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From Micro to Macro via Production Networks†

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A modern economy is an intricately linked web of specialized production units, each relying on the flow of inputs from their suppliers to produce their own output, which in turn is routed towards other downstream units. In this essay, I argue that the structure of this production network is key in determining whether and how microeconomic shocks—affecting only a particular firm or technology along the chain—propagate throughout the economy and shape aggregate outcomes. Therefore, understanding the structure of this production network can better inform both academics on the origins of aggregate fluctuations and policymakers on how to prepare for and recover from adverse shocks that disrupt these production chains.

Two recent events have brought to the forefront the importance of interconnections between firms and sectors in aggregate economic performance. Consider first the 2011 earthquake in Japan. While the triple tragedy of the earthquake, the ensuing tsunami, and the near nuclear meltdown at Fukushima surely resulted in a significant destruction of human and physical capital, its effects would have been largely restricted to the affected areas were it not for the disruption of national

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and global supply chains that it entailed. As Kim and Reynolds (2011) reported for Reuters in the aftermath of the earthquake:

> Supply chain disruptions in Japan have forced at least one global automaker to delay the launch of two new models and are forcing other industries to shutter plants. . . . The automaker is just one of dozens, if not hundreds, of Japanese manufacturers facing disruptions to their supply chains as a result of the quake, the subsequent tsunami and a still-unresolved nuclear threat.

On a grander scale, the financial crisis, the 2007–2009 recession, and its aftermath have brought with them a renewed emphasis on the complex web of linkages that constitute the backbone of the US economy. Terms like "too interconnected to fail" or "systemically important firms" have become commonplace in public discourse. While this network lingo originated in the confines of an intertwined financial sector, it is increasingly used to describe the transmission of disturbances across individual actors in the economy. One prime example is the reasoning offered in the congressional testimony of Ford's chief executive officer, Alan Mulally (2008), when requesting the government to bail out Ford's key competitors, General Motors and Chrysler:

> If any one of the domestic companies should fail, we believe there is a strong chance that the entire industry would face severe disruption. Ours is in some significant ways an industry that is uniquely interdependent—particularly with respect to our supply base, with more than 90 percent commonality among our suppliers. Should one of the other domestic companies declare bankruptcy, the effect on Ford's production operations would be felt within days—if not hours. Suppliers could not get financing and would stop shipments to customers. Without parts for the just-in-time inventory system, Ford plants would not be able to produce vehicles.

The common theme across these two examples is that the organization of production along supply chain networks exposes the aggregate economy to disruptions in critical nodes in these chains. In particular, whenever the linkage structure in the economy is dominated by a small number of hubs supplying inputs to many different firms or sectors, aggregate fluctuations may arise for two related, but distinct, reasons. First, fluctuations in these hub-like production units can propagate throughout the economy and affect aggregate performance, much in the same way as a shutdown at a major airport has a disruptive impact on scheduled flights throughout a country. In either case, there are no close substitutes in the short run and every user is affected by disturbances at the source. Second, the presence of these hubs provides shortcuts through which these supply chain networks become easily navigable. That is, hubs shorten distances between otherwise disparate parts of the economy that do not directly trade inputs. The upshot of this is that these production hubs act as powerful shock conductors, helping to transmit shocks originating elsewhere in the network.

In this essay, I argue that these production networks, by facilitating the propagation of otherwise localized disturbances, provide a bridge between the micro, involving the myriad of unforeseen events affecting individual production decisions, and the macro, i.e., their synchronized behavior defining the business cycle.

This synchronization of production decisions over time has led most of modern macroeconomics to assume the presence of some sort of aggregate shock, at times lifting all boats, at times generating widespread recessions. In doing so, however, modern business cycle theory has assumed—rather than explained—comovement across producers from the outset. Moreover, after decades of research, the origins of these aggregate shocks remain elusive, thus casting doubt on their assumed existence. Against this backdrop, the promise of production networks is to open the black-box of comovement by viewing it as the endogenous outcome of micro shocks propagating across input linkages.

I will begin by showing how this novel view can be easily mapped to a standard multisector general equilibrium setting where different sectors are interlinked by input-output relations. In particular, through a series of stylized examples, I will explore how the propagation of sectoral shocks—and hence aggregate volatility—depends on different arrangements of production, that is, on different "shapes" of the underlying production network.

The natural follow-up question is whether we can discipline the set of admissible "shapes" by looking at actual data on production networks. I will do this by exploring, from a network perspective, the empirical properties of a large-scale production network as given by detailed US input-output data.

Given the properties we observe in the data, I then use the model to ask a range of questions: Is the organization of the economy along production networks a source of aggregate fluctuations? Can we understand empirical patterns of sectoral comovement through this lens? Is the level of sectoral comovement a function of how far apart the different sectors are in the production network? Do central sectors in the production network comove more with the aggregate? In short, can traditional tools of network analysis—such as distance across nodes or centrality of a given node—help to further our understanding of what shapes comovement?

Finally, I show that the structure of the production network and the strength of the propagation mechanism it entails is crucial when confronting a deep-seated and influential logic which, to this day, justifies the continued appeal to an exogenous synchronization device, in the form of aggregate shocks. This argument, dating back at least to Lucas (1977), goes as follows: given that uncorrelated micro disturbances, by definition, occur randomly across production nodes, won't these micro-shocks tend to average out as we disaggregate the economy into finer and finer definitions of what a production unit is? In other words, won't these local disturbances tend to be diversified away? In turn, doesn't this imply that we must resort to the convention of aggregate shocks? By bringing theory and empirics together, I will argue that the answer to these questions is likely to be "no."

A Simple Model of Production Networks

I start by showing how these production networks can be mapped into a basic general equilibrium setting—a static variant of a textbook multisector model without aggregate shocks, following closely the methods we used in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). I then discuss how different ways of organizing these production networks can generate different magnitudes of aggregate volatility.

Networks of Input Flows: A General Equilibrium Benchmark

Consider an economy where production takes place at n distinct nodes, each specializing in a different good. These goods serve a dual role in the economy: on the one hand, each good is potentially valued by households as final consumption; on the other hand, the same good can be used as an intermediate input to be deployed in the production of other goods. Here I will focus on this latter role and simplify the final demand side of this economy substantially by assuming that households value the different goods equally and, as a consequence, consume them in equal proportions. In the same spirit, I will assume households provide labor services inelastically to the goods' producers in the economy and spend all the resulting wage income in the consumption of the n goods.[1]

A natural interpretation for these production nodes is to equate them with the different sectors of an economy. I assume that the production process at each of these sectors is well approximated by a Cobb–Douglas technology with constant returns to scale, combining a primary factor—which in this case is labor—and intermediate inputs. The output of sector i is then given by:

$$x_i = (z_i l_i)^{1-\alpha} \left(\prod_{i=1}^{n} x_{ij}^{\omega_{ij}} \right)^{\alpha} .$$

In this Cobb–Douglas production function, the first term shows the contribution from primary factors to production. The amount of labor hired by sector i is given by l_i, while $1 - \alpha$ is the share of labor in production. The added element in this first term is z_i, a sector-specific productivity disturbance, shifting the production possibilities frontier of sector i in a random fashion. This is the only source of uncertainty in this simple economy. I assume further that these productivity shocks are independent across producers of goods in the economy. The absence of any exogenous correlating device—that is, the lack of any aggregate technology shocks—allows us to focus solely on the question of interest: can interconnections across production technologies, in the form of intermediate inputs flows, generate endogenous comovement across otherwise unrelated producers of goods?

[1] In other words, on the final demand side I will be assuming that the representative household has a Cobb–Douglas utility function with the same weights over the different goods and has no disutility of labor.

