Networks and the Macroeconomy: An Empirical Exploration*

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Abstract

The propagation of macroeconomic shocks through input-output and geographic networks can be a powerful driver of macroeconomic fluctuations. We first exposit that in the presence of Cobb-Douglas production functions and consumer preferences, there is a specific pattern of economic transmission whereby demand-side shocks propagate upstream (to input supplying industries) and supply-side shocks propagate downstream (to customer industries) and that there is a tight relationship between the direct impact of a shock and the magnitudes of the downstream and the upstream indirect effects. We then investigate the short-run propagation of four different types of industry-level shocks: two demand-side ones (the exogenous component of the variation in industry imports from China and changes in federal spending) and two supply-side ones (TFP shocks and variation in knowledge/ideas coming from foreign patenting). In each case, we find substantial propagation of these shocks through the input-output network, with a pattern broadly consistent with theory. Quantitatively, the network-based propagation is larger than the direct effects of the shocks, sometimes by severalfold. We also show quantitatively large effects from the geographic network, capturing the fact that the local propagation of a shock to an industry will fall more heavily on other industries that tend to collocate with it across local markets. Our results suggest that the transmission of various different types of shocks through economic networks and industry interlinkages could have first-order implications for the macroeconomy.

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1 Introduction

How small shocks are amplified and propagated through the economy to cause sizable fluctuations is at the heart of much macroeconomic research. Potential mechanisms that have been proposed range from investment and capital accumulation responses in real business cycle models (e.g., Kydland and Prescott, 1982), to Keynesian multipliers (e.g., Diamond, 1982, Kiyotaki, 1988, Blanchard and Kiyotaki, 1987, Hall, 2009, Christiano, Eichenbaum and Rebelo, 2011), to credit market frictions facing firms or households (e.g., Bernanke and Gertler, 1989, Kiyotaki and Moore, 1997, Guerrieri and Lorenzoni, 2012, Mian and Sufi, 2013), to the role of real and nominal rigidities and their interplay (Ball and Romer, 1990), and to the consequences of (potentially inappropriate or constrained) monetary policy (e.g., Friedman and Schwartz, 1971, Eggertsson and Woodford, 2003, Farhi and Werning, 2013).

A class of potentially-promising approaches based on the spread of small shocks from firms or disaggregated sectors through their economic and other links to other units in the economy has generally been overlooked, however. The idea is simple. A shock to a single firm (or sector) could have much larger impacts on the macroeconomy if it reduces the output of not only this firm (or sector), but also of others that are connected to it through a network of input-output linkages. The macroeconomic importance of this idea was dismissed by Lucas's (1977) famous essay on business cycles on the basis of the argument that if shocks that hit firms or disaggregated sectors are idiosyncratic, they would then wash out when we aggregate across these units and look at macroeconomic fluctuations — due to a law of large numbers-type argument. Despite this powerful dismissal, this class of approaches has attracted recent theoretical attention. An important paper by Gabaix (2011) showed how the law of large numbers need not apply, opening the way to sizable macroeconomic fluctuations from idiosyncratic firm-level shocks, when the firm-size distribution has very fat tails, so that shocks hitting the larger firms cannot be balanced out by those affecting smaller firms.[1] Carvalho (2008), Acemoglu, Ozdaglar and Tahbaz-Salehi (2010, 2014), Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) and Baqaee (2015) built on the multi-sector framework first developed by Long and Plosser (1983) to show how input-output linkages can also neutralize the force of the law of large numbers because shocks hitting sectors that are particularly important as suppliers to other sectors will not wash out and can translate into aggregate fluctuations.

One attractive aspect of these network-based approaches to the amplification and propagation of shocks is that they naturally lend themselves to an empirical analysis that can inform the importance of the proposed mechanisms, and the current paper undertakes such an empirical investigation. We are not the first to empirically study these interactions. One branch of

[1] Earlier contributions on this theme include Jovanovic (1987) and Durlauf (1993) who showed how idiosyncratic shocks can accumulate into aggregate risk in the presence of strong strategic complementarities, and Bak, Chen, Scheinkman and Woodford (1993) who proposed a model of macroeconomic "self-organized criticality" capable of generating macroeconomic fluctuations from small shocks due to nonlinear interactions between firms and industries.

existing research has provided model-based quantitative evaluation of the importance of these interactions (e.g., Horvath, 1998, 2000, Carvalho, 2008, Foerster, Sarte and Watson, 2011). A number of recent papers have instead focused on observable large shocks to a set of firms or industries and have traced their impact through the input-output network. Acemoglu, Autor, Dorn, Hanson and Price (2015) do this focusing on the spread of the impact of increased Chinese competition into the U.S. economy through the input-output linkages and local labor markets, though focusing on 10-year or 20-year effects. Boehm, Flaaen and Nayar (2014), Barrot and Sauvagnat (2014), and Carvalho, Nirei, Saito and Tahbaz-Salehi (2014) focus on the transmission of natural disasters, such as the 2011 Japanese earthquake, through the global input-output linkages.[2] Our paper contributes to this literature by studying the spread of four different types of shocks through the U.S. input-output network at business cycle frequencies. We also add to this by evaluating the contribution of the "geographic network" of industries — which measures the collocation patterns of industries across different commuting zones — to the inter-industry propagation of macroeconomic shocks.[3]

We begin by developing some theoretical implications of the propagation of shocks through the input-output linkages. Most notably, theory predicts that supply-side (productivity) shocks propagate downstream much more strongly than upstream — meaning that downstream customers of directly-hit industries are affected much more strongly than their upstream suppliers. In contrast, demand shocks (e.g., from imports or government spending) propagate upstream much more strongly than downstream — meaning that upstream suppliers of directly-hit industries are affected much more strongly than their downstream customers. This pattern results from the fact that supply-side shocks change the prices faced by customer industries, creating powerful downstream propagation, while demand-side shocks have much more minor (or no) effects on prices and propagate upstream as affected industries adjust their production levels and thus input demands. In the simplified benchmark model studied in much of the literature, where both production functions and consumer preferences are Cobb-Douglas (so that income and substitution effects cancel out), these effects emerge particularly clearly: there is no upstream effect from supply-side shocks and no downstream effect from demand-side shocks. In addition, we show that there is a clear restriction on the quantitative magnitude of the own effect (measuring how a shock to an industry affects that industry) and the network effects.

Our empirical work focuses on four different types of industry-level shocks, all propagating through the input-output linkages at the level of 392 industries as measured by the Bureau of Economic Analysis input-output tables. Our four shocks are: (1) variation from the exogenous component of imports from China; (2) changes in federal government spending (affecting industries differentially on the basis of their dependence on demand from the federal gov-

[2] Acemoglu, Akcigit and Kerr (2015) look at the medium-run spread of new ideas through the innovation (knowledge-flow) network of the U.S. economy.

[3] Though our evidence shows that microeconomic (industry-level) shocks are important and propagate strongly, it does not directly speak to the issues discussed in the previous paragraph, that is, to whether a law of large numbers-type argument will ensure that they wash out at the macro level.

ernment); (3) TFP shocks; and (4) knowledge/productivity stimuli coming from variation in foreign industry patents. For each one of these four shocks, we construct the downstream and upstream network effects by using information from the input-output tables — namely by taking the inner product of the corresponding row or column of the input-output matrix with a vector of shocks at the industry level. We then estimate parsimonious models of industry-level value added , employment and productivity on their own lags, an industry's own shocks, and downstream and upstream effects from shocks hitting other industries.[4]

A brief summary of our results is as follows. For each one of these four shocks, we find propagation through the input-output network to be statistically and economically important, and broadly consistent with theory. In particular, for the two demand-side shocks — Chinese imports and federal government spending — we find that upstream propagation is substantially stronger than downstream effects, which are often zero or of opposite sign. In contrast, for the two supply-side shocks — TFP and foreign patenting — there is strong downstream propagation and limited to no upstream effects. In addition, in each case, the quantitative restrictions between own effects and network effects implied by theory are typically verified. We also find the general patterns to be quite robust to different weighting schemes, additional controls, and different lag structures.

The quantitative effects are sizable. We find that a one standard-deviation variation for each one of our four shocks leads to network effects (either upstream or downstream depending on the shock) that account for between 2% to 8% of industry value added growth. This is typically larger, sometimes severalfold, than the quantitative impact of own shocks (which corresponds to how much an industry responds to its own stimulus without the additional network-based propagation). Moreover, each one of these four shocks appears to be additive, so that the network effect of the four of them combined is about four times this magnitude. Figure 1 gives an indication of the magnitude of network effects relative to the response to own shocks.[5] It depicts the impulse response functions to a one-time standard-deviation shock from one of our baseline specifications. The different panels not only show that network effects are more pronounced than own effects, but also highlight that in response to a typical range of shocks, own and network effects combine to account for a 6% value added growth effect, and up to

[4] We should add at this point that despite our use of the term "shocks," we would like to be somewhat cautious in claiming that our estimates correspond to causal effects of purely exogenous shocks on endogenous economic outcomes. Even though we specify our regression equations to guard against the most obvious forms of endogeneity (contemporaneous shocks affecting both left- and right-hand side variables and Manski's (1993) reflection problem that would result from having grouped endogenous variables on the right-hand side), our shocks themselves may be endogenous to economic decisions in the recent past. For imports from China, because we are focusing on the exogenous component of the variation, we are fairly confident that our estimates are informative about causal effects. The same applies, perhaps with some additional caveats, to federal spending shocks, since we exploit variation across industries in their differential responsiveness to such aggregate changes. For the TFP and foreign patenting measures, the endogeneity concerns are more severe. Nevertheless, even in these cases we believe that our regressions are informative about the propagation of these "pre-determined" shocks through the input-output and geographic networks.

[5] Here, consistent with theory, "network effects" refer to downstream effects for supply-side shocks and upstream effect for demand-side shocks.

11% in the case of trade.

We finally consider the effect of geographic collocation ("overlay") of industries. The geographic overlay of industries reflects the importance of localized networks, as industries with substantial exchanges frequently locate near each other to reduce transportation costs and facilitate information transfer (e.g., Fujita, Krugman and Venables, 1999).[6] After deriving a theoretically-motivated measure of how shocks to industries should propagate through the geographic overlay of industries, we show that geographic effects add another dimension of network-based propagation. While our main results are robust to these additional controls for geographic patterns, which demonstrates that input-output networks are operating above-and-beyond localized factors like regional business cycles, the geographic network also turns out to be a powerful transmitter of shocks from one industry to others. In fact, even though our estimates of the spread of shocks across collocating industries is slightly less robust than our baseline results, the effects appear quantitatively as large or even larger.

Overall, we interpret our results as suggesting that network-based propagation, particularly but not exclusively through the input-output linkages, might be playing a sizable role in macroeconomic fluctuations, and certainly a more important one than typically presumed in modern macroeconomics.

The rest of the paper proceeds as follows. Section 2 presents the theoretical model on input-output networks and shock propagation. Section 3 describes our data and provided descriptive statistics. Section 4 presents our empirical results focusing exclusively on national input-output connections, while Section 5 further adds in the geographic overlay. The last section concludes.

2 Theory

In this section, we develop some simple theoretical implications of input-output linkages, and then turn to a discussion of the macroeconomic consequences of the geographic concentration of industries in certain areas.

2.1 Input-Output Linkages

We start with a model closely related to Long and Plosser (1983) and Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012), which will clarify the role of input-output linkages.

Consider a static perfectly competitive economy with n industries, and suppose that each industry $j = 1, ..., n$ has a Cobb-Douglas production function of the form:[7]

$$y_j = e^{z_j} l_j^{\alpha_j^l} \prod_{i=1}^{n} x_{ji}^{a_{ji}}. \tag{1}$$

[6] Recent work looking at the local coagglomeration of industries includes Ellison, Glaeser, and Kerr (2010), Greenstone, Hornbeck and Moretti (2010), and Helsley and Strange (2014).

[7] The main results we emphasize do not depend on the absence of physical capital, for example, with a

Here x_{ji} is the quantity of goods produced by industry i used as inputs by industry j, l_j is labor, and z_j is a Hicks-neutral productivity shock (representing both technological and other factors affecting productivity). We assume that, for each j, $\alpha_j^l > 0$, and $a_{ji} \geq 0$ for all i (where $a_{ji} = 0$ implies that the output of industry i is not used as an input for industry j), and

$$\alpha_j^l + \sum_{i=1}^{n} a_{ji} = 1,$$

so that the production function of each industry exhibits constant returns to scale.

The output of each industry is used as input for other industries or consumed in the final good sector. The market-clearing condition for industry j can then be written as

$$y_j = c_j + \sum_{k=1}^{n} x_{kj} - G_j, \tag{2}$$

where c_j is final consumption of the output of industry j, and G_j denotes government purchases of good j, which are assumed to be wasted or spent on goods households do not directly care about. We introduce government purchases to be able to model demand-side shocks in a simple fashion.

The preference side of this economy is summarized by a representative household with a utility function

$$u(c_1, c_2, ..., c_n, l) = \gamma(l) \prod_{i=1}^{n} c_i^{1/n}, \tag{3}$$

where $\gamma(l)$ is a decreasing (differentiable) function capturing the disutility of labor supply.

The government imposes a lump-sum tax, T, to finance its purchases (and thus $T = \sum_{i=1}^{n} p_i G_i$). Since its income comes only from labor, wl, the representative household's budget constraint can be written as

$$\sum_{i=1}^{n} p_i c_i = wl - T.$$

We focus on the *competitive equilibrium* of this static economy, which is defined in the usual fashion, so that all consumers and firms maximize and the market-clearing conditions for each good and labor are satisfied. These market-clearing conditions naturally incorporate the sales of inputs to other sectors as already specified in (2). The amount of government spending and taxes are taken as given in this competitive equilibrium.

Given the constant returns to scale production function of each sector specified in (1), prices satisfy the zero profit conditions of the n sectors in the competitive equilibrium and

production function that takes the form

$$y_j = e^{z_j} l_j^{\alpha_j^l} k_j^{\alpha_j^k} \prod_{i=1}^{n} x_{ji}^{a_{ji}}.$$

We suppress capital to simplify the notation and discussion.

therefore

$$a_{ji} = \frac{p_{ji} x_{ji}}{p_j y_j}. \tag{4}$$

We now summarize some of the major implications of this framework, which rely both on input-output linkages as a propagation mechanism and on the Cobb-Douglas production functions (which imply a unitary elasticity of substitution between inputs).

In preparation for the main results we will present, let $\mathbf{A}$ denote the matrix of a_{ij}'s,

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & & \cdots & \\ a_{21} & a_{22} & & & \\ & & \ddots & & \\ & & & & \\ & & & & a_{nn} \end{pmatrix}.$$

Then we define

$$\mathbf{H} \equiv (\mathbf{I} - \mathbf{A})^{-1} \tag{5}$$

as the *Leontief inverse* of the economy, with typical entry denoted by h_{ij}, and we also use the notation $\mathbf{m}$ to denote the column vector of import shocks, and $\mathbf{z}$ to denote a column vector of productivity shocks.

Proposition 1 *The full impact on output in sector i from productivity (supply-side) shocks is*

$$d \ln y_i = h_{ii} \times dz_i + \sum_{j \neq i} h_{ij} \times dz_j. \tag{6}$$

This implies that in response to productivity shocks, there are no upstream effects (i.e., no effect on suppliers of affected industries), and only downstream effects (i.e., only effects on customers of affected industries).

Suppose $\gamma(l) = (1 - l)^{\lambda}$. Then the full impact on output in sector i from demand-side (government spending) shocks is

$$d \ln y_i = \hat{h}_{ii} \times (1 - \Gamma) \times \frac{dG_i}{p_i y_i} - \Gamma \times \sum_{j \neq i} \hat{h}_{ji} \times \frac{dG_j}{p_i y_i}, \tag{7}$$

where $\Gamma = \frac{1}{n(1+\lambda)}$ and $\hat{h}_{ij}$'s are the entries of the Leontief inverse of the matrix $\hat{\mathbf{H}} = (\mathbf{I} - \hat{\mathbf{A}})^{-1}$, and $\hat{\mathbf{A}}$ is the matrix with entries given by $\hat{a}_{ij} = \frac{p_{ij} x_{ij}}{p_j y_j}$ (i.e., sales from industry j to industry i normalized by sales of industry j). This implies that demand-side shocks do not propagate downstream (i.e., to customers of affected industries), only upstream (i.e., only to suppliers of affected industries).

Proposition 1 and equations (6) and (7) form the basis of our empirical strategy, and link output in a sector, say i, to its own "shock," dz_i, as well as to "shocks" hitting all other industries working through the input-output linkages of the economy. In particular, in equation

(6), $h_{ii} \times dz_i$ is the own shock, while $\sum_{j \neq i} h_{ij} \times dz_j$ is the network effect. Similarly, in equation (7), $\hat{h}_{ii} \times (1 - \Gamma) \times dG_i/p_i y_i$ is the own shock and $-\Gamma \times \sum_{j \neq i} \hat{h}_{ji} \times dG_j/p_i y_i$ is the network effect. These equations have three important implications.

First, when properly scaled by the entries of the Leontief matrix, the own and the network effects should have identical coefficients. This result immediately extends to the employment equation by observing that the employment effects are derived from the output effects. For example, if $\alpha_j^l = \alpha^l$, the employment effects are proportional to the output effects (simply scaled by α^l).[8]

Second, as noted in the Introduction and the proposition, the nature of network effects in response to the demand-side and supply-side shocks are rather different. For supply-side shocks we have the term $\sum_{j \neq i} h_{ij} \times dz_j$, implying that the impact goes downstream (and *not at all* upstream). For demand-side shocks, the main propagation comes from the term $-\Gamma \times \sum_{j \neq i} \hat{h}_{ji} \times dG_j/p_i y_i$, signifying that it goes upstream — the $\hat{h}_{ji}$ term signifies the spread of a shock to industries that are suppliers of the affected industries. This is not to imply that there is no impact whatsoever on other industries. Because government spending has to be financed by taxes, this leaves less money for consumption, leading to a proportionate decline in consumption and thus in net output across all sectors. This is captured by the Γ term, and can be seen most clearly when $\gamma' = 0$ ($\lambda = 0$), so that there is no labor supply response. We do not refer to this as "downstream propagation" since it is not caused by the shock being transmitted from one industry to others through the input-output linkages. Moreover, in our empirical analysis, this proportionate decline will be taken out by time effects, so that our empirical strategy should indeed find no downstream propagation and only upstream propagation.

