THE CONGLOMERATE NETWORK

KENNETH R. AHERN[a]
LEI KONG[b]
XINYAN YAN[c]

Abstract

This paper represents the economy as a network of conglomerate firms that transmit idiosyncratic shocks from one industry to another. The strength of inter-industry connections in the network is determined by two factors: conglomerates' market shares and the distributions of conglomerates' total sales across industries. These two factors generate a network-based measure of cross-industry concentration that nests the widely-used Herfindahl index as a special case. Using establishment-level micro-data on public and private firms and controlling for alternative connections, we show that industry growth rates comove more strongly within industry pairs that have higher cross-industry concentration in the conglomerate network.

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[a] University of Southern California, Marshall School of Business, 701 Exposition Blvd., Ste. 231, Los Angeles, CA 90089, and National Bureau of Economic Research. E-mail: kenneth.ahern@marshall.usc.edu
[b] University of Alabama, Culverhouse College of Business, Box 870224, Tuscaloosa, AL 35487. Email: lkong@cba.ua.edu
[c] University of Dayton, School of Business Administration, Dayton, OH 45469. E-mail: xyan02@udayton.edu.

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A long literature on conglomerate firms studies how economic shocks transmit within firms' internal markets. Though prior research differs on whether internal markets improve efficiency (Stein, 1997; Maksimovic and Phillips, 2002; Giroud and Mueller, 2015) or create distortions (Scharfstein and Stein, 2000; Rajan, Servaes, and Zingales, 2000), a common assumption is that the effects of internal markets remain inside the firm.

However, empirical observation suggests that the internal activities of conglomerates might influence external markets, too. For example, in 2019, among the 100 largest public firms in the US, 78 were multi-divisional conglomerates. Out of the $25.8 trillion in sales reported in Compustat segment data in 2019, 66% of sales were generated by conglomerates. Given conglomerates' outsized role in aggregate economic activity, it is reasonable to consider whether their internal activities spill over to external markets.

In this paper, we show that the transmission of idiosyncratic shocks within conglomerates' internal networks generates significant comovement across industries. To formalize our intuition, we model the economy as a bipartite network of firms and industries. In this network, firms are only connected to industries, and industries are only connected to firms. The strength of the connections between firms and industries is based on shares of 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. This follows the intuition that a shock to a firm with a larger market share has a greater influence on the industry's total fluctuations. In the opposite direction, 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. This follows the intuition that a firm will be more affected by an industry-level shock if a larger fraction of its sales comes from the industry.

To create direct connections, we collapse the bipartite network into two separate unipartite networks, one with industry-to-industry links and the other with firm-to-firm links. In the firm-to-firm network, firms are connected to other firms through common industry affiliations. In this network, shocks transmit between firms through intra-industry market forces.

In the dual perspective, industries are connected to other industries through conglomerate firms that operate in both industries. In this network, shocks transmit between industries through conglomerate firms' internal forces. The duality of firms and industries in our framework is in the spirit of Alchian and Demsetz (1972), who argue that in a frictionless setting, contracts within a firm are identical to contracts across a market.

Focusing on the industry-to-industry network, we derive two types of connections between industries. First, we calculate the *transmission* between two industries as the strength of the connection from an industry to its affiliated firms and then from these firms to the other industry. We assume that when an industry shock transmits from one industry to another through a conglomerate firm, the firm internally reallocates the shock across segments according to the segments' relative sizes. As we discuss later, this reallocation policy most closely matches the theory of Williamson (1975) in which firms optimally allocate resources to segments according to their marginal revenue products.

Second, we calculate a projection from firms onto industries that reflects inter-industry connections through shared exposure to firms. The *shared in-links* of an industry-pair is the strength of industry connections based on the commonality of market shares of the firms that operate in both industries. In contrast to the transmission network, this projection does not depend on internal reallocations. 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. If we calculate the shared in-links of an industry with itself, we generate the widely-used Herfindahl-Hirschman Index (HHI). Just as variance is the special case of covariance for one random variable, our network approach shows that HHI is a special case of a more general concept of cross-industry concentration. For this reason, the shared in-links of two industries is a measure of co-concentration that we call CoHHI.

Though this network framework is based on just a few simple assumptions, it provides new insights to guide our empirical analysis. In particular, we can decompose total variance and covariance of growth rates into fundamental shocks scaled by concentration. First, we show that the total variance of an industry's growth rate is the sum of the variance of an industry-specific shock and the variance of firm-specific shocks scaled by the HHI of the industry. More concentrated industries are more volatile because they have greater exposure to idiosyncratic firm-level growth shocks. Second, the total covariance of two industries' growth rates equals to the variance of firm-specific shocks scaled by the CoHHI of the two industries. Intuitively, industries that share the same conglomerate firms will face common firm-level shocks and comove more closely.

In our empirical analysis, we use two complementary datasets: 1) establishment-level data on sales and employment from the National Establishment Time Series (NETS) for the near universe of public and private firms in the US for the years 1991 to 2018, and 2) segment-level data on sales and assets from Compustat for all public firms in the US for the years 1997 to 2018. By running all of our tests in two different samples, we mitigate concerns that our results could be driven by biases in the data.

We first show that the conglomerate network is empirically distinct from other forms of industry connections. In particular, the conglomerate network is only weakly correlated with the input-output network, consistent with the notion that conglomerate firms diversify for reasons beyond vertical integration, such as economies of scope (Teece, 1980), co-insurance (Lewellen, 1971), or agency conflicts (Jensen, 1986). Additionally, the conglomerate network is not driven by product similarity, as measured by Hoberg and Phillips (2016).

To test the relationship between the conglomerate network and the covariance of industry growth, we first run cross-sectional tests, guided by our decomposition. Consistent with our framework, we find that more concentrated industries have higher variance and that industries with higher CoHHI have stronger covariance in growth rates. The results hold for growth in sales, assets, and employment. The economic magnitudes of the results are meaningful. After partialling out single-segment firms, about 10-12% of industry-comovement of sales growth across all industry pairs can be attributed to conglomerate firms that span industries. Restricting to industry pairs that share at least one conglomerate firm, the fraction is about 30%.

We next estimate panel regressions with industry-pair and year fixed effects. The industry-pair fixed effects capture time-invariant characteristics at the industry and industry-pair level that could influence the comovement of industry growth rates, such as persistent asset similarity, average volatility, the labor share in production, and geographic proximity. The year fixed effects control for general macroeconomic trends that could influence the comovement of industry growth rates. We also control for time-varying input-output linkages and product market similarity. Thus, our empirical model isolates the correlation between abnormal time-series variation in the conglomerate network and the comovement of industry growth.

The panel regressions show that when two industries have stronger connections in the conglomerate network, their growth rates comove more closely, consistent with our predictions. The results hold for employment growth, asset growth, and sales growth using both shared in-links and transmission connections in both NETS and Compustat data. These results are also economically meaningful. A one-standard deviation increase in the strength of the conglomerate connection between two industries corresponds to a 0.24 to 0.32-standard deviation increase in the comovement of industry employment growth and a 0.68-standard deviation increase in asset growth.

We next address the concern that our results are driven by the endogenous choice of firms to operate in industries that would have comoved with each other anyway. First, we note that the conglomerate network is based on market shares, which are not endogenously chosen by firms, but are determined by market forces. Second, the industry-pair fixed effects in our tests control for all time-invariant factors that cause industries to comove, while the time-varying variables control for the most common economic determinants of comovement. Though we cannot rule out all alternative explanations, our research design implies that for our main results to be spurious, there would need to be an omitted time-varying factor that is not only highly correlated with time-varying market shares, but also orthogonal to major economic determinants of diversification.

To further address endogeneity concerns, we use a quasi-natural experiment to identify the transmission of economic shocks through the conglomerate network. Following Pierce and Schott (2016), we exploit cross-sectional variation in industries' exposure to tariff rate shocks from the granting of normal trade relations to China in 2000. Using the predetermined conglomerate network from 1999 to mitigate reverse causation, and controlling for industry fixed effects, year fixed effects, and customer-supplier links, 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 following the shock. These results show that a specific, identifiable industry shock can be traced through the conglomerate network.

Finally, we conduct a battery of robustness tests. First, we find similar results using employment data from the US Census County Business Patterns data. Second, we find similar results when we use lagged measures of the conglomerate network, which helps further mitigate concerns of reverse causation. Third, we increase the minimum size threshold of public firms in our sample to show that there is little evidence of truncation bias caused by using Compustat data to construct our conglomerate network. Results are also robust to excluding small firms in the NETS data. Fourth, we show that our results persist when we construct our network using coarser industry definitions. We also provide evidence of the transmission of shocks within conglomerates, as shown in prior research, and an alternative transmission network based on a "winner-take-all" model.

This paper makes two central contributions. First, we present empirical evidence of inter-industry transmission of economic shocks through conglomerate firms. This finding extends the large literature on the internal workings of conglomerate firms to show that they also produce external effects. Prior research studies the causes and effects of within-firm reallocation of resources (Lamont, 1997; Shin and Stulz, 1998; Matsusaka and Nanda, 2002; Giroud and Mueller, 2015) and the motivations for diversification (Lewellen, 1971; Aggarwal and Samwick, 2003; Villalonga, 2004). In contrast, we provide a macro-level, industry-to-industry perspective of reallocations, taking as given the reasons for diversification and the various micro-level mechanisms of internal reallocations documented in the prior literature.

Our results also contribute to the literature on the spillover from firms to industries (Gabaix, 2011) and from industries to industries (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012). More recently, Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2020) find that firm size is related to aggregate fluctuations in a firm-level customer-supplier network. Additional empirical evidence of the spread of idiosyncratic shocks through production networks is found in Ahern and Harford (2014) and Barrot and Sauvagnat (2016). In contrast to these papers, we show that industry-specific shocks transmit across the economy through the internal redistribution of conglomerate firms.

Our approach is also related to 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; Loualiche, Vickers, and Ziebarth, 2019; Giroud, Lenzu, Maingi, and Mueller, 2022). In contrast to shocks that are spread within firms across geographic space, we show multi-segment firms facilitate the external spread of economic shocks across industry space. Our results also relate to recent literature on the importance of common ownership (Azar, Schmalz, and Tecu, 2018; Antón, Ederer, Giné, and Schmalz, 2018; Ederer and Pellegrino, 2021). While this line of research focuses on partial ownership by institutional investors, we study controlling ownership by conglomerate firms.

The second contribution of this paper is to provide a network interpretation of HHI. HHI is the leading metric of industry concentration among academics, practitioners, and policy-makers, including the DOJ, FTC, FCC, FDIC, and the Federal Reserve. Our network interpretation of HHI offers an alternative perspective on the meaning of concentration. Moreover, this is the first paper to show that HHI is a special case of a more general 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 of the network's structure. In our setting, one 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 conglomerate firms that operate in multiple 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 of economic affiliations. Because of the importance of conglomerates in the dual industry representation, throughout the paper, we call this affiliation network the conglomerate network.

We use the conglomerate network to study how shocks transmit through the economy. In the more typical firm perspective, shocks transmit through firms' shared exposure to industry conditions. In the dual industry perspective, shocks transmit through industries' shared exposures to firm conditions. Thus, our framework assumes that conglomerates internally reallocate shocks from one sector to another and that industries reallocate shocks from one firm to another. Because we study shared exposures, rather than direct linkages, this approach contrasts with research on input-output networks, where firms buy and sell directly from other firms.

Our approach is agnostic about the nature of the economic shock and can accommodate any shock that influences growth rates, such as demand shocks, supply shocks, or credit shocks. Similarly, our framework allows for different redistribution policies. As discussed below, we focus our analysis on a particular redistribution policy within firms, but we consider other policies as well.

The underlying assumption that redistributions occur through both conglomerates and markets is supported by a large literature. In particular, prior theoretical research argues that within-firm redistribution could be caused by corporate socialism (Scharfstein and Stein, 2000), optimal reallocation to equate marginal revenue products of capital or labor (Williamson, 1975), or the trade-off between the benefit of flexible investments versus the costs of agency-driven over-investment (Matsusaka and Nanda, 2002). A large body of empirical evidence also supports these assumptions (Maksimovic and Phillips, 2002; Seru, 2014; Tate and Yang, 2015; Giroud and Mueller, 2019). Similarly, the assumption that market forces within an industry redistribute firm-level idiosyncratic shocks from one firm to another is also supported by a large literature. As summarized in Shea (2002), these forces could be consumption complementarities, external economies of scale, or aggregate demand spillovers, among other mechanisms. The generality of these assumptions reflects our focus not on the transmission of shocks within firms or within industries but on the firm-to-firm and industry-to-industry transmission of shocks.

Finally, we limit the scope of our analysis by assuming the network is given, as is common in network models. For example, research on production networks does not typically model why a customer chooses one set of suppliers over another set (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2020). Similarly, though prior research on the diversification discount recognizes that the decision to diversify is endogenous (Campa and Kedia, 2002), it rarely attempts to identify the specific industries in which a firm will choose to operate. Though our theoretical analysis does not consider the formation of the network, we address endogeneity concerns in our empirical tests.

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, the key economic assumption in our framework is 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. In a purely graph-theoretical perspective, the connections between nodes are abstract. Using market shares to define the connections gives economic meaning to the network. 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.

Defining connections between firms and industries based on market shares and segment shares is intuitive. However, it is a non-trivial assumption. Our particular definitions of F and H imply a specific form of internal redistribution within firms. Defining F and H differently implies different redistribution policies. After describing the transmission mechanism between industries and firms below, we discuss the interpretation of these assumptions.

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, which indicate that firms and industries do not have direct connections in the bipartite graph, reflect our emphasis to abstract the conglomerate network from other types of 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).

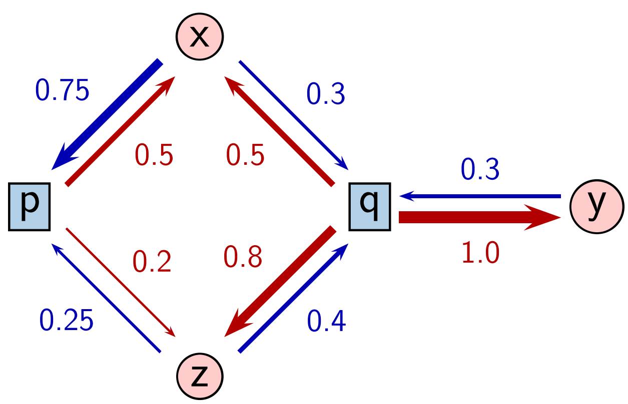


FIGURE I
A Network with Two Industries and Three Firms
This figure presents a graphical representation of an example network. The firms are x, y, and z, and the industries are p and q. Blue arrows reflect matrix H, the effect of firms on industries. Red arrows reflect matrix F, the effect of industries on firms.

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 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 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 is weaker than the links that lead into industry p. In contrast, the strength of the links that lead out of industry q is stronger than the links that lead into it.

Second, the diagonal entries in A^2 represent the transmission from a node back to itself after two links in the network. For 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. In a network setting, the diagonals of A^2 represent a feedback loop, or an 'echo,' as denoted in Sharifkhani and Simutin (2021). In the sense of the redistribution of a shock, we can also think of the diagonal of A^2 as the residual fraction of the shock that is not transmitted to other nodes.

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.

Internal Redistribution Policies

As mentioned above, the choice to define F and H based on segment shares and market shares leads to a specific internal redistribution policy. In growth rates, this assumption implies that a firm that receives an industry growth shock of g in a segment with proportion

f of total firm sales will internally reallocate the shock so that each of its segments receives an equal growth shock of $f \cdot g$. Thus, each segment will grow at the same rate. Equivalently, in dollar values, an industry growth shock to one segment will be reallocated to all segments in proportion to the relative size of the segment within the firm.