These interconnections between production nodes come into play with the second term of the production function, which reflects the contribution of intermediate inputs from other sectors. Thus, the term x_{ij} denotes the amount of good j used in the production of good i. The exponent ω_{ij} (≥ 0) in the production function gives the share of good j in the total intermediate input use by sector i.[2] For a given sector i, the associated list of ω_{ij}'s thus encodes a sort of production recipe. Each nonzero element of this list singles out a good that needs to be sourced in order to produce good i. Whenever a ω_{ij} is zero, we are simply stating that sector i cannot usefully incorporate j as input in production, no matter what input prices sector i is currently facing. Note further that all production technologies are, deliberately, being kept largely symmetric: all goods are equally valued by final consumers and all production technologies are equally labor-intensive (specifically, they all share the same α).[3] The only difference across sectors then lies in the bundle of intermediate inputs specified by their production recipe—that is, which goods are necessary as inputs in the production process of other goods.

When we stack together all production recipes in the economy, we obtain a collection of n lists, or rows, each row giving the particular list of ω_{ij}'s associated with the production technology in sector i. This list-of-lists is nothing other than an input-output matrix, W, summarizing the structure of intermediate input relations in this economy. Crucially for this paper, all information in W can be equivalently represented by a network, something that has been acknowledged at least since Solow (1952) but rarely put to use. The production network, W, which is the central object of this essay, is then defined by three elements: i) a collection of n vertices or nodes, each vertex corresponding to one of the sectors in the economy; ii) a collection of directed edges, where an edge between any two vertices denotes an input-supplying relationship between two sectors; and iii) a collection of weights, each of which is associated with a particular directed edge and given by the exponent ω_{ij} in the production function.

The question is now whether different production networks—that is, different arrangements of who sources inputs from whom—matter for comovement and aggregate fluctuations. An initial clue is provided by the general equilibrium solution of the economy just described. In equilibrium, (the logarithm of) aggregate

[2] I will further assume that these shares sum to one for any sector i. As a consequence of the Cobb–Douglas constant-returns-to-scale assumption and competitive factor markets, these shares are constant over time. Anticipating the discussion below, they can be read off the entries of input-output tables, measuring the value of spending on input j as a share of total intermediate input purchases of sector i.

[3] Additionally, it should be stressed that by imposing a convenient, but nevertheless particular, Cobb–Douglas structure to aggregate across intermediate inputs, I am also imposing a unit elasticity of substitution across inputs. In reality, for any given technology, there will be some inputs that are crucial and difficult to substitute away from, even if their price rises substantially—think fresh fish for sushi restaurants in Japan in the aftermath of the Fukushima disaster and the ensuing contamination scare—while others would seem more substitutable—advertising seems like a prime example. Unfortunately, at least at very disaggregated levels, we have little evidence regarding the likely range of these elasticities. At intermediate levels of aggregation—for example, two-digit industries—Atalay (2014) provides evidence in favor of strong complementarity across intermediate inputs.

value added, y, is simply a weighted sum of the (logarithm of) micro-level productivity shocks, ε_i:

$$y = \sum_{i=1}^{n} v_i \, \varepsilon_i,$$

where the weights, v_i, are determined by the production network, W.[4] This characterization has two important consequences. First, aggregate output is itself random, which means that we now have a simple theory of why aggregate output might fluctuate over time. Second, the magnitude of these aggregate fluctuations can now be traced back to the production network, in particular, how strongly the underlying network propagates micro-shocks across sectors, as encoded by the weights v_i.

To understand the specific propagation mechanism at play in this setting, it is perhaps useful to go through a thought experiment. Imagine that a favorable productivity shock hits one sector in the economy, leaving the productivity of all others unchanged. To be concrete, think for example of a major, unanticipated, breakthrough in the production technology of semiconductors which decreases the marginal cost of production significantly. Clearly, this supply shock will increase the production and decrease the price of semiconductors. As a result of this shock, the electronic components sector, which is the key sector downstream of semiconductors, also sees its marginal cost decline as one of its key inputs has just become cheaper. Electronic component producers will react to this by expanding production and decreasing their own price. A second round of adjustment now ensues as the many sectors downstream of electronic components—computers, precision machines, or communication devices among many others—adjust in the same way. As the original shock percolates further through the production network, a cascade of adjustments is underway. Ultimately, every sector that is directly or indirectly downstream of semiconductors will find it optimal to increase production by some amount, potentially leading to a synchronized expansion of economic activity across the board.

Notice that an outside observer focusing solely on aggregate measurements of the economy and ignoring the structure of intermediate input trade would conclude that a mysterious aggregate productivity shock had just occurred, the source of which would necessarily be elusive. In fact, only one of the many production technologies

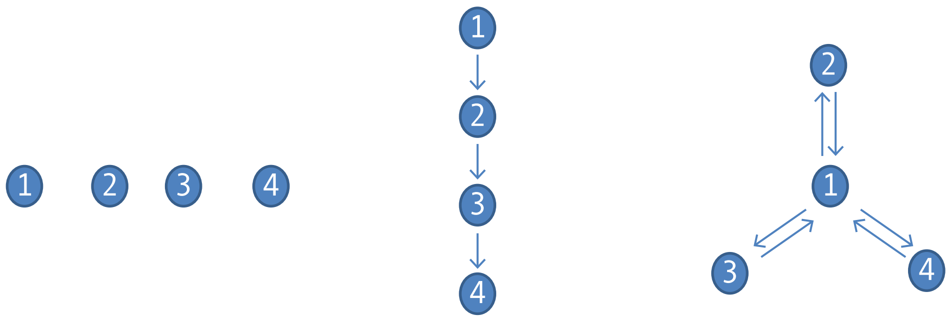
[4] The competitive equilibrium solution of this basic model economy yields an expression for the logarithm of aggregate value added (that is, GDP), y, given by:

$$y = \mathbf{v}'\boldsymbol{\varepsilon}, \text{ and}$$

$$\mathbf{v} = \frac{(1 - \alpha)}{n}\,[I - \alpha W']^{-1}\,\mathbf{1},$$

where $\mathbf{1}$ is a $n \times 1$ vector of ones and $\boldsymbol{\varepsilon}$ is a $n \times 1$ vector of the (logarithm of) sector specific productivity shocks, that is, $\varepsilon_i \equiv \log(z_i)$. Aggregate GDP, y, is a weighted sum of the underlying micro shocks and hence a random variable itself. The $n \times 1$ vector $\mathbf{v}$ gives the appropriate weight to each sector. When a productivity shock hits a given sector, all of the adjustments described in the main text are encapsulated in the term $[I - \alpha W']^{-1}$. The latter object is nothing other than the celebrated "Leontief inverse" matrix of input-output analysis.

Figure 1
Three Production Networks on Four Nodes



Note: From left to right: a horizontal economy with no input trade, a vertical economy with a source and a sink, and a star economy with a central node.

in this economy is now more productive. The comovement induced by this idiosyncratic shock is a feature of general equilibrium adjustments working their way through the network of input linkages.

Three Variations on a Theme: Network Structure Matters

These cascading effects via input-output linkages open the door to thinking about comovement across sectors and aggregate fluctuations without resorting to aggregate shocks. But whether and how an idiosyncratic shock propagates across the economy via these linkages depends critically on the way the production network is arranged.

To understand how the structure of production networks can matter for comovement, I now show that different production networks imply different levels for the volatility of aggregate output. Specifically, I explore three variations on a four-node economy, by considering three different arrangements of an underlying production network, as depicted in Figure 1. Each of these networks will imply a different strength for the model's internal propagation mechanism. These can be summarized by what I will call a network multiplier: by how much the particular network structure of the economy amplifies idiosyncratic volatility.