To understand the intuition for these results, consider productivity shocks first. A shock that reduces productivity in industry j will reduce its production and increase its price. This will adversely affect all of the industries that purchase inputs from industry j. But this direct effect will be further augmented in the competitive equilibrium because these first-round-affected industries will change their production and prices, creating indirect downstream effects on other industries. The Leontief inverse captures these downstream effects in their entirety. Why there are no economic effects working upstream through the input-output network is related to the Cobb-Douglas nature of the production functions and preferences. Any impact on upstream industries will depend on the balance of a quantity effect (less is produced in industry j after an adverse productivity shock) and price effect (each unit produced in industry j is now more expensive). With Cobb-Douglas technologies and preferences from households, these two effects exactly cancel out. Clearly Cobb-Douglas is an approximation, though arguably not a bad one since the U.S. input-output matrix appears to be fairly stable over time, as shown, for example, in Acemoglu et al. (2012) (and with non-Cobb-Douglas technologies this would not be the case). Our empirical results also give additional credence to the notion that

[8] The function of form assumption $\gamma(l) = (1 - l)^\lambda$ is imposed to simplify the expressions.

this is a fairly good approximation. In any case, it should be emphasized that the qualitative nature of the results emphasized in the proposition — that supply shocks will have larger downstream effects than upstream effects — holds true with non-Cobb-Douglas technologies and preferences, since even in this case quantity and price effects would at least partially offset each other (and in fact, Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015b, show that, under general production technologies, similar results to those in Proposition 1 can be obtained as first-order approximations).

The intuition for the implications of demand-side shocks is closely related. With government spending shocks, affected industries have to increase their production to meet the increased demand from the government. But given that they are using inputs from other supplier industries, this is only possible if industries supplying inputs to them also expand their inputs (proportionately to the role of these inputs in the production function of the affected industries). This is the logic for upstream propagation of demand-side shocks. Why there is no downstream propagation — beyond the proportionate decline in the consumption of all sectors from the representative household's budget constraint — is also instructive. Since all sectors have constant returns to scale, prices in this economy are entirely independent of the demand side. Government spending shocks change quantities but not prices (see the Appendix). But this implies that the channel through which downstream propagation took place in response to productivity shocks — changing relative prices — is entirely absent, accounting for the lack of downstream propagation in response to demand-side shocks.

Third, equations (6) and (7) also highlight that what matters in our theoretical framework are the contemporaneous shocks (e.g., dz_i), not some future anticipated shocks.[9] This motivates our use of current (or one period lagged shocks) on the right-hand side of our estimating equations.

Finally, we further note that the implications of import shocks are also very similar to government spending shocks, since a decline in imports (without imposing trade balance) is analogous to an increase in government spending on the same sectors, and for this reason, we have not separately introduced these shocks in our theoretical model.

2.2 The Effects of the Geographic Network

Another important set of interlinkages, which could be represented as network effects, relates to geographic overlay over industries (corresponding to how industries collocate in various local labor markets, for example as measured by commuting zones). Thinking through these geographic interactions is important both to ensure that in our empirical work our input-output network effects do not capture these geographic interlinkages, and also as another

[9] This can be seen straightforwardly by considering a dynamic version of the model (without additional intertemporal linkages), in which case equations (6) and (7) would apply with time subscripts, with only dz_{it} being relevant for time t outcomes. In the presence of irreversible investments and/or other intertemporal linkages at the sectoral level, expectations of future shocks would also matter.

transmitter of shocks from some industries to others (which has also been largely overlooked in the macroeconomic literature).

Let us start with a simple reduced-form model capturing local demand effects

$$d\ln y_{r,i} = \eta \sum_{j\neq i} \frac{y_{r,j}}{y_r} d\ln y_{r,j} + dz_i, \tag{8}$$

where $y_{r,i}$ is the output of industry i in region r, and dz_i is an industry shock normalized to have a unit impact on the industry's output (in a region). In what follows, take η to be small (and in particular less than 1).

This equation captures the idea that if industries in a given region (local labor market) are hit by negative shocks, this will reduce economic activity and adversely affect output and employment in other industries, which is consistent with empirical evidence reported in Autor, Dorn and Hanson (2013) and Mian and Sufi (2015). For example, if a large employer in a given local labor market shuts down, this will reduce the demand and thus employment and output of other local employers. The most obvious channel for this is through some local demand effects, though other local linkages would also lead to a relationship similar to (8).

The functional form in this equation is intuitive and implies that the impact of a proportional decline in industry j on industry i in the same region will be scaled by the importance of industry j in the region's output $(y_{r,j}/y_r)$. Note also that, for simplicity's sake, we ignore the network effects coming from input-output linkages in this subsection.

The next step is to solve the within-region equilibrium implied by (8). Doing this with matrix algebra, we can write

$$\mathbf{d}\ln \mathbf{y}_{r,i} = (\mathbf{I}-\mathbf{B})^{-1}\,\mathbf{dz}_i, \tag{9}$$

where

$$\mathbf{B} = \begin{pmatrix} 0 & \eta\frac{y_{r,2}}{y_r} & \eta\frac{y_{r,3}}{y_r} & \dots & \\ & 0 & & & \\ & & 0 & & \\ & & & 0 & \\ & & & & 0 \end{pmatrix}$$

Given our analysis of input-output models, it is not surprising that a Leontief inverse type matrix is playing a central role here. But in this instance, it is useful for us to go beyond this matrix representation. In particular, when η is small as we have assumed, second- and higher-order terms in η can be ignored, and the within-region equilibrium can be expressed in the following form:[10]

$$d\ln y_{r,i} \approx dz_i + \eta \sum_{j\neq i} \frac{y_{r,j}}{y_r} dz_j.$$

[10] More formally, when η is small, the inverse $(\mathbf{I}-\mathbf{B})^{-1}$ necessarily exists, and thus has an infinite series expansion of the form:

$$(\mathbf{I}-\mathbf{B})^{-1} = \mathbf{I} + \mathbf{B} + \mathbf{B}^2 + \mathbf{B}^3 + \dots$$

Moreover, when η is small, we can also approximate this inverse with the first two terms, which leads to the next equation. In our empirical work, we experimented with higher-order terms and did not find additional effects, and thus decided to focus on this first-order approximation.

Intuitively, this equation describes the within-region equilibrium as a function of shocks to all industries (solving out all "endogenous" terms from the right-hand side). Now using the fact that $d \ln y_{r,i} = dy_{r,i}/y_{r,i}$, and summing across regions, we obtain

$$dy_i = \sum_r dy_{r,i} \approx y_i dz_i + \eta \sum_r \sum_{j \neq i} \frac{y_{r,i} y_{r,j}}{y_r} dz_j,$$

which then enables us to obtain a simple representation of the geographic effects:

$$d \ln y_i \approx dz_i + \eta \sum_{j \neq i} \texttt{geographic\_overlay}_{i,j} dz_j, \tag{10}$$

where

$$\texttt{geographic\_overlay}_{i,j} \equiv \sum_r \frac{y_{r,i} y_{r,j}}{y_i y_r}$$

is the non-centered cross-region correlation coefficient of industries i and j, normalized by their national levels of production, and represents their tendency to collocate.

Intuitively, this equation captures the fact that industries will be impacted not only by their direct shocks but also by the shocks of other industries that tend to collocate with them. For example, if coal and steel industries are always in the same few regions, the steel industry will be negatively affected nationally not only when there is a negative shock to itself but also when there is a negative shock to the coal industry, because when the coal industry is producing less in the region, other industries in that region are also adversely affected, and steel is overrepresented among these industries that happened to be in the same region as coal.

Though the term we have for geographic overlay is simple and intuitive, it is based on an approximation that involves ignoring all terms that are second or higher order in η, thus posing the natural question of whether including some of these additional terms would lead to additional insights. To provide a partial answer to this question, we now include second-order terms (thus ignoring only third- or higher-order terms in η), which leads to a natural generalization of (10). In particular, the within-region equilibrium can now be expressed as

$$d \ln y_{r,i} \approx di_i + \eta \sum_{j \neq i} \frac{y_{r,j}}{y_r} dz_j + \eta^2 \sum_{j \neq i} \frac{y_{r,j}}{y_r} \sum_{k \neq j} \frac{y_{r,k}}{y_r} dz_k.$$

Now summing across regions and repeating the same steps as above, we obtain

$$d \ln y_i = dz_i + \eta \sum_{j \neq i} \texttt{geographic\_overlay}_{i,j} dz_j + \eta^2 \sum_{j \neq i} \sum_{k \neq j,i} \overline{\texttt{geographic\_overlay}}_{i,j,k} dz_j$$

where the additional geographic overlay term, which includes triple collocation patterns, is

$$\overline{\texttt{geographic\_overlay}}_{i,j,k} \equiv \sum_r \frac{y_{r,i} y_{r,j} y_{r,k}}{y_i y_r^2}. \tag{11}$$

3 Data and Descriptive Statistics

This section describes our various data sources and the construction of the key measures of downstream and upstream effects and the geographic network.

3.1 Data Sources

Our core industry-level data for manufacturing come from the NBER-CES Manufacturing Industry Database (Becker, Grey and Marvakov, 2013). We utilize data for the years 1991-2009. Using the first change as a baseline, our estimations cover 17 changes from 1992 $\rightarrow$ 1993 to 2008 $\rightarrow$ 2009. In the first four changes, we have 392 four-digit industries; thereafter, we have 384 industries for 6560 total observations. Throughout, we focus on (real) value added as our measure of output.

To construct our linkages between industries, we use the Bureau of Economic Analysis' 1992 Input-Output Matrix and the 1991 County Business Patterns database as described further below. In the next section, we describe the data used for each shock when introducing the specified analysis.

3.2 Upstream and Downstream Networks

The construction of customer and supplier networks follows Acemoglu et al. (2015). For example, we construct the matrix $\mathbf{A}$ introduced in Section 2 from the 1992 "Make" and "Use" Tables of the Bureau of Economic Analysis. This matrix has input share entries corresponding to

$$Input\%_{j\to i} = a_{ij} \equiv \frac{Sales_{j\to i}}{Sales_i}.$$

As emphasized in Section 2, this quantity measures the total sales of inputs from industry j to industry i, normalized by the total sales (or equivalently the total costs) of industry i. This quantity is also exactly what the input-output tables of the Bureau of Economic Analysis record, loosely corresponding to how many dollars worth of tires the car industry purchases to make one dollar worth of car sales, etc.

The Leontief inverse is then simply computed as $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$.

For constructing upstream effects, we again follow the theory and use

$$Output\%_{i\to j} = \frac{Sales_{i\to j}}{Sales_i} \equiv a_{ji}\frac{Sales_j}{Sales_i}.$$

3.3 Geographic Overlay

We also measure the geographic overlay of two industries using the metric developed in the theory section,

$$\texttt{geographic\_overlay}_{i,j} \equiv \sum_r \frac{y_{r,i}y_{r,j}}{y_i y_r}.$$

We define regions through BEA commuting zones and utilize 1991 County Business Patterns data to measure the overlay. We also calculated the higher-order geographic overlay term (11). In practice, however, we observed very little additional explanatory power with the second metric and thus focus simply on the direct collocation case.

3.4 Correlation Matrices

Table 1a shows the correlation matrix of these interconnections, excluding own-industry interconnections (i.e., network diagonals). Upstream and downstream shock measures are moderately correlated (in the 0.3-0.4 range) and somewhat less strongly correlated with geographic overlay, indicating that input-output linkages operate, for the most part, beyond common geographies.

Table 1b depicts the correlation of our four measures of shocks with each other, and shows that our different shocks are only weakly correlated, assuaging concerns that we may be tracing the effects of omitted shocks when modeling the effect of each shock one at the time. Column 5 of Table 1b reports the average between-industry correlation for each shock (e.g., how correlated is, say, the federal spending shock of an industry with the federal spending shocks of other industries). This is relevant in part because the high between-industry correlation of shocks might create spurious network effects in the presence of omitted higher-order impact of own shocks. The relatively low between-industry correlations, except for the federal spending shock, are comforting in this regard. The higher between-industry correlation for the federal spending shock is unsurprising since it is constructed from the interaction of aggregate time-series variation in federal spending with a time-invariant measure of federal spending dependency of each industry (as detailed further below).

4 Results: The Input-Output Network

This section provides our primary empirical results that quantify shock propagation through the input-output networks, leaving the analysis of the geographic network to the next section. We focus on four shocks: (1) import penetration; (2) federal spending changes; (3) TFP growth; and (4) foreign patenting growth. The first two correspond to demand-side shocks, while the latter two are supply-side, approximating productivity shocks. We first consider each shock by itself, describing how we measure it, and studying its empirical properties in isolation. After cycling through all four shocks independently, we jointly model them and provide an extended discussion of economic magnitudes.

4.1 Empirical Approach

Throughout, our main estimating equations are direct analogs of equations (6) and (7) in the theory section, and take the following form:

$$\begin{aligned}\Delta \ln Y_{i,t} \quad = \quad & \eta_t + \psi \Delta \ln Y_{i,t-1} + \beta^{\text{own}} Shock_{i,t-1} \\ & + \beta^{\text{upstream}} Upstream_{i,t-1} + \beta^{\text{downstream}} Downstream_{i,t-1} + \varepsilon_{i,t},\end{aligned} \tag{12}$$

where i indexes industries, η_t denotes a full set of time effects, $\varepsilon_{i,t}$ is an error term, and $Y_{i,t}$ stands for one of three industry-level variables from the NBER manufacturing database: real value added (using the industry's shipments deflator), employment, and real labor productivity (real value added divided by employment).

In our baseline results, time periods correspond to years. We start with a model that only considers the core regressors outlined in equation (12), and then we show robustness checks that add extra controls. We allow only a single lag of the dependent variable on the right-hand side for parsimony, and the role of additional lags is taken up in robustness checks.

The key regressors are $Shock_{i,t-1}$, the industry's own direct shock (taken from one of the four shocks introduced above), and $Upstream_{i,t-1}$ and $Downstream_{i,t-1}$ which stand for the shocks working through the network. These network shocks are always computed from the interaction of the vector of shocks hitting other industries and a vector representing the interlinkages between the focal industry and the rest (e.g., the row or the column of the input-output matrix); we provide exact details below.

The upstream and downstream terminology in network analyses has some ambiguity, so we pause to specify our exact usage. We label "upstream effects" as those arising from shocks to customers of an industry that flow up the input-output chain; in parallel, we describe "downstream effects" as those arising from shocks to suppliers of an industry that flow down the input-output chain. Henceforth, for clarity, we use "upstream" and "downstream" terms to describe exclusively the effects. When there is a need to describe where the shock originates, we will use the terms "customer" and "supplier" to avoid confusion.

Thus, we measure downstream effects (due to supplier shocks) and upstream effects (due to customer shocks) closely mimicking the theoretical equations, (6) and (7). In particular, these are given by the weighted averages of shocks hitting all industries using entries of the Leontief inverse matrices as weights:

$$Downstream_{i,t} = \sum\nolimits_j Input\%_{j \to i}^{1991} \cdot Shock_{j,t}, \tag{13}$$

and

$$Upstream_{i,t} = \sum\nolimits_j Output\%_{i \to j}^{1991} \cdot Shock_{j,t}. \tag{14}$$

Throughout, input-output linkages (and thus the Leontief inverse entries) are pre-determined and measured in 1991. Thus, downstream and upstream effects are simply a function of shocks in connected industries working through a pre-determined input-output network.

Several other points are worth noting. First, we lag both own and network shocks by one period, simply to avoid any concern about contemporaneous measurement issues from our dependent variables to shocks (e.g., in the case of TFP) and about contemporaneous joint determination. It should be stressed, however, that we do not claim that this timing will enable us to estimate causal effects. Rather, we rely on the plausible exogeneity of shocks, especially for imports from China and federal government spending, and caution that this exogeneity is likely to be absent in the case of the TFP and foreign patenting shocks.

Second, equation (12) is formulated in changes, and shocks are always specified in changes as detailed below. The specification could have alternatively been written in levels together with an industry fixed effect. The advantage of the current formulation is that it both follows more directly from and connects to our theoretical model, and imposes that the error term is stationary in differences, which is generally a better description of macro time-series.

Finally, in what follows, unless otherwise stated, we standardize the $Shock_{i,t-1}$ variable so that a unit increase corresponds to a one standard-deviation change in the positive direction (e.g., decrease in imports or increase in TFP), and the $Upstream_{i,t-1}$ and $Downstream_{i,t-1}$ variables are constructed in the same units. This implies that the coefficient on the $Shock_{i,t-1}$ variable will measure the impact of a one standard-deviation increase in the industry's own shock, whereas the coefficients on $Upstream_{i,t-1}$ and $Downstream_{i,t-1}$ will measure the impact of a one standard-deviation increase in the shock of all customers and suppliers of an industry — and that all of these coefficients are directly comparable and are expected to be positive where theory predicts a network-based effect.

4.2 China Import Shocks

Our first shock relates to the growth of imports from China and follows Autor et al. (2013) and Acemoglu et al. (2015). Acemoglu et al. (2015) show this pattern for decade-long adjustments, and we extend this analysis to shorter frequencies considered in macroeconomics. As highlighted in Section 2, this demand-side shock should have greater upstream effects than downstream effects, and in the case of Cobb-Douglas, downstream effects should not even be present.

