

How Shocks to Large Manufacturing Companies Affect the Whole Economy: Estimating the Effects of Shockwaves through Business Networks in Eight European Countries

Anamarija CIJAN* – Jože P. DAMIJAN** – Črt KOSTEVC*

Abstract

This paper examines how externally originating disturbances – such as drops in demand or supply constraints – are transmitted and amplified through existing production networks, where firms' exposure is determined by their horizontal, backward and forward linkages to the largest five firms. Using firm-level data from eight European countries between 2006 and 2019, we measure each firm's network position through linkages in its own industry and in the downstream and upstream industries. Our results reveal three key contributions. First, as shown by the fixed effects model, demand shocks tend to flow upstream to suppliers, while supply shocks more strongly affect downstream buyers which is aligned with theory. Second, industry analysis reveals that the effects of firm linkages become more pronounced during periods of economic shocks, as their impact is amplified under both demand and supply shocks. Third, our results suggest that economies with lower market concentration – where SMEs dominate – exhibit more pronounced shock transmission, highlighting the role of network structure in amplifying shocks. These findings emphasize the critical role of production networks in amplifying firm-level shocks and underline the need for policies that reduce systemic vulnerabilities in granular economies.

Keywords: *input-output networks, idiosyncratic shocks, supply-side shocks, demand-side shocks, firm performance*

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* Anamarija CIJAN, corresponding author – Črt KOSTEVC, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia; e-mail: anamarija.cijan@ef.uni-lj.si, ORCID: 0000-0003-3068-5189; e-mail: crt.kostevc@ef.uni-lj.si, ORCID: 0000-0001-7260-1962

** Jože P. DAMIJAN, University of Ljubljana, School of Economics and Business, Kardeljeva ploščad 17, 1000 Ljubljana, Slovenia; University of Leuven, Oude Markt 13, 3000 Leuven, Belgium; e-mail: joze.damijan@ef.uni-lj.si, ORCID: 0000-0001-9150-1174



Introduction

Macroeconomic research has long sought to explain how economic fluctuations arise from systemic factors such as investment and capital accumulation responses in real business cycle models (e.g., Kydland and Prescott, 1982), Keynesian multipliers (e.g., Christiano et al., 2011) and the effects of monetary policy (e.g., Eggertsson and Woodford, 2003; Farhi and Werning, 2016). However, recent studies suggest that small, firm-specific shocks can cascade through the economy, amplifying fluctuations through production networks and supply chains (Acemoglu et al., 2016a; Carvalho and Tahbaz-Salehi, 2019). Despite this growing recognition, existing research largely underestimates the role of interfirm linkages, treating firm-level disturbances as independent or averaging out in aggregate (Gabaix, 2011; di Giovanni et al., 2014). This paper tests the hypothesis that interfirm input-output linkages amplify idiosyncratic shocks from the largest manufacturing firms, significantly impacting the performance of their associated firms. Using firm-level data from eight European countries over 2006 – 2019, we provide evidence that shocks to a small number of large manufacturing firms reverberate through the network, generating broader consequences for suppliers, customers and peers. Importantly, our objective is not to model the endogenous generation of shocks by dominant firms, but to examine how externally originating disturbances are transmitted and amplified through the existing network structure. The heterogeneity we document therefore arises from differences in firms' exposure to common shocks. We challenge conventional economic theory by showing that shocks to the largest firms intensify rather than dissipate as they spread through supply chains, ultimately affecting performance of associated firms. The increasing fragility of global production networks – exposed by geopolitical tensions, energy crises and technological disruptions – highlights this interdependence. Events including semiconductor shortages (Xiong et al., 2025) and COVID-19 supply chain disruptions (Cheema-Fox et al., 2021) demonstrate how localized shocks can have widespread effects, which existing models struggle to predict. Moreover, the global financial crisis (GFC) underscored the importance of firm and sector interconnections (Acemoglu et al., 2010).

We make several key contributions. First, we provide empirical evidence that idiosyncratic shocks to a small number of large manufacturing firms significantly affect the performance of their connected firms, challenging the traditional view that such shocks average out in the aggregate. In economies with dense interfirm linkages, shocks to large firms are amplified rather than absorbed. Here, on average, countries with lower market concentration exhibit larger absolute coefficient values. Second, industry analysis shows that firm linkages exert a more pronounced influence during shocks, with their effects becoming amplified in the

presence of both supply-side and demand-side disruptions. Third, fixed effects model shows that the direction of shock propagation aligns with theory as supply-side shocks spread more strongly downstream, while demand-side shocks propagate more intensely upstream, with network effects often exceeding the direct impact. Fourth, using firm-level data from eight European countries, we demonstrate that these network effects are widespread and robust across national contexts. Overall, these findings emphasize the critical role of network structures and call for more nuanced and targeted policy interventions.

Importantly, the granularity literature shows that shocks to very large firms can influence aggregate fluctuations due to firm size distribution (e.g. Gabaix, 2011). Our paper complements this view by emphasizing the role of production networks as an amplification mechanism. We show that even demand and supply shocks can generate heterogeneous firm-level outcomes once propagated through buyer-supplier linkages, highlighting network structure as a key determinant of shock transmission.

This paper is organized as follows: first, we provide a review of the relevant literature, followed by a theoretical model. Section four describes the data used in this paper, while section five outlines the empirical approach and the main empirical results along with several robustness checks. Finally, section six concludes.

1. Literature Review

A well-established view in economics is that the production of goods and services is built on a complex network of interactions between numerous suppliers and customers (Carvalho and Tahbaz-Salehi, 2019). Leontief (1941, p. 3) argues that there are interrelationships among even the most remote parts of a national economy. Consequently, disturbances within specific firms or industries can spill over via input linkages to other segments of the economy, potentially transforming isolated microeconomic shocks into macroeconomic fluctuations (Carvalho and Tahbaz-Salehi, 2019). The significance of production networks goes beyond the input-output literature that originated from Leontief's work and can even be traced back to classical economics. For example, von Neumann (1945) emphasized that goods are primarily produced from other goods, aside from natural factors of production.

Traditional theory or more precisely, the diversification argument, based on the law of large numbers, suggests that microeconomic shocks to firms or sectors have negligible aggregate effects (as argued by Lucas in 1977), with fluctuations diminishing according to $1/\sqrt{n}$ in an economy consisting of n sectors that is affected by independent shocks. However, this theory overlooks interconnections between

firms and sectors, which can propagate through the economy, potentially causing aggregate fluctuations to stabilize more slowly. This notion, known as granularity, implies sectoral shocks have a greater impact on aggregate fluctuations (Acemoglu et al., 2012). The diversification argument fails to account for interconnections between firms and sectors, which can propagate idiosyncratic shocks throughout the economy. This was evident during the GFC, where cascade effects from the collapse of key suppliers or dealers could lead to widespread disruptions across industries (Acemoglu et al., 2012). Additionally, Gabaix (2011) shows that when firm sizes are highly concentrated, aggregate volatility declines slowly and idiosyncratic shocks to large firms can generate macroeconomic fluctuations. Here, firm size concentration plays a role similar to asymmetric production networks in Acemoglu et al. (2012), as both allow micro-level shocks to affect aggregate outcomes.

More precisely, in an economy with non-interacting sectors, the diversification argument implies that independent sectoral shocks average out at rate $\sqrt{n}$ by the law of large numbers. Even when sectors are symmetrically interconnected and rely equally on one another's outputs, aggregate output remains a symmetric function of sectoral shocks and the diversification argument continues to apply (Acemoglu et al., 2012). Nonetheless, when input-output linkages are asymmetric, this argument breaks down. In such economies, shocks to central sectors propagate strongly through the production network and do not average out as the number of sectors increases, generating sizable aggregate fluctuations and invalidating the diversification argument (Acemoglu et al., 2012). Additionally, the upper tail of the firm-size distribution follows a power law, implying the presence of a small number of very large units. When idiosyncratic shocks scale with firm size, this generates a small number of large shocks that do not average out at the aggregate level, violating the diversification argument. In the presence of economic linkages, such shocks can therefore generate sizable aggregate fluctuations (Anthonisen, 2016).

