Intersectoral Network-Based Channel of Aggregate TFP Shocks

Working Paper Series

Kristina Barauskaite

(Bank of Lithuania, ISM University of Management and Economics)[†]

Anh D.M. Nguyen

(Bank of Lithuania, Vilnius University)[‡]

June 2019[§]

[†] Barauskaite: Economics Department, Bank of Lithuania and ISM University of Management and Economics. Email: KGriskeviciene@lb.lt or barauskaitekristina@gmail.com.

[‡] Nguyen: Economics Department, Bank of Lithuania and Faculty of Economics and Business Administration, Vilnius University. Email: anguyen@lb.lt.

ABSTRACT

This study investigates the role of intersectoral networks in the transmission of aggregate technology shocks to sectors' growth. First, we develop a theoretical model to obtain insights into the propagation of shocks through input-output linkages, which suggests that the network effect arises via sectoral downstream linkages. We then quantitatively assess this theoretical implication with US manufacturing industries, where the aggregate technology shocks are derived from a dynamic factor model. We find that aggregate technology shocks lead to an increase in the output growth of the sector, both directly and indirectly via its intersectoral linkages. More interestingly, we document a crucial role of the intersectoral network channel, which contributes about 50 percent of the total effect. In addition, the network-based effect comes mostly from downstream linkages of sectors, which is broadly consistent with theory.

1   Introduction

A burgeoning literature has shown that network linkages are important for aggregate fluctuations as well as for the transmissions of shocks to economic activities. For instance, Acemoglu et al. (2012) argue that idiosyncratic shocks to a single firm could cause large effects on the macroeconomic level, i.e. reducing not only the output of this firm, but also of others that are linked to it through input-output linkages. Acemoglu, Akcigit and Kerr (2016) investigate the short-run propagation of demand-type and supply-type micro shocks and find that the network-based effect is larger than the direct effect of the shocks. While the literature on the aggregate effects of idiosyncratic shocks has been flourishing, the role of networks in propagating aggregate shocks remains a generally understudied area. An exception is Ozdagli and Weber (2017), who quantify the importance of network effects in response to monetary policy shocks, which are interpreted as aggregate *demand* shocks. The authors use spatial autoregressions to break down the overall effect into direct and network (indirect) effects and find that the latter contributes $50\% - 85\%$ of the total effect. Little is known, however, about whether networks also play a role in propagating aggregate technology shocks, an important type of aggregate *supply* shock in the macroeconomic literature. Shedding light on this issue is a key contribution of our article.

First, we develop a theoretical model to obtain insights into the propagation of aggregate technology shocks through input-output linkages. Our theoretical model, built on that of Long and Plosser (1983) and Acemoglu, Akcigit and Kerr (2016), features a perfectly competitive economy with n sectors/industries and a representative household. The production function of each sector is modeled by a Cobb-Douglas specification. Unlike those studies, however, in our study, productivity is assumed to be driven by both common (or aggregate)

and idiosyncratic factors, the former of which is our interest. Each sector chooses labor and inputs from other industries to maximize its profit. Meanwhile, the representative household makes decisions on consumption and labor supply to maximize her utility. We then show the role of the network as a channel in transmitting the effects of aggregate TFP shocks to the economy. Specifically, the theoretical model suggests that the shocks propagate downstream the network. Such a result is somewhat expected because Acemoglu, Akcigit and Kerr (2016) find a similar pattern for industry-level TFP shocks. Nevertheless, changes in industry-level TFP can be caused by aggregate or/and idiosyncratic TFP shocks. We supplement Acemoglu, Akcigit and Kerr (2016) by analyzing the role of networks in the propagation and transmission of aggregate TFP shocks.

Based on the theoretical model, we develop our empirical counterpart and estimate with US input-output tables and industry-level data of 385 industries. There are two main empirical issues. First, the analysis requires a measure of aggregate TFP shocks. To obtain such a measure, we utilize a prevailing assumption that aggregate TFP shocks are the common factor affecting across sectoral TFPs. Then, we apply a dynamic factor model to extract this common factor from a sectoral TFP series (Stock and Watson, 2012). The other issue is to measure the intersectoral network effects, for which we apply the approach of Acemoglu, Akcigit and Kerr (2016). Briefly, we use US make-use input-output tables to evaluate the downstream (i.e. seller to buyer), and upstream (i.e. buyer to seller) effects of the shocks. Consequently, our approach allows us to decompose the overall impact of aggregate technology shocks into direct and higher-order network effects.

We find that aggregate technology shocks have a positive impact on sectors' output growth, i.e. real value added growth, both directly and indirectly via the network, in which

the latter contributes about 50 percent of the total effect. Furthermore, we show that the network effect arises mostly via downstream linkages, as predicted by the theoretical model. These findings are robust across a variety of modelling schemes, i.e. using instrument variables, controlling for fixed effects, and taking idiosyncratic TFP shocks into account. We also obtain similar results when evaluating the impacts on employment. These findings indicate that the intersectoral network is an important propagating channel for aggregate technology shocks throughout the economy.

The article is structured as follows. Section 2 presents the related literature. Section 3 presents the theoretical model, followed by a discussion on the empirical model and the construction of aggregate TFP shocks in Section 4. In Section 5, we describe the data and the construction of upstream and downstream network channels. Section 6 presents results. Finally, Section 7 concludes.

2   Related literature

Recent research has examined the importance of network linkages in economic outcomes.[1] Notably, Acemoglu et al. (2012) argue that microeconomic idiosyncratic shocks can lead to aggregate fluctuations in the presence of intersectoral input–output linkages, therefore questioning the famous diversification argument of Lucas (1977) that microeconomic shocks would average out and are less likely to have a significant impact on aggregate variables.[2] This result is further supported by Carvalho et al. (2014), Atalay (2017), Baqaee (2018), and Caliendo et al. (2018). Relatedly, di Giovanni et al. (2014) examine the role of individual

---

[1]For instance, Allen and Gale (2000), Gai and Kapadia (2010), Elliott et al. (2014) and Acemoglu et al. (2015), among many others, investigate financial contagion via network linkages. Meanwhile, Kali and Reyes (2010), Chaney (2014), Johnson (2014) and Reyes et al. (2014) utilize the structure of international trade networks to explain certain features of trade and economic activities.

[2]Gabaix (2011) also shows that if the distribution of firm sizes is fat-tailed then the diversification argument breaks down.

firms in international business-cycle comovement and demonstrate that direct linkages on comovement at the micro level has significant macro implications. Oberfield (2018) provides a theoretical foundation for production network linkages.

Our work particularly relates to studies that explore the role of production networks in the transmission of shocks to economic activities. In this branch of research, Acemoglu, Akcigit and Kerr (2016) investigate the short-run propagation of four different types of industry-level shocks, i.e two demand-side shocks and two supply-side ones, and find that network-based propagation is larger than the direct effect of the shocks. Carvalho et al. (2016), Barrot and Sauvagnat (2016), and Boehm et al. (Forthcoming) consider the role of input-output linkages as a mechanism for the propagation and amplification of exogenous shocks caused by natural disasters, i.e. the Great East Japan Earthquake. Our work is mostly related to Ozdagli and Weber (2017), who build on Acemoglu, Akcigit and Kerr (2016) to explore the role played by network effects in response to monetary policy shocks, interpreted as aggregate demand shocks. Specifically, Ozdagli and Weber (2017) use spatial autoregressions to decompose the overall effect of monetary policy shocks into a direct (demand) effect and a network effect and find that the latter contributes $50\% - 85\%$ of the overall effects. None of these studies, however, asks whether the intersectoral connection is also an important propagation mechanism of aggregate technology shocks.

This study is connected to the literature on the role of productivity on firms' growth. For instance, Jovanovic (1982) and Hopenhayn (1992) consider productivity shocks as the driver of firm's performance and growth. Pozzi and Schivardi (2016) argue that TFP shocks have a negligible impact on inputs (number of hours worked, capital used in production and intermediates). A comprehensive review of this matter is provided by Syverson (2011). The

role of networks as a transmission channel of TFP shocks, however, has not been analyzed in these studies.

Furthermore, our work is related to the literature on the impacts of aggregate technology shocks on the economy. Several transmission channels have been documented in the literature on labor, investment and capital accumulation responses, real and nominal rigidities, and financial frictions. In this respect, see, for instance, Kydland and Prescott (1982), Gali (1999), Bernanke et al. (1999), Smets and Wouters (2007), and Christensen and Dib (2008). Our paper provides novel empirical evidence that supports the potential role of network linkages as a transmission mechanism of aggregate technology shocks on the economy.

