et al., 2018). Relatedly, Liu (2019) demonstrates how production-network position can matter for industrial policy and presents evidence from modern China. These studies underscore that national aggregates alone can conceal substantial sectoral and geographic heterogeneity in exposure.

Recent research has expanded the analysis of production networks by studying endogenous supplier formation, network fragility, and propagation during large disruptions. Elliott et al. (2022) show how firms’ sourcing decisions can generate fragile production networks, while Bonadio et al. (2021) quantify the international transmission of pandemic-related shocks through global supply chains. In the context of trade policy, Grossman et al. (2024) examine how tariffs disrupt established supply-chain relationships and induce costly input reallocation. These studies emphasize adjustment margins that are not captured by fixed input-output coefficients, including supplier substitution, inventories, and the reorganization of sourcing relationships.

Recent evidence also documents the growing importance of domestic production networks within China. Using administrative value-added-tax invoices, Chen et al. (2022) show that Chinese production has become increasingly fragmented across provinces and that coastal and inland regions play distinct roles in domestic value chains. This evidence reinforces the importance of measuring indirect regional and sectoral exposure rather than relying exclusively on the location of direct exporters.

This paper contributes to the production-network literature through a comparative measurement exercise and an application to Chinese export demand. It applies a common upstream–downstream accounting framework at three levels of aggregation: across advanced and emerging economies, across detailed Chinese industries, and across Chinese provinces. This multilevel approach shows that similar aggregate measures of network exposure can conceal substantial differences in the sectors and regions through which shocks may propagate. The paper also examines whether a positive foreign-demand shock to Chinese industries is associated with outcomes among their domestic suppliers and customers. Complementing recent work that models endogenous supplier

formation or studies pandemic, disaster, and tariff-induced supply disruptions, the analysis treats input-output relationships as predetermined exposure measures and focuses on the directional pattern of propagation from export demand.

The rest of the paper is organized as follows. Section 2 presents the empirical framework. Section 3 describes the data and construction of the network and trade-exposure measures. Section 4 presents features of the network channel in advanced and emerging market economies, with particular attention to China. Section 5 presents suggestive evidence on export exposure and industry outcomes in China, and Section 7 concludes.

2 Empirical Framework

To analyze the effects of sector-specific shocks through the input-output network, we use the framework of Acemoglu et al. (2016a). In their model, supply-side productivity shocks propagate downstream more powerfully than upstream. In contrast, demand shocks propagate upstream. Supply-side shocks change the prices faced by customer industries, creating downstream propagation. Demand-side shocks have smaller effects on prices and propagate upstream as affected industries adjust their production levels and input demands. Under Cobb–Douglas production functions and consumer preferences, a closed-form solution can be used to quantify the network effects of a supply or demand shock.

2.1 A three-sector example

Consider an increase in foreign demand for Chinese machinery. The immediate effect is an increase in the sales and output of the machinery industry itself. To produce the additional machinery, firms purchase more steel, transportation, and business services. The producers of those inputs consequently experience an increase in demand even if they do not export directly. This is the first round of upstream propagation: a demand shock to a customer industry raises activity among its direct suppliers.

The response does not end with the machinery industry’s direct suppliers. Steel producers responding to the additional machinery demand purchase more coal, electricity, transport, and other intermediate inputs. Coal and electricity producers are therefore affected through steel even when they have no direct transaction with machinery producers. These responses are higher-order upstream effects. The same logic applies to other branches of the production chain. For example, transportation providers purchase fuel and maintenance services, while business-service providers purchase information and communications services. A single increase in machinery exports can thus reach industries that are several links away from the initially exposed industry.

A simple numerical example illustrates the distinction. Suppose that producing one additional yuan of machinery requires 0.25 yuan of steel, 0.10 yuan of transportation, and 0.05 yuan of business services. A 100-yuan increase in foreign demand then generates 40 yuan of additional demand among machinery’s direct suppliers in the first round. Suppose further that producing one yuan of

steel requires 0.30 yuan of coal and 0.10 yuan of electricity. The 25-yuan first-round increase in steel production generates an additional 7.5 yuan of coal demand and 2.5 yuan of electricity demand in the next round. Coal and electricity production in turn requires other inputs, producing further, progressively smaller rounds of adjustment. The numbers are purely illustrative, but they show why summing only direct purchases understates the total exposure of the economy to the original shock.

The Leontief inverse, $(\mathbf{I} - \mathbf{A})^{-1} = \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \dots$, provides a compact way to summarize these rounds. The identity matrix $\mathbf{I}$ records the initially affected industry's own response. The matrix $\mathbf{A}$ captures direct input requirements and hence the first round of supplier exposure. The term $\mathbf{A}^2$ captures suppliers to those suppliers, and the remaining powers capture progressively more distant paths through the production network. The empirical upstream variable removes the focal industry's own shock and combines the remaining direct and higher-order paths using the observed industry-level shock vector.

It is useful to distinguish four objects that recur in the empirical analysis:

Own effect. The response of the machinery industry to the foreign-demand shock that directly affects its exports.

First-order upstream effect. The response of machinery's direct input suppliers, including steel, transportation, and business services.

Higher-order upstream effect. The response of suppliers to those direct suppliers, such as coal and electricity producers serving the steel industry, together with still more distant suppliers.

Downstream exposure. The exposure of industries that use machinery output as an intermediate input. This channel is conceptually distinct from upstream demand propagation. It is especially relevant when machinery experiences a supply or productivity shock that changes the price or availability of machinery inputs for its customers.

Thus, the direction of propagation depends on the nature of the disturbance. The export shock studied below is a demand shock and should principally travel upstream, from machinery producers toward their direct and indirect suppliers. A supply-side disturbance originating in machinery would instead be expected to travel downstream toward industries that use machinery in production. This distinction motivates including the own, upstream, and downstream measures separately in the empirical specification.

The response of sectoral output growth is estimated as

$$\begin{aligned} \Delta \ln Y_{i,t} = & \delta_t + \varphi \Delta \ln Y_{i,t-1} + \beta_{\text{own}} \text{Shock}_{i,t-1} \\ & + \beta_{\text{up}} \text{Upstream}_{i,t-1} + \beta_{\text{down}} \text{Downstream}_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \quad (1)$$

where i indexes sectors, δ_t denotes time effects, $\varepsilon_{i,t}$ is an error term, and $Y_{i,t}$ is a sector-specific outcome such as output, value added, or employment. The upstream and downstream regressors represent shocks working through the network, while $\text{Shock}_{i,t-1}$ represents a sectoral supply or demand shock.

The construction of downstream and upstream exposure follows Acemoglu et al. (2015). Let $\mathbf{A}$ denote the input-share matrix, with entries

$$a_{ij} = \frac{\text{Sales}_{j \rightarrow i}}{\text{Sales}_i}. \quad (2)$$

This measures sales of inputs from sector j to sector i , normalized by the total sales (or total costs) of sector i . Under Cobb–Douglas production, these input shares are constant with respect to prices. The downstream network measure is based on the Leontief inverse

$$\mathbf{H} = (\mathbf{I} - \mathbf{A})^{-1}. \quad (3)$$

Let h_{ji} denote an element of this matrix. To construct the network effect of demand-side shocks, the orientation of the sales matrix is reversed so that the corresponding elements h_{ij} capture upstream exposure.

Downstream exposure to supplier shocks and upstream exposure to customer shocks are calculated as

$$\text{Downstream}_{i,t} = \sum_j (h_{ji} - \mathbf{1}\{j = i\}) \text{Shock}_{j,t}, \quad (4)$$

$$\text{Upstream}_{i,t} = \sum_j (h_{ij} - \mathbf{1}\{j = i\}) \text{Shock}_{j,t}. \quad (5)$$

The summation includes sector i , but subtracts the direct effect because equation (1) controls separately for the focal sector’s own shock. The input-output linkages are predetermined and measured in a fixed year. Consequently, upstream and downstream exposures are functions of shocks in connected industries working through a predetermined input-output network.

3 Data and Measurement

The analysis combines four related sources. The World Input-Output Database (WIOD) provides a harmonized basis for the cross-country comparisons and the industry-year regressions. A detailed national input-output table from the National Bureau of Statistics of China (NBS) is used to characterize China’s domestic production structure at a finer level of sectoral detail. Finally, the 2012 Chinese multi-regional input-output (MRIO) table constructed by Mi et al. (2018) is used to measure linkages across provinces. Table 1 summarizes the principal variables and sources.

3.1 World Input-Output Database

We use the November 2016 release of WIOD (Timmer et al., 2015, 2016). The release covers 43 economies, together with a model for the rest of the world, annually from 2000 through 2014. Industries are classified into 56 sectors following the International Standard Industrial Classification, Revision 4 (ISIC Rev. 4), and the national accounts follow the 2008 System of National Accounts.

The world input-output tables report transactions in current US dollars, while the accompanying Socio-Economic Accounts provide industry-level employment, gross output, and value added in both current and constant prices using the same industry classification.

The cross-country exercise covers the G7 economies—Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States—and seven large emerging market economies—Brazil, China, India, Indonesia, Mexico, Russia, and Turkey. For the descriptive comparison, we use the 2014 WIOD matrix, the final year of the 2016 release. We construct the matrix of direct input coefficients by dividing purchases from supplying industry j by the gross output of purchasing industry i , and compute the Leontief inverse as described in Section 2. Each sector’s within-sector and cross-sector requirements are then weighted by its share of national gross output before aggregation.

For presentation, the 56 WIOD industries are combined into 13 broad groups. Agriculture comprises ISIC section A; mining is section B; manufacturing is section C; utilities combine sections D and E; construction is section F; wholesale and retail trade is section G; transport combines divisions H49–H53; information combines divisions J58–J63; finance is section K; real estate is section L; professional activities are section M; service activities are section N; and the residual group contains accommodation and food services and the remaining public, social, household, and extraterritorial activities in sections I and O–U. All network calculations are performed at the 56-industry level; this aggregation is used only to display the results in Figures 2 and 3 and Tables 1–4.

To obtain country-level measures, we aggregate industry exposure using industry gross-output shares. Let $\omega_{ic} = Y_{ic} / \sum_k Y_{kc}$ denote industry i ’s share of gross output in country c . Aggregate downstream and upstream network exposure are respectively

$$E_c^d = \sum_i \omega_{ic} \sum_{j \neq i} h_{ji,c}, \quad E_c^u = \sum_i \omega_{ic} \sum_{j \neq i} h_{ij,c}. \quad (6)$$

The diagonal is excluded so that these measures capture exposure through other industries rather than the focal industry’s own component. Appendix Section D.1 provides further details on the aggregation and treatment of the diagonal.