Consider first the simplest baseline case: an empty network where there is no intermediate input trade in the economy. In terms of the production function given earlier, all sectors use only labor to produce the respective consumption good, and no sector provides intermediate inputs to any other sector (that is, all $\omega_{ij} = 0$ in the production function above). Following Bigio and La'O (2013), I dub this case the horizontal economy. In this economy, shocks to any given sector will not affect any other sector as the propagation mechanism described above is mute. As such, there is no amplification of micro-level volatility, and the network multiplier, m_H, is equal to 1.[5] If this example seems of little practical relevance, it is worth remembering that this horizontal economy closely corresponds to the modeling of intermediate goods in most of the macroeconomics literature. Typically, these models assume that intermediate goods are produced with primary inputs alone—that is, there are no flows across intermediate inputs producers—and are then combined into a final consumption good by a so-called "final good aggregator." In our horizontal economy, the different consumption goods are combined into an aggregate consumption bundle through the household's utility function.

In the context of supply chains, it is perhaps more intuitive to consider what Bigio and La'O (2013) call a vertical economy, one in which inputs flow unidirectionally from a well-defined upstream sector (think mining of rare earth minerals, for example), whose output is successively transformed (magnets made from such minerals, which in turn are an input into speakers), and ultimately incorporated in the final downstream sector (your smartphone). In network parlance, this is a tree or line structure with a single source (the upstream node, with no incoming links) and a single sink (the downstream node, with no outgoing links).[6] Just as in the horizontal economy, shocks to each sector's productivity growth have a direct contribution to aggregate output and hence to aggregate volatility. But because sectors are now interlinked, further indirect contributions to aggregate volatility arise. For example, productivity fluctuations at the most upstream source, sector 1, now have a first-round effect on its immediate downstream customer, sector 2; a smaller, second-round effect on sector 3; and an even smaller third round effect on sector 4. Sectors 2, 3, and 4 will then contribute to aggregate volatility in a similar manner as sector 1 except, being closer to the sink node, they contribute with fewer higher-order indirect effects. Taken together, the presence of these indirect effects—absent in the horizontal economy—implies that the production network amplifies idiosyncratic volatility leading to a network multiplier $m_V > m_H = 1$. This source-sink arrangement of the production network also

[5] In the horizontal economy, equilibrium aggregate output is given by $y = \frac{(1-\alpha)}{n} \sum_{i=1}^{n} \varepsilon_i$ (using the equation from the previous footnote). Given that, by assumption, there is no correlation in the productivity shocks across technologies, the variance of aggregate output is simply $\sigma_y^2 = \frac{(1-\alpha)^2 \sigma_\varepsilon^2}{4} m_H$, where m_H, the network multiplier associated to the horizontal economy, is equal to 1. In the vertical economy, aggregate output volatility is now given by $\sigma_y^2 = \frac{(1-\alpha)^2 \sigma_\varepsilon^2}{4} m_V$, where the network multiplier for this vertical economy is $m_V = [(1+\alpha+\alpha^2+\alpha^3)^2 + (1+\alpha+\alpha^2)^2 + (1+\alpha)^2 + 1]/4$. Clearly $m_V > m_H$ for any positive share of intermediate inputs. Aggregate output volatility in the star economy is equal to $\sigma_y^2 = \frac{(1-\alpha)^2 \sigma_\varepsilon^2}{4} m_s$ where the network multiplier is now given by $m_S = \left[\left(\frac{3\alpha+1}{1-\alpha^2}\right)^2 + 3\left(\frac{1+\alpha/3}{1-\alpha^2}\right)^2\right]/4$. Comparing expressions, it is straightforward to show that $m_S > m_V > m_H$.

[6] See Antràs, Chor, Fally, and Hillberry (2012) for a related discussion on how to extract upstreamness measures from input-output data.

highlights the disproportionate role of fluctuations occurring in more central technologies. In this example, sector 1 is the main source of fluctuations in the economy, as every other sector in the economy is (directly or indirectly) downstream of it.

Finally, consider a more exotic configuration in which a single general purpose technology functions as a hub in the network, its output being used as the sole intermediate input of all other sectors. Each of the other sectors are now populated by specialized input producers, each of which is necessary for the general purpose technology to operate. Call this the star economy. While necessarily stylized, this star economy captures an important feature of the input-output data I analyze below, where general purpose inputs—real estate and construction, banking and finance, energy sectors, or various forms of information technologies—emerge as hubs in the production network. Perhaps not surprisingly, this particular shape of the production network yields the highest volatility across the three example economies just described, that is, the associated network multiplier $m_S > m_V > m_H$. This heightened volatility comes from two sources. First, productivity fluctuations in the hub sector now have a direct, first-round, impact on every sector in the economy. Second, despite the fact that the remaining technologies are now peripheral, fluctuations in these sectors now propagate to all other sectors, as a second-order effect through their effect on the hub sector. Thus, hub technologies contribute to aggregate volatility in two ways. First, and similarly to the source nodes in the vertical economy, hub sectors act as an important source of shocks. However, in this star economy, a new role emerges: hub sectors act also as an important conductor of shocks occurring elsewhere in the economy.

These three examples demonstrate the possibility that the particular shape of the production network may have a bearing on aggregate volatility. But these are just a few out of the many configurations possible, even in a highly stylized economy with only four nodes. What happens when we take the number of nodes to be very large? How are we to choose among this rich menu of possibilities? How can we summarize the relevant features of these production networks in data? To make progress on these questions, it is necessary to take this network perspective to data on disaggregated input flows.

Mapping Production Networks to Data

The empirical counterpart to a network of production technologies consisting of nodes that represent different sectors and directed flows that capture input transactions between sectors is given by input-output data. To investigate the network structure of sector-to-sector input flows, I use the US Bureau of Economic Analysis Commodity-by-Commodity Direct Requirements Detailed Tables. While the data is available from 1972 to 2002 (at five-year intervals) here I only make use of the 2002 vintage of this data. This breaks down the US economy into 417 sectors, which I will take as nodes in the sectoral input-network. Each nonzero (i, j) entry is a directed edge of this network—that is, a flow of inputs from supplying sector j to customer i.[7] It is worth keeping in mind that the total dollar value of these flows is of the same order of magnitude as aggregate GDP itself. While, for double-counting reasons, these transactions do not show up in GDP figures, a very large amount of resources are devoted yearly to intermediate-input transactions.

For some of the empirical analysis below, I will be focusing only on properties of the extensive margin of input trade across sectors. To do this, I use only the binary information contained in this input-output data—that is, who sources inputs from whom—and disregard the weights associated with such input linkages. More specifically, I only consider a link to be present if the associated input transaction is above 1 percent of a sector's total input purchases. With this threshold rule, I am discarding very small transactions between sectors and focusing on the main components of the bill of goods necessary to the production of any given sector. Following this rule, I account for about 80 percent of the total value of intermediate input trade in the US economy in 2002. Whenever I bring in the intensive margin, I will be using all of the input-output data in the form of intermediate input shares. Note that these shares conveniently map to the Cobb–Douglas coefficients for intermediate goods in the production functions introduced in the previous section. The 2002 matrix of all such intermediate input shares $W_{02} = \{\omega_{ij}\}_{i,j=1}^{n}$ is then the directed, weighted network under scrutiny.

Figure 2 provides a network representation of the input-output data in 2002. Despite its apparent complexity, we can provide some order by focusing on some key statistics summarizing this network. Thus, a first-order characterization of this network is its sparsity or low "density"[8]: there are only 5,217 nonzero edges out of a possible 417^2, yielding a network density of 0.03. To put it another way: at this level of disaggregation, most sectors consist of very specialized technologies that only supply inputs to a handful of other sectors. As a result, the number of sectors supplied by the average sector—that is, the average "degree" of this network—is relatively low at about 11 relative to the total number of sectors in the network.