We first define $ChinaTrade$ to capture this industry exposure to rising Chinese trade,

$$ChinaTrade_{j,t} = -\frac{\text{U.S. Imports from China}_{j,t}}{\text{U.S. market size}_{j,1991}}.$$

This variable, however, is clearly endogenous, as it will tend to be higher when the industry in question has lower productivity growth for other reasons, creating greater room for a rise in imports, and is thus not a good measure of shocks for our analysis. To deal with this endogeneity concern, we follow Autor et al. (2013) and Acemoglu et al. (2015) and instrument this variable with its exogenous component, defined as the lagged change in import penetration from China to eight major non-U.S. countries relative to 1991 U.S. market volume, Austria, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland:

$$ChinaTrade_{j,t}^{IV} = -\frac{\text{Non-U.S. Imports from China}_{j,t}}{\text{U.S. market size}_{j,1991}}.$$

This instrument has the advantage of not being directly affected by changes in productivity in the U.S. economy.[11]

The downstream and upstream effects are calculated from (13) and (14) adapted to this case. For example, for the downstream effects coming from supplier industries, we model the shock:

$$Downstream_{i,t}^{Trade} = \sum\nolimits_j Input\%_{j\to i}^{1991} \cdot \Delta ChinaTrade_{j,t}. \tag{15}$$

We also construct the network instruments using the same reasoning as in (13) and (14). For example, for the downstream effects this simply takes the form of

$$Downstream_{i,t}^{TradeIV} = \sum\nolimits_j Input\%_{j\to i}^{1991} \cdot \Delta ChinaTrade_{j,t}^{IV}.$$

In summary, we have three endogenous variables, $ChinaTrade_{j,t}$, $Downstream_{i,t}^{Trade}$ and $Upstream_{i,t}^{Trade}$, and three instruments, $ChinaTrade_{j,t}^{IV}$, $Downstream_{i,t}^{TradeIV}$ and $Upstream_{i,t}^{TradeIV}$. The first stages for these three variables are shown in Appendix Table 1.

Tables 2a-2c present our estimates of own and network effects from this exercise, using a table format which we replicate for each subsequent shock. Table 2a presents our baseline results for the three outcome variables, considering one and three lags for the dependent variable. Upstream effects that come from trade shocks to an industry's customers strongly influence the size of the focal sector, similar to Acemoglu et al. (2015). Recall that we have standardized (in terms of standard-deviation units) and normalized all of our shocks to be positive, so that an increase in imports from China corresponds to a negative value of the shocks, and thus positive coefficients imply that rising imports from China reduce value added and employment in the affected industries. In this light, the results in Column 1 indicate that a one standard-deviation own-industry shock reduces the industry's value added growth by 3.4%.[12] Perhaps more interestingly, they also indicate that a similar one standard-deviation change in customers of an industry has a much larger impact, corresponding to a reduction in value added growth of 8% through upstream effects — that is, working upstream from customer industries to their suppliers. Interestingly, and consistent with the theory outlined in Section 2, downstream effects are of opposite sign and insignificant. Finally, the bottom row of the table tests the other implication from the theory highlighted in Proposition 1, that

[11] First-stage equations naturally also control for all other covariates from the second stage, including the lagged dependent variable, to ensure consistent estimation. But of course, the only excluded instrument is the exogenous component of the change in import penetration.

[12] The unweighted standard deviation in industry growth rates for our sample is 0.15 for log value-added growth and 0.10 for log employment growth.

the own effect (plus the relevant diagonal entry from the Leontief inverse matrix, i.e., the coefficient on $h_{ii} \cdot \Delta ChinaTrade_{i,t-1}$) should be equal to the upstream effect. For value added, this restriction is marginally rejected at 10%, though it is not rejected in any of the other columns.[13]

Column 2 shows that the overall pattern is similar when two more lags of the dependent variable are included on the right-hand side, even though these lags show some evidence of additional persistence. In particular, not only are the quantitative implications very similar, but it is again the upstream effects that are significant while the downstream ones are not.

Panel A of Figure 1a depicts the impulse response of value added to a one standard-deviation Chinese import shock, using the specification from Column 2 with three lags and focusing on own and upstream effects (since it is upstream effects that should matter with demand-side shocks). Responses are measured through log growth rates and translated into levels off of a base initial value of one. It shows clearly the quantitatively more important impact of network effects relative to the own shock as well as the over-time evolution of the effects.

Columns 3 and 4 turn to employment. The overall pattern and even the quantitative magnitudes are very similar, with clear upstream effects and no downstream effects, and the theory-implied restrictions receive support from our estimates. Panel A of Figure 1b depicts the impulse response of employment to the same shock as in Figure 1a.

Columns 5 and 6 turn to labor productivity. Here we find no robust patterns, which is not surprising since Columns 1-4 document that the numerator and denominator move in the same direction and by similar amounts.

Table 2b considers robustness checks as indicated by column headers. Panel A considers real value added growth, and Panel B considers employment growth. Column 2 shows that the results are very similar without the own-shock term. Our baseline estimates are unweighted. Column 3 shows that the results are very similar when we weight observations by log sales in 1991. Column 4 adopts the more aggressive weighting strategy of using 1991 employment levels as weights, thus giving much greater weight to larger industries, again leading to very similar results. Columns 5-7 consider a series of more demanding specifications where we include a full set of two-, three- and four-digit SIC dummies. Since our specification in equation (12) is in changes, this amounts to including linear time trends for these industry groupings. The results are generally fairly robust, although the downstream effects do move around and sometimes become larger (though they continue to remain far from statistical significance).

An additional issue is that the presence of the lagged dependent variable on the right-hand side of our estimating equation, (12), introduces the possibility of biased estimates when the

[13] This restriction is not tested directly from the reported regression, but instead from a related regression where own effects reflect the diagonal elements of the Leontief inverse matrix. We chose to report specifications in which the own effects are not scaled in this manner to maintain transparency. In any case, the coefficient estimates when we undertake this scaling are very similar to those reported in the tables in the paper.

time dimension is short due to the obtaining consistent estimates of the persistence parameter, ψ, with short panels as noted by Nickell (1981). We further investigate this issue in Appendix Table 2a. In particular, our main concern here is with the network effects, which may inherit the bias of the parameter ψ in short panels. One way of ensuring that this bias is not responsible for our results is to impose different values for the parameter ψ and verify that this has no or little impact on our results (see Acemoglu, Naidu, Restrepo and Robinson, 2014). Appendix Table 2a performs this exercise for the China trade shock and documents that both own and upstream effects are highly significant and similar to our baseline estimates for any value of ψ between our estimate of this parameter in Table 2a ($\psi = 0$) and the full unit root limit ($\psi = 1$), becoming only a little weaker at the full unit root case of $\psi = 1$ (while downstream effects remain insignificant except marginally at $\psi = 1$).

Table 2c considers longer time periods, and thus linking our results more closely to Acemoglu et al. (2015), who focused on a decadal panel. For two-year periods, we prepare nine time periods from $1991 - 1993$ to $2007 - 2009$. For three-year periods, we consider six time periods from $1991 - 1994$ to $2006 - 2009$. For four-year periods, we consider four time periods from $1991 - 1995$ to $2003 - 2007$. For five-year periods, we consider $1991 - 1996, 1996 - 2001$, and $2001 - 2006$. In each case, the first period is used up to create the network lags. The downstream customer effects and own-industry effects tend to grow with longer time periods.

In addition to these robustness checks, Appendix Table 3 reports results where we vary the number of lags included for own-industry shocks and network shocks. We report in the table the sums of the coefficients across the deeper lags and their statistical significance. These variants yield quite similar conclusions to our reported estimations.

One might also wish to express these quantitative impacts in terms of actual dollars or employment levels. We next do this for their 2009 values, focusing again on a one standard-deviation shock using $\Delta Y_{t+1} = Y_{t=2009}[\exp(\beta^{Upstream}) - 1]$. The resulting upstream impacts are far from trivial: about \$153 billion of value added and 430,000 jobs (on a base of approximately \$2 trillion of value added and 11 million jobs in U.S. manufacturing).

4.3 Federal Spending Shocks

The next analysis considers changes in U.S. federal government spending levels, which are anticipated to operate similar to trade shocks by affecting industries through heightened demand from industrial customers. We first calculate from the 1992 BEA Input-Output Matrix the share of sales for each industry that went to the federal government,

$$FedSales\%_i = \frac{Sales_{i \to Fed}}{Sales_i}.$$

This share ranges from zero dependency for about 10% of industries to over 50% for the top percentile of industries in terms of dependency. Some prominent examples and their share of sales include 3731 Ship Building and Repairing (76%), 3761 Guided Missiles and Space

Vehicles (74%), 3482 Small Arms Ammunition (65%), and 3812 Search, Detection, Navigation, Guidance, Aeronautical and Nautical Systems and Instruments (51%).

We interact this measure with the log change in federal government expenditures,

$$FederalShock_{i,t} = FedSales\%_i^{1991} \cdot \Delta \ln FederalSpending_{t-1},$$

holding fixed the industry dependency to its 1991 level. Intuitively, the specification anticipates greater "shocks" from aggregate federal budget changes for industries that have larger initial shares of sales to the federal government. The change in federal spending is lagged one year to reflect the fact that procurement frequently extends into the following year. Using again our example of downstream effects from shocks to supplier industries, we model,

$$Downstream_{i,t}^{Federal} = \sum_j Input\%_{j \to i}^{1991} \cdot FederalShock_{j,t}.$$

A similar approach is taken for the other network metrics.

Because this variable focuses on federal spending changes in the aggregate, driven by among other things swings in political moods, ideology, identity of the government, wars and budget exigencies, and is then constructed with the interaction of these aggregate changes with the time-invariant and pre-determined dependency of each industry on federal spending, we believe that it can be taken as plausibly exogenous to the contemporaneous productivity or supply-side shocks hitting the focal industry.

The structure of Tables 3a-3c is identical to those examining trade shocks. The results are also very similar. For example, in Table 3a, upstream effects are again significant and quantitatively sizable (about three to five times as large as own effects). Downstream effects are statistically insignificant, although sometimes positive and of similar magnitude to the upstream effects. The theory-implied restriction tested and reported in the bottom row is again broadly supported (it is never rejected at 5%). In addition, the own effect is insignificant when we only control for one lag of the dependent variable, but significant both in Columns 2 and 4 when we control for three lags.

Tables 3b and 3c as well as Appendix Tables 2b and 3 perform the same robustness checks and show that the above-mentioned patterns are generally quite robust.

All in all, the propagation of this very different demand-side shock appears remarkably similar to the propagation of the import shocks, and in both cases in line with the theory we have used to motivate our approach.

The economic magnitudes are again far from trivial. Panel B of Figures 1a and 1b again show the impulse response function from own and upstream effects in response to a one standard-deviation shock to federal spending (once again with the specification with three lags from Column 2 of Table 3a), and indicate considerably larger upstream effects than the own effect. In terms of actual numbers, such a shock would directly boost manufacturing value added by \$16 billion and employment by 65,000 jobs due to the own effect, and by an additional \$39 billion and 119,000 jobs through the upstream effects.

4.4 TFP Shocks

We next turn to supply-side shocks, starting with TFP. Baseline TFP shocks for manufacturing industries are the lagged change in four-factor TFP taken from the NBER Productivity Database. Importantly, these TFP measures control for materials, and thus should not be mechanically a function of downstream effects (changes in prices and quantities in industries supplying inputs to the focal industry).

Similar to our other network-based measures, these are constructed by aggregating these industry-level log components of TFP in connected industries. Continuing our illustration using downstream effects from shocks to supplier industries, we model

$$Downstream_{i,t}^{TFP} = \sum\nolimits_j Input\%_{j \to i}^{1991} \cdot \Delta \ln TFP_{j,t}.$$

We should caution that the case for the exogeneity of the TFP shocks is weaker, because past TFP may be endogenous to other shocks (e.g., to capacity utilization or labor hoarding) which have a persistent impact on value added and factor demands. With this caveat, we still believe that TFP shocks, which are predetermined, are informative about how supply-side shocks spread through the input-output network.

The structure of Tables 4a-4c is identical to those examining trade and federal spending shocks. Consistent with theory, it is now downstream effects that are more sizable and important, though in this case there are some statistically significant estimates of upstream effects as well. For example, in Column 1 of Table 4a, downstream effects are estimated to have a coefficient of 0.060 (standard error = 0.020), while upstream effects come in at 0.024 (standard error = 0.011). Interestingly, own effects are small and imprecise for value added, but more precisely estimated (though still about half of the upstream effects) for employment. The theoretical restriction tested in the bottom row is now rejected for value added, where the own effects are small, but is far from being rejected for employment where the own effects are more precisely estimated. The robustness checks reported in Tables 4b and 4c confirm this overall pattern.[14]

Economic magnitudes can again be gleaned from Figures 1a and 1b (Panel C), and in terms of actual numbers, a one standard-deviation TFP shock is estimated to have a direct effect of \$14 billion and 76,000 jobs, while its downstream linkages are once again larger at \$93 billion and 119,000 jobs.

4.5 Foreign Patenting Shocks

Our final shock represents changes in patented technology frontiers. Since this shock also captures supply-side changes in productivity (or efficiency), responses to it should be similar to those to TFP shocks.

[14] However, in this case, Appendix Table 2c shows that the results are sensitive to the exact value of the persistence parameter, ψ.

Baseline patent shocks for manufacturing industries in Tables 5a-5c are the lagged log change in USPTO granted patents filed by overseas inventors associated with the industry. We measure foreign patent shocks using USPTO granted patents through 2009. We develop a new concordance of patent classes to four-digit manufacturing industries that extends the earlier work of Silverman (1999), Johnson (1999), and Kerr (2008). Continuing our downstream effects example, we have

$$Downstream_{i,t}^{ForeignPatent} = \sum\nolimits_j Input\%_{j\to i}^{1991} \cdot \Delta \ln Patents_{j,t}^{Foreign}.$$

These foreign patents quantify technology changes in the world technology frontier that might be exogenous to the U.S. economy (e.g., using patents filed by car manufacturers in Germany and Japan to measure the exogenous expansion of automobile technologies). There are two additional difficulties in this case, however. First, foreign patenting may be correlated with past technological improvements in the U.S. sectors, which might have persistent effects. Second, and perhaps more importantly, improved technology abroad may directly impact U.S. firms through fiercer product market competition, not just through technology and productivity spillovers (e.g., Bloom et al. 2013).[15] These concerns make us more cautious in interpreting the foreign patenting shocks, especially for own effects, though we believe that this analysis is still informative about network-based propagation.

Tables 5a-5c show strong downstream effects with again no evidence of sizable upstream effects. The theory-implied restrictions in the bottom row of the table is rejected for value added (but not for employment), which reflects the very small and sometimes incorrectly-signed estimates of own effects. One possible explanation for this pattern of own effects is that, as already noted, an increase in foreign patents in one's own industry likely signals fiercer competition from international competitors. The network effects, which should be less impacted by these considerations, are again quite similar to our theory's predictions.

In terms of economic magnitudes, a one standard-deviation shock would create downstream effects of about \$87 billion in terms of value added and 196,000 jobs, and Panel D of Figures 1a and 1b also depict the impulse responses of value added and employment to such a shock.

4.6 VAR Analysis

Our empirical specification, equation (12) above, directly built on our theoretical model (in particular, equations (6) and (7)), and expressed the endogenous response of value added (and employment) to shocks hitting all industries. An alternative would be to follow the vector auto regression (VAR) models and express endogenous variables as a function of own shocks and the values of the endogenous variables of linked industries. The analog of equation (12) in this

[15] Bloom et al. (2013) develop a strategy for controlling for this competition effect, but the implementation of their strategy is not feasible given our industry-level data.

case would be

$$\begin{aligned}\Delta \ln Y_{i,t} &= \eta_t + \psi \Delta \ln Y_{i,t-1} + \beta^{\text{own}} Shock_{i,t-1} \\ &\quad + \beta^{\text{upstream}} \Delta \ln Y_{i,t-1}^{Upstream} + \beta^{\text{downstream}} \Delta \ln Y_{i,t-1}^{Downstream} + \varepsilon_{i,t},\end{aligned} \tag{16}$$

which only features the shock hitting sector i, and models upstream and downstream effects from the changes in value added) of linked industries — the terms $\Delta \ln Y_{i,t-1}^{Upstream}$ and $\Delta \ln Y_{i,t-1}^{Downstream}$. This equation could also be derived from our theoretical framework. Relative to our empirical model, (12), this specification, (16), faces two related problems. First, the terms $\Delta \ln Y_{i,t-1}^{Upstream}$ and $\Delta \ln Y_{i,t-1}^{Downstream}$ generate a version of Manski's well-known reflection problem (Manski, 1993), as outcome variables of one industry are being regressed on the contemporaneous (or one period lagged) outcomes of other industries, creating the possibility of spurious correlation. Second, these terms are also more likely to be correlated with each other, potentially leading to multicollinearity, which will make distinguishing these various effects more difficult.

These problems notwithstanding, we now estimate equation (16) to show that the results from this complementary approach are broadly similar. To avoid the most severe form of the reflection problem, throughout we instrument for the upstream and downstream effects, $\Delta \ln Y_{i,t-1}^{Upstream}$ and $\Delta \ln Y_{i,t-1}^{Downstream}$, using the first and second lags of each shocks as experienced in the network (i.e., our instruments are the core regressors in equation (12), $Upstream_{i,t-1}$ and $Downstream_{i,t-1}$). We report two specifications per shock. In the first, we model and instrument the focal part of the network relevant for each shock (e.g., upstream effects for supply-side shocks and downstream effects for demand-side shocks). In the second specification, we include and instrument for both upstream and downstream effects. Also, in the case of China trade shocks, we continue to instrument for the own shock, $Shock_{i,t-1}$ as well.

The results of this exercise are reported in Table 6 and are quite consistent with our baseline findings. Even though this empirical specification is more demanding for the reasons explained above, the specifications focusing on China trade and TFP shocks give very similar results, and specifications using federal spending shocks also lead to similar results for value added, though not for employment. Foreign patenting results do not hold with in this approach, however.

Figure 2 reports impulse response functions akin to Figures 1a and 1b using the results from Table 6, where we trace out a one-standard deviation upstream or downstream network component in terms of value added or employment, as instrumented by each shock, alongside the direct effect of the shock. For brevity, we only plot the stable and theory-consistent estimates, which are the ones that are meaningful to compare to our baseline results. Focusing on those, we see that the resulting magnitudes are comparable to, though somewhat larger than, our main estimates.

