THE IMPORTANCE OF INDUSTRY LINKS IN MERGER WAVES*

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Abstract

Prior research finds that economic shocks lead to merger waves within an industry. However, industries do not exist in isolation. In this paper, we argue that both intra- and inter-industry merger waves are driven by customer-supplier relations between industries. To test our theory, we construct an industry network using techniques from the social-networking literature, where inter-industry connections are determined by the strength of supplier and customer relations. First, we find that the strength of industry network ties strongly predicts inter-industry merger activity in the cross-section. Second, we show that merger waves propagate across the industry network over time: high levels of merger activity in an industry lead to subsequently high levels of activity in connected industries. By using a network approach, we provide new insight into understanding why mergers occur in waves.

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It is well documented that merger waves cluster within industries (Mitchell and Mulherin, 1996; Andrade, Mitchell, and Stafford, 2001; Harford, 2005). This clustering is caused in part by economic industry-level shocks. Technology, regulatory, and other shocks lead firms to adjust to the new economic environment via mergers (Gort, 1969). For example, the easing of ownership limits provided by the Telecommunications Act of 1996 led to a merger wave of media firms, including Viacom–Paramount, Disney–ABC, and Time Warner–Turner Broadcasting, among others. More generally, Harford (2005) provides systematic evidence that merger waves follow industry shocks.

However, industries do not exist in isolation. Product market relationships between customers and suppliers connect multiple industries through a network of trade. This observation has at least two important implications for merger waves. First, an industry-level economic shock may lead to inter-industry merger waves, rather than intra-industry waves. For instance, the mergers following the Telecom Act of 1996 listed above include mergers of firms that produce media content (Paramount, Disney, and Time Warner) with firms that distribute the content (Viacom, ABC, and Turner). More generally, unexpected shifts in demand or price uncertainty may make it difficult to write long term vertical contracts, which leads to vertical integration (Fan, 2000). Since economic shocks may affect customer-supplier relations, it follows that mergers may occur along a supply-chain.

Second, we expect that the industrial re-organization that is realized from a merger wave within an industry may lead to subsequent merger waves in industries that are connected through the trade network. Continuing with our example, when radio stations were consolidated following the 1996 Telecom Act, radio playlists became less diverse (Williams, Brown, and Alexander, 2002). This may help explain the subsequent consolidation of the record industry through mergers (Vivendi–Universal, AOL–Time Warner, Sony–BMG). A specific form of this effect is the countervailing market power theory of Galbraith (1952), where industry consolidation in an upstream (downstream) industry leads to industry consolidation in a downstream (upstream) industry to counteract the monopoly (monopsony) power created through merger. Empirical evidence consistent with this theory is reported in Bhattacharyya and Nain (2008) and Becker and Thomas (2008), where mergers in one industry affect the likelihood of mergers in related industries.

To empirically test the relationship between merger activity and industry relations, we construct a network of industry trade flows using input-output data from the U.S Bureau of Economic Analysis. We employ methods first developed in social networking and graph theory research to analyze the relationship between the industry network and the network of inter-industry mergers. The network approach allows us to consider higher order effects of the propagation of industry shocks through the economy. For example, network analysis measures an industry's connection with another industry differently depending upon on how connected is the second industry. The second industry's connections are in turn measured by the connections of its trading partners, and so on. Using the network approach is important because it provides a much richer analysis than is possible using a supply-chain approach. In fact, this is the first paper to model product market relationships as a network. Though we use this approach to investigate merger waves, we believe this approach will have many important applications in a wide range of future research.

We first report that product market relationships strongly predict merger activity both within and across industries. The simple correlation between an industry's centrality in the industry trade network and the merger network is 35%. Results from both an ordinary-least squares regression and from more advanced exponential random graph models (ERGM) show that the inter-industry mergers are more likely between two industries when they have stronger supplier-customer relationships, controlling for industry valuation, returns, concentration, and macroeconomic shocks. The results from the ERGM model imply that the probability that inter-industry trade relations predict inter-industry mergers is above 95%. This effect is present in every year from 1986 to 2008 and is stronger during market booms and aggregate merger waves. These results imply that economic fundamentals drive merger waves not only within an industry, but also across industries.