To illustrate, consider a firm with three segments, A, B, and C with sales of \$5, \$3, and \$2, for total firm sales of \$10. A 10% positive shock to segment A causes an increase in sales of \$0.50 to the firm. Through investments, the firm reallocates the \$0.50 across the three segments in proportion to their relative sizes, so A receives \$0.25, B receives \$0.15, and C receives \$0.10. Thus, after internal reallocation, each segment experiences an equivalent shock of 5%.

This form of reallocation is most closely matched to Williamson's (1975) theory that firms optimally reallocate shocks based on their segments' marginal revenue products. When one segment receives a shock, corporate headquarters optimally reallocates resources such that all segments have equal marginal revenue products. This is similar to the neoclassical theory of Maksimovic and Phillips (2002), in which a conglomerate optimally expands the sizes of its segments until their marginal returns are equal across all segments, though their relative sizes may vary because of differences in organizational ability. Our framework is consistent with a steady-state equilibrium of Williamson (1975) and Maksimovic and Phillips (2002), in which all segments have equal marginal revenue products and headquarters redistributes resources *pro rata* based on a segment's relative size.[1]

Beyond the theoretical interpretation, empirical evidence also supports *pro rata* internal reallocations. For example, Giroud and Mueller (2019) find that multi-region firms reallocate employment levels across establishments to equalize marginal revenue products, as in Williamson (1975). More generally, empirical evidence shows that the scale of segment-level

[1]Though our framework does generate transfers from larger to smaller divisions, it is different than the reallocation in models of corporate socialism or influence (Scharfstein and Stein, 2000; Rajan, Servaes, and Zingales, 2000). In these models, the reallocations from large to small segments are larger than *pro rata* because the goal of the headquarters is to make divisions more equal in size.

investment is positively correlated with the size of the segment (Duchin and Sosyura, 2013; Bardolet, Brown, and Lovallo, 2017).

Though our main analysis focuses on *pro rata* reallocations, our framework is flexible enough to accommodate other assumptions about reallocations. First, an assumption that conglomerates operate segments as if they were stand-alone firms is equivalent to an identity transmission matrix. Because firms do not reallocate shocks internally, shocks do not transmit from one industry to another through conglomerates. In our empirical tests, this is the null hypothesis. Second, we test an alternative "winner-take-all" reallocation policy by defining H and F matrices to reallocate all shocks to the largest segment.

Finally, we note that to the degree that the assumption of *pro rata* reallocations is overly simplistic, our transmission network should have less explanatory power in the data. Thus, the validity of the assumptions in our framework will be tested in our empirical analysis.

B.2. Network Projections

The second type of transformation is a projection from firms onto industries and vice versa. In contrast to the transmission network, these projection networks do not rely on any assumptions about internal reallocations of firms. Instead, they simply measure the shared exposure of industries to firm-level shocks and the shared exposure of firms to industry-level shocks.

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.

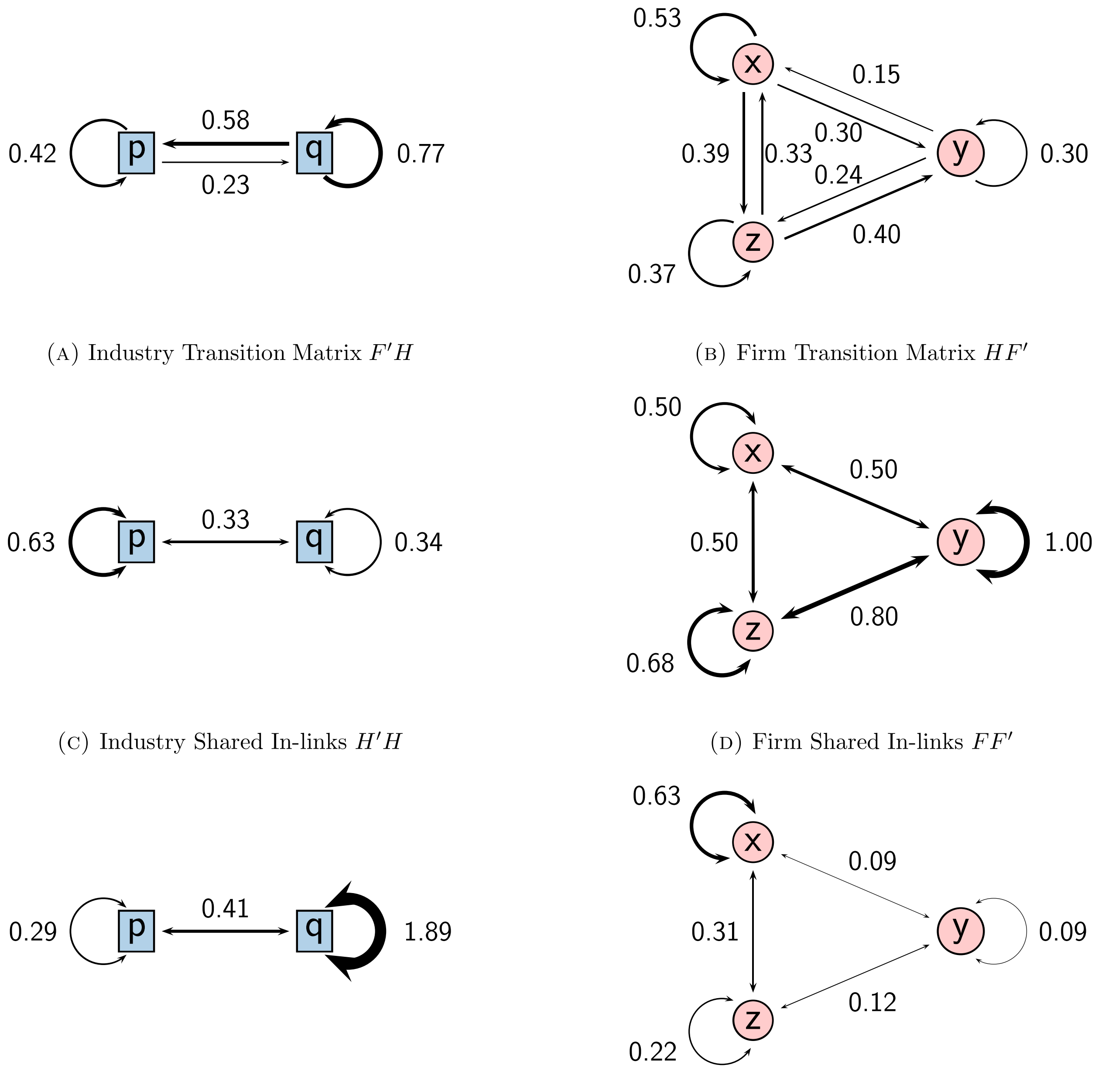
The second projection reflects the strength of shared out-links:

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

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 network projection matrix $H'H$ embeds 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



(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).

$\vec{h}_j \cdot \vec{h}_k = h_{1,j}h_{1,k} + h_{2,j}h_{2,k} + \cdots + h_{n,j}h_{n,k}$. 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 generalize HHI to derive 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 and receive the same shocks from the same set of firms, then the two industries have high co-concentration, and Industry CoHHI is larger.

Just like variance is a special case of covariance where both random variables are identical, HHI is a special case of CoHHI. CoHHI reflects the similarity of concentration of sales across firms in different industries. Industry HHI reflects the CoHHI of an industry with itself.[2]

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 affect 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.

[2]It is beyond the scope of this paper to identify relevant thresholds of CoHHI, similar to the HHI thresholds used by regulators. In our defense, we note that HHI was first developed in Hirschman (1945), but it wasn't until Stigler (1964) that HHI was connected to profitability in Cournot models, and until 1982 that the DOJ and FTC first published HHI thresholds in their guidelines for horizontal mergers (Scheffman, Coate, and Silvia, 2002).

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

Our network transformations in Section I.A and I.B are based on standard techniques in the network literature. In this section, we show that these transformations are not arbitrary from an economic point of view. Specifically, we show that, with some simplifying assumptions, these transformations are directly related to important economic constructs such as variances and covariances of industry and firm growth. We assume at time $\tau = 0$, 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 homoskedasticity, such 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.[3]

In particular, the snapshot of the growth rate of industry j at $\tau = 0$ 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 $\vec{g}_{ind,0} = \vec{\eta} + H'\vec{\varepsilon}$. 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 $\tau = 0$ 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 $\tau = 0$ 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 variances 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. For industry j, the variance is

$$Var(g_{j,0}) = \sigma_\eta^2 + \sigma_\varepsilon^2 HHI_j. \tag{9}$$

[3] The decay reflects the fraction of the initial shock that is passed from one industry to another, with the remainder absorbed either within the firm or industry. For example, a cash flow shock to a segment that accounts for 10% of a firm's sales may absorb more than 10% of the shock.

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. Thus, the covariance in growth rates at $\tau = 0$ is

$$Cov(g_{j,0}, g_{k,0}) = \sigma_{\varepsilon}^2 CoHHI_{j,k}. \quad (10)$$

This derivation shows that CoHHI is directly proportional to the covariance of growth rates, just as HHI is directly proportional to the variance of 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.

Moving shocks forward one cycle in the network, the variance-covariance matrix of growth rates at $\tau = 1$ is

$$(11) \qquad Cov(\vec{g}_1) = \delta^2 \begin{bmatrix} \sigma_\eta^2 H'FF'H + \sigma_\varepsilon^2 H'FH'HF'H & \sigma_\eta^2 H'FF'HF' + \sigma_\varepsilon^2 H'FH'HF' \\ \sigma_\eta^2 FH'FF'H + \sigma_\varepsilon^2 FH'HF'H & \sigma_\varepsilon^2 FH'HF' + \sigma_\eta^2 FH'FF'HF' \end{bmatrix}.$$

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. In the limit, this process derives the eigenvector centrality of industries in the conglomerate network. We discuss network centrality in more detail in the Online Appendix.

To help interpret the covariance matrix, we again focus on the industry-to-industry portion of the covariance matrix. At $\tau = 1$, shocks have made a full cycle in the network, represented by the transmission network A^2. For brevity of notation, we denote the entry in row j and column k of $F'H$ as $t_{j,k}$, which records the strength of transmission from industry j to industry k. Using this notation, the variance of the growth rate for industry j at $\tau = 1$, after a full cycle in the network, is as follows:

$$(12) \qquad Var(g_{j,1}) = \delta^2 \left[\sigma_\eta^2 \sum_{r=1}^{m} t_{r,j}^2 + \sigma_\varepsilon^2 \sum_{r=1}^{m} t_{k,j}^2 HHI_r + 2\sigma_\varepsilon^2 \sum_{r=2}^{m} \sum_{s=1}^{r-1} t_{s,j} t_{r,j} CoHHI_{s,r} \right].$$

This equation shows that after one cycle in the network, the variance of industry j's growth rate has three components. The first component is the variance of industry-level shocks scaled by the sum of the square of transmission links from all other industries into industry j. This reflects industry j's exposure to all other industry shocks through the conglomerate network. The second component is the firm-level variance scaled by the sum of the transmission strength into industry j from all other industries weighted by the other industries' HHI measures. Thus, if industry j has stronger connections to concentrated industries, its variance is higher because of higher exposure to firm-level shocks in connected industries. Finally, the last component is the sum of all combinations of industries' CoHHI measure multiplied by their transmission strengths and the variance of firm-level shocks.

The covariance of the growth rate of industry j and industry k at $\tau = 1$, is as follows:

(13)

$$Cov(g_{j,1}g_{k,1}) = \delta^2 \left[\sigma_\eta^2 \sum_{r=1}^{m} t_{r,j}t_{r,k} + \sigma_\varepsilon^2 \sum_{r=1}^{m} t_{r,j}t_{r,k}HHI_r + \sigma_\varepsilon^2 \sum_{r=2}^{m}\sum_{s=1}^{r-1} \left(t_{s,j}t_{r,k} + t_{r,j}t_{s,k}\right) CoHHI_{s,r} \right].$$

This equation shows that the covariance in the growth rates of industries j and k is determined by the similarity of their exposure to industry shocks through the transmission network plus the similarity of their exposure to firm-level shocks through within-industry concentration and common in-links (CoHHI).

II. The Empirical Conglomerate Network

II.A. Data Sources

To provide robust empirical analyses, we test all of our predictions using two alternative data sources. First, we collect segment level information of publicly-traded 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) 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 three variables: net sales, identifiable total assets, and the primary NAICS code of the segment.

Second, to address Compustat's lack of private firms, we test all of our predictions using establishment-level data provided in the National Establishment Time Series (NETS) database provided by Walls & Associates. In contrast to Compustat's limited scope, the NETS data cover the near universe of business establishments in the United States, both public and private, where an establishment is a business or plant at a single physical location. The data cover over 71 million establishments from 1990 to 2019. For each establishment, NETS provides the location, industry code, ultimate owner, employment level, and sales. As an alternative to Compustat's reported segments, we use these granular establishment-level observations to construct each firm's sales by industry segment from the ground up. This has the advantage that we need not rely on Compustat segments to be strictly organized by industry. To our knowledge, NETS data are the most comprehensive establishment-level data available other than confidential Census micro-data. Its unique level of coverage has led the NETS database to become widely used in recent research.[4]

Compustat and NETS are complementary datasets, each with their own advantages and disadvantages. In particular, an advantage of Compustat data is that they are sourced from audited, financial statements reported to the Securities and Exchange Commission, but a disadvantage is that they are limited to publicly-traded firms. In contrast, NETS data include all firms, public and private, but they are sourced from Dun & Bradstreet (D&B), a private, for-profit firm that provides credit scoring services. However, this disadvantage is mitigated by the fact that D&B has a profit-driven incentive to maintain its reputation of accurate and comprehensive data. An advantage of Compustat is that it has data on assets at the segment-level, whereas NETS does not. In contrast, NETS has complete coverage of employment at the establishment-level, whereas Compustat only provides employment data at the consolidated level for a subset of firms.

[4]See Rossi-Hansberg, Sarte, and Trachter (2020), Bernstein, McQuade, and Townsend (2021), Faccio and Hsu (2017), Farre-Mensa, Hegde, and Ljungqvist (2020), Crouzet and Mehrotra (2020), and Borisov, Ellul, and Sevilir (2021). For a detailed description of the NETS database, see Kolko, Neumark, and Lefebvre-Hoang (2007) and Barnatchez, Crane, and Decker (2017).

For our study, we exploit the advantages of each dataset. In particular, we construct the conglomerate network separately using the sales data in Compustat and the sales data in NETS. To measure industry growth rates, we use asset growth from Compustat and employment growth from NETS. We also measure sales growth using data from both Compustat and NETS. Though our framework provides both firm-level and industry-level predictions, we focus on the industry-level network to reduce selection bias in publicly-traded company data and computational complexity for the millions of firms in the NETS database.

Using both Compustat and NETS data reduces the chances that our results are driven by data limitations. However, in Section V, we go a step further and provide additional assurances by running robustness tests for both Compustat and NETS. In particular, we show that our results using Compustat data are not driven by omitting small firms and that our results using NETS data are not driven by over-sampling small firms.

A.1. Industry Definitions

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. For Compustat data, to obtain the time-consistent industry definitions, we follow Pierce and Schott (2016) and create "families" of industry codes that group related 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 our Compustat analyses refer to these families. This adjustment allows us to control for time-invariant industry properties using fixed effects. The NETS data provides time-invariant industry definitions at the four-digit SIC code level, which do not need to be converted to families.