4.7 Combined Shock Analysis

Table 7a and 7b estimate own, upstream and downstream effects simultaneously from several of the shocks so far analyzed in isolation. This is relevant for two related reasons. First, we would like to verify that our downstream and upstream effects indeed capture network-based propagation of different types of shocks rather than some other omitted characteristics, and attempting to simultaneously estimate these effects provides some information on this concern. Second, it is important to quantify whether the simultaneous operation of all of these networked effects creates attenuation, which will be relevant for our quantitative evaluation.

In Table 7a, we start with the first three shocks (leaving out the foreign patenting shocks because of the concerns about own effects discussed above). The estimates of upstream and downstream effects in this joint analysis are remarkably similar to our previous results, and the pattern is also similar in Table 7b when we include foreign patenting shocks. These results both bolster our confidence in the patterns documented so far and also suggest that the quantitative magnitudes of the propagation through these input-output networks is larger when we consider all four shocks simultaneously (and presumably might be even larger when additional shocks are considered).

To quantify impacts from this joint exercise, we now consider one standard-deviation changes of the three shocks, imports from China, federal spending and TFP, simultaneously. The impulse response functions from this exercise are shown in Figure 3. In terms of actual numbers, our estimates imply that the combined direct effects (from own shocks) are \$81 billion in terms of value added and 318,000 jobs. The upstream network components from trade and federal spending would further add \$309 billion and 864,000 jobs, while the downstream TFP component would be \$97 billion and 141,000 jobs. Thus, the network elements jointly continue to account for more fluctuation than direct components. The lower panels show similar results when including foreign patenting shocks.

5 Results: The Geographic Network

We next turn to an analysis of the geographic network's impact on the propagation of shocks. The theory in Section 2 describes how shocks to an industry can also propagate regionally (e.g., within commuting zones) because they depress economic activity, impacting the decisions of other industries in the area. Though a full analysis of these local interactions is beyond the scope of the present effort (see, for example, the treatment of Acemoglu et al. (2015) for medium-frequency import shocks on local economies), we can nonetheless get a sense of the importance of these channels of propagation by looking at the impact of a shock to a particular industry on other industries that tend to collocate with it. This is essentially the idea of the geographic network introduced above.

We start with the analysis of the propagation of each one of our four shocks through the geographic network in Table 8a. The top panel is for value added while the bottom panel is for employment (we do not report results for labor productivity to conserve space). We present specifications that just focus on geographic effects and ones that simultaneously include downstream and upstream effects, with own-industry effects always included. Two conclusions follow from Table 8a. First, the inclusion of geographic effects has little impact on our estimates of downstream and upstream effects, which continue to adhere to theory. Second, geographic effects are also significant and quantitatively large in some cases, particularly for federal spending and foreign patenting shocks when we focus on value added, though less consistently than the network effects reported so far. For example, the results for employment are much less precisely estimated.

Table 8b considers all of these effects simultaneously, which is particularly relevant since they are all working through the same geographic networks. In this case, some of the geographic effects are even more precisely estimated, in particular for trade and federal spending shocks. Table 8c investigates the robustness of these results to the same checks considered for the input-output linkages earlier, and shows that the overall patterns are fairly robust.

The economic magnitudes of these effects that include geography are substantial. Figure 4 shows the impulse response functions including own and the network effects in response to a one standard-deviation shock in specifications that also include geographic effects. Input-output network effects continue to be sizable. Geographic effects are also large, even if less stable across specifications. For example, in joint estimations that include all four shocks, we estimate own-industry effects at $35 billion in terms of value added and 130,000 jobs, upstream network effects at $217 billion and 645,000 jobs, downstream network effects at $176 billion and 296,000 jobs, and the geographic overlay variable accounts for $263 billion in terms of value added and 542,000 jobs, though in some other specifications the contribution of the geographic variables is much less. Nevertheless, the implied magnitudes of some of these geographic effects are quite large and necessitated deeper investigation.[16]

6 Conclusion

The idea that idiosyncratic firm- or industry-level shocks could spread through a network of interconnections in the economy, propagating and amplifying their initial impact has had obvious appeal to economists, who have often been in search of sources of large aggregate fluctuations. Though their potential import was initially downplayed because of the belief that their aggregation across many units (disaggregated industries or firms) would limit their macroeconomic impact, there has been a recent revival of interest in such network-based propagation of mi-

[16] The magnitudes of these geographic effects are comparable to the estimates in Acemoglu et al. (2015), who follow Autor et al. (2013) and measure the effect of China trade shocks on local labor markets. The latter finds an aggregate reduction of over 1.5 million manufacturing jobs through direct and network effects. In terms of our framework, their estimates correspond to a combination of own effects and geographic spillovers; they also control for changes in the underlying population in regions in their econometric specification.

croeconomic shocks. This paper contributes to an empirical investigation of the role of such propagation, focusing primarily on input-output linkages but also on connections through the geographic collocation patterns of industries.

One feature that makes propagation through the input-output network particularly attractive for empirical study is that theory places fairly tight restrictions on the form of the transmission of these effects. In particular, in response to demand-side shocks, upstream propagation (to the suppliers of the directly affected industries) should be more pronounced than downstream propagation (to the customers of the directly affected industries), whereas in response to supply-side shocks, the reverse ordering should hold. In fact, when production technologies and consumer preferences are Cobb-Douglas, there should only be upstream propagation with demand-side shocks and only downstream propagation with supply-side shocks. Moreover, the quantitative magnitudes of the direct effects and the downstream/upstream effects are pinned down by theory.

After reviewing these theoretical basics, we turn to an empirical investigation of the propagation of four different types of shocks — China import shocks and federal government spending shocks on the demand side, and TFP and foreign patenting shocks on the supply side. In each case, we study these shocks first in isolation and then in combination with the other shocks, and separately estimate own (direct) effects as well as downstream and upstream effects. Throughout, our focus is on annual variation, which appears more relevant for the question of macroeconomic fluctuations, though we verify the robustness of our results to lower-frequency analysis.

Our empirical results paint a fairly uniform pattern across the different types of shocks. In each case, the patterns are consistent with theory — in the case of demand-side shocks, upstream effects strongly overshadow downstream effects, which are often zero or in the opposite direction, and the converse is true with supply-side shocks. Moreover, the theory-implied quantitative restrictions are often verified, excepting the foreign patenting shocks. Equally important, we also find the network-based propagation of shocks to be quantitatively sizable, and in each case, more important than the direct effect of the shock — sometimes as much as five times as important. These patterns appear to be fairly robust across specifications and different control strategies.

In addition to the propagation of shocks through the input-output network, the geographic spread of economic shocks could potentially be important. For example, many economic transactions, particularly for non-tradables, take place within the local economy (e.g., a county or commuting zone). If so, a negative shock to an industry concentrated in an area will impact firms and workers in that area. Though a full analysis of this geographic dimension requires detailed data with geography/industry breakdown, we also undertake a preliminary investigation of these linkages by focusing on the collocation patterns of industries. The idea is simple: if two industries tend to collocate strongly, meaning that wherever one industry plays a major role in the local economy, the other industry is also likely to be overrepresented, then shocks to the first industry will tend to be felt more strongly by this collocating industry than other, geographically less-connected industries. We derive a theoretical relationship showing how industry-level shocks spread to other industries depending on collocation patterns and then empirically investigate this linkage.

Our results in this domain are slightly less robust, but still indicate a fairly sizable impact of the propagation of shocks through the geographic collocation network. In fact, quantitatively this channel appears to be, if anything, somewhat more important than the transmission of shocks to the input-output network. Interestingly, however, controlling for this geographic channel does not attenuate or weaken the evidence we find for the propagation of shocks with input-output network.

Though ours is not the first paper showing that certain shocks spread through the network of input-output linkages (and also of geographic connections), we still consider our paper as part of the early phase of this emerging literature documenting the empirical power of network-based propagation of shocks. Several areas of future work look promising from our vantage point. First, as already noted, the geographic spread of shocks can be better studied by using data and empirical methods that cover multiple geographic scales and levels of interaction, and even better would be to incorporate measures of the geographic span of the operations and plants of multi-unit firms using the Census Bureau's Longitudinal Business Database. We intend to undertake such an analysis in the near future.

Second, the input-output network we utilize is still fairly aggregated. The theoretical logic applies at any level of disaggregation, and even at the level of firms. Though firm input-output linkages require some care (since many such relations may be non-competitive due to the presence of relationship-specific investments or holdup problems), the same ideas can also be extended to the firm-level network of input-output linkages. Atalay, Hortacsu and Syverson (2014) and Atalay, Hortacsu, Roberts and Syverson (2011) take first steps in constructing such firm-level networks, which can then be used for studying this type of propagation.

Third, the simple but powerful nature of the theory we have already exploited in this paper also suggests that more structural approaches could be quite fruitfully applied in this domain, which will enable more rigorous testing of some of the theoretical predictions of this class of models. For example, the Leontief inverse matrix also puts a considerable amount of discipline about the co-movement of value added and employment across industries resulting from shocks spreading through the input-output network, which can be formally investigated.

Fourth, the role of the input-output and the geographic network in the propagation of industry-level (micro) shocks suggests that these networks may also be playing a role in the amplification of macro shocks — such as aggregate demand, monetary and financial shocks — which appears a generally understudied area.

Fifth, the two types of networks we have focused on are by no means the only ones that may matter for macroeconomic outcomes. Two others that have recently been investigated are the financial network, which can lead to the propagation and contagion of shocks hitting some financial institutions to the rest of the financial system (e.g., Allen and Gale, 2000, Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015a, Elliott, Golub and Jackson, 2014, Cabrales, Gottardi and Vega-Redondo, 2014), and the idea/innovation network, which can lead to the spread of new knowledge, innovations and practices (studied, e.g., in Acemoglu, Akcigit and Kerr, 2015, as well as indirectly in Bloom et al., 2013). Our decision to abstract from these was partly because of our empirical frame, which centers on industry-level shocks, and also because of our focus on shorter-run fluctuations (whereas the propagation of new ideas and innovations through the innovation network is likely to be more important at five- or ten-year frequencies or even longer). Nevertheless, combining these various types of network linkages may be a fruitful area for future research.

Finally, in addition to the propagation of shocks to other industries or firms, the network linkages emphasized here can also fundamentally change the nature of macroeconomic outcomes and their volatility. For example, Acemoglu, Ozdaglar and Tahbaz-Salehi (2014) show how tail macroeconomic risk can be created from the propagation of microeconomic shocks through the input-output network, while Schennach (2013) suggests that these types of network effects may change the persistence properties of macroeconomic time-series. These new areas also constitute fruitful directions for future research.

Appendix: Proof of Proposition 1

Part 1. Let us set government purchases equal to zero for this part of the proof. Recall that profit maximization implies

$$a_{ji} = \frac{p_i x_{ji}}{p_j y_j}, \text{ and } \alpha_j^l = \frac{w l_j}{p_j y_j}. \tag{17}$$

Utility maximization in turn yields

$$p_i c_i = p_j c_j. \tag{18}$$

Since total household income is equal to labor income and in this part we have no government purchases, we also have

$$\sum_{i=1}^{n} p_i c_i = wl,$$

which yields

$$p_i c_i = \frac{wl}{n}, \ \forall i. \tag{19}$$

Moreover, the first-order condition for labor supply implies

$$-\frac{g'(l)l}{g(l)} = 1,$$

and thus labor supply is determined independent of the equilibrium wage rate because given the preferences in (3), income and substitutions cancel out.

Let us now take logs in (1) and totally differentiate to obtain

$$d\ln y_j = dz_j + \alpha_j^l d\ln l_j + \sum_{i=1}^{n} a_{ji} d\ln x_{ji}. \tag{20}$$

Let us next totally differentiate (17) to obtain

$$d\ln y_j + d\ln p_j = d\ln x_{ji} + d\ln p_i,$$

and

$$d\ln y_j + d\ln p_j = d\ln l_j + d\ln w.$$

Substituting these two equations into (20), we have

$$d\ln y_j = dz_j + \alpha_j^l(d\ln y_j + d\ln p_j - d\ln w) + \sum_{i=1}^{n} a_{ji}(d\ln y_j + d\ln p_j - d\ln p_i).$$

Next recalling that l remains constant, differentiating (18) and (19), and combining with the previous two equations to eliminate prices, we obtain

$$d\ln y_j = dz_j + \alpha_j^l(d\ln y_j - d\ln c_j) + \sum_{i=1}^{n} a_{ji}(d\ln y_j - d\ln c_j + d\ln c_i).$$

Noting that $\alpha_j^l + \sum_{i=1}^{n} a_{ji} = 1$, this simplifies to

$$d\ln c_j = dz_j + \sum_{i=1}^{n} a_{ji} d\ln c_i,$$

which can be rewritten in matrix form as

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

where $\mathbf{d}\ln\mathbf{c}$ and $\mathbf{dz}$ are the vectors of $d\ln c_j$ and dz_j respectively, which is a unique solution given by

$$\mathbf{d}\ln\mathbf{c} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{dz}, \tag{21}$$

in view of the fact that the largest eigenvalue of $\mathbf{A}$ is less than 1. Next combining (2) and (17), we have

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

which implies that

$$\mathbf{d}\ln\mathbf{y} = \mathbf{d}\ln\mathbf{c}. \tag{22}$$

Then combining (21) with (22) we obtain

$$\mathbf{d}\ln\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{dz}.$$

This yields the desired result, (6).

Part 2. Normalize $\mathbf{z} = \mathbf{1}$ for this part of the proof. Consider the unit cost function of sector j, which is

$$C(\mathbf{p}, w) = B_j w^{\alpha_j^l} \prod_{i=1}^{n} p_i^{a_{ji}},$$

where

$$B_j = \left[\frac{1}{\alpha_j^l}\right]^{\alpha_j^l} \prod_{i=1}^{n} \left[\frac{1}{a_{ji}}\right]^{a_{ji}}$$

Zero profit condition for producer j implies

$$\ln p_j = \ln B_j + \alpha_j^l \ln w + \sum_{i=1}^{n} a_{ji} \ln p_i \text{ for all } j \in \{1, .., n\}.$$

Let us choose $w = 1$ as the numeraire. Then, these equations define an n equation system in n prices (for a given vector of productivities $\mathbf{z}$, in this instance normalized to 1), with solution

$$\ln\mathbf{p} = (\mathbf{I} - \mathbf{A})^{-1}(\mathbf{b} + \boldsymbol{\alpha}),$$

where $\mathbf{b}$ is the vector with entries given by $\ln B_i$ and $\boldsymbol{\alpha}$ is the vector with entries given by $\alpha_i^l \ln w$.

This shows that, for a given vector of productivities, the equilibrium price vector is uniquely determined regardless of the value of the vector of government purchases **G**. Thus demand-side shocks have no impact on equilibrium prices, which are entirely determined by the supply side. But then from (19), the consumption vector remains unchanged, and from (2), total net supply of all sectors have to remain constant regardless of the change in **G**. We can then obtain the change in the total production in the economy using (2) combined with (17), which with unchanged prices simply implies

$$d\ln y_j = d\ln x_{ji} \text{ and } d\ln y_j = d\ln l.$$

Household maximization implies that, even though prices are fixed, labor supply will change because of changes in consumption (resulting from government purchases). In particular, the following first-order condition determines the representative household's labor supply

$$\frac{wl}{wl-T} = -\frac{l\gamma'(l)}{\gamma(l)},$$

with $T = \sum_{i=1}^{n} p_i G_i$.

When $\gamma(l) = (1-l)^{\lambda}$,

$$l = \frac{1+\lambda\sum_{i=1}^{n} p_i G_i}{1+\lambda}$$

Therefore, we have that

$$\begin{aligned} p_i c_i &= \frac{lw-T}{n} \\ &= \frac{1}{(1+\lambda)n} - \frac{1}{(1+\lambda)n}\sum_{i=1}^{n} p_i G_i \end{aligned}$$

which implies

$$dp_i c_i = -\frac{\sum_{i=1}^{n} dp_i G_i}{(1+\lambda)n}.$$

The resource constraint then implies:

$$dy_i = dc_i + \sum_{j=1}^{n} dx_{ji} + dG_i.$$

Combining the previous two equations

$$\frac{dp_i y_i}{p_i y_i} = \sum_{j=1}^{n} a_{ji}\frac{dp_j y_j}{p_i y_i} + \frac{dG_i}{p_i y_i} - \frac{1}{(1+\lambda)n}\sum_{j=1}^{n}\frac{dG_j}{p_i y_i}.$$

Writing this in matrix form noting that, because prices are constant, $\frac{dp_i y_i}{p_i y_i} = d\ln y_i$, we have

$$\begin{aligned}
\mathbf{d}\ln\mathbf{y} &= \hat{\mathbf{A}}^T\mathbf{d}\ln\mathbf{y} + \mathbf{\Lambda}\mathbf{dG} \\
&= \left(\mathbf{I} - \hat{\mathbf{A}}^T\right)^{-1}\mathbf{\Lambda}\mathbf{dG} \\
&= \hat{\mathbf{H}}^T\mathbf{\Lambda}\mathbf{dG}
\end{aligned}$$

where $\hat{\mathbf{H}} = \left(\mathbf{I} - \hat{\mathbf{A}}\right)^{-1}$,

$$\hat{\mathbf{A}} = \begin{pmatrix} \hat{a}_{11} & \hat{a}_{12} & & \cdots & \\ \hat{a}_{21} & \hat{a}_{22} & & & \\ & & \ddots & & \\ & & & & \\ & & & & \hat{a}_{nn} \end{pmatrix},$$

with entries $\hat{a}_{ij} = \frac{p_{ij}x_{ij}}{p_j y_j}$, and

$$\mathbf{\Lambda} = \begin{pmatrix} \left(1 - \frac{1}{(1+\lambda)n}\right)\frac{1}{p_1 y_1} & -\frac{1}{(1+\lambda)n}\frac{1}{p_1 y_1} & & \cdots & \\ -\frac{1}{(1+\lambda)n}\frac{1}{p_2 y_2} & \left(1 - \frac{1}{(1+\lambda)n}\right)\frac{1}{p_2 y_2} & & & \\ & & \ddots & & \\ & & & & \\ & & & & \left(1 - \frac{1}{(1+\lambda)n}\right)\frac{1}{p_n y_n} \end{pmatrix},$$

which yields the desired result, (7).

