THE CONGLOMERATE NETWORK*

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Abstract

This paper proposes a network model of the economy in which conglomerate firms transmit idiosyncratic shocks from one industry to another. The strength of inter-industry connections is determined by the conglomerate's share of total industry sales and by the industry's share of the conglomerate's total sales. The empirical results show that industry growth rates comove more strongly within industry pairs that are more closely connected in the conglomerate network. These results hold after controlling for industry-pair and year fixed effects, reverse causality, and in tests that exploit exogenous cross-sectional industry shocks from import tariff changes. Finally, our model also provides a new cross-industry extension for the widely-used Herfindahl index of concentration.

In a seminal paper, Gabaix (2011) shows that aggregate economic growth is driven by a small number of very large firms. Because economic activity is sufficiently concentrated in this small set of firms, their idiosyncratic shocks are not averaged out by the large number of little firms, which leads to aggregate fluctuations. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) present a related explanation for aggregate fluctuations based on the inter-sectoral transmission of shocks through input-output (IO) links. As in Gabaix, it is the concentration of IO links within a small number of very influential sectors that causes idiosyncratic shocks to contribute to aggregate fluctuations. These papers highlight the importance of understanding the role of idiosyncratic shocks as the source of aggregate fluctuations.

Our paper contributes to this line of research, starting from a simple observation: the largest firms in the economy tend to be conglomerates that span multiple industries. This means that the large idiosyncratic shocks in Gabaix are actually transmitted across multiple industries, similar to the transmission of shocks in Acemoglu et al. At the same time, the shocks to large firms' individual segments may be relatively small. For example, one of the largest firms in the world, Amazon, receives the bulk of its revenues from its retail operations, but within the retail sector, Amazon commands a relatively small share of the total market. In contrast, Amazon receives only 12% of its revenues from its computing services division, but maintains a dominant 33% market share within that industry. Thus, the notion of idiosyncratic firm-level shocks in Gabaix must be understood in the context of multi-segment firms.

In this paper, we consider how shocks to multi-segment conglomerates transmit across the economy through internal markets. We start with a novel model of the transmission of shocks from one industry to another through a bipartite, affiliation network of firms and industries. In the bipartite network, firms are only affiliated with industries and industries are only affiliated with firms. We define the strength of connections between firms and industries in proportion to their total outputs. Specifically, we assume that a growth shock transmits from a firm to an industry with a strength proportional to the firm's share of total industry sales. Similar to Gabaix (2011), an idiosyncratic shock to a firm that accounts for a large share of industry output has a greater influence on the industry's total fluctuations. Likewise, we assume that a shock transmits from an industry to a firm with a strength proportional to the industry's share of the firm's total sales.

For instance, Amazon's exposure to fluctuations in the computing services industry will only affect 12% of Amazon's total sales. Thus, in our network, each firm-industry pair is characterized by two connections running in opposite directions, each with its own strength.

Using the dual perspectives of a bipartite network, we create two separate unipartite networks, one for industry-to-industry links and one for firm-to-firm links. In the first perspective, industries are connected to other industries through conglomerate firms that operate in both industries. In the dual perspective, firms are connected to other firms through common industry affiliations. For both unipartite networks, we derive three forms of connections. For brevity, we only describe the industry-level connections at this point, but the firm-level connections are analogous.

First, we calculate the strength of the inter-industry *transmission* from an industry to its affiliated firms and then from these firms to another industry. Because we allow for weighted and directed links in the bipartite network, the transmission strength between two industries is not necessarily symmetric. This means that the strength of the connection running from industry X to industry Y could be larger than the strength of the connection running in the opposite direction.

Second, we calculate two projections from firms onto industries. In one projection, we calculate the *shared in-links* of an industry-pair, which represents the commonality of market shares among the firms that operate in both industries. In the second projection, we calculate the *shared out-links* of an industry-pair, which represents the commonality in firms' exposures to industry shocks among firms that operate in two industries. Because the projections represent shared links of two industries, they are symmetric.

Though this network model is simple, it provides new insights on a number of important topics. First, our model provides a microfoundation for standard measures of industry concentration. In particular, just as variance is a special case of covariance, our model shows that the widely-used Herfindahl-Hirschman Index (HHI) is a special case of a more general measure of cross-industry concentration that we call CoHHI. As described above, CoHHI is the projection that represents the shared in-links of two industries. Thus, CoHHI reflects the degree to which the market shares of firms in two industries overlap. If the same firms command the same market shares in each industry, then the two industries will have the same level of exposure to the same firm-specific idiosyncratic shocks. Using the covariance analogy, the CoHHI of an industry with itself is identical to HHI.

Thus, our network provides a new interpretation of HHI as the concentration of in-links into an industry.

Second, our model generates new predictions on the variance and covariance of growth rates across industries. We assume the growth rate of a firm segment is the sum of a firm-specific shock and an industry-specific shock. Our model predicts that the variance of an industry's growth rate equals the sum of the industry-specific growth rate plus the variance of firm-specific growth scaled by the HHI of the firms in the industry. We also show that the covariance of two industries' growth rates equals to firm-specific variance scaled by the CoHHI of the two industries. Intuitively, industries that share the same conglomerate firms will face common firm-level shocks. In the dual representation, we show that diversified firms, with lower concentrations of in-links from industries, have lower volatility in their growth rates.

Third, like Acemoglu et al. (2012), our model describes how idiosyncratic shocks transmit throughout an economy. In particular, our model predicts the paths and timing of the transmission of shocks from one industry to another. We show that industry centrality in the conglomerate network is directly proportional to the size of an industry's sales as a fraction of the economy's total sales. This finding echoes Gabaix's result on the importance of large firms and also mimics the findings in Acemoglu et al., which shows that centrality in the input-output network is directly proportional to the size of the industry relative to the economy.

To bring our theoretical framework to the data, we use segment data from Compustat for all public firms in the US for the years 1997 to 2018. Though our theoretical framework provides both firm-level and industry-level representations of the economy, we focus on the industry-level analysis to reduce selection bias concerns. To create a panel of industries, we follow Pierce and Schott (2016) and create industry families to provide time-series consistency. In an average sample year, our empirical tests are based on industry definitions with over 500 unique industries.

We first show that the conglomerate network exhibits features of scale-free networks, including a fat-tailed distribution of inter-industry connections. Thus, the network is sparse with relatively few central industries and many peripheral industries. Consistent with small world networks, the maximum path between industries in an average year is 7.5 links, out of over 500 different industries. We also show that during the sample period, the network evolved into a more concentrated network as industries dropped links to more peripheral industries while retaining links to more central industries. These statistics provide a new perspective on the importance of conglomerate firms in the economy. Though conglomerate firms are less common than single segment firms, their large size and scope leaves a large footprint across the economy.

To estimate the relationship between the inter-industry connections in the conglomerate network and the inter-industry transmission of shocks, we first estimate cross-sectional regressions of the covariance of industry growth rates on HHI and CoHHI. We find that the volatilities of sales, asset, and investment growth are positively correlated with industry concentration, consistent with concentrated industries having less diversification across individual firm-level shocks. Second, we find that CoHHI is positively correlated with the covariance of economic growth rates in the cross-section of industries. This result is consistent with our theoretical framework in which industries have shared exposure to common shocks from conglomerate firms that span multiple industries.

Next, to further isolate the correlation between the conglomerate network and the covariance of industry volatilities, we estimate panel regressions using industry-pair and year fixed effects. To capture a yearly measure of cross-industry comovement in industry outcomes, the dependent variable is the squared difference of industry growth rates between industries. The industry-pair fixed effects captures both time-invariant industry and industry-pair characteristics that could influence the comovement of industry growth rates. This includes traits such as average volatility, the labor share in production, the average firm size, and the persistent component of input-output relations. The year fixed effects control for general macroeconomic trends that could influence the comovement of industry growth rates. We also control for input-output linkages and product market similarity using the text-based measure of Hoberg and Phillips (2016). Thus, our empirical model isolates the correlation between abnormal time-series variation in the conglomerate network and the comovement of industry growth rates.

The panel regressions show that when inter-industry connections strengthen in the the conglomerate network, the comovement of growth rates increases, as predicted by the model. The results hold for both in-links, out-links, and the transmission network for sales growth and asset growth. For investment growth, only shared out-links and the transmission network are significantly related. The economic magnitude of the results is meaningful. Compared to an industry-pair with no conglomerate link, the formation of a link is associated with a squared difference in growth rates that is lower by about 30%, relative to the median squared difference.

Next, because we construct the conglomerate network using only publicly-traded firms' segment data, we test for the generalizability of our results using employment data from the US Census County Business Patterns data, which covers nearly all establishments in the private sector. We find similar results using these data, which implies that the predictive power of the conglomerate network is not limited to public firms.

Second, we run two tests to address the concern that omitted variables drive our baseline results. In the first set of tests, we find similar results to our baseline tests when we estimate the same relationships using lagged measures of the conglomerate network. These results mitigate concerns of reverse causation in which the conglomerate network responds to changes in the comovement of industry growth, rather than vice versa. The next test exploits cross-sectional variation in industries' exposure to tariff rate shocks from the granting of normal trade relations to China in 2000 (Pierce and Schott, 2016). We find that industries with stronger connections in the conglomerate network to those industries most affected by the tariff shock had larger declines in employment, controlling for industry fixed effects, year fixed effects, and customer-supplier links. These results provide further evidence that economic shocks transmit through the conglomerate network.

This paper makes two central contributions. First, we present a model and empirical evidence of inter-industry transmission of economic shocks through conglomerate firms. As discussed above, these findings build on Gabaix (2011) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). Ahern and Harford (2014) also show that merger activity transmits through input-output links. More recently, Herskovic, Kelly, Lustig, and Nieuwerburgh (2020) studies the role of firm size on aggregate fluctuations in firm-level customer-supplier networks. In contrast to these papers, we show that industry-specific shocks transmit from one industry to another through conglomerate firms' internal markets. Our results also relate to the growing literature on the importance of common ownership (Azar, Schmalz, and Tecu, 2018; Antón, Ederer, Giné, and Schmalz, 2018). While this line of research focuses on partial ownership by institutional investors, we study controlling ownership by conglomerate firms. Our findings are also consistent with the notion that local shocks spread to wider geographic regions through multi-regional firms (di Giovanni, Levchenko, and Mejean, 2014; Kleinert, Martin, and Toubal, 2015; Giroud and Mueller, 2019). In contrast to shocks that are spread through geographic space, we show internal capital markets facilitate the spread of economic shocks through industry space. Finally, this paper also relates to the large literature on internal capital markets (Stein, 1997; Lamont, 1997; Shin and Stulz, 1998).

The second contribution of this paper is to provide a novel, economic interpretation of HHI. Even though HHI was not developed from economic theory,[1] it has become the standard metric of industry concentration among academics, practitioners, and policy-makers. For example, during 2011 to 2020, HHI is referenced in 4.5% of all articles published in the top five economics journals, which represents an increase of 87% relative to the 2000s. Second, HHI is a primary filter to identify non-competitive markets among a wide range of regulatory agencies, including the DOJ, FTC, FCC, FDIC, and the Federal Reserve. Our framework provides a new microfoundation for the calculation of HHI based on a network of firms and industries. To our knowledge, this provides one of the only economic interpretations of HHI.[2] Moreover, we use our framework to derive a new measure of cross-industry concentration, CoHHI.