3.2 National input-output data for China

The detailed analysis of China’s production structure uses the 2012 national input-output table published by the National Bureau of Statistics of China (National Bureau of Statistics of China, 2015). The benchmark table records intermediate purchases and sales among 139 product sectors at producers’ prices. We retain the detailed sector structure when calculating direct requirements and the Leontief inverse, and aggregate industries only when presenting the manufacturing and economy-wide results in Tables 2 and 3. The five-digit industry descriptions reported in the original source are matched to the broader categories used in the tables by their NBS sector codes and descriptions.

The published national table is a competitive input-output table: imported and domestically

produced goods are not separately allocated across intermediate users within the transaction matrix. The national network measures therefore capture the technological input requirements recorded in the table, rather than exclusively domestic supplier relationships. This distinction is most relevant for industries that rely heavily on imported intermediate inputs. The separate regional exercise described below uses a noncompetitive MRIO construction that removes international imports from domestic interregional flows.

3.3 Regional input-output data

Regional linkages are calculated from the 2012 Chinese MRIO table developed by Mi et al. (2018). The table covers 30 mainland regions—excluding Hong Kong, Macao, Taiwan, and Tibet—and 30 economic sectors in each region. It is built from the surveyed 2012 provincial input-output tables and estimated interregional trade flows. The original provincial tables are competitive tables; Mi et al. (2018) separate imported from domestically produced inputs and reconcile provincial output, value added, international trade, and interregional flows to produce a noncompetitive national MRIO table.

An entry in the MRIO transaction matrix records the value of output produced by sector j in region r and used as an intermediate input by sector i in region s . Diagonal regional blocks therefore describe transactions among industries located in the same region, while off-diagonal blocks describe intermediate shipments across regional borders. We normalize each column by the gross output of the purchasing region-sector and compute the corresponding Leontief inverse.

For each province, the within-region component sums direct and higher-order linkages for which the supplying and purchasing industries are located in the same province. The interregional network component sums paths that connect the province to industries located elsewhere in China. Both components are aggregated across the province’s 30 industries using their shares in provincial gross output. The measures shown in Table 4 therefore reflect both a province’s sectoral composition and the intensity of its within-province and cross-province production linkages.

3.4 Outcome variables and trade exposure

The industry-year regressions combine the WIOD Socio-Economic Accounts with bilateral flows from the world input-output tables. Real value added is measured in constant prices, and employment is the number of persons engaged in each industry. The dependent variables are annual changes in the logarithm of real value added and employment. Because employment is a headcount, it requires no price adjustment.

The trade variable measures the annual change in Chinese exports to the United States, normalized by the industry’s gross output in 2000. Bilateral exports include intermediate and final deliveries recorded in the WIOD world tables. Following the shift-share logic in Autor et al. (2013), exports to the United States are instrumented with the corresponding change in Chinese exports to Austria, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland, again normalized by the industry’s 2000 gross output. The trade variables are subsequently standardized,

so that the coefficients in Table 5 describe the association with a one-standard-deviation change in exposure. The export series and base-year output are recorded in current US dollars in WIOD; the real outcome variable is taken directly from the constant-price Socio-Economic Accounts.

The estimation panel covers 2002–2014. Starting in 2002 permits construction of the annual changes and the lagged shock appearing in equation (1), using 2000 as the predetermined base year for industry size and network weights. The all-industry sample is a balanced panel of 44 industries observed for 13 years, yielding 572 observations. The manufacturing sample contains 18 industries observed over the same 13 years, yielding 234 observations. Relative to the 56-industry WIOD classification, industries are excluded when a consistent bilateral export series or the outcome and lagged exposure variables required for estimation cannot be constructed. The manufacturing count excludes repair and installation activities, which do not have a comparable bilateral merchandise-export series.

Table 1: Variables and data sources

Variable	Definition	Source	Coverage
Real value-added growth	Annual change in log industry value added measured at constant prices	WIOD 2016 Socio-Economic Accounts	44 industries, 2002–2014
Employment growth	Annual change in log persons engaged by industry	WIOD 2016 Socio-Economic Accounts	44 industries, 2002–2014
Export shock	Annual change in Chinese exports to the United States divided by industry gross output in 2000; standardized for estimation	WIOD 2016 world input-output tables	44 industries; 18 manufacturing industries
National input shares	Intermediate purchases from each supplying industry divided by purchasing-industry gross output	WIOD 2016; NBS 2012 national input-output table	56 WIOD industries; 139 NBS sectors
Regional exposure	Within-region and interregional Leontief requirements, aggregated using province-industry output shares	Mi et al. (2018)	30 regions and 30 sectors, 2012

Notes: The descriptive cross-country statistics use the 2014 WIOD matrix. The regression network is fixed at its 2000 value. The regional table excludes Hong Kong, Macao, Taiwan, and Tibet. Bilateral exports include intermediate and final deliveries recorded in WIOD.

4 Network Linkages in Large Economies and China

4.1 Network propagation in large economies

We use the World Input-Output Database, which presents matrices of inter-industrial flows of goods and services, to calculate network measures for the G7 economies (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) and the seven largest emerging market economies (Brazil, China, India, Indonesia, Mexico, Russia, and Turkey). For each country, data are available for 56 sectors classified according to ISIC Revision 4.

Figure 1 compares the overall network channel across countries. The indirect channel ranges from approximately 30 to 50 percent in the sample, suggesting that it can amplify sector-specific disturbances throughout the economy. The network measure is largest for China and is close to 50 percent of total economy output.

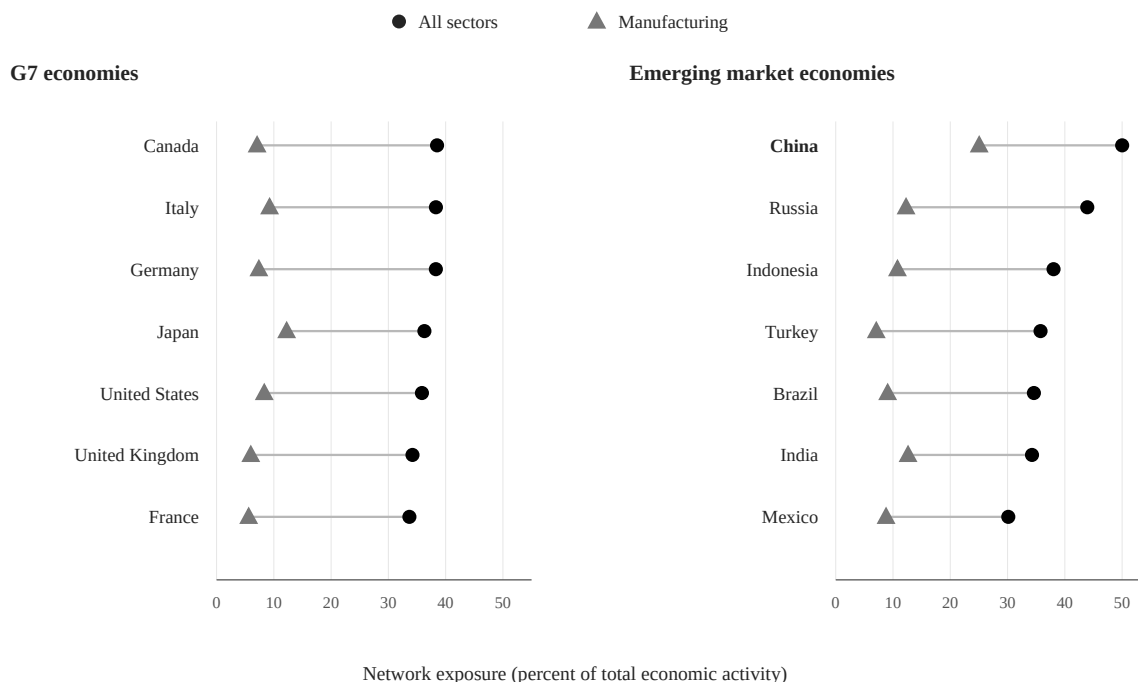


Figure 1: Network exposure across selected economies

Notes: The figure reports the calculated share of total economic activity exposed through the production network, separately for all sectors and manufacturing. Economies are ordered by the all-sector measure within each group. The horizontal scale is common across panels.

Source: Authors' calculations using the 2014 World Input–Output Database.

Appendix Tables 8 and 9 report the sectoral composition of the cross-country network measures. China has the largest aggregate network exposure in the sample, at approximately 50 percent of total economic activity, followed by Russia at about 44 percent. Among the G7 economies, aggregate exposure ranges from approximately 34 percent in France and the United Kingdom to 39 percent in Canada. Manufacturing accounts for a particularly large share of China's exposure: its contribution is 25.1 percentage points in the downstream calculation and 25.8 percentage points in the upstream calculation. In advanced economies, exposure is distributed more broadly across manufacturing, professional activities, services, wholesale and retail trade, transportation, and finance. Thus, countries with similar aggregate network exposure can differ substantially in the sectors through which shocks are likely to propagate.

4.2 Network propagation in China

The indirect propagation channel in China is sizeable. For nonmanufacturing sectors, downstream and upstream industries determine input costs to an extent comparable to own-sector effects. A closer look at manufacturing indicates that shocks to these industries also have the potential to amplify through network linkages. Table 2 reports the ten manufacturing industries with the greatest downstream network exposure; the same ten industries also have the greatest upstream network exposure. The complete ranking is reported in Appendix Table 6.

Heavy intermediate-input industries occupy the top of the ranking. Processing of ferrous metals and chemical manufacturing have the largest downstream network components, followed by petroleum processing and non-metallic minerals. Their upstream network components are also large, indicating that these industries are connected both to important suppliers and to customers elsewhere in the production structure. These statistics measure potential exposure through the 2012 production network rather than realized responses to a particular shock.

Table 2: Manufacturing industries with the largest network exposure

Industry	Downstream exposure		Upstream exposure	
	Network	Within sector	Network	Within sector
Processing ferrous metals	13.7	0.9	10.5	0.9
Manufacturing chemicals	13.1	1.2	9.6	0.4
Processing petroleum	10.9	< 0.1	9.5	0.4
Manufacturing non-metallic minerals	9.9	0.4	8.9	1.2
Processing non-ferrous metals	8.4	0.7	8.2	< 0.1
Food processing	6.7	0.4	7.2	0.4
Manufacturing electrical equipment	6.5	0.4	6.9	0.4
Manufacturing metals	5.9	0.2	6.3	0.8
Manufacturing rubber and plastics	5.8	0.3	6.1	0.2
Manufacturing general-purpose machinery	5.0	0.4	6.0	1.5

Notes: Entries are percentage-point shares weighted by industry size in the total economy. Industries are ordered by downstream network exposure; these are also the ten industries with the greatest upstream network exposure. The network and within-sector components are reported separately to avoid reproducing the dual-axis stacking in the source figure. Values are rounded to one decimal; < 0.1 denotes a positive value below 0.05.