Theoretical framework upon which the literature builds can be broadly categorized into two categories. The first category consists of papers that build on the multisector model of Long and Plosser (1983), such as those by Horvath (1998; 2000), Dupor (1999), Shea (2002), Conley and Dupor (2003), Acemoglu et al. (2010; 2016c), Carvalho (2010; 2014), Jones (2013) and Atalay (2017). These models are log-linear propagation models and follow the tradition of Leontief (1936) by incorporating linear-geometric diffusion. As demonstrated by Hulten (1978), the propagation of total factor productivity shocks in these models is, at least locally, connected to the distribution of firm sizes. This implies that for a firm to be systemically important, it must have high sales (Baqae, 2018). The second category includes models that do not meet the conditions of Hulten's theorem. These models, such as those by Jovanovic (1987), Durlauf (1993) and Scheinkman

and Woodford (1994), are characterized by strong nonlinearities, where the sales distribution is not a decisive sufficient statistic and they do not exhibit the geometric diffusion patterns typical of input-output models.

Empirically, this study closely aligns with the literature that focuses on network-based methods for amplifying and propagating shocks. Several studies offer evidence for the relevance of such propagation mechanisms. Acemoglu et al. (2016a) find that in the US, for demand-side shocks, upstream effects exceed downstream effects which are minimal or in the opposite direction, while the opposite is true for supply-side shocks. Di Giovanni et al. (2014) use French data to show that firm linkages are about three times more significant than direct firm shocks in driving aggregate fluctuations. Foerster et al. (2011) show that idiosyncratic shocks' role grew significantly after the mid-1980s in the US, accounting for half of the quarterly variation in industrial production. Atalay (2017) analyses US data and reveals that goods from different industries are complementary inputs in downstream industries' productions which indicates that industry-specific shocks are more significant than previously realized. Acemoglu et al. (2016b) examine how increased Chinese competition spread its impact throughout the US economy via input-output linkages and local labour markets, causing decline in US manufacturing employment and to weak overall job growth.

Also, as already mentioned, the granular approach illustrates how a few large firms can disproportionately drive macroeconomic fluctuations via firm size distributions. Here, empirical evidence shows that idiosyncratic shocks to the largest firms explain substantial portions of GDP or sales volatility in various countries, including the US (Gabaix, 2011; Baqaee and Farhi, 2019) and the European countries (Ebeke and Eklou, 2017; Fornaro and Luomaranta, 2018; Blanco-Arroyo et al., 2018; Di Giovanni et al., 2014). Finally, Anthonisen (2016) extends Gabaix (2011) and Acemoglu et al. (2012) in a dynamic DSGE framework with network linkages, showing that when firm sizes follow a Zipf distribution, idiosyncratic firm-level shocks propagate through the network and generate aggregate fluctuations, whereas diversification holds when firm sizes have finite moments.

2. Theoretical Model

The paper builds on the model proposed by Acemoglu et al. (2016a). The model also closely follows Long and Plosser (1983) as well as Acemoglu et al. (2012).

Assume a static economy that is perfectly competitive and is comprised from n industries. Each industry $k = 1, \dots, n$ exhibits a Cobb-Douglas production function of the following form:

$$y_k = e^{z_k} l_k^{\alpha_k^l} \prod_{j=1}^n x_{kj}^{a_{kj}} \quad (1)$$

where x_{kj} represents the quantity of goods produced by industry j that are used as inputs by industry k . Next, l_k is labour, z_k is a Hicks-neutral productivity shock that entails both technological and other factors that affect productivity. For each k , $\alpha_k^l > 0$ and $a_{kj} \geq 0$ for all j . In case $a_{kj} = 0$ the output of industry j is not utilised as an input for industry k . Also, the production function of each industry has constant returns to scale, i.e., $\alpha_k^l + \sum_{j=1}^n a_{kj} = 1$.

A Cobb-Douglas production function indicates that the output of each industry is either utilised as input for other industries or consumed in the final good sector. To include the demand from other industries, the market-clearing condition for industry k is as follows: $y_k = c_k + \sum_{j=1}^n x_{jk}$, whereby c_k represents final

consumption of the output of industry k . Next, to show preference side of this economy a representative household exhibits the following utility function:

$$u(c_1, c_2, \dots, c_n, l) = \gamma(l) \prod_{k=1}^n c_k^{\beta_k}, \text{ whereby } \beta_k \in (0, 1) \text{ presents the weight of good } k \text{ in}$$

the representative household's preferences, while the normalisation is $\sum_{k=1}^n \beta_k = 1$.

Also, $\gamma(l)$ represents a decreasing (differentiable) function that entails the disutility of labour supply.

Assuming the outcome stems only from labour, wl , the budget constraint of the representative household is $\sum_{k=1}^n p_k c_k = wl$. Also, we assume competitive equilibrium of this static economy, where all firms maximise profits, prices are given and the market-clearing conditions for each good and labour are satisfied, while the representative household maximises its utility. In this competitive equilibrium the wage is set to be as the numeraire ($w = 1$). Profit maximisation and the Cobb-

Douglas production functions suggest the following: $\frac{p_j x_{kj}}{p_k y_k} = a_{kj}$.

Next, A denotes the matrix of a_{kj} 's. The Leontief inverse of the input-output matrix A has a typical entry labelled as h_{kj} and is labelled as: $H \equiv (I - A)^{-1}$.

Furthermore, the impact of supply- (productivity shock on the EU market) and demand-side (dynamics of import on the EU market) shocks on the output of sector k can be written as the sum of its own effect (the first part of the equation) and network effect (the second part of the equation):

$$d \ln y_k = dz_k + \sum_{j=1}^n (h_{kj} - 1_{j=k}) \times dz_j \quad (2)$$

Hereby, $1_{j=k}$ represents the indicator function for $j = k$. One needs to acknowledge that the equation indicates that no upstream effects are observed in response to productivity shocks. In other words, there are no effects on suppliers of affected industries, as only downstream effects are observed, i.e. only the effects on customers of affected industries are observed.

The equations that depicts the impacts of both supply- and demand-side shocks represent the basis of the empirical work. These equations link the output of sector k to its own shock dz_k and to shocks that are hitting all other industries through the input-output linkages of the economy, with the network effect being depicted by $\sum_{j=1}^n (h_{kj} - 1_{j=k}) \times dz_j$. The latter expression entails the propagation of the own shock through the input-output linkages, $h_{kj} - 1$, along with the network effect and then subtracts the own effect with the help of the indicator function $1_{j=k}$. The latter has the value 1 when $j = k$ and the value 0 otherwise. This eliminates the double count of this direct effect.

The crucial factor for network effects lies not in the direct entries of the input-output matrix, $\mathbf{A}$ or $\hat{\mathbf{A}}$, but rather in its Leontief inverse. As an illustration, a negative productivity shock to industry j will decrease its production, while its price will increase. That in turn adversely affects all industries that purchase inputs from industry j . This direct impact will further be amplified in the competitive equilibrium; accordingly, these industries that will firstly be affected will alter their production and prices. Thus, indirect negative effects on other customer industries will be noted. The Leontief inverse seizes these indirect effects.

3. Data

We use firm-level data from the Orbis database (Bureau van Dijk) provided by KU Leuven, which includes both listed and unlisted firms. The financial and balance sheet data are sourced from national business registries. While most

countries require limited liability firms to register, the criteria for reporting balance sheet information vary (see Kalemli-Ozcan et al., 2022 for detailed information). The database provides annual data from 2006 to 2019 on the following two variables: firm ID, sales, number of employees, short-term and long-term debt and total assets.