Last but not least, our work associates with the literature that stresses the importance of the aggregate shocks. To start with, Norrbin and Schlagenhauf (1991) show that both aggregate and sectoral factors are important for explaining variations in output, with aggregate factors playing the more important role. Meanwhile, Karadimitropoulou and León-Ledesma (2013) and Beck et al. (2016) emphasize the role of country and region-specific factors in explaining aggregate fluctuations rather than sectoral-specific factors. Garin et al. (2018) document a fall in the contribution of aggregate shocks to the variance of aggregate output; nevertheless, this type of shock still plays a non-trivial role, explaining about 30 percent of aggregate fluctuations in the post-1983 period. Meanwhile, using factor methods, Foerster et al. (2011) find that industrial production variability is mostly associated with common factors, and that the post-1983 decline in aggregate volatility is associated with a decline in the variability of common factors. Although the role of sector-specific shocks increased in the post-1983 period, aggregate shocks still explain more than 50 percent of the variability of industrial production. This implies that independent sectoral factors themselves are

not capable of fully explaining aggregate fluctuations. Consequently, it remains important to analyze the effects of common aggregate shocks as well as the associated transmission mechanisms.

3   The theoretical model

In this section, we develop a theoretical model to show how aggregate technology shocks propagate through input-output linkages to economic activities.[3] This model builds on Long and Plosser (1983) and is also closely related to Acemoglu et al. (2012), Acemoglu, Akcigit and Kerr (2016), and Ozdagli and Weber (2017).

The model features the economy as perfectly competitive with n industries and a representative household. The production function of each industry follows a Cobb-Douglas specification, as in (1), whose productivity shock is assumed to be driven by both common and idiosyncratic shocks:

$$y_i = e^{(\zeta_i z + v_i)} l_i^{\alpha_i^l} \prod_{j=1}^{n} x_{ij}^{a_{ij}}, \tag{1}$$

where y_i is the output of industry i, l_i is labor input, α_i^l is a share of labor, x_{ij} presents the amount of good j used in the production of good i and a_{ij} is the share of goods of industry j needed in the production of i goods. In addition, z is the common component among the sectoral TFP with a factor loading of ζ_i and v_i is an idiosyncratic component. The notation i in the factor loading ζ_i implies that the impact of the common component on the sectoral TFP is allowed to be heterogeneous, e.g. some sectors are more influenced by the common TFP component than others.

The industry i chooses labor and inputs from other industries to maximize its profit as

---

[3]In the Online Appendix A, we present the detailed theoretical model.

follows:

$$\Pi = p_i y_i - w l_i - \sum_{j=1}^{n} p_j x_{ij}$$

$$s.t. \qquad y_i = e^{(\zeta_i z + v_i)} l_i^{\alpha_i^l} \prod_{j=1}^{n} x_{ij}^{a_{ij}},$$

where w stands for wage of labor (the wages are chosen as the numeraire, set $w{=}1$) and p_i for the price of good i.

Meanwhile, the representative household makes decisions on consumption and labor supply to maximize her utility based on preferences and budget constraint:

$$U = \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i}$$

$$s.t. \qquad \sum_{i=1}^{n} p_i c_i = wl,$$

where $\gamma(l)$ captures the disutility of labor supply, which is a decreasing function, and β_i shows the share of good c_i in the household preferences such as $\sum_{i=1}^{n} \beta_i = 1$.

Based on the optimization of firms and household, the change in (the log of) consumption good c_i, denoted by $d(lnc_i)$, by an aggregate TFP shock z is described by:

$$d(\ln c_i) = \zeta_i dz + \sum_{j=1}^{n} a_{ij}(d(\ln c_j)).$$

Define $\mathbf{d}\ln\mathbf{c} = [d(\ln c_1), \dots, d(\ln c_n)]'$ and $\boldsymbol{\zeta}\mathbf{dz} = [\zeta_1, \dots, \zeta_n]' dz$, we obtain:

$$\mathbf{d}\ln\mathbf{c} = \boldsymbol{\zeta}\mathbf{dz} + \mathbf{A}\mathbf{d}\ln\mathbf{c},$$

where $\mathbf{A}$ is matrix of a_{ij}'s. Combining with the market clearing condition, $y_i = c_i + \sum_{j=1}^{n} x_{ji}$, we derive:

$$\mathbf{d}\ln\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}\boldsymbol{\zeta}\mathbf{dz}, \tag{2}$$

where $L = (\mathbf{I} - \mathbf{A})^{-1}$, which is also known as the "Leontief inverse of the input-output matrix" A. Based on (2), the impact of an aggregate technology shock on the output of sector i is

described by:

$$d(\ln y_i) = \zeta_i dz + \sum_{j=1}^{n} (l_{ij} - 1)\zeta_j dz, \qquad (3)$$

where the l_{ij}'s are elements from the L matrix. In the following section, we explain in detail the Leontief matrix L and its components.

This final equation shows that the output of sector i $(d \ln y_i)$ is affected by the aggregate shock z via two channels: i) directly, as presented by $\zeta_i dz$, and ii) through the intermediate production network, as presented by $\sum_{j=1}^{n} (l_{ij} - 1)\zeta_j dz$, which captures the effects via sectors $j's$ that provide inputs for sector i's production. This implies that aggregate technology shocks propagate downstream the network.

4 The empirical model

4.1 The general framework

Based on the theoretical model in (3), we propose the empirical counterpart as follows:

$$\Delta \ln Y_{i,t} = \delta_t + \iota \Delta \ln Y_{i,t-1} \mathbf{I} + \sum_{j=p}^{q} \beta_j^o Own_{i,t-j} + \sum_{k=p}^{q} \beta_k^d Down_{i,t-k} + \sum_{m=p}^{q} \beta_m^u Up_{i,t-m} + \varepsilon_{i,t}, \quad (4)$$

where δ_t captures the time effect (with the annual frequency), $\varepsilon_{i,t}$ is the error term, and $0 \leq p \leq q \leq 1$ capture the time structure of the effects, e.g. only contemporaneous $(p = q = 0)$, only lagged $(p = q = 1)$ as in Acemoglu, Akcigit and Kerr (2016), and both contemporaneous and lagged effects $(p = 0$ and $q = 1)$. $Y_{i,t}$ represents a measure of activity of the industry i. In our baseline model, real value added (RVADD) is used as a measure of $Y_{i,t}$, and we also conduct robustness checks with employment.[4] The indicator $\mathbf{I}$ is equal to 1 in the model that takes into account the lag of the dependent variable; for instance, to capture the possibility of persistent changes in $Y_{i,t}$, and 0 otherwise.

---

[4]The real value added is calculated by dividing the (nominal) value added data by the corresponding industry's shipments deflator.

As shown in (4), three important regressors are $Own_{i,t}$, $Down_{i,t}$, and $Up_{i,t}$. The first regressor, $Own_{i,t}$, denotes the own effect of the aggregate TFP changes to the TFP of sector i, imitating $\zeta_i dz$ in the theoretical section. Meanwhile, $Down_{i,t}$ and $Up_{i,t}$ capture downstream and upstream effects, respectively. Specifically, the downstream effect $Down_{i,t}$ implies the *indirect* effects of aggregate shocks to industry i via its suppliers that flow down the input-output chain, closely mimicking the term $\sum_{j=1}^{n}(l_{ij}-1)Own_j$ in (3). In order to measure the downstream effect for sector i, we first construct a Leontief inverse matrix $\mathbf{L}$, as will be discussed in Section 5.2, and then multiply it with the own direct effects across all sectors in the following way:

$$Down_{i,t} = \sum_j (l_{ij} - 1_{j=i})Own_{j,t}. \tag{5}$$

where l_{ij} is the *ij-th* element of $\mathbf{L}$. Note that the summation for downstream connections is over all sectors in the economy, including connections within the sector i itself ($j = i$). Because the own effect to industry i is directly controlled $Own_{i,t}$, to avoid double counting we subtract $1_{j=i}$, which represents an indicator function for $j = i$.

Although the theoretical model suggests that aggregate TFP shocks, a type of supply-side shock, would spread downstream the input-output network, it is interesting to investigate the upstream effect of this type of shock from the data's point of view and then justify the intuition from the theoretical model. To do so, we construct the upstream effect $Up_{i,t}$ to capture the indirect effects of aggregate shocks to industry i via its customers that flow up the input-output chain, as presented below:

$$Up_{i,t} = \sum_j (t_{ji} - 1_{j=i})Own_{j,t}, \tag{6}$$

where t_{ji} is the *ji-th* element of T which is the upstream linkages, as will be discussed in Section 5.2. As in the case of the downstream effect, to avoid double counting we subtract

$1_{j=i}$, which represents an indicator function for $j = i$.