I. The Theoretical Conglomerate Network

To construct the conglomerate network of industries, we start with a bipartite graph, also known as a two-mode network or an affiliation network, in which there are two types of nodes that are disjoint, independent sets and each type of node is connected only to nodes of the other type. Typical examples of affiliation networks include football players and football clubs, co-authors and publications, and corporate directors and corporate boards. Much of the research on networks in economics studies one-node networks with an implicit assumption of an underlying two-mode network. For instance, corporate boards typically do not have direct connections with other corporate boards, but instead, have indirect connections through shared directors in an affiliation network.

In our network, the two types of nodes are firms and industries. Firms are affiliated with industries and industries are affiliated with firms. Because two-mode networks have two distinct types of nodes, they allow for dual perspectives on the network's structure. In our setting, one

[1]HHI was originally developed to meet two ad hoc criteria of concentration measures (Hirschman, 1945; Herfindahl, 1950). Hirschman acknowledges that HHI is not a unique solution.

[2]Stigler (1964) shows that HHI is directly related to profitability in Cournot competition models. Our microfoundation applies to all industries.

representation of the network is from the perspective of firms: firms are connected to each other through shared industry affiliations. This perspective is the commonplace view of the relationship between firms and industries. The dual representation of the network from the perspective of industries is less commonplace: industries are connected to other industries by firms that operate in both industries. In this perspective, conglomerate firms that span multiple industries are the conduits for economic shocks to transmit between industries. Though the firm perspective is the basis for the common assumption that firms in the same industry face the same economic shocks, the industry perspective is an equally valid representation of the same underlying two-mode network. Because of the importance of conglomerates in the dual representation, throughout the paper, we call this affiliation network the conglomerate network.

The transmission of economic shocks in the conglomerate network is distinct from an input-output network where firms buy and sell directly from other firms. Instead, the economic shocks in the affiliation network transmit through firms' shared exposure to industry conditions, or equally, through industries' shared exposures to firm conditions. We do not specify the source of these shocks in our theoretical framework. We only assume that economic forces that affect the growth rate of an industry will affect the growth rate of firms within that industry. Likewise, we assume that economic forces that affect a firm's growth rate will affect the growth rates of the industries in which the firm operates. The generality of these assumptions reflects our focus not on the source of shocks, but on their transmission.

I.A. Formal Definitions

To formalize these assumptions, we assume the economy has $i = 1, \ldots, n$ firms and $j = 1, \ldots, m$ industries. Let S be the $n \times m$ bi-adjacency matrix in which entry $s_{i,j}$ denotes firm i's sales in industry j. Thus, the total sales for firm i is $\Sigma_j^m s_{i,j}$. The total sales for industry j is $\Sigma_i^n s_{i,j}$. Below, we use capital letters to denote matrices, lower case letters to denote matrix elements, and $\vec{x}$ to represent vectors.

We normalize S in two ways. First, we generate the matrix of market shares, H, by normalizing S by its column sums. Thus, the market share of firm i in industry j is $h_{i,j} = \frac{s_{i,j}}{\Sigma_i^n s_{i,j}}$. Similarly, we generate the matrix of industries' firm shares, F, by normalizing S by its row sums: $f_{i,j} = \frac{s_{i,j}}{\Sigma_j^m s_{i,j}}$.

Thus, each entry of F represents the fraction of firm i's total sales that are attributed to industry j. By normalizing industries and firms by their total sales, we focus on the relative importance of the connections between industries and firms, rather than the size of each node.

We allow the connections between firms and industries in the conglomerate network to be directional and weighted. In particular, we assume that growth shocks that transmit from a firm node to an industry node are weighted by the firm's market share in the industry, as recorded in H. Intuitively, a firm-level shock will affect an industry's growth in proportion to the firm's fraction of the industry's total sales. Analogously, we assume that shocks that transmit from an industry to a firm are weighted by the size of the industry segment in the firm's overall operation, as recorded in F. We denote this fraction as an industry's firm share, analogous to a firm's market share. Intuitively, an industry-wide growth shock will affect a firm's growth in proportion to the industry's importance in the firm's total sales.

We combine F and H into an $(m+n) \times (m+n)$ adjacency matrix A that represents the complete, weighted and directed bipartite graph, as follows,

$$A = \begin{bmatrix} 0 & F' \\ H & 0 \end{bmatrix}. \tag{1}$$

The first m rows and columns of A refer to industries and the last n rows and columns refer to firms. Matrix A represents the effect of a shock in the row entry on the column entry. F' represents the effect of a shock transmitting from an industry to a firm. H represents the effect of a shock transmitting from a firm to an industry. The zero matrices on the diagonals reflect that in the bipartite graph, firms and industries do not have direct connections. Also note that A is not symmetric, which reflects the directional nature of the bipartite network.

To illustrate our network setting, consider a simple example with three firms (x, y, and z) that operate in two industries (p and q). Their segment sales are given in matrix S, and we normalize

S by row sums and column sums to generate F and H, as follows:

$$S = \begin{array}{c} \\ x \\ y \\ z \end{array}\!\!\begin{array}{c} \begin{array}{cc} p & q \end{array} \\ \begin{bmatrix} 3 & 3 \\ 0 & 3 \\ 1 & 4 \end{bmatrix} \end{array}, \qquad F = \begin{array}{c} \\ x \\ y \\ z \end{array}\!\!\begin{array}{c} \begin{array}{cc} p & q \end{array} \\ \begin{bmatrix} 0.50 & 0.50 \\ 0.00 & 1.00 \\ 0.20 & 0.80 \end{bmatrix} \end{array}, \qquad H = \begin{array}{c} \\ x \\ y \\ z \end{array}\!\!\begin{array}{c} \begin{array}{cc} p & q \end{array} \\ \begin{bmatrix} 0.75 & 0.30 \\ 0.00 & 0.30 \\ 0.25 & 0.40 \end{bmatrix} \end{array}. \tag{2}$$

Figure I provides a graphical representation of this network, where blue arrows refer to the effect of firms on industries (H) and red arrows refer to effects of industries on firms (F), where the weights of the connections are determined by a firm's market share (blue arrows) or an industry's firm share (red arrows).

This example illustrates our definition of the strengths of connections in the conglomerate network. Because firm x receives half of its sales from industry p, a growth shock in industry p will affect half of firm x's sales. In contrast, the same industry shock in p only affects firm z by 0.2, because firm z only receives 20% of its sales from industry p. An identical interpretation exists for the dual of the network. A growth shock in firm x has a larger effect in industry p than q because firm x has a market share of 75% in industry p, but only 30% in industry q.

I.B. Network Transformations

To study the inter-industry and inter-firm connections, we transform the bipartite graph in matrix A into a unipartite graph in three ways. The first transformation represents the strength of transmissions between nodes of the same type based on the compound effect of shocks from one industry to another through affiliated firms, or from one firm to another through industry affiliations. The second and third transformations are projections from one set of nodes onto the other. The projections reflect the strength of shared in-links or shared out-links between nodes of the same type.

B.1. Network Paths

The first transformation of the network generates the strength of the paths that lead from one node to another of the same type. In particular, we denote

$$\text{Transmission Matrix} = A^2 = \begin{bmatrix} F'H & 0 \\ 0 & HF' \end{bmatrix}. \tag{3}$$

In a bipartite network, it takes two links to connect nodes of the same type (e.g., one link from an industry node to firm nodes, and a second link from firm nodes to industry nodes). If A was an unweighted adjacency matrix consisting of zeros and ones, A^2 would count the number of unique paths with a length of two that connect two industry nodes. If more paths connect two industries, they would have a stronger connection. In our case, using weighted links, the entry in the j'th row and k'th column of $F'H$ reflects the compound effect of a transition from industry j to industry k through conglomerate firms that operate in both industries. Likewise, in the bottom-right quadrant of A^2, HF' represents the compound effect of inter-firm transitions through industries. Note also that A^2 is a left stochastic matrix, where each column sums to one.

In our numerical example, the first entry in $F'H$ represents the effect of a shock transitioning from industry p back to industry p. In particular, this is the effect of moving from p to x, then x to p $(0.50 \cdot 0.75)$ plus the effect of moving from p to z then z to p $(0.20 \cdot 0.25)$, which equals 0.425. Likewise, the effect of moving from p to q is the effect of moving from p to x, then x to q $(0.50 \cdot 0.30)$ plus the effect of moving from p to z then z to q $(0.20 \cdot 0.40)$, which equals 0.230. Panel A of Figure II presents a visual representation of the transition matrix.

Notice that this is matrix is not symmetric. The effect of moving from p to q is 0.230 compared to the effect of moving from q to p, which is 0.575. The asymmetry is caused by asymmetry in the strength of the nodes' in-links relative to their out-links. In Figure I, note that the strength of links that lead out of industry p are weaker than the links that lead into industry p. In contrast, the strength of the links that lead out of industry q are stronger than the links that lead into it.

Panel B of Figure II presents the firm-to-firm transition of our numerical example. A shock in firm x has the greatest effect back on firm x and the least effect on firm y. As in industries, the transition matrix for firms is asymmetric.

B.2. Network Projections

The second type of transformation is a projection from firms onto industries and vice versa. The first projection reflects the strength of shared in-links:

$$\text{Shared in-links} = A'A = \begin{bmatrix} H'H & 0 \\ 0 & FF' \end{bmatrix}. \tag{4}$$

$A'A$ reflects the strength of the in-links that two nodes share and the diagonal of the matrix is the sum of the squared weights of the in-links for each node. This reflects how similar two nodes are to each other based on the strength of their common exposures. If two industries receive shocks from the same firms, in the same proportions, then they will be more closely related in this projection. Because the projection is based on shared in-links, it is a symmetric matrix.

Panels C and D of Figure II present a visual representation of the strength of shared in-links for our numerical example. At the firm-level, firm z has a smaller connection to x than it does to y. This is because firms z and y share strong common in-links from industry q, whereas firms x and z share weak common in-links from industry p. Thus firm z has a more similar exposure to firm y from industry shocks than it does to firm x.

The second projection reflects the strength of shared out-links:

$$\text{Shared out-links} = AA' = \begin{bmatrix} F'F & 0 \\ 0 & HH' \end{bmatrix} \tag{5}$$

If A was an unweighted, binary matrix, AA' would reflect the number of out-links with the same destination that two nodes share in common. Using weighted connections, as in our case, AA' reflects the strength of the out-links that two nodes share and the diagonal of the matrix is the sum of the squared weights of the out-links for each node. This reflects how similar two nodes are to each other based on the strength of the commonality of destinations for shocks. If two industries tend to have similar effects on the same firms, then the industries have higher connections in this projection.

I.C. Concentration Measures in the Conglomerate Network

The conglomerate network provides a new interpretation of standard measures of industry concentration. First note that the columns of H are n-dimensional vectors representing the market shares of the n firms in each industry. Denote an arbitrary column j in H as $\vec{h}_j$. As defined above, the entries of the matrix of shared in-links, $H'H$, are equivalent to the dot products of the columns of H. Therefore, for two industries, j and k, the row j and column k entry of $H'H$ is $\vec{h}_j \cdot \vec{h}_k = h_{1,j}h_{1,k} + h_{2,j}h_{2,k} + \cdots + h_{n,j}h_{n,k}$. The diagonal entries of $H'H$ are the dot products of an industry's market share vector with itself. For industry j, this is $h_{1,j}^2 + h_{2,j}^2 + \cdots h_{n,j}^2$. Thus, the diagonal entries of $H'H$ are the Herfindahl-Hirschman Indices (HHI) of industry concentration.