Following Bajgar et al. (2020), we use unconsolidated accounts to avoid duplication. We adopt a balanced sample approach, ensuring firms are present throughout the entire period and replace missing, negative, or zero values for sales with linear interpolation. Firms with missing values after interpolation or those with sales growth rates exceeding 20% (following Gabaix, 2011) are excluded.¹ Industries are categorized using 2-digit NACE codes. Bajgar et al. (2020) examine how accurately Orbis reflects the overall firm population across countries and industries. Coverage differs by country as France and Italy have moderate overall coverage with most mid-sized and large enterprises in the database; Hungary fluctuates over time; Sweden aligns well with official data; Slovenia's coverage is patchy across particular years yet the presence of large enterprises does ensure that Orbis still picks up a substantial fraction of total activity in some segments; Poland suffers from rounding issues; and Portugal sees a mid-2000s coverage jump (Bajgar et al., 2020). While other European countries are available in Orbis, their coverage is either incomplete or inconsistent over time, particularly for manufacturing firms, which are central to our analysis of production networks. By focusing on these eight countries, we ensure consistent, high-quality data for both large and mid-sized firms, which is essential for accurately measuring shocks and their propagation through firm networks.

We restrict the analysis to manufacturing firms mainly due to the following reasons. Firstly, generally, production networks, input-output linkages and shock propagation are most clearly defined and empirically observable in manufacturing. Manufacturing firms rely heavily on intermediate inputs and operate within well-defined upstream and downstream supply chains, which makes the measurement of horizontal, backward and forward linkages particularly meaningful. In contrast, service sectors often feature less standardized input structures and weaker buyer-supplier relationships, which would complicate the interpretation of network spillovers. Focusing on manufacturing therefore ensures that the network measures and shock transmission mechanisms are well identified and consistent with the production-network literature.

¹ Several studies utilizing Orbis data employ interpolation and imputation techniques to enhance data quality (Kalemli-Ozcan et al., 2022; Fujimoto et al., 2022; Gal, 2013). These methodological adjustments contribute to more reliable firm-level analyses and improve the robustness of empirical findings. For a detailed discussion of potential biases associated with these methods, see Kalemli-Ozcan et al. (2022).

Secondly, manufacturing plays a central role across the European economies, underpinning production networks, employment and export performance across member states. As an example, in 2023, the manufacturing sector accounted for approximately one quarter of the EU business economy’s net turnover, amounting to EUR 9.9 trillion (Eurostat, 2025).

Finally, our focus on manufacturing is consistent with the production-network and granularity literature; for example, Acemoglu et al. (2012) study network structures and shock propagation using manufacturing data. The subjects covered are manufacturing firms operating in the following industries: Food, beverages, tobacco, Textiles, apparel, leather, Paper, printing, Pharmaceuticals, refined petroleum products, Chemicals products, Other non-metallic mineral products, Basic metals, Fabricated metal products, Machinery and equipment, Computer, transport, other, Electrical equipment, Motor vehicles and Other transport equipment. Lastly, data for network-based measures are obtained from OECD IO tables, data for labour productivity from OECD Data Explorer and trading data are obtained from CEPII – BACI database.

Table 1 provides data on average concentrations across industries of the largest five firms in the industry (ranked by their lagged sales) relative to all firms in the industry by country between 2006 – 2019. On average the largest five manufacturing firms account for around 42% of all sales across industries and countries. The highest concentration rate is in Slovenia, while the lowest is in Italy.

Table 1

Concentration of the Largest Five Firms in the Industry Relative to All Firms in the Industry, by Country

Country	Concentration of the largest five firms (2006 – 2019)
Italy	0.24
Spain	0.34
France	0.34
Poland	0.39
Portugal	0.43
Hungary	0.51
Sweden	0.52
Slovenia	0.60
Average	0.42

Source: Orbis database.

Table 2 provides data on average concentrations across industries of the largest five firms (ranked by their lagged sales) relative to all firms in the industry between 2006 – 2019. The highest concentration rate is in Pharmaceuticals, refined petroleum products, whereas the lowest concentration rate is in Fabricated metal products.

Table 2

Concentration of the Largest Five Firms in the Industry Relative to All Firms in the Industries across Countries, by Manufacturing Industries

Manufacturing industry	Concentration of the largest five firms (2006 – 2019)
Fabricated metal products	0.15
Food, beverages, tobacco	0.21
Other non-metallic mineral products	0.28
Machinery and equipment	0.29
Textiles, apparel, leather	0.30
Computer, transport, other	0.33
Paper, printing	0.34
Chemicals products	0.41
Electrical equipment	0.48
Basic metals	0.53
Motor vehicles	0.64
Other transport equipment	0.71
Pharmaceuticals, refined petroleum products	0.81
Average	0.42

Source: Orbis database.

4. Empirical Approach

We examine how different types of shocks propagate through input-output networks, focusing on the largest five manufacturing firms in each industry and their impact on the performance of connected firms. First, we define three types of interfirm linkages: horizontal (within-sector), forward (downstream) and backward (upstream) connections to capture the structure of the production network. Second, we construct measures of both supply- and demand-side shocks. Following the literature we treat productivity shocks as supply-side shocks (e.g., Acemoglu et al., 2016a; Carvalho and Tahbaz-Salehi, 2019), while demand-side shocks are proxied by interconnections in sales across foreign markets (e.g., Acemoglu et al., 2016a; Bems et al., 2010). Third, we present baseline models that test whether firm sales are influenced by direct shocks within their own industry and by shocks to the largest firms in connected industries. We estimate these effects at three levels: (i) fixed effects model for the full sample average, (ii) pooled OLS regression for industry-specific and (iii) for country-specific analyses. This multi-level approach allows us to identify heterogeneity across industries and countries. Robustness checks include alternative definitions of large firms, the use of export exposure in place of import exposure to capture demand-side shocks and the inclusion of year fixed effects.

Importantly, all shocks are defined at the level appropriate to the economic mechanism they capture. Labor productivity shocks are measured at the manufacturing-sector level as changes in gross value added per hour worked, capturing broad efficiency trends common to all firms. Although these shocks are constant across firms, heterogeneous outcomes arise through differences in exposure via

horizontal, backward and forward linkages, therefore, identification relies on the network structure. Import-related demand shocks are measured at the industry level, reflecting variation in exposure to foreign competition and input supply conditions across sub-industries. Moreover, network exposures are computed using sector-level weights, aggregating upstream, downstream and own-sector shocks, which ensures consistent measurement and meaningful heterogeneity in propagation. As horizontal, backward and forward exposures use different weights, they are not collinear. While shocks to individual firms are not directly observed, this approach captures how demand and supply shocks propagate through production networks, with large firms amplifying transmission, consistent with other production-network and granular-economy frameworks, including Acemoglu et al. (2016a).

4.1. Input-Output Linkages

To formulate downstream and upstream effects, this paper follows Acemoglu et al. (2016a) and Damijan (2016). The matrix $\mathbf{A}$ from the theoretical model is built on the input-output tables from OECD.² The matrix $\mathbf{A}$ has input share entries

that correspond to: $a_{kj} \equiv \frac{\text{Sales and purchases}_{j \rightarrow k}}{\text{Sales and purchases}_k}$, where j denotes suppliers and

k denotes buyers. Input-output tables from OECD show the sale and purchase relationships between producers and consumers within an economy. They depict flows – sales and purchases – of final and intermediate goods and services that are defined according to industry outputs (OECD, 2024a). The mechanism of spillovers used in the model highlights how a firm's performance is influenced by its own performance and three types of performance-related spillovers. Horizontal spillovers arise from the top five firms in a sector, while backward and forward spillovers result from distress in supplier and buyer sectors, respectively.