Next, we explore the diffusion of merger activity across the industry network. As hypothesized above, we find empirical evidence that unusually high merger activity in one industry is positively correlated with subsequently high merger activity in the industries to which it is connected through the customer-supplier network. Specifically, the occurrence of high merger activity in an industry is at least three times more likely if one of its supplier or customer industries experienced high merger activity in the prior year. The marginal probability of unusually high merger activity in the next year ranges from 75% to 99% if connected industries experience high merger activity in the current year. This result is also robust to controls for aggregate market returns, industry market-to-book, dispersion of industry returns, financing liquidity, aggregate merger volume, and the occurrence of deregulatory shocks.

This paper extends the literature on merger waves in a new direction. Prior work has investigated the role of economic shocks (Mitchell and Mulherin, 1996; Harford, 2005) versus market mis-valuation (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf, Robinson, and Viswanathan, 2005) as determinants of merger waves. We do not attempt to disentangle this issue, but rather present new evidence to explain how merger waves propagate across an economy. However, we should point out that our evidence on the importance of economic links in explaining how merger activity spreads between industries is inconsistent with a theory of mergers based on mis-valuation. In particular, purely mis-valuation driven mergers would not be expected to cluster in industry pairings with strong economic ties.

Our paper is more closely related to recent research that investigates the role of industry relations on corporate finance. In addition to Becker and Thomas (2008) and Bhattacharyya and Nain (2008) cited above, Fee and Thomas (2004) and Shahrur (2005) use vertical relationships to test the effects of horizontal mergers on market power. Hertzel, Li, Officer, and Rodgers (2008) find that suppliers to firms that file for bankruptcy suffer negative and significant wealth effects. Our paper is the first to focus on inter-industry mergers and also the first to use network analysis to study inter-industry effects.

Finally, we note that although it is generally accepted and intuitive that some mergers are motivated by vertical integration, very little about vertical mergers has actually been documented. In fact, Fan and Goyal (2006) report that prior to their paper, even basic facts such as the proportion of mergers that are vertical were unknown. Only recently, Kedia, Ravid, and Pons (2008) investigates wealth effects in vertical mergers, finding that the wealth effects are greater when market-based transactions are more uncertain. In contrast, by explicitly examining vertical relations among industries and expanding the analysis to include indirect relations in an economic network setting, we increase the understanding of the role that vertical product market relationships play in overall merger activity.

I. Data Sources and Methods

A. Industry Trade Network

Since 1967, the U.S. Bureau of Economic Analysis (BEA) has produced input-output (IO) tables of product market relations for years ending in two and seven for roughly 500 unique industries. However, the industry definitions of each BEA report differs from prior reports. This means that we must choose one of the BEA reports to use throughout our study, since our unit of observation is an industry-pair. We use the 1997 IO definitions in our study because it evenly splits our merger data (described below) into two equal time periods. The 1997 report is also concurrent with the largest aggregate merger activity in our sample period. If instead, we matched merger data to the most recent IO industry definitions, we would not be able to compare one set of industries to the prior set. The necessity of using just one IO report makes finding significant relationships between IO relations and mergers less likely as more noise is introduced.

The 1997 IO report defines commodity outputs and producing industries. An industry may produce more than one commodity (though the output of an industry is typically dominated by one commodity). The 'Make' table of the IO report records the dollar value of each commodity produced by the producing industry. There are 480 commodities and 491 industries in the Make table. The 'Use' table defines the dollar value of each commodity that is purchased by each industry or final user. There are 486 commodities in the Use table purchased by 504 industries or final users. Costs are reported in both purchaser and producer costs (the differences are due to retail and wholesale markups, taxes, and other transaction costs). The six additional commodities that are in the Use table but not in the Make table are,

1. Noncomparable imports
2. Used and secondhand goods
3. Rest of world adjustment to final uses
4. Compensation of employees
5. Indirect business tax and nontax liability
6. Other value added

The thirteen industries or final users in the Use table that are not in the Make table include personal consumption expenditures, private fixed investment, change in private inventories, exports and imports, and federal and state government expenditures. We modify the Make table to include employee compensation as a commodity that is solely produced by the employee compensation industry. This allows employee compensation to be included as an input in production. Without including labor costs, some inputs may appear to be a larger component of total inputs than otherwise.