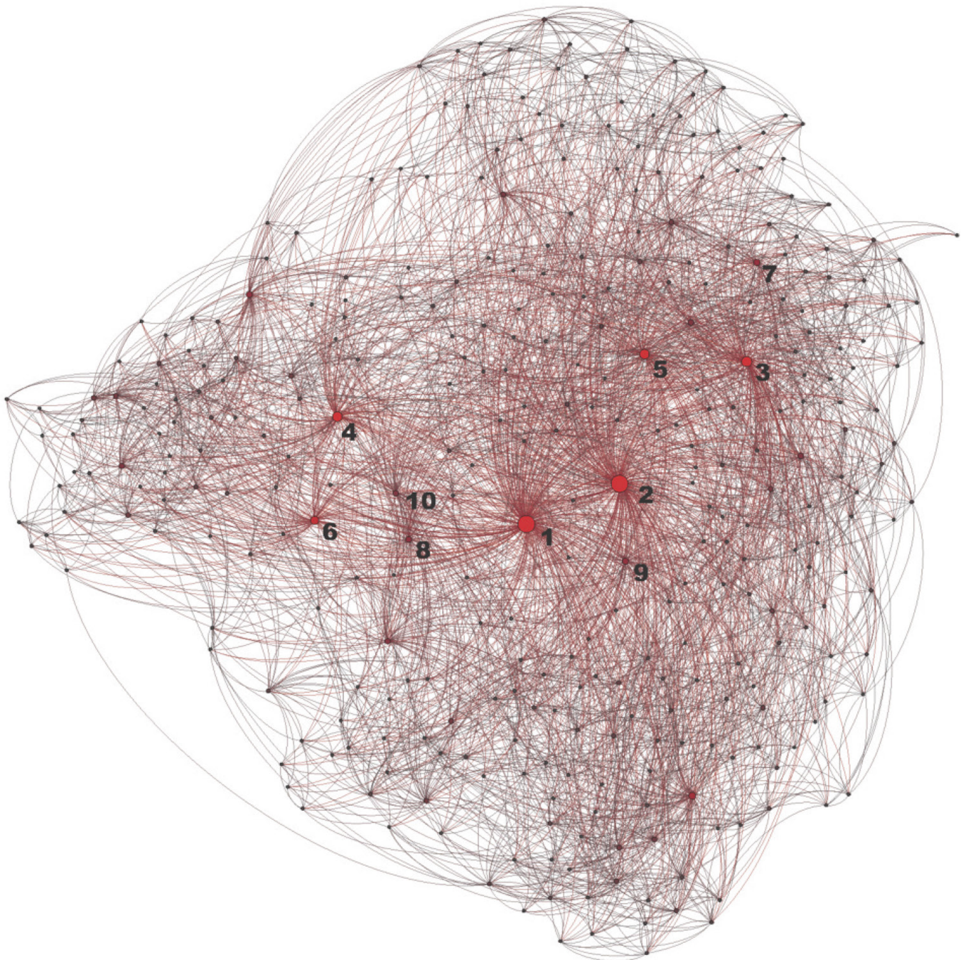
The Small World of Production Networks

Looking more closely at the figure, another first-order feature emerges: there is extensive heterogeneity across sectors in their role as input suppliers. In the data, highly specialized input suppliers coexist alongside general purpose input suppliers,

[7] This constitutes the least coarse sectoral data available worldwide and underlies the network analysis in Carvalho (2010) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). Input-output tables are available for a large cross-section of countries at a considerably coarser level. In particular, the input-output accounts from the STAN database (OECD) consist of 47 sectors and are benchmarked for 37 countries near the year 2000. Based on this data, Blöchl, Theis, Vega-Redondo, and Fisher (2011) and McNerney, Fath, and Silverberg (2013) provide a cross-country comparative perspective on the network structure of intersectoral flows.

[8] Network density is defined by the fraction of edges that are present in the network relative to the total number of possible edges, n^2. See, for example, Jackson (2008) for textbook definitions of this and other network objects.

Figure 2
The Production Network Corresponding to US Input-Output Data in 2002

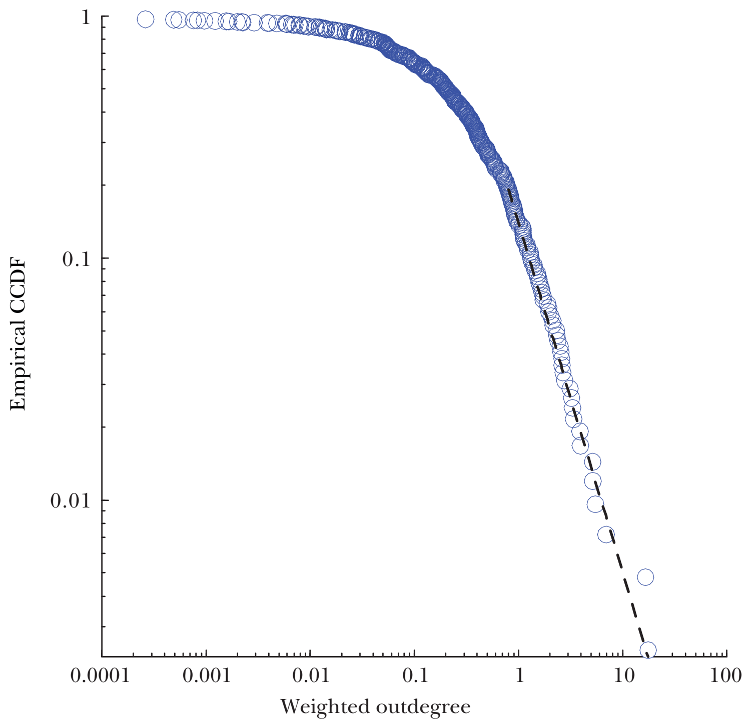


Source: Bureau of Economic Analysis, detailed input-output table for 2002. The Figure is drawn with the software package Gephi.
Notes: Each node in the network corresponds to a sector in the 2002 input-output data. Each edge corresponds to an input-supply relation between two sectors. Larger nodes closer to the center of the network represent sectors supplying inputs to many other sectors. The 1–10 labels give the ranking for 10 top input suppliers: Wholesale Trade (1), Real Estate (2), Electric Power Generation and Distribution (3), Management of Companies and Enterprises (4), Iron and Steel Mills (5), Depository Credit Intermediation (6), Petroleum Refineries (7), Nondepository Credit Intermediation (8), Truck Transportation(9), and Advertising (10).

such as iron and steel mills, petroleum refineries or real estate, some of the hub-like sectors in Figure 2.

This heterogeneity along the input-supply margin can be conveniently summarized by looking at another network object, its “weighted outdegree” distribution.

Figure 3
The Weighted Outdegree Distribution Associated with 2002 US Input-Output Data



Source: Bureau of Economic Analysis, detailed input-output table for 2002. For more details, see Data Appendix available with this paper at http://e-jep.org.
Notes: The x-axis gives the weighted outdegree for each sector, presented on a log scale. The y-axis, also in log scale, gives the probability of finding a sector with weighted outdegree larger than or equal to *x*, that is the empirical counter-cumulative distribution (CCDF).

Define the weighted outdegree of a sector as $d_{out}^{j} = \sum_{i=1}^{n} \omega_{ij}$, that is, the sum over all the weights of the network in which sector *j* appears as an input-supplying sector. This measure ranges from 0 if a sector does not supply inputs to any other sectors, to *n* if a single sector is the sole input supplier of every sector in the economy. According to this weighted measure, the typical input-supplier in the data has a weighted outdegree of about 0.5. An average input-supplying technology according to this metric would correspond to, for example, cutting tools manufacturing (with a weighted outdegree of 0.45 and supplying seven other sectors). Many smaller and more specialized input suppliers can be found in the data, such as optical lens manufacturing (with a weighted outdegree of 0.09 and supplying three other sectors only) alongside a handful of general purpose sectors, supplying inputs to many other technologies like iron and steel mills (with a weighted outdegree of 5.5, supplying 100 other sectors).