A related concern with our framework is that firm boundaries are definite, but industry boundaries are subjective. We address this concern in a few ways. First, we note that

NAICS codes were developed in the 1990s by a consortium of federal economic and statistical agencies, including the Bureau of Economic Analysis, US Department of Commerce, Bureau of the Census, and the Bureau of Labor Statistics. These agencies designed the classification system on the principle that industry definitions should be based on a single economic concept of the similarity of production processes. The boundaries of industries are limited by the degree of homogeneity of the production process among the establishments in the industry, subject to a minimum threshold of economic significance. Thus, though industry definitions are not as clearly delineated as corporate ownership, they are not arbitrary.[5]

Empirical evidence on the role of sectoral shocks for aggregate outcomes also supports the validity of industry codes. In particular, Carvalho and Gabaix (2013) shows that both the sectoral-level sales vector of the economy (as in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)) as well as the firm-level sales vector (as in Gabaix (2011)) help explain aggregate volatility. Because their formulation uses only the changing weights of sectors and firms in total output, their results suggest that the boundaries of industries are defined in an economically meaningful way and are not arbitrarily redefined to maintain equality in the size of sectors.

The second way we address this potential concern is to control for industry links based on the alternative industry definitions provided by Hoberg and Phillips (2016) (HP). HP use the text of the product definitions provided in firms' 10-K filings to identify the similarity of two firms' outputs. Thus, HP's definitions are likely to be closer to a classification scheme based on the demand-side, compared to NAICS's scheme based on the supply-side. The third way we address this concern is to use a different level of industry aggregation in robustness tests, described below.

[5]More information on the development and principles guiding NAICS is available on the US Census Bureau's website: https://www.census.gov/naics/?008967

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 exhibits relatively little variation around the average degree. Second, random graphs are not clustered, in 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 creates 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. When α increases above 3, the network begins to resemble a random network.

B.1. The Structure of the Conglomerate Network in the Cross-Section

Figure III represents the complementary cumulative degree distributions of the conglomerate networks in 2007 in log scale using NETS and Compustat data. A linear relationship indicates a fat tailed, power law distribution. The dashed line in Panel A of the figure corresponds to an α of 2.8 for NETS data, estimated following Clauset, Shalizi, and Newman (2009). For the Compustat data in Panel B, the α is 3.3. These estimates of α are comparable to 3.1 for the input-output network of industries, as estimated in Ahern and Harford

(2014). For both NETS and Compustat, over our sample period, α is estimated to be about 2.85 in an average year. In 67% of yearly observations from Compustat we cannot reject the hypothesis that the network is power law distributed. For NETS data, the fraction is 50%. Thus, these statistics show that the degree distributions of the conglomerate networks have substantially fat tails, and in the median years, they follow a power law distribution. This means that the NETS and Compustat-based networks are characterized by relatively few hub industries with many connections to other industries and relatively large numbers 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 in the Compustat network 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. In the NETS data, the average is 4.8 and the median is 1.2. The clustering coefficient of the average industry in the Compustat network is 39%; for the median industry it is 32%, which is large relative to clustering in social networks. In the NETS data, clustering is even larger at 46%, on average. Finally, in an average year, the maximum path length between any two industries in the Compustat network 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. Similarly, for the NETS data, the average maximum path is 12.2 out of 551 industries in an average year. Online Appendix Figures I and II provide visual representations of the network.[6]

B.2. Time-Series Evolution of the Conglomerate Network

[6]We discuss the statistics for the binary network for ease of exposition, but the interpretation of the weighted networks is 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.

Figure IV plots the time series of network statistics normalized to 1997 values. For the most part, the NETS and Compustat-based networks exhibit similar trends. First, the power law scaling parameter α has decreased over this period, while the variation in degree across nodes and clustering has increased. These trends indicate that the conglomerate network has evolved towards an ultra small world network with more prominent hubs. Second, the eigenvector centrality of the average node has decreased which indicates that the average industry reduced the number of connections to more peripheral industries. The only trend that differs between NETS and Compustat is that the average degree has increased in NETS data, but decreased in Compustat data. This implies that industries have become more connected through conglomerates of smaller, private firms, rather than through larger public, public firms. These results are consistent with Hoberg and Phillips (2021) who use text of product descriptions to show that conglomerate firms have become more focused in related industries over our sample period.

B.3. Central Industries in the Conglomerate Network

Table I presents the most central industries in the conglomerate network for NETS and Compustat. Within the transmission networks, motor vehicle parts is central in both NETS and Compustat. In addition, motor vehicles, engineering services, and management services are also central in the NETS transmission network, while petroleum refining, electric services, and general industrial machinery are central in the Compustat transmission network. High centrality in this network indicates that these industries are at the center of economic activity that is transmitting through conglomerate firms. The most central industries in the CoHHI network of shared in-links are clothing mills, household vacuums and cooking equipment in the NETS network, compared to food-related industries of coffee, cheese, and frozen foods in the Compustat network. High centrality in this industry reflects that these industries have high shared in-links with many other industries. In particular, clothing mills and food producers are dominated by firms that operate in multiple industries with similar market shares in each. Finally, the most central industries in the NETS shared out-link network are real estate-related industries, while in the Compustat network, energy-related industries are most central. These are industries that are highly connected to other industries through conglomerates with similar levels of exposure to common industry shocks.

The differences between the central industries in the NETS and Compustat data highlight the key distinctions between the data sources. In particular, Compustat omits a large number of industries dominated by private firms, such as apartment building operators, real estate developers, engineering services, and commercial research. In contrast, Compustat emphasizes large energy firms and financial intermediaries. Using both data sources provides a robust approach to understanding sectoral variation in outcomes.

III. Comovement of Industry Growth Rates: Empirical Evidence

In this section of the paper, we test whether the empirical evidence matches the key predictions of the theoretical framework. In particular, we test whether industries co-move more closely when they are more closely connected in the conglomerate network. Because we make simplifying assumptions in our theoretical framework, our goal is not to calibrate the framework to the data, but to use it to help guide the tests and rationalize the results.

III.A. Cross-Sectional Tests

First, we test the relationship between industry growth covariance and the conglomerate network as presented in Equation 8. In particular, 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).[7]

[7]Equation 8 relates instantaneous growth rates with industry network at $t = 0$. Because we do not observe instantaneous growth rates at each period, we proxy for these relationships using growth rates observed over the time series.

The results presented in Table II show that there is a positive cross-sectional correlation between CoHHI and the covariance of employment growth, asset growth, and sales growth. This implies that industries with higher CoHHI connections also have higher comovement of fundamental economic growth rates. The comovement of industry growth rates is driven by conglomerate firms with large market shares in multiple industries.[8] Because the covariance of an industry with itself is also included in the regression, this result is consistent with the 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.

In the Online Appendix, we extend this analysis by relaxing the homoskedasticity assumption on the orthogonalized shocks, η and ε. In particular, we assume that the shocks are drawn from industry and firm-specific distributions, such that $\eta_j \sim N(0, \zeta_j^2)$ and $\varepsilon_i \sim N(0, \xi_j^2)$. This assumption generates a system of $m+n$ equations that express the observable variances of m industries and n firms as the sums of $m+n$ unknown industry and firm-specific shock variances weighted by market shares (H) and firm shares (F). Using a subset of the firms in NETS to reduce measurement error, we first solve for the $m + n$ unknown industry and firm-specific shock variances, ζ_j^2 and ξ_i^2. Using these values of shock variances and the conglomerate network, we estimate model-implied pair-wise industry growth covariances.

We find that the model-implied estimates of industry covariance are highly statistically correlated with industry covariances directly observed in the data. These results show that even without any assumptions on the nature of industry covariance and ignoring all other factors that could influence cross-industry comovement, such as input-output relations or geographic proximity, we are able to predict the heterogeneity of industry covariances using only the conglomerate network and estimates of industry and firm-specific shock variances.[9] See the Online Appendix for details.

[8]In unreported tests, we verify that our results hold when we estimate the network correlations using exponential random graph models, following Ahern and Harford (2014).

[9]We thank Bruno Pellegrino for suggesting this analysis.

A.1. Economic Magnitudes

To better understand the magnitude of the cross-sectional results, we decompose industry comovement into a component based on single-segment firms and a component based on conglomerate firms. For each industry in an industry pair, we calculate its sales growth excluding the sales of any conglomerate firm that operates in both industries. Using these hypothetical growth rates based on single-segment firms, we calculate the covariances and correlations of the growth rates for all industry pairs.[10] This procedure yields two sets of cross-sectional measures of industry comovement for all industry-pairs: 1) total comovement based on all firms, and 2) comovement based on single-segment firms, excluding the influence of conglomerate firms. To estimate the portion of comovement explained by the prevalence of conglomerates in the industry pair, we calculate the R^2 in a regression of the single-segment comovement on the total comovement. Thus, $1 - R^2$ provides a measure of the fraction of industry comovement explained by conglomerate firms.

We find that about 10% of total correlation can be attributed to conglomerates. Restricted to industry pairs that share any conglomerate firms, the portion explained is about 30%. For covariances, about 12% of the cross-sectional variation across industry pairs is attributed to conglomerates. These tests implicitly control for all factors common to an industry pair, such as input-output connections, common investors, and geographic proximity, because the only change we made was to artificially exclude conglomerate firms. These results are economically meaningful, especially given that during this time period, the common view is that conglomerates have become less relevant, compared to the 1960s–1980s. We would also expect that in other countries, like Korea and Japan, where conglomerates are more common, the portion of total industry comovement explained by conglomerates will be higher.

[10]We randomly sample 350 industries out of the more than 900 industries to reduce computation time of identifying and removing all spanning firms in each industry pairs out of the tens of millions of firms in the NETS data.

III.B. Panel Tests

Next, 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 $\tau = 0$, is as follows:

(14)
$$(g_j - g_k)^2 = (\eta_j - \eta_k)^2 + 2(\eta_j - \eta_k)\left(\sum_{i=1}^{n} h_{i,j}\varepsilon_i - \sum_{i=1}^{n} h_{i,k}\varepsilon_i\right) + \left(\sum_{i=1}^{n} h_{i,j}\varepsilon_i - \sum_{i=1}^{n} h_{i,k}\varepsilon_i\right)^2.$$

In expectation, the squared difference of growth rates is:

$$\begin{aligned} E\left[(g_{j,1} - g_{k,1})^2\right] &= E(g_{j,1}^2) + E(g_{k,1}^2) - 2E(g_{j,1}g_{k,1}) \\ &= 2\sigma_\eta^2 + \sigma_\varepsilon^2\left(HHI_j + HHI_k\right) - 2\sigma_\varepsilon^2 CoHHI_{j,k}. \end{aligned} \tag{15}$$

The signs of the coefficients imply that, all else equal, two concentrated industries are likely to have less similar time series of growth rates, while two co-concentrated industries are likely to have more similar growth rates. This reflects that concentrated industries have greater idiosyncratic firm-specific risk, but co-concentrated industries share common firm-level risk. The alternative hypothesis is that if all divisions within conglomerates operate independently from each other, such that there is no within-firm transmission of shocks, we would expect to find no statistical relationship between industry comovement and industry concentration and co-concentration.

Because we impose strong assumptions in deriving Equation 15, to test the relationship empirically, we estimate a more generalized and flexible version of the prediction in the following regression:

$$
\begin{aligned}
(g_{j,\tau} - g_{k,\tau})^2 = {} & \gamma_1 \text{Shared In-Links (Co-HHI)}_{jk,\tau} \\
& + \gamma_2 \text{Shared Out-Links}_{jk,\tau} \\
& + \phi(HHI_{j,\tau} + HHI_{k,\tau}) \\
& + \rho_\tau + \delta_{jk} + \psi \, \text{Controls}_{jk,\tau} + \varepsilon_{jk,\tau},
\end{aligned} \tag{16}
$$

where $g_{i,\tau}$ represents industry i's growth rate at time τ, Shared In-Links (Co-HHI)$_{ij,\tau}$ and Shared Out-Links$_{ij,\tau}$ represent network connections at time τ, ρ_τ 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 Out-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. Our goal is not to calibrate a model, but to use it as a guide for understanding the patterns in the data.

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 shown in Equation 13, the covariance of growth rates after one cycle in the network is a function of HHI, CoHHI, and the transmission network. We estimate a more general empirical model, as follows:

$$
\begin{aligned}
(g_{j,\tau} - g_{k,\tau})^2 = {} & \beta_1 \text{Transmission}_{jk,\tau} + \phi(HHI_{j,\tau} + HHI_{k,\tau}) + \rho_\tau \\
& + \delta_{jk} + \psi \, \text{Controls}_{jk,\tau} + \varepsilon_{jk,\tau},
\end{aligned} \tag{17}
$$

where the Transmission variable is the (i, j) entry for industries i and j of $F'H + H'F$. This is a symmetric matrix that allows for transmissions to go from industry i to j or vice versa.

We do not control for CoHHI because it is highly correlated with the transmission network, though the results are qualitatively similar if we include CoHHI as a dummy variable.

III.C. Controls for Alternative Explanations

In both regressions, the industry pair fixed effects, δ_{ij}, account for time-invariant cross-sectional variation in industry pairs. 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, the geographic location of industries, and the importance of intangible assets. We also include time fixed effects, ρ_τ, 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. In Compustat, the dummy is defined based on the presence of a connection. Because NETS is built from establishment level data, without any reporting thresholds, as in Compustat, almost all industry-pairs have positive, though small, connections. Therefore, we define the dummy variable in NETS based on the 90th percentile.[11]

The regressions also include variables to control for vertical customer-supplier relationships and product-market similarities. First, we measure the customer-supplier connections between industry pairs using data from the industry-by-industry total requirement table from the Benchmark Input-Output (IO) Accounts released by the Bureau of Economic Analysis (BEA). These data measure the dollar amount of intermediary industry output required per dollar of final demand. We use the most recent data until the next release becomes available. For example, from year 1997 to 2001, we use the 1997 total requirement table. In a few cases, our industry pairs cannot be matched to the IO industries; however our results are qualitative unchanged if we drop these industry pairs from the sample instead.

[11]We cluster standard errors at the industry-pair level, but our results persist if we double cluster standard errors by each industry of the pair.

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 because this implies the HP measure is below a minimum threshold.

In sum, these regressions isolate time-series variation in the connection strength between industries in the conglomerate network, while controlling for the most likely alternative explanations. Our goal is not to argue that industry comovement is explained only by the conglomerate network, but to show that the conglomerate network is a reliable source of comovement. For an alternative variable to subsume the effect of the conglomerate network, it would need to be uncorrelated with both vertical input-output relations and the HP relatedness measure, but also to vary through time at the industry-pair level in accordance with the time variation of the industry-pair strength in the conglomerate network. Though these main tests rule out the large majority of alternative explanations, we consider sampling bias and endogeneity concerns in robustness tests.

III.D. Summary Statistics

Table III provides summary statistics for all of variables used in the panel regressions for NETS and Compustat data. Sales growth in the median industry-year for the large, public Compustat firms is 2.67% versus 1.35% for the small, private NETS firms. Employment growth in NETS is negative at the mean and median, while asset growth in Compustat is positive in the median but negative in the mean. Squared differences in these rates vary considerably, with larger variation in Compustat compared to NETS. All of the network measures are skewed because the network is sparse, with most industry pairs having no connection.

III.E. Correlations of Alternative Industry Connections

A potential concern with the conglomerate network is that it could be highly correlated with input-output (IO) or HP links. In Online Appendix Table I, we present the average yearly correlation between our conglomerate network measures and the IO, HP, and HHI measures. In an average year, CoHHI has a correlation of 2.1% with HP in the NETS data and 1.2% in the Compustat data. The correlation between CoHHI and IO connections is 3% to 4% in the two data sets. Similarly, the correlations between the transmission matrix and IO and HP are less than 10%, on average. Online Appendix Figure III shows that the time-series of cross-sectional correlation between the measures of the conglomerate network, IO, and HP are persistently low every year. In sum, these results show that the conglomerate network is not just a proxy for existing measures of industry connectedness. Instead, the conglomerate network represents a unique form of inter-industry connections. Nevertheless, we include these variables in our tests as alternative explanations of industry comovement.