Firstly, HL_{it}^{jk} represents intra-sectoral spillovers (horizontal spillovers) which arise from the largest five firms ($k = 5$) in the sector. These spillovers can be viewed either as competitive effects within the same sector or as agglomeration effects within the sector stemming from the largest five firms in the sector. Therefore, horizontal spillovers are defined as the share of a sector's j 's output produced by the largest five firms in the sector:

$$HL_{it}^{jk} = \frac{\sum_{k=1}^m Y_t^{jk}}{\sum_{i=1}^n Y_t^j}; i = 1, \dots, n; k = 1, \dots, m \quad (3)$$

² We construct spillover variables through horizontal and vertical linkages using the OECD 2015 input-output tables (NACE Rev. 1, 34 two-digit sectors). These tables are matched to firm-level data by primary NACE Rev. 2 code.

Next, we account for vertical spillovers from the largest five firms ($k = 5$) on their upstream suppliers. These backward linkages (BL_t^{jk}) are calculated as the sum of the output of sector r purchased by firms in sector j , weighted by the share of sector j 's output produced by the largest five firms:

$$BL_t^{jk} = \sum_{r,j=1}^n (\alpha_{jrt} HL_t^{jk}); r, j = 1, \dots, n, k = 1, \dots, m \quad (4)$$

Here, α_{jrt} (where $0 \leq \alpha_{jrt} \leq 1$) represents the proportion of sector r 's output consumed by sector j . These direct input requirements are derived from the input-output tables of a specific country.

Finally, we consider forward linkages, where FL_t^{jk} is defined as the weighted share of output produced by the largest five firms ($k = 5$) in the sector:

$$FL_t^{jk} = \sum_{m,j}^n (\sigma_{jmt} HL_t^{jk}); m, j = 1, \dots, n, k = 1, \dots, m \quad (5)$$

Here, σ_{jmt} (where $0 \leq \sigma_{jmt} \leq 1$) represents the proportion of sector j 's output consumed by sector m , which is derived from the input-output tables of a specific country.

The linkage measures enter in logarithmic form so that their coefficients can be comparable with the logged dependent variable. The transformation also limits the influence of extreme values.

4.2. Productivity Shocks

Firstly, we examine supply-side shocks. Following the literature, productivity shocks are widely recognized as supply-side shocks, as they directly impact firms' ability to produce goods and services. These shocks propagate through input-output networks, primarily affecting downstream industries (Acemoglu et al., 2016a). Here, we use annual growth rate data on labour productivity from OECD Productivity Database.³ More specifically, labor productivity shocks are measured as changes in gross value added per hour worked by sectors (OECD Data Explorer, 2024), averaged across EU countries, capturing broad efficiency trends common to all manufacturing firms. Sector-level measurement ensures stable, comparable

³ Data is extracted from: OECD Data Explorer (2024). *Economy: Productivity – Productivity by industry*. Available from: <<https://data-explorer.oecd.org>>. Economic activity coverage in OECD database is provided in ISIC Rev. 4. The data is matched to firm-level data by primary NACE Rev. 2 code.

estimates across countries and years and is consistent with the production-network literature, including Carvalho (2014). Productivity growth is thus examined as the average of the EU27 countries and is defined as follows:

$$\Delta Productivity Growth_{EU,t} = \frac{Productivity_{EU,t} - Productivity_{EU,t-1}}{Productivity_{EU,t-1}} \quad (6)$$

To identify episodes of productivity shocks, we construct a dummy variable (*Supply* in the equations below) equal to 1 when productivity growth falls below industry's long run mean by more than one standard deviation and 0 otherwise. This ensures that the analysis focuses exclusively on adverse (negative) shocks. The dummy thus captures large negative deviations relative to the long-run industry average. This threshold-based identification strategy aligns with established empirical literature that treats large deviations from average behaviour as indicative of structural or exogenous shocks. Similar approaches are found in Bloom (2009), who defines uncertainty shocks using extreme movements in implied volatility and Jordà et al. (2016), who classify credit booms and crises based on deviations exceeding standard deviation thresholds over time. Network-based measures are then constructed by interacting natural logarithm of horizontal, forward and backwards linkages with the beforementioned dummy that denotes a supply-side shock (*Supply*):

$$Supply_t^{HL} = \ln HL_{it}^{jk} * Supply \quad (7)$$

$$Supply_t^{FL} = \ln FL_{it}^{jk} * Supply \quad (8)$$

$$Supply_t^{BL} = \ln BL_{it}^{jk} * Supply \quad (9)$$

Nonetheless, as in Acemoglu et al. (2016a), we remain cautious in claiming that our estimates capture causal effects of purely exogenous shocks on endogenous economic outcomes. Here, predetermined productivity shocks still seem to be informative about how these shocks spread through the input-output network.

4.3. Aggregate Demand Shocks

Building on the literature, fluctuations in imports – increases or decreases in import values – serve as demand-side shocks, influencing firms through shifts in foreign demand. Accordingly, Acemoglu et al. (2016a) identify import demand shocks from China as a primary channel for demand-side disruptions, affecting upstream suppliers through global value chains. Similarly, Bems et al. (2010) highlight that import contractions during recessions act as demand-side shocks, causing ripple effects throughout the global supply chain.

Therefore, we analyse demand-side shocks by focusing on changes in import dynamics. More precisely, we examine shifts in the import values of the top ten trading partners for each country from CEPII – BACI database.⁴ Importantly, import-related demand shocks are constructed as industry-specific deviations in import dynamics, capturing differences in industries' exposure to foreign competition and input supply conditions. These changes directly impact aggregate demand originating from abroad. Here, changes in aggregate demand for a specific country, denoted as c , are calculated by industries (i) as a year-over-year growth in the import value of the ten largest markets for country c .

$$\Delta \text{AggregateDemand}_{c,i,t} = \frac{\text{Import}_{c,i,t} - \text{Import}_{c,i,t-1}}{\text{Import}_{c,i,t-1}} \quad (10)$$

Following a similar approach as before, we define a dummy variable (denoted *Demand* in the equations below) that equals 1 when import growth falls more than one standard deviation below its industry's long run mean and 0 otherwise. Again, this design ensures that the analysis focuses exclusively on adverse shocks while capturing large negative deviations relative to the long-run industry average. Network-based measures are then constructed by interacting natural logarithm of horizontal, forward and backwards linkages with the beforementioned dummy that denotes a demand-side shock (*Demand*):

$$\text{Demand}_t^{HL} = \ln HL_{it}^{jk} * \text{Demand} \quad (11)$$

$$\text{Demand}_t^{FL} = \ln FL_{it}^{jk} * \text{Demand} \quad (12)$$

$$\text{Demand}_t^{BL} = \ln BL_{it}^{jk} * \text{Demand} \quad (13)$$

Due to the fact that this variable focuses on the aggregate and is then interacted with time- invariant and predetermined dependency of each industry on aggregate demand, it can be seen as exogenous to the productivity or other supply-side shocks that hit the industry in domestic market (Acemoglu et al., 2016a). Moreover, Berman et al. (2015) examine the interconnections between exports and domestic sales. They identify exogenous shocks that influence the firms' demand on foreign markets in order to examine annual exports variations and show that exogenous variations in foreign sales exhibit positive correlation with domestic sales. Autor et al. (2013) examine shifts in product demand affecting US local labor markets

⁴ Data is extracted from: CEPII (2024). *BACI*. Available from: <https://www.cepii.fr/CEPII/en/bdd_modelle/bdd_modelle_item.asp?id=37>. BACI is a comprehensive dataset that details bilateral trade flows for 200 countries at the product level. It is based on the Harmonized System (HS) nomenclature at the six-digit code level. The data is matched to firm-level data by primary NACE Rev. 2 code.

due to China's export growth. Therefore, as a robustness check for demand-side shocks, we also examine changes in export dynamics.