We wish to create matrices from the Use and Make tables that record flows of inputs and outputs between industries. Following Becker and Thomas (2008) we calculate $SHARE$, an $I \times C$ matrix (Industry x Commodity) that records the percentage of commodity c produced by industry i. The USE matrix is a $C \times I$ matrix that records the dollar value of industry i's purchases of commodity c as an input. The $REVSHARE$ matrix is $SHARE \times USE$ and is the $I \times I$ matrix of dollar flows from the customer industry on column j to supplier industry on row i. Finally, the $CUST$ matrix is $REVSHARE$ in producers' prices divided by the sum of all sales for an industry (in producers' prices). The $SUPP$ matrix is $REVSHARE$ in purchasers prices divided by the sum of all purchases (in purchasers' prices) by industry. The $CUST$ matrix records the percentage of industry i's sales that are purchased by industry j. The $SUPP$ matrix records the percentage of industry j's input that are purchased from industry i. These two matrices describe the trade flows between all industries in the economy.

Because we will match merger data to the IO industries we follow the correspondence tables between the 1997 IO industries and the 1997 6-digit NAICS codes provided by the BEA. In many cases, each IO industry corresponds to one 6-digit IO industry. In other cases, a single IO industry is comprised of multiple 6-digit NAICS codes. In one case, Construction, the 2-digit NAICS code 23, corresponds to 13 different IO industries. Since we can not distinguish between the IO industries we collapse the 13 IO industries into one industry composed of all NAICS codes in the 2-digit code 23. Thus, accounting for this and including only IO industries that have corresponding NAICS codes (this excludes governments and export/import adjustments) we are left with 471 industries.

B. Merger Data

Merger data is from SDC Thomson Platinum database. We collect all mergers that meet the following criteria:

- Announcement dates between 1/1/1986 and 12/31/2008
- Both target and acquirer are U.S. firms
- The acquirer buys 20% or more of the target's shares
- The acquirer owns 51% or more of the target's shares after the deal
- Only completed mergers

Since the focus of this study is merger activity, rather than wealth effects, we do not restrict the legal form of organization of the target or acquirer. This produces a sample of 48,359 observations. By not restricting our sample to public firms, we have a much more complete sample than is typically used in existing merger research. For each observation we record the value of the deal, the date, and the primary NAICS codes of the acquirer and target. Because SDC records NAICS codes using 2007 NAICS definitions we convert all NAICS codes from SDC to 1997 NAICS codes to match to the IO data. Then for each deal we map the 1997 NAICS to the appropriate 1997 IO industry. Due to missing NAICS codes we are left with 45,695 observations.

Next, we record merger activity both yearly and cross-sectionally for each directed IO industry-pair of acquirer and target industries. This produces $471^2 = 221,841$ unique pairs. Directed industry pairs means that we differentiate between acquirer and target industries. For each time window (yearly and cross-sectionally) we record the number and dollar value of mergers where the acquirer was in industry i and the target was in industry j. This means we have separate observations for deals involving acquirers in industry i that are buying targets in industry j and deals involving acquirers in industry j that are buying targets in industry i. Since in non-horizontal mergers, it is likely that the acquirer could be in either industry, we also record the data in a non-directed way between two industries. This yields $\frac{1}{2} \times 471 \times (471 + 1) = 111,156$ unique industry pairs per window of observation.

Finally, we record the product market relations between industries from the $SUPP$ and $CUST$ matrices for both directions of relations. This means we record the percentage of total sales bought by the customer industry assuming that the acquirer is the customer and separately that the target is the customer. We do the same for the percentage of supplier inputs purchased by the customer industry, assuming the acquirer is the supplier in one variable, and assuming the target is the acquirer in the second variable.

C. Network Measures

A primary innovation of this paper is to treat the industry input-output matrix as a network. Any network can be described by an $N \times N$ adjacency matrix, A, consisting of N unique 'nodes' or 'vertices'. The nodes are connected through 'edges.' Emphasizing the importance of edges in a network, nodes are most generally defined as an endpoint of an edge. In this paper, a node is an industry and an edge is either a product market relationship or a merger relationship. Each entry in the adjacency matrix A, denoted a_{ij}, for row i and column j, records the strength of the connection between nodes i and j. A binary matrix simply records a one if there is a connection and zero if no connection, but different values may also be assigned in a weighted adjacency matrix to indicate the strength of the connection. In addition, A is not restricted to be symmetric so that connections may be directional.

To illustrate these concepts, Figure 1 presents representations of two simple networks of six industries in the timber sector. These networks are a subset of the entire IO industry network we use in later tests. Each network consists of six nodes that are connected through directed weighted edges. Panel (a) presents the network of customers as an adjacency matrix (from the $CUST$ matrix) and Panel (b) presents the non-labor supplier network as an adjacency matrix (from the $SUPP$ matrix). Panel (c) presents both the customer and supplier network in a graphical representation.