III.F. Baseline Results

Table IV presents estimates of Equation 16, the relationship between shared in-links and out-links on the comovement of industry growth rates.[12] For both NETS and Compustat, and for employment growth, 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 industry-pair and

[12]For brevity, we subsume the coefficients on our control variables in Tables IV and V. We present the complete results in Online Appendix Tables III to VI.

year 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.

Also consistent with the theoretical network, in every specification, 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.

The relationship between industry comovement and the conglomerate network is economically meaningful. In particular, in the NETS data, a one-standard deviation increase in CoHHI is related to a 0.24 standard deviation reduction in the squared difference of growth rates of employment. For sales growth, the effect is a 0.32 standard deviation reduction. In the Compustat data, a one-standard deviation increase in CoHHI is related to a 0.68 standard deviation reduction in the squared difference of growth rates of assets and sales. The larger magnitude of the effect in Compustat data is likely explained by its focus on larger firms than NETS.

Next, Table V presents estimates of Equation 17, the transmission network on the comovement of industry growth rates. The estimates show that the transmission network is negatively and significantly related to difference in industry growth rates for sales and asset growth. The relationship is not significant for employment growth. This means that when two industries become connected through the transmission network, their sales and asset growth rates comove more closely. As before, the sum of industry HHIs has the opposite relationship to the transmission network, consistent with our prediction. The economic magnitudes are largest for Compustat, with a decline of 0.79 standard deviations in the squared difference of asset growth for a one-standard deviation increase in transmission, and a decline of 0.36 standard deviations in sales growth.

III.G. Industry-Level Tests

In addition to the industry-pair tests, we also estimate industry-level tests of the effect of distance in the conglomerate network on the comovement of industry growth rates. In particular, we estimate each industry's exposure to the growth rates of other industries through the conglomerate network at different distances. Because the Compustat data is relatively sparse, we weight the growth rates of all other industries by whether they are one or two links away in the conglomerate network. Because NETS data are more dense, and more industry pairs are connected, even if only slightly, we use the continuous measure of the squared transmission network (A^2) instead of the discrete distance in Compustat.

Table VI shows that industries growth rates are higher when the growth rates of connected industries' growth rates are higher. This result holds in NETS and Compustat for employment, sales, and asset growth. The effect is equally strong in the NETS data when weighting by squared transmission. In Compustat, the effect is smaller for the relationship of firms that are two links away.

To provide additional evidence that the results are driven by the conglomerate network, we calculate a placebo variable in which industries are randomly assigned a transmission strength using the empirical distribution of linkages in the data. If the results were driven by macroeconomic factors, rather than connections in the conglomerate network, the results would persist in the placebo test. However, Table VI shows that the placebo variable is unrelated to an industry's growth rate in NETS and Compustat, for employment, sales, and asset growth.

Overall, these results show that industries comove with other industries in the network, even if they are not directly connected. Because these results control for IO-weighted growth rates of other industries, year fixed effects, and industry fixed effects, the results are not driven by customer-supplier links, macroeconomic fluctuations, or cross-sectional heterogeneity in industry traits.

IV. Endogeneity Concerns: A Quasi-Natural Experiment

Conglomerate firms do not randomly choose the industries in which they operate. Instead, it is reasonable to believe that firms choose to diversify into industries that tend to comove with each other, which could produce correlations similar to the results we have shown. Thus, in contrast to our hypothesis that conglomerates transmit shocks from one industry to another, it is possible that the entirety of the shocks would have been transmitted even without the conglomerate network. In this section, we address this concern.

First, it is important to recognize that the conglomerate network is not formed through endogenous choice. In our approach, the strength of the ties between industries is based on both the firms' industry shares and firms' market shares. While firms endogenously choose the industries in which they operate, they do not endogenously choose their market shares in each industry. In particular, CoHHI is a measure of the commonality of market shares held by the same firm in two different industries, not just the choice to operate in both industries. In addition, our framework generates predictions about the relationship between HHI and comovement, which are also supported in the empirical results. Because firms do not endogenously choose HHI, these results cannot be caused by the endogenous choice of firms.

Second, to the degree that the conglomerate network is endogenously determined, it is important to note that all of our results persist after controlling for industry-pair fixed effects. Thus, any time-invariant factor that leads industries to comove is absorbed by these fixed effects. In addition, we control for remaining time-series variation that is driven by major economic determinants of conglomeration, including vertical customer-supplier relationships and complimentary assets of Hoberg and Phillips. As mentioned above, for our results to be spurious, there would need to be an underlying time-varying factor explaining all of the remaining time-series correlation that is both orthogonal to vertical relations and asset complementarity and also causes both comovement among industry growth rates and firms to increase their market shares within these industries at the same time.

Though the above arguments help to limit the magnitude of endogeneity concerns, as an additional analysis 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. Though this setting does not provide an exogenous change to the network, it does identify a specific exogenous shock that we can observe transmitting through the 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, $F'H$. To help address reverse causation, we use the 1999 network to ensure it is exogenous to the NTR shock in 2000. Thus, the results are not driven by conglomerates forming new industry linkages in response to the tariff shock.

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. Thus, our weighting scheme provides for variation in an industry's exposure to the NTR gap based on the magnitude of the gap and the magnitude of the connection to the affected industry. We also normalize the measure by the sum of the column, excluding industry i. Therefore, Transmission NTR $\text{gap}_i = \frac{\sum_{k \neq i} \text{Transmission}_{k,i} \times \text{NTR gap}_k}{\sum_{k \neq i} \text{Transmission}_{k,i}}$. 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. This reflects the change in employment for more exposed industries relative to less exposed industries.

Table VII presents the results of these tests. Following Pierce and Schott (2016), we use employment growth from the Census County Business Patterns database and construct the network using NETS data. We calculate the strength of network linkages using data for all industries, but estimate regression coefficients using a sample of manufacturing industries, following Pierce and Schott. 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 VII, 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, as above. 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 input-output network. 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 conglomerate network prior to the NTR shock to rule out reverse causality and include input-output relations to control for alternative explanations. 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.

V. Robustness Tests

In this section, we address potential concerns related to sampling bias, endogeneity, industry definitions, and mechanisms. First, to address concerns about data limitations of NETS and Compustat, in Online Appendix Table VII, we estimate the main regressions using industry level employment data from the US Census Bureau's County Business Patterns (CBP) files from 1997 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 data in CBP files covers the universe of firms, both publicly listed and private. Consistent with the baseline results, we find that a stronger CoHHI link (constructed from Compustat data) between industries is associated with strong comovement in their growth rates of employment.

Second, Barnatchez, Crane, and Decker (2017) shows that the though NETS employment data are highly correlated with Census data across counties and industries, small establishments with less than 10 employees tend to be over-represented and biased because of imputation. As noted above, because measures of industrial concentration give greater weight to larger firms, the small-firm bias in NETS is less likely to affect our results. In addition, to the extent that NETS data relies on imputation, the variability of growth rates across industries will shrink, making it more difficult for us to find statistically significant determinants of comovement (Neumark, Wall, and Zhang, 2011). To further address these concerns, we re-estimate our main tests using only the 1000 largest firms in NETS and find qualitatively similar results. The results are presented in Online Appendix Tables XII, XIII, XIV, and XV.

Third, because Compustat data is more widely available than NETS, it is important to test its reliability for future research on conglomerate networks. We have already shown that the Compustat results for sales growth are replicated in NETS. To further alleviate concerns that using large publicly traded firms to construct our network creates truncation bias in our results, we run a series of robustness tests. To test how changing the size threshold of the available Compustat data affects our results, we estimate the main tests using a sample that excludes observations of firms that are below the 25th percentile of sales in a given year in Compustat. Online Appendix Table XVI shows that our results are nearly identical as in the main tests that use the full Compustat sample. In Online Appendix Table XVII, we use a more extreme threshold of the 50th percentile of sales. The magnitude of the results are smaller, but they are still statistically significant. Likewise, Online Appendix Table XVIII shows that the results are nearly identical when we exclude foreign firms.

Fourth, we compare Compustat data to the Economic Census data published by the US Census Bureau. For each industry, we calculate the ratio of Compustat sales to Census sales. We then divide industries into those that have above-median representation by Compustat firms and those with below-median representation. We find that the total Census-level sales of the average industry with above-median representation is statistically identical to the Census-level sales of the average industry with below-median representation. This means that large and small industries, as measured by Census data, are equally represented by Compustat data. This helps alleviate any concerns that Compustat data is biased towards large industries because it is biased towards large firms. These results suggest that future research can construct reliable conglomerate networks using Compustat data and give credibility to prior research using Compustat to construct product market networks (Atalay, Hortaçsu, Roberts, and Syverson, 2011; Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2020).

Fifth, we reconstruct our network measures using SIC 3-digit industry definitions, which are considerably more coarse than the NAICS codes we use in our main tests: the number of industry-pairs in the network based on 3-digit SIC codes is only about 25% of the number of industry-pairs in the main specifications. Online Appendix Table XIX shows that our main results are robust to constructing the network using these more coarse industry definitions.

Sixth, to help address reverse causality concerns, we note that we used lagged variables in the tariff shock tests in Table VII. To provide additional robustness, in Online Appendix Tables VIII, IX, X, and XI, we also re-estimate our main equations using lagged explanatory variables with industry-pair fixed effects. These tests control for any time-invariant determinant of industry comovement (industry-pair fixed effects) as well as reverse causation in the time-series, in which firms tend to diversify into industries that have recently experienced greater comovement (lagged explanatory variables). The results are qualitatively similar as the main results.

Seventh, we use the tariff shock to provide direct evidence that shocks transmit from one segment to another within the same conglomerate firm, as predicted in theories of internal capital markets. We create a variable that measures a firm-segment's exposure to the tariff shock from other segments within the same conglomerate, similar to our industry-level measure in Table VII. We find that a segment's sales growth is lower when other segments within the same firm have greater exposure to the tariff shock, consistent with prior literature on internal reallocation. The results and further details are in the Online Appendix.

Finally, we define the transmission network using an alternative internal reallocation policy in which all shocks are directed to the largest segment, by sales. Under the assumption that, on average, shocks are more likely to be positive than negative, this approximates a "winner-takes-all" reallocation policy. We find that this reallocation policy has little explanatory power to explain comovement of industries. This provide a placebo test that the significant results based on the *pro rata* transmission network in our main tests are not spurious. We provide more details in the Online Appendix.

VI. Conclusion

At its most granular level, economic activity is random and disorganized. At any given time, there are innumerable transactions of countless goods and services between atomistic individuals. 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, 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 framework 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. From the affiliation network, we create three unique inter-industry networks that represent 1) the strength of the links from an industry through conglomerate firms, back to other industries, 2) two industries' commonality of shared in-links from overlapping conglomerate firms, and 3) the strength of shared out-links from industries to common firms.

The network perspective provides a new interpretation 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. Just as variance is a special case of covariance, HHI is a special case of CoHHI.

The framework decomposes the empirical volatility of an industry's growth rate into two parts: 1) an industry-specific volatility of industry growth rates and 2) 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 framework using panel data from two distinct datasets, which cover the near universe of firms in the US, both public and private. We show that the stronger is the connection between two industries in the conglomerate network, the stronger is their comovement of growth rates of sales, assets, 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 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 in the conglomerate network 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 and influence sectoral comovement. 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 a network-based interpretation 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 activity within and across industries.

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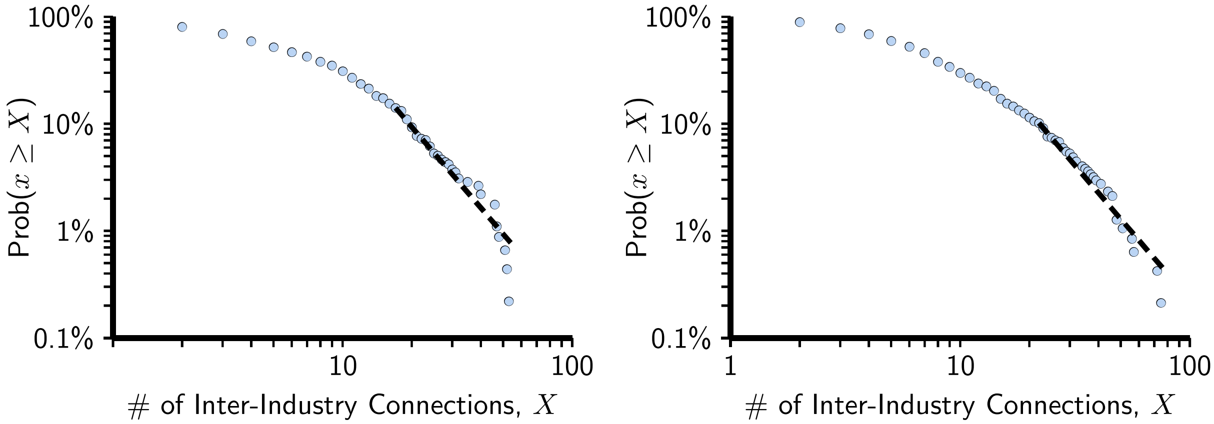


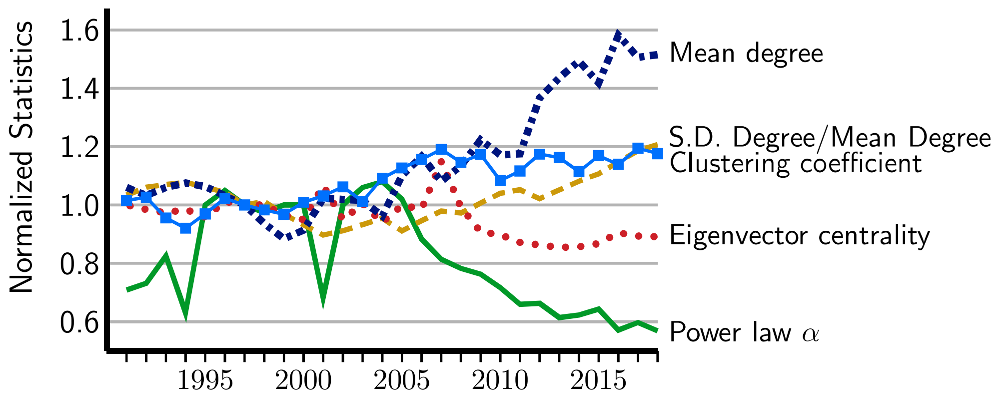
(A) NETS Data

(B) Compustat Data

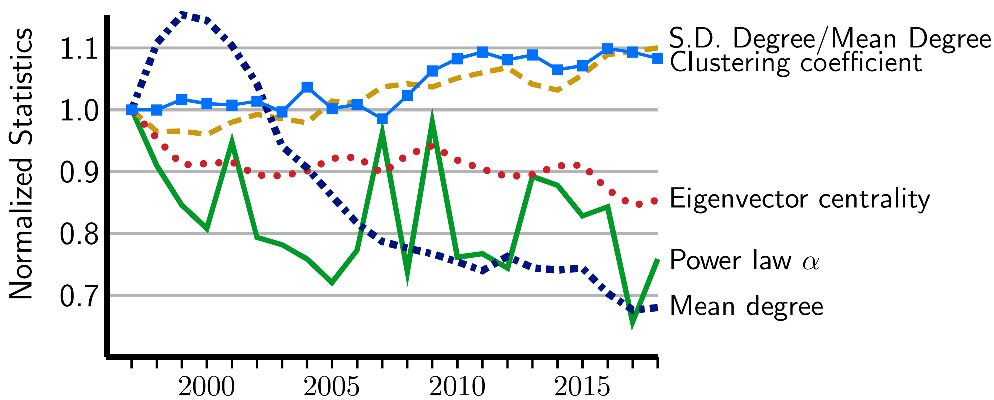
Figure III

Degree Distribution of Binary Conglomerate Network

These figures represent the distribution of degree centrality in log-log scale in the 2007 binary conglomerate networks created from NETS data (Panel A) and Compustat data (Panel B). 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 $P(k) = ck^{-\alpha}$.