Using the conglomerate network, we can extend this derivation of HHI to generate a measure of cross-industry concentration. For two industries, j and k, we define,

$$\text{Industry CoHHI}_{j,k} = (H'H)_{j,k} = \vec{h}_j \cdot \vec{h}_k = h_{1,j}h_{1,k} + h_{2,j}h_{2,k} + \cdots + h_{n,j}h_{n,k}. \tag{6}$$

Industry CoHHI is the commonality in the pattern of firms' market shares across two industries. If the same firms have similar market shares in both industries, then Industry CoHHI will be larger. Thus, Industry CoHHI reflects the similarity of concentration of sales across firms in different industries. In turn, this means that the standard definition of Industry HHI is a special case of Industry CoHHI with itself.

This representation provides a microfoundation for the calculation of industry concentration as the sum of squared market shares, which is not justified in Hirschman (1945) or Herfindahl (1950).[3] In addition, using the conglomerate network to derive HHI reveals that HHI is a special case of a more general measure of CoHHI, which reflects the similarity between industries' market share distributions. Using the network perspective, these results also show that standard HHI measures can be thought of as the concentration of in-links of an industry. In other words, if two

[3]Hirschman designed HHI to meet two criteria that he argued that any measure of industry concentration should include: 1) concentration should be related to the dispersion of market shares and 2) concentration should be declining with the number of firms in an industry. Hirschman's measure accomplished these two goals, though the square of market shares was not justified. In fact, Hirschman recognized that his concentration measure is not the only measure that could meet these criteria. Herfindahl (1950) justified using the square of market shares by considering HHI as a weighted average of market shares where the weights were the market shares, themselves. However, he did not justify using the shares as weights versus logged market shares, the square root of market shares, or any other weighting scheme.

industries receive the same shocks from the same set of firms, then the two industries have high co-concentration.

We can apply a similar idea to the projection of out-links, AA'. At the industry level, $F'F$ reflects the commonality of out-links from industries to firms. If two industries tend to effect the same set of firms, then the two industries have higher co-concentration of destinations. This would happen when firms have the same fraction of sales from the same industries. Industries with focused firms will tend to have higher out-link concentration. Thus, this projection represents a new measure of industry concentration that is complementary to standard HHI.

Because of the duality of the bipartite graph, we can also provide similar measures of concentration at the firm level. In particular, FF' represents the Firm CoHHI matrix in which the diagonals are the Firm HHIs of concentration, and the off-diagonal elements are the Co-HHI between firms. Firm HHI measures the concentration of a firm's sales across industries. A firm with equal sales in two industries has a lower Firm HHI than a firm with the majority of its sales in one industry. The Firm Co-HHI reflects the commonality of two firm's distribution of sales across industries. Two firms that tend to sell the same fractions of their total sales in each industry will have a higher Co-HHI.

I.D. The Variance of Growth Shocks in the Conglomerate Network

In this section, we use our model to derive predictions on the covariance of industry and firm growth rates. We assume at time $t = 0$, firm i receives a shock ε_i and industry j receives a shock η_j. Both shocks are random variables with mean 0 and standard deviations σ_ε and σ_η, such that $cov(\varepsilon_k, \varepsilon_l) = 0$ for all (k, l) when $k \neq l$; $cov(\eta_k, \eta_l) = 0$ for all (k, l) when $k \neq l$; and $cov(\varepsilon_k, \eta_l) = 0$ for all (k, l). Thus, ε represents firm-level growth shocks after removing industry-level growth shocks, η, and vice versa. For simplicity, we assume that σ_ε is the same across firms and σ_η is the same across industries. In vector form, $\vec{\eta}$ is the $m \times 1$ vector of industry shocks and $\vec{\varepsilon}$ is the $n \times 1$ vector of firm shocks.

We assume shocks transmit from one node to another over time. In a bipartite graph, one step in the network, enacted by an application of the A matrix, represents an aggregation of a node's own shock plus the weighted average of the shocks of connected nodes. Two applications of the adjacency matrix (A^2) to a shock vector represents a complete transition of shocks back to their original node type. Therefore, to study the transition of shocks through the network, we take snapshots of the network after every complete transition of shocks, where the initial shock is a node's own shock plus the aggregation of its connected nodes' shocks. During every complete transition, we assume the shocks decay with rate δ.

In particular, the snapshot of the growth rate of industry j at $t = 0$ can be written as the industry-specific growth shock plus the weighted average of the growth rates of the firms operating in industry j. This is $g_{j,0} = \eta_j + \sum_{i=1}^{n} h_{i,j}\varepsilon_i$. Therefore, the vector of industry growth rates is $\vec{g}_{ind,0} = \vec{\eta} + \delta H'\vec{\varepsilon}$. The growth rate of firms follows the same pattern: the firm's specific growth rate plus the industry-specific growth rates weighted by the industry's firm share. This is, $\vec{g}_{firm,0} = \vec{\varepsilon} + F\vec{\eta}$. In matrix notation, the initial growth rates at $t = 0$ are

$$\vec{g}_0 = (I + A')\vec{\nu} = \begin{bmatrix} I & H' \\ F & I \end{bmatrix} \begin{bmatrix} \vec{\eta} \\ \vec{\varepsilon} \end{bmatrix} = \begin{bmatrix} \vec{\eta} + H'\vec{\varepsilon} \\ \vec{\varepsilon} + F\vec{\eta} \end{bmatrix}. \tag{7}$$

The variance-covariance matrix of growth rates at $t = 0$ is

$$Cov(\vec{g}_0) = \begin{bmatrix} \sigma_\eta^2 I + \sigma_\varepsilon^2 H'H & \sigma_\eta^2 F' + \sigma_\varepsilon^2 H' \\ \sigma_\eta^2 F + \sigma_\varepsilon^2 H & \sigma_\varepsilon^2 I + \sigma_\eta^2 FF' \end{bmatrix}. \tag{8}$$

The upper-left entry of this matrix represents the variance-covariance matrix of industry growth rates. The diagonal elements reflect the variance of industry growth rates which equal the variance of industry-specific shocks plus the variance of firm-specific shocks scaled by the industry's HHI. Thus, assuming all firm-level shocks are equally distributed, more concentrated industries have higher variance of growth rates. This is driven by concentrated industries' greater exposure to relatively few idiosyncratic firm-specific shocks. The off-diagonal elements of the industry-level variance-covariance matrix equal the variance of firm-specific shocks scaled by the CoHHI between two industries. This follows from the network interpretation of $H'H$ as the strength of shared in-links. Two industries with greater shared in-links from the same firms have higher co-variance in their growth rates.

The variance-covariance matrix of firm-level growth rates is $\sigma_\varepsilon^2 I + \sigma_\eta^2 FF'$. This is the dual interpretation of the industry-level matrix. On the diagonal, firm growth rates have a variance equal to the firm-level variance plus industry-level variance scaled by the firm's HHI across segments. Diversified conglomerate firms with operations in multiple sectors face lower industry-specific variance, compared to focused, single-segment firms. The off-diagonal elements in the firm-level variance-covariance matrix are equal to industry-specific variance scaled by firm-level CoHHI. Firms that operate in the same industries have greater shared in-links and thus, have higher covariance in their growth rates.

The off-diagonal $n \times m$ matrix, $\sigma_\eta^2 F' + \sigma_\varepsilon^2 H'$, in $Cov(\vec{g}_0)$ reflects the covariance in growth rates between firms and industries. This covariance is equal to the sum of the firm-specific variance σ_ε^2 scaled by the strength of the link from the firm to the industry plus the industry-specific variance scaled by the strength of the link from the industry to the firm. Intuitively, the covariance of growth rates between firms and industries is the sum of the firm and industry specific variance scaled by the strength of the connection between the firm and industry.

The variance-covariance matrix of growth rates at $t = 1$ is

$$Cov(\vec{g}_1) = \delta^2 \begin{bmatrix} \sigma_\eta^2 H'FF'H + \sigma_\varepsilon^2 H'FH'HF'H & \sigma_\eta^2 H'FF'HF' + \sigma_\varepsilon^2 H'FH'HF' \\ \sigma_\eta^2 FH'FF'H + \sigma_\varepsilon^2 FH'HF'H & \sigma_\eta^2 FH'FF'HF' + \sigma_\varepsilon^2 FH'HF' \end{bmatrix}. \tag{9}$$

This variance-covariance matrix represents that as shocks pass through the network over time, they repeatedly transmit from firms to industries and back to firms.

If we take the sum of the growth rates from $t = 0, \ldots, \infty$, we have the following

$$\begin{aligned} \sum_{t=0}^{\infty} \vec{g}_t &= \left[I + \delta(A')^2 + \left(\delta(A')^2\right)^2 + \left(\delta(A')^2\right)^3 + \cdots \right] \left(I + A'\right) \vec{\nu} \\ &= \left[I - \delta(A')^2 \right]^{-1} (I + A')\vec{\nu} \end{aligned} \tag{10}$$

where the infinite sum converges because A^2 is a stochastic matrix. The term $\left[I - \delta(A')^2\right]^{-1}$ is the Leontief inverse. Thus, Equation 10 represents the transformation of initial shocks into industry and firm growth rates after passing through the conglomerate network an infinite number of times. This can be interpreted as the steady state outcome of the transition matrix A^2. In addition, as Carvalho (2014) points out, the Leontief inverse is equivalent to the Katz-Bonacich eigenvector centrality of a network. Thus, Equation 10 also implies that the long-run industry and firm growth rates equal the product of their eigenvector centrality in the conglomerate network with their initial shock.

These properties of the conglomerate network are identical to the properties of the industry-level input-output networks studied in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and the firm-level input-output network studied in Herskovic, Kelly, Lustig, and Nieuwerburgh (2020). In particular, both papers show that the Leontief inverse describes how network structure affects aggregate growth rates. Acemoglu et al. include the Leontief inverse in a measure they call the influence vector $\vec{v}$ of an industry, which is equivalent to both Katz-Bonacich eigenvector centrality and the "sales vector" of the economy, in which each element reflects sector i's sales as a fraction of the total sales in the economy. Acemoglu et al. note that the second representation is related to Gabaix's finding that firm-level productivity contributes to aggregate productivity in proportion with firm size.

Our conglomerate network has the same representations of the influence vector as the IO network, except the weights in our measure represent the strength of the bi-partite network of conglomerates. In particular, the eigenvector centrality of the industries and firms in our network matrix A^2 is also the sales vector of the economy, $\vec{v}$. Thus, like Acemoglu et al., given a vector of idiosyncratic industry shocks $\vec{\eta}$, the aggregate shock to the economy is $\vec{v}_{ind}\,'\vec{\eta}$. Equivalently, the aggregate shock to the economy from firm-level shocks is $\vec{v}_{ind}\,'\vec{\varepsilon}_{firm}$, as in Herskovic et al.

In sum, our model generates the same implications for the importance of a single industry or firm in the conglomerate network as derived in the production network. This is an important distinction. In our model, firms are diversified, unlike in Gabaix (2011), which affects their centrality, and thus, their influence on the aggregate economy. Herskovic, Kelly, Lustig, and Nieuwerburgh (2020) present a similar intuition based on the concentration of customers in the input-output network. Our model is also distinct from Herskovic et al., because we allow for both industry-specific and firm-specific shocks. As demonstrated above, the covariance of firm growth rates depends both on firm-specific shocks, and also industry-specific shocks. Finally, our approach is distinct from existing work on production networks, because we study the transmission of shocks through internal capital markets of conglomerate firms.