Though input-output relations are often modeled as a linear chain, Figure 1 reveals that the path from raw materials to finished goods is much more complex, even in this reduced subset of the network. The forestry support industry provides inputs into the nurseries and logging industries. Of all non-labor inputs in the forest nurseries industry, 64% are purchased from the forestry support industry (a_{21} in Panel (b)), though of all sales by the forestry support industry, only 14% are purchased by the forest nurseries industry (a_{21} in Panel (a)). Weighted asymmetric network ties are evident throughout this sector. For example, the forest nursuries industry also supplies to the logging and sawmill industries, though the connection to logging is stronger than to sawmills. Pulp mills receive inputs from both the logging and sawmill industries. Finally the sawmill industry supplies to the wood doors industry.

The complexity of networks is obvious even in such a simple subset of the data. Given a network structure, the $CUST$ and $SUPP$ matrices defined above can be thought of as adjacency matrices with 471 nodes where connections are weighted by the directional strength of the IO relationships. Using the same industry nodes, where industry connections are the number and value of mergers between industries, we generate an additional network based on the inter-industry M&A activity.

Increasing the number of nodes to 471 and increasing the number of connections exponentially provides an extremely complex network of industry relations. To analyze these networks we use techniques first developed in graph theory and social networks. We employ two measures of network centrality: degree centrality and eigenvector centrality. The degree centrality of a given node in a network is simply the number of links that come from it, answering the question: how many direct connections does it have? Formally, node i's degree centrality is the sum of its row in the network's adjacency matrix where connections are binary. If connections are weighted values, then the degree is referred to as strength.

The other centrality measure we consider is eigenvector centrality, formally defined by Bonacich (1972) as the principal eigenvector of the network's adjacency matrix. Intuitively, a node will be considered more central if it is connected to other nodes that are themselves central. If we define the eigenvector centrality of node i as c_i, then c_i is proportional to the sum of the c_j's for all other nodes $j \neq i$:

$$c_i = \frac{1}{\lambda} \sum_{j \in M(i)} c_j = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} c_j \tag{1}$$

where $M(i)$ is the set of nodes that are connected to node i and λ is a constant. In matrix notation, this is

$$\mathbf{Ac} = \lambda \mathbf{c} \tag{2}$$

Thus, $\mathbf{c}$ is the principal eigenvector of the adjacency matrix.

There are other measures of centrality and network statistics in general. We choose to focus on degree centrality and eigenvector centrality because they best reflect how shocks would propagate through an economy. Borgatti (2005) shows that these two measures capture a flow process across a network that is not restricted by prior history (such as a viral infection like chicken pox would be, since a node is immune after receiving the virus) and allows for a shock to spread in two different directions at the same time (as opposed to a package that moves along a network which can only be in one place at one time). Therefore, these measures of centrality allow an economic shock that flows to the same industry from two different sources to have a larger impact than a single shock, and allows the shock to spread in parallel to multiple industries simultaneously.

II. Empirical Tests of Mergers and Industry-Relations

A. Summary Statistics

A.1. Mergers

Figure 2 summarizes the time series of aggregate merger data in our sample. This figure primarily establishes that our merger sample is similar to those used in other studies of mergers and of clustering of merger activity in particular. As is typical, the 1980s merger wave looks rather small in comparison to the activity in the mid to late 1990s. The most recent wave that began in 2003–2004 now has a clear end in 2008 due to the financial crisis.

Table I describes the industry-level merger data. In the entire sample across all years, there are a total of 45,695 mergers and acquisitions representing total deal value of \$14.3 trillion in 2008 dollars. Of these, 20,428 are intra-industry, horizontal mergers, representing \$6.9 trillion in deals. The remaining 25,267 deals are inter-industry deals, accounting for \$7.4 trillion. From the 471 IO industries, there are 110,685 possible pairwise inter-industry combinations. Across all of these, the average industry pair had 0.23 mergers over the 23 year sample period and 95% had no mergers at all. This means that though inter-industry mergers are more common than intra-industry mergers in our sample, they are not uniformly distributed across industry-pairs, but rather, are highly clustered. Out of all 110,685 industry-pairs, only five percent of the pairs account for all 25,267 inter-industry deals.