(A) NETS Data



(B) Compustat Data

FIGURE IV

Time Series of the Binary Conglomerate Network

Five summary statistics are calculated yearly on the binary conglomerate network for NETS data (Panel A) and Compustat data (Panel B). Mean degree is the number of inter-industry links into an average industry. Eigenvector centrality is the Katz-Bonacich centrality score with an alpha of 90% of the network for an average industry. Clustering coefficient is the fraction of industries that are connected to nodes 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.

TABLE I

Most Central Industries in the Conglomerate Network

This table lists the most central industries in the conglomerate network, using four different networks based on Katz-Bonacich centrality with an attenuation factor equal to 90% of the max attentuation. This measure is a form of eigenvector centrality that accounts for the centrality of the industries to which an industry is connected, but also allows all industries a minimum level of centrality. 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 results using NETS data. Panel B presents results using Compustat data. The top five industries listed are the industries that appeared most often in the yearly top five industry list across 1997 to 2018 for Compustat and 1990 to 2018 for NETS.

Binary Network	Transmission Network	Shared In-Link Network	Shared Out-Link Network
Panel A: NETS data			
Turbine generators	Motor vehicle parts	Knit underwear mills	Apt. building operators
Aircraft engines/parts	Motor vehicles	Household vacuums	Real estate agents/managers
Household cooking equip.	Engineering services	Knit outerwear mills	Nonres. building operators
Knit underwear mills	Commercial phys. research	Hsehld cooking equip.	Subdividers/developers
Household vacuums	Management services	Mobile homes	Individual/family services
Panel B: Compustat data			
Personal/business credit	Petroleum refining	Roasted coffee	Electric services
Mortgage banks/dep. functions	Crude petroleum/nat. gas	Cheese; natural/proc.	Gas production/distribution
Computer integrated systems	Motor vehicle parts	Frozen specialties	Crude petroleum/nat. gas
General industrial machinery	Electric services	Cookies and crackers	Natural gas transmission
Patent owners and lessors	General ind. machinery	Groceries & rel. prods.	Petroleum refining

TABLE II

Industry Covariance and Shared Network Links in the Cross-Section

Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Data source:	*NETS*		*Compustat*	
Dependent variable:	*Covariance of Employment growth*	*Covariance of Sales growth*	*Covariance of Asset growth*	*Covariance of Sales growth*
Shared in-links (CoHHI)	4.136***	8.201***	3.028***	5.171***
	(0.604)	(0.684)	(1.069)	(1.094)
Same industry dummy	0.253***	0.429***	10.354***	8.864***
	(0.022)	(0.028)	(0.659)	(0.573)
Constant	0.041***	0.089***	0.293***	0.406***
	(< 0.001)	(< 0.001)	(0.010)	(0.010)
Adjusted R^2	0.054	0.063	0.014	0.016
Observations	475,800	475,800	250,096	249,856

TABLE III

Summary Statistics: Panel Data

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

			Percentile			
	Mean	S.D.	25th	50th	75th	Observations
Panel A: NETS Data						
Employment growth	−0.459	7.618	−3.730	−0.441	2.612	13,274,242
Sales growth	1.532	10.413	−3.350	1.348	6.094	13,265,143
(Employment growth$_i$ - Employment growth$_j$)^2	1.051	3.497	0.045	0.220	0.795	13,270,758
(Sales growth$_i$ - Sales growth$_j$)^2	1.842	5.212	0.090	0.433	1.503	13,260,061
Shared in-links (Co-HHI)	0.025	0.346	0.000	0.000	0.000	13,744,601
Shared out-links	4.839	100.340	0.000	0.000	0.002	13,744,601
Shared in-links dummy	9.998	29.998	0.000	0.000	0.000	13,744,601
Transmission	0.065	0.567	0.000	0.000	0.002	13,744,601
Transmission dummy	10.000	30.000	0.000	0.000	0.000	13,744,601
Sum of HHI	11.824	12.214	3.479	7.756	16.065	13,744,601
Input-Output link	1.737	16.496	0.000	0.011	0.130	13,752,393
Hoberg-Phillips similarity	0.041	0.447	0.000	0.000	0.000	13,752,393
Panel B: Compustat Data						
Asset growth	−0.954	32.751	−12.480	1.102	13.506	3,781,760
Sales growth	−0.274	32.654	−12.292	2.668	14.639	3,827,922
(Asset growth$_i$ - Asset growth$_j$)^2	21.693	36.750	0.997	5.844	25.814	3,482,085
(Sales growth$_i$ - Sales growth$_j$)^2	20.884	35.911	0.947	5.557	24.139	3,570,850
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	0.118	2.018	0.000	0.000	0.000	4,113,989
Transmission dummy	1.396	11.731	0.000	0.000	0.000	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

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 employment, assets, or sales using NETS (13,263,940 observations) or Compustat data (3,474,363 observations). All regressions include the following controls: input-output links, Hoberg-Phillips similarity, and industry-pair and year fixed effects. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Panel A: NETS Data						
Dependent variable:	*Employment growth*			*Sales growth*		
Shared in-links (Co-HHI)	−2.450***	−2.451***		−4.879***	−4.880***	
	(0.570)	(0.570)		(0.939)	(0.939)	
Shared out-links		−0.008***			−0.008***	
		(0.003)			(0.003)	
Shared in-links dummy			−0.012***			−0.067***
			(0.004)			(0.007)
Sum of HHI	1.678***	1.678***	1.673***	5.581***	5.581***	5.570***
	(0.024)	(0.024)	(0.024)	(0.043)	(0.043)	(0.043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.082	0.082	0.082	0.075	0.075	0.075
Panel B: Compustat Data						
Dependent variable:	*Asset growth*			*Sales growth*		
Shared in-links (Co-HHI)	−23.258***	−22.459***		−22.494***	−21.710***	
	(2.635)	(2.643)		(2.583)	(2.594)	
Shared out-links		−3.634***			−3.552***	
		(1.363)			(1.147)	
Shared in-links dummy			−1.881***			−1.722***
			(0.226)			(0.215)
Sum of HHI	1.688***	1.685***	1.672***	2.513***	2.511***	2.499***
	(0.116)	(0.116)	(0.116)	(0.112)	(0.112)	(0.112)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.054	0.054	0.054	0.068	0.068	0.068

Table V

Comovement of Industry Growth and the Transmission Network

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 employment, assets, or sales using NETS (13,263,940 observations) or Compustat data (3,474,363 observations). All regressions include the following controls: input-output links, Hoberg-Phillips similarity, and industry-pair and year fixed effects. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Panel A: NETS Data				
Dependent variable:	*Employment growth*		*Sales growth*	
Transmission $(F'H + H'F)$	0.069		-2.423^{***}	
	(0.559)		(0.818)	
Transmission dummy		-0.027^{***}		-0.059^{***}
		(0.005)		(0.007)
Sum of HHI	1.673^{***}	1.672^{***}	5.572^{***}	5.570^{***}
	(0.024)	(0.024)	(0.043)	(0.043)
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.082	0.082	0.075	0.075
Panel B: Compustat Data				
Dependent variable:	*Asset growth*		*Sales growth*	
Transmission $(F'H + H'F)$	-7.978^{***}		-5.440^{***}	
	(1.735)		(1.805)	
Transmission dummy		-1.881^{***}		-1.722^{***}
		(0.226)		(0.215)
Sum of HHI	1.682^{***}	1.672^{***}	2.509^{***}	2.499^{***}
	(0.116)	(0.116)	(0.112)	(0.112)
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.054	0.054	0.068	0.068

TABLE VI

Industry-Level Growth and Transmission Network Links

Coefficient estimates from panel regressions at the industry-level where the dependent variable is the industry growth rate for employment, assets, or sales using NETS (23,060 observations) or Compustat data (10,161 observations). Transmission-weighted growth is the growth rate of all other industries, weighted by their transmission link in the conglomerate network. Transmission-weighted placebo randomizes the transmission strength across industries. Transmission^2-weighted growth is the growth of industries two links away from the focal industry in the transmission network in NETS. Average growth at a distance of two is the average growth rate of industries that are exactly two links away from the focal industry in Compustat. Controls include the growth rate of other industries weighted by their IO strength to the focal industry, and year and industry fixed effects. Coefficients and industry-clustered standard errors (in parentheses) are in percentages. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Panel A: NETS Data						
Dependent variable:	*Employment growth*			*Sales growth*		
Transmission-weighted growth	32.309***			58.070***		
	(3.844)			(3.528)		
Transmission-weighted placebo		−2.362			0.324	
		(1.856)			(1.864)	
Transmission^2-weighted growth			35.105***			63.364***
			(4.830)			(4.380)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.192	0.187	0.191	0.162	0.140	0.157
Panel B: Compustat Data						
Dependent variable:	*Asset growth*			*Sales growth*		
Transmission-weighted growth	15.006***		14.993***	18.233***		18.260***
	(2.066)		(2.097)	(2.262)		(2.289)
Transmission-weighted placebo		2.878			2.677	
		(1.821)			(1.815)	
Average Growth at distance of two			−3.368			12.928*
			(6.816)			(6.720)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.041	0.034	0.040	0.061	0.052	0.061

Table VII

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 from NETS. 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 industry-clustered 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$_i$	−8.809***	−5.838***	−8.814***	−2.964
	(1.407)	(1.912)	(1.400)	(1.991)
Post × Transmission NTR Gap$_i$		−9.873***		−7.272*
		(3.812)		(4.249)
Post × Placebo NTR Gap$_i$			−1.441	
			(2.133)	
Post × IO Customer NTR Gap$_i$				−5.021
				(3.124)
Post × IO Supplier NTR Gap$_i$				−4.402
				(4.708)
Industry and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.161	0.162	0.161	0.162
Observations	6,137	6,137	6,137	6,120

Online Appendix
"The Conglomerate Network"
Kenneth R. Ahern, Lei Kong, and Xinyan Yan

I. The Centrality of the Conglomerate Network

To understand the long-run outcome of shocks transmitting through the network, we consider the sum of the growth rates from $\tau = 0, \ldots, \infty$, as follows

$$\sum_{\tau=0}^{\infty} \vec{g}_t = \left[I + \delta(A')^2 + \left(\delta(A')^2\right)^2 + \left(\delta(A')^2\right)^3 + \cdots \right] (I + A')\, \vec{\nu}$$

$$= \left[I - \delta(A')^2 \right]^{-1} (I + A')\vec{\nu}, \tag{OA.1}$$

where the infinite sum converges because A^2 is a stochastic matrix. The term $[I - \delta(A')^2]^{-1}$ is the Leontief inverse. Thus, Equation OA.1 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 OA.1 also implies that the long-run industry and firm growth rates equal the product of their Katz-Bonacich eigenvector centrality in the conglomerate network with their initial shock.

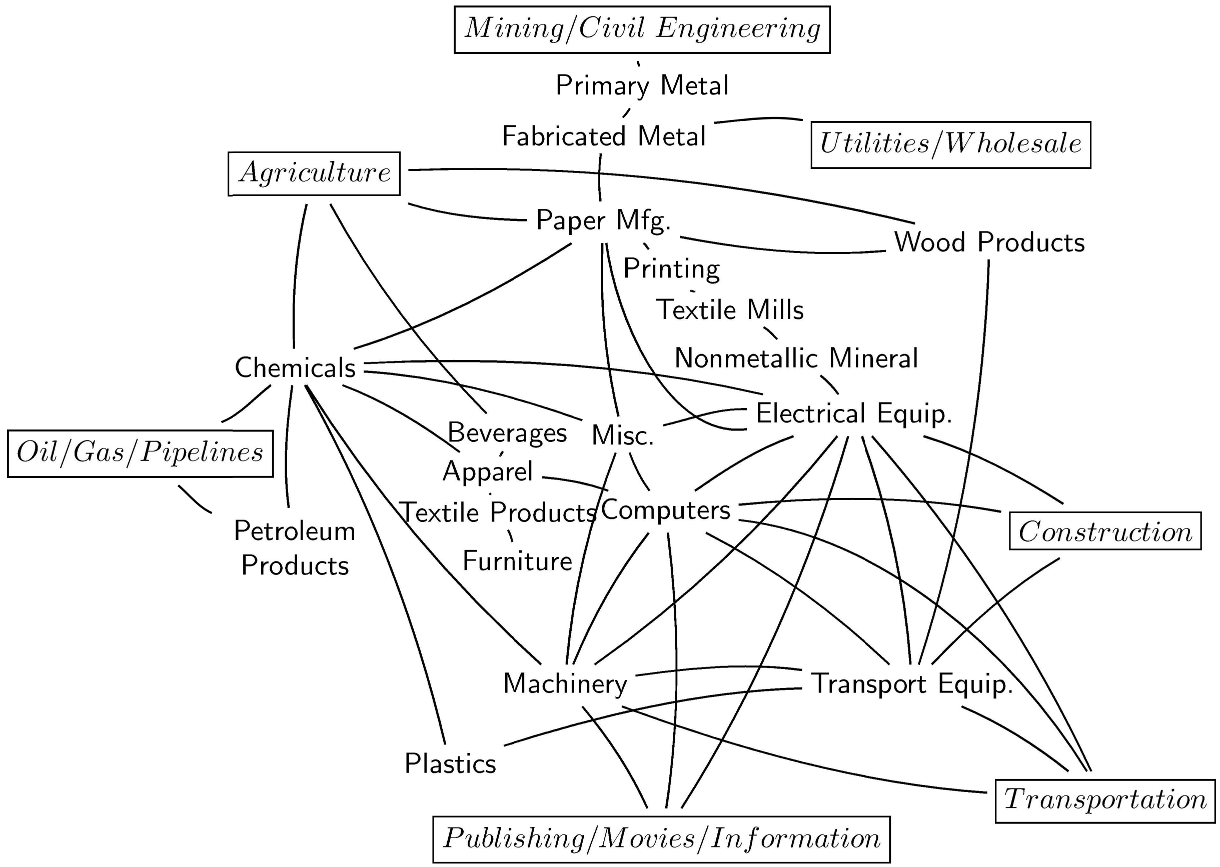
These properties of the conglomerate network are identical to the properties of the industry-level input-output networks studied in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and the firm-level input-output network studied in Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2020). In particular, 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 $\vec{v}_{firm}\,'\vec{\varepsilon}$, as in Herskovic et al.

In sum, our framework generates the same implications for the importance of a single industry or firm in the conglomerate network as derived in the production network, but with an important distinction. In our framework, firms are diversified, unlike in Gabaix (2011), which affects their centrality, and thus, their influence on the aggregate economy. Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2020) present a similar intuition based on the concentration of customers in the input-output network. Our work is similar to Herskovic et al. because they allow for shocks at different levels of aggregation, including firm, industry, and economy-wide shocks. Our approach is distinct from Herskovic et al. because we focus on connections through conglomerate ownership, whereas they focus on customer-supplier connections.