The empirical procedure includes three main steps. In the first step, we estimate the effects of aggregate TFP changes to the TFP of each industry ($Own_{i,t}$). Second, we construct downstream and upstream network linkages, denoted by L and T in (5) and (6), respectively. From the first two steps, it is straightforward to obtain the downstream ($Down_{i,t}$) and upstream ($Up_{i,t}$) effects of aggregate TFP shocks to the suppliers and customers of an industry. Finally, we estimate (4) to obtain both direct and indirect effects of the shocks to sectors' growth on average.

4.2   The aggregate TFP shocks

Following the intuition from the theoretical model as well as its empirical counterpart, in the first step we quantify the impacts of aggregate TFP shocks in driving the sectoral TFPs, i.e. $Own_{i,t}$. To do so, we use a dynamic factor model:[5,6]

$$x_{it} = \zeta_{it}x_t + u_{it}, \tag{7}$$

where x_t is the common factor, imitating the aggregate TFP shock with ζ_{it} being the factor loading to the TFP of sector i, and u_{it} is the unobserved idiosyncratic components. Hence, the product $\zeta_{it}x_t$ captures the effect of the aggregate TFP shock to the TFP of sector i, which is denoted by $Own_{i,t}$ in the general framework. We consider a single common factor, which is also supported by Bai and Ng (2002)'s criteria, as discussed in the Online Appendix

---

[5]See Stock and Watson (2012) for a review of the dynamic factor model. Kose et al. (2003), Del Negro and Otrok (2008), and Mumtaz et al. (2011) also use this type of model to investigate the common dynamic properties of business-cycle fluctuations across countries.

[6]An alternative approach is to use country-level TFP variation as a proxy for x_t. However, by using a dynamic factor model, we can utilize the assumption of orthogonal shocks to better distinguish between the aggregate and idiosyncratic shocks.

B. The unobserved common factor is assumed to follow an $AR(1)$ process:

$$x_t = \beta_0 + \beta_1 x_{t-1} + \sigma^{1/2}\epsilon_t, \quad \epsilon_t \sim N(0,1). \tag{8}$$

Meanwhile, the idiosyncratic component u_{it} is independent across i and is assumed to follow an autoregressive process:

$$u_{it} = d_i u_{it-1} + \sigma_i^{1/2} e_{it}, \quad e_{it} \sim N(0,1). \tag{9}$$

As mentioned in the related literature, some studies document the changing role of common factors. To take this feature into account, the factor loading on the common factor, ζ_{it}, is allowed to be time-varying, based on a random walk process as follows:

$$\zeta_{it} = \zeta_{it-1} + q_i^{1/2}\tau_{it}, \quad \tau_{it} \sim N(0,1). \tag{10}$$

The combination of (7)-(10) results in a state-space model in which the observed variables are x_{it} for $i = 1,..N$ and the set of unobserved variables, i.e. state variables, includes x_t and ζ_{it} with $i = 1,..N$. The states' innovations τ_{it} and e_{it} are assumed to be uncorrelated with one another.

It is well-known that the dynamic factor model is subject to scale and sign identification problems. First, the scaling issue means that when we multiply the factor loading $\zeta_{i,t}$ by λ and divide the factor x_t by λ, we obtain an equivalent model. To avoid this issue, we set the variance of ϵ_t, i.e. σ, to a fixed value (Kose et al., 2003). Second, we cannot identify the sign of the factors and factor loadings separately, i.e. the likelihood is the same if x_t and ζ_{it}, for all i, are multiplied by -1. However, this is not a problem in our application because we use the first principal component of the data to initialize the factor in the estimation procedure with the Gibbs sampling method, as presented below (Del Negro and Otrok, 2008). Moreover, the

model only requires the product of the factor and its loadings, so the sign identification is not problematic in our application.

The product of state variables in the measurement equation (7) makes it non-linear. To handle this non-linearity, we follow Kose et al. (2003) and Mumtaz and Surico (2012) in utilizing the Gibbs sampling algorithm to approximate the marginal posterior distribution for the parameters and states.

Before making draws with the Gibbs procedure, we set the priors for parameters and starting values for the states, which are both included in $\Psi = (q_i, \beta^x, \sigma, x_t, d_i, \zeta_{it}, \sigma_i)$, where $\beta^x = [\beta_0, \beta_1]'$. To set prior for q_i, we use the standardized first principal component estimate of the sectoral TFPs changes as a proxy for $\hat{x}_t$ and estimate $x_{it} = \zeta_i \hat{x}_t + u_{it}$ by OLS and obtain $var(\zeta_i)$. We then set the prior for q_i as $IG(q_{0,i}, t_0)$ where $q_{0,i} = var(\zeta_i)$ and $t_0 = 2$. For the parameters relating to the dynamics of common factor x_t, we assume that β^x has a normal distribution with a mean $\beta^x = [0, 0.5]'$ and $V^x = I_2$. As mentioned above, the variance of ϵ_t is fixed to the value that is the variance of ϵ_t from the OLS regression of $\hat{x}_t = \beta_0 + \beta_1 \hat{x}_{t-1} + \sigma^{1/2}\epsilon_t$. In addition, the initial condition for x_t is set to the initial values of the principal component $\hat{x}_t$.

Regarding the dynamics of the idiosyncratic components u_{it}, d_i is assumed to have a normal distribution with a mean $d_i = \hat{d}_i^{OLS}$ and $V^d = 1$, where $\hat{d}_i^{OLS}$ is the OLS estimate of (9) using the residuals from the OLS regressions of $x_{it} = \zeta_i \hat{x}_t + u_{it}$. For the variance of idiosyncratic shock σ_i, we use an inverse-gamma distribution with scale parameter $k = 0.05$ and degrees of freedom $D = 5$.

We apply the Gibbs sampling algorithm to draw from the conditional posterior distributions, using 22000 iterations, but discard the first 2000 iterations as burn-in. The steps for

the Gibbs sampling are as follows:

1. $H(\beta^x | \Psi^{-1})$: Here Ψ^{-1} denotes all remaining parameters. Given a draw for x_t and a fixed variance σ, the conditional posterior for β^x is normal and can be drawn easily.

2. $H(d_i | \Psi^{-1})$: Given u_{it} and σ_i, the conditional posterior for d_i is normal and can be drawn easily.

3. $H(q_i | \Psi^{-1})$: Given a draw for ζ_{it}, the conditional posterior for q_i is an inverse-gamma and can be drawn straightforwardly.

4. $H(\zeta_{it} | \Psi^{-1})$: Given a draw for q_i, the factor x_t, the variance σ_i, and the AR(1) coefficient d_i, the measurement equation (7) is a sequence of time-varying parameter linear regressions with serial correlation. We use a GLS transformation to eliminate serial correlation, the model can be cast in a state-space form and the factor loadings can be easily drawn based on the Carter and Kohn (1994) algorithm.

5. $H(\sigma_i | \Psi^{-1})$: Given a draw of x_t and ζ_{it}, the residuals from (7) are obtained. Combined with a draw for d_i, we can draw σ_i from a posterior inverse gamma distribution.

6. $H(x_t | \Psi^{-1})$: Given the remaining parameters, the model can be written in a multivariate state-space representation, from which we draw x_t.

5 Data and network calculations

5.1 Data description

Data is used from several sources. First, annual TFP, value added, total sectoral shipments deflator, and employment data are from the joint National Bureau of Economic Research

(NBER) and U.S. Census Bureau's Center for Economic Studies (CES) Manufacturing Industry Database. This database covers the period from 1958 to 2011 for four-digit 1987 SIC industries. Second, data for the construction of intermediate production linkages is taken from the Bureau of Economic Analysis (BEA) Input-Output Database. Following Acemoglu, Autor, Dorn, Hanson and Price (2016), we use the 1992 database by combining "Make" and "Use" tables, as described in Section 5.2 below.

It is important to mention that the industry codes under the I-O database differ from those under the NBER-CES database. I-O data codes are comprised of six digits and the NBER-CES database provides industries under four-digit 1987 SIC codes. BEA provides the crosswalks tables for industry codes. However, some codes in the I-O database belong to 2 or more different industries under 1987 SIC codes. We follow Acemoglu, Autor, Dorn, Hanson and Price (2016) for converting I-O database codes into four-digit 1987 SIC industries while constructing downstream and upstream network channels. In short, we include 385 four-digit industries, following data availability.