Source: Authors' calculations using the 2012 five-digit input-output table from the National Bureau of Statistics of China.

Network linkages appear economically significant and have the potential to propagate disturbances across China's economy. As shown in Table 3, the network component is approximately 30 percent of total economic activity in both the downstream and upstream calculations. Within manufacturing, the corresponding shares are approximately 20 percent downstream and 21 percent upstream. These descriptive shares summarize potential exposure through the observed production structure; they are not estimates of the output loss caused by a realized shock.

Table 3: Economy-wide network exposure in China

	All sectors	Manufacturing
Downstream network exposure	30.0	20.0
Upstream network exposure	30.0	21.0

Notes: Entries are network-exposure shares of total economic activity, in percent. They measure potential propagation through the observed input-output structure rather than realized causal effects. Values are rounded to one decimal.

Source: Authors' calculations using the 2012 five-digit input-output table from the National Bureau of Statistics of China.

4.3 Regional network channel in China

Shocks can also propagate through regional networks. We use the multi-regional input-output data of Mi et al. (2018), which cover 30 industries and 30 regions in China. The own and network measures account for linkages internal and external to each region and depend on its sectoral composition. Local exposure may capture spillovers through local labor markets, while network exposure captures changes in demand attributable to connected sectors and regions. Table 4 reports the ten regions with the greatest downstream and upstream network exposure; the complete ranking appears in Appendix Table 7.

Jiangsu and Shandong have the largest interregional network components in both directions, followed by Guangdong, Zhejiang, and Henan. The ranking is not limited to the major coastal exporters: inland provinces including Henan and Sichuan also appear among the most exposed regions. This pattern illustrates how a province can be connected to external disturbances through domestic supply chains even when the original shock occurs elsewhere. As with the sectoral measures, these values describe potential exposure through the 2012 network rather than realized causal effects.

Table 4: Regions with the largest network exposure

Region	Interregional network	Within region
<i>Panel A: Downstream exposure</i>		
Jiangsu	4.8	2.6
Shandong	4.4	3.1
Guangdong	3.3	2.4
Zhejiang	2.9	1.7
Henan	2.7	1.2
Hebei	2.5	1.1
Liaoning	2.4	0.9
Sichuan	1.8	0.7
Shanghai	1.6	0.9
Anhui	1.5	0.5
<i>Panel B: Upstream exposure</i>		
Jiangsu	4.8	2.9
Shandong	4.7	3.2
Guangdong	3.2	2.7
Zhejiang	2.7	2.0
Henan	2.7	1.4
Liaoning	2.5	1.0
Hebei	2.5	1.3
Sichuan	1.8	0.8
Shanghai	1.6	1.0
Hunan	1.5	0.7

Notes: Entries are percentage-point shares weighted by region size in the total economy. Each panel ranks regions by its interregional network component. Values are rounded to one decimal.

Source: Authors' calculations using the 2012 China multi-regional input-output table from Mi et al. (2018).

5 Empirical Evidence from Export Exposure in China

5.1 Empirical approach and interpretive limits

The empirical analysis asks whether changes in foreign demand affecting one Chinese industry are transmitted to other industries through predetermined input-output linkages. A regression of industry outcomes directly on observed exports would not answer this question. Chinese exports to the United States may rise because an industry becomes more productive, receives policy support, expands capacity, or experiences other favorable supply conditions. The same unobserved changes can raise value added and employment directly. Conversely, weak domestic performance may encourage firms to redirect sales abroad. These channels create both omitted-variable bias and reverse-causality concerns.

Following the approach of Autor et al. (2013) and Acemoglu et al. (2016a), we construct an industry-level export exposure measure and instrument it with export growth to a set of other

high-income destinations. Let

$$X_{j,t} = \frac{\Delta \text{Exports}_{j,t}^{US}}{Y_{j,2000}}, \quad (7)$$

where $\Delta \text{Exports}_{j,t}^{US}$ is the annual change in Chinese industry j 's exports to the United States and $Y_{j,2000}$ is the industry's gross output in the base year. Normalizing by predetermined output expresses export growth relative to the industry's initial size and prevents mechanically large industries from dominating the exposure measure. A positive value denotes an increase in export demand.

The excluded instrument is

$$Z_{j,t} = \frac{\sum_{c \in \mathcal{C}} \Delta \text{Exports}_{j,t}^c}{Y_{j,2000}}. \quad (8)$$

The comparison set $\mathcal{C}$ contains Austria, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Thus, the instrument uses the change in Chinese exports in the same industry to eight other high-income economies, scaled by the same predetermined measure of industry size. The relevance argument is that changes in China's competitiveness or export penetration that raise sales to the United States should also raise sales to other high-income destinations. Year fixed effects absorb movements common to all Chinese industries, including aggregate exchange-rate changes, nationwide business-cycle conditions, and common changes in world demand. The remaining first-stage variation comes from differences across industries and over time in the extent to which Chinese exports expand simultaneously in the United States and the comparison markets.

Both the observed trade exposure and the instrument are propagated through the fixed production network. Using the notation of Section 2, the endogenous upstream and downstream regressors are

$$X_{i,t}^{up} = \sum_j (h_{ij} - \mathbf{1}\{j = i\}) X_{j,t}, \quad (9)$$

$$X_{i,t}^{down} = \sum_j (h_{ji} - \mathbf{1}\{j = i\}) X_{j,t}. \quad (10)$$

Their excluded instruments apply exactly the same network transformations to the eight-country shock:

$$Z_{i,t}^{up} = \sum_j (h_{ij} - \mathbf{1}\{j = i\}) Z_{j,t}, \quad (11)$$

$$Z_{i,t}^{down} = \sum_j (h_{ji} - \mathbf{1}\{j = i\}) Z_{j,t}. \quad (12)$$

In the two-stage least-squares specification, the own export exposure, upstream exposure, and downstream exposure are instrumented by $Z_{i,t}$, $Z_{i,t}^{up}$, and $Z_{i,t}^{down}$, respectively. All three shocks enter with a one-year lag. Before estimation, the own and network measures are standardized; the reported coefficients therefore correspond to a one-standard-deviation change in the relevant exposure.

The network matrix is fixed at its 2000 value, before the outcome changes used in the estimation sample. Holding the matrix constant has two purposes. First, it prevents contemporaneous changes in supplier-customer relationships from responding mechanically to the export shock or the outcome. Second, it ensures that changes in network exposure arise from changes in shocks hitting connected industries, not from changes in the estimated network itself. Predetermination of the weights does not by itself make the trade shock exogenous, but it removes one source of simultaneity in the construction of the upstream and downstream variables.

The baseline regressions include year fixed effects and the lagged change in the dependent variable, as in equation (1). They are unweighted, so each industry-year observation contributes equally rather than in proportion to industry size. Standard errors are clustered by industry to allow arbitrary serial correlation and heteroskedasticity within an industry over time. The full sample contains 44 industries observed from 2002 through 2014; the manufacturing specification contains 18 industries over the same period. As described in Section 3, industries without a consistent bilateral export series or the outcome and lagged exposure measures required by the specification are excluded.

Conditional on the controls, the estimates use two related sources of variation. The own-exposure coefficient uses industry-year variation in US export growth predicted by export growth to the eight comparison countries. The network coefficients additionally use heterogeneity in industries' predetermined positions in the production network: two industries facing similar own-export conditions can have different upstream exposure because their customers experience different predicted export shocks, and different downstream exposure because their suppliers experience different predicted shocks. This variation explains how the coefficients are constructed, but it does not by itself establish exogeneity. The theoretical prediction that a demand shock should be transmitted more strongly upstream than downstream provides a pattern against which to interpret the estimates, not a test of the exclusion restriction.

The exclusion restriction requires the eight-country export measure and its network transformations to affect an industry's value added or employment only through the component of US export exposure captured by the first stage and the modeled production-network channels. This assumption is unlikely to hold exactly in this application. Common Chinese productivity improvements, industrial policies, capacity expansions, or industry-specific global demand shocks may raise exports to both the United States and the comparison countries while also affecting Chinese outcomes directly. More fundamentally, exports to the eight comparison countries are themselves a source of foreign demand for Chinese industries and can therefore affect Chinese value added and employment directly.

The specification is consequently not treated as delivering a clean causal estimate of a US-specific export-demand shock. At most, the instrument isolates a component of US export growth associated with broader changes in Chinese export penetration. This draft does not report first-stage or weak-instrument diagnostics, so the strength of the instruments cannot be assessed here. We place greater weight on whether the directional pattern matches the model's prediction, particularly the

contrast between upstream and downstream exposure, and interpret the estimates as suggestive evidence consistent with network propagation.

5.2 Empirical estimates and suggestive patterns

Table 5 reports coefficient estimates and industry-clustered standard errors. Significance stars are omitted, and inference is conveyed by the displayed standard errors. Because the dependent variables are changes in logarithms, coefficients are expressed in log points. The three standardized exposures enter simultaneously, so each coefficient is a conditional association with a one-standard-deviation change in the relevant lagged exposure. These estimates should not be read as elasticities, as effects of a one-percent increase in exports, or as definitive causal estimates.

Own-industry response. The own-exposure estimates are positive in all four columns. In the all-sector sample, a one-standard-deviation increase in own export exposure is associated with increases of 0.146 log points in real-value-added growth and 0.157 log points in employment growth. Each coefficient is approximately twice its displayed standard error. The positive signs are economically intuitive: stronger foreign demand can raise desired production, which firms may meet through greater capacity utilization, more intermediate purchases, and eventually more workers or hours.

The manufacturing estimates are 0.037 log points for value added and 0.100 log points for employment, both small relative to their displayed standard errors. The table therefore shows a clearer positive own-industry pattern in the broader sample than within manufacturing. With only 18 industry clusters, inference in that subsample is relatively fragile; positive point estimates alone do not establish positive effects.

Upstream propagation. The most notable pattern is the positive association for suppliers when their customers experience rising export demand. In the all-sector sample, the upstream coefficients are 0.544 log points for value added and 0.515 log points for employment. Both are a little more than twice their displayed standard errors. The estimates are economically large, but the underlying change is a one-standard-deviation movement in a Leontief-weighted exposure, not a one-percent export increase. It is therefore clearest to describe 0.544 as log points, not automatically as a “54.4 percent effect.”

This is the channel predicted by demand propagation. An exporting customer purchases more materials, energy, transportation, and business services; direct suppliers receive new orders, and their suppliers can expand in turn. The Leontief inverse incorporates these higher-order rounds. In manufacturing, the estimates are smaller—0.175 log points for value added and 0.173 for employment—and each is less than one displayed standard error from zero. The positive point estimates are consistent with demand traveling from exporting customers toward their suppliers, but the manufacturing estimates are imprecise and cannot establish that mechanism causally.