4.4. Empirical Model

To examine the impact of the largest firms on the performance of other firms, we analyse the largest five firms ($k = 5$) in the industry, ranked by their lagged sales. Using lagged sales ensures that large firms remain included in the sample of large firms, even if they experience a negative shock (Gabaix 2011; Konings et al. 2022). In all models presented below, all variables are expressed in natural logarithms, except for the dummy variables.

Firstly, we use fixed effects model to examine whether and how firm sales are influenced by supply-side and demand-side shocks, considering the role of firm linkages. The fixed effects model has the following form:

$$\begin{aligned} \ln Y_{it} = & \beta_1 + \beta_2 \ln Y_{i,t-1} + \beta_3 Shock_t + \beta_4 Shock_{t-1}^{HL} + \beta_5 Shock_{t-1}^{FL} \\ & + \beta_6 Shock_{t-1}^{BL} + \beta_7 \ln HL_{i,t-1}^{jk} + \beta_8 \ln FL_{i,t-1}^{jk} + \beta_9 \ln BL_{i,t-1}^{jk} + \beta_{10} \ln GVC_{t-1} Country + \\ & + \beta_{11} \ln FirmSize_{t-1} + \beta_{12} \ln Debt / Assets_{t-1} + \beta_{13} \gamma_{ic}^{jk} + \varepsilon_{it} \end{aligned} \quad (14)$$

Here (and also in the model (15) presented below), Y_{it} represents firm sales and ε_{it} is an error term. Period t correspond to years, i denotes firms and j depicts industry. $Shock_{t-1}^{HL}$, $Shock_{t-1}^{FL}$ and $Shock_{t-1}^{BL}$ represent lagged interaction terms between a supply-side or demand-side shock dummy and horizontal, forward and backward linkages, respectively. Regressors $\ln HL_{i,t-1}^{jk}$, $\ln FL_{i,t-1}^{jk}$ and $\ln BL_{i,t-1}^{jk}$ show, respectively, lagged horizontal, forward and backward linkages of the largest five firms in the industry. The variable $Shock$ refers to a binary indicator capturing either a supply-side or demand-side shock. Firm fixed effects are depicted in γ_{ic}^{jk} , while standard errors are clustered at the firm level. Controlling variables include GVC participation, firm size and financial leverage.⁵ Importantly, we take $k = 5$ for our main findings while we take $k = 3$ and $k = 10$ for the robustness checks.

Secondly, we examine cross-country and industry differences by regressing sales (using pooled OLS estimation) on various variables. The model has the following form:

⁵ The data on GVC participation comes from the Trade in Value Added (TiVA) 2025 edition, utilising principal indicators in shares. The latter are generated as the sum of foreign value added in gross exports and domestic value added embodied in foreign gross exports. Firm size is included in the number of employees and financial leverage is the ratio of total debt (short-term plus long-term) to total assets.

$$\begin{aligned}
\ln Y_{it} = & \beta_1 + \beta_2 \ln Y_{i,t-1} + \beta_3 Shock_t + \beta_4 Shock_{t-1}^{HL} + \beta_5 Shock_{t-1}^{FL} + \\
& + \beta_6 Shock_{t-1}^{BL} + \beta_7 \ln HL_{i,t-1}^{jk} + \beta_8 \ln FL_{i,t-1}^{jk} + \beta_9 \ln BL_{i,t-1}^{jk} + \beta_{10} Shock_t Country + \\
& + \beta_{11} Shock_{t-1}^{HL} Country + \beta_{12} Shock_{t-1}^{FL} Country + \beta_{13} Shock_{t-1}^{BL} Country + \\
& + \beta_{14} \ln HL_{i,t-1}^{jk} Country + \beta_{15} \ln BL_{i,t-1}^{jk} Country + \beta_{16} \ln FL_{i,t-1}^{jk} Country + \\
& + \beta_{17} \ln GVC_{i,t-1} Country + \beta_{18} \ln FirmSize_{i,t-1} + \beta_{19} \ln Debt / Assets_{i,t-1} + \varepsilon_{it} \quad (15)
\end{aligned}$$

Please refer to equation (14) for the notations used, noting that the following interaction variables have been added. Country interactions with network-measures are captured by variables $Shock_{t-1}^{HL} * Country$, $Shock_{t-1}^{FL} * Country$ and $Shock_{t-1}^{BL} * Country$. Also, country interactions with input-output linkages are depicted as $\ln HL_{i,t-1}^{jk} * Country$, $\ln FL_{i,t-1}^{jk} * Country$ and $\ln BL_{i,t-1}^{jk} * Country$. The interaction of shock dummy with countries is denoted as $Shock_t * Country$. We make two separate analyses. Firstly, we run regression (15) for all industries together to analyse cross-country differences and secondly, to examine industry differences, the regression is conducted for each industry separately. We use robust standard errors clustered at country level to ensure valid inference. Here, we again assume $k = 5$ for our main findings and assume $k = 3$ and $k = 10$ for the robustness estimations. Here, the controlling variables are again GVC participation, firm size and financial leverage as controlling variables.

Downstream effects arise from shocks to a sector's suppliers down the input-output chain, while upstream effects originate from shocks to its customers located up the chain. Both types of effects are constructed as weighted averages of shocks affecting all industries, using entries from the Leontief inverse matrix as weights. Following Acemoglu et al. (2016a), the following methodological considerations are worth noting. First, input-output linkages – and consequently the Leontief inverse weights – are predetermined and based on data from 2015. As a result, both downstream and upstream effects reflect shocks transmitted through a predetermined production network. Second, both own-sector and network-based shocks are lagged by one period to mitigate concerns regarding simultaneity and reverse causality, as well as to address potential joint determination with the dependent variables. Lastly, we acknowledge the presence of negative coefficients in our main regression specification. To address this concern, we estimate simplified regressions in which we isolate the effects of forward and backward linkages on sales.

4.5. Empirical Results

The next subsection begins with the interpretation of overall results, obtained by fixed effects model from equation (14). This is then followed by both industry

and cross-country analysis based on estimates from model (15). Finally, we conduct a series of robustness checks. Full results are available upon request. Importantly, we acknowledge that some coefficients on the shocks and their interactions are positive while others are negative. This reflects heterogeneous propagation of negative shocks through the network: a firm's exposure via horizontal, backward and forward linkages, as well as dynamic adjustments captured by lagged sales, determine the net effect. We focus on the magnitude of coefficients to highlight the strength of shock transmission, while their signs indicate the direction of network effects.

Overall Results

We begin our analysis with a fixed effects model from equation (14) to investigate how firm sales are influenced by supply-side and demand-side shocks, accounting for the role of firm linkages. The results show that the latter have sizable effects (see Table 3). We also evaluate the extent to which the empirical results align with theoretical predictions.

Table 3

Supply-Side and Demand-Side Shock in the Largest Five Firms, Fixed Effects Model

	Supply-side shock	Demand-side shock
Lagged sales	0.779*** (0.002)	0.781*** (0.002)
Shock	0.026*** (0.000)	-0.023*** (0.001)
Hor. spillover (Top-5)	0.026*** (0.002)	0.022*** (0.002)
Shock x Hor. spillover (Top-5)	0.004*** (0.001)	0.008*** (0.001)
Backw. spillover (Top-5)	-0.100*** (0.006)	-0.130*** (0.006)
Shock x Backw. spillover (Top-5)	0.002*** (0.000)	-0.023*** (0.001)
Forw. spillover (Top-5)	0.129*** (0.004)	0.114*** (0.004)
Shock x Forw. spillover (Top-5)	-0.006*** (0.001)	0.013*** (0.001)
Firm size	0.095*** (0.002)	0.095*** (0.002)
Debt/Assets	-24.454** (11.777)	-24.308** (11.792)
GVC participation	0.108*** (0.005)	0.011** (0.005)
Const.	1.114*** (0.105)	2.546*** (0.101)
Obs.	1,244,597	1,244,597
R ²	0.632	0.634
Number of unique IDs	118,941	118,941

Notes: Dependent variable: Natural logarithm of sales. Fixed effects estimations. Standard errors in the parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Largest firms are identified based on their lagged sales.