II. Network Visualizations

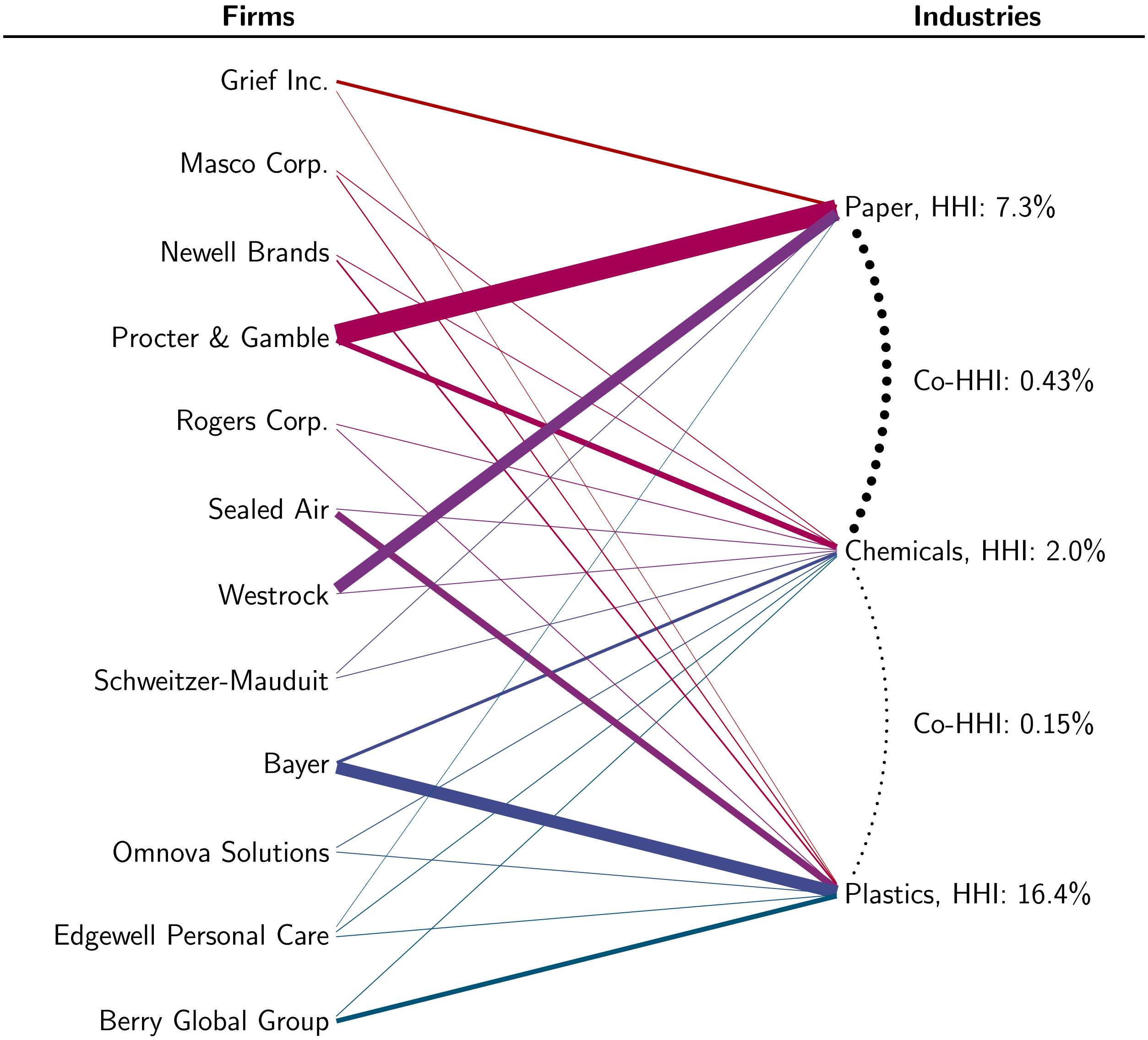
To help visualize the conglomerate network, Online Appendix Figure I presents the CoHHI network for manufacturing industries in 2015. Each inter-industry connection represents a CoHHI score above a minimum threshold. Industries listed in boxes are aggregated to more coarse definitions for brevity. To give further intuition for the structure of the network, Online Appendix Figure II 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.



Online Appendix Figure I

Conglomerate Network in Manufacturing in 2015

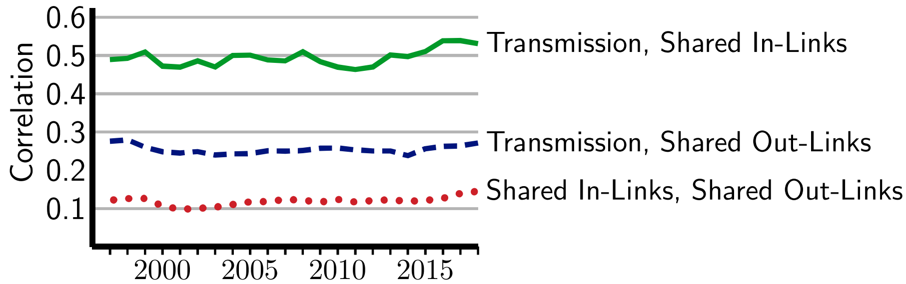
Each node in the network is a three-digit manufacturing industry, except non-manufacturing industries, which are aggregated at a higher level and presented in boxes. Lines between industries represent Co-HHI measures above a minimum threshold. Because many of the manufacturing industries are connected 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.



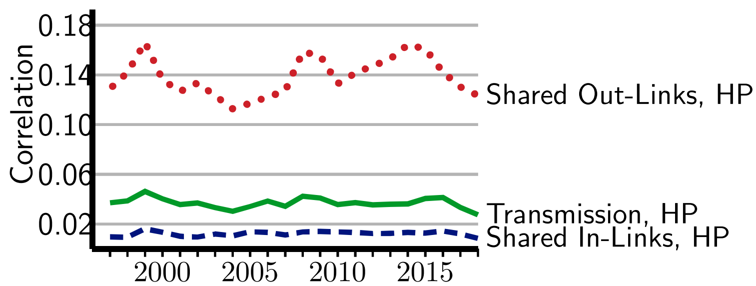
Online Appendix Figure II

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

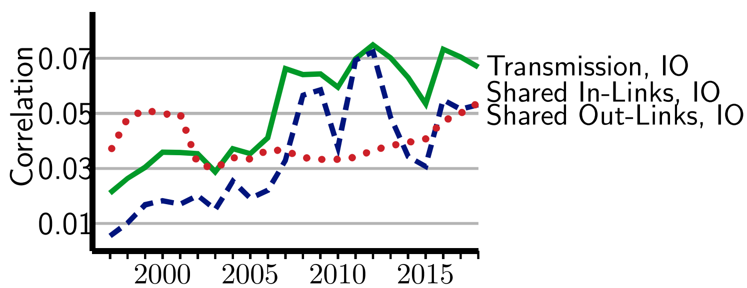
This figure represents the affiliation network of three manufacturing industries, defined at the three-digit NAICS level: Paper, Chemicals, and Plastics. The listed firms are those that operate in at least two of the three industries. Each industry contains additional firms not represented in the figure that do not operate segments in at least two of these three industries. The widths 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.



(A) Conglomerate Network



(B) Hoberg-Phillips (HP) and Conglomerate Network



(C) Input-Output (IO) and Conglomerate Network

Online Appendix Figure III

Yearly Cross-Sectional Correlation of Industry Relations

Each panel presents the yearly cross-sectional correlation of an industry-pair measure, excluding own-industry pairs using Compustat data. Panel A presents the correlations of the conglomerate network measures, Panel B presents the correlations of the conglomerate network measures with Hoberg-Phillips (HP) measures of industry connections, and Panel C presents the correlations of the conglomerate network with the Input-Output network (IO).

III. Out of Sample Cross-Sectional Tests

In Table II, we estimate the variance-covariance matrix of industry growth rates as presented in Equation 8. In this derivation, we assumed that all orthogonalized firm and industry shocks are drawn from identical distributions such that the variance of all firm shocks is σ_ε^2 and the variance of all industry shocks is σ_η^2. Under this assumption, we then showed that the conglomerate network can help explain the observed covariances of growth rates across industries.

In this section, we expand the analysis by 1) relaxing the assumption of homoskedasticity to allow each firm and industry shock to be drawn from unique distributions, and 2) estimating the unobserved shock variances. We still assume that orthogonalized shocks are independent across time (no auto-correlation) and across industries and firms (no cross-correlations). Using both the connections in the conglomerate network and the estimates of the orthogonalized firm-specific and industry-specific variances, we predict the covariances in industry growth rates. Thus, under the assumptions of heteroskedasticity, no serial correlations, and no cross-correlations, the relationship between our model-implied covariances and the observed covariances in the data indicates the extent to which the conglomerate network helps explain industry comovement.[13]

From Equation 7, the vector of growth rates is defined as:

$$\vec{g}_0 = (I + A')\vec{\nu} = \begin{bmatrix} I & H' \\ F & I \end{bmatrix} \begin{bmatrix} \vec{\eta} \\ \vec{\varepsilon} \end{bmatrix} = \begin{bmatrix} \vec{\eta} + H'\vec{\varepsilon} \\ \vec{\varepsilon} + F\vec{\eta} \end{bmatrix}. \tag{OA.2}$$

The variance-covariance matrix is

$$Cov(\vec{g}_0) = E\left(\begin{bmatrix} \eta\eta' + H'\varepsilon\varepsilon' H & \eta\eta' F' + H'\varepsilon\varepsilon' \\ \varepsilon\varepsilon' H + F\eta\eta' & \varepsilon\varepsilon' + F\eta\eta' F' \end{bmatrix} \right). \tag{OA.3}$$

[13]We thank Bruno Pellegrino for suggesting this approach.

In contrast to the main paper, we allow each industry and firm to have a unique distribution such that $\eta_j \sim N(0, \zeta_j^2)$ and $\varepsilon_i \sim N(0, \xi_i^2)$. If we indicate the ith row and jth column of H as h_{ij}, we can write the observed variances of the m industries recorded on the diagonals of the upper-left block of Equation OA.3 as a set of m equations:

$$Industry\ 1\ Variance = \zeta_1^2 + h_{11}^2\xi_1^2 + h_{21}^2\xi_2^2 + h_{31}^2\xi_3^2 + \cdots + h_{n1}^2\xi_n^2$$
$$Industry\ 2\ Variance = \zeta_2^2 + h_{12}^2\xi_1^2 + h_{22}^2\xi_2^2 + h_{32}^2\xi_3^2 + \cdots + h_{n2}^2\xi_n^2$$
$$\vdots$$
$$Industry\ m\ Variance = \zeta_m^2 + h_{1m}^2\xi_1^2 + h_{2m}^2\xi_2^2 + h_{3m}^2\xi_3^2 + \cdots + h_{nm}^2\xi_n^2$$

and the variance of the n firms on the diagonals of the lower-right block as n equations:

$$Firm\ 1\ Variance = \xi_1^2 + f_{11}^2\zeta_1^2 + f_{12}^2\zeta_2^2 + f_{13}^2\zeta_3^2 + \cdots + f_{1m}^2\zeta_m^2$$
$$Firm\ 2\ Variance = \xi_2^2 + f_{21}^2\zeta_1^2 + f_{22}^2\zeta_2^2 + f_{23}^2\zeta_3^2 + \cdots + f_{2m}^2\zeta_m^2$$
$$\vdots$$
$$Firm\ n\ Variance = \xi_n^2 + f_{n1}^2\zeta_1^2 + f_{n2}^2\zeta_2^2 + f_{n3}^2\zeta_3^2 + \cdots + f_{nm}^2\zeta_m^2.$$

Thus, the variance of the observed growth rate of an industry is decomposed into two parts: the variance of the orthogonalized industry-specific shock and the weighted sum of the variances of orthogonalized firm-specific shocks, where weights are based on the firms' market shares. This implies that industry variance is larger if it faces more volatile industry-specific shocks or if its firms have larger idiosyncratic volatility, weighted by the market share of the firms. Likewise, the variance of the observed growth rates of firms is based on the variance of firm-specific shocks plus the variance of industry-specific shocks, weighted by the size of the industry sales as a fraction of the firm's total sales.

This derivation represents a system of $n+m$ equations with $n+m$ unknowns, where the unknown variables are the unobservable orthogonalized shock variances of firms and industries, $\begin{bmatrix}\zeta_1 \cdots & \xi_n\end{bmatrix}$. Therefore, in an ideal setting, we can use observations of the H and F matrices and the vector of observed industry and firm variances to solve for the vector of unobserved orthogonalized shock variances. Once we have estimates of the unobservable shock variances, we can then predict covariances as the off-diagonal elements of Equation OA.3. Therefore, this procedure uses only the estimated shock variances and the H and F matrices to predict the covariances. In this sense, the test provides an out-of-sample prediction because observed covariances are not used as an input into the prediction.

There are a number of challenges to implementing this analysis with real-world data. First, we only observe growth rates of firms and industries over time, not instantaneous variances or covariances of the growth rates of firms or industries. Instead, we must estimate variances of growth rates using time-series data for each firm and industry. However, the H and F matrices are not constant over time. Thus, to match the cross-sectional estimates of variances and covariances, we need to create a purely cross-sectional measure of H and F. To do this, we calculate the time-series average sales matrix S using the entire time series, then compute a time-series average of H and F from this average sales matrix.

Second, estimating the variance of growth rates at a firm level is noisy. Some firms have long time series, but many do not. For example, estimating growth rates from a period of four years of sales only provides three observed growth rates, which provides little statistical power. In addition, the growth pattern of many small firms is not stable over time. They tend to have high growth initially then lower growth as they mature. Thus, the volatility of the growth rates in the time series is not the same as the instantaneous volatility of growth.

Third, the system of $n+m$ equations involves tens of millions of firm-level observations in the NETS data. Solving this system is computationally intensive and requires iterative estimations with an arbitrary tolerance level. Using Compustat data means that many industries are only thinly populated. In addition, because the system is perfectly identified, there exists only one solution to the system of equations. Given that our framework ignores other potential drivers of observed firm and industry variances, for a given set of estimated variances from the data, the solution to the system of equations could include negative values for the orthogonalized shock variances. Because it is a perfectly identified linear system, these negative shock variances are the only solution possible to match the data. Negative estimates of variance represent an inconsistency with the assumptions of the model.

To address these estimation challenges, we do the following. For each year, we identify the top 10,000 firms in NETS by total sales. Over the entire sample period, this identifies about 35,000 firms. For these firms, we calculate the variance of their sales growth and identified those with positive variances that were less than the median variance. This generated a sample of 16,535 firms operating in 973 industries. We then calculate the variances of the observed industry and firm growth rates using this sample. To create the H and F matrices, we create an S matrix of sales by industry from these observations and take the time-series average over the entire time period. With the observed variances and H and F matrices, we solve the system of 17,508 equations to estimate the unobservable industry and firm shock variances. Using these shock variances we calculate the model-implied cross-industry covariance matrix as in Equation OA.3. Next, we estimate the cross-industry covariances directly from the time-series data of growth rates for the 973 industries in our sample to produce a data-implied cross-industry covariance matrix. We winsorize both the model-implied and data-implied covariances at the 5% level to exclude outliers.

We regress the covariances taken directly from the data on the model-implied covariances. The regression results are as follows:

$$\text{Observed Cov}(g_{sales,i}, g_{sales,j}) = \underset{(14.29)}{0.001} + \underset{(8.95)}{6.709} \times \text{Model-Implied Cov}(g_{sales,i}, g_{sales,j})$$

where industry-clustered t-statistics are reported in parenthesis in a sample of 472,876 observations.

These results show that the model-implied covariances are strongly related to the directly observed covariances. These results demonstrate that ignoring all other factors that could influence cross-industry comovement, such as common suppliers or customers, regulatory regimes, geographic proximity, or similarity in labor or assets, we are able to statistically predict the heterogeneity of cross-industry covariances using only observed within-firm and industry variances and the conglomerate network.