The all-sector upstream coefficients exceed the own coefficients, but their ratio is not a literal multiplier. Each exposure is standardized, and the network measure aggregates shocks across many

connected industries. A standard-deviation change therefore represents a different underlying export change for each regressor. The relatively large standard errors also imply substantial uncertainty about the exact magnitude.

Downstream exposure. The downstream estimates are negative in every specification, ranging from -0.083 to -0.165 log points, and are small relative to their displayed standard errors. Unlike a productivity shock, stronger export demand does not necessarily lower an industry's prices or expand the supply available to domestic customers. Downstream users may therefore receive little benefit. Under capacity constraints, foreign demand could even divert output from domestic users or raise input prices.

The table does not establish such crowding out: the displayed standard errors are large and admit positive as well as negative associations. The defensible conclusion is that the estimates contain no clear downstream pattern. Their directional contrast with the positive upstream estimates nevertheless fits a demand shock, which travels naturally toward suppliers, better than a supply shock that makes output cheaper or more abundant for customers.

Value added and employment. There is little evidence that value added responds systematically more strongly than employment. In the all-sector sample, the own estimates are 0.146 and 0.157 , while the upstream estimates are 0.544 and 0.515 . In manufacturing, the upstream responses are almost identical (0.175 and 0.173), while own employment exceeds own value added. These gaps are small relative to their standard errors and are not established differences across outcomes.

Either ranking is plausible. Capacity utilization, inventories, hours, and intermediate purchases can allow output to move before headcount, whereas labor-intensive industries or firms expecting persistent demand may hire quickly. The upstream point estimates are positive for both margins, but the table cannot separate hours from headcount or short-run from longer-run adjustment.

Manufacturing and the full economy. Manufacturing is highly tradable and intensively connected, making it a natural setting for network propagation. Nevertheless, the upstream coefficients are larger in the full sample. The broader network may capture demand transmitted to transportation, wholesale trade, energy, finance, and business services that support exports; a manufacturing restriction can truncate these paths. The manufacturing results also use only 234 observations and 18 clusters, versus 572 observations in the full sample.

This is not proof that manufacturing linkages are weaker: the standardized coefficients come from differently composed samples with different exposure distributions. A pooled specification interacting exposure with a manufacturing indicator would be needed to test the difference formally.

Economic magnitude and interpretation. Overall, the table shows positive own-industry associations in the full sample, relatively large positive upstream associations in the full sample, and no clear downstream pattern. The corresponding manufacturing estimates are smaller relative to their uncertainty. These are coefficients on standardized exposures, not elasticities or effects of

a one-percent export increase. The own and upstream coefficients also cannot simply be added without specifying a joint change in the underlying shocks.

The exclusion-restriction concerns remain important: productivity, policy, capacity, global demand, and exports to the comparison countries may affect both the instrument and Chinese outcomes. Because the current draft does not report first-stage or weak-instrument diagnostics, Table 5 is interpreted as a suggestive directional comparison rather than a basis for definitive causal magnitudes or policy counterfactuals.

Table 5: Industry outcomes and export exposure

	$\Delta \log$ real value added		$\Delta \log$ employment	
	All sectors	Manufacturing	All sectors	Manufacturing
Own exposure $t - 1$	0.146 (0.072)	0.037 (0.069)	0.157 (0.076)	0.100 (0.106)
Upstream exposure $t - 1$	0.544 (0.241)	0.175 (0.283)	0.515 (0.227)	0.173 (0.266)
Downstream exposure $t - 1$	-0.165 (0.259)	-0.083 (0.277)	-0.155 (0.247)	-0.086 (0.271)
Observations	572	234	572	234
Year fixed effects	Yes	Yes	Yes	Yes
Unweighted	Yes	Yes	Yes	Yes

Notes: Own, upstream, and downstream US export exposures are instrumented with the corresponding exposures constructed from Chinese exports to eight comparison countries. Standard errors are clustered by industry. All exposure measures are standardized and enter with a one-year lag. The regressions include the lagged dependent variable. Significance stars are omitted; clustered standard errors appear in parentheses. Because first-stage and weak-instrument diagnostics are not reported in the current draft and the exclusion restriction is demanding, the estimates are interpreted as suggestive associations rather than definitive causal effects.

5.3 Limitations and interpretation

Several limitations qualify the interpretation of both the descriptive network measures and the regression estimates. First, input-output tables describe transactions between representative sectors rather than relationships between individual firms. Aggregation suppresses substantial heterogeneity within an industry: firms differ in their suppliers, customer bases, import intensity, productivity, market power, and ability to absorb shocks. Two firms assigned to the same sector can therefore face very different effective network exposures. Sector-level estimates are informative about average patterns of interdependence, but they cannot identify which firms transmit a shock, which firms are most vulnerable, or whether a small number of large firms account for the measured linkage.

Second, the Leontief framework treats input coefficients and production relationships as fixed. This is useful for tracing exposure through a given network, but it does not allow firms to substitute away from disrupted or expensive inputs, change suppliers, alter their production technology, or redirect sales across customers. Such adjustment may attenuate propagation when alternative inputs and suppliers are available. Conversely, search costs, relationship-specific investment, capacity

constraints, and contractual rigidities may make substitution difficult in the short run. The fixed-coefficient calculations should therefore be understood as propagation through the observed production structure, not as a complete model of firms’ equilibrium adjustment. Their accuracy is likely to be greater over short horizons than over periods in which firms can reorganize their supply chains.

Third, the international, national, and regional exercises are based on input-output tables with different industrial classifications and levels of aggregation. The WIOD comparison uses 56 sectors, the detailed Chinese national table contains much finer industries, and the multi-regional table organizes transactions among 30 industries and 30 regions. Crosswalks necessarily combine activities that are separate in one source but not in another, and a linkage can appear stronger or weaker as sectors are aggregated. For this reason, magnitudes from the three exercises are not perfectly comparable. Their common qualitative patterns are more informative than small numerical differences across tables.

Fourth, the instrumental-variable strategy does not eliminate every source of endogeneity. Growth in Chinese exports to the eight comparison countries can reflect common Chinese productivity improvements, industrial policy, capacity expansion, or industry-specific global demand. These forces may also affect Chinese value added and employment directly. Moreover, sales to the comparison countries are themselves a source of demand. The exclusion restriction may therefore fail, and the current draft does not report first-stage diagnostics with which to assess instrument strength. The coefficients are interpreted as suggestive patterns consistent with network propagation rather than as definitive causal effects of US export demand.

Finally, the descriptive network statistics and figures measure exposure or potential propagation. They summarize the share of activity connected through observed input-output relationships and show where a shock could travel if production coefficients remained fixed. They do not show that a shock occurred, that every exposed linkage was activated, or that the calculated network component caused realized changes in output or employment. Realized effects depend on the nature and persistence of the shock, spare capacity, inventories, prices, substitution possibilities, policy responses, and other margins of adjustment. Accordingly, the descriptive evidence maps the architecture of possible transmission, while Table 5 provides suggestive empirical evidence on whether one type of demand shock is associated with outcomes along that architecture.

6 Policy implications

The network perspective broadens the set of industries and places that policymakers may wish to monitor during trade disruptions. An industry that exports directly is an obvious point of exposure, but it is not the only potentially vulnerable part of the economy. When foreign demand falls, exporting firms may reduce their purchases of materials, energy, transportation, and business services. Losses can therefore be transmitted upstream to industries that sell little abroad themselves. The positive upstream estimates in Table 5 are consistent with this mechanism operating in the

opposite direction when export demand rises.

One practical implication is that assessments based only on direct export shares can provide an incomplete picture of vulnerability. If temporary assistance, credit support, worker adjustment programs, or monitoring systems are triggered solely by an industry’s own exports, they may miss domestic suppliers whose revenues depend heavily on exposed customers. Input-output information can complement direct trade measures by identifying industries with substantial indirect exposure. This does not imply that every connected supplier should receive assistance. Network exposure is a screening measure, and any intervention would still require evidence of realized losses, limited private adjustment, and a clearly defined market failure.

The regional results make the same point geographically. Coastal provinces account for much of China’s direct trade, but inland provinces can supply raw materials, components, energy, or services to firms located elsewhere. They may consequently be exposed to a foreign-demand shock through interregional supply chains even when their own recorded exports are modest. Combining customs data with multi-regional input-output linkages could help authorities distinguish direct export exposure from indirect exposure through customers in other provinces. Such information may be useful for anticipating local employment or fiscal pressures that would otherwise appear disconnected from the original trade disturbance.

Sectoral centrality can also help prioritize information collection during trade or supply disruptions. Industries that supply many sectors, occupy positions on important production paths, or have few substitutes may transmit shocks widely. Monitoring inventories, capacity utilization, delivery times, employment, and prices in these sectors could provide earlier evidence of propagation than waiting for aggregate outcomes. Centrality should not be equated mechanically with systemic importance, however: a central sector with ample inventories and easy substitution may pose less risk than a less central but highly specialized bottleneck. Network measures are therefore best used alongside current market information rather than as automatic policy rules.

Finally, greater diversification of customers and suppliers may reduce dependence on any single market or input source. Firms with alternative buyers can redirect sales after a demand shock, while multiple qualified suppliers can make production more resilient to disruption. Diversification is not costless: maintaining redundant relationships can sacrifice scale economies, relationship-specific investment, or access to the most efficient producer. Policies that improve information, logistics, standards compatibility, and market access may facilitate diversification without prescribing a particular supply-chain structure.

These implications are deliberately limited. The estimates display patterns consistent with network propagation, but they do not compare policy instruments, quantify externalities, or incorporate the fiscal and behavioral costs of intervention. They therefore do not establish whether assistance is warranted, which firms should receive it, or the optimal balance between resilience and efficiency. The main policy contribution is diagnostic: direct exposure should be supplemented with upstream, downstream, and interregional linkages when mapping where a disruption may be transmitted.

7 Conclusion

This paper examines how sector-specific shocks can propagate through production networks in China. It combines international, national, and interregional input-output tables to describe the structure of upstream and downstream linkages and then studies whether changes in Chinese export demand are associated with outcomes in directly and indirectly exposed industries. This framework extends the analysis beyond the industries receiving the initial shock and highlights the roles of suppliers, customers, and regional production linkages.

The descriptive evidence indicates that China has substantial potential for network propagation. Its aggregate network exposure is approximately 50 percent of total economic activity, the largest among the economies considered in the cross-country comparison. Manufacturing occupies an especially important position in China’s national production structure, while the regional input-output table reveals substantial linkages across provinces. The empirical estimates also display a directional pattern consistent with the theoretical mechanism. In the full sample, greater own-industry export exposure is associated with higher value-added and employment growth. The upstream estimates are positive and relatively large, consistent with suppliers benefiting when their customers experience stronger foreign demand. By contrast, the downstream estimates are negative but imprecisely estimated. This asymmetry is consistent with interpreting the trade shock as a demand shock: expanding exporters purchase more inputs from their suppliers but do not necessarily reduce input prices or expand the supply available to their domestic customers. The corresponding manufacturing-sample estimates are smaller relative to their uncertainty and should therefore be interpreted cautiously.