Figure 3 reports the empirical distribution associated with the 2002 input-output data. The x-axis is the weighted outdegree for each sector, presented on a log scale. The y-axis, also in log scale, gives the probability that a sector selected at random from the population has an outdegree larger than or equal to x. Thus, the upper left-hand portion of the distribution—where specialized technologies like optical lens manufacturing are located—shows that nearly 100 percent of sectors have an outdegree greater than 0.01; the middle portion of the distribution shows that only about one-tenth of all sectors have an outdegree greater than 1; and the right-hand side of the distribution, where we find general purpose technologies like iron and steel mills or petroleum refineries, shows that only about 1 percent of all sectors have an outdegree measure greater than 5.

Clearly, the empirical distribution of weighted outdegree measures is skewed and spans several orders of magnitude, reflecting the very unequal status of different technologies in their role as input suppliers. As in other instances where extreme inequality is a key characteristic—like the cross-section of incomes, city sizes, or firm sizes—the right tail of this distribution is well approximated by a so-called power law distribution. This kind of distribution implies a strong fat-tailed behavior in that the probability of finding superstar technologies, far out in the right tail, is large enough to render the variance of this distribution infinite.[9] The upshot of this is that, even as we disaggregate the economy into finer and finer definitions of technologies, large input-supplying sectors do not vanish.

The presence of this small number of hub-like sectors renders these input-output networks into small and closely knitted worlds. In other words, despite the low density of sectoral interactions—despite the fact that most sectors do not trade with each other—each sector is only a few input-supply links away from most other sectors. In network parlance, these types of networks are referred to as "small-world networks" in which most nodes are not neighbors of one another, but where most nodes can be reached from every other by a small number of hops or steps along the directed edges.

More precisely, in the network literature, small worlds are defined by appealing to two related statistics: i) the diameter of the network, defined as the maximum length of the shortest path, which is the largest number of steps that separate sector i from sector j for all possible pairs of sectors (i, j); and ii) the average distance, defined as the average length of these shortest paths for all pairs (i, j). When I apply these statistics to the detailed input-output data, I obtain a low diameter (relative to 417, the total number of sectors) of 10 and a small average distance of 4, thus confirming the small-world nature of the US production network.

[9] The apparent linearity in the tail of the outdegree distribution when shown in log scales is usually associated with a power law distribution. We say that the outdegree distribution follows a power-law if the associated counter-cumulative probability distribution $P(x)$—giving the probability of finding sectors with outdegree equal to or greater than x—is given by:

$$P(x) = cx^{-\zeta} \text{ for } \zeta > 1 \text{ and } x > 0,$$

where c is a positive constant and ζ is known as the tail index. A well-known property of this distribution is that for $1 < \zeta < 2$, the outdegree distribution has diverging second (and above) moments. The straight line in Figure 3 shows the maximum likelihood fit implied by $\zeta = 1.44$. See Gabaix (2009) for a review of power laws and their applications in economics.

The small-world property has obvious implications for the dynamics of processes taking place on networks. In the context of social networks, if it takes only six steps for a rumor to spread from any person to any other in society, a rumor will likely spread much faster than if it takes 100 steps. Similarly, as I will argue further below, if one considers the effect of a production disturbance, shutdown, or default, to a specific firm or technology, the small-world effect implies that the original shock will spread quickly to most sectors, thus affecting the performance of the aggregate economy.

Searching for Central Nodes in the Production Network

Until now I have focused attention on key technologies as defined by their weighted outdegree ranking. These superstar technologies are certainly important both as sources of volatility and when propagating shocks occurring in other sectors. However, a sector can be key in other ways. For example, consider a sector that looks average by its weighted outdegree ranking, but that nevertheless is a key input supplier to a widely used general purpose technology. Despite the fact that the immediate customers downstream of this sector are few, indirectly—through the downstream hub—many production processes can potentially be affected by disturbances in the specialized upstream node.[10]

Identifying the central input-supplying technologies and ranking their roles in an economy requires applying an appropriate measure of "node centrality" to the production network. While network analysis has developed a variety of centrality measures, here I will focus on so-called "influence measures" of centrality, where nodes are considered to be relatively more central in the network if their neighbors are themselves well-connected nodes. The best known of these recursively defined centrality measures is called "eigenvector centrality." Variants of it have been deployed in the sociology literature, notably Bonacich (1972) and Katz (1953), in computer science with Google's PageRank algorithm (Brin and Page 1998), or in social networks literature within economics (for example, Ballester, Calvo-Armengol, and Zenou 2006). In our setting, the Katz–Bonacich measure assigns to each sector a centrality score that is the sum of some baseline centrality level (equal across sectors), and the centrality score of each of its downstream sectors, defined in the same way.[11] Thus, as in the example above, a sector's

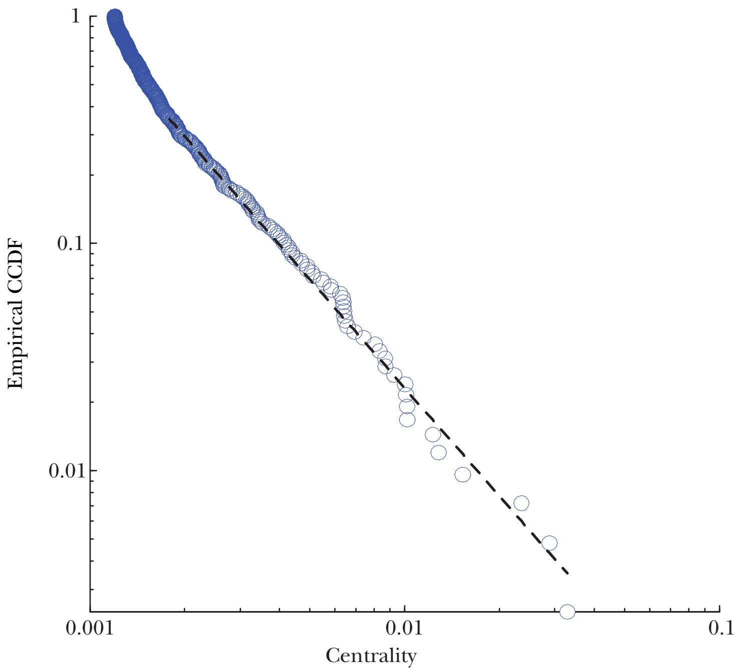
[10] Much in the same way as the impact of an academic article need not be evaluated by its citation count alone but also by the impact of the (downstream) articles citing it.

[11] To derive the Katz–Bonacich eigenvector centrality measure in our setting consider assigning, to each sector j, a centrality weight, $c_j > 0$, which is defined by some baseline centrality level η, equal across all sectors, plus a term which is proportional to the weighted sum of the centrality weights of its downstream sectors: $c_j = \lambda \sum_i W_{ij} c_i + \eta$, for some parameter $\lambda > 0$. In matrix form, $\mathbf{c} = \lambda W'\mathbf{c} + \eta \mathbf{1}$, where W is the matrix representation of our production network, $\mathbf{1}$ is a vector of ones, and $\mathbf{c}$ is the vector of centrality scores, $\mathbf{c}'_j s$. This implies that the vector of centralities is given by:

$$\mathbf{c} = \eta(I - \lambda W')^{-1}\mathbf{1}.$$

Recalling the expression for equilibrium log GDP in the basic model, the vector $\mathbf{c}$ is nothing but the vector of Katz–Bonacich centralities given an input-output network W where we restrict $\eta = \frac{1-\alpha}{n}$, $\lambda = \alpha$ (and where α was the share of intermediate inputs in production).