IV. Alternative Internal Allocation Policies

Theories of internal capital markets assume a range of different reallocation policies. In our main tests, we assume that resources are allocated *pro rata* within the firm, which is most consistent with a firm with equalized marginal revenue products across its divisions (Williamson, 1975). This interpretation is based on our intuitive assumption that the exposure level of an industry to a firm-level shock is equal to the firm's market share in the industry. Likewise, the exposure level of a firm to an industry-level shock is equal to the share of the firm's total sales originating in that industry.

An alternative reallocation policy is the corporate socialism model of Rajan, Servaes, and Zingales (2000). This model assumes that when a conglomerate's segments are dissimilar in the sizes of their resources and opportunities, internal reallocations can flow from more efficient to less efficient divisions. In contrast, when segments are more similar, the opposite allocation occurs. Thus, the headquarters has the incentive to transfer resources *ex ante* from larger to smaller divisions to reduce inefficiency. In contrast, Stein (1997) assumes that headquarters allocates shocks to the divisions with higher profitability because it allows the firm managers to expropriate larger private benefits.

These alternative policies do not map as cleanly into our network setting because they rely on allocations that are conditional on positive versus negative shocks. Instead, because our model is suited for understanding variance and covariance, it treats positive and negative shocks symmetrically. However, to provide an alternative model, we re-define the H matrix to always transmit segment-level shocks to the firm's largest segment. In particular, the largest segments are the only nonzero elements in H, the value of which is defined by firm size divided by industry size as opposed to segment size divided by industry size in the *pro rata* case. This is similar to the winner-picking theory of Stein (1997) under the assumption that all shocks are positive and that the largest segment generates the greatest profits for expropriation. In reality, some shocks are negative, which will counteract the winner-picking policy. Even if this is not a perfect match to the theory, it still provides an alternative allocation mechanism to the *pro rata* allocation policy used in the main paper.

Online Appendix Table XXI presents the results of these tests. The transmission matrix based on largest segments does not significantly explain comovement in employment growth rates across industries, either in a continuous form or in a dummy variable form. Likewise, it is not significantly related to comovement in sales growth comovement, either. Instead, the *pro rata* reallocation matrix is significantly related to comovement in sales growth and employment growth.

While these results show that the reallocation policy based on largest segment does not explain comovement, we acknowledge that this is not an exact match to winner-picking policies. However, these results do show that the choice of internal reallocation policy does influence whether the transmission matrix can explain industry comovement. It also provides evidence that the *pro rata* transmission matrix is not significant for spurious reasons.

V. Additional Tables

In this section, we provide expanded results and additional robustness checks.

- Online Appendix Table I provides the correlations between inter-industry measures.
- Online Appendix Table II provides an overview of the main and robustness tests.
- Online Appendix Table III provides the complete results from Panel A of Table IV.
- Online Appendix Table IV provides the complete results from Panel B of Table IV.
- Online Appendix Table V provides the complete results from Panel A of Table V.
- Online Appendix Table VI provides the complete results from Panel B of Table V.
- Online Appendix Table VII provides robustness tests for Panel A of Table IV using data from the County Business Patterns of the US Census.
- Online Appendix Table VIII provides robustness tests of Panel A of Table IV using lagged explanatory variables.
- Online Appendix Table IX provides robustness tests of Panel B of Table IV using lagged explanatory variables.
- Online Appendix Table X provides robustness tests of Panel A of Table V using lagged explanatory variables.
- Online Appendix Table XI provides robustness tests of Panel B of Table V using lagged explanatory variables.
- Online Appendix Table XII provides robustness tests of Panel A of Table IV using the largest 1000 firms in NETS.
- Online Appendix Table XIII provides robustness tests from Panel A of Table V using the largest 1000 firms in NETS.
- Online Appendix Table XIV provides robustness tests of Panel A of Table IV using lagged explanatory variables with the largest 1000 firms in NETS.
- Online Appendix Table XV provides robustness tests of Panel A of Table V using lagged explanatory variables with the largest 1000 firms in NETS.

- Online Appendix Table XVI provides robustness tests of Panel B of Table IV excluding firms below the 25th size percentile.
- Online Appendix Table XVII provides robustness tests of Panel B of Table IV excluding firms below the 50th size percentile.
- Online Appendix Table XVIII provides robustness tests of Panel B of Table IV excluding foreign firms.
- Online Appendix Table XIX provides robustness tests of Panel B of Table IV using 3-digit industry definitions.
- Online Appendix Table VII provides additional results on the internal reallocation of shocks following the WTO tariff shock.
- Online Appendix Table XXI provides results using a modified winner-picking internal reallocation policy.

Online Appendix Table I

Correlations of Industry Measures

This table presents the average annual cross-sectional correlations between the measures of cross-industry relations.

Panel A: NETS Data					
	HP	HHI	$F'H$	$H'H$	$F'F$
Input-Output (IO)	0.087	−0.061	0.094	0.034	0.111
Hoberg-Phillips (HP)		−0.025	0.085	0.021	0.073
Sum of HHI (HHI)			0.014	0.081	−0.037
Transmission ($F'H$)				0.387	0.148
CoHHI ($H'H$)					0.020
Panel B: Compustat Data					
	HP	HHI	$F'H$	$H'H$	$F'F$
Input-Output (IO)	0.068	−0.006	0.071	0.039	0.062
Hoberg-Phillips (HP)		−0.076	0.050	0.012	0.124
Sum of HHI (HHI)			−0.012	0.026	−0.056
Transmission ($F'H$)				0.436	0.224
CoHHI ($H'H$)					0.092

Online Appendix Table II

Summary of Empirical Results and Robustness

This table indicates all of the tests conducted in the paper and appendix and whether the relationship tested is statistically significant.

	Shared Links			Transmission		
	Asset Growth	Employee Growth	Sales growth	Asset Growth	Employee Growth	Sales growth
NETS						
Concurrent						
All	—	Yes	Yes	—	Dummy only	Yes
Top 1000	—	Yes	Dummy only	—	Dummy only	Yes
Lagged						
All	—	Yes	Yes	—	Dummy only	Yes
Top 1000	—	Yes	Yes	—	Dummy only	Yes
Compustat						
Concurrent						
All	Yes	—	Yes	Yes	—	Yes
Top 75th percentil	Yes	—	Yes	—	—	—
Top 50th percentile	Yes	—	Yes	—	—	—
Only domestic	Yes	—	Yes	—	—	—
Coarse industry definitions	Yes	—	Yes	—	—	—
Lagged						
All	Yes	—	Yes	Yes	—	Yes
Census CBP						
Concurrent	—	Yes	—	—	Dummy only	—
Lagged (WTO Shock)	—		—	—	Yes	—

ONLINE APPENDIX TABLE III

Comovement of Industry Growth and Shared Network Links: NETS Data

This table provides the complete results from Panel A of Table IV in the main paper. 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 assets or sales using NETS data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*			*Sales growth*		
Shared in-links (Co-HHI)	−2.450***	−2.451***		−4.879***	−4.880***	
	(0.570)	(0.570)		(0.939)	(0.939)	
Shared out-links		−0.008***			−0.008***	
		(0.003)			(0.003)	
Shared in-links dummy			−0.012***			−0.067***
			(0.004)			(0.007)
Sum of HHI	1.678***	1.678***	1.673***	5.581***	5.581***	5.570***
	(0.024)	(0.024)	(0.024)	(0.043)	(0.043)	(0.043)
Input-Output link	−0.168***	−0.168***	−0.169***	−0.189***	−0.189***	−0.191***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Hoberg-Phillips similarity	1.401***	1.403***	1.405***	2.385***	2.387***	2.397***
	(0.399)	(0.399)	(0.399)	(0.373)	(0.373)	(0.373)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.082	0.082	0.082	0.075	0.075	0.075
Observations	13,263,940	13,263,940	13,263,940	13,253,246	13,253,246	13,253,246

ONLINE APPENDIX TABLE IV

Comovement of Industry Growth and Shared Network Links: Compustat Data

This table provides the complete results from Panel B of Table IV in the main paper. 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 assets and sales using Compustat data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Asset growth*			*Sales growth*		
Shared in-links (Co-HHI)	−23.258***	−22.459***		−22.494***	−21.710***	
	(2.635)	(2.643)		(2.583)	(2.594)	
Shared out-links		−3.634***			−3.552***	
		(1.363)			(1.147)	
Shared in-links dummy			−1.881***			−1.722***
			(0.226)			(0.215)
Sum of HHI	1.688***	1.685***	1.672***	2.513***	2.511***	2.499***
	(0.116)	(0.116)	(0.116)	(0.112)	(0.112)	(0.112)
Input-Output link	0.193	0.194	0.201	1.027***	1.029***	1.036***
	(0.367)	(0.367)	(0.367)	(0.361)	(0.361)	(0.361)
Hoberg-Phillips similarity	−29.959***	−29.878***	−29.656***	−20.894***	−20.808***	−20.598***
	(5.658)	(5.654)	(5.639)	(4.362)	(4.360)	(4.355)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.054	0.054	0.054	0.068	0.068	0.068
Observations	3,474,363	3,474,363	3,474,363	3,563,872	3,563,872	3,563,872

Online Appendix Table V

Comovement of Industry Growth and the Transmission Network: NETS Data

This table provides the complete results from Panel A of Table V in the main paper. 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 employment or sales using NETS. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*		*Sales growth*	
Transmission $(F'H + H'F)$	0.069		-2.423^{***}	
	(0.559)		(0.818)	
Transmission dummy		-0.027^{***}		-0.059^{***}
		(0.005)		(0.007)
Sum of HHI	1.673^{***}	1.672^{***}	5.572^{***}	5.570^{***}
	(0.024)	(0.024)	(0.043)	(0.043)
Input-Output link	-0.169^{***}	-0.169^{***}	-0.191^{***}	-0.190^{***}
	(0.013)	(0.013)	(0.014)	(0.014)
Hoberg-Phillips similarity	1.404^{***}	1.409^{***}	2.397^{***}	2.402^{***}
	(0.399)	(0.399)	(0.373)	(0.373)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.082	0.082	0.075	0.075
Observations	13,263,940	13,263,940	13,253,246	13,253,246

Online Appendix Table VI

Comovement of Industry Growth and the Transmission Network: Compustat Data

This table provides the complete results from Panel B of Table V in the main paper. 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 assets or sales using Compustat data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Asset growth*		*Sales growth*	
Transmission $(F'H + H'F)$	-7.978^{***}		-5.440^{***}	
	(1.735)		(1.805)	
Transmission dummy		-1.881^{***}		-1.722^{***}
		(0.226)		(0.215)
Sum of HHI	1.682^{***}	1.672^{***}	2.509^{***}	2.499^{***}
	(0.116)	(0.116)	(0.112)	(0.112)
Input-Output link	0.188	0.201	1.023^{***}	1.036^{***}
	(0.367)	(0.367)	(0.361)	(0.361)
Hoberg-Phillips similarity	-30.010^{***}	-29.656^{***}	-20.866^{***}	-20.598^{***}
	(5.661)	(5.639)	(4.361)	(4.355)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.054	0.054	0.068	0.068
Observations	3,474,363	3,474,363	3,563,872	3,563,872

Online Appendix Table VII

Comovement of Employment Growth and Network Links: Census Data

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. Data are from the County Business Paterns data from the US Census. Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and industry-pair 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

Online Appendix Table VIII

Comovement of Industry Growth and Lagged Shared Links: NETS Data

This table presents regressions identical to Online Appendix Table III except all of the independent variables are lagged one year. 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 assets or sales using NETS data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*			*Sales growth*		
Shared in-links (Co-HHI)	−3.364***	−3.364***		−12.753***	−12.752***	
	(0.810)	(0.810)		(2.006)	(2.006)	
Shared out-links		−0.006***			0.012***	
		(0.002)			(0.003)	
Shared links dummy			−0.035***			−0.105***
			(0.004)			(0.012)
Sum of HHI	3.253***	3.252***	3.246***	17.584***	17.584***	17.557***
	(0.035)	(0.035)	(0.035)	(0.183)	(0.183)	(0.183)
Input-Output link	−0.188***	−0.187***	−0.189***	−0.003	−0.004	−0.009
	(0.009)	(0.009)	(0.009)	(0.024)	(0.024)	(0.025)
Hoberg-Phillips similarity	0.445**	0.447**	0.453**	1.375***	1.371***	1.403***
	(0.213)	(0.213)	(0.213)	(0.473)	(0.473)	(0.473)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.059	0.059	0.059	0.055	0.055	0.055
Observations	13,269,776	13,269,776	13,269,776	13,269,776	13,269,776	13,269,776

ONLINE APPENDIX TABLE IX

Comovement of Industry Growth and Lagged Shared Links: Compustat Data

This table presents regressions identical to Online Appendix Table IV except all of the independent variables are lagged one year. 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 assets or sales using NETS data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Asset growth*			*Sales growth*		
Shared in-links (Co-HHI)	−16.219***	−15.881***		−13.645***	−13.254***	
	(2.556)	(2.561)		(2.897)	(2.911)	
Shared out-links		−1.544			−1.789	
		(1.132)			(1.095)	
Shared links dummy			−0.661***			−0.620***
			(0.236)			(0.225)
Sum of HHI	−1.230***	−1.231***	−1.237***	0.136	0.135	0.129
	(0.119)	(0.119)	(0.119)	(0.120)	(0.120)	(0.120)
Input-Output link	0.010	0.011	0.010	−0.006	−0.005	−0.004
	(0.358)	(0.358)	(0.358)	(0.342)	(0.342)	(0.342)
Hoberg-Phillips similarity	−7.429	−7.389	−7.283	−13.092**	−13.044**	−12.951**
	(5.486)	(5.485)	(5.484)	(5.489)	(5.487)	(5.483)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.056	0.056	0.056	0.066	0.066	0.066
Observations	3,202,103	3,202,103	3,202,103	3,278,544	3,278,544	3,278,544

Online Appendix Table X
Comovement of Industry Growth and the Lagged Transmission Network: NETS Data

This table presents regressions identical to Online Appendix Table V except all of the independent variables are lagged one year. 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 employment or sales using NETS. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*		*Sales growth*	
Transmission ($F'H + H'F$)	0.398		-4.241^{***}	
	(0.565)		(1.455)	
Transmission dummy		-0.022^{***}		-0.077^{***}
		(0.004)		(0.012)
Sum of HHI	3.245^{***}	3.245^{***}	17.558^{***}	17.555^{***}
	(0.035)	(0.035)	(0.183)	(0.183)
Input-Output link	-0.188^{***}	-0.188^{***}	-0.007	-0.007
	(0.009)	(0.009)	(0.025)	(0.025)
Hoberg-Phillips similarity	0.449^{**}	0.454^{**}	1.403^{***}	1.407^{***}
	(0.213)	(0.213)	(0.473)	(0.473)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.059	0.059	0.055	0.055
Observations	13,269,776	13,269,776	13,269,776	13,269,776

Online Appendix Table XI

Comovement of Industry Growth and the Lagged Transmission Network: Compustat Data

This table presents regressions identical to Online Appendix Table V except all of the independent variables are lagged one year. 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 assets or sales using Compustat data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Asset growth*		*Sales growth*	
Transmission $(F\prime H + H\prime F)$	−8.746***		−7.203***	
	(1.588)		(1.752)	
Transmission dummy		−0.661***		−0.620***
		(0.236)		(0.225)
Sum of HHI	−1.235***	−1.237***	0.131	0.129
	(0.119)	(0.119)	(0.120)	(0.120)
Input-Output link	0.006	0.010	−0.009	−0.004
	(0.358)	(0.358)	(0.342)	(0.342)
Hoberg-Phillips similarity	−7.562	−7.283	−13.181**	−12.951**
	(5.489)	(5.484)	(5.493)	(5.483)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.056	0.056	0.066	0.066
Observations	3,202,103	3,202,103	3,278,544	3,278,544