These findings have implications for how trade exposure is assessed. Direct exporters are not the only industries potentially affected by changes in foreign demand. Domestic suppliers and inland provinces may be exposed through sectoral and interregional supply chains even when they export little directly. Input-output measures can therefore complement direct trade statistics when policymakers monitor disruptions and identify where adjustment pressures may emerge. Measures of sectoral centrality may also help prioritize data collection during trade or supply disturbances, while greater diversification of customers and suppliers may reduce dependence on individual markets or production relationships. The analysis does not, however, identify the optimal policy response or establish that every industry with high measured exposure should receive assistance.

The results require careful interpretation. Sector-level input-output tables suppress firm-level heterogeneity, and fixed production coefficients do not capture substitution among suppliers, customers, or technologies. Differences in industrial classification also limit exact comparisons across the international, national, and regional exercises. Most importantly, exports to the comparison countries used in the instrument may reflect common Chinese productivity, capacity, policy, or global-demand shocks. The descriptive network measures should consequently be interpreted as measures of exposure and potential propagation rather than realized causal effects. Similarly, the regression estimates provide evidence consistent with upstream propagation but do not establish definitive causal magnitudes.

Future work could strengthen the analysis by using firm-to-firm transaction data, allowing production relationships to change over time, and examining specific trade or supply disruptions with more sharply identified sources of variation. Such extensions would help distinguish potential network exposure from realized transmission and clarify when production networks absorb shocks and when they amplify them.

A Additional Cross-Country Figures

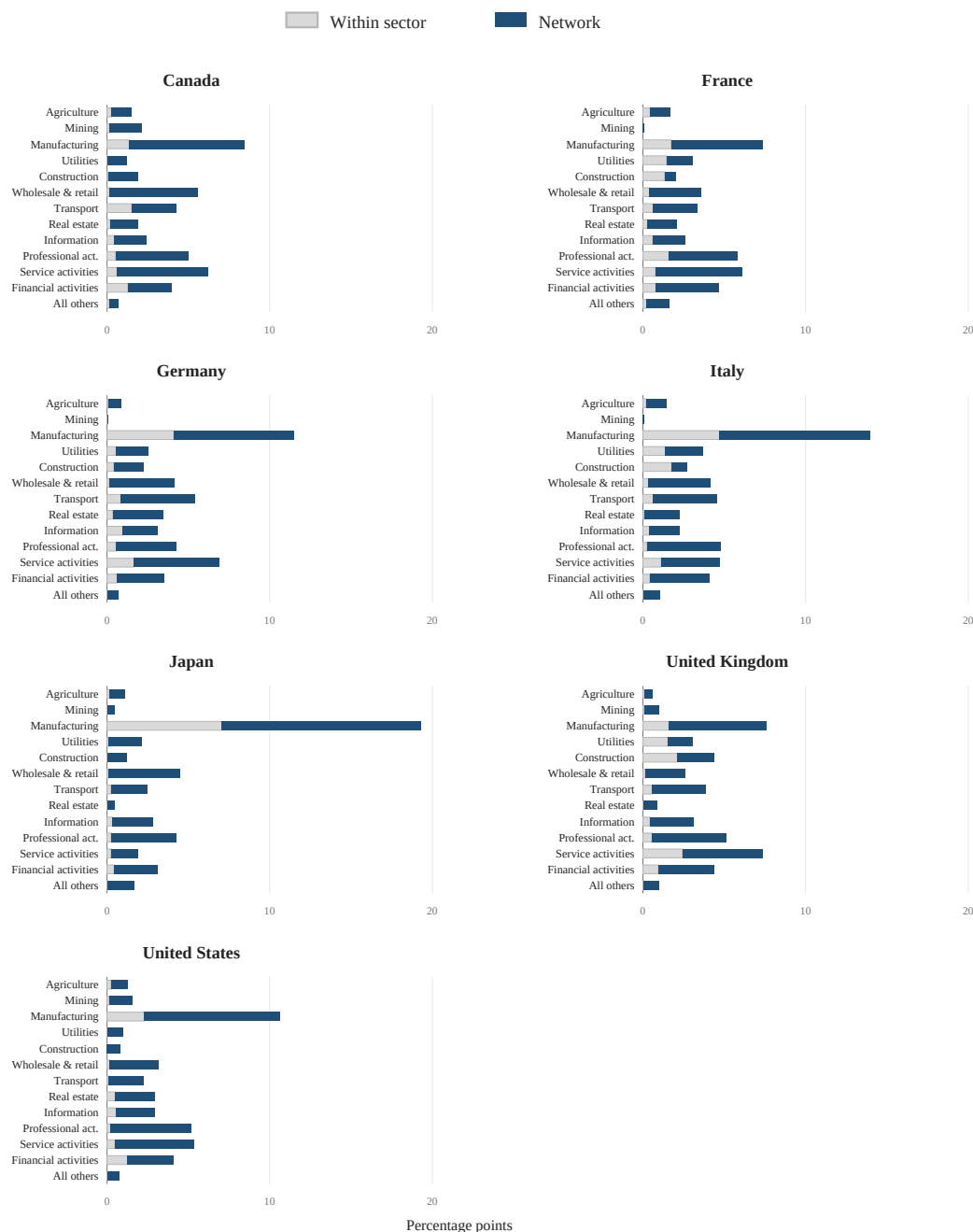


Figure A1: Sectoral composition of downstream network exposure in G7 economies
Notes: Bars report percentage-point shares of total economic activity. The within-sector component captures exposure within the focal sector, while the network component captures exposure through other sectors. The 56 WIOD industries are aggregated into 13 broad sector groups. All country panels use a common horizontal scale and identical sector ordering.
Source: Authors' calculations using the World Input–Output Tables (WIOD).

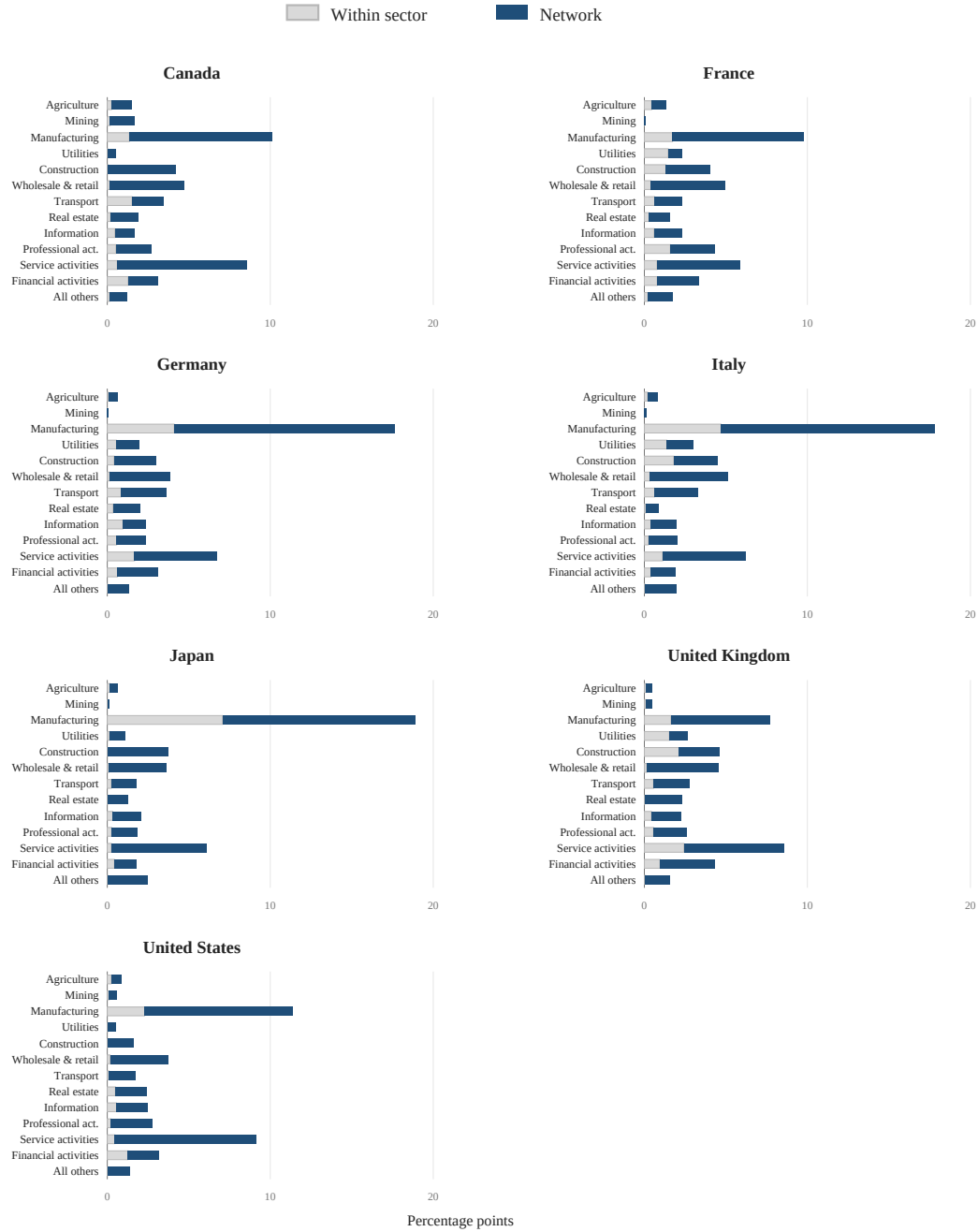


Figure A2: Sectoral composition of upstream network exposure in G7 economies

Notes: Bars report percentage-point shares of total economic activity. The within-sector component captures exposure within the focal sector, while the network component captures exposure through other sectors. The 56 WIOD industries are aggregated into 13 broad sector groups. All country panels use a common horizontal scale and identical sector ordering.

Source: Authors' calculations using the World Input–Output Tables (WIOD).