Looking across all possible inter-industry pairings for any given industry, the mean number of cross-industry mergers for an industry is 53.7 and the median is 13. This compares with an average of 43.4 and median of 4 for intra-industry mergers. Twenty percent of industries had no intra-industry mergers during the sample period, compared with 2.6% for inter-industry mergers. These summary statistics indicate that mergers cluster by industry and also by industry-pairs. Second, using a more refined measure of industry classifications than Fama-French 49 or two-digit SIC codes reveals that inter-industry mergers are slightly more common than intra-industry mergers, in contrast to most reports.

A.2. Industry Input-Output Relationships

Table II presents summary statistics of the input-output relationships. We divide the sample into inter-industry pairs, intra-industry pairs, and inter-industry pairs that have substantial trade relations. To identify industry pairs with a substantial relationship, we follow Fan and Goyal (2006) and require either (1) that a customer industry buys at least 1% of a supplier industry's total output (Customer %), or (2) that a supplying industry supplies at least 1% of the total inputs of a customer industry (Supplier %). This is necessary since most industry-pairs have almost zero trade relationships. Across all 110,685 inter-industry pairs the mean percentage of sales purchased by a customer is only 0.22%. Likewise, the percentage of inputs that one industry supplies to another in an average industry-pair is only 0.26%. More than 95% of industry-pairs have customer and supplier relationships less than 1%. This matches the merger sample, where 95% of industry-pairs had no inter-industry mergers.

In the inter-industry pairs with substantial trade flows, the average percentage of total sales purchased is 5% and the median is 2.2%. The average percentage of total inputs supplied is 3.9% and the median is 2.1%. Intra-industry pairs also exhibit trade flows. In this case the industry uses a portion of its output as an input. For example, a firm that produces energy must also use energy in its production process. The median supply and customer relationships are 1.1% and 1.5% and close to 50% of industries have supplier and customer relationships less than 1%.

To visually compare merger activity to product market relationships, Figure 3 plots the number of mergers, the supplier percentage, and the customer percentage, each in the 471×471 grid of IO industries. The ordering of industry numbers follows the IO industry numbering, which roughly follows the NAICS ordering convention. Each coordinate in the grid reflects an industry-pair. The diagonal represent intra-industry relationships. Darker points indicate either more mergers in Panel A, or a higher percentage of customer/supplier relationships in Panels B and C. When there is no merger activity or industry relationship, the grid is white. This figure does not record directionality of the merger or trade relationship, so only the lower triangular area is relevant.

The large amount of white space in each sub-figure in Figure 3 reflects the clustering by industry-pairs reported in Tables I and II. Just as each industry only trades with a select few customer and supplier industries, mergers also cluster by industry-pairs. In addition, certain industries are important suppliers and customers of many other industries. In particular, the horizontal lines in the Supplier Relationship figure at 428 (Management of companies and enterprises), 378 (Wholesale Trade), 408 (Real Estate), and 407 (Monetary Authority and Depository Credit Intermediation) reflect that these industries comprise a significant part of the input costs of the majority of industries. Likewise, the vertical lines in the Customer Relationship figure at 33 (Construction) and again 378 (Wholesale Trade) reflects the importance of these two industries as customers of most other industries. The clustering of mergers displays a similar pattern where many inter-industry mergers include the same industries, notably 407 (Monetary Authority), 408 (Real Estate), and 378 (Wholesale Trade).

A.3. Network Measures

The above results indicate that mergers and product-market relationships are concentrated in specific industry-pairs. The visual evidence in Figure 3 also emphasizes that industries are connected through a network of trade. In this section, we investigate these networks in more detail.

In Table III, we present the 15 most central industries in the IO network and those in the merger network according to degree centrality. The 'Management of companies and enterprises' industry is the most central industry in the IO network. This is not surprising since this industry comprises firms that hold securities of companies and consists mainly of financial holding companies, typically banks. The other industries that are central in the IO network are also not surprising: Wholesale and retail trade, real estate, construction, motor vehicle parts, and the others are clearly important and well-connected industries.

Many of the most central industries in the IO network are also among the most central in the merger network. These are the industries that had inter-industry mergers with the largest number of different industries, not necessarily the most mergers overall. This means that these industries are also well-connected through mergers, just as in the IO network. While not a formal test, one can immediately see that there is a fair amount of overlap between the lists. Wholesale and retail trade, real estate, motor vehicle parts, management of companies and enterprises, and telecommunications are ranked in the top 15 of both centrality measures. The high amount of overlap indicates that industries that are economically central are also central in the merger network – being involved in many inter-industry mergers.