Figure 4
The Distribution of Sector Centralities Associated with 2002 US Input-Output Data



Source: Bureau of Economic Analysis, detailed input-output tables for 2002. For more details, see the Data Appendix available with this paper at http://e-jep.org.
Notes: On the x-axis is the Bonacich centrality score of the different sectors in the 2002 input-output data, where I have imposed a baseline centrality measure of $\eta = (1 - 0.5)/417$ and a parameter for weighting downstream sectors of $\lambda = 0.5$. The y-axis gives the probability of finding a sector with a centrality score larger than or equal to *x*, that is, the empirical counter-cumulative distribution (CCDF).

centrality need not be dictated by its outdegree alone, but will also be determined by its customers' outdegree, its customers' customers' outdegree, and so on ad infinitum.

Remarkably, the sector-centrality scores obtained in this way exactly coincide with the sector-specific weights, v_i, appearing in the expression for equilibrium aggregate output obtained in the previous section. As a result, aggregate growth and volatility in our simple multisector model now depends on a well-defined network object: the collection of network centralities of the different production technologies. Intuitively, more central production technologies in the production network—those having more direct or indirect downstream customers—are relatively more important in determining aggregate volatility.

On the x-axis of Figure 4 is the (Bonacich) measure of centrality of sectors in the 2002 input-output data. The y-axis gives the probability of finding a sector with a centrality score larger than or equal to *x*. Thus, 100 percent of the sectors have a centrality measure that is greater than or equal to the most peripheral node in the network—hunting and trapping—with a centrality score of 0.001; about 10 percent of the sectors in the network have a centrality measure greater than 0.004, that of warehousing and storage; and only about 1 percent have a centrality measure greater 0.01, that of truck transportation.

As in the outdegree distribution, there is large variation in the network centrality of different nodes, again in the form of a power-law distribution.[12] Far out in the right tail, we find the central production nodes in the network. Through the lenses of our model, sectors such as real estate, management of companies and enterprises, advertising, wholesale trade, telecommunications, iron and steel mills, truck transportation, and depository credit intermediation alongside a variety of energy-related sectors—petroleum refineries, oil and gas extraction, and electric power generation and distribution—are seemingly key to US aggregate volatility as they sit at the center of the production network.[13]

Production Networks, Comovement, and Aggregate Fluctuations

Our model of production networks stresses the role of input-supply linkages: an idiosyncratic shock affecting a single sector will be transmitted to its downstream neighbors in the network and, via the latter, propagate further downstream to other production nodes which are only indirectly connected with the original sector. Does this model generate testable implications? Can this network perspective shed new light on the comovement patterns at the heart of business cycle fluctuations?

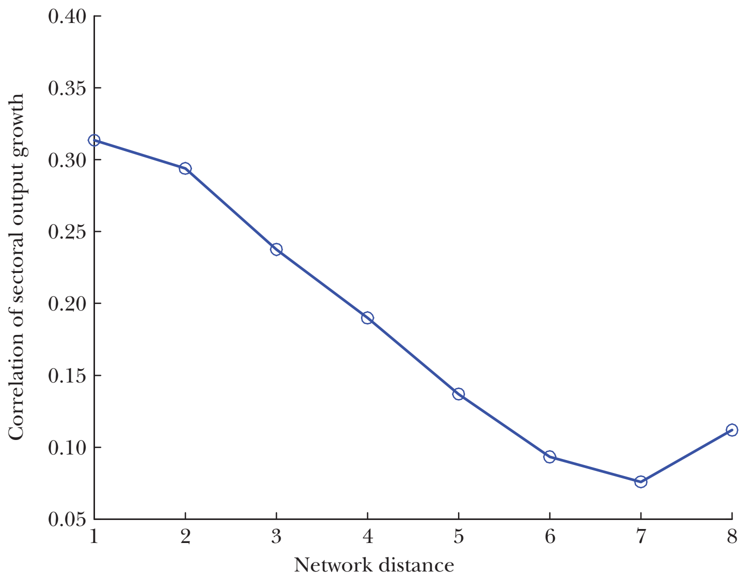
Networked Perspectives on Comovement

Comovement across sectors is the hallmark of cyclical fluctuations. As stressed throughout this essay, comovement is endogenous from a production networks perspective: synchronization arises from micro shocks propagating across input linkages. Importantly, this perspective also implies that a very particular pattern of comovement should hold in the data. To see this note that, as an original sectoral shock to productivity makes its way downstream, its effect should weaken. Intuitively, a shock generating a given response in the output and price of the original input-supplying sector will generate more muted responses further downstream as that input is a smaller part of the total input bill of these sectors. Thus, two sectors that are closer in terms of their network distance should comove more.

[12] As discussed in note 9, with regard to Figure 3, the straight line plotted in the figure gives the power-law fit to this data with a tail parameter $\xi = 1.48$.

[13] Clearly, many of these sectors are the superstar sectors that also rank high according to the outdegree measure. Accordingly, the rank correlation between centrality and outdegree is a very high 0.95. Nevertheless, some sectors do change their ranking substantially between these measures. Oil and gas extraction, together with other mining activities such as coal, provide the best examples of highly central sectors in the network that are nevertheless middling according to their weighted outdegree measure. This is because they are key suppliers of downstream general purpose technologies such as petroleum refineries or electric power generation.

Figure 5
Network Distance and Comovement of Sectoral Output Growth



Source: NBER-CES Manufacturing Industry Database and Bureau of Economic Analysis detailed input-output tables for 1987.
Notes: The x-axis gives the network distance across any pair of sectors. The y-axis gives the average correlation of sectoral output growth across all sector pairs at a given distance in the production network.

To test this hypothesis, I compute sector-level (real) value-added growth rates from the NBER-CES Manufacturing Industry database containing information for 459 four-digit SIC manufacturing sectors for the period 1958–2009. For each pair of sectors, I then compute the respective pair-wise correlation of growth rates over the entire sample period and correlate it against the measure of network distance in the previous section, which I calculate from the 1987 detailed input-output matrix, choosing this date to represent roughly a midpoint of the data.[14]

In Figure 5, the x-axis gives the network distance across any pair of sectors. The y-axis gives the average correlation of sectoral output growth across all sector pairs at a given distance in the production network. Clearly, sectors that are closer in the production network do comove more. Across all pairs of sectors that directly trade inputs, the average annual growth rate correlation is 0.32. Conversely, for pairs of sectors that are very distant in the network, the average correlation is only around 0.1. Another way to relate network distance and comovement is to look at averages in the population. Across all sector pairs, the average growth rate correlation in the

[14] The 1987 input-output data disaggregates the economy into 510 sectors. The concordance between this input-output table and the NBER database, which only covers manufacturing sectors, is the one used in Holly and Petrella (2012), which I gratefully acknowledge.

data is 0.21. This is strikingly close to the average growth rate correlation between sectors that are four links away, the average distance in the network.

From the vantage point of production networks, this is no coincidence: the average level of sectoral comovement in the data, and hence aggregate volatility, is in fact implied by a short average distance in our small world of production networks. Were the production network to be arranged in some other way, thus altering its shock-conducting properties, the average level of comovement would change accordingly.

Note that it would be very difficult to rationalize this feature of comovement across sectors in a setup with aggregate shocks alone. First, were all sectors to respond equally to some exogenous aggregate pulse, Figure 5 should simply display a horizontal line: that is, comovement should not vary systematically with network distance. Alternatively, if we were to assume that sectors have different sensitivities to this aggregate shock, the only way to generate a similar pattern to the one observed in the data would be to impose in addition a condition that sectors tend to source inputs from similarly sensitive sectors. It is unclear what could justify this very strong assumption. In contrast, the empirical relation between comovement and network distance observed in the data is an immediate implication of our standard general equilibrium model of production networks.