Source: Own work.

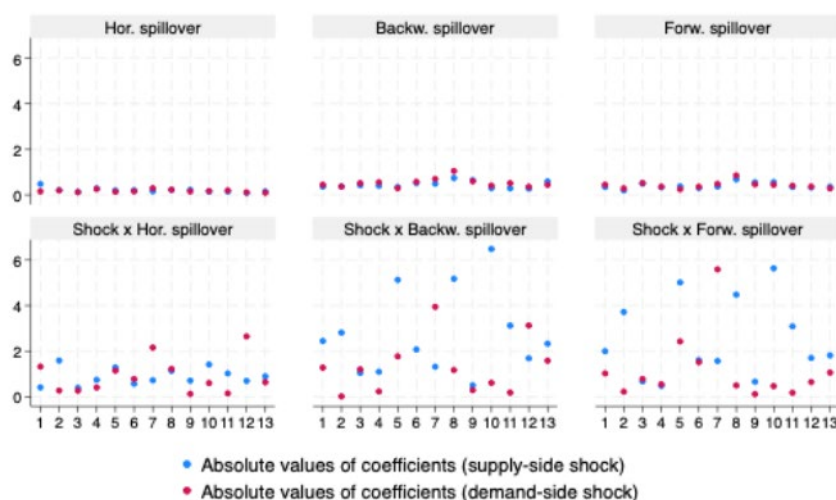
Accordingly, economic theory suggests that supply-side shocks – productivity shocks – tend to propagate more strongly downstream through forward linkages, whereas demand-side shocks – aggregate demand fluctuations – propagate more strongly upstream via backward linkages. The interaction coefficients between the shock dummy and linkage types reveal that backward linkages are more prominent during demand-side shocks, while forward linkages exert greater influence under supply-side shocks, confirming the theory. In both specifications, horizontal effects remain the least pronounced.

4.6. Industry Effects

Secondly, we estimate model (15), to further investigate the industry heterogeneity in shock transmission, focusing on both the interaction effects between shocks and interfirm linkages as well as the broader role these linkages play. Our analysis shows that the most significant effects on firm-level sales are observed in manufacturing firms operating in Machinery and equipment and Fabricated metal products. On the other hand, the industries with the lowest average absolute coefficient values are Electrical equipment and Other non-metallic mineral products, pinpointing a more limited role of interfirm linkages in shock transmission within these industries.

Figure 1

Absolute Values of the Coefficients for Both Shock Types across Industries



Note: 1-Basic metals, 2-Chemicals products, 3-Computer, transport, other, 4-Electrical equipment, 5-Fabricated metal products, 6-Food, beverages, tobacco, 7-Machinery and equipment, 8-Motor vehicles, 9-Other non-metallic mineral products, 10-Other transport equipment, 11-Paper, printing, 12-Pharmaceuticals, refined petroleum products, 13-Textiles, apparel, leather.

Source: ORBIS database.

Figure 1 presents the average absolute values of the estimated coefficients for both shocks across all industries. Backward and forward linkages exhibit larger impacts than horizontal linkages, whose effects are relatively modest. Transmission therefore operates along the vertical dimension of the production chain rather than within sectors, which is what the theoretical framework leads one to expect. Average absolute magnitudes are also larger for the interaction terms than for the linkage variables on their own, suggesting that network exposure matters when a shock materialises. Clearly, how a disturbance travels through the economy thus depends on the architecture of these linkages.

4.7. Country Effects

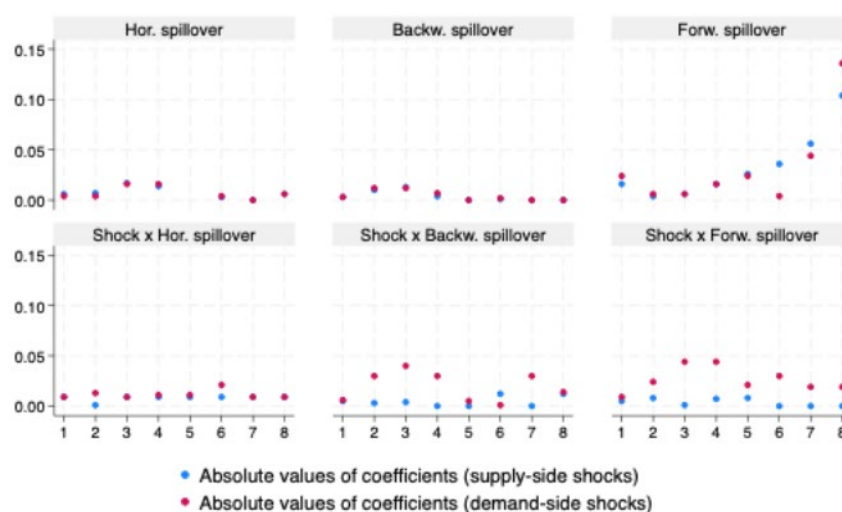
Additionally, we investigate cross-country heterogeneity in shock transmission by analysing coefficients $\beta_{11} - \beta_{16}$ from model (15). Results are presented in Table 6 in the Appendix. Figure 2 illustrates the absolute values of the coefficients for both demand- and supply-side shocks across all countries. On average, Sweden shows the largest absolute coefficient values. On the other hand, France displays the weakest effects. Notably, the coefficients for backward and horizontal linkages remain relatively stable across both shock types. In contrast, the interaction terms vary more substantially, highlighting that the impact of shocks is context-dependent and may intensify through certain linkages under specific conditions. From a cross-country perspective, there is little variation in the linkage coefficients themselves, which is mostly true for backward and horizontal linkages. To further explore the sources of cross-country heterogeneity, some explanations are provided below.

The regression results across selected countries reveal mostly shared patterns as well as some country-specific differences in the responsiveness of firm-level sales to shocks affecting large firms and the associated interfirm linkages. On average, countries with lower market concentration – economies dominated by small and medium-sized enterprises (SMEs) – exhibit larger absolute coefficient values. This pattern is particularly evident in Italy, Spain and Poland. As an example, Italy's pronounced propagation and linkages effects might reflect the presence of dense regional industrial clusters (OECD, 2024b), while Spain shows strong effects, driven by its extensive SME networks and regional economic hubs (Martinho et al., 2021). On the other hand, countries with higher market concentration – Slovenia, Hungary and Portugal – show lower average absolute coefficient values, exhibiting weaker shock transmission and interlinkage effects. France and Sweden emerge as outliers. For France, both interfirm linkages and shock transmission effects are relatively low even though the SMEs dominate the market which may be due to the relatively favourable environment for SMEs. The latter

is supported by several policy instruments that provide extensive assistance to SMEs and newly established firms as the support in France appears particularly comprehensive compared to other countries (OECD, 2025). For Sweden, the strong sensitivity to interfirm linkages along with weaker direct shock transmission might show firm-level resilience strategies, including diversified supply chains and inventory buffers (Videnord, 2025).

Figure 2

Absolute Values of the Coefficients for Both Shock Types across All Countries



Note: 1-France, 2-Hungary, 3-Italy, 4-Poland, 5-Portugal, 6-Slovenia, 7-Spain, 8-Sweden.