II. The Empirical Conglomerate Network

II.A. Data

We collect segment level information of conglomerate firms from the Compustat Historical Segment data. For corporate segments that represent at least 10 percent or more of consolidated sales in a different industry, SFAS No. 14 requires that firms report accounting information on a segment-level basis for fiscal years ending after December 15, 1977. To rectify the inadequacies of SFAS No. 14, the Financial Accounting Standards Board (FASB) further issued SFAS No. 131 in June 1997, which requires that, for fiscal periods beginning after December 15, 1997, firms identify industry segments for external reporting purposes in the manner that management views operating segments for internal decision-making purposes. To ensure the time-series comparability of our conglomerate network, we use the Compustat Historical Segment data from 1997 to 2018 to construct our conglomerate network. Specifically, for each segment, we collect the following five variables: net sales, capital expenditures, identifiable total assets, and SIC (NAICS) code.

One complication of the long-time horizon considered in this paper is that the scheme of industry classifications changes over time, such as the change from the SIC to the NAICS in 1997 and subsequent versions of NAICS from 2002 to 2017. To obtain the time-consistent industry definitions, we follow Pierce and Schott (2016) and create "families" of industry codes that group related SIC and NAICS categories together across different industry classification schemes. For example, if an industry code splits into several codes from 1997 to 2002, the industry code in 1997 and its subsequent "children" would be grouped into the same family. Therefore, unless otherwise noted, industries in this paper refer to these families. This adjustment allows us to control for time-invariant industry properties using fixed effects.

II.B. The Structure of the Conglomerate Network

Networks exist across a continuum of types. On one extreme, random graphs contain nodes that are connected to each other with an equal probability (Erdős and Rényi, 1959). Thus, random graphs do not have central hubs. In addition, the number of connections to a node (degree) in a random graph exhibit relatively little variation around the average degree. Second, random graphs are not clustered. Clustering measures the extent to which a nodes' neighbors are also connected with each other. At the other extreme of network types are ultra small world networks. These networks have very large hubs, with undefined degree variance. This means that the degree of an arbitrary network varies widely around the mean. The presence of prominent hubs in these networks reduces the average distance between all nodes and create clusters of nodes. See Barabási (2016) for a detailed discussion of network types.

One way to measure the structure of a network is by its degree distribution. Random graphs have symmetric binomial degree distributions. Ultra small world networks have fat tailed degree distributions with long right tails indicating that a small number of nodes have many connections and a large number of nodes have few connections. A particular fat tailed distribution is the power law distribution, also known as the scale free distribution, $p(X > x) \sim Cx^{-\alpha}$, where $\alpha > 2$ is the scaling parameter. The lower is the α, the longer is the right tail. As α increases above 3, the network begins to resemble a random network.

II.C. The Structure of the Conglomerate Network in Cross-Section

Figure III represents the complementary cumulative degree distribution of the conglomerate network in 1997 in log scale. A linear relationship indicates a fat tailed, power law distribution. The dashed line in the figure corresponds to an α of 3.44, estimated following Clauset, Shalizi, and Newman (2009). This α is comparable to 3.1 for the input-output network of industries, as estimated in Ahern and Harford (2014). Over our sample period, α is estimated to be 2.8 in an average year, though in 60% of years we reject the hypothesis that the network is power law distributed. Thus, these statistics show that the degree distribution of the conglomerate network has a substantially fat tail, even if not precisely a power law distribution. This means that the network is characterized by a relatively few hub industries with many connections to other industries and a relatively large number of industries with few inter-industry connections.

Additional network statistics confirm that the conglomerate network has a fat tail. In an average year, the average industry is connected to 6.8 other industries (degree centrality), though the median industry is connected to 3.3 other industries, consistent with a skewed degree distribution. The clustering coefficient of the average industry is 39%; for the median industry it is 32%, which is large relative to clustering in social networks. Finally, in an average year, the maximum path length between any two industries in the largest component is 7.5 links (7 at the median). Given that the largest component has 573 industries in an average year, this reflects that the conglomerate network exhibits small-world network features.[4]

II.D. Time-Series Evolution of the Conglomerate Network

Figure IV plots the time series of network statistics. First, the power law scaling parameter α has decreased over this period, while the variation in degree across nodes and clustering increased. This indicates that the network has evolved towards a ultra small world network with more prominent hubs. Second, from 2000 to 2019, average degree centrality decreased by more than 30% while eigenvector centrality decreased less noticeably. These results indicate that the average industry reduced its number of connections by removing connections to more peripheral industries.

These results highlight the changes in conglomerate ownership over the last two decades. While fewer industries are connected through conglomerate firms, the connections that remain are stronger and more centralized. In addition, industries are now more clustered together through conglomerates than in the past.

II.E. Central Industries in the Conglomerate Network

Table I presents the most central industries in the network. The industries that are most likely connected to other industries through shared in- and out-links are general industrial machinery, personal and business credit, patent owners, mortgage banks, plastics, and information services. In the transmission network, the industries with the highest degree centrality are large manufacturing industries: motor vehicles, electric utilities, petroleum, and apparel. Controlling for the centrality of the connected industries using eigenvector centrality, we find that food industries are the most central. This implies that the large manufacturing industries that have high degree centrality are not connected to other industries that are also central, whereas the food industries are.

[4]We discuss the statistics for the binary network for ease of exposition, but the interpretation of the weighted networks are similar. We report statistics for the giant component of the network, which is the largest set of interconnected nodes in a network. In an average year, 75% of industries are in the largest connected component. The remaining industries are typically in very small components of one or two industries. We also exclude self-loops from the statistics, where an industry is connected to itself.

To help visualize the conglomerate network, Figure V presents the CoHHI network for manufacturing industries in 2015. Each inter-industry connection represents a CoHHI score above a minimum threshold. Industries listed in boxes are aggregated to more coarse definitions for brevity.

To give further intuition for the structure of the network, Figure VI provides a detailed representation of the links between the paper, chemicals, and plastic industries. The firms listed are those firms that operate in at least two of the three industries. The CoHHI of the paper and chemicals industries is driven by their common exposure to the same firms, with Procter & Gamble as a key conduit. Likewise, the chemicals and plastics industries are connected through common exposure to conglomerate firms, with Bayer as the strongest connection.

III. Empirical Evidence on The Comovement of Industry Growth Rates

In this section of the paper, we study the correlation between the conglomerate network and the comovement of cross-industry variance. Though our framework provides both firm-level and industry-level predictions, we focus on the industry-level to reduce selection biased in publicly-traded company data.

III.A. Cross-Sectional Tests

First, we estimate the cross-sectional industry-to-industry variance-covariance matrix in Equation 8. In particular, following the model, we regress the time-series covariance of industry growth rates on the time-series average strength of industry connections in the CoHHI network, plus a dummy variable that indicates the diagonal entries in the matrix (i.e., an industry paired with itself). We study three industry growth rates in our baseline tests: sales growth, asset growth, and investment growth.

Table II shows that there is a positive cross-sectional correlation between CoHHI and and the covariance of sales growth and asset growth rates, consistent with the theoretical framework. These results imply that industries with higher CoHHI connections also have higher comovement of fundamental economic growth rates. The intuition is that the comovement of industry growth rates is driven by conglomerate firms with large market shares in multiple industries.

Next, the dummy variable that indicates observations of an industry paired with itself isolates an industry's HHI and its variance of growth rates. The positive coefficient on the dummy variable reflects that more concentrated industries have more volatile growth rates. This result is consistent with the model's intuition that concentrated industries have greater exposure to firm-specific shocks. These results show that industry volatility is driven, in part, by large firms as in Gabaix (2011), but only if the firms have large market shares within the industry.

III.B. Panel Tests

Second, we estimate panel regressions with fixed effects to isolate the effect of changes in the conglomerate network on within-industry-pair changes in comovement. To estimate a panel model with yearly observations, we cannot use the time-series covariance as our dependent variable. Instead, to motivate our empirical model, note that the squared difference of two industries' growth rates at $t = 0$, is as follows:

$$(g_j - g_k)^2 = (\eta_j - \eta_k)^2 + 2(\eta_j - \eta_k)\left(\sum_{i=1}^{n} h_{i,j}\varepsilon_i - \sum_{i=1}^{n} h_{i,k}\varepsilon_i\right) + \left(\sum_{i=1}^{n} h_{i,j}\varepsilon_i - \sum_{i=1}^{n} h_{i,k}\varepsilon_i\right)^2 \tag{11}$$

In expectation, the squared difference of growth rates is:

$$E\left[(g_{j,1} - g_{k,1})^2\right] = 2\sigma_\eta^2 + \sigma_\varepsilon^2\left(HHI_j + HHI_k\right) - 2\sigma_\varepsilon^2 CoHHI_{j,k}. \tag{12}$$

To test this relationship empirically, we estimate a more generalized version of the model's prediction in the following regression:

$$\begin{aligned}(g_{j,t} - g_{k,t})^2 = \;& \gamma_1 \text{Shared In-Links (Co-HHI)}_{jk,t} \\ & + \gamma_2 \text{Shared Out-Links}_{jk,t} \\ & + \phi(HHI_{j,t} + HHI_{k,t}) \\ & + \tau_t + \delta_{jk} + \psi\,\text{Controls}_{jk,t} + \varepsilon_{jk,t}\end{aligned} \tag{13}$$

where $g_{i,t}$ represents industry i's growth rate at time t, Shared In-Links (Co-HHI)$_{ij,t}$, and Shared Out-Links$_{ij,t}$ represent network connections at time t, τ_t is a time fixed effect, δ_{ij} is an industry pair fixed effect, and Controls include time-varying industry-pair control variables, discussed below. This regression is estimated using undirected industry-pairs because the explanatory variables represent undirected links. We include Shared In-Links in our regression tests, even though they do not appear in the theoretical formulation, because shocks might transfer in the opposite direction than we have assumed.

The regression above does not include the transmission network because it is derived from the covariance of growth rates at the initial period. If we allow for higher order connections in the network, we need to include the transmission network. As above, we estimate a more general empirical model than predicted by the theoretical model:

$$(g_{j,t} - g_{k,t})^2 = \beta_1 \text{Transmission}_{jk,t} + \phi(HHI_{j,t} + HHI_{k,t}) + \tau_t + \delta_{jk} + \psi\, \text{Controls}_{jk,t} + \varepsilon_{jk,t} \quad (14)$$

Because the transmission matrix reflects the directed flow of shocks from one industry to another, the unit of observation in Equation 14 is an ordered industry pair.

In both regressions, the industry pair fixed effects, δ_{ij} account for time-invariant cross-sectional variation in industry pairs (directed or undirected). This controls for any cross-industry trait that remains stable over time, such as the nature of the product (e.g., goods vs. services), the level of government regulation, access to capital, and the importance of intangible assets. We also include time fixed effects, τ_t to control for economy-wide fluctuations and to isolate within-industry pair fluctuations. Finally, we also run specifications that use a dummy variable that represents the presence of a connection in the network, without regard to the strength of the connection. For the shared links networks, this dummy variable is identical in the in-links and out-links networks.

The regressions also include variables to control for customer-supplier relationships and product-market similarities. We measure the customer-supplier connections between industry pairs using data from the industry-by-industry total requirement table from the Benchmark Input-Output Accounts released by the Bureau of Economic Analysis (BEA). These data measure the dollar amount of industry output required per dollar of industry output delivered to final demand. We use the most recent data for years 1997, 2002, 2007, 2012, and 2017. For example, from year 1997 to 2001, we use the 1997 total requirement table.