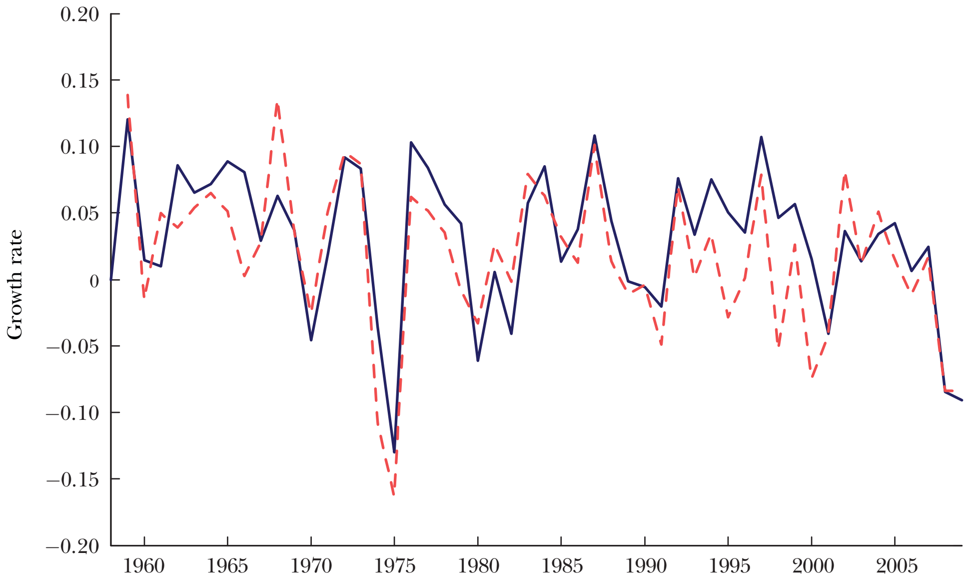
As argued earlier, low average distances between sectors are a consequence of hubs: that is, low average distances between sectors arise from the existence of general purpose inputs that shorten the path between otherwise disparate technologies. These hubs are, by definition, central nodes in the production network, only a short distance away from the majority of sectors. As such, by the same network-distance–comovement argument, they should comove more with all sectors in the economy and hence with aggregates. Additionally, the presence of these hubs will also render other sectors in the economy—those supplying the inputs on which the hubs rely—more central. The upshot of this is that productivity fluctuations in these very central technologies in the network—those having more (direct or indirect) downstream customers—should be relatively more correlated with aggregate output growth.

I again resort to the NBER manufacturing data and to the 1987 input-output data to assess the validity of this prediction. I use the former to aggregate sectoral growth rates and derive a time series of aggregate manufacturing real growth in value added. I use the input-output data to calculate the measure of (Bonacich) network centrality—discussed in the previous section—for each manufacturing sector.[15] As a proxy for productivity fluctuations occurring in central nodes, I take the simple average of total factor productivity growth across the ten most central sectors in the production network.

Figure 6 plots the resulting series for (aggregate) manufacturing value-added growth and our index of productivity fluctuations in the ten most central technologies,

[15] For the centrality calculation, I pick $\alpha = 0.5$, the average share of intermediate inputs in gross output, and $n = 459$, the total number of sectors.

Figure 6
Comovement of Productivity Growth in Central Sectors and Aggregate Output Growth



Source: NBER-CES Manufacturing Industry Database and Bureau of Economic Analysis detailed input-output tables for 1987.
Notes: The solid line gives manufacturing real value added growth for the period 1959–2009. The dashed line gives the simple average of total factor productivity growth across the ten most central sectors in the production network.

for the period 1959–2009. Clearly, the two series track each other very closely. Over the entire sample period the coefficient of correlation is 0.80 and highly significant. As our network perspective predicts, this correlation is much higher than that obtaining for the average centrality sector in the economy (0.29). From an applied perspective, this suggests that analysts and policymakers looking to predict the short-run behavior of macroeconomic aggregates could benefit from tracking economic activity in only a handful of central or systemic sectors.

Several concerns can be raised about this calculation. First, perhaps causality runs the other way: not from key sectors to aggregate economic performance as a networked perspective implies, but instead from aggregate shocks affecting key sectors disproportionately. For this to be the case, productivity in relatively more central technologies would need to be more cyclically sensitive. While it is a priori unclear why "cyclical sensitivity" should correlate with this very particular and nonobvious network centrality measure, this identification problem has not been conclusively dealt with in the literature.

An alternative critique is that this correlation simply reflects an underlying accounting identity and contains no economic meaning beyond that. After all, high-centrality sectors are likely among the larger sectors in the economy. Hence movements in economic activity in these large sectors, for which productivity might be acting as a proxy, would mechanically translate into movement in aggregates. If this critique is valid, were we to remove the contribution of these key sectors to aggregate growth, we should then observe a much lower correlation between productivity growth in high-centrality nodes and aggregate output growth. This can be easily tested by constructing a counterfactual aggregate manufacturing output growth series where we zero out the contribution of the ten most central technologies. Reassuringly, the correlation between this counterfactual aggregate series and our index of productivity fluctuations in these ten most central technologies is still a very high 0.76. This is consistent with our network perspective: hub sectors are important sources of aggregate fluctuations not because they are large but because they synchronize economic activity across the board.

Confronting the (Other) Lucas Critique

While promising as a way to understand the origins of comovement and aggregate fluctuations, a skeptic might still reasonably argue that all the intuition and results above are just a figment of aggregation. Surely, as we disaggregate the economy into finer and finer sectors, independent disturbances across nodes will tend to average out, leaving aggregates unchanged and thus yielding a weak propagation mechanism. In fact, this "diversification" argument has a distinguished pedigree in macroeconomics and was invoked, for example, by Lucas (1977) to do away with the entire outlook proposed in these pages:

> In a complex modern economy, there will be a large number of such shifts in any given period, each small in importance relative to total output. There will be much "averaging out" of such effects across markets. Cancellation of this sort is, I think, the most important reason why one cannot seek an explanation of the general movements we call business cycles in the mere presence, per se, of unpredictability of conditions in individual markets.

This intuitive yet powerful indictment has been playing out over the years in the modern equilibrium business cycle literature and underlies much of its continued appeal to aggregate taste shifters or technology shocks. Can a production network perspective undo this argument? How does aggregate volatility behave when we take the number of nodes in the production network to be very large—as it surely is in the economy—while keeping the assumption of no aggregate shocks?

We can recreate Lucas's (1977) "diversification" argument in our networked economy. To see it at play, recall the horizontal economy example introduced above. From that discussion it is immediate that, for a generic number of sectors, n, aggregate volatility in horizontal economies, σ_y is of the order of magnitude of $\frac{\sigma_\varepsilon}{\sqrt{n}}$. That is, as we disaggregate the horizontal economy further, into more and more production nodes, aggregate volatility declines to zero at very rapid rate of $\sqrt{n}$. This implies that, holding micro-volatility (σ_ε) fixed, as we move from an economy populated by 100 sectors to one with, say, 10,000 sectors, the implied standard deviation of aggregate GDP will be an order of magnitude lower.

However, the network perspective on input flow data renders clear what is mistaken about this argument: the US economy looks nothing like a horizontal economy where intermediate input producers exist in isolation of each other. Instead, the production of each good in the economy relies on a complex set of linkages across sectors. As we have seen, these linkages function as a potential propagation mechanism of idiosyncratic shocks throughout the economy. How strong is this propagation mechanism once we take on board empirical properties of production networks? How strong is the multiplier associated with the actual US production network?