5.2   Construction of upstream and downstream network channels

To identify the network channels and separate them from the direct effect of the shock, we need to construct upstream and downstream intermediate production linkages. First, we use the make-use I-O Tables available from the BEA. The "Use" table (U) is a matrix that represents how much each commodity is being used by industries and final consumers. This matrix is presented as a commodities-industries relation. The "Make" table (M) is a matrix that represents the value of each commodity produced by each industry. This matrix carries the dimension of the industries-by-commodities. Neither the "Make" nor the "Use" table is necessarily square since they are presented in different dimensions, implying that the same

commodity can be made and used in more than one industry.

In order to construct the downstream channel, we first get the direct requirements matrix, **A** by combining the "Make" and "Use" tables. The direct requirements matrix is filled with technical coefficients a_{ij}'s that shows the ratio between the sales of j sector to i sector and the total sales of i sector as follows:

$$a_{ij} = \frac{Sales_{j \longrightarrow i}}{TotalSales_i}. \tag{11}$$

These technical coefficients, so called input shares, present how supply side shock spreads directly to the downstream sectors. In other words, technical coefficients present in-degrees of the sectors as presented in Fig. 1.
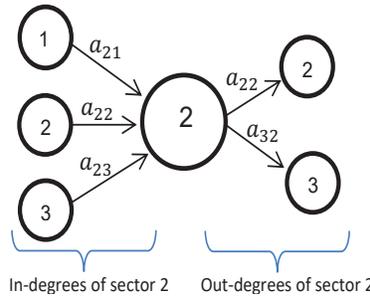
Figure 1 – In-degrees (input shares) example

In order to capture the full downstream effect, we calculate the Leontief inverse matrix $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$, where each component l_{ij} of L represents the total downstream channels, as described by equation (2).

Additionally, in order to examine whether aggregate technology shocks propagate upstream, we construct the upstream channel by using the previously combined input shares together with the total sales of the industries by applying the following transformation:

$$\bar{a}_{ji} = \frac{Sales_{i \longrightarrow j}}{TotalSales_i} = a_{ji} \frac{TotalSales_j}{TotalSales_i}, \tag{12}$$

where $\bar{a}_{ji}$ represents the direct upstream relations of the sectors which form the $\bar{\mathbf{A}}$ matrix. Like for the downstream effect, in order to capture the full upstream network we calculate the following $\mathbf{T} = (\mathbf{I} - \bar{\mathbf{A}})^{-1}$, where the coefficients t_{ji} represents the total upstream channels.

6 Results

This section describes the empirical results regarding the effects of aggregate TFP shocks on the production of sectors, directly and indirectly through the intersectoral input-output network. In what follows, we first present the baseline results, after which we extend the discussion in several important dimensions, including potential endogeneity, fixed effects, and controlling for production factors. In addition, we relate our results with Acemoglu, Akcigit and Kerr (2016)'s by conducting a robustness check that takes idiosyncratic TFP factors into account. In the Online Appendix C, we analyze the impacts of aggregate TFP shocks on sectors' employment.

6.1 Baseline results

Our baseline results, which are obtained from the pooled OLS, are presented in the first column of Table 1. The estimates indicate that an aggregate TFP shock, which is equivalent to one standard-deviation TFP change, leads to a direct increase in the growth of sectoral output by 15 percent. Meanwhile, the contemporaneous indirect effect via the suppliers of intermediate products (i.e. downstream) is of an increase by 12 percent. Both the downstream and own effects are statistically significant at the 1 percent level. At the same time, we capture a relatively small upstream effect of this shock, leading to an increase by 2 percent in the industry's value added growth. The upstream effect is statistically significant at the 5 percent level. In total, the network effects, i.e. both downstream and upstream, account for

about 50 percent of the total effects of the aggregate TFP shock on sectoral RVADD growth.

Our results are in line with Ozdagli and Weber (2017), who find that intersectoral network

contributes from 50 to 85 percent to the overall effect of a monetary policy shock.

Table 1 – Baseline Results

$\Delta \ln \text{RVADD}_{i,t}$	Baseline	Equicorrelated errors	AR1 errors	Control for lagY	Control for lags Y&X's	With IV
Downstream$_{i,t}$	0.121*** (0.019)	0.120*** (0.022)	0.122*** (0.022)	0.122*** (0.019)	0.115*** (0.020)	0.140*** (0.039)
Upstream$_{i,t}$	0.021** (0.011)	0.021 (0.014)	0.021 (0.014)	0.021* (0.011)	0.017 (0.011)	-0.008 (0.023)
Own effect$_{i,t}$	0.150*** (0.009)	0.150*** (0.010)	0.149*** (0.010)	0.150*** (0.009)	0.146*** (0.009)	0.150*** (0.017)
$\Delta \ln \text{RVADD}_{i,t-1}$				-0.021* (0.012)	-0.029** (0.013)	
Downstream$_{i,t-1}$					0.028 (0.020)	
Upstream$_{i,t-1}$					0.014 (0.011)	
Own effect$_{i,t-1}$					0.018** (0.008)	
Constant	0.051*** (0.006)	0.051*** (0.006)	0.051*** (0.006)	0.053*** (0.006)	0.059*** (0.006)	0.037* (0.020)
Observations	19250	19250	19250	19250	19250	18480

Note: Table presents the effects of aggregate TFP shocks on sectors' RVADD growth, directly and indirectly through network linkages. Downstream and upstream flows use the Leontief inverse to provide the full chain of material interconnections within manufacturing. The year fixed effects are included. In the model with instrument variables (IV), we use instruments for variables coming into the model in a contemporaneous manner. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in brackets.

It is well known that pooled OLS tends to underestimate standard errors; thus, robust standard errors are used for inference in all cases. In addition, we conduct two further exercises that control for different specifications of serial correlations, including equicorrelated and AR(1) errors, as presented in the second and third columns, respectively. It appears that estimated error correlations are negligible and insignificant. Therefore, it is not surprising that these extensions do not alternate our main results, particularly those concerning the own and downstream effects, but the effect via the upstream linkages is no longer significant. Furthermore, the baseline results hold when we take into the account the lagged dependent variable, that is, the fourth column, as well as the lags of both dependent and explanatory variables, that is, the fifth column.

Finally, one might argue that the process in Section 4.2 might not result in purely exogenous aggregate TFP shocks. If this was the case, ignoring potential endogeneity could bias the results. Therefore, we conduct another exercise in which we use instruments for variables coming into the model in a contemporaneous manner, i.e. $Own_{i,t}$, $Down_{i,t}$, and $Up_{i,t}$, and estimate with 2SLS. Specifically, we use the first three lags of those variables as instruments.[7] The F statistics in the first stage are 75, 145, and 108 for $Own_{i,t}$, $Down_{i,t}$, and $Up_{i,t}$, respectively, which are considerably larger than the rule-of-thumb value of 10. Hence, the hypothesis of weak instruments is rejected. Using the minimum eigenvalue as suggested by Stock et al. (2002) for a joint statistic leads to a similar conclusion. As shown in the sixth column, we do not find any substantial difference in comparison with our baseline results, in which the network effects account for up to 50 percent of the total effects of aggregate TFP shocks on sectoral growth.

---

[7]As shown above, the error correlations are not significant and negligible. This therefore provides a justification for using lags as instruments.

6.2 Fixed-effect models

As mentioned in Section 4.1, we do estimations in changes, hence likely eliminating fixed effects. However, it is interesting to investigate if our results hold when they are modeled with fixed effects. The main results of these tests are presented in Table 2. Estimates in the first column (standard fixed-effect model) and in the second column (fixed-effect model with IV) suggest that the effects of TFP shocks on the growth of real value added are in line with those suggested by the baseline model, reaching a 12-15 percent increase through network channels and around a 15 percent direct increase in the growth of the sectoral RVADD. In addition to the standard fixed-effects model, the third column presents the results for dynamic panel and the fourth column presents the results for dynamic panel with bias correction. Here, we apply the iterative bootstrap procedure suggested by Everaert and Pozzi (2007) to correct the bias which potentially occurs in a dynamic panel model with fixed-effects. The results, again, are in line with those presented above, and the network effects contribute between 40 to 50 percent to the total effects of the aggregate TFP shocks.