Second, we control for time-varying asset similarities between industry pairs based on the text-based product similarity measure of Hoberg and Phillips (2016) (HP). To convert their similarity measures to our industry pairs, we identify stand-alone firm-pairs with positive HP similarity in each industry pair. We then calculate the average similarities between these firm pairs in our industry-pairs to proxy for asset similarity. Specifically, for industry pair (i, j), with m stand-alone firm-pairs (k, l) with positive HP similarity, where k denotes firms in industry i and l denotes firms in industry j, the asset similarity of industry pair (i, j) is $\frac{\sum_m HP_{k,l}}{m}$, where $HP_{k,l}$ is the text-based product similarity of the firm pair (k, l). We assign a zero to industry pairs with missing similarity scores.[5]

In sum, these regressions are designed to isolate how time-series variation in the comovement of two industries' growth rates is explained by time-series variation in the strength of the connection between the industries in the conglomerate network. If two industries' connection through conglomerates becomes stronger, we expect to see stronger comovement in their growth rates. After presenting these baseline results, we consider sampling bias and endogeneity in robustness tests.

Table III provides summary statistics for all of variables used in the panel regressions. In the median industry-year, sales growth is 2.67%, asset growth is 1.1%, investment growth is 4.40%, and employment growth is -0.90%. Squared differences in these rates vary considerably. In an average year, the squared difference of sales growth is 20.88%, compared to 5.56% at the median. Asset growth is similar, but squared differences in investment and employee growth rates are much lower. This indicates that there is less variation across industries in investment growth and employee growth than sales and asset growth. All of the network measures are skewed because the network is sparse, with most industry pairs having no connection. The dummy variables indicates that 1.4% of industry-pairs are connected.

III.C. Baseline Results

Table IV presents estimates of the relationship between shared in-links and out-links on the comovement of industry growth rates. For sales growth and asset growth, an increase in the strength of shared links is negatively correlated with the squared differences in growth rates. Thus, consistent with our prediction, as industries become more closely connected in the conglomerate network, their growth rates comove more closely. Because we control for year fixed effects and

[5]Our results are qualitative unchanged if we drop these industry pairs from the sample instead.

industry-pair fixed effects, these results are not driven by cross-sectional differences in the nature of industries, nor are they explained by economy-wide fluctuations in the time-series of growth rate levels or correlations. In addition, the results are not driven by customer-supplier relationships or asset similarities.

For investment growth, shared out-links are statistically related to comovement in growth rates, but shared in-links are not. This might reflect that investment growth rates reflect cash-flow shocks, rather than growth rate shocks. In this case, the strength of shared out-links would correspond to the transmission of level shocks in the opposite direction, rather than growth shocks. This may also explain why the input-output and Hoberg-Phillips measures reverse directions for investment growth.

Also consistent with the model, the sum of HHI is positively correlated with squared differences in growth rates with a high degree of statistical significance. This reflects that industries with greater internal concentration have weaker connections to other industries. Thus, an increase in an industry's HHI reduces the comovement of its growth rate with other industries.

It is easiest to interpret the magnitude of the dummy variable for the squared difference of growth rates. For all three outcome variables, the presence of a connection reduces the squared difference in growth rates by about 8.5% of the average squared difference and about 31% of the median squared difference. The squared difference in the investment growth rate is reduced by 56% of the median if there exists a conglomerate connection compared to industry pairs without a connection. For comparison, a one standard deviation increase in the sum of HHI is associated with an increase of squared differences in growth rates equal to 45% of the median for sales growth and 29% of the median for asset growth.

Next, Table V presents the estimates of the transmission network on the comovement of industry growth rates. The Transmission dummy variable is identical to the shared links dummy variable, but we include it here because the sample sizes are different in these tests. The estimates show that the transmission network is negatively and significantly related to difference in industry growth rates for sales, asset, and investment growth. Thus, as the connection between two industries in the transmission network increases, the growth rates of the industries comove more closely. As before, the sum of industry HHIs has the opposite relationship to the transmission network, consistent with the prediction. These regression results provide strong support for the model's predictions.

III.D. Robustness Tests

Though the above results show that inter-industry strength in the conglomerate network is correlated with the strength of the comovement of industry growth rates, there are potential concerns related to sampling bias and endogeneity. Below, we address these two concerns in additional robustness tests.

D.1. Employment Growth from CBP Data

One potential concern with the baseline results is that the dependent and explanatory variables are both derived from data restricted to publicly-traded firms that are subject to reporting requirements for segment-level accounting data. Therefore, the results may be driven by measurement errors within publicly traded firms. Second, the results may not generalize to the full economy, including private firms.

To address this concern, we estimate the model using industry level employment data from the US Census Bureau's County Business Patterns (CBP) files from 1991 to 2018. These data offer the most detailed view of the United States' industrial structure available to the public. They provide annual data on employment at a detailed industry level, which covers nearly all establishments with paid employees in the private sector of the United States. Therefore, unlike the Compustat Segment data, the industry employment in CBP files contain the universe of firms, both publicly listed and private.

Table VI presents the estimated regressions of the growth rate in employment on the conglomerate network. The results are consistent with the baseline results. In particular, a stronger CoHHI link between industries is associated with strong comovement in their growth rates of employment. The transmission network is also correlated with employment growth, though the relationship is only found for the dummy variable for transmission links. There is no significance of shared out-links for employment growth. In sum, the consistency of these results helps alleviate the concern that our network is not generalizable beyond Compustat segments data.

D.2. Lagged Explanatory Variables

A second potential concern with our baseline results is that the dependent variable and explanatory variables are concurrent yearly observations. Thus, both variables could be driven by an omitted variable. Alternatively, it is possible that reverse causation drives our results such that growth rates cause firms to increase the size of their operations in industries with correlated growth rates. To test for a causal relationship between the conglomerate network and the comovement of growth rates requires exogenous variation in the conglomerate network, which we do not observe. However, to better understand the potential for a causal relationship between the network and growth rates, we run robustness tests using lagged explanatory variables.

Table VII presents the results for the network of shared links and Table VIII presents the results for the transmission network. Though the coefficient estimates are smaller in magnitude, they are still highly statistically significant. With the exception of the statistical relationship of shared out-links on investment growth, all of the results are qualitatively similar to the concurrent regressions. While we cannot claim that the conglomerate network is the only mechanism for the diffusion of economic shocks, this evidence provides compelling evidence against reverse causality.

D.3. WTO Shock

As an additional analysis of the propagation of industry shocks within the conglomerate network, we study the effect of the United States granting Permanent Normal Trade Relations (PNTR) to China. PNTR was granted by Congress in October 2000 and became effective when China joined the World Trade Organization (WTO) at the end of 2001. Before the conferral of PNTR, the tariff rates of US imports from China required annual renewals, which had imposed a great amount of uncertainty on the trade relations between China and US. Although PNTR did not change the import tariff rates that the United States actually applied to Chinese goods, it removed the uncertainty associated with these annual renewals. Without the yearly renewal of favorable rates, US import tariffs would have increased substantially.

Pierce and Schott (2016) show that granting PNTR to China caused declines in employment within US industries that were most at risk of higher tariffs without PNTR (exposed industries). We exploit the same shock to test whether employment growth declined for industries that were not directly affected by PNTR, but were connected to the exposed industries through the conglomerate network. This allows us to test whether a specific identifiable shock transmits through the conglomerate network.

Following Pierce and Schott (2016), we measure the NTR gap as the difference between the non-NTR rates to which tariffs would have risen in the industry if annual renewal had failed and the NTR tariff rates that were locked in by PNTR. This shock is time-invariant for each industry and therefore absorbed by industry fixed effects. However, as in Pierce and Schott, we can identify the effect of the NTR gap through its interaction with a dummy variable, *Post*, which is equal to one from 2001 onward to indicate years after the passage of PNTR.

To identify industries that could potentially receive the NTR shock from the exposed industries through the conglomerate network, we use the transmission network, $F'H$. We use the 1999 network to ensure it is exogenous to the NTR shock in 2000. For each industry k in the transmission network, we weight the NTR gap by the entries in the kth column of $F'H$. These entries represent the shocks from row industries that transmit to industry k. We also normalize the measure by the sum of the column, excluding industry i. Therefore, $\text{NTR gap}_k \times \text{Transmission}_k = \frac{\sum_{i \neq k} \text{Transmission}_{i,k} \times \text{NTR gap}_i}{\sum_{i \neq k} \text{Transmission}_{i,k}}$. As above, this variable is identified through the interaction with the post dummy variable. If the employment shock transmits through the conglomerate network, we expect to find a negative coefficient on the interaction between the strength of the conglomerate network and the NTR gap.

Table IX presents the results of these tests. Column 1 replicates the findings in Pierce and Schott (2016). US industries directly exposed to the NTR shock experience a significant decline in employment. Column 2 shows that this shock transmits through the conglomerate network. Industries with greater network connections to the industries directly exposed to the NTR shock also experience declines in employment. These results provide further evidence that economic shocks transmit across industries through conglomerate firms.

In columns 3 and 4 of Table IX, we provide two more robustness checks. In column 3 we create a placebo variable identical to the interaction between the transmission network and the NTR gap by randomly assigning industries to the actual network weights in the transmission network. We find that there is no correlation between this placebo network and employment growth. This implies that our main results are not caused by a general network-wide trend. Finally, in column 4, we include the strength of network connections from the 1997 BEA commodity requirement input-output tables. We find that downstream industries are affected by the shock, though upstream industries are not, consistent with Pierce and Schott (2016). However, we still find that the transmission network is significantly related to employment in connected industries.

These tests are important because they allow us to exploit the cross-sectional variation in the exposure to an identifiable shock. We also use the predetermined network structure prior to the NTR shock to rule out reverse causality. In addition, our dependent variable is not based on public firm filings in Compustat. Even after these controls, we still find that the conglomerate network serves as a conduit to spread economic shocks.

IV. Conclusion

To organize an analysis of the economy, researchers typically partition economic activity into a set of isolated industries, grouped together by common suppliers, production processes, technology, or customers. At the same time, in the real world, economic activity is grouped together by common control derived from ownership, typically organized as firms. These two groupings create overlapping boundaries of economic activity, in which industries are groupings of firms, but at the same time, some firms are groupings of industries. In this paper, we organize these overlapping groupings into a unified network of industries and firms. Using this network perspective, we show that economic activity transmits across the economy through conglomerate firms that span multiple industries.

The core of our model is an affiliation network in which industries are affiliated with firms and firms are affiliated with industries, but firms have no direct connections with other firms and industries have no direct connections with other industries. This creates a directed, and weighted network in which shocks transmit from firms to industries in proportion to a firm's market share of total industry sales and from industries to firms in proportion to the fraction of a firm's sales attributed to the industry. From the affiliation network, we create three inter-industry networks that vary in the interpretation and strength of their connections. In the first network, inter-industry connections represent the strength of the links from an industry through conglomerate firms, back to other industries. The connections in the second network represent two industries' commonality of shared in-links from overlapping conglomerate firms. The final network represents the strength of shared out-links from industries to common firms.

An important new perspective offered by our network is a microfoundation for the widely-used Herfindahl-Hirschman Index (HHI). We show that HHI is a special case of a more general measure we call CoHHI which represents the shared in-links of an industry. If the same firms command more similar market shares in two industries then the industries have a higher CoHHI. This reflects a measure of cross-industry sales concentration through overlapping firms. Furthermore, just as statistical variance is a special case of covariance, HHI is a special case of CoHHI. This derivation also provides an economic rationale for HHI's specific formulation as the sum of squared market shares, which is an ad hoc choice made in the original papers by Hirschman and Herfindahl.