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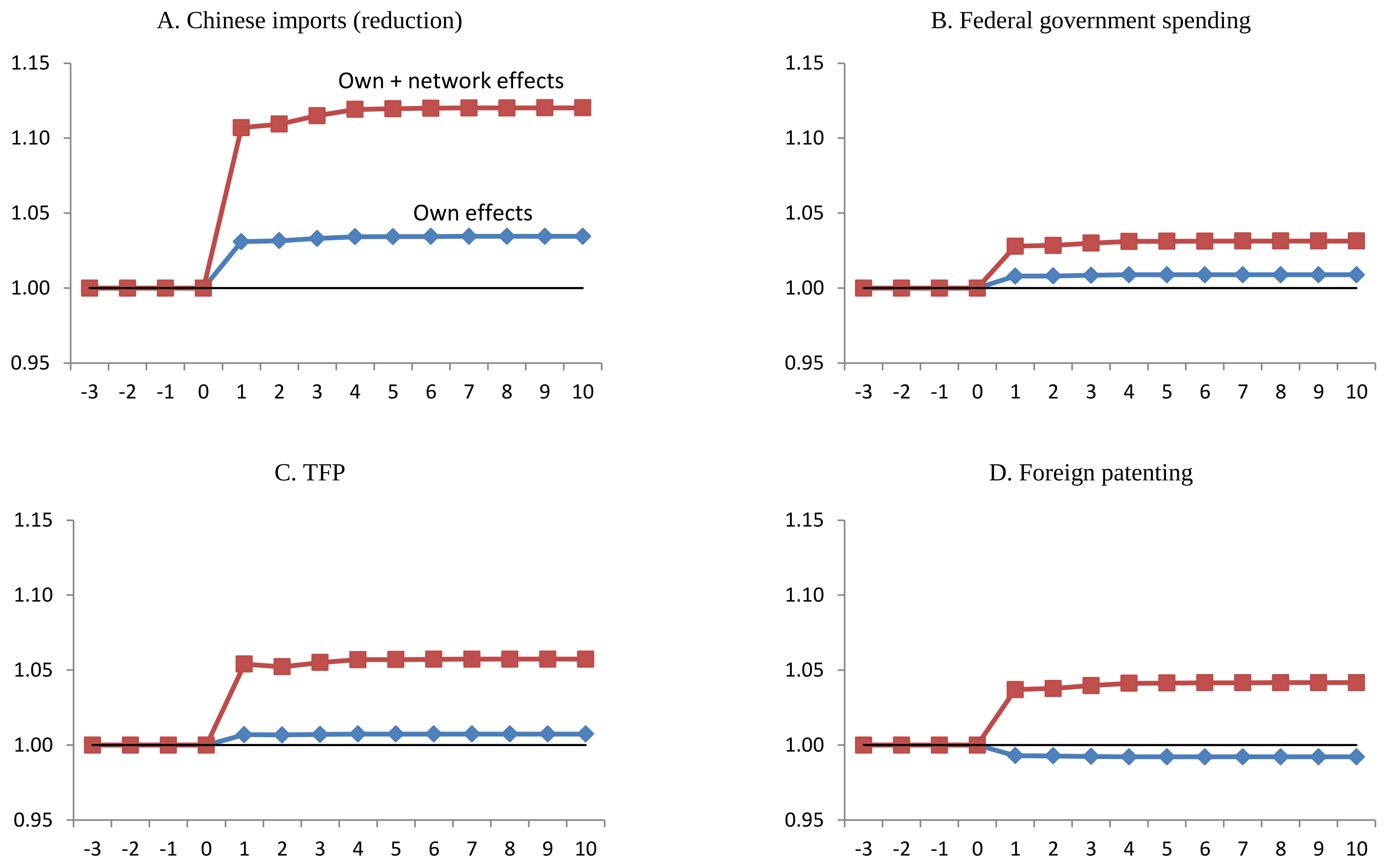
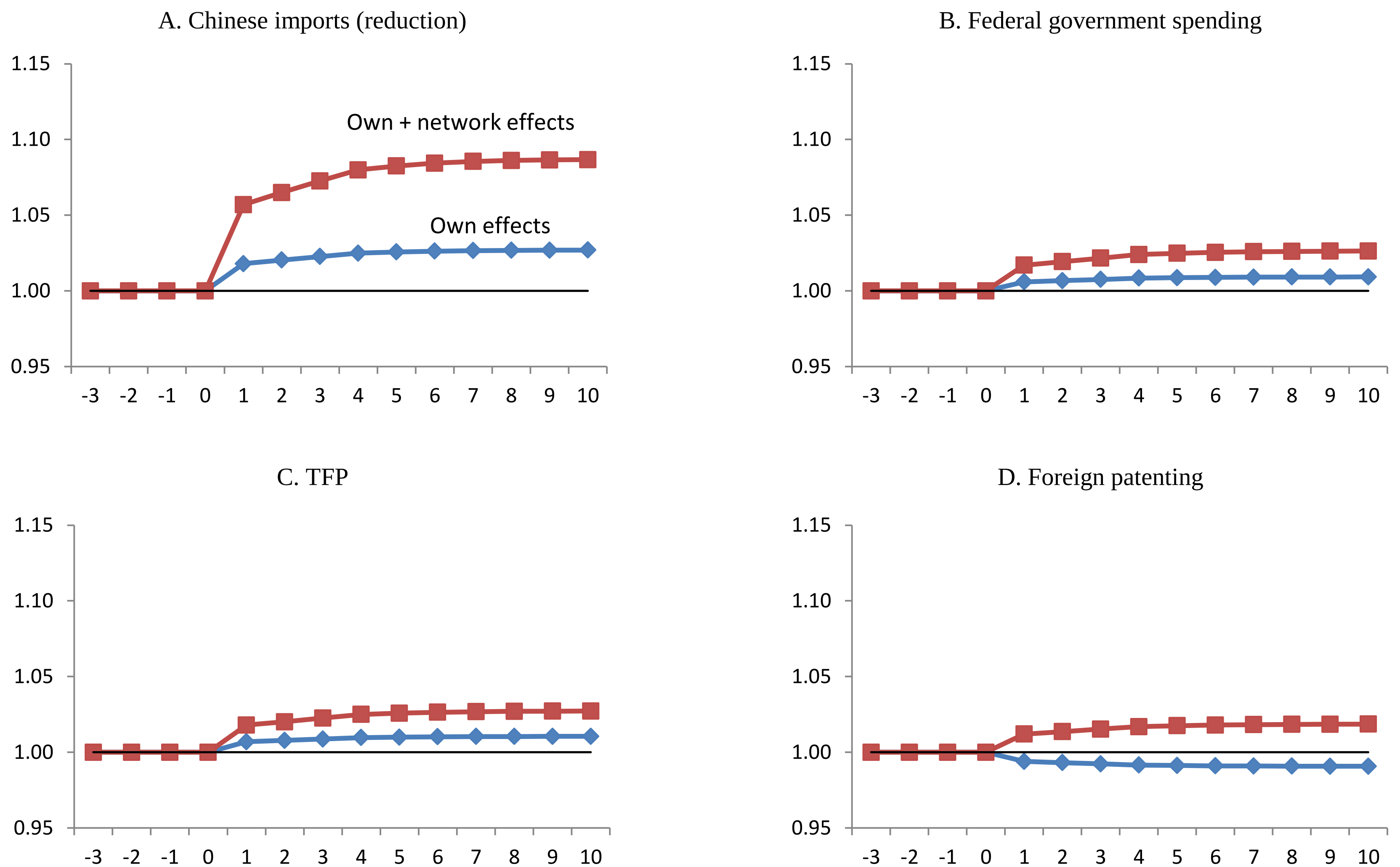
Figure 1a: Responses to a one standard-deviation shock taken in isolation, value-added



Notes: Figure plots estimated response to a one standard-deviation shock taken in isolation. Trade shocks are presented in positive terms to be visually comparable to the other shocks considered. Network effects focus on upstream contributions for the demand-side shocks of trade and federal spending and downstream contributions for the productivity shocks of TFP and foreign patenting. Responses are measured through log growth rates per the estimating equation and translated into levels off of a base initial level of one. The lag structure for the dependent variables includes three lags. Base regressions are recorded in Tables 2a, 3a, 4a, and 5a.

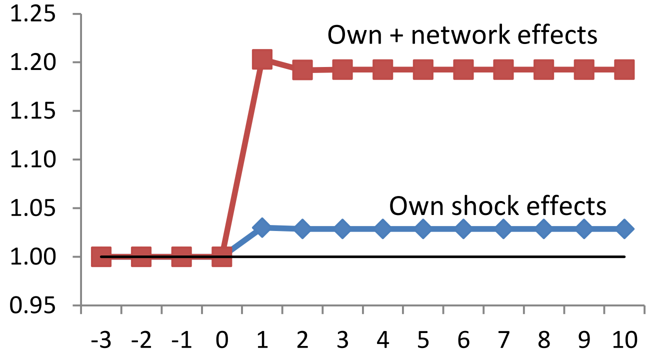
Figure 1b: Responses to a one standard-deviation shock taken in isolation, employment



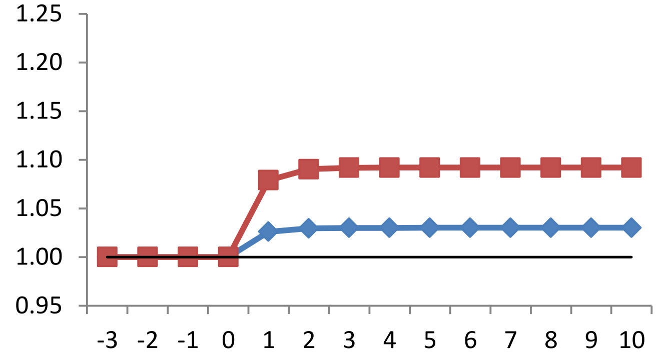
Notes: See Figure 1a.

Figure 2: VAR responses to a one standard-deviation shock taken in isolation

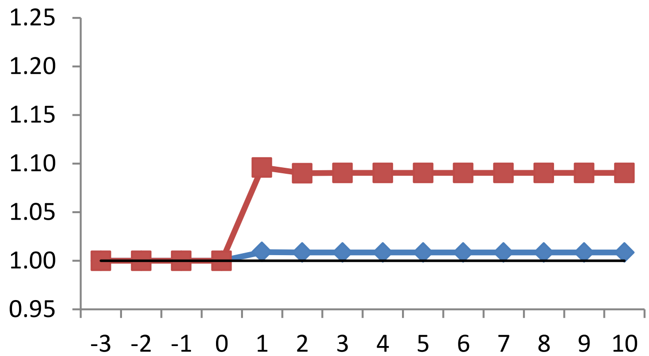
A. Chinese imports (reduction), value added



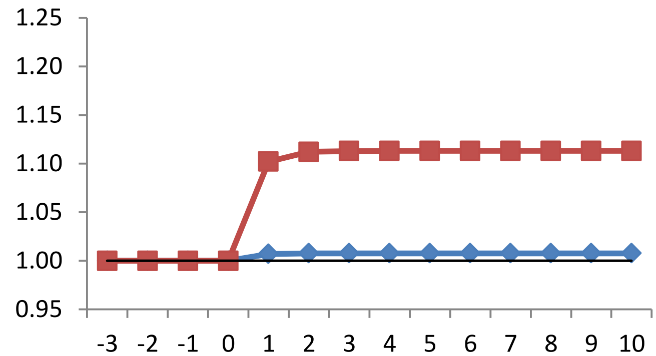
B. Chinese imports (reduction), employment



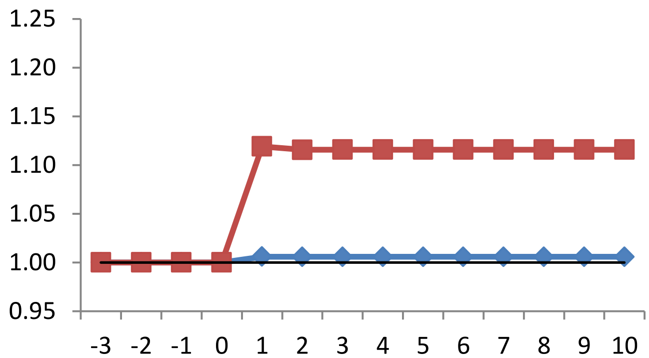
C. TFP, value added



D. TFP, employment

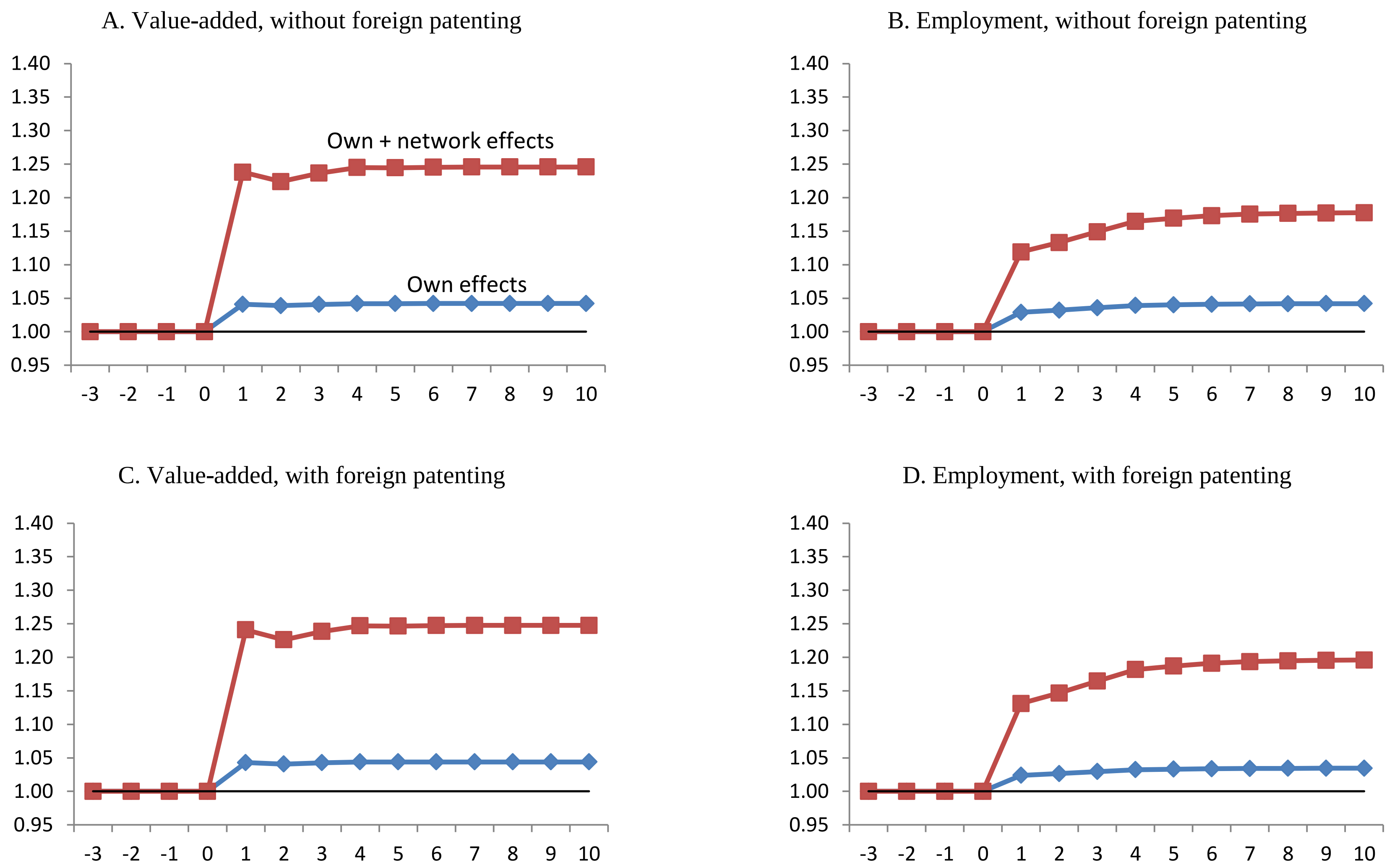


E. Federal government spending, value added



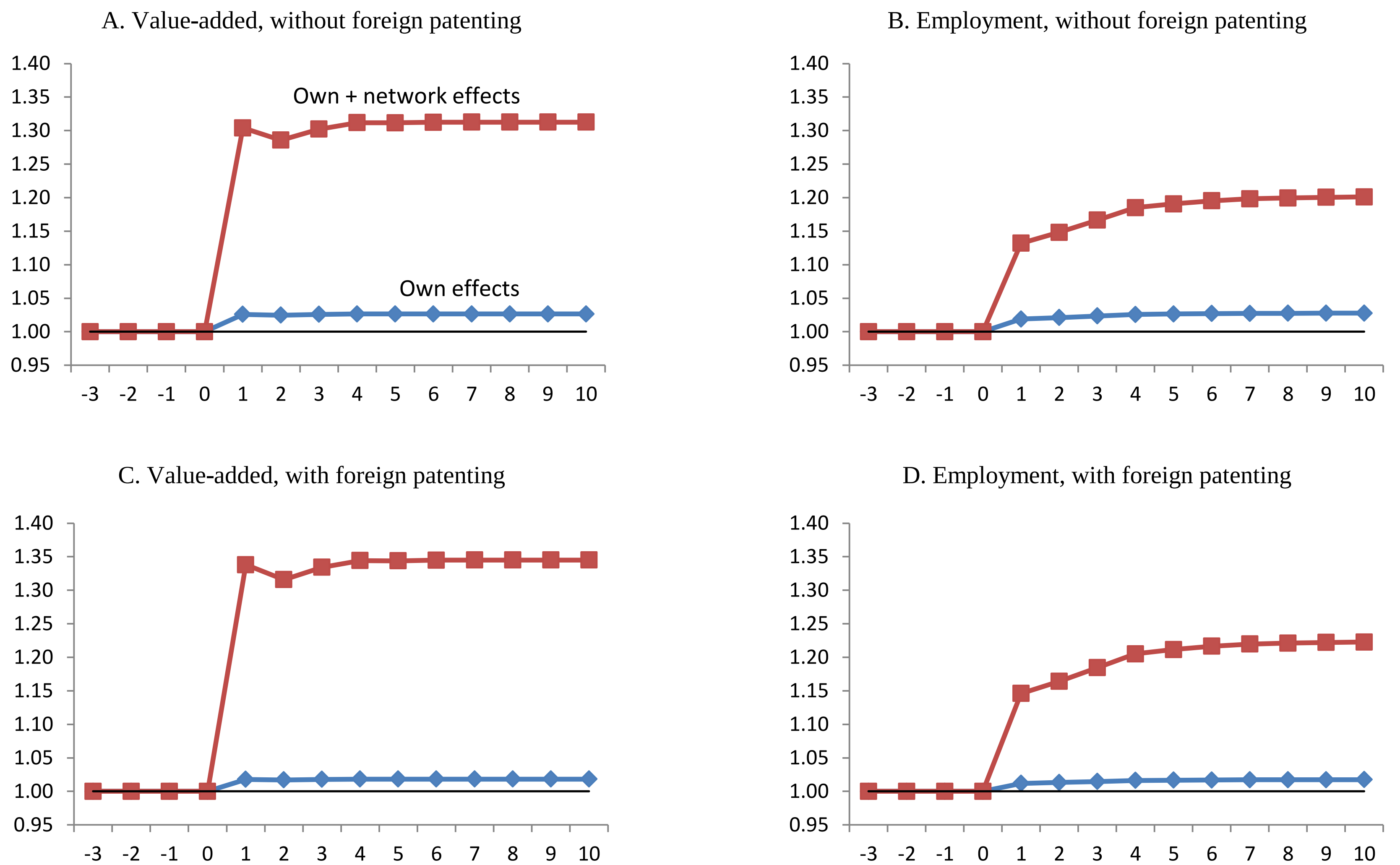
Notes: See Figure 1a. Figure plots estimated intermediated network effects akin to a VAR analysis. Estimations use upstream and downstream shocks in instrumental variable specifications where the endogenous regressor is the lagged actual value-added or employment change in the network. Results with foreign patenting and employment for federal spending are excluded. Base regressions are recorded in Table 6.