Table **2** – Fixed-effect Panel

$\Delta \ln \text{RVADD}_{i,t}$	Fixed-effect (FE)	Fixed-effect with IV	FE&Dynamic panel	FE&Dynamic panel with bias correction
Downstream$_{i,t}$	0.119***	0.146***	0.117***	0.117***
	(0.022)	(0.043)	(0.024)	(0.024)
Upstream$_{i,t}$	0.021	-0.009	0.015	0.016
	(0.014)	(0.023)	(0.014)	(0.016)
Own effect$_{i,t}$	0.150***	0.149***	0.145***	0.145***
	(0.010)	(0.019)	(0.010)	(0.009)
$\Delta \ln \text{RVADD}_{i,t-1}$			-0.086***	-0.067**
			(0.017)	(0.026)
Downstream$_{i,t-1}$			0.026	0.023
			(0.025)	(0.031)
Upstream$_{i,t-1}$			0.017	0.015
			(0.013)	0.018
Own effect$_{i,t-1}$			0.027***	0.024**
			(0.009)	(0.012)
Observations	19250	18480	19250	19250

Note: Table presents the estimates of models with fixed effects. The year fixed effects are included. Downstream and upstream flows use the Leontief inverse to provide the full chain of material interconnections within manufacturing. The year fixed effects are included. In the model with instrument variables (IV), we use instruments for variables coming into the model in a contemporaneous manner. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in brackets.

6.3   Controls for employment and capital

This section investigates if the impacts of aggregate TFP shocks hold when we control for the factors of production: employment and capital. Specifically, we consider four different models: pooled OLS (in line with our baseline), a model with instrument variables, a model with fixed-effects, and fixed-effects with instrument variables. The estimates are presented in Table 3, suggesting that our results are robust. The lagged employment and capital appear to be statistically significant at the 1 percent level in the first two cases, but not in those with fixed effects (in the third and fourth columns). It is important to mention that the overall

pattern of the direct and network effects remain similar to the baseline, that is, the network effects account for about 50 percent of the total effects of aggregate TFP shocks. In more detail, the direct effect of the shock is around 15 percent, and the network effect fluctuates between 12-15 percent. The own and downstream effects are statistically significant at the 1 percent level. Meanwhile, the upstream effect is only statistically significant at the 5 percent level in the pooled OLS model.

Table 3 – Controls for Employment and Capital

$\Delta \ln \text{RVADD}_{i,t}$	Pooled OLS	With IV	With Fixed-effect	With Fixed-effect and IV
Downstream$_{i,t}$	0.118***	0.136***	0.119***	0.146***
	(0.019)	(0.039)	(0.022)	(0.043)
Upstream$_{i,t}$	0.022**	-0.004	0.021	-0.009
	(0.011)	(0.023)	(0.014)	(0.023)
Own effect$_{i,t}$	0.151***	0.151***	0.150***	0.149***
	(0.009)	(0.017)	(0.010)	(0.019)
$\Delta \ln \text{Employment}_{i,t-1}$	0.049***	0.050***	0.002	0.001
	(0.014)	(0.015)	(0.015)	(0.015)
$\Delta \ln \text{Capital}_{i,t-1}$	0.198***	0.200***	-0.022	-0.034
	(0.027)	(0.028)	(0.025)	(0.027)
Constant	0.041***	0.040**	0.051***	0.033***
	(0.006)	(0.020)	(0.006)	(0.007)
Observations	19250	18480	19250	18480

Note: Table presents the estimates of models when controlling for employment and capital. Downstream and upstream flows use the Leontief inverse to provide the full chain of material interconnections within manufacturing. The year fixed effects are included. In the model with instrument variables (IV), we use instruments for variables coming into the model in a contemporaneous manner. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in brackets.

6.4 Control for idiosyncratic shocks

It is interesting to investigate if our results remain when we include both idiosyncratic and aggregate shocks in a single framework. This type of exercise allows us to relatively evaluate

the impacts of aggregate and idiosyncratic shocks; at the same time, it allows us to relate our results to previous studies, specifically Acemoglu, Akcigit and Kerr (2016). To obtain the idiosyncratic shocks, we subtract the aggregate component from the sectoral TFP growth. Due to possible existing endogeneity in idiosyncratic factors, their corresponding variables are lagged in the model. Unlike the aggregate case, we find that using lags as instruments for idiosyncratic ones does not pass the test of weak instruments. Hence, the way we specify our regression to handle idiosyncratic shocks is in line with how Acemoglu, Akcigit and Kerr (2016) specify their regression in their analysis of industry-level TFP shocks.

Table 4 – Control for Idiosyncratic Shocks

$\Delta \ln \text{RVADD}_{i,t}$	Pooled OLS	With IV	With Fixed-effect	With Fixed-effect and IV
Downstream aggregate$_{i,t}$	0.119*** (0.019)	0.123*** (0.039)	0.117*** (0.022)	0.131*** (0.043)
Upstream aggregate$_{i,t}$	0.018* (0.011)	-0.020 (0.023)	0.019 (0.014)	-0.020 (0.024)
Own aggregate$_{i,t}$	0.153*** (0.009)	0.156*** (0.017)	0.152*** (0.010)	0.156*** (0.020)
Downstream idiosyncratic$_{i,t-1}$	0.055*** (0.008)	0.057*** (0.009)	0.033*** (0.009)	0.036*** (0.009)
Upstream idiosyncratic$_{i,t-1}$	0.027*** (0.006)	0.035*** (0.007)	0.023*** (0.008)	0.031*** (0.010)
Own idiosyncratic$_{i,t-1}$	-0.002 (0.002)	-0.002 (0.002)	-0.006*** (0.002)	-0.006*** (0.002)
Constant	0.017** (0.007)	0.039* (0.020)	0.031*** (0.007)	0.032*** (0.007)
Observations	19250	18480	19250	18480

Note: Table presents the estimates of models that control for idiosyncratic shocks. Downstream and upstream flows use the Leontief inverse to provide the full chain of material interconnections within manufacturing. The year fixed effects are included. In the model with instrument variables (IV), we use instruments for variables coming into the model in a contemporaneous manner. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. In brackets are robust standard errors.

Table 4 presents the results when controlling for idiosyncratic factors. We find that the

effect of aggregate TFP shocks remains as above: the direct effect is about 15-16 percent, while the network effect is around 12.5 percent. Regarding the idiosyncratic shocks on the suppliers of the intermediate products, OLS and 2SLS estimates suggest that the downstream sector's value added growth increases by 6 percent, while the models with a fixed effect indicate about 3-4 percent. The idiosyncratic upstream effect leads to an increase of 2-3 percent in the industry's value added growth, half of the corresponding downstream effects. All downstream and upstream effects are statistically significant at the 1 percent level. The lagged direct effects, however, are relatively small, even insignificant in the OLS and 2SLS models, which is similar to those in Acemoglu, Akcigit and Kerr (2016).

For a further robustness check, we use the same model specification as in Acemoglu, Akcigit and Kerr (2016) and relate our results to theirs. This exercise is represented in Table 5. First, as presented in the first column, we use Acemoglu, Akcigit and Kerr (2016)'s model specification with the extended sample 1958-2009, instead of the 1991-2009 sample used in their analysis. Nevertheless, we obtain nearly identical results with Acemoglu, Akcigit and Kerr (2016),[8] suggesting that industry-level TFP shocks affect sectors mostly via downstream network channels. The second and third columns present the estimates of our model when separately incorporating aggregate and idiosyncratic shocks. The estimates of idiosyncratic shocks suggest that the sectoral growth of real value added increases by 5 percent due to downstream effects, and that it increases by 2 percent due to upstream effects. All these estimates are significant at the 1 percent level. In addition, we find that the (lagged) own effect of an idiosyncratic TFP shock is relatively weak, which may explain the small own effect in Acemoglu, Akcigit and Kerr (2016). Nonetheless, the lagged effects of aggregate shocks to

---

[8] Acemoglu, Akcigit and Kerr (2016) report downstream effect of 6 percent (significant at the 1 percent level), upstream effect of 2.4 percent (significant at the 5 percent level), and own effect equal to 0.4 percent (not significant).