B. Tests of the Relationship Between Merger and IO Networks

We now conduct formal analyses of our hypothesis. The first is a traditional correlation analysis, testing whether industries with high IO centrality also have high inter-industry merger centrality. We use both measures of centrality: degree centrality (the number of other industries to which each industry is connected) and eigenvector centrality (the sum of weighted connections to a given industry, weighted by how connected the other industry itself is).

Table IV presents the correlation matrix for the centrality measures. Within each network, the two centrality measures are highly correlated, more so in the merger network. More importantly, the centrality measures are correlated across networks, so that central industries in the IO network are likely to be central industries in the merger network. For industry eigenvector centrality, the correlation between the IO and merger networks is a significant 35.15%. For degree centrality, the correlation is 26.32%, also highly significant.

The second analysis of the relation between the IO network and the merger network uses a network analysis technique called Exponential Random Graph Models (ERGM). Essentially, ERGM treats the entire network as an outcome to be explained or predicted, much as we might typically treat an announcement return as a dependent variable to be explained. Somewhat more specifically, ERGM tries "to describe parsimoniously the local selection forces that shape the global structure of a network."[1]

[1]An excellent overview of ERGM is provided in Hunter, Handcock, Butts, Goodreau, and Morris (2008, p. 2). For more technical references see the papers cited in Robins and Morris (2007).

To make the fundamental idea of ERGM more concrete, given a set of N nodes, if we let G denote a random graph on these nodes (i.e., a random set of connections), and let g denote a particular graph on the N nodes, then,

$$P_\theta(G = g) = \frac{\exp\{\theta' s(g)\}}{\sum_{\text{all graphs } h} \exp\{\theta' s(h)\}} \tag{3}$$

where

$$\theta \equiv \text{An unknown vector of parameters} \tag{4}$$

$$s(g) \equiv \text{A known vector of network statistics on } g \tag{5}$$

Similarly to a maximum-likelihood estimator, we wish to estimate θ, the unknown parameters of the model, which are the coefficients on the $s(g)$. However, finding all possible random graphs is computationally challenging. As a feasible alternative, Markov Chain Monte Carlo simulations of the random graphs are performed.

In our context, the local forces we focus on are edge covariance. While we previously conceptualized the IO network and merger network as two separate networks to be compared, they can just as easily be thought of as a single network of industries with two different types of edges – one type describing IO connections between industries and another type describing merger connections between the same set of industries. As the edge covariance's name suggests, it formally analyzes the degree to which the two different types of edges in the network covary. Specifically, controlling for the number of possible edges in the network, it assesses the ability of IO edges to predict merger edges. This measure considers the network as a whole and we will perform the analysis on both the annual merger networks as well as the overall merger network formed by taking all mergers over our sample period. Additionally, this technique can take into account the strength of the connection, so it is assessing more than just whether an economic IO connection predicts a merger connection. Rather, we can ask whether strong economic connections predict high rather than low merger activity.

We present the results of the ERGM analysis in Table V and Figure 4. The coefficient estimates measure an independent variable's marginal effect on the conditional log-odds ratio of the likelihood of the strength of a connection in the merger network. The independent variables are the collection of connections in each of four IO networks. The first network, 'Target Buys from Acquirer' is the industry network where connections between industries are the dollar values of the Target's industry's purchases from the Acquirer's industry. The coefficient estimate of the variable 'Connections,' measures the marginal change on the M&A network from adding a random connection. Since the independent variables are networks, the 'Connections' variable is similar to a constant variable in an OLS regression.

It is clear from the results in Table V that the IO network explains the merger network. In the cross-sectional ERGM analysis, each of the four ways of measuring the industry trade network has a positive and significant coefficient. Further, as there are four different ways of assessing the economic connection, we test each. We have no a priori reason to believe that one measure of the economic connection between two industries is inherently more important for predicting merger activity than another. Since a log-odds ratio above six implies a probability of 99%, all of the IO networks are highly predictive of the M&A network. When we include all four together, we find that they all significantly predict the merger network, each incrementally contributing to an understanding of the occurrence and intensity of merger activity between industries. This is reflected in the lower Akaike Information Criterion (AIC) score in the fifth regression. The AIC measure indicates the goodness-of-fit *between* the models, but the level of an AIC score is uninformative by itself.