To answer this question we need two ingredients. First, recall that generically the aggregate volatility is a function of the centrality scores of the different technologies in the US production network. Second, as we have seen, there is extensive heterogeneity in these centrality scores: a relatively small number of hub-like sectors are far more central than the vast majority of nodes in the production network. Based on these two observations, it is possible to show that, for empirically relevant production networks, aggregate volatility is of the order of magnitude of $\frac{\sigma_\varepsilon}{n^{1-1/\xi}}$ rather than $\frac{\sigma_\varepsilon}{\sqrt{n}}$, where ξ is nothing else than the slope of the centrality score distribution in Figure 4.[16] This parameter governs the degree of "inequality" in this distribution: the more unequal is this distribution—which is to say, the more important is the role of a few central input-suppliers in the network—the closer ξ is to 1. The upshot of this is that, in a world where superstar technologies act as powerful shock conductors, aggregate volatility decays much more slowly with the number of sectors, rendering Lucas's (1977) diversification arguments second order.

To understand the power of this seemingly abstruse distinction, consider the following back-of-the-envelope calculation. From the NBER manufacturing data, the standard deviation of total factor productivity growth for a typical narrowly defined sector is 0.06. For, say, 500 sectors, the horizontal economy would then imply aggregate volatility of the order of magnitude of 0.003, a non-starter as a theory of the aggregate business cycle, as Lucas (1977) had argued. Instead, if we use the estimate for ξ associated with Figure 3, which is approximately 1.4 (see footnotes 9 and 12), our theory of production networks now implies non-negligible aggregate volatility of the order of 0.01. In a nutshell, sizeable aggregate fluctuations may originate

[16] Under the assumption of idiosyncratic shocks, aggregate volatility in our simple model of production networks is given by:

$$\sigma_y = \sigma_\varepsilon \sqrt{\sum_{i=1}^{n} v_i^2},$$

where v_i is the centrality of node i in the production network. Based on a power law distribution of centrality scores, it is possible to show, by applying Gabaix's (2011) theorem (on the asymptotic behavior of sums of independent random variables with power law weights) that for the empirically relevant fat-tailed regime ($1 < \xi < 2$) aggregate volatility is of the order of magnitude of $\frac{\sigma_\varepsilon}{n^{1-1/\varepsilon}}$ rather than $\frac{\sigma_\varepsilon}{\sqrt{n}}$.

from microeconomic shocks once salient characteristics of the production network are incorporated into the analysis.

Taken together, the networked structure of production is consistent with distinctive patterns of comovement in the data and opens the way for a deeper understanding of the sources of aggregate fluctuations without resorting to convenient, but ultimately elusive, aggregate shocks.[17]

Looking Ahead

Viewing the economy as a complex production network may seem, at least initially, as little more than a fuzzy analogy coated in big words. In this essay, I have attempted to show that this perspective can indeed offer testable hypotheses and insights by mapping it to a standard general equilibrium setup and showing how this provides guidance for empirical explorations of input-output data. Looking at sectoral comovement from this vantage point, I have shown that the immediate implications of this networked perspective cannot be reasonably refuted. Furthermore, as I have discussed, theory and empirics together provide a challenge to a long-standing "irrelevance" indictment in the literature. To go beyond these suggestive possibility results, a small but fast-expanding literature on production networks is hard at work on a number of important challenges.

First, while throughout this essay I have equated nodes to sectors, input sourcing decisions actually take place at the level of the plant or of the firm. So what constitutes the relevant node: firms, sectors, or both? Relative to sectors, progress on firm-level production networks needs to deal with several added complications. On the theory side, it is more difficult to brush aside the complexities of market structure (as I have done here by appealing to identical, perfectly competitive firms inside each sector). Also, at this level of disaggregation it is clear that we have to distinguish between easily substitutable inputs and crucial, hard-to-substitute inputs where firms are locked-in and switching costs are large. On the empirical side, relative to sector-level data, input-output information at the firm-level is in very short supply. Recent advances in developing a theory of firm-level networks (Oberfield 2013) and the availability of novel data sources provide important first steps in this direction. For examples of firm-level data sources, see Bernard, Moxnes, and

[17] These conclusions are related to and reinforce the results of an earlier strand of the literature on cascading behavior in production networks. One of the early papers is Bak, Chen, Scheinkman, and Woodford (1993), where the authors describe the distribution of production avalanches triggered by random independent demand events. See also Jovanovic (1987) for a notable antecedent to this line of research and La'O (2013) for a thought provoking follow-up. These different contributions are not based on an empirical description of the network structure, but instead assume very simple interaction structures across agents, such as circle networks or periodic lattices.

Saito (2014) and Carvalho, Nirei, and Saito (2014) for data on Japan, and Atalay, Hortacsu, Roberts, and Syverson (2011) for US data.[18]

Second, the quantification and empirical validation of the network viewpoint is another active area of research. Work with calibrated dynamic extensions of the simple multisector model set forth here (Carvalho 2010; Atalay 2014) finds a far from negligible role for idiosyncratic shocks, echoing the earlier findings of Horvath (1999). Our results in Carvalho and Gabaix (2013) regarding the dynamics of aggregate volatility are consistent with these findings, although we work with a much simpler setting. In Carvalho (2010), I generalize the theoretical findings on the decay of aggregate volatility (discussed in the previous section of this essay) to a class of dynamic multisector general equilibrium models. In another strand of the literature, Foerster, Sarte, and Watson (2011) and Holly and Petrella (2012) explore econometrically the equilibrium structure of these models and conclude that input-output linkages serve as a powerful amplifier of otherwise independent shocks. At the firm-level, a variety of methods have been deployed—reduced-form correlations, model-derived decompositions of aggregate volatility, and natural experiments—to argue that the network structure of production matters quantitatively (Kelly, Lustig, and Van Nieuwerburgh 2013; di Giovanni, Levchenko, and Medjean 2014; and Carvalho, Nirei, and Saito 2014). Finally, the explicit incorporation of the spatial dimension of these production networks—that is, acknowledging the uneven distribution of production nodes across space—holds the promise of both better understanding the mechanics of shock propagation and of potentially isolating arguably exogenous shocks affecting only small parts of the network (Caliendo, Parro, Rossi-Hansberg, and Sarte 2014; Carvalho, Nirei, and Saito 2014).

Third, production network considerations may have a bearing on other areas of research in economics. Perhaps the most immediate candidate would be an open economy extension of the setup considered here. Can comovement across countries be the result of the international transmission of shocks through global supply chain networks? The recent contributions of di Giovanni and Levchenko (2010) and Johnson (forthcoming) are encouraging early steps in this broad direction, but there is still nearly everything to explore from a network perspective. Relatedly, recent theoretical work on global supply chains and the network structure of international trade can be another fruitful source of cross-talk on production networks (Antràs and Chor 2013; Chaney forthcoming; Costinot, Vogel, and Wang 2013).

In light of the recent financial and economic crisis, another promising agenda is to look at financial frictions from a production network perspective. Despite the seminal contribution of Kyotaki and Moore (1997), the possibility of cascading liquidity shocks in a network of producers has been consistently overlooked. Recent work by Bigio and La'O (2013) showing that production networks can serve as a

[18] A burgeoning micro-literature on pricing and intermediation in networks can offer additional insights on the theory side. For recent contributions in this area see, for example, Choi, Galeotti, and Goyal (2014); Kotowski and Leister (2014); Manea (2014); and Nava (2014).

powerful amplification mechanism for liquidity shocks represents an important step in this under-researched direction, but more remains to be done.

Finally, once one recognizes that network structure is linked to macroeconomic outcomes, a more ambitious question emerges: what determines these structures? This requires developing a theory where the network of input flows is the endogenous outcome of a well-defined economic model. This research direction is virtually unexplored, but see Oberfield (2013) and Carvalho and Voigtländer (2014) for some first steps.

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