Source: ORBIS database.

4.8. Robustness Checks

As part of the robustness analysis, we vary the number of the largest firms within each industry, denoted by k . In addition to the baseline specification using the top five firms, we re-estimate model (14) employing the the largest three and ten firms (the results are provided in Table 4). Firstly, the re-estimation of the fixed effects models indicates that the core findings remain stable across different specifications. In particular, with respect to supply-side shocks, forward linkages exhibit generally stronger effects than backward linkages, which is consistent with both theoretical predictions and the empirical results presented earlier. In contrast, under demand-side shocks, backward linkages mostly continue to demonstrate greater influence than forward linkages. Furthermore, horizontal linkages persistently display weaker effects relative to both forward and backward linkages, corroborating previous findings and the broader literature. Our main results focus on

the top five firms, which are the most central and influential in each industry, while robustness examinations with the top three and top ten firms confirm that the findings are not sensitive to the exact number of firms included.

Table 4
Supply-Side and Demand-Side Shock across Different Specifications of Large Firms, Fixed Effects Model

	Supply-side shock (top 3)	Demand-side shock (top 3)	Supply-side shock (top 10)	Demand-side shock (top 10)
Lagged sales	0.779*** (0.002)	0.780*** (0.002)	0.780*** (0.002)	0.781*** (0.002)
Shock	0.027*** (0.000)	−0.023*** (0.001)	0.025*** (0.000)	−0.024*** (0.001)
Hor. spillover	0.025*** (0.002)	0.021*** (0.002)	0.032*** (0.002)	0.027*** (0.002)
Shock x Hor. spillover	0.003*** (0.001)	0.007*** (0.001)	0.005*** (0.001)	0.009*** (0.001)
Backw. spillover	−0.064*** (0.005)	−0.096*** (0.005)	−0.122*** (0.006)	−0.156*** (0.006)
Shock x Backw. spillover	0.003*** (0.000)	−0.022*** (0.001)	0.003*** (0.000)	−0.024*** (0.001)
Forw. spillover	0.127*** (0.003)	0.111*** (0.003)	0.117*** (0.005)	0.108*** (0.005)
Shock x Forw. spillover	−0.005*** (0.001)	0.012*** (0.001)	−0.008*** (0.001)	0.012*** (0.001)
Firm size	0.094*** (0.002)	0.094*** (0.002)	0.095*** (0.002)	0.095*** (0.002)
Debt/Assets	−24.495** (11.798)	−24.335** (11.811)	−24.394** (11.755)	−24.261** (11.771)
GVC participation	0.104*** (0.005)	0.011** (0.005)	0.112*** (0.005)	0.015*** (0.005)
Const.	0.468*** (0.094)	1.932*** (0.091)	1.702*** (0.113)	3.119*** (0.108)
Obs.	1,244,597	1,244,597	1,244,597	1,244,597
R ²	0.633	0.634	0.632	0.634
Number of unique IDs	118,941	118,941	118,941	118,941

Notes: Dependent variable: Natural logarithm of sales. Fixed effects estimations. Standard errors in the parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Largest firms are identified based on their lagged sales.

Source: Own work.

Finally, in addition to examining import dynamics, we extend our analysis to export dynamics in the context of demand-side shocks for the five largest firms. Here, we re-estimate fixed effects model. The results from the fixed effects model are presented in Table 5. The findings are consistent with previous analysis. Overall, the magnitude of the estimated effects and the number of statistically significant coefficients remain largely consistent.

Finally, we re-estimate the baseline specification with year fixed effects included (Table 7 in the Appendix). As the supply-side shock is constructed from EU27 aggregate labour productivity and takes a single value per year, it is collinear

with a full set of year dummies by construction; its coefficient is consequently not identified in this specification and the year effects in that column are themselves largely insignificant. In the demand-side model, by contrast, the year dummies are significant, which is consistent with the import-based shock varying across country-industry within a year and therefore leaving the year effects separately identified. Taken together, this test indicates that not including year effects in the baseline specification does not drive our central results. The coefficients are comparable in magnitude, while two horizontal coefficients lose significance. The baseline model can therefore be read as delivering reliable estimates of how shocks travel through network linkages. What the test also makes clear is that the uninteracted shock coefficient is not identified once year effects are included and we accordingly refrain from interpreting it as a clean estimate of the direct effect of a shock. To sum up, all the robustness tests strengthen the credibility of the empirical strategy.

Table 5
Robustness Check for Demand-Side Shock in the Largest Five Firms, Fixed Effects Model

	Demand-side shock
Lagged sales	0.781*** (0.002)
Shock	-0.017*** (0.001)
Hor. spillover (Top-5)	0.017*** (0.002)
Shock x Hor. spillover (Top-5)	0.000 (0.001)
Backw. spillover (Top-5)	-0.126*** (0.006)
Shock x Backw. spillover (Top-5)	-0.011*** (0.001)
Forw. spillover (Top-5)	0.130*** (0.004)
Shock x Forw. spillover (Top-5)	0.010*** (0.001)
Firm size	0.095*** (0.002)
Debt/Assets	-24.321** (11.777)
GVC participation	0.022*** (0.005)
Const.	2.163*** (0.102)
Obs.	1,244,597
R²	0.632
Number of unique IDs	118,941

Notes: Dependent variable: Natural logarithm of sales. Fixed effects estimations. Standard errors in the parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Largest firms are identified based on their lagged sales.

Source: Own work.

Conclusions

We show that idiosyncratic shocks propagate through input–output networks, amplifying their initial effects and influencing firm performance. Where an earlier literature treated such disturbances as averaging out in the aggregate, more recent contributions trace their diffusion along buyer-supplier relationships. Firstly, using fixed-effects model, we estimate direct and indirect effects, finding demand-side shocks mainly affect upstream firms, supply-side shocks downstream and indirect effects exceed direct ones which is aligned with theory that predicts demand-side shocks spread more strongly upstream, while supply-side shocks spread downstream. Secondly, our industry analysis reveals that firm linkages intensify during shocks, magnifying effects under shock conditions. The cross-country estimates, finally, point to stronger transmission in economies where SMEs dominate the market, which indicates that network structure governs the degree of amplification. Results are robust across specifications. Our results support a long-standing nonetheless often underemphasized insight of the invisible linkages among firms.

The structural importance of interdependence is hardly a new insight as it runs from Leontief's (1941) early accounting of flows through to von Neumann's (1945) classical formulation. What recent episodes have added is a vivid demonstration of how much these connections matter. During the GFC, for example, certain firms were treated as too interconnected to be allowed to fail, precisely because their collapse threatened systemic disruption (Acemoglu et al., 2010). The pandemic, in turn, laid bare how fragile global supply chains had become and pushed the resilience of production networks back onto the research and policy agenda (Cheema-Fox et al., 2021).

One can list several implications arising from this paper, as for policymakers, understanding shock transmission can enable more targeted crisis interventions rather than broad stimulus measures (Acemoglu et al., 2016b). Firms that map their own supply-chain vulnerabilities are better placed to design sourcing strategies and manage risk (Carvalho et al., 2021). Investors who account for interdependencies between firms should be able to anticipate sector-wide downturns and systemic exposures more accurately (Allen and Gale, 2000; Elliott et al., 2014). While our findings provide empirical support to the idea that key firms can have systemic importance – often used to justify subsidies, industrial strategies and bailouts (Baqaee, 2018) – there are opportunities for future research. For instance, as Acemoglu et al. (2016a) suggest, analyzing the geographic transmission of shocks could reveal important geographic dynamics. A further avenue is to extend the analysis to other network types, financial ones above all, where contagion across institutions and sectors remains incompletely understood (e.g., Allen and Gale, 2000; Elliott et al., 2014).