Figure 3: Combined response to joint one standard-deviation shocks, without geographic effects



Notes: See Figure 1a. Figure plots estimated response to joint one-time standard-deviation shocks. Panels A and B exclude foreign patenting, which has a negative own effect, while Panels C and D include it. Base regressions are recorded in Tables 7a and 7b.

Figure 4: Combined response to joint one standard-deviation shocks, with geographic effects



Notes: See Figures 1a and 3. Figure plots estimated response to joint one-time standard-deviation shocks that includes geographic effects. Base regressions are recorded in Appendix Table 4.

Table 1a: Correlation matrix of network interconnections

	Downstream Leontief	Upstream Leontief	Geographic overlay
	(1)	(2)	(3)
Downstream Leontief	1		
Upstream Leontief	0.348	1	
Geographic overlay	0.108	0.275	1

Notes: Downstream networks represent inputs from supplier industries into the focal industry's production, expressed as a share of the focal industry's sales (e.g., rubber inputs into the tire industry as a share of the tire industry's sales). Upstream networks represent sales from the focal industry to industrial customers, expressed as a share of the focal industry's sales (e.g., sales of tires to car manufacturers as a share of the tire industry's sales). Both networks are measured from the 1991 BEA Input-Output Matrix. Shares allow for flows to non-manufacturing industries and customers and thus do not sum to 100% within manufacturing. Leontief connections provide the full chain of interconnections in the network matrix. Geographic overlay is measured as the sum across regions of the interaction of a focal industry's employment share in the region times the share of regional activity for other industries. Regions are defined through commuting zones and use 1991 industrial activity from the County Business Patterns database. Correlations are statistically significant at the 1% level.

Table 1b: Correlation matrix of shocks

	China trade shock	Federal spending shock	TFP shock	Foreign patenting shock	Correlation Coefficient
	(1)	(2)	(3)	(4)	(5)
China trade shock	1				0.200
Federal spending shock	0.031	1			0.452
TFP shock	-0.021	0.017	1		-0.002
Foreign patenting shock	-0.023	0.030	0.003	1	0.003

Notes: Baseline trade shocks for manufacturing industries are the lagged change in imports from China relative to 1991 US market volume, following Autor et al. (2013). A negative value is taken such that positive coefficients correspond to likely beneficial outcomes, similar to other shocks. All trade analyses instrument US imports with the rise in Chinese imports in eight other advanced countries, and this table reports the correlation of the IV component. Baseline federal spending shocks for manufacturing industries are the lagged log change in national federal spending interacted with the 1992 share of sales from industries that went to the federal government. Baseline TFP shocks for manufacturing industries are the lagged log change in four-factor TFP taken from the NBER Productivity Database. Baseline patent shocks for manufacturing industries are the lagged change in USPTO patents filed by overseas inventors associated with the industry. These correlations are presented after year fixed effects are removed from each shock. The Correlation Coefficient column presents the average pairwise correlation of the given shock series between any two industries.

Table 2a: Baseline for China trade shock analysis

	Δ Log real value added		Δ Log employment		Δ Log real labor productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Dependent variable t-1	0.019	0.020	0.149***	0.132***	-0.117***	-0.120***
	(0.025)	(0.025)	(0.020)	(0.019)	(0.028)	(0.033)
Δ Dependent variable t-2		0.047**		0.109***		-0.057
		(0.024)		(0.020)		(0.037)
Δ Dependent variable t-3		0.033		0.089***		-0.002
		(0.021)		(0.016)		(0.033)
Downstream effects t-1	-0.140	-0.124	-0.056	-0.044	-0.100	-0.108
	(0.086)	(0.081)	(0.040)	(0.037)	(0.099)	(0.099)
Upstream effects t-1	0.076***	0.076***	0.049***	0.039***	0.021	0.021
	(0.024)	(0.023)	(0.016)	(0.015)	(0.013)	(0.014)
Own effects t-1	0.034***	0.031***	0.023***	0.018***	0.007	0.007
	(0.009)	(0.009)	(0.005)	(0.004)	(0.007)	(0.007)
Observations	6560	5776	6560	5776	6560	5776
p-value: Upstream=Own	0.078	0.058	0.108	0.161	0.320	0.341

Notes: Estimations consider network structures and the propagation of trade shocks. Baseline trade shocks for manufacturing industries are the lagged change in imports from China relative to 1991 US market volume, following Autor et al. (2013). A negative value is taken such that positive coefficients correspond to likely beneficial outcomes, similar to other shocks. Explanatory variables aggregate these industry-level components by the indicated network connecting industries. These network explanatory variables are expressed as lagged changes in non-log values. Downstream and upstream flows use the Leontief inverse to provide the full chain of material interconnections within manufacturing. All trade analyses instrument the direct and network effects from US imports with the rise in Chinese imports in eight other advanced countries. Upstream=Own test uses the exact formula discussed in the text and is calculated through unreported auxiliary regressions. Variables are winsorized at the 0.1% level and initial shocks are transformed to have unit standard deviation for interpretation. Estimations include year fixed effects, report standard errors clustered by industry, and are unweighted. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2b: Robustness checks on China trade shock analysis

	Baseline estimation	Excluding own lagged shock	Weighting by 1991 log sales	Weighting by 1991 employees	Adding SIC2 fixed effects	Adding SIC3 fixed effects	Adding SIC4 fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Δ Log real value added			
Δ Dependent variable t-1	0.019	0.021	0.023	0.114	-0.008	-0.038*	-0.071***
	(0.025)	(0.025)	(0.026)	(0.071)	(0.025)	(0.023)	(0.020)
Downstream effects t-1	-0.140	-0.022	-0.152*	-0.209*	0.000	0.138	0.192
	(0.086)	(0.083)	(0.086)	(0.123)	(0.109)	(0.106)	(0.129)
Upstream effects t-1	0.076***	0.068***	0.078***	0.075**	0.051**	0.053*	0.051
	(0.024)	(0.023)	(0.023)	(0.034)	(0.023)	(0.032)	(0.042)
Own effects t-1	0.034***		0.033***	0.022	0.018**	0.015	0.016
	(0.009)		(0.009)	(0.014)	(0.009)	(0.010)	(0.014)
Observations	6560	6560	6560	6560	6560	6560	6560
p-value: Upstream=Own	0.078		0.061	0.111	0.159	0.252	0.421
				B. Δ Log employment			
Δ Dependent variable t-1	0.149***	0.156***	0.153***	0.257***	0.097***	0.044**	0.010
	(0.020)	(0.021)	(0.020)	(0.034)	(0.020)	(0.019)	(0.020)
Downstream effects t-1	-0.056	0.024	-0.055	-0.034	0.009	0.036	0.080
	(0.040)	(0.037)	(0.040)	(0.059)	(0.049)	(0.054)	(0.067)
Upstream effects t-1	0.049***	0.044***	0.051***	0.048**	0.029*	0.014	0.012
	(0.016)	(0.016)	(0.016)	(0.022)	(0.016)	(0.018)	(0.025)
Own effects t-1	0.023***		0.023***	0.020***	0.009**	0.005	0.001
	(0.005)		(0.005)	(0.007)	(0.004)	(0.004)	(0.005)
Observations	6560	6560	6560	6560	6560	6560	6560
p-value: Upstream=Own	0.108		0.087	0.227	0.217	0.619	0.634

Notes: See Table 2a.

Table 2c: Longer changes on China trade shock analysis

	Baseline annual analysis	Using two-year periods	Using three-year periods	Using four-year periods	Using five-year periods
	(1)	(2)	(3)	(4)	(5)
			A. Δ Log real value added		
Δ Dependent variable t-1	0.019	0.085**	0.092*	0.027	0.072
	(0.025)	(0.037)	(0.047)	(0.056)	(0.076)
Downstream effects t-1	-0.140	-0.323***	-0.417**	-1.549***	-1.092
	(0.086)	(0.120)	(0.198)	(0.348)	(0.671)
Upstream effects t-1	0.076***	0.089***	0.149***	0.292***	0.719***
	(0.024)	(0.024)	(0.040)	(0.067)	(0.175)
Own effects t-1	0.034***	0.041***	0.087***	0.118***	0.153***
	(0.009)	(0.010)	(0.017)	(0.029)	(0.054)
Observations	6560	3080	1920	1152	768
p-value: Upstream=Own	0.078	0.060	0.123	0.008	0.001
			B. Δ Log employment		
Δ Dependent variable t-1	0.149***	0.242***	0.284***	0.266***	0.297***
	(0.020)	(0.028)	(0.041)	(0.047)	(0.058)
Downstream effects t-1	-0.056	-0.041	-0.207***	-0.055	0.685*
	(0.040)	(0.058)	(0.076)	(0.221)	(0.408)
Upstream effects t-1	0.049***	0.063***	0.100***	0.215***	0.655***
	(0.016)	(0.019)	(0.027)	(0.060)	(0.160)
Own effects t-1	0.023***	0.036***	0.067***	0.102***	0.111***
	(0.005)	(0.008)	(0.012)	(0.027)	(0.039)
Observations	6560	3080	1920	1152	768
p-value: Upstream=Own	0.108	0.176	0.225	0.062	0.001

Notes: See Table 2a. All sample periods start with 1991 and extend as far as data allow. For example, Column 5 effectively considers 1996->2001 and 2001->2006, with lags extending back to 1991->1996.

Table 3a: Baseline for federal spending shock analysis

	Δ Log real value added		Δ Log employment		Δ Log real labor productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Dependent variable t-1	0.019	0.018	0.158***	0.135***	-0.117***	-0.119***
	(0.025)	(0.024)	(0.021)	(0.019)	(0.030)	(0.036)
Δ Dependent variable t-2		0.051**		0.116***		-0.057
		(0.023)		(0.019)		(0.038)
Δ Dependent variable t-3		0.038*		0.102***		-0.002
		(0.021)		(0.016)		(0.035)
Downstream effects t-1	0.017	0.023	0.007	0.013	0.007	0.004
	(0.021)	(0.021)	(0.015)	(0.012)	(0.016)	(0.017)
Upstream effects t-1	0.022**	0.020**	0.010*	0.011**	0.012	0.010
	(0.009)	(0.008)	(0.006)	(0.005)	(0.008)	(0.008)
Own effects t-1	0.004	0.008**	0.003	0.006***	0.001	0.002
	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)
Observations	6560	5776	6560	5776	6560	5776
p-value: Upstream=Own	0.090	0.197	0.338	0.401	0.166	0.315

Notes: See Table 2a. Estimations consider network structures and the propagation of federal spending shocks. Baseline federal spending shocks for manufacturing industries are the lagged log change in national federal spending interacted with the 1992 share of sales from industries that went to the federal government.

Table 3b: Robustness checks on federal spending shock analysis

	Baseline estimation	Excluding own lagged shock	Weighting by 1991 log sales	Weighting by 1991 employees	Adding SIC2 fixed effects	Adding SIC3 fixed effects	Adding SIC4 fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Δ Log real value added			
Δ Dependent variable t-1	0.019	0.019	0.023	0.115*	-0.011	-0.042*	-0.076***
	(0.025)	(0.025)	(0.026)	(0.068)	(0.025)	(0.024)	(0.021)
Downstream effects t-1	0.017	0.034*	0.015	0.008	-0.006	0.029	-0.040
	(0.021)	(0.019)	(0.020)	(0.014)	(0.021)	(0.024)	(0.062)
Upstream effects t-1	0.022**	0.022**	0.022**	0.030**	0.012	0.025*	0.069***
	(0.009)	(0.009)	(0.010)	(0.014)	(0.008)	(0.015)	(0.023)
Own effects t-1	0.004		0.004	0.001	0.002	0.005	0.011
	(0.003)		(0.003)	(0.002)	(0.003)	(0.005)	(0.011)
Observations	6560	6560	6560	6560	6560	6560	6560
p-value: Upstream=Own	0.090		0.093	0.050	0.256	0.211	0.030
				B. Δ Log employment			
Δ Dependent variable t-1	0.158***	0.159***	0.163***	0.269***	0.099***	0.041**	0.006
	(0.021)	(0.021)	(0.021)	(0.033)	(0.020)	(0.019)	(0.019)
Downstream effects t-1	0.007	0.021**	0.006	0.007	-0.011	0.018	-0.046
	(0.015)	(0.010)	(0.013)	(0.007)	(0.015)	(0.013)	(0.046)
Upstream effects t-1	0.010*	0.010*	0.009	0.009	0.004	0.016***	0.020*
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.011)
Own effects t-1	0.003		0.003	0.001	0.002	0.009**	0.022**
	(0.003)		(0.003)	(0.001)	(0.003)	(0.004)	(0.009)
Observations	6560	6560	6560	6560	6560	6560	6560
p-value: Upstream=Own	0.338		0.367	0.205	0.738	0.297	0.887

Notes: See Table 3a.

Table 3c: Longer changes on federal spending shock analysis

	Baseline annual analysis	Using two-year periods	Using three-year periods	Using four-year periods	Using five-year periods
	(1)	(2)	(3)	(4)	(5)
	A. Δ Log real value added				
Δ Dependent variable t-1	0.019	0.094**	0.114**	0.083	0.138*
	(0.025)	(0.037)	(0.048)	(0.059)	(0.072)
Downstream effects t-1	0.017	0.031	0.094*	0.197**	0.122
	(0.021)	(0.033)	(0.054)	(0.095)	(0.130)
Upstream effects t-1	0.022**	0.020	0.037*	0.056	-0.009
	(0.009)	(0.014)	(0.021)	(0.039)	(0.051)
Own effects t-1	0.004	0.013***	0.023**	0.011	0.017
	(0.003)	(0.005)	(0.010)	(0.016)	(0.016)
Observations	6560	3080	1920	1152	768
p-value: Upstream=Own	0.090	0.668	0.587	0.314	0.632
	B. Δ Log employment				
Δ Dependent variable t-1	0.158***	0.264***	0.332***	0.346***	0.379***
	(0.021)	(0.027)	(0.040)	(0.047)	(0.054)
Downstream effects t-1	0.007	0.029	0.051	0.044	0.176*
	(0.015)	(0.021)	(0.032)	(0.044)	(0.102)
Upstream effects t-1	0.010*	0.018**	0.040***	0.063***	-0.025
	(0.006)	(0.008)	(0.013)	(0.023)	(0.036)
Own effects t-1	0.003	0.006*	0.015***	0.022***	0.036***
	(0.003)	(0.004)	(0.006)	(0.008)	(0.013)
Observations	6560	3080	1920	1152	768
p-value: Upstream=Own	0.338	0.251	0.095	0.092	0.121

Notes: See Table 3a.

Table 4a: Baseline for TFP shock analysis

	Δ Log real value added		Δ Log employment		Δ Log real labor productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Dependent variable t-1	-0.024	-0.031	0.141***	0.118***	-0.194***	-0.211***
	(0.040)	(0.041)	(0.021)	(0.020)	(0.029)	(0.034)
Δ Dependent variable t-2		0.049**		0.118***		-0.071**
		(0.023)		(0.019)		(0.034)
Δ Dependent variable t-3		0.037*		0.102***		-0.008
		(0.020)		(0.016)		(0.032)
Downstream effects t-1	0.060***	0.047**	0.016*	0.011	0.047***	0.043**
	(0.020)	(0.020)	(0.009)	(0.009)	(0.018)	(0.018)
Upstream effects t-1	0.024**	0.020*	0.009	0.008	0.015*	0.014
	(0.011)	(0.012)	(0.006)	(0.006)	(0.009)	(0.009)
Own effects t-1	0.004	0.007	0.006***	0.007***	0.011**	0.013***
	(0.007)	(0.006)	(0.002)	(0.002)	(0.005)	(0.004)
Observations	6560	5776	6560	5776	6560	5776
p-value: Downstream=Own	0.005	0.039	0.299	0.654	0.034	0.097

Notes: See Table 2a. Estimations consider network structures and the propagation of TFP shocks. Baseline TFP shocks for manufacturing industries are the lagged log change in four-factor TFP taken from the NBER Productivity Database.