ONLINE APPENDIX TABLE XII
Comovement of Industry Growth and Shared Network Links: NETS Data
Largest 1000 Firms

This table recalculates the complete results from Panel A of Table IV in the main paper using only the largest 1000 firms in the NETS data. 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 assets or sales using NETS data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*			*Sales growth*		
Shared in-links (Co-HHI)	−3.030***	−2.900***		−2.788	−2.203	
	(0.591)	(0.593)		(1.726)	(1.733)	
Shared out-links		−0.119***			−0.503***	
		(0.027)			(0.040)	
Shared links dummy			−0.020***			−0.074***
			(0.004)			(0.007)
Sum of HHI	1.749***	1.752***	1.742***	3.084***	3.087***	3.082***
	(0.023)	(0.023)	(0.023)	(0.059)	(0.059)	(0.059)
Input-Output link	−0.223***	−0.225***	−0.224***	−0.175***	−0.177***	−0.176***
	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)
Hoberg-Phillips similarity	1.102***	1.099***	1.108***	1.737***	1.738***	1.748***
	(0.399)	(0.399)	(0.399)	(0.364)	(0.364)	(0.364)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.094	0.093	0.094	0.078	0.078	0.078
Observations	13,258,908	13,239,621	13,258,908	13,243,402	13,224,128	13,243,402

Online Appendix Table XIII

Comovement of Industry Growth and the Transmission Network: NETS Data Largest 1000 Firms

This table provides the complete results from Panel A of Table V in the main paper using only the largest 1000 firms in the NETS data. 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 employment or sales using NETS. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*		*Sales growth*	
Transmission ($F\prime H + H\prime F$)	−0.136		−2.450***	
	(0.108)		(0.182)	
Transmission dummy		−0.018***		−0.113***
		(0.004)		(0.006)
Sum of HHI	1.747***	1.753***	3.106***	3.126***
	(0.023)	(0.023)	(0.059)	(0.059)
Input-Output link	−0.226***	−0.226***	−0.180***	−0.179***
	(0.014)	(0.014)	(0.016)	(0.016)
Hoberg-Phillips similarity	1.099***	1.103***	1.699***	1.741***
	(0.399)	(0.399)	(0.364)	(0.364)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.094	0.094	0.078	0.078
Observations	13,222,191	13,222,191	13,206,713	13,206,713

ONLINE APPENDIX TABLE XIV

Comovement of Industry Growth and Lagged Shared Links: NETS Data
Largest 1000 Firms

This table presents regressions identical to Online Appendix Table III except all of the independent variables are lagged one year and the data are restricted to the largest 1000 firms in NETS. 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 assets or sales using NETS data. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*			*Sales growth*		
Shared in-links (Co-HHI)	−0.710	−0.551		−2.839**	−2.338*	
	(0.582)	(0.585)		(1.221)	(1.229)	
Shared out-links		−0.140***			−0.425***	
		(0.026)			(0.040)	
Shared links dummy			0.018***			−0.024***
			(0.005)			(0.007)
Sum of HHI	1.132***	1.135***	1.129***	4.252***	4.247***	4.246***
	(0.023)	(0.023)	(0.023)	(0.044)	(0.044)	(0.043)
Input-Output link	−0.266***	−0.266***	−0.266***	−0.136***	−0.135***	−0.137***
	(0.013)	(0.013)	(0.013)	(0.017)	(0.017)	(0.017)
Hoberg-Phillips similarity	0.301	0.294	0.300	−0.759**	−0.768**	−0.754**
	(0.248)	(0.248)	(0.248)	(0.324)	(0.324)	(0.324)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.102	0.102	0.102	0.084	0.084	0.084
Observations	12,798,591	12,781,219	12,798,591	12,783,075	12,765,708	12,783,075

Online Appendix Table XV
Comovement of Industry Growth and the Lagged Transmission Network: NETS Data
Largest 1000 Firms

This table presents regressions identical to Online Appendix Table V except all of the independent variables are lagged one year and the data are restricted to the largest 1000 firms in NETS. 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 employment or sales using NETS. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Dependent variable:	*Employment growth*		*Sales growth*	
Transmission $(F\prime H + H\prime F)$	−0.034		−2.204***	
	(0.104)		(0.180)	
Transmission dummy		−0.015***		−0.116***
		(0.003)		(0.006)
Sum of HHI	1.125***	1.131***	4.252***	4.276***
	(0.023)	(0.023)	(0.044)	(0.044)
Input-Output link	−0.268***	−0.268***	−0.139***	−0.139***
	(0.013)	(0.013)	(0.017)	(0.017)
Hoberg-Phillips similarity	0.276	0.278	−0.812**	−0.772**
	(0.248)	(0.248)	(0.324)	(0.324)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.102	0.102	0.085	0.085
Observations	12,761,871	12,761,871	12,746,360	12,746,360

Online Appendix Table XVI

Comovement of Industry Growth and Shared Network Links: Robustness to Excluding Compustat Firms Below the 25th Percentile of Sales

This table replicates Panel B of Table IV of the main paper, but uses observations from networks that exclude firms with sales below the 25th percentile of sales per year. The 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) and assets (Panel B). Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and industry-pair clustered 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)	−18.747***		−17.932***	
	(2.615)		(2.629)	
Shared out-links		−5.021***	−3.727***	
		(1.310)	(1.244)	
Shared links dummy				−1.295***
				(0.221)
Sum of HHI	2.511***	2.505***	2.508***	2.498***
	(0.111)	(0.111)	(0.111)	(0.111)
Input-Output link	0.465	0.462	0.466	0.470
	(0.322)	(0.322)	(0.322)	(0.322)
Hoberg-Phillips similarity	−16.455***	−16.170***	−16.376***	−16.216***
	(4.279)	(4.271)	(4.277)	(4.273)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.061	0.061	0.061	0.061
Observations	3,252,468	3,252,468	3,252,468	3,252,468

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	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel B: Asset growth				
Shared in-links (Co-HHI)	-18.059^{***}		-17.229^{***}	
	(2.609)		(2.617)	
Shared out-links		-5.062^{***}	-3.812^{***}	
		(1.474)	(1.410)	
Shared links dummy				-1.441^{***}
				(0.233)
Sum of HHI	2.657^{***}	2.651^{***}	2.654^{***}	2.643^{***}
	(0.114)	(0.114)	(0.114)	(0.114)
Input-Output link	−0.150	−0.154	−0.149	−0.145
	(0.326)	(0.325)	(0.326)	(0.325)
Hoberg-Phillips similarity	-20.197^{***}	-19.936^{***}	-20.124^{***}	-19.975^{***}
	(5.538)	(5.527)	(5.534)	(5.527)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.052	0.052	0.052	0.052
Observations	3,161,000	3,161,000	3,161,000	3,161,000

Online Appendix Table XVII

Comovement of Industry Growth and Shared Network Links
Robustness to Excluding Compustat Firms Below the Median Size

This table replicates Panel B of Table IV of the main paper, but uses observations from networks that exclude firms with sales below the median sales level per year. The 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) and assets (Panel B). Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and industry-pair clustered 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)	−9.299***		−8.279***	
	(2.825)		(2.847)	
Shared out-links		−6.341***	−5.525***	
		(1.643)	(1.592)	
Shared links dummy				−0.963***
				(0.241)
Sum of HHI	2.429***	2.421***	2.424***	2.417***
	(0.119)	(0.119)	(0.119)	(0.119)
Input-Output link	1.321***	1.327***	1.328***	1.332***
	(0.365)	(0.365)	(0.365)	(0.365)
Hoberg-Phillips similarity	0.618	0.851	0.723	0.785
	(4.989)	(4.983)	(4.986)	(4.987)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.063	0.063	0.063	0.063
Observations	2,593,920	2,593,920	2,593,920	2,593,920

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	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel B: Asset growth				
Shared in-links (Co-HHI)	-10.991^{***}		-9.946^{***}	
	(2.671)		(2.686)	
Shared out-links		-6.566^{***}	-5.591^{***}	
		(1.684)	(1.624)	
Shared links dummy				-1.180^{***}
				(0.258)
Sum of HHI	3.702^{***}	3.693^{***}	3.697^{***}	3.688^{***}
	(0.119)	(0.119)	(0.119)	(0.119)
Input-Output link	0.544	0.549	0.550	0.557
	(0.370)	(0.370)	(0.370)	(0.370)
Hoberg-Phillips similarity	-15.681^{***}	-15.428^{***}	-15.581^{***}	-15.498^{***}
	(5.282)	(5.275)	(5.279)	(5.276)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.049	0.049	0.049	0.049
Observations	2,509,535	2,509,535	2,509,535	2,509,535

Online Appendix Table XVIII

Comovement of Industry Growth and Shared Network Links
Robustness to Excluding Foreign Firms in Compustat Data

This table replicates Panel B ofTable IV of the main paper, but uses observations from networks that exclude firms incorporated outside of the U.S. The 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) and assets (Panel B). Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and industry-pair clustered 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)	−21.811***		−20.918***	
	(2.448)		(2.471)	
Shared out-links		−6.244***	−4.365***	
		(1.362)	(1.284)	
Shared links dummy				−2.050***
				(0.236)
Sum of HHI	1.800***	1.793***	1.797***	1.784***
	(0.113)	(0.113)	(0.113)	(0.113)
Input-Output link	0.490	0.488	0.494	0.498
	(0.329)	(0.330)	(0.330)	(0.330)
Hoberg-Phillips similarity	−16.236***	−15.930***	−16.157***	−15.973***
	(4.323)	(4.310)	(4.320)	(4.311)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.070	0.070	0.070	0.070
Observations	3,371,361	3,371,361	3,371,361	3,371,361

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	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel B: Asset growth				
Shared in-links (Co-HHI)	-22.676^{***}		-22.294^{***}	
	(2.223)		(2.235)	
Shared out-links		-3.901^{**}	-1.875	
		(1.579)	(1.479)	
Shared links dummy				-2.084^{***}
				(0.237)
Sum of HHI	1.588^{***}	1.583^{***}	1.586^{***}	1.571^{***}
	(0.112)	(0.112)	(0.112)	(0.112)
Input-Output link	-0.817^{**}	-0.820^{**}	-0.815^{**}	-0.808^{**}
	(0.340)	(0.340)	(0.340)	(0.340)
Hoberg-Phillips similarity	-17.680^{***}	-17.447^{***}	-17.644^{***}	-17.428^{***}
	(5.050)	(5.036)	(5.048)	(5.036)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.058	0.058	0.058	0.058
Observations	3,289,294	3,289,294	3,289,294	3,289,294

Online Appendix Table XIX

Comovement of Industry Growth and Shared Network Links
Robustness to Coarse Industry Definitions in Compustat

This table replicates Panel B of Table IV of the main paper, but uses observations from networks based on 3-Digit SIC codes. The 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) and assets (Panel B). Variable definitions are provided in the text. All regressions include industry-pair fixed effects and year fixed effects. Coefficients and industry-pair clustered 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)	-18.393^{***}		-16.487^{***}	
	(5.047)		(4.984)	
Shared out-links		-4.906^{***}	-4.582^{***}	
		(0.919)	(0.909)	
Shared links dummy				-1.041^{***}
				(0.207)
Sum of HHI	2.570^{***}	2.562^{***}	2.568^{***}	2.555^{***}
	(0.231)	(0.231)	(0.231)	(0.231)
Input-Output link	-0.171^{***}	-0.170^{***}	-0.170^{***}	-0.169^{***}
	(0.053)	(0.053)	(0.053)	(0.053)
Hoberg-Phillips similarity	−1.504	−1.309	−1.403	−1.270
	(4.592)	(4.596)	(4.592)	(4.574)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.066	0.066	0.066	0.066
Observations	845,868	845,868	845,868	845,868

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	Dependent variable: $(g_k - g_j)^2$			
	(1)	(2)	(3)	(4)
Panel B: Asset growth				
Shared in-links (Co-HHI)	-13.935^{***}		-11.982^{**}	
	(4.709)		(4.726)	
Shared out-links		-5.010^{***}	-4.774^{***}	
		(0.946)	(0.941)	
Shared links dummy				-1.160^{***}
				(0.223)
Sum of HHI	0.019	0.013	0.018	0.006
	(0.237)	(0.237)	(0.237)	(0.237)
Input-Output link	-0.303^{***}	-0.302^{***}	-0.302^{***}	-0.301^{***}
	(0.057)	(0.056)	(0.056)	(0.056)
Hoberg-Phillips similarity	-22.009^{***}	-21.804^{***}	-21.876^{***}	-21.797^{***}
	(4.361)	(4.354)	(4.357)	(4.375)
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.053	0.053	0.053	0.053
Observations	821,164	821,164	821,164	821,164

Online Appendix Table XX

Transmission of Tariff Shocks Within Conglomerates

This table presents coefficient estimates from panel regressions where the dependent variable is the industry growth rate of sales. NTR Gap is the difference between the non-Normal Trade Relations tariff rate and the NTR tariff rate. Other NTR Gap is based on other segments within the conglomerate firm. Firm-clustered standard errors are in parentheses. Statistical significance is indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

	Dependent variable: Sales growth			
	1999 Fixed Network		*Placebo Network*	
	(1)	(2)	(3)	(4)
Post × NTR Gap_i	0.002	0.002	−0.054	−0.050
	(0.063)	(0.063)	(0.057)	(0.057)
NTR Gap_i	−0.859		0.576*	
	(0.883)		(0.313)	
Post × Other NTR Gap_i	−0.197**	−0.194**	0.013	0.018
	(0.079)	(0.079)	(0.062)	(0.062)
Other NTR Gap_i	−1.857*		−0.201	
	(1.122)		(0.153)	
Segment fixed effects	Yes		Yes	
Segment-industry fixed effects		Yes		Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.268	0.270	0.269	0.271
Observations	24,143	24,095	24,143	24,095

Online Appendix Table XXI

Comovement of Industry Growth and the Transmission Network: Winner-takes-all

This table provides robust tests for the results of Table V in the main paper where the transmission network is defined differently. 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 employment or sales using NETS. *Largest Segment Transmission* assumes the firm reallocates all shocks to the largest division. *Pro Rata Transmission* assumes shocks are transmitted *pro rata* as in the main analysis. Controls include sum of HHI, Input-output links, and Hoberg-Phillips similarity. Coefficients and industry-pair clustered standard errors (in parentheses) are in percentages. Statistical significance indicated by ***, **, and * for significance at 0.01, 0.05, and 0.10.

Panel A: Employment growth				
Largest Segment Transmission	0.400	0.413		
	(0.661)	(0.701)		
Pro Rata Transmission		−0.033		
		(0.593)		
Largest Segment Transmission Dummy			0.000	0.006
			(0.005)	(0.005)
Pro Rata Transmission Dummy				−0.027***
				(0.005)
Controls	Yes	Yes	Yes	Yes
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.082	0.082	0.082	0.082
Observations	13,263,940	13,263,940	13,263,940	13,263,940
Panel B: Sales growth				
Largest Segment Transmission	−1.144	−0.194		
	(0.897)	(0.917)		
Pro Rata Transmission		−2.375***		
		(0.843)		
Largest Segment Transmission Dummy			−0.029***	−0.017***
			(0.006)	(0.006)
Pro Rata Transmission Dummy				−0.057***
				(0.007)
Controls	Yes	Yes	Yes	Yes
Industry-pair and year fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.075	0.075	0.075	0.075
Observations	13,253,246	13,253,246	13,253,246	13,253,246