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Appendix

Table 6

Supply-Side and Demand-Side Shock in the Largest Five Firms at a Country Level

		Supply-side shocks in largest 5 firms	Demand-side shocks in largest 5 firms
	Lagged sales	0.987*** (0.001)	0.988*** (0.001)
Shock	ES	0.012*** (0.000)	−0.055*** (0.000)
	FR	0.016*** (0.000)	0.026*** (0.000)
	HU	0.006*** (0.000)	0.055*** (0.000)
	IT	0.022*** (0.000)	0.038*** (0.000)
	PL	0.018*** (0.000)	0.004*** (0.000)
	PT	0.002*** (0.000)	0.041*** (0.000)
	SE	0.033*** (0.000)	0.041*** (0.000)
	SI	0.028*** (0.000)	0.011*** (0.000)
Hor. spillover (Top-5)	ES	−0.003*** (0.001)	−0.003*** (0.001)
	FR	0.006*** (0.000)	0.004*** (0.000)
	HU	0.007*** (0.000)	0.004*** (0.000)
	IT	0.017*** (0.000)	0.016*** (0.000)
	PL	0.014*** (0.000)	0.016*** (0.000)
	PT	−0.001 (0.001)	0.001 (0.001)
	SE	0.006*** (0.000)	0.006*** (0.000)
	SI	0.003*** (0.000)	0.004*** (0.000)
Shock x Hor. spillover (Top-5)	ES	0.008*** (0.000)	0.009*** (0.000)
	FR	−0.008*** (0.000)	−0.002*** (0.000)
	HU	−0.010*** (0.000)	0.004*** (0.000)
	IT	−0.004*** (0.000)	−0.006*** (0.000)
	PL	−0.005*** (0.000)	−0.021*** (0.000)
	PT	−0.007*** (0.000)	−0.024*** (0.000)
	SE	−0.008*** (0.000)	−0.009*** (0.000)
	SI	−0.007*** (0.000)	−0.038*** (0.000)

Backw. spillover (Top-5)	ES	–0.002*** (0.000)	0.000*** (0.000)
	FR	0.003*** (0.000)	0.003*** (0.000)
	HU	0.010*** (0.000)	0.012*** (0.000)
	IT	0.013*** (0.000)	0.012*** (0.000)
	PL	0.004*** (0.000)	0.007*** (0.000)
	PT	–0.001** (0.000)	–0.003*** (0.000)
	SE	–0.009*** (0.000)	–0.009*** (0.000)
	SI	0.001*** (0.000)	0.002*** (0.000)
Shock x Backw. spillover (Top-5)	ES	–0.003*** (0.000)	–0.033*** (0.000)
	FR	0.005*** (0.000)	0.024*** (0.000)
	HU	0.003*** (0.000)	–0.010*** (0.000)
	IT	0.004*** (0.000)	–0.019*** (0.000)
	PL	–0.002*** (0.000)	–0.001*** (0.000)
	PT	–0.000*** (0.000)	0.025*** (0.000)
	SE	0.012*** (0.000)	0.016*** (0.000)
	SI	0.011*** (0.000)	0.032*** (0.000)
Forw. spillover (Top-5)	ES	0.056*** (0.001)	0.044*** (0.001)
	FR	–0.043*** (0.001)	–0.020*** (0.001)
	HU	–0.060*** (0.001)	–0.051*** (0.001)
	IT	–0.055*** (0.001)	–0.050*** (0.001)
	PL	–0.045*** (0.001)	–0.063*** (0.001)
	PT	–0.031*** (0.002)	–0.024*** (0.002)
	SE	–0.164*** (0.001)	–0.186*** (0.001)
	SI	–0.025*** (0.000)	–0.048*** (0.000)
Shock x Forw. spillover (Top-5)	ES	–0.006*** (0.000)	0.019*** (0.000)
	FR	0.005*** (0.000)	–0.017*** (0.000)
	HU	0.008*** (0.000)	0.005*** (0.000)
	IT	0.001*** (0.000)	0.025*** (0.000)
	PL	0.007*** (0.000)	0.025*** (0.000)
	PT	0.008*** (0.000)	0.002*** (0.000)
	SE	–0.001*** (0.000)	–0.003*** (0.000)
	SI	–0.003*** (0.000)	0.011*** (0.000)

Country	FR	0.977*** (0.038)	0.261*** (0.041)
	HU	1.333*** (0.010)	0.769*** (0.009)
	IT	1.018*** (0.013)	0.876*** (0.012)
	PL	0.888*** (0.008)	0.871*** (0.010)
	PT	1.229*** (0.012)	0.637*** (0.014)
	SE	4.819*** (0.010)	4.890*** (0.011)
	SI	0.844*** (0.004)	0.832*** (0.005)
	Constant	-1.489*** (0.002)	-0.823*** (0.004)
GVC participation	ES	0.118*** (0.002)	0.000 (0.002)
	FR	-0.052*** (0.001)	0.016*** (0.002)
	HU	-0.086*** (0.002)	0.014*** (0.002)
	IT	-0.109*** (0.001)	-0.088*** (0.001)
	PL	-0.063*** (0.002)	0.025*** (0.002)
	PT	-0.119*** (0.002)	-0.008*** (0.002)
	SE	-0.283*** (0.001)	-0.170*** (0.002)
	SI	-0.072*** (0.002)	0.039*** (0.002)
Firm size		0.022*** (0.002)	0.022*** (0.002)
Debt-Assets		-20.825** (6.853)	-20.677** (6.619)
Observations		1,244,597	1,244,597
R-squared		0.984	0.984

Notes: Dependent variable: Natural logarithm of sales. Pooled OLS estimations. Standard errors in the parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1. Largest firms are identified based on their lagged sales.

Source: Own work.

Table 7

Supply-Side and Demand-Side Shock in the Largest Five Firms with Year Fixed Effects

	Supply-side shock	Demand-side shock
Lagged sales	0.780*** (0.002)	0.780*** (0.002)
Shock	–0.063 (0.079)	–0.008*** (0.001)
Hor. spillover (Top-5)	0.000 (0.002)	0.006*** (0.002)
Shock x Hor. spillover (Top-5)	0.003*** (0.001)	0.001 (0.001)
Backw. spillover (Top-5)	–0.159*** (0.006)	–0.154*** (0.006)
Shock x Backw. spillover (Top-5)	0.003*** (0.000)	–0.017*** (0.001)
Forw. spillover (Top-5)	0.032*** (0.005)	0.034*** (0.005)
Shock x Forw. spillover (Top-5)	–0.005*** (0.001)	0.014*** (0.001)
Firm size	0.094*** (0.002)	0.094*** (0.002)
Debt/Assets	–24.031** (11.755)	–24.040** (11.778)
GVC participation	0.319*** (0.014)	0.330*** (0.014)
Const.	–0.104 (0.081)	–0.042*** (0.001)
2009	–0.085 (0.079)	–0.005** (0.002)
2010	0.011*** (0.001)	0.012*** (0.001)
2011	–0.092 (0.081)	–0.032*** (0.001)
2012	–0.100 (0.079)	–0.031*** (0.001)
2013	–0.066 (0.079)	–0.003*** (0.001)
2014	–0.049 (0.079)	0.016*** (0.001)
2015	0.025*** (0.001)	0.029*** (0.001)
2016	–0.014 (0.081)	0.044*** (0.001)
2017	–0.033 (0.079)	0.029*** (0.001)
2018	–0.078 (0.079)	–0.015*** (0.002)
2019	4.452*** (0.172)	4.060*** (0.154)
Obs.	1,244,597	1,244,597
R ²	0.637	0.637
Number of unique IDs	118,941	118,941

Notes: Dependent variable: Natural logarithm of sales. Fixed effects estimations. Standard errors in the parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Largest firms are identified based on their lagged sales.

Source: Own work.