Table 5 – **Comparison with Acemoglu, Akcigit and Kerr (2016) (AAK)**

$\Delta \ln \text{RVADD}_{i,t}$	AAK	Separate		Combined	
		Aggregate	Idiosyncratic	Aggregate	Idiosyncratic
Downstream$_{i,t-1}$	0.056***	0.071***	0.050***	0.069***	0.052***
	(0.008)	(0.020)	(0.009)	(0.020)	(0.009)
Upstream$_{i,t-1}$	0.025***	0.014	0.021***	0.014	0.020***
	(0.005)	(0.011)	(0.007)	(0.011)	(0.007)
Own effect$_{i,t-1}$	0.008***	0.072***	0.001	0.076***	0.005*
	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)
$\Delta \ln \text{RVADD}_{i,t-1}$	−0.079***	−0.044***	−0.039**	−0.084***	
	(0.019)	(0.013)	(0.018)	(0.018)	
Constant	−0.016**	0.032***	−0.020***	0.003	
	(0.006)	(0.006)	(0.007)	(0.007)	
Observations	19250	19250	19250	19250	

Note: Table presents the results obtained from model specification used in Acemoglu, Akcigit and Kerr (2016). Model specifications used:
i) Acemoglu, Akcigit and Kerr (2016):

$$\Delta \ln Y_{i,t} = \delta_t + \iota \Delta \ln Y_{i,t-1} + \beta^o Own_{i,t-1} + \beta^d Down_{i,t-1} + \beta^u Up_{i,t-1} + \varepsilon_{i,t},$$

ii) Separate for idiosyncratic

$$\Delta \ln Y_{i,t} = \delta_t + \iota \Delta \ln Y_{i,t-1} + \beta^o OwnIdio_{i,t-1} + \beta^d DownIdio_{i,t-1} + \beta^u UpIdio_{i,t-1} + \varepsilon_{i,t}$$

Separate for aggregate

$$\Delta \ln Y_{i,t} = \delta_t + \iota \Delta \ln Y_{i,t-1} + \beta^o OwnAggr_{i,t-1} + \beta^d DownAggr_{i,t-1} + \beta^u UpAggr_{i,t-1} + \varepsilon_{i,t},$$

iii) Combined:

$$\Delta \ln Y_{i,t} = \delta_t + \iota \Delta \ln Y_{i,t-1} + \beta^o OwnIdio_{i,t-1} + \beta^d DownIdio_{i,t-1} + \beta^u UpIdio_{i,t-1} + \beta^o OwnAggr_{i,t-1} + \beta^d DownAggr_{i,t-1} + \beta^u UpAggr_{i,t-1} + \varepsilon_{i,t}.$$

Downstream and upstream flows use the Leontief inverse to provide the full chain of material interconnections within manufacturing. The year fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in brackets.

the suppliers of intermediate goods cause an increase by 7 percent in sectoral RVADD growth; a direct effect results in a 7 to 8 percent increase. We do not capture any upstream effect of aggregate TFP shocks. Therefore, we obtain similar findings on the impacts of aggregate TFP shocks and the role of network channel. As another robustness check, we take both aggregate and idiosyncratic shocks into the same model and present the results in the last 2 columns of the table. This exercise leads to similar findings, and thus confirms our results.

Overall, we corroborate the findings of Acemoglu, Akcigit and Kerr (2016) regarding the importance of the network channel to the propagation of idiosyncratic shocks. Furthermore, we complement their findings by providing evidence that the intersectoral network also plays an important role in propagating aggregate TFP shocks to sectors' growth and economic activities. Our results therefore also complement the work of Ozdagli and Weber (2017), who report that intersectoral network play an important role in the transmission of aggregate shocks.

7   Conclusion

This study investigates whether the intersectoral linkages of intermediate products affect the spread of aggregate technology shocks to sectors' growth. To do so, we develop a theoretical model to obtain insights into the propagation and transmission of these shocks through input-output linkages. Based on those insights, the empirical model is specified and estimated using data from US manufacturing industries. Our approach allows us to quantitatively decompose the overall effect of aggregate technology shocks on the growth of sectors into direct and higher-order network effects, in which network linkages are constructed from input-output tables. Our empirical results indicate the importance of both the direct effect and the indirect one via network linkages, the latter contributing about 50 percent of the overall effect. Additionally, we find that aggregate technology (supply) shocks propagate mostly downstream the network. Therefore, our study contributes novel evidence that the intersectoral network is a potential propagation channel for aggregate technology shocks throughout the economy.

References

Acemoglu, D., Akcigit, U. and Kerr, W. (2016), '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. (2016), '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), 'Systemic risk and stability in financial networks', *American Economic Review* **105**(2), 564–608.

Allen, F. and Gale, D. (2000), 'Financial contagion', *Journal of Political Economy* **108**(1), 1–33.

Atalay, E. (2017), 'How important are sectoral shocks?', *American Economic Journal: Macroeconomics* **9**(4), 254–80.

Bai, J. and Ng, S. (2002), 'Determining the Number of Factors in Approximate Factor Models', *Econometrica* **70**(1), 191–221.

Baqaee, D. R. (2018), 'Cascading Failures in Production Networks', *Econometrica* **86**(5), 1819–1838.

Barrot, J.-N. and Sauvagnat, J. (2016), 'Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks', *The Quarterly Journal of Economics* **131**(3), 1543–1592.

Beck, G. W., Hubrich, K. and Marcellino, M. (2016), 'On the importance of sectoral and regional shocks for price-setting', *Journal of Applied Econometrics* **31**(7), 1234–1253.

Bernanke, B., Gertler, M. and Gilchrist, S. (1999), The Financial Accelerator in a Quantitative Business Cycle Framework, *in* J. Taylor and M. Woodford, eds, 'Handbook of Macroeconomics', Elsevier, 1341–1393.

Boehm, C. E., Flaaen, A. and Pandalai-Nayar, N. (Forthcoming), 'Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tohoku Earthquake', *The Review of Economics and Statistics* .

Caliendo, L., Parro, F., Rossi-Hansberg, E. and Sarte, P.-D. (2018), 'The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy', *Review of Economic Studies* **85**(4), 2042–2096.

Carter, C. K. and Kohn, R. (1994), 'On gibbs sampling for state space models', *Biometrika* **81**(3), 541–553.

Carvalho, V. M., Nirei, M., Saito, Y. and Tahbaz-Salehi, A. (2016), 'Supply chain disruptions: Evidence from the great east japan earthquake'.

Carvalho, V. M. et al. (2014), 'From micro to macro via production networks', *Journal of Economic Perspectives* **28**(4), 23–48.

Chaney, T. (2014), 'The network structure of international trade', *American Economic Review* **104**(11), 3600–3634.

Christensen, I. and Dib, A. (2008), 'The financial accelerator in an estimated new keynesian model', *Review of Economic Dynamics* **11**(1), 155–178.

Del Negro, M. and Otrok, C. (2008), 'Dynamic factor models with time-varying parameters: measuring changes in international business cycles'.

di Giovanni, J., Levchenko, A. A. and Mejean, I. (2014), 'Firms, destinations, and aggregate fluctuations', *Econometrica* **82**(4), 1303–1340.

Elliott, M., Golub, B. and Jackson, M. O. (2014), 'Financial networks and contagion', *American Economic Review* **104**(10), 3115–3153.

Everaert, G. and Pozzi, L. (2007), 'Bootstrap-based bias correction for dynamic panels', *Journal of Economic Dynamics and Control* **31**(4), 1160–1184.

Foerster, A. T., Sarte, P.-D. G. and Watson, M. W. (2011), 'Sectoral versus aggregate shocks: A structural factor analysis of industrial production', *Journal of Political Economy* **119**(1), 1–38.

Gabaix, X. (2011), 'The granular origins of aggregate fluctuations', *Econometrica* **79**(3), 733–772.

Gai, P. and Kapadia, S. (2010), Contagion in financial networks, *in* 'Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences', 466, The Royal Society, 2401–2423.

Gali, J. (1999), 'Technology, employment, and the business cycle: do technology shocks explain aggregate fluctuations?', *American Economic Review* **89**(1), 249–271.

Garin, J., Pries, M. J. and Sims, E. R. (2018), 'The relative importance of aggregate and sectoral shocks and the changing nature of economic fluctuations', *American Economic Journal: Macroeconomics* **10**(1), 119–48.

Hopenhayn, H. A. (1992), 'Entry, Exit, and Firm Dynamics in Long Run Equilibrium', *Econometrica* **60**(5), 1127–1150.

Johnson, R. C. (2014), 'Trade in intermediate inputs and business cycle comovement', *American Economic Journal: Macroeconomics* **6**(4), 39–83.

Jovanovic, B. (1982), 'Selection and the Evolution of Industry', *Econometrica* **50**(3), 649–670.

Kali, R. and Reyes, J. (2010), 'Financial contagion on the international trade network', *Economic Inquiry* **48**(4), 1072–1101.

Karadimitropoulou, A. and León-Ledesma, M. (2013), 'World, country, and sector factors in international business cycles', *Journal of Economic Dynamics and Control* **37**(12), 2913–2927.