The conglomerate network also provides predictions on the covariance of growth rates across industries. Assuming idiosyncratic firm and industry shocks, we show that the volatility of an industry's growth equals a common volatility of industry growth rates plus firm-level volatility weighted by the HHI of the industry. The covariance of industry growth rates is equal to firm-level volatility weighted by the CoHHI between the two industries. Thus CoHHI describes the comovement of growth rates across the economy.

We test the predictions of our model using a panel of segment level data from 1997 to 2018. We show that the stronger is the connection between two industries in the conglomerate network, the stronger is the comovement of their growth rates of sales, asset levels, investment, and employment. These results persist after controlling for industry-pair fixed effects, year fixed effects, changes in industry HHIs, customer-supplier links, and asset similarity measures. To help identify a causal relationship, we use lagged values of network connections and find qualitatively similar results. We also exploit the cross-sectional variation in industries' exposure to tariff rate shocks following the granting of normal trade relations to China. We find that employment falls more in industries that have stronger connections to the industries directly affected by the tariff rate shock.

We believe our results have far-reaching implications. First, they help explain how idiosyncratic shocks aggregate to macroeconomic fluctuations. Second, they provide a new perspective on the incidence of diversified conglomerates across industries and time. Third, the conglomerate network generates a new measure of cross-industry concentration, CoHHI, and gives an economic microfoundation to HHI. Given the prevalence of HHI in academic research and among policy-makers, we believe this measure will be useful for understanding the organizational structure of economic acivity within and across industries.

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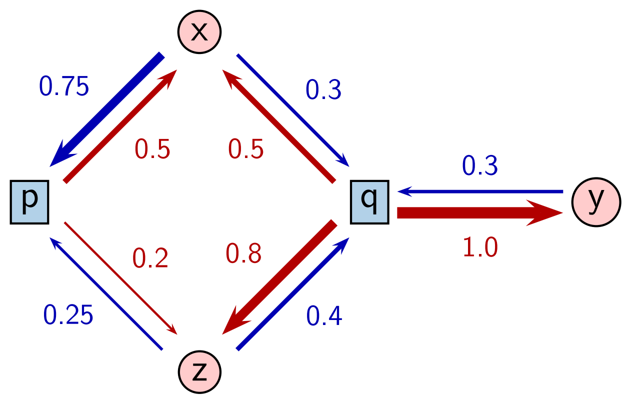
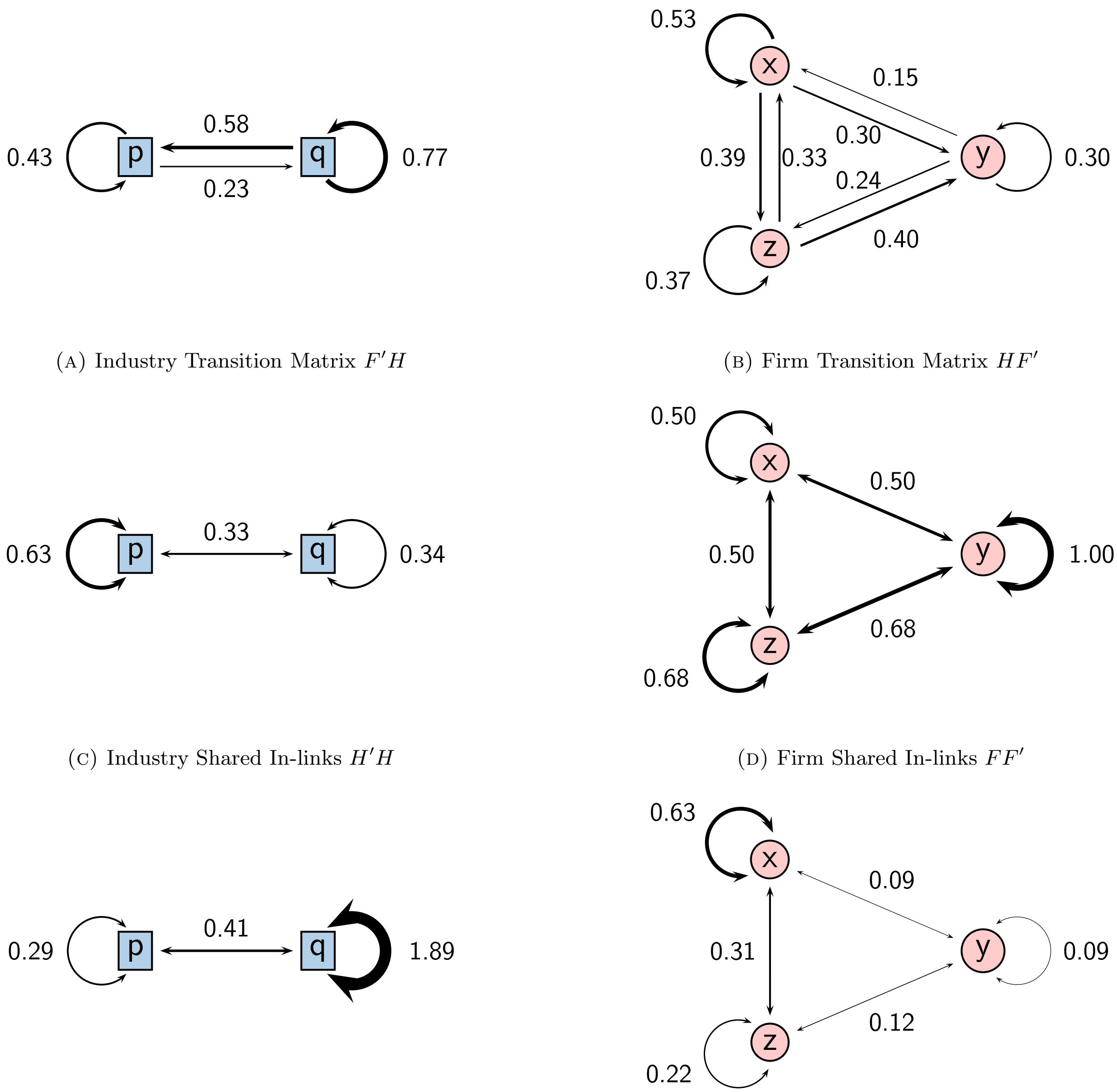


FIGURE I

A Network with Two Industries and Three Firms

This figure presents a graphical representation of an example network. The firms are x, y, and z, and the industries are p and q. Blue arrows reflect matrix H, the effect of firms on industries. Red arrows reflect matrix F, the effect of industries on firms.



(A) Industry Transition Matrix $F'H$

(B) Firm Transition Matrix HF'

(C) Industry Shared In-links $H'H$

(D) Firm Shared In-links FF'

(E) Industry Shared Out-links $F'F$

(F) Firm Shared Out-links HH'

FIGURE II

Three Transformations of the Conglomerate Network

Panels A and B present transition matrices for industries (A) and firms (B). Panels C and D present projection matrices of shared in-links for industries (C) and firms (D). Panels E and F present projection matrices of shared out-links for industries (E) and firms (F).

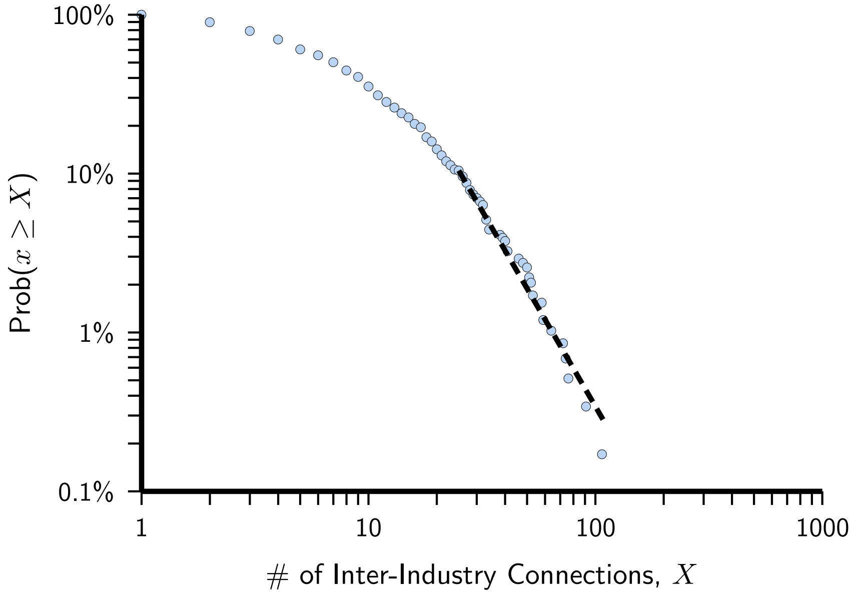


FIGURE III
Degree Distribution of Binary Conglomerate Network
This figure represents the distribution of degree centrality in log-log scale in the 1997 binary conglomerate network. Circles represent the degree centrality of industries, indicating how many direct connections an industry has to other industries. The dashed line is the from the estimate of α in the power distribution $P(k) = ck^{-\alpha}$.

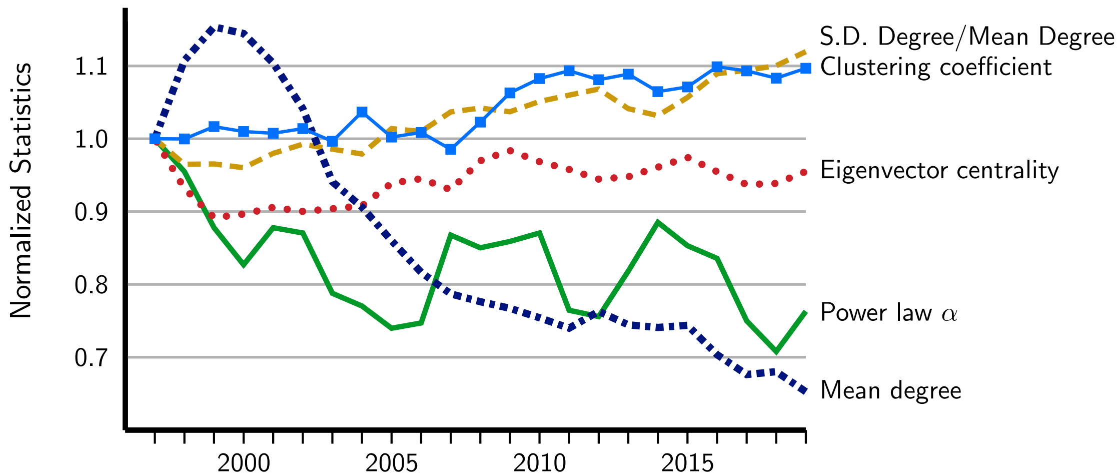


Figure IV

Time Series of the Binary Conglomerate Network

Five summary statistics are calculated yearly on the binary conglomerate network. Mean degree is the number of inter-industry links into an average industry. Eigenvector centrality is the eigenvector value for the largest eigenvalue of the network for an average industry. Clustering coefficient is the fraction of industries that are connected to a node that are also connected to each other for the average industry. Power law α is the estimate of the scaling parameter of the power law distribution $P(x) = Cx^{-\alpha}$. S.D. Degree/Mean Degree is the standard deviation of industry degree divided by the average degree. All statistics are normalized by dividing by the values in 1997.