Table 4b: Robustness checks on TFP shock analysis

	Baseline estimation	Excluding own lagged shock	Weighting by 1991 log sales	Weighting by 1991 employees	Adding SIC2 fixed effects	Adding SIC3 fixed effects	Adding SIC4 fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Δ Log real value added			
Δ Dependent variable t-1	-0.024	-0.002	-0.024	-0.075	-0.080**	-0.126***	-0.147***
	(0.040)	(0.024)	(0.040)	(0.073)	(0.039)	(0.038)	(0.039)
Downstream effects t-1	0.060***	0.062***	0.060***	0.077**	0.039*	0.027	0.027
	(0.020)	(0.021)	(0.020)	(0.034)	(0.020)	(0.018)	(0.019)
Upstream effects t-1	0.024**	0.024**	0.025**	0.054***	0.021*	0.017	0.020
	(0.011)	(0.011)	(0.011)	(0.016)	(0.011)	(0.012)	(0.013)
Own effects t-1	0.004		0.005	0.025*	0.010	0.014**	0.012**
	(0.007)		(0.007)	(0.014)	(0.006)	(0.006)	(0.005)
Observations	6560	6560	6560	6560	6560	6560	6560
p-value: Downstream=Own	0.005		0.006	0.149	0.152	0.523	0.440
				B. Δ Log employment			
Δ Dependent variable t-1	0.141***	0.154***	0.146***	0.252***	0.081***	0.020	-0.015
	(0.021)	(0.021)	(0.021)	(0.032)	(0.021)	(0.019)	(0.020)
Downstream effects t-1	0.016*	0.025***	0.016*	0.024*	0.002	0.011	0.013
	(0.009)	(0.009)	(0.009)	(0.012)	(0.009)	(0.010)	(0.011)
Upstream effects t-1	0.009	0.012**	0.009	0.022***	0.007	0.010	0.010
	(0.006)	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)	(0.007)
Own effects t-1	0.006***		0.006***	0.003	0.007***	0.008***	0.009***
	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	6560	6560	6560	6560	6560	6560	6560
p-value: Downstream=Own	0.299		0.317	0.106	0.563	0.808	0.728

Notes: See Table 4a.

Table 4c: Longer changes on TFP shock analysis

	Baseline annual analysis	Using two-year periods	Using three-year periods	Using four-year periods	Using five-year periods
	(1)	(2)	(3)	(4)	(5)
			A. Δ Log real value added		
Δ Dependent variable t-1	-0.024	0.067	0.157***	0.123*	0.125*
	(0.040)	(0.047)	(0.056)	(0.069)	(0.068)
Downstream effects t-1	0.060***	0.189***	0.118*	0.253***	0.269**
	(0.020)	(0.047)	(0.067)	(0.089)	(0.104)
Upstream effects t-1	0.024**	0.033	0.041	-0.055	-0.077
	(0.011)	(0.021)	(0.036)	(0.050)	(0.056)
Own effects t-1	0.004	-0.004	-0.027	-0.032	-0.016
	(0.007)	(0.013)	(0.022)	(0.031)	(0.037)
Observations	6560	3080	1920	1152	768
p-value: Downstream=Own	0.005	0.000	0.022	0.001	0.006
			B. Δ Log employment		
Δ Dependent variable t-1	0.141***	0.252***	0.336***	0.349***	0.363***
	(0.021)	(0.028)	(0.042)	(0.047)	(0.054)
Downstream effects t-1	0.016*	0.015	-0.016	0.032	0.053
	(0.009)	(0.022)	(0.027)	(0.036)	(0.053)
Upstream effects t-1	0.009	0.017	0.021	-0.069**	-0.099**
	(0.006)	(0.010)	(0.018)	(0.033)	(0.039)
Own effects t-1	0.006***	0.006	-0.004	-0.011	-0.016
	(0.002)	(0.004)	(0.006)	(0.008)	(0.014)
Observations	6560	3080	1920	1152	768
p-value: Downstream=Own	0.299	0.718	0.695	0.274	0.251

Notes: See Table 4a.

Table 5a: Baseline for foreign patent shock analysis

	Δ Log real value added		Δ Log employment		Δ Log real labor productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Dependent variable t-1	0.020	0.020	0.159***	0.138***	-0.117***	-0.120***
	(0.025)	(0.025)	(0.021)	(0.020)	(0.030)	(0.036)
Δ Dependent variable t-2		0.051**		0.117***		-0.057
		(0.023)		(0.020)		(0.038)
Δ Dependent variable t-3		0.037*		0.100***		-0.003
		(0.021)		(0.016)		(0.035)
Downstream effects t-1	0.043***	0.044***	0.018***	0.018***	0.027***	0.028***
	(0.011)	(0.011)	(0.006)	(0.006)	(0.009)	(0.009)
Upstream effects t-1	-0.000	0.000	-0.001	-0.000	0.001	0.002
	(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
Own effects t-1	-0.006	-0.007*	-0.008***	-0.006**	0.003	0.002
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Observations	6543	5761	6543	5761	6543	5761
p-value: Downstream=Own	0.000	0.000	0.000	0.001	0.014	0.014

Notes: See Table 2a. Estimations consider network structures and the propagation of foreign patent shocks. Baseline patent shocks for manufacturing industries are the lagged change in USPTO patents filed by overseas inventors associated with the industry.

Table 5b: Robustness checks on foreign patent shock analysis

	Baseline estimation	Excluding own lagged shock	Weighting by 1991 log sales	Weighting by 1991 employees	Adding SIC2 fixed effects	Adding SIC3 fixed effects	Adding SIC4 fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Δ Log real value added			
Δ Dependent variable t-1	0.020	0.020	0.024	0.120*	-0.012	-0.042*	-0.075***
	(0.025)	(0.025)	(0.026)	(0.070)	(0.025)	(0.024)	(0.021)
Downstream effects t-1	0.043***	0.039***	0.042***	0.044**	0.040***	0.038***	0.038***
	(0.011)	(0.011)	(0.011)	(0.021)	(0.011)	(0.011)	(0.011)
Upstream effects t-1	-0.000	0.000	0.000	0.007	0.000	0.000	0.000
	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)	(0.004)	(0.005)
Own effects t-1	-0.006		-0.006	0.004	-0.003	-0.003	-0.004
	(0.004)		(0.004)	(0.007)	(0.004)	(0.004)	(0.004)
Observations	6543	6543	6543	6543	6543	6543	6543
p-value: Downstream=Own	0.000		0.000	0.115	0.000	0.001	0.000
				B. Δ Log employment			
Δ Dependent variable t-1	0.159***	0.160***	0.163***	0.270***	0.099***	0.044**	0.012
	(0.021)	(0.021)	(0.021)	(0.034)	(0.020)	(0.019)	(0.020)
Downstream effects t-1	0.018***	0.013**	0.018***	0.014*	0.015**	0.014**	0.013**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Upstream effects t-1	-0.001	-0.000	-0.001	0.001	-0.001	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Own effects t-1	-0.008***		-0.007***	-0.004	-0.004	-0.003	-0.003
	(0.003)		(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Observations	6543	6543	6543	6543	6543	6543	6543
p-value: Downstream=Own	0.000		0.000	0.039	0.007	0.016	0.024

Notes: See Table 5a.

Table 5c: Longer changes on foreign patent shock analysis

	Baseline annual analysis	Using two-year periods	Using three-year periods	Using four-year periods	Using five-year periods
	(1)	(2)	(3)	(4)	(5)
	A. Δ Log real value added				
Δ Dependent variable t-1	0.020	0.099***	0.113**	0.075	0.133*
	(0.025)	(0.038)	(0.050)	(0.060)	(0.071)
Downstream effects t-1	0.043***	-0.032	0.040	0.088	-0.012
	(0.011)	(0.023)	(0.034)	(0.064)	(0.067)
Upstream effects t-1	-0.000	-0.020**	-0.013	0.004	0.014
	(0.005)	(0.009)	(0.012)	(0.018)	(0.021)
Own effects t-1	-0.006	0.012	-0.015	0.044*	0.004
	(0.004)	(0.011)	(0.017)	(0.023)	(0.033)
Observations	6543	3072	1915	1149	766
p-value: Downstream=Own	0.000	0.127	0.167	0.557	0.861
	B. Δ Log employment				
Δ Dependent variable t-1	0.159***	0.265***	0.330***	0.324***	0.347***
	(0.021)	(0.028)	(0.041)	(0.046)	(0.053)
Downstream effects t-1	0.018***	0.005	0.046**	0.104***	0.039
	(0.006)	(0.012)	(0.023)	(0.037)	(0.048)
Upstream effects t-1	-0.001	-0.011**	-0.009	0.005	0.006
	(0.003)	(0.005)	(0.008)	(0.012)	(0.015)
Own effects t-1	-0.008***	-0.002	-0.022**	-0.006	-0.006
	(0.003)	(0.007)	(0.010)	(0.015)	(0.030)
Observations	6543	3072	1915	1149	766
p-value: Downstream=Own	0.000	0.656	0.018	0.013	0.490

Notes: See Table 5a.

Table 6: VAR estimations for intermediated shocks

	China trade		Federal spending		TFP		Foreign patenting	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Δ Log real value added				
Δ Dependent variable t-1	-0.045	-0.060	-0.025	-0.011	-0.057	-0.063	0.312***	0.244**
	(0.039)	(0.044)	(0.027)	(0.041)	(0.044)	(0.044)	(0.109)	(0.098)
Δ Downstream real value added t-1		0.038		-0.036	0.087***	0.080***	-0.735***	-0.398**
		(0.112)		(0.116)	(0.025)	(0.025)	(0.268)	(0.200)
Δ Upstream real value added t-1	0.173***	0.171***	0.113**	0.114**		0.017		-0.162*
	(0.059)	(0.061)	(0.045)	(0.052)		(0.011)		(0.086)
Own shock t-1	0.030***	0.030***	0.006**	0.007*	0.009	0.009	-0.012*	-0.006
	(0.008)	(0.008)	(0.003)	(0.004)	(0.007)	(0.007)	(0.007)	(0.006)
Observations	6168	6168	6560	6560	6560	6560	6543	6543
				B. Δ Log employment				
Δ Dependent variable t-1	0.132***	0.084	0.185***	0.079	0.089***	0.081***	0.310***	0.268***
	(0.023)	(0.146)	(0.025)	(0.080)	(0.028)	(0.026)	(0.059)	(0.058)
Δ Downstream employment t-1		0.097		0.158	0.095**	0.091**	-0.264***	-0.278***
		(0.295)		(0.115)	(0.041)	(0.044)	(0.098)	(0.099)
Δ Upstream employment t-1	0.053***	0.035	-0.045*	-0.018		0.017		0.085**
	(0.014)	(0.054)	(0.024)	(0.031)		(0.025)		(0.038)
Own shock t-1	0.026***	0.022*	0.005**	0.003	0.007***	0.007***	-0.012***	-0.013***
	(0.004)	(0.011)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Observations	6168	6168	6560	6560	6560	6560	6543	6543

Notes: See Tables 2a-5a. Rather than model network shocks directly, estimations consider intermediated approaches where the shock indicated by the column header instruments for changes in upstream and downstream economic activity in terms of real value added or employment. Estimations control for own shock and use two lags of upstream and downstream components. In each estimation pair, the first specification considers the focal network element for the shock in question. The second specification adds in the non-focal element where the first stage fit can be weak.

Table 7a: Joint analysis without foreign patenting shocks

		Δ Log real value added		Δ Log employment	
		(1)	(2)	(3)	(4)
Δ Dependent variable t-1		-0.040	-0.048	0.126***	0.105***
		(0.041)	(0.041)	(0.020)	(0.020)
Δ Dependent variable t-2			0.041*		0.108***
			(0.022)		(0.020)
Δ Dependent variable t-3			0.033		0.090***
			(0.021)		(0.016)
Trade:	Downstream effects t-1	-0.042	-0.025	-0.006	0.017
		(0.083)	(0.081)	(0.043)	(0.040)
	Upstream effects t-1	0.106***	0.107***	0.065***	0.054***
		(0.030)	(0.031)	(0.020)	(0.020)
	Own effects t-1	0.030***	0.028***	0.022***	0.016***
		(0.009)	(0.009)	(0.005)	(0.004)
Federal:	Downstream effects t-1	-0.003	0.001	-0.006	0.003
		(0.024)	(0.025)	(0.017)	(0.014)
	Upstream effects t-1	0.036**	0.041***	0.021**	0.023***
		(0.014)	(0.014)	(0.009)	(0.008)
	Own effects t-1	0.001	0.004	0.001	0.005*
		(0.003)	(0.004)	(0.003)	(0.003)
TFP:	Downstream effects t-1	0.061***	0.049**	0.019*	0.013
		(0.020)	(0.020)	(0.010)	(0.010)
	Upstream effects t-1	0.029**	0.027**	0.013*	0.011
		(0.013)	(0.013)	(0.007)	(0.008)
	Own effects t-1	0.007	0.009	0.007***	0.008***
		(0.007)	(0.007)	(0.002)	(0.002)
Observations		6560	5776	6560	5776

Notes: See Table 2a.

Table 7b: Joint analysis with foreign patenting shocks

		Δ Log real value added		Δ Log employment	
		(1)	(2)	(3)	(4)
Δ Dependent variable t-1		-0.043	-0.050	0.125***	0.105***
		(0.041)	(0.041)	(0.020)	(0.020)
Δ Dependent variable t-2			0.040*		0.108***
			(0.022)		(0.020)
Δ Dependent variable t-3			0.032		0.089***
			(0.021)		(0.016)
Trade:	Downstream effects t-1	-0.059	-0.042	-0.016	0.008
		(0.082)	(0.080)	(0.044)	(0.040)
	Upstream effects t-1	0.106***	0.107***	0.066***	0.054***
		(0.030)	(0.031)	(0.020)	(0.019)
	Own effects t-1	0.032***	0.030***	0.022***	0.017***
		(0.009)	(0.009)	(0.005)	(0.004)
Federal:	Downstream effects t-1	-0.006	-0.003	-0.008	0.001
		(0.023)	(0.025)	(0.017)	(0.014)
	Upstream effects t-1	0.035**	0.040***	0.020**	0.023***
		(0.014)	(0.014)	(0.009)	(0.008)
	Own effects t-1	0.001	0.004	0.001	0.005*
		(0.003)	(0.004)	(0.003)	(0.003)
TFP:	Downstream effects t-1	0.062***	0.051**	0.019*	0.014
		(0.021)	(0.021)	(0.010)	(0.010)
	Upstream effects t-1	0.030**	0.028**	0.013*	0.011
		(0.013)	(0.014)	(0.008)	(0.008)
	Own effects t-1	0.007	0.009	0.007***	0.008***
		(0.007)	(0.007)	(0.002)	(0.002)
Patent:	Downstream effects t-1	0.043***	0.043***	0.017***	0.016**
		(0.011)	(0.011)	(0.006)	(0.007)
	Upstream effects t-1	0.002	0.002	0.000	0.000
		(0.005)	(0.005)	(0.003)	(0.003)
	Own effects t-1	-0.007*	-0.007*	-0.007***	-0.006**
		(0.004)	(0.004)	(0.003)	(0.003)
Observations		6543	5761	6543	5761

Notes: See Table 2a.

Table 8a: Geographic effects and networks analysis with single shocks

		Δ Log real value added							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Dependent variable t-1		0.022	0.019	0.018	0.017	-0.013	-0.024	0.021	0.020
		(0.025)	(0.025)	(0.024)	(0.024)	(0.040)	(0.040)	(0.025)	(0.025)
Trade:	Geographic effects t-1	0.001	0.002						
		(0.007)	(0.007)						
	Downstream effects t-1		-0.142*						
			(0.086)						
	Upstream effects t-1		0.076***						
			(0.024)						
	Own effects t-1	0.032***	0.034***						
		(0.009)	(0.009)						
Federal:	Geographic effects t-1			0.021**	0.018**				
				(0.009)	(0.009)				
	Downstream effects t-1				0.005				
					(0.021)				
	Upstream effects t-1				0.018**				
					(0.008)				
	Own effects t-1			0.004	0.003				
				(0.003)	(0.003)				
TFP:	Geographic effects t-1					0.005	0.003		
						(0.005)	(0.005)		
	Downstream effects t-1						0.060***		
							(0.020)		
	Upstream effects t-1						0.023**		
							(0.011)		
	Own effects t-1					0.007	0.004		
						(0.007)	(0.007)		
Patent:	Geographic effects t-1							0.004***	0.003***
								(0.001)	(0.001)
	Downstream effects t-1								0.041***
									(0.011)
	Upstream effects t-1								-0.001
									(0.004)
	Own effects t-1							-0.002	-0.006
								(0.004)	(0.004)
Observations		6560	6560	6560	6560	6560	6560	6543	6543

Notes: See Table 2a. Estimations include additional effects from indicated shocks and the geographic overlay of industries. Geographic overlay is measured as the sum across regions of the interaction of a focal industry's employment share in the region times the share of regional activity for other industries. Regions are defined through commuting zones and use 1991 industrial activity from the County Business Patterns database.