Kose, M. A., Otrok, C. and Whiteman, C. H. (2003), 'International business cycles: World, region, and country-specific factors', *American Economic Review* **93**(4), 1216–1239.

Kydland, F. E. and Prescott, E. C. (1982), 'Time to build and aggregate fluctuations', *Econometrica: Journal of the Econometric Society* 1345–1370.

Long, J. B. and Plosser, C. I. (1983), 'Real business cycles', *Journal of Political Economy* **91**(1), 39–69.

Lucas, R. E. (1977), Understanding business cycles, *in* 'Carnegie-Rochester conference series on public policy', 5, Elsevier, 7–29.

Mumtaz, H., Simonelli, S. and Surico, P. (2011), 'International comovements, business cycle and inflation: A historical perspective', *Review of Economic Dynamics* **14**(1), 176–198.

Mumtaz, H. and Surico, P. (2012), 'Evolving international inflation dynamics: world and country-specific factors', *Journal of the European Economic Association* **10**(4), 716–734.

Norrbin, S. C. and Schlagenhauf, D. E. (1991), 'The importance of sectoral and aggregate shocks in business cycles', *Economic Inquiry* **29**(2), 317–335.

Oberfield, E. (2018), 'A theory of input-output architecture', *Econometrica* **86**(2), 559–589.

Ozdagli, A. and Weber, M. (2017), Monetary policy through production networks: Evidence from the stock market, National Bureau of Economic Research.

Pozzi, A. and Schivardi, F. (2016), 'Demand or productivity: What determines firm growth?', *The RAND Journal of Economics* **47**(3), 608–630.

Reyes, J., Wooster, R. and Shirrell, S. (2014), 'Regional trade agreements and the pattern of trade: A networks approach', *The World Economy* **37**(8), 1128–1151.

Smets, F. and Wouters, R. (2007), 'Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach', *American Economic Review* **97**, 586–606.

Stock, J. H. and Watson, M. (2012), 'Dynamic factor models', *Oxford Handbook on Economic Forecasting* .

Stock, J. H., Wright, J. H. and Yogo, M. (2002), 'A survey of weak instruments and weak identification in generalized method of moments', *Journal of Business & Economic Statistics* **20**(4), 518–529.

Syverson, C. (2011), 'What determines productivity?', *Journal of Economic Literature* **49**(2), 326–65.

A Online Appendix: The detailed theoretical model

A.1 Producers

The model features a perfectly competitive economy with n industries and a representative household. Each industry has a Cobb-Douglas production function as in Eq. (13) whose productivity shock is assumed to be driven by both aggregate/common and idiosyncratic shocks:

$$y_i = e^{(\zeta_i z + v_i)} l_i^{\alpha_i^l} \prod_{j=1}^{n} x_{ij}^{a_{ij}}, \tag{13}$$

where z is a common shock, ζ_i shows the impact of a common shock to the industry i and v_i is an idiosyncratic shock, l_i is labor input in industry i, α_i^l is a share of labor in industry i, x_{ij} presents the amount of good j used in the production of good i and a_{ij} is the share of goods of industry j needed in the production of i goods.

The industry i chooses labor and inputs from other industries to maximize its profit as follows:

$$\Pi = p_i y_i - w l_i - \sum_{j=1}^{n} p_j x_{ij}$$

$$s.t. \quad y_i = e^{(\zeta_i z + v_i)} l_i^{\alpha_i^l} \prod_{j=1}^{n} x_{ij}^{a_{ij}}, \tag{14}$$

where w stands for wage of labor (the wages are chosen as the numeraire, set $w=1$) and p_i the price of good i. The optimal conditions for industry i's decisions are shown in the following Eq. (15) and Eq. (16):

$$\frac{\partial \Pi}{\partial x_{ij}} = \frac{a_{ij} p_i y_i}{x_{ij}} - p_j \quad \Rightarrow a_{ij} p_i y_i = p_j x_{ij} \quad \Rightarrow a_{ij} = \frac{p_j x_{ij}}{p_i y_i}, \tag{15}$$

$$\frac{\partial \Pi}{\partial l_i} = \frac{\alpha_i^l p_i y_i}{l_i} - w \quad \Rightarrow \alpha_i^l p_i y_i = w l_i \quad \Rightarrow \alpha_i^l = \frac{w l_i}{p_i y_i}. \tag{16}$$

A.2 Household

Meanwhile, the representative household makes decisions on consumption and labor supply to maximize her utility based on preferences and budget constraint as in Eq. (17).

$$U = \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i}$$
$$s.t. \quad \sum_{i=1}^{n} p_i c_i = wl, \tag{17}$$

where $\gamma(l)$ captures the disutility of labor supply, which is a decreasing function, and β_i shows the share of good c_i in the household preferences such as $\sum_{i=1}^{n} \beta_i = 1$. The utility maximization is solved using the Lagrangian equation:

$$L = \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i} + \eta(wl - \sum_{i=1}^{n} p_i c_i). \tag{18}$$

By taking the partial derivatives with respect to l_i and c_i, we obtain the following Eq. (19) and Eq. (20):

$$\frac{\partial L}{\partial l_i} = \gamma'(l) \prod_{i=1}^{n} c_i^{\beta_i} + \eta w = 0 \qquad \Rightarrow \gamma'(l) \prod_{i=1}^{n} c_i^{\beta_i} = -\eta w, \tag{19}$$

$$\frac{\partial L}{\partial c_i} = \frac{\beta_i \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i}}{c_i} - \eta p_i = 0 \qquad \Rightarrow \frac{\beta_i}{c_i} \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i} = \eta p_i. \tag{20}$$

From Eq. (20),

$$\frac{\beta_i}{p_i c_i} \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i} = \eta \qquad \Rightarrow \frac{\beta_i}{p_i c_i} U = \eta \qquad \Rightarrow \frac{\beta_j}{p_j c_j} U = \eta$$
$$\Rightarrow \frac{\beta_i}{p_i c_i} U = \frac{\beta_j}{p_j c_j} U \qquad \Rightarrow \frac{\beta_i}{p_i c_i} = \frac{\beta_j}{p_j c_j} \qquad \Rightarrow \frac{p_i c_i}{\beta_i} = \frac{p_j c_j}{\beta_j}. \tag{21}$$

By combining the budget constraint with Eq. (21) we derive:

$$\sum_{j=1}^{n} p_j c_j = wl \qquad \Rightarrow \sum_{j=1}^{n} \frac{p_j c_j \beta_j}{\beta_j} = wl \qquad \Rightarrow p_i c_i (1 + \frac{\sum_{j \neq i} \beta_j}{\beta_i}) = wl$$
$$\Rightarrow p_i c_i (\frac{\sum_{j=1}^{n} \beta_j}{\beta_i}) = wl \qquad \Rightarrow p_i c_i (\frac{1}{\beta_i}) = wl \tag{22}$$
$$\Rightarrow p_i c_i = \beta_i wl \qquad and \qquad \frac{\beta_i}{p_i c_i} = \frac{1}{wl}.$$

While combining Eq. (19), Eq. (20) and Eq. (22) we get:

$$
\frac{-\gamma'(l)\prod_{i=1}^{n}c_i^{\beta_i}}{w} = \frac{\beta_i\gamma(l)\prod_{i=1}^{n}c_i^{\beta_i}}{p_ic_i} \qquad \Rightarrow \frac{-\gamma'(l)}{w\gamma(l)} = \frac{\beta_i}{p_ic_i} \qquad \Rightarrow
$$
$$
\Rightarrow \frac{-\gamma'(l)}{w\gamma(l)} = \frac{1}{wl} \qquad \Rightarrow \frac{-\gamma'(l)l}{\gamma(l)} = 1,
$$
(23)

showing that wage rate does not affect the labor supply, and that the substitution and income

effects cancel out.

By taking into account that total labor l remains constant, differentiating Eq. (22) leads

to:

$$
d(\ln p_i) + d(\ln c_i) = d(\ln \beta_i) + d(\ln w) + d(\ln l) \qquad \Rightarrow \qquad d(\ln p_i) = -d(\ln c_i). \qquad (24)
$$

A.3   Impacts of an aggregate TFP shock

We derive from Eq. (13), Eq. (15), and Eq. (16):[9]

$$
d(\ln y_i) = \zeta_i d(z) + \alpha_i^l d(\ln l_i) + \sum_{j=1}^{n} a_{ij}d(\ln x_{ij}). \qquad (25)
$$

$$
d(\ln p_i) + d(\ln y_i) = d(\ln p_j) + d(\ln x_{ij}), \qquad (26)
$$

and

$$
d(\ln p_i) + d(\ln y_i) = d(\ln w) + d(\ln l_i). \qquad (27)
$$

From Eqs. (25) - (27), we obtain:

$$
d(\ln y_i) = \zeta_i d(z) + \alpha_i^l(d(\ln y_i) + d(\ln p_i)) + \sum_{j=1}^{n} a_{ij}(d(\ln y_i) + d(\ln p_i) - d(\ln p_j)). \qquad (28)
$$

Then using Eq. (24),

$$
d(\ln y_i) = \zeta_i d(z) + \alpha_i^l(d(\ln y_i) - d(\ln c_i)) + \sum_{j=1}^{n} a_{ij}(d(\ln y_i) - d(\ln c_i) + d(\ln c_j)). \qquad (29)
$$

---

[9]Note that in this part $d(v_i) = 0$.