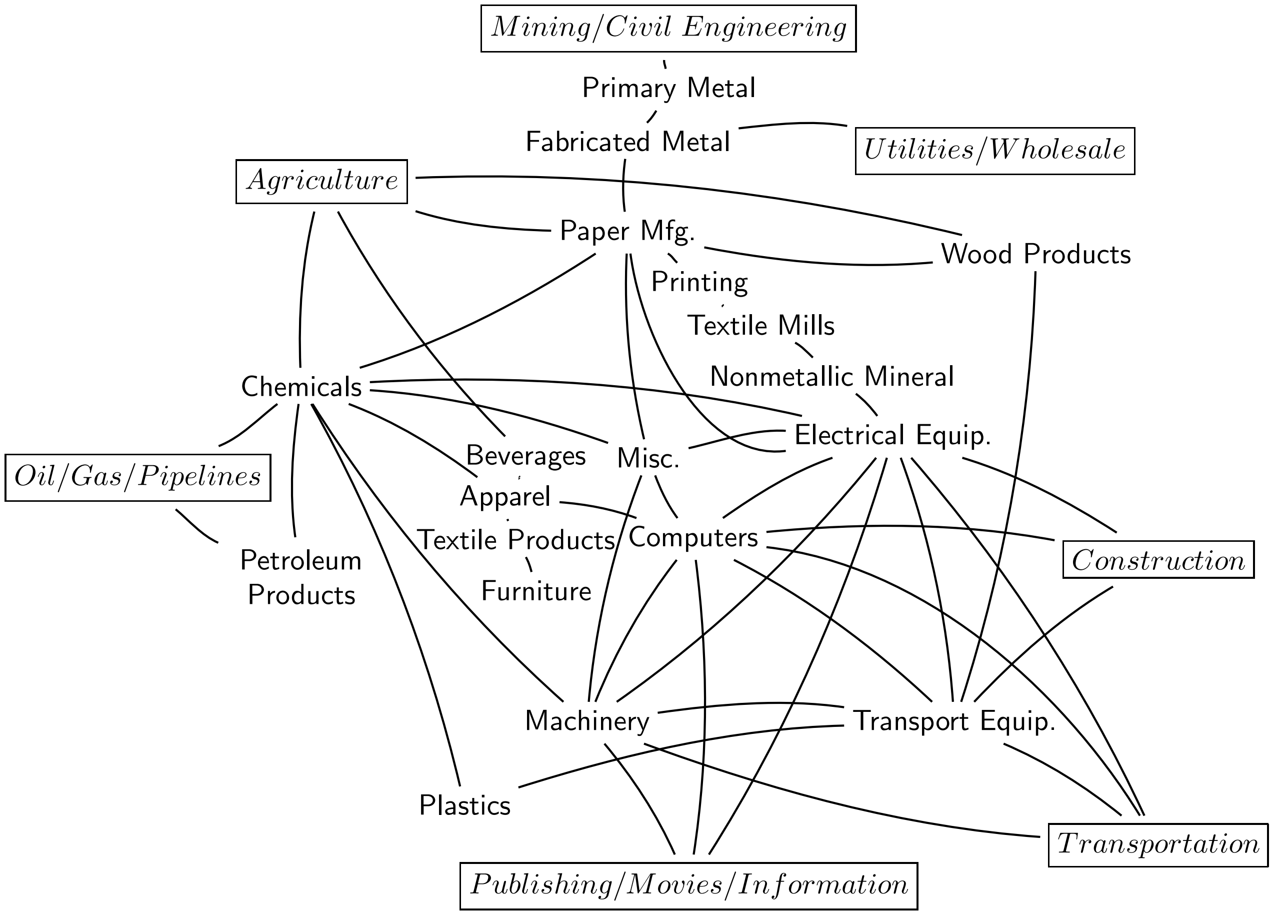


FIGURE V
Conglomerate Network in Manufacturing in 2015
Each node in the network is a three-digit manufacturing industry, except non-manufacturing industries, which are aggregated at a higher level and presented in boxes. Lines between industries represent Co-HHI measures above a minimum threshold. Because many of the manufacturing industries are connected to credit and securities industries in the Co-HHI network, we omit these links for ease of viewing the other Co-HHI connections. Data are from Compustat.

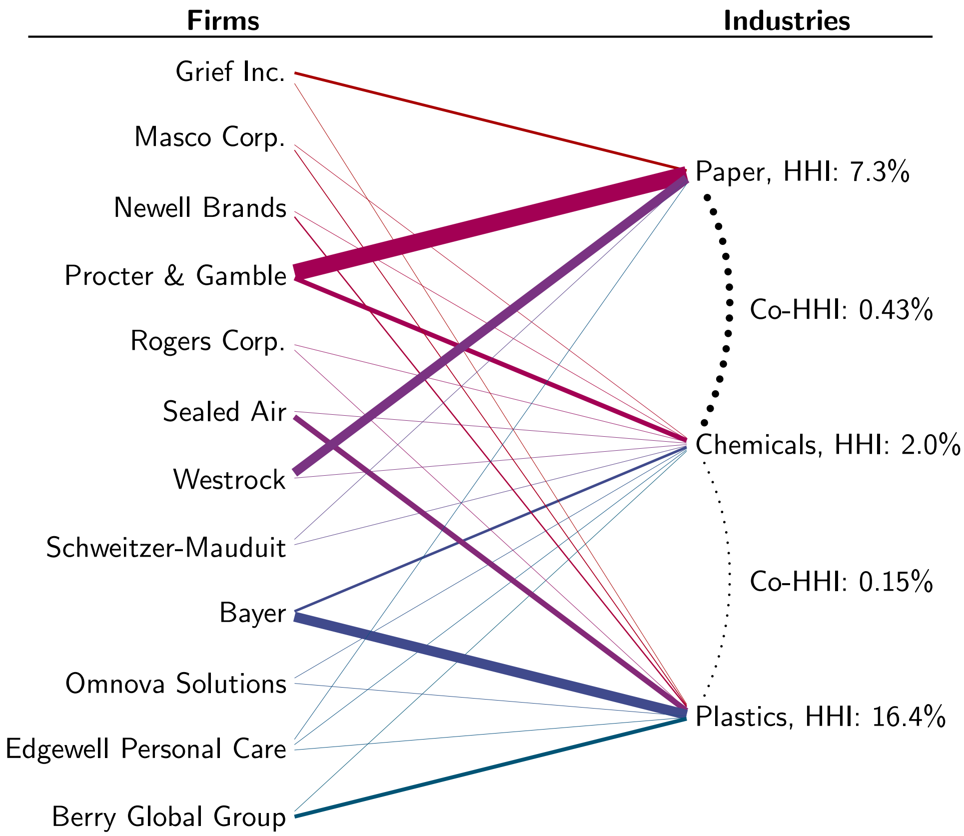


Figure VI

The Affiliation Network of the Paper, Chemicals, and Plastics Industries

This figure represents the affiliation network of three manufacturing industries, defined at the three-digit NAICS level: Paper, Chemicals, and Plastics. The listed firms are those that operate in at least two of the three industries. Each industry contains additional firms not represented in the figure that do not operate segments in at least two of these three industries. The width of the lines are scaled by firms' market shares in each industry. There is a weak Co-HHI relationship between Plastics and Paper not shown in the figure. Data are from Compustat for year 2015.

TABLE I

Most Central Industries in the Conglomerate Network

This table list the most central industries in the conglomerate network, using four different networks. The binary network is an undirected, unweighted network that records any connection between industries through conglomerate firms. The transmission network represents directed, weighted connections through the transmission from industries to firms and back to industries. The shared in-link network represents an undirected, weighted network of industry connections based on common conglomerate firms that span industries. The shared out-link network represents an undirected, weighted network of industry connections based on firms' common exposures to industry shocks. Panel A presents industries based on degree centrality. For the binary network, this is a count of links. For the weighted networks, the degree centrality is the sum of the weights per industry. Eigenvector centrality accounts for the centrality of the industries to which an industry is connected. The top five industries listed are the industries that appeared most often in the yearly top five industry list across 1997 to 2018.

Binary Network	Transmission Network	Shared In-Link Network	Shared Out-Link Network
Panel A: Degree Centrality			
Gen. Industrial Machinery/Equip.	Motor vehicle parts/acc.	Cheese; natural/processed	Gen. Industrial Machinery/Equip.
Personal/Business Credit	Electric services	Frozen specialties, nec	Electric services
Patent owners and lessors	Petroleum refining	Roasted coffee	Gas production/distribution
Mortgage banks/depository functions	Motor vehicles/car bodies	Household refrig./freezers	Crude petroleum/natural gas
Other plastics/mechanical rubber	Apparel and accessories	Cookies and crackers	Computer systems design
Panel B: Eigenvector Centrality			
Personal/Business Credit	Roasted coffee	Roasted coffee	Electric services
Mortgage banks/depository functions	Cookies and crackers	Cheese; natural/processed	Crude petroleum/natural gas
Computer integrated systems design	Frozen specialties, n.e.c.	Frozen specialties, nec	Gas production/distribution
General Industrial Machinery/Equip.	Toilet preparations	Cookies and crackers	Natural gas transmission
Information retrieval services	Sausages/Prepared meats	Sausages/Prepared meats	Petroleum products, n.e.c.

TABLE II

The Conglomerate Network and Growth Rate Covariance: Cross-Sectional Tests

This table presents coefficient estimates from regressions where the dependent variable is the industry-pair time-series covariance of growth rates of sales, assets, and investments, including own-industry covariance (variance). Industry pair covariances are calculated using yearly observations from 1997 to 2018. The dependent variable is calculated as the average CoHHI measure over the sample period. Coefficients and standard errors (in parentheses) are in percentages. Standard errors are clustered at the industry level. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Sales growth	*Asset growth*	*Investment growth*
	(1)	(2)	(3)
Shared in-links (Co-HHI)	5.171***	3.028***	0.129
	(1.097)	(1.085)	(0.133)
Same industry dummy	8.864***	10.354***	0.184**
	(0.571)	(0.660)	(0.087)
Constant	0.406***	0.293***	0.007***
	(0.029)	(0.029)	(0.001)
Adjusted R^2	0.016	0.014	0.009
Observations	249,856	250,096	254,679

Table III

Summary Statistics: Panel Data

This table presents summary statistics for the variables used in the regression analysis. All variables are in percentages. Summary statistics are presented for non-directed industry-pair observations.