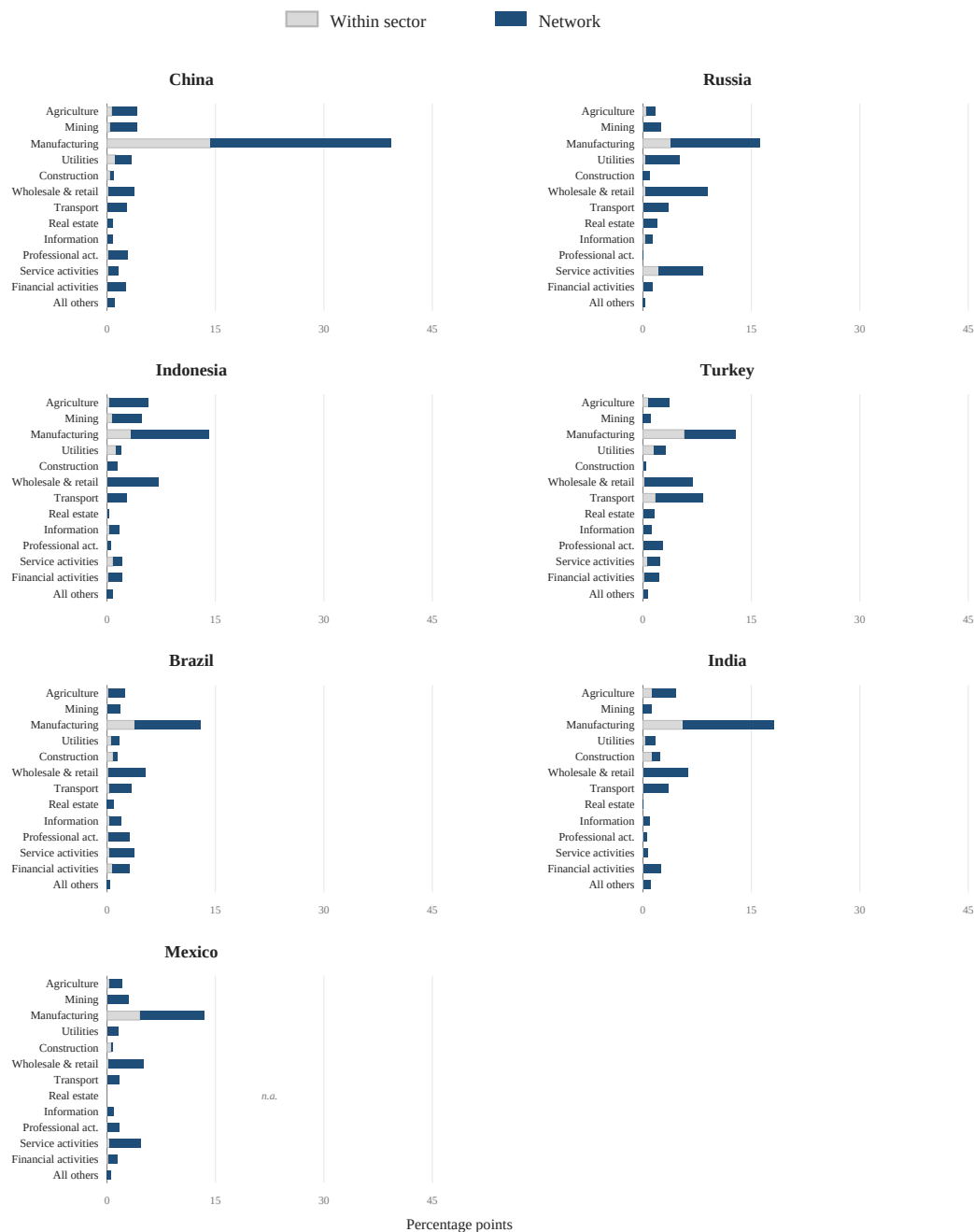


Figure A3: Sectoral composition of downstream network exposure in emerging market economies

Notes: Bars report percentage-point shares of total economic activity. The within-sector component captures exposure within the focal sector, while the network component captures exposure through other sectors. The 56 WIOD industries are aggregated into 13 broad sector groups. Countries are ordered by aggregate network exposure. All country panels use a common horizontal scale and identical sector ordering. Mexico's real-estate entry is unavailable and is marked "n.a."

Source: Authors' calculations using the World Input–Output Tables (WIOD).

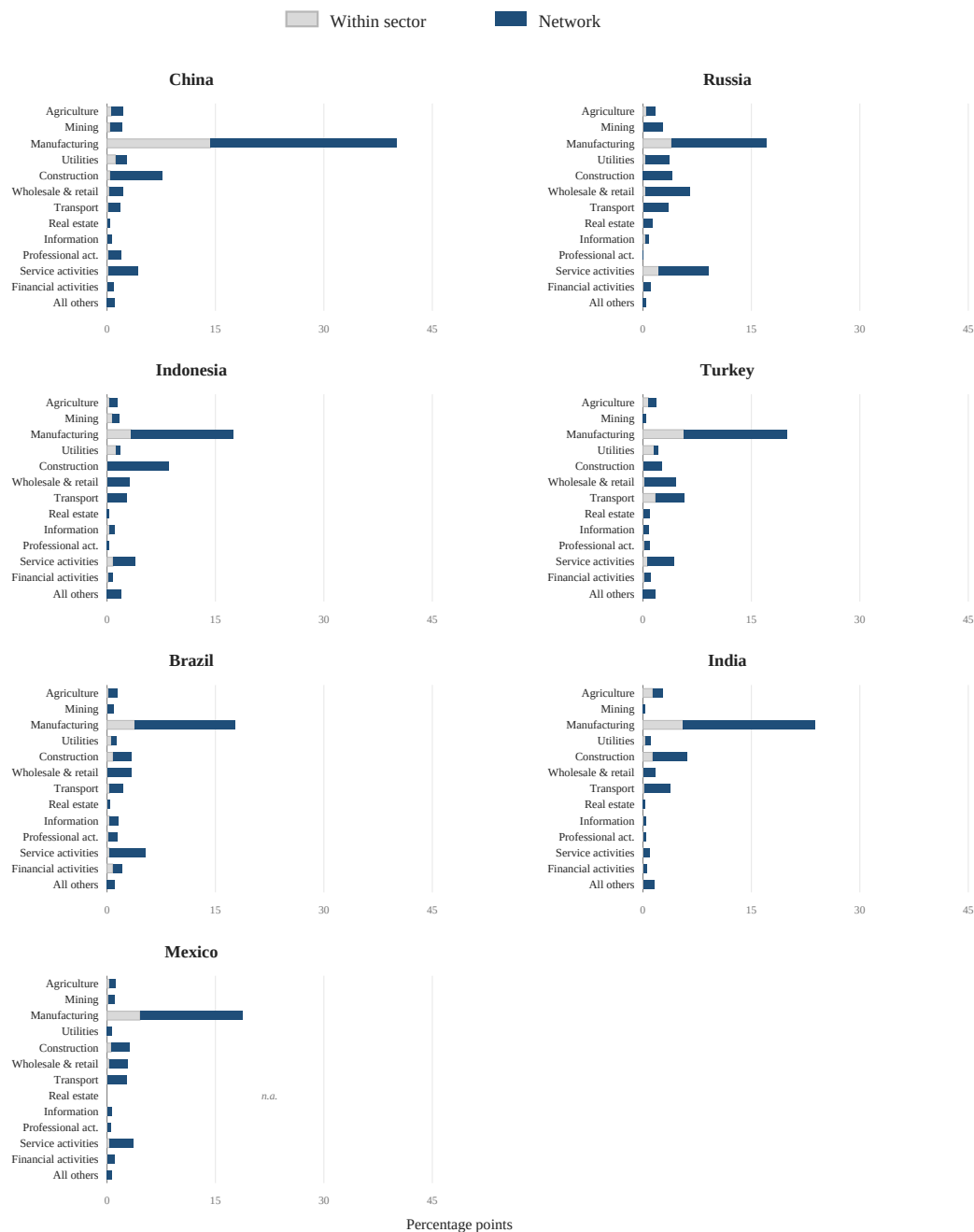


Figure A4: Sectoral composition of upstream network exposure in emerging market economies
Notes: Bars report percentage-point shares of total economic activity. The within-sector component captures exposure within the focal sector, while the network component captures exposure through other sectors. The 56 WIOD industries are aggregated into 13 broad sector groups. Countries are ordered by aggregate network exposure. All country panels use a common horizontal scale and identical sector ordering. Mexico's real-estate entry is unavailable and is marked "n.a."

Source: Authors' calculations using the World Input–Output Tables (WIOD).

B Complete Manufacturing-Industry Ranking

Table 6: Network exposure across manufacturing industries

Rank	Industry	Downstream exposure		Upstream exposure	
		Network	Within sector	Network	Within sector
1	Processing ferrous metals	13.7	0.9	10.5	0.9
2	Manufacturing chemicals	13.1	1.2	9.6	0.4
3	Processing petroleum	10.9	< 0.1	9.5	0.4
4	Manufacturing non-metallic minerals	9.9	0.4	8.9	1.2
5	Processing non-ferrous metals	8.4	0.7	8.2	< 0.1
6	Food processing	6.7	0.4	7.2	0.4
7	Manufacturing electrical equipment	6.5	0.4	6.9	0.4
8	Manufacturing metals	5.9	0.2	6.3	0.8
9	Manufacturing rubber and plastics	5.8	0.3	6.1	0.2
10	Manufacturing general-purpose machinery	5.0	0.4	6.0	1.5
11	Manufacturing computers	4.5	1.5	5.8	0.2
12	Manufacturing textiles	4.5	0.7	4.8	0.3
13	Manufacturing medicines	2.3	0.1	4.5	0.7
14	Manufacturing automobiles	2.3	0.8	4.1	0.7
15	Processing timber	2.1	0.2	3.8	< 0.1
16	Manufacturing special-purpose machinery	2.0	0.2	3.3	0.1
17	Manufacturing paper	2.0	0.2	2.6	0.1
18	Printing and recorded media	1.6	< 0.1	2.4	< 0.1
19	Use of waste resources	1.6	< 0.1	2.4	0.1
20	Manufacturing beverages	1.5	0.1	2.1	0.1
21	Manufacturing chemical fibers	1.3	0.1	1.9	0.1
22	Manufacturing measuring instruments	1.2	< 0.1	1.6	0.2
23	Manufacturing cultural, educational, art, and sports goods	1.2	< 0.1	1.3	< 0.1
24	Manufacturing apparel	1.2	< 0.1	1.1	0.2
25	Manufacture of tobacco	1.1	< 0.1	1.1	0.1
26	Manufacturing foods	0.8	0.1	1.0	< 0.1
27	Manufacturing transportation equipment	0.6	0.1	0.9	< 0.1
28	Manufacturing footwear	0.6	0.1	0.5	< 0.1
29	Other manufacturing	0.4	< 0.1	0.5	< 0.1
30	Manufacture of furniture	0.3	< 0.1	0.2	< 0.1
31	Repair of metal items	0.3	< 0.1	0.2	< 0.1

Notes: Industries are ranked by downstream network exposure. Entries are percentage-point shares weighted by industry size in the total economy. The network and within-sector components are reported separately. Values are rounded to one decimal; < 0.1 denotes a positive value below 0.05. The nonmanufacturing benchmark displayed in the source figure is excluded.

Source: Authors' calculations using the 2012 five-digit input-output table from the National Bureau of Statistics of China.