Note that $\alpha_i^l + \sum_{j=1}^n a_{ij} = 1$, so

$$d(\ln y_i) = \zeta_i d(z) + (\alpha_i^l + \sum_{j=1}^n a_{ij})(d(\ln y_i) - d(\ln c_i)) + \sum_{j=1}^n a_{ij}(d(\ln c_j))$$

$$\Rightarrow \quad d(\ln y_i) = \zeta_i d(z) + d(\ln y_i) - d(\ln c_i) + \sum_{j=1}^n a_{ij}(d(\ln c_j)) \quad (30)$$

$$\Rightarrow \quad d(\ln c_i) = \zeta_i d(z) + \sum_{j=1}^n a_{ij}(d(\ln c_j)),$$

which in the matrix form can be written as:

$$\mathbf{d}\ln\mathbf{c} = \boldsymbol{\zeta}\mathbf{dz} + \mathbf{A}\mathbf{d}\ln\mathbf{c}, \quad (31)$$

where $\mathbf{d}\ln\mathbf{c}$ and $\boldsymbol{\zeta}\mathbf{dz}$ are vectors of $d\ln c_i$ and $\zeta_i dz$ and $\mathbf{A}$ is matrix of a_{ij}'s. The solution of

Eq. (31) can be written as:

$$\mathbf{d}\ln\mathbf{c} - \mathbf{A}\mathbf{d}\ln\mathbf{c} = \boldsymbol{\zeta}\mathbf{dz} \quad \Rightarrow \quad (\mathbf{I} - \mathbf{A})\mathbf{d}\ln\mathbf{c} = \boldsymbol{\zeta}\mathbf{dz}$$

$$(32)$$

$$\Rightarrow \quad \mathbf{d}\ln\mathbf{c} = (\mathbf{I} - \mathbf{A})^{-1}\boldsymbol{\zeta}\mathbf{dz}$$

where again $\mathbf{d}\ln\mathbf{c}$ and $\boldsymbol{\zeta}\mathbf{dz}$ are vectors of $d\ln c_i$ and $\zeta_i dz$ and $(\mathbf{I} - \mathbf{A})^{-1}$ matrix represents

Leontief inverse L.

Combining the market clearing condition, $y_i = c_i + \sum_{j=1}^n x_{ji}$, with Eqs. (15) and (16), we

get:

$$\frac{y_j}{c_j} = 1 + \sum_{i=1}^n a_{ij}\frac{\beta_i y_i}{\beta_j c_i},$$

which implies that

$$\mathbf{d}\ln\mathbf{y} = \mathbf{d}\ln\mathbf{c}.$$

Then consequently

$$\mathbf{d}\ln\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}\boldsymbol{\zeta}\mathbf{dz}, \quad (33)$$

where $L = (\mathbf{I} - \mathbf{A})^{-1}$. Therefore,

$$d\ln y_i = \zeta_i dz + \sum_{j=1}^n (l_{ij} - 1)\zeta_j dz, \quad (34)$$

where the l_{ij}'s are elements from the L matrix.

This final equation shows that the output of sector i $(d \ln y_i)$ is affected by the aggregate shock z via two channels: i) directly, as presented by $\zeta_i dz$ and ii) through the intermediate production network, as presented by $\sum_{j=1}^{n}(l_{ij}-1)\zeta_j dz$. More interestingly, it suggests that aggregate TFP shocks propagate downstream the network.

B   Online Appendix: The Bai and Ng (2002)'s criteria

Bai and Ng (2002) develop an econometric theory to determine the number of factors in a model of large dimensions. Specifically, given a bounded integer, Bai and Ng (2002) propose four main criteria to choose the number of factors r such that $r \leq k_{max}$ as follows:

$$PC_1(k) = V(k, \hat{F}^k) + k\hat{\sigma}^2(\frac{N+T}{NT})ln(\frac{NT}{N+T})$$
$$PC_2(k) = V(k, \hat{F}^k) + k\hat{\sigma}^2(\frac{N+T}{NT})ln(C_{NT}^2)$$
$$IC_1(k) = ln(V(k, \hat{F}^k)) + k(\frac{N+T}{NT})ln(\frac{NT}{N+T})$$
$$IC_2(k) = ln(V(k, \hat{F}^k)) + k(\frac{N+T}{NT})ln(C_{NT}^2)$$

where $V(k, \hat{F}^k)$ is simply the average residual variance when k factors are assumed for each cross-section unit, N is the cross-section dimension and T is the time dimension, and $C_{NT}^2 = min\{N, T\}$.

Based on simulations with a variety of combinations over N and T, Bai and Ng (2002) show that when $min\{N, T\}$ is 40 or larger, the proposed tests give precise estimates of the number of factors.

In what follows, we use these four criteria to determine the number of common factors in the 385 series of changes in TFP over 51 years, i.e. $N = 385$ and $T = 51$. We present the results in Table 6 over different values of k_{max} up to 10, a value that is already higher than the one suggested by a rule such as $8int[(min\{N,T\}/100)^{1/4}]$, as discussed in Bai and Ng (2002).

Table 6 – Bai and Ng (2002)'s criteria: Number of factors

	k_{max}
	2	3	4	5	6	7	8	9	10
PC_1	1	1	1	1	2	2	4	4	4
PC_2	1	1	1	1	2	2	3	4	4
IC_1	1	1	1	1	1	1	1	1	1
IC_2	1	1	1	1	1	1	1	1	1

The results show that when $k_{max} \leq 5$, all four criteria suggest only a single common factor. With $6 \leq k_{max} \leq 10$, the PC-based type chooses from 2 to 4 common factors, while the IC-based measure indicate a common factor. As shown in Bai and Ng (2002), the IC criteria tend to underparameterize the number of common factors while the PC criteria tend to overparameterize them. Because the IC criteria do not depend on the choice of k_{max} through the variance of the errors, this may be desirable in practice (Bai and Ng, 2002). Hence, we opt to choose a single common factor as suggested by the IC criteria.

C   Online Appendix: Effects on employment

In addition to real value added, we investigate the impact of aggregate TFP shocks on sectors' employment. The results are shown in Table 7, suggesting that an aggregate TFP shock leads to a direct increase in the growth of employment of around 4-6 percent. Meanwhile, the shock on the suppliers of the intermediate products affects the downstream sector's employment from 7 to 11 percent. Both downstream and own effects are statistically significant at the 1

Table 7 – Impact on Employment

$\Delta \ln$ Employment $_{i,t}$	Pooled OLS	With IV	With Fixed-effect	With Fixed-effect and IV
Downstream$_{i,t}$	0.065***	0.101***	0.065***	0.110***
	(0.012)	(0.027)	(0.019)	(0.030)
Upstream$_{i,t}$	-0.001	-0.021	-0.002	-0.024
	(0.005)	(0.014)	(0.009)	(0.015)
Own effect$_{i,t}$	0.035***	0.056***	0.036***	0.057***
	(0.004)	(0.010)	(0.006)	(0.011)
$\Delta \ln$ Employment $_{i,t-1}$	0.109***	0.110***	0.050***	0.048***
	(0.010)	(0.011)	(0.012)	(0.013)
Constant	0.016***	-0.051***	0.018***	0.005
	(0.004)	(0.012)	(0.004)	(0.004)
Observations	19250	18480	19250	18480

Note: Table presents the effects of aggregate TFP shocks on sectors' employment directly and indirectly through the network channel. Downstream and upstream flows use the Leontief inverse to provide the full chain of material interconnections within manufacturing. The year fixed effects are included. In the model with instrument variables (IV), we use instruments for variables coming into the model in a contemporaneous manner. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. In brackets are robust standard errors.

percent level. We do not find any evidence of upstream effects of this shock on employment.

Again, our results are robust when analyzing the effects onto sectors' employment.