			Percentile			
	Mean	S.D.	25th	50th	75th	Observations
Sales growth	−0.274	32.654	−12.292	2.668	14.639	3,827,922
Asset growth	−0.954	32.751	−12.480	1.102	13.506	3,781,760
Investment growth	5.524	5.276	2.537	4.395	6.966	4,113,580
Employment growth	−1.309	9.785	−6.085	−0.897	3.446	3,316,726
(Sales growth$_i$ − Sales growth$_j$)^2	20.884	35.911	0.947	5.557	24.139	3,570,850
(Asset growth$_i$ − Asset growth$_j$)^2	21.693	36.750	0.997	5.844	25.814	3,482,085
(Investment growth$_i$ − Investment growth$_j$)^2	0.584	2.971	0.018	0.089	0.326	4,112,106
(Employment growth$_i$ − Employment growth$_j$)^2	1.687	3.278	0.092	0.458	1.674	3,269,717
Shared in-links (Co-HHI)	0.039	1.112	0.000	0.000	0.000	4,113,989
Shared out-links	0.162	3.269	0.000	0.000	0.000	4,113,989
Shared links dummy	1.396	11.731	0.000	0.000	0.000	4,113,989
Transmission	0.064	1.403	0.000	0.000	0.000	4,113,989
Transmission dummy	1.396	11.731	0.000	0.000	0.000	4,113,989
HHI	52.977	31.230	26.546	47.127	83.672	4,113,989
Sum of HHI	102.521	44.546	66.740	103.022	132.622	4,113,989
Input-Output link	1.132	9.542	0.000	0.004	0.063	4,113,989
Hoberg-Phillips similarity	0.037	0.437	0.000	0.000	0.000	4,113,989

Table IV

Comovement of Industry Growth and Shared Network Links

This table presents coefficient estimates from panel regressions where the dependent variable is $(g_k - g_j)^2$, where g_i is the growth rate of industry i for sales (Panel A), assets (Panel B), and investments (Panel C). Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and standard errors (in parentheses) are in percentages. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel A: Sales growth				
Shared in-links (Co-HHI)	−22.494***		−21.710***	
	(2.583)		(2.594)	
Shared out-links		−4.897***	−3.552***	
		(0.361)	(0.361)	
Shared links dummy				−1.722***
				(0.215)
Sum of HHI	2.513***	2.508***	2.511***	2.499***
	(0.112)	(0.112)	(0.112)	(0.112)
Input-Output link	1.027***	1.025***	1.029***	1.036***
	(0.361)	(0.361)	(0.361)	(0.361)
Hoberg-Phillips similarity	−20.894***	−20.580***	−20.808***	−20.598***
	(4.362)	(4.355)	(4.360)	(4.355)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.068	0.068	0.068	0.068
Observations	3,563,872	3,563,872	3,563,872	3,563,872

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	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel B: Asset growth				
Shared in-links (Co-HHI)	-23.258^{***}		-22.459^{***}	
	(2.635)		(2.643)	
Shared out-links		-5.042^{***}	-3.634^{***}	
		(0.367)	(0.367)	
Shared links dummy				-1.881^{***}
				(0.226)
Sum of HHI	1.688^{***}	1.682^{***}	1.685^{***}	1.672^{***}
	(0.116)	(0.116)	(0.116)	(0.116)
Input-Output link	0.193	0.189	0.194	0.201
	(0.367)	(0.367)	(0.367)	(0.367)
Hoberg-Phillips similarity	-29.959^{***}	-29.653^{***}	-29.878^{***}	-29.656^{***}
	(5.658)	(5.641)	(5.654)	(5.639)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.054	0.054	0.054	0.054
Observations	3,474,363	3,474,363	3,474,363	3,474,363
Panel C: Investment growth				
Shared in-links (Co-HHI)	-0.247		-0.227	
	(0.249)		(0.251)	
Shared out-links		-0.113^{**}	-0.096^{**}	
		(0.025)	(0.025)	
Shared links dummy				-0.049^{***}
				(0.011)
Sum of HHI	0.286^{***}	0.286^{***}	0.286^{***}	0.286^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
Input-Output link	-0.173^{***}	-0.173^{***}	-0.173^{***}	-0.172^{***}
	(0.025)	(0.025)	(0.025)	(0.025)
Hoberg-Phillips similarity	0.389	0.394	0.391	0.394
	(0.265)	(0.265)	(0.265)	(0.265)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.138	0.138	0.138	0.138
Observations	4,106,177	4,106,177	4,106,177	4,106,177

TABLE V

Comovement of Industry Growth and Transmission Network Links

This table presents coefficient estimates from panel regressions where the dependent variable is $(g_k - g_j)^2$, where g_i is the growth rate of industry i for sales (columns 1–2), assets (columns 3–4), and investments (columns 5–6). Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and standard errors (in parentheses) are in percentages. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Dependent variable: $(g_k - g_j)^2$					
	Sales growth		*Asset growth*		*Investment growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
Transmission	−6.465***		−9.495***		−0.244**	
	(2.009)		(1.908)		(0.114)	
Transmission dummy		−1.721***		−1.881***		−0.049***
		(0.152)		(0.160)		(0.008)
Sum of HHI	2.510***	2.499***	1.683***	1.672***	0.286***	0.285***
	(0.079)	(0.080)	(0.082)	(0.082)	(0.006)	(0.006)
Input-Output link	1.001***	1.014***	0.243	0.255	−0.248***	−0.248***
	(0.251)	(0.251)	(0.255)	(0.255)	(0.017)	(0.017)
Hoberg-Phillips similarity	−20.785***	−20.587***	−29.939***	−29.687***	0.427**	0.433**
	(3.082)	(3.079)	(4.000)	(3.988)	(0.189)	(0.189)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.068	0.068	0.054	0.054	0.138	0.138
Observations	7,127,744	7,127,744	6,948,726	6,948,726	8,212,354	8,212,354

Table VI

Comovement of Employment Growth and Network Links

This table presents coefficient estimates from panel regressions where the dependent variable is $(g_k - g_j)^2$, where g_i is the growth rate of industry i employment. Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and standard errors (in parentheses) are in percentages. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Dependent variable: $(g_k - g_j)^2$					
	(1)	(2)	(3)	(4)	(5)	(6)
Shared in-links (Co-HHI)	−0.542**		−0.569**			
	(0.231)		(0.232)			
Shared out-links		0.093	0.137			
		(0.114)	(0.114)			
Shared links dummy				−0.047**		
				(0.020)		
Transmission					−0.150	
					(0.145)	
Transmission dummy						−0.047***
						(0.014)
Sum of HHI	0.036***	0.036***	0.036***	0.035***	0.036***	0.035***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)
Input-Output link	0.279***	0.278***	0.279***	0.279***	0.287***	0.287***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.025)	(0.025)
Hoberg-Phillips similarity	0.583	0.589	0.581	0.589	0.580*	0.582*
	(0.478)	(0.478)	(0.478)	(0.478)	(0.338)	(0.338)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.169	0.169	0.169	0.169	0.169	0.169
Observations	3,264,827	3,264,827	3,264,827	3,264,827	6,529,654	6,529,654

Table VII

Comovement of Industry Growth and Lagged Shared Network Links

This table presents coefficient estimates from panel regressions where the dependent variable is $(g_k - g_j)^2$, where g_i is the growth rate of industry i for sales (Panel A), assets (Panel B), and investments (Panel C). Explanatory variables are lagged by one year. Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and standard errors (in parentheses) are in percentages. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel A: Sales growth				
Shared in-links (Co-HHI)	−13.645***		−13.254***	
	(2.897)		(2.911)	
Shared out-links		−2.607**	−1.789	
		(0.342)	(0.342)	
Shared links dummy				−0.620***
				(0.225)
Sum of HHI	0.136	0.132	0.135	0.129
	(0.120)	(0.120)	(0.120)	(0.120)
Input-Output link	−0.006	−0.007	−0.005	−0.004
	(0.342)	(0.342)	(0.342)	(0.342)
Hoberg-Phillips similarity	−13.092**	−12.924**	−13.044**	−12.951**
	(5.489)	(5.483)	(5.487)	(5.483)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.066	0.066	0.066
Observations	3,278,544	3,278,544	3,278,544	3,278,544

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	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel B: Asset growth				
Shared in-links (Co-HHI)	-16.219^{***}		-15.881^{***}	
	(2.556)		(2.561)	
Shared out-links		-2.528^{**}	-1.544	
		(0.358)	(0.358)	
Shared links dummy				-0.661^{***}
				(0.236)
Sum of HHI	-1.230^{***}	-1.234^{***}	-1.231^{***}	-1.237^{***}
	(0.119)	(0.119)	(0.119)	(0.119)
Input-Output link	0.010	0.007	0.011	0.010
	(0.358)	(0.358)	(0.358)	(0.358)
Hoberg-Phillips similarity	-7.429	-7.257	-7.389	-7.283
	(5.486)	(5.484)	(5.485)	(5.484)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.056	0.056	0.056	0.056
Observations	3,202,103	3,202,103	3,202,103	3,202,103
Panel C: Investment growth				
Shared in-links (Co-HHI)	-0.154		-0.146	
	(0.251)		(0.253)	
Shared out-links		-0.047	-0.037	
		(0.029)	(0.029)	
Shared links dummy				-0.037^{***}
				(0.011)
Sum of HHI	0.317^{***}	0.317^{***}	0.317^{***}	0.316^{***}
	(0.009)	(0.009)	(0.009)	(0.009)
Input-Output link	-0.247^{***}	-0.247^{***}	-0.247^{***}	-0.247^{***}
	(0.029)	(0.029)	(0.029)	(0.029)
Hoberg-Phillips similarity	0.626^{**}	0.629^{**}	0.627^{**}	0.630^{**}
	(0.284)	(0.284)	(0.284)	(0.284)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.115	0.115	0.115	0.115
Observations	3,712,631	3,712,631	3,712,631	3,712,631

TABLE VIII

Comovement of Industry Growth and Lagged Transmission Network Links

This table presents coefficient estimates from panel regressions where the dependent variable is $(g_k - g_j)^2$, where g_i is the growth rate of industry i for sales (columns 1–2), assets (columns 3–4), and investments (columns 5–6). Explanatory variables are lagged by one year. Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and standard errors (in parentheses) are in percentages. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Dependent variable: $(g_k - g_j)^2$					
	Sales growth		*Asset growth*		*Investment growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
Transmission	−8.670***		−10.512***		−0.163	
	(1.953)		(1.739)		(0.107)	
Transmission dummy		−0.620***		−0.661***		−0.037***
		(0.159)		(0.167)		(0.008)
Sum of HHI	0.132	0.129	−1.234***	−1.237***	0.316***	0.316***
	(0.085)	(0.085)	(0.084)	(0.084)	(0.006)	(0.006)
Input-Output link	−0.156	−0.152	0.050	0.054	−0.309***	−0.309***
	(0.238)	(0.238)	(0.249)	(0.249)	(0.020)	(0.020)
Hoberg-Phillips similarity	−13.024***	−12.869***	−7.491*	−7.309*	0.658***	0.662***
	(3.880)	(3.875)	(3.880)	(3.878)	(0.203)	(0.203)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.066	0.056	0.056	0.115	0.115
Observations	6,557,088	6,557,088	6,404,206	6,404,206	7,425,262	7,425,262

Table IX

Transmission of Tariff Shocks Through the Conglomerate Network

This table presents coefficient estimates from panel regressions where the dependent variable is the industry growth rate of employment. NTR Gap is the difference between the non-Normal Trade Relations tariff rate and the NTR tariff rate. Post × Transmission NTR Gap_i is the transmission gap weighted by the transmission matrix from the conglomerate network. IO Customer and IO Supplier are inter-industry connections from the input-output network. Coefficients and standard errors (in parentheses) are in percentages. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Dependent variable: Employment growth			
	(1)	(2)	(3)	(4)
Post × NTR Gap_i	−7.420***	−5.756***	−7.428***	−2.250
	(1.457)	(1.674)	(1.453)	(1.999)
Post × Transmission NTR Gap_i		−4.640**		−4.091*
		(2.074)		(2.166)
Post × Placebo NTR Gap_i			0.460	
			(2.193)	
Post × IO Customer NTR Gap_i				−7.683**
				(3.207)
Post × IO Supplier NTR Gap_i				−2.060
				(4.976)
Industry and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.176	0.176	0.175	0.178
Observations	5,375	5,375	5,375	5,358