Table 8a: Geographic effects and networks analysis with single shocks, continued

		Δ Log employment							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Dependent variable t-1		0.152***	0.149***	0.159***	0.158***	0.142***	0.141***	0.159***	0.159***
		(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Trade:	Geographic effects t-1	0.004	0.004						
		(0.004)	(0.004)						
	Downstream effects t-1		-0.059						
			(0.041)						
	Upstream effects t-1		0.049***						
			(0.016)						
	Own effects t-1	0.022***	0.023***						
		(0.005)	(0.005)						
Federal:	Geographic effects t-1			0.005	0.004				
				(0.003)	(0.003)				
	Downstream effects t-1				0.005				
					(0.014)				
	Upstream effects t-1				0.009				
					(0.006)				
	Own effects t-1			0.003	0.003				
				(0.002)	(0.003)				
TFP:	Geographic effects t-1					0.003	0.002		
						(0.003)	(0.003)		
	Downstream effects t-1						0.016*		
							(0.009)		
	Upstream effects t-1						0.009		
							(0.006)		
	Own effects t-1					0.007***	0.006***		
						(0.002)	(0.002)		
Patent:	Geographic effects t-1							0.000	0.000
								(0.001)	(0.001)
	Downstream effects t-1								0.018***
									(0.006)
	Upstream effects t-1								-0.001
									(0.003)
	Own effects t-1							-0.006**	-0.008***
								(0.003)	(0.003)
Observations		6560	6560	6560	6560	6560	6560	6543	6543

Notes: See Table 2a.

Table 8b: Geographic effects and joint networks analysis

		Δ Log real value added		Δ Log employment	
		(1)	(2)	(3)	(4)
Δ Dependent variable t-1		-0.028	-0.047	0.130***	0.124***
		(0.040)	(0.041)	(0.021)	(0.020)
Trade:	Geographic effects t-1	0.125***	0.113***	0.055***	0.049***
		(0.035)	(0.034)	(0.018)	(0.017)
	Downstream effects t-1		-0.048		-0.014
			(0.078)		(0.045)
	Upstream effects t-1		0.095***		0.061***
			(0.029)		(0.019)
	Own effects t-1	0.032***	0.033***	0.023***	0.023***
		(0.009)	(0.009)	(0.005)	(0.005)
Federal:	Geographic effects t-1	0.112***	0.101***	0.046***	0.040***
		(0.032)	(0.031)	(0.015)	(0.014)
	Downstream effects t-1		-0.036		-0.018
			(0.023)		(0.017)
	Upstream effects t-1		0.026**		0.017**
			(0.012)		(0.009)
	Own effects t-1	0.001	-0.001	0.002	0.001
		(0.004)	(0.004)	(0.003)	(0.003)
TFP:	Geographic effects t-1	0.032***	0.027***	0.014***	0.012**
		(0.010)	(0.010)	(0.005)	(0.005)
	Downstream effects t-1		0.055***		0.016*
			(0.019)		(0.010)
	Upstream effects t-1		0.024*		0.011
			(0.013)		(0.008)
	Own effects t-1	0.008	0.007	0.008***	0.007***
		(0.006)	(0.006)	(0.002)	(0.002)
Patent:	Geographic effects t-1	0.005***	0.004***	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
	Downstream effects t-1		0.039***		0.016**
			(0.011)		(0.006)
	Upstream effects t-1		0.002		0.000
			(0.005)		(0.003)
	Own effects t-1	-0.002	-0.006*	-0.005**	-0.007***
		(0.004)	(0.004)	(0.003)	(0.003)
Observations		6543	6543	6543	6543

Notes: See Table 2a.

Table 8c: Robustness checks on joint geographic analysis

		Baseline estimation	Excluding own lagged shock	Weighting by 1991 log sales	Weighting by 1991 employees	Adding SIC2 fixed effects	Adding SIC3 fixed effects	Adding SIC4 fixed effects
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		A. Δ Log real value added						
Δ Dependent variable t-1		-0.028	0.009	-0.027	-0.065	-0.074*	-0.120***	-0.139***
		(0.040)	(0.023)	(0.040)	(0.070)	(0.039)	(0.038)	(0.038)
Trade:	Geographic effects t-1	0.125***	0.121***	0.121***	0.068**	0.090***	0.074**	0.047
		(0.035)	(0.034)	(0.035)	(0.029)	(0.032)	(0.030)	(0.031)
	Own effects t-1	0.032***		0.031***	0.020*	0.020**	0.020**	0.023*
		(0.009)		(0.009)	(0.011)	(0.009)	(0.010)	(0.013)
Federal:	Geographic effects t-1	0.112***	0.112***	0.110***	0.063**	0.086***	0.075***	0.012
		(0.032)	(0.030)	(0.032)	(0.026)	(0.029)	(0.028)	(0.030)
	Own effects t-1	0.001		0.000	-0.001	-0.001	0.004	0.014
		(0.004)		(0.004)	(0.003)	(0.004)	(0.005)	(0.009)
TFP:	Geographic effects t-1	0.032***	0.032***	0.030***	0.011*	0.025***	0.022**	0.018**
		(0.010)	(0.010)	(0.010)	(0.006)	(0.010)	(0.009)	(0.009)
	Own effects t-1	0.008		0.008	0.031**	0.011*	0.015**	0.013**
		(0.006)		(0.007)	(0.014)	(0.006)	(0.006)	(0.005)
Patent:	Geographic effects t-1	0.005***	0.005***	0.005***	0.002***	0.005***	0.005***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Own effects t-1	-0.002		-0.001	0.007	0.000	-0.000	-0.001
		(0.004)		(0.004)	(0.006)	(0.004)	(0.004)	(0.004)
Observations		6543	6560	6543	6543	6543	6543	6543

Notes: See Table 2a.

Table 8c: Robustness checks on joint geographic analysis, continued

		Baseline estimation	Excluding own lagged shock	Weighting by 1991 log sales	Weighting by 1991 employees	Adding SIC2 fixed effects	Adding SIC3 fixed effects	Adding SIC4 fixed effects
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		B. Δ Log employment						
Δ Dependent variable t-1		0.130***	0.156***	0.135***	0.240***	0.081***	0.020	-0.019
		(0.021)	(0.020)	(0.020)	(0.034)	(0.021)	(0.019)	(0.019)
Trade:	Geographic effects t-1	0.055***	0.057***	0.053***	0.030**	0.027*	0.030*	0.036**
		(0.018)	(0.017)	(0.017)	(0.012)	(0.015)	(0.015)	(0.018)
	Own effects t-1	0.023***		0.023***	0.022***	0.011***	0.007*	0.004
		(0.005)		(0.005)	(0.007)	(0.004)	(0.004)	(0.004)
Federal:	Geographic effects t-1	0.046***	0.050***	0.043***	0.027***	0.022*	0.021	0.010
		(0.015)	(0.014)	(0.014)	(0.010)	(0.013)	(0.013)	(0.017)
	Own effects t-1	0.002		0.002	0.000	0.001	0.009**	0.021***
		(0.003)		(0.002)	(0.001)	(0.003)	(0.004)	(0.007)
TFP:	Geographic effects t-1	0.014***	0.014***	0.013***	0.006**	0.008*	0.009*	0.011**
		(0.005)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.005)
	Own effects t-1	0.008***		0.008***	0.006***	0.008***	0.009***	0.010***
		(0.002)		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Patent:	Geographic effects t-1	0.001	0.001	0.001	0.001	0.001	0.001	0.000
		(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	Own effects t-1	-0.005**		-0.005**	-0.002	-0.003	-0.002	-0.002
		(0.003)		(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations		6543	6560	6543	6543	6543	6543	6543

Notes: See Table 2a.

Appendix Table 1: First-stage relationships for Chinese imports instruments

	Real value-added growth, one lag			Real value-added growth, three lags		
	Downstream effects t-1	Upstream effects t-1	Own effects t-1	Downstream effects t-1	Upstream effects t-1	Own effects t-1
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Log real value added t-1	-0.012***	-0.014	-0.008	-0.013***	-0.015	-0.023
	(0.004)	(0.010)	(0.084)	(0.005)	(0.011)	(0.082)
Δ Log real value added t-2				-0.004	0.032**	-0.027
				(0.005)	(0.015)	(0.068)
Δ Log real value added t-3				-0.005	0.004	-0.018
				(0.005)	(0.013)	(0.080)
IV Downstream effects t-1	0.638***	0.101**	0.832**	0.640***	0.110**	0.835**
	(0.041)	(0.044)	(0.368)	(0.041)	(0.045)	(0.364)
IV Upstream effects t-1	0.005	0.886***	-0.244**	0.005	0.879***	-0.237***
	(0.009)	(0.045)	(0.076)	(0.009)	(0.045)	(0.077)
IV Own effects t-1	-0.001	-0.008***	0.461***	-0.001	-0.009***	0.458***
	(0.002)	(0.003)	(0.075)	(0.002)	(0.003)	(0.073)
Shea's Partial R-Squared	0.361	0.514	0.224	0.360	0.509	0.222

Notes: See Table 2a.

Appendix Table 2a: Variations in psi parameter for China trade shock analysis

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
						A. Δ Log real value added					
Downstream effects t-1	-0.146*	-0.116	-0.086	-0.056	-0.026	0.004	0.034	0.065	0.095	0.125	0.155*
	(0.087)	(0.083)	(0.080)	(0.078)	(0.076)	(0.074)	(0.074)	(0.074)	(0.075)	(0.077)	(0.080)
Upstream effects t-1	0.077***	0.073***	0.069***	0.064***	0.060***	0.056***	0.052***	0.048***	0.043**	0.039**	0.035*
	(0.024)	(0.022)	(0.021)	(0.020)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Own effects t-1	0.034***	0.033***	0.033***	0.032***	0.032***	0.031***	0.031***	0.030***	0.030***	0.029***	0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
						B. Δ Log employment					
Downstream effects t-1	-0.073	-0.062	-0.050	-0.038	-0.027	-0.015	-0.003	0.008	0.020	0.032	0.043
	(0.046)	(0.042)	(0.039)	(0.037)	(0.035)	(0.034)	(0.034)	(0.035)	(0.036)	(0.039)	(0.042)
Upstream effects t-1	0.056***	0.052***	0.047***	0.042***	0.038***	0.033***	0.028***	0.024**	0.019**	0.014	0.010
	(0.018)	(0.017)	(0.016)	(0.014)	(0.013)	(0.012)	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)
Own effects t-1	0.026***	0.024***	0.022***	0.020***	0.018***	0.016***	0.014***	0.012***	0.010***	0.008**	0.006
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Notes: See Table 2a. Estimations impose the psi parameter for the lagged dependent variable dependence given in the column header.

Appendix Table 2b: Variations in psi parameter for federal spending shock analysis

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
						A. Δ Log real value added					
Downstream effects t-1	0.017	0.016	0.014	0.012	0.010	0.009	0.007	0.005	0.004	0.002	0.000
	(0.022)	(0.020)	(0.018)	(0.016)	(0.014)	(0.012)	(0.011)	(0.009)	(0.008)	(0.008)	(0.008)
Upstream effects t-1	0.022**	0.020**	0.018**	0.017**	0.015**	0.013**	0.011**	0.009**	0.007**	0.005*	0.004
	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Own effects t-1	0.004	0.004	0.003	0.003	0.003	0.003	0.002*	0.002**	0.002**	0.001**	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
						B. Δ Log employment					
Downstream effects t-1	0.009	0.008	0.007	0.006	0.005	0.004	0.003	0.002	0.001	0.000	-0.001
	(0.016)	(0.015)	(0.014)	(0.013)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.008)	(0.007)
Upstream effects t-1	0.011	0.010*	0.009*	0.009*	0.008*	0.007*	0.007*	0.006*	0.005*	0.004*	0.004
	(0.007)	(0.006)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Own effects t-1	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.002	0.002*	0.002**	0.002***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: See Table 3a. Estimations impose the psi parameter for the lagged dependent variable dependence given in the column header.

Appendix Table 2c: Variations in psi parameter for TFP shock analysis

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
						A. Δ Log real value added					
Downstream effects t-1	0.059***	0.054***	0.050**	0.045**	0.040*	0.035	0.031	0.026	0.021	0.017	0.012
	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.022)	(0.022)	(0.023)	(0.024)	(0.024)	(0.025)
Upstream effects t-1	0.023**	0.021*	0.019*	0.017	0.015	0.013	0.011	0.008	0.006	0.004	0.002
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)
Own effects t-1	0.002	-0.011***	-0.023***	-0.035***	-0.047***	-0.059***	-0.072***	-0.084***	-0.096***	-0.108***	-0.120***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
						B. Δ Log employment					
Downstream effects t-1	0.018*	0.017*	0.016*	0.015	0.013	0.012	0.011	0.010	0.009	0.007	0.006
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Upstream effects t-1	0.010	0.009	0.009	0.008	0.007	0.006	0.005	0.004	0.003	0.003	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Own effects t-1	0.010***	0.007***	0.005***	0.003	0.000	-0.002	-0.004**	-0.007***	-0.009***	-0.011***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)

Notes: See Table 4a. Estimations impose the psi parameter for the lagged dependent variable dependence given in the column header.

Appendix Table 2d: Variations in psi parameter for foreign patenting shock analysis

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
						A. Δ Log real value added					
Downstream effects t-1	0.043***	0.041***	0.039***	0.037***	0.036***	0.034***	0.032**	0.030**	0.028**	0.026*	0.024
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.014)	(0.015)
Upstream effects t-1	-0.000	0.000	0.001	0.001	0.002	0.003	0.003	0.004	0.005	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
Own effects t-1	-0.006	-0.005	-0.005	-0.004	-0.003	-0.002	-0.002	-0.001	-0.000	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)
						B. Δ Log employment					
Downstream effects t-1	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***	0.018**	0.018**	0.018**	0.018**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Upstream effects t-1	-0.002	-0.001	-0.001	0.000	0.001	0.001	0.002	0.003	0.003	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Own effects t-1	-0.009***	-0.008***	-0.007***	-0.006**	-0.006**	-0.005	-0.004	-0.003	-0.002	-0.001	-0.000
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)

Notes: See Table 5a. Estimations impose the psi parameter for the lagged dependent variable dependence given in the column header.

Appendix Table 3: Summed coefficients over deeper lags

	Δ Log real value added				Δ Log employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Include 3 lags of DV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Include 3 lags of own shock		Yes		Yes		Yes		Yes
Include 3 lags of network shocks			Yes	Yes			Yes	Yes
Table 2a: Imports								
Downstream effects	-0.124	-0.121	-0.191*	-0.225**	-0.044	-0.040	-0.034	-0.065*
Upstream effects	0.076***	0.079***	0.067***	0.074***	0.039***	0.045***	0.038***	0.043***
Own effects	0.031***	0.042***	0.030***	0.046***	0.018***	0.029***	0.018***	0.032***
Table 3a: Federal Spending								
Downstream effects	0.023	0.023	0.042*	0.036*	0.013	0.013	0.015	0.015
Upstream effects	0.020**	0.020**	0.018**	0.018**	0.011**	0.011**	0.013***	0.013***
Own effects	0.008**	0.010***	0.008**	0.009***	0.006***	0.007***	0.006***	0.006***
Table 4a: TFP								
Downstream effects	0.047**	0.048**	0.085**	0.087**	0.011	0.012	-0.005	-0.003
Upstream effects	0.020*	0.019*	0.017	0.017	0.008	0.008	0.013	0.014*
Own effects	0.007	-0.001	0.007	-0.002	0.007***	0.005*	0.007***	0.006*
Table 5a: Foreign Patent								
Downstream effects	0.044***	0.043***	0.037*	0.030	0.018***	0.018***	0.022**	0.021**
Upstream effects	0.000	0.001	-0.014**	-0.014**	-0.000	0.000	-0.009**	-0.009**
Own effects	-0.007*	0.001	-0.007*	0.003	-0.006**	-0.004	-0.006**	-0.005

Notes: Table documents the sum of coefficients across variations of lag structure. Columns 1 and 5 are baseline specifications from respective tables.

Appendix Table 4: Joint estimates reported in Figure 4

		Δ Log real value added		Δ Log employment	
		(1)	(2)	(3)	(4)
Δ Dependent variable t-1		-0.046	-0.049	0.109***	0.108***
		(0.041)	(0.041)	(0.019)	(0.019)
Δ Dependent variable t-2		0.040*	0.039*	0.108***	0.108***
		(0.021)	(0.021)	(0.019)	(0.019)
Δ Dependent variable t-3		0.028	0.026	0.096***	0.095***
		(0.019)	(0.019)	(0.016)	(0.016)
Trade:	Geographic effects t-1	0.063***	0.060***	0.024***	0.026***
		(0.017)	(0.018)	(0.007)	(0.008)
	Downstream effects t-1	0.018	0.007	0.027	0.021
		(0.043)	(0.043)	(0.025)	(0.026)
	Upstream effects t-1	0.076***	0.076***	0.039***	0.039***
		(0.024)	(0.024)	(0.015)	(0.015)
	Own effects t-1	0.013***	0.013***	0.007***	0.007***
		(0.004)	(0.004)	(0.002)	(0.002)
Federal:	Geographic effects t-1	0.065***	0.062***	0.019***	0.022***
		(0.019)	(0.020)	(0.007)	(0.008)
	Downstream effects t-1	-0.016	-0.020	0.001	-0.002
		(0.022)	(0.022)	(0.013)	(0.013)
	Upstream effects t-1	0.029***	0.030***	0.019***	0.019***
		(0.011)	(0.011)	(0.007)	(0.007)
	Own effects t-1	0.005	0.005	0.005**	0.005**
		(0.004)	(0.004)	(0.003)	(0.003)
TFP:	Geographic effects t-1	0.004	0.005	0.004	0.002
		(0.005)	(0.006)	(0.003)	(0.004)
	Downstream effects t-1	0.041**	0.043**	0.008	0.009
		(0.019)	(0.019)	(0.009)	(0.009)
	Upstream effects t-1	0.017	0.017	0.007	0.006
		(0.012)	(0.012)	(0.007)	(0.007)
	Own effects t-1	0.008	0.008	0.007***	0.007***
		(0.006)	(0.006)	(0.002)	(0.002)
Patent:	Geographic effects t-1		0.000		-0.001
			(0.001)		(0.001)
	Downstream effects t-1		0.044***		0.018***
			(0.011)		(0.006)
	Upstream effects t-1		-0.001		-0.001
			(0.005)		(0.003)
	Own effects t-1		-0.008**		-0.007**
			(0.004)		(0.003)
Observations		5776	5761	5776	5761

Notes: See Table 2a.