C Complete Regional Ranking

Table 7: Network exposure across Chinese regions

D rank	U rank	Region	Downstream exposure		Upstream exposure	
			Network	Within region	Network	Within region
1	1	Jiangsu	4.8	2.6	4.8	2.9
2	2	Shandong	4.4	3.1	4.7	3.2
3	3	Guangdong	3.3	2.4	3.2	2.7
4	4	Zhejiang	2.9	1.7	2.7	2.0
5	5	Henan	2.7	1.2	2.7	1.4
6	7	Hebei	2.5	1.1	2.5	1.3
7	6	Liaoning	2.4	0.9	2.5	1.0
8	8	Sichuan	1.8	0.7	1.8	0.8
9	9	Shanghai	1.6	0.9	1.6	1.0
10	11	Anhui	1.5	0.5	1.5	0.7
11	10	Hunan	1.5	0.6	1.5	0.7
12	12	Hubei	1.4	0.6	1.5	0.7
13	13	Fujian	1.4	0.7	1.5	0.7
14	14	Inner Mongolia	1.2	0.5	1.2	0.6
15	15	Beijing	1.1	0.6	1.1	0.7
16	16	Jiangxi	1.1	0.6	1.1	0.7
17	20	Tianjin	1.1	0.6	1.0	0.7
18	18	Shaanxi	1.1	0.3	1.0	0.4
19	17	Shanxi	1.0	0.3	1.1	0.3
20	19	Heilongjiang	1.0	0.3	1.0	0.3
21	21	Jilin	0.9	0.5	1.0	0.5
22	22	Guangxi	0.9	0.3	0.9	0.4
23	24	Chongqing	0.7	0.4	0.6	0.5
24	23	Yunnan	0.6	0.2	0.7	0.2
25	25	Xinjiang	0.5	0.2	0.5	0.2
26	26	Gansu	0.5	0.1	0.5	0.2
27	27	Guizhou	0.5	0.2	0.5	0.2
28	28	Hainan	0.2	0.1	0.2	0.1
29	29	Ningxia	0.2	0.1	0.2	0.1
30	30	Qinghai	0.1	< 0.1	0.1	0.1

Notes: D rank and U rank order regions by their downstream and upstream interregional network components, respectively. Entries are percentage-point shares weighted by region size in the total economy. Values are rounded to one decimal; < 0.1 denotes a positive value below 0.05.

Source: Authors' calculations using the 2012 China multi-regional input-output table from Mi et al. (2018).

D Detailed Tables and Heat Maps

D.1 Aggregation of network-exposure shares

Let Y_{ic} denote gross output in industry i and country c , and define the industry's output weight as

$$\omega_{ic} = \frac{Y_{ic}}{\sum_k Y_{kc}}. \quad (13)$$

Let $h_{ji,c}$ denote the (j, i) element of the downstream Leontief inverse: it measures the total direct and higher-order requirement from supplying industry j associated with one unit of output in purchasing industry i . Reversing the orientation of the input-output network gives the upstream element $h_{ij,c}$, which traces exposure from industry i toward its direct and indirect customers. Country-level

downstream and upstream network exposure are aggregated as

$$E_c^d = \sum_i \omega_{ic} \sum_{j \neq i} h_{ji,c}, \quad E_c^u = \sum_i \omega_{ic} \sum_{j \neq i} h_{ij,c}. \quad (14)$$

The restriction $j \neq i$ removes the diagonal from the network component, so E_c^d and E_c^u capture exposure through other industries rather than the focal industry's own component. Because the Leontief inverse includes the identity matrix, the within-sector component reported in the appendix tables is calculated separately as

$$W_c = \sum_i \omega_{ic} (h_{ii,c} - 1), \quad (15)$$

where subtracting one removes the initial unit of the industry's own output. The entries in the tables equal these weighted contributions multiplied by 100 and are therefore expressed as percentage-point shares of total economic activity. For the broad sector columns, the weighted contributions are summed over the detailed WIOD industries assigned to each group.

Table 8: Downstream own and network effects

Country	Component	Agric.	Mining	Manufact.	Utilities	Construct.	Wholesale and retail	Transport	Real estate	Information	Professional activities	Service activities	Financial activities	All others	Total
CHN	Within sector	0.67	0.42	14.32	1.16	0.43	0.26	0.14	0.05	0.14	0.21	0.22	0.08	0.00	18.11
	Network	3.48	3.68	25.05	2.29	0.40	3.57	2.62	0.72	0.72	2.65	1.34	2.50	1.00	50.01
RUS	Within sector	0.48	0.13	3.93	0.37	0.02	0.38	0.05	0.06	0.33	0.00	2.24	0.06	0.00	8.04
	Network	1.17	2.37	12.28	4.67	0.92	8.55	3.44	1.89	1.03	0.00	6.09	1.20	0.31	43.92
CAN	Within sector	0.26	0.18	1.36	0.02	0.06	0.16	1.52	0.21	0.46	0.53	0.61	1.28	0.14	6.79
	Network	1.21	1.96	7.08	1.19	1.84	5.45	2.73	1.71	1.98	4.48	5.61	2.69	0.57	38.50
ITA	Within sector	0.20	0.00	4.71	1.38	1.80	0.34	0.63	0.09	0.41	0.26	1.12	0.41	0.03	11.38
	Network	1.21	0.10	9.26	2.32	0.93	3.79	3.92	2.13	1.87	4.50	3.60	3.67	1.00	38.30
DEU	Within sector	0.07	0.00	4.11	0.56	0.42	0.14	0.85	0.36	0.97	0.58	1.67	0.63	0.01	10.36
	Network	0.77	0.06	7.39	2.00	1.81	3.97	4.54	3.08	2.14	3.71	5.23	2.91	0.69	38.29
IDN	Within sector	0.33	0.73	3.35	1.25	0.11	0.13	0.11	0.00	0.33	0.02	0.83	0.18	0.00	7.37
	Network	5.33	4.11	10.78	0.66	1.33	7.04	2.71	0.25	1.41	0.48	1.23	1.88	0.84	38.03
JPN	Within sector	0.16	0.02	7.07	0.13	0.02	0.10	0.25	0.02	0.34	0.27	0.25	0.44	0.05	9.12
	Network	0.96	0.41	12.24	2.02	1.19	4.36	2.21	0.45	2.50	3.97	1.66	2.66	1.66	36.29
USA	Within sector	0.25	0.12	2.29	0.03	0.00	0.17	0.11	0.50	0.56	0.23	0.47	1.27	0.03	6.02
	Network	1.02	1.42	8.33	0.94	0.81	3.02	2.13	2.43	2.38	4.95	4.87	2.82	0.73	35.86
TUR	Within sector	0.78	0.02	5.70	1.56	0.10	0.26	1.71	0.06	0.11	0.15	0.64	0.18	0.01	11.27
	Network	2.94	1.12	7.08	1.59	0.34	6.63	6.54	1.48	1.07	2.61	1.73	1.99	0.64	35.76
BRA	Within sector	0.19	0.08	3.84	0.60	0.83	0.14	0.35	0.02	0.36	0.20	0.33	0.78	0.00	7.73
	Network	2.27	1.76	9.07	1.12	0.54	5.16	3.03	0.94	1.66	2.85	3.38	2.39	0.44	34.60
IND	Within sector	1.33	0.00	5.56	0.33	1.32	0.08	0.17	0.03	0.13	0.09	0.07	0.11	0.08	9.30
	Network	3.28	1.18	12.63	1.36	1.10	6.09	3.40	0.05	0.81	0.50	0.52	2.44	0.91	34.27
GBR	Within sector	0.11	0.09	1.62	1.53	2.13	0.15	0.56	0.02	0.44	0.56	2.43	0.96	0.07	10.68
	Network	0.49	0.88	5.98	1.51	2.26	2.42	3.31	0.84	2.67	4.58	4.93	3.44	0.92	34.21
FRA	Within sector	0.45	0.00	1.73	1.46	1.33	0.40	0.63	0.29	0.59	1.59	0.78	0.79	0.22	10.27
	Network	1.23	0.07	5.61	1.59	0.68	3.20	2.73	1.81	1.98	4.21	5.29	3.89	1.39	33.67
MEX	Within sector	0.31	0.13	4.57	0.02	0.59	0.27	0.07	n.a.	0.09	0.08	0.35	0.14	0.00	6.61
	Network	1.78	2.85	8.79	1.53	0.16	4.85	1.57	n.a.	0.78	1.65	4.36	1.24	0.56	30.13

Notes: Entries are percentage-point shares weighted by industry size in the total economy. “Within sector” is the own-sector component; “Network” is the contribution from other sectors. Sectors are aggregated from 56 WIOD industries. Aggregate network exposure is identical across the downstream and upstream calculations because reversing the orientation of the input-output network changes the allocation of exposure across sectors but not the country-level weighted total. The two tables therefore differ in sectoral composition rather than in aggregate exposure.

Source: Authors’ calculations using the World Input–Output Tables (WIOD).

Table 9: Upstream own and network effects

Country	Component	Agric.	Mining	Manufact.	Utilities	Construct.	Wholesale and retail	Transport	Real estate	Information	Professional activities	Service activities	Financial activities	All others	Total
CHN	Within sector	0.67	0.42	14.32	1.16	0.43	0.26	0.14	0.05	0.14	0.21	0.22	0.08	0.00	18.11
	Network	1.58	1.64	25.83	1.55	7.21	1.93	1.66	0.33	0.56	1.74	4.02	0.83	1.11	50.01
RUS	Within sector	0.48	0.13	3.93	0.37	0.02	0.38	0.05	0.06	0.33	0.00	2.24	0.06	0.00	8.04
	Network	1.25	2.59	13.10	3.34	4.05	6.17	3.48	1.19	0.44	0.00	6.85	1.03	0.43	43.92
CAN	Within sector	0.26	0.18	1.36	0.02	0.06	0.16	1.52	0.21	0.46	0.53	0.61	1.28	0.14	6.79
	Network	1.22	1.51	8.74	0.50	4.16	4.55	1.93	1.67	1.21	2.17	7.98	1.82	1.05	38.50
ITA	Within sector	0.20	0.00	4.71	1.38	1.80	0.34	0.63	0.09	0.41	0.26	1.12	0.41	0.03	11.38
	Network	0.58	0.12	13.12	1.65	2.69	4.79	2.69	0.80	1.57	1.76	5.10	1.51	1.94	38.30
DEU	Within sector	0.07	0.00	4.11	0.56	0.42	0.14	0.85	0.36	0.97	0.58	1.67	0.63	0.01	10.36
	Network	0.57	0.10	13.53	1.42	2.53	3.71	2.78	1.64	1.39	1.79	5.06	2.47	1.29	38.29
IDN	Within sector	0.33	0.73	3.35	1.25	0.11	0.13	0.11	0.00	0.33	0.02	0.83	0.18	0.00	7.37
	Network	1.12	0.99	14.19	0.64	8.51	3.05	2.58	0.32	0.75	0.28	3.00	0.63	1.96	38.03
JPN	Within sector	0.16	0.02	7.07	0.13	0.02	0.10	0.25	0.02	0.34	0.27	0.25	0.44	0.05	9.12
	Network	0.48	0.10	11.82	0.95	3.73	3.52	1.51	1.22	1.75	1.59	5.83	1.37	2.42	36.29
USA	Within sector	0.25	0.12	2.29	0.03	0.00	0.17	0.11	0.50	0.56	0.23	0.47	1.27	0.03	6.02
	Network	0.60	0.47	9.11	0.51	1.60	3.56	1.66	1.93	1.94	2.54	8.68	1.90	1.37	35.86
TUR	Within sector	0.78	0.02	5.70	1.56	0.10	0.26	1.71	0.06	0.11	0.15	0.64	0.18	0.01	11.27
	Network	1.04	0.45	14.22	0.63	2.49	4.33	3.95	0.85	0.71	0.75	3.70	0.90	1.75	35.76
BRA	Within sector	0.19	0.08	3.84	0.60	0.83	0.14	0.35	0.02	0.36	0.20	0.33	0.78	0.00	7.73
	Network	1.26	0.85	13.94	0.71	2.56	3.28	1.85	0.36	1.25	1.19	5.02	1.29	1.04	34.60
IND	Within sector	1.33	0.00	5.56	0.33	1.32	0.08	0.17	0.03	0.13	0.09	0.07	0.11	0.08	9.30
	Network	1.41	0.27	18.31	0.65	4.75	1.57	3.59	0.29	0.36	0.32	0.84	0.45	1.44	34.27
GBR	Within sector	0.11	0.09	1.62	1.53	2.13	0.15	0.56	0.02	0.44	0.56	2.43	0.96	0.07	10.68
	Network	0.39	0.35	6.08	1.12	2.50	4.38	2.22	2.29	1.80	2.06	6.14	3.39	1.50	34.21
FRA	Within sector	0.45	0.00	1.73	1.46	1.33	0.40	0.63	0.29	0.59	1.59	0.78	0.79	0.22	10.27
	Network	0.87	0.07	8.07	0.82	2.72	4.59	1.67	1.29	1.71	2.73	5.05	2.54	1.53	33.67
MEX	Within sector	0.31	0.13	4.57	0.02	0.59	0.27	0.07	n.a.	0.09	0.08	0.35	0.14	0.00	6.61
	Network	0.79	0.90	14.12	0.66	2.56	2.58	2.59	n.a.	0.62	0.40	3.29	0.95	0.69	30.13

Notes: Entries are percentage-point shares weighted by industry size in the total economy. “Within sector” is the own-sector component; “Network” is the contribution from other sectors. Sectors are aggregated from 56 WIOD industries. Aggregate network exposure is identical across the downstream and upstream calculations because reversing the orientation of the input-output network changes the allocation of exposure across sectors but not the country-level weighted total. The two tables therefore differ in sectoral composition rather than in aggregate exposure.

Source: Authors’ calculations using the World Input–Output Tables (WIOD).

(a) Downstream network exposure

Country	Agric.	Mining	Manufact.	Utilities	Construct.	Wholesale & retail	Transport	Real estate	Information	Professional	Services	Financial	All others	Total
CHN	3.5	3.7	25.0	2.3	0.4	3.6	2.6	0.7	0.7	2.6	1.3	2.5	1.0	50.0
RUS	1.2	2.4	12.3	4.7	0.9	8.6	3.4	1.9	1.0	0.0	6.1	1.2	0.3	43.9
CAN	1.2	2.0	7.1	1.2	1.8	5.5	2.7	1.7	2.0	4.5	5.6	2.7	0.6	38.5
ITA	1.2	0.1	9.3	2.3	0.9	3.8	3.9	2.1	1.9	4.5	3.6	3.7	1.0	38.3
DEU	0.8	0.1	7.4	2.0	1.8	4.0	4.5	3.1	2.1	3.7	5.2	2.9	0.7	38.3
IDN	5.3	4.1	10.8	0.7	1.3	7.0	2.7	0.2	1.4	0.5	1.2	1.9	0.8	38.0
JPN	1.0	0.4	12.2	2.0	1.2	4.4	2.2	0.5	2.5	4.0	1.7	2.7	1.7	36.3
USA	1.0	1.4	8.3	0.9	0.8	3.0	2.1	2.4	2.4	4.9	4.9	2.8	0.7	35.9
TUR	2.9	1.1	7.1	1.6	0.3	6.6	6.5	1.5	1.1	2.6	1.7	2.0	0.6	35.8
BRA	2.3	1.8	9.1	1.1	0.5	5.2	3.0	0.9	1.7	2.9	3.4	2.4	0.4	34.6
IND	3.3	1.2	12.6	1.4	1.1	6.1	3.4	0.0	0.8	0.5	0.5	2.4	0.9	34.3
GBR	0.5	0.9	6.0	1.5	2.3	2.4	3.3	0.8	2.7	4.6	4.9	3.4	0.9	34.2
FRA	1.2	0.1	5.6	1.6	0.7	3.2	2.7	1.8	2.0	4.2	5.3	3.9	1.4	33.7
MEX	1.8	2.8	8.8	1.5	0.2	4.9	1.6	n.a.	0.8	1.7	4.4	1.2	0.6	30.1

(b) Upstream network exposure

Country	Agric.	Mining	Manufact.	Utilities	Construct.	Wholesale & retail	Transport	Real estate	Information	Professional	Services	Financial	All others	Total
CHN	1.6	1.6	25.8	1.5	7.2	1.9	1.7	0.3	0.6	1.7	4.0	0.8	1.1	50.0
RUS	1.2	2.6	13.1	3.3	4.1	6.2	3.5	1.2	0.4	0.0	6.9	1.0	0.4	43.9
CAN	1.2	1.5	8.7	0.5	4.2	4.6	1.9	1.7	1.2	2.2	8.0	1.8	1.1	38.5
ITA	0.6	0.1	13.1	1.7	2.7	4.8	2.7	0.8	1.6	1.8	5.1	1.5	1.9	38.3
DEU	0.6	0.1	13.5	1.4	2.5	3.7	2.8	1.6	1.4	1.8	5.1	2.5	1.3	38.3
IDN	1.1	1.0	14.2	0.6	8.5	3.1	2.6	0.3	0.8	0.3	3.0	0.6	2.0	38.0
JPN	0.5	0.1	11.8	1.0	3.7	3.5	1.5	1.2	1.8	1.6	5.8	1.4	2.4	36.3
USA	0.6	0.5	9.1	0.5	1.6	3.6	1.7	1.9	1.9	2.5	8.7	1.9	1.4	35.9
TUR	1.0	0.4	14.2	0.6	2.5	4.3	4.0	0.8	0.7	0.7	3.7	0.9	1.7	35.8
BRA	1.3	0.8	13.9	0.7	2.6	3.3	1.9	0.4	1.3	1.2	5.0	1.3	1.0	34.6
IND	1.4	0.3	18.3	0.6	4.7	1.6	3.6	0.3	0.4	0.3	0.8	0.5	1.4	34.3
GBR	0.4	0.3	6.1	1.1	2.5	4.4	2.2	2.3	1.8	2.1	6.1	3.4	1.5	34.2
FRA	0.9	0.1	8.1	0.8	2.7	4.6	1.7	1.3	1.7	2.7	5.1	2.5	1.5	33.7
MEX	0.8	0.9	14.1	0.7	2.6	2.6	2.6	n.a.	0.6	0.4	3.3	0.9	0.7	30.1

Figure A5: Sectoral composition of downstream and upstream network exposure

Notes: Entries are percentage-point shares of total economic activity. Darker shading indicates larger network exposure. Mexico's real-estate entry is unavailable and is marked "n.a."

Source: Authors' calculations using the World Input–Output Tables (WIOD).

References

- Acemoglu, D., Akcigit, U., and Kerr, W. R. (2016a). Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*, 30(1):273–335.
- Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016b). Import competition and

- the great US employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.
- Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.
- Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015). Networks, shocks, and systemic risk. NBER Working Paper 20931, National Bureau of Economic Research.
- Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–2168.
- Baqae, D. R. and Farhi, E. (2018). The macroeconomic impact of microeconomic shocks: Beyond hulten’s theorem. NBER Working Paper 23145, National Bureau of Economic Research.
- Barrot, J.-N. and Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *Quarterly Journal of Economics*, 131(3):1543–1592.
- Bonadio, B., Huo, Z., Levchenko, A. A., and Pandalai-Nayar, N. (2021). Global supply chains in the pandemic. *Journal of International Economics*, 133:103534.
- Carvalho, V. M. (2008). Aggregate fluctuations and the network structure of intersectoral trade. Technical report, Center for Research, Entrepreneurship and Innovation.
- Carvalho, V. M., Nirei, M., Saito, Y. U., and Tahbaz-Salehi, A. (2021). Supply chain disruptions: Evidence from the great east japan earthquake. *Quarterly Journal of Economics*, 136(2):1255–1321.
- Chen, Q., Gao, Y., Pei, J., de Vries, G., and Wang, F. (2022). China’s domestic production networks. *China Economic Review*, 72:101767.
- Elliott, M., Golub, B., and Leduc, M. V. (2022). Supply network formation and fragility. *American Economic Review*, 112(8):2701–2747.
- Gabaix, X. (2009). The granular origins of aggregate fluctuations. NBER Working Paper 15286, National Bureau of Economic Research.
- Grossman, G. M., Helpman, E., and Redding, S. J. (2024). When tariffs disrupt global supply chains. *American Economic Review*, 114(4):988–1029.
- Liu, E. (2019). Industrial policies in production networks. *Quarterly Journal of Economics*, 134(4):1883–1948.
- Mi, Z. et al. (2018). A multi-regional input-output table mapping china’s economic outputs and interdependencies in 2012. *Scientific Data*, 5:180155.
- National Bureau of Statistics of China (2015). Input-output table of china 2012. China Statistical Yearbook 2015 and detailed national input-output tables. National Accounts Department, Beijing.

- Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. J. (2015). An illustrated user guide to the world input-output database: The case of global automotive production. *Review of International Economics*, 23:575–605.
- Timmer, M. P., Los, B., Stehrer, R., and de Vries, G. J. (2016). An anatomy of the global trade slowdown based on the wiod 2016 release. GGDC Research Memorandum 162, University of Groningen.
- Wu, H. X. and Ito, K. (2015). Reconstructing china’s supply-use and input-output tables in time series. RIETI Discussion Paper 15-E-004, Research Institute of Economy, Trade and Industry.