In column 6 of Table V we add industry characteristics that have been shown to affect mergers as additional explanatory variables. The industry economic shock index is calculated similarly to Harford (2005). For each industry, we find the first principal component of the medians of the absolute value of changes in cash flow, asset turnover, R&D, capital expenditures, employee growth, return on assets, and sales growth for each firm in the industry. We rank this principal component across industries and time and choose industry-years in the top quartile as "shock" years. This variable measures shocks to economic fundamentals at the industry level. We also add the median market-to-book, mean returns, and standard deviation of returns for all firms in each industry, using data from Compustat and CRSP. Lastly, we include the eight-firm concentration ratio as provided by the most recent Economic Census of the United States. Since these tests are cross-sectional, we take the average of the time series of each of these variables as our control variables.

After including these control variables we find that the industry connections are still positively and significantly related to merger activity. In fact all of the coefficient estimates of the IO connections increase after adding the controls. This result is particularly strong since the data limitations of the control variables reduces the size of the network in the analysis, and hence the strength of the industry connection variables. Though these tests account for an average effect of the control variables, the interpretation of their effect on merger activity is unclear since they are likely to change over time. Therefore, we separately estimate ERGMs for each year in the sample period.

Figure 4 presents the $t-$statistics from each of the four explanatory IO networks in ERGM tests which are run using yearly M&A network data. The edge covariance coefficients are highly significant in each year, as they were in the overall sample. We note that the importance of industry connections is not smaller during aggregate merger waves or periods of high stock market valuation. That is, economic connections between industries are more important in explaining merger activity during waves than at other times. This is consistent with the hypothesis that shocks propagating through the IO network generate aggregate merger waves. In unreported results, the $t-$statistics of the industry-level control variables vary considerably over time, in contrast to the much more stable $t-$statistics of the IO network variables.

Although ERGM analysis is the best way to analyze our question, it is new to the literature. As a check, we repeat our analysis with OLS regressions. Regressing the value and count of mergers between industries on the four measures of their IO connectedness produces the same inferences – IO connections are highly significant in explaining merger activity.

Our overall conclusion from the analysis in this section is that the IO network is quite important in explaining merger activity, as represented in the merger network. Consequently, in order to better understand why mergers occur and why they cluster in time, one needs to consider the merger activity in the context of the economic IO network and the activity in connected industries. In the next section, we ask exactly that question: whether we can dynamically explain merger activity in a given industry with merger activity in connected industries.

C. Diffusion of Merger Activity Across the Industry Network

Prior work has made some progress toward understanding periods of heightened merger activity within industries and in the economy as a whole — so called merger waves. Gort (1969), Mitchell and Mulherin (1996), and Harford (2005) all point to economic disturbances that motivate asset reshuffling within and across industries. Some recent work has focused on specific industry connections such as Fee and Thomas (2004), Shahrur (2005), and Hertzel, Li, Officer, and Rodgers (2008), who focus on vertical relations.

To date, however, no one to our knowledge has considered a model of merger activity within an industry based on heightened merger activity in all connected industries. In this section we test such a model using the merger activity in connected industries, weighted by the distance between industries in the network, to predict merger activity within the primary industry. First, to illustrate how diffusion of merger activity across related industries occurs, we present an example from the timber-related industries we discussed above.

C.1. Diffusion of Mergers Across the Forest Industry

The forest industry is an ideal setting to illustrate merger diffusion because it experienced a large external shock which led to a subsequent reorganization of various industries. In 1990, the Northern Spotted Owl was listed as “threatened” under the Endangered Species Act. Further injunctions in 1991 and the enactment of the Northwest Forest Plan in 1994 led to the protection of 24.4 million acres of federal land in Washington, Oregon, and California, the historic home of the timber industry (Ferris, 2009). At the time, much of the timber supply came from logging on federal land. Smaller sawmills and logging companies that relied on the federal lands were squeezed out by larger suppliers that owned private nurseries. In addition, the industry moved away from the Northwest and towards the South were timber tracts were privately owned. However, the protection of the old-growth timber led to a severe and permanent supply shock.

Panel (a) of Figure 5 presents the time-series of the volume and price of timber in Oregon from 1986 to 2008. The volume of timber harvested dropped precipitously from about 8.5 billion board feet in 1989 to about 4 billion board feet in 1997. This supply shock caused the price index of timber to rise from 6,155 in 1989 to 11,047 in 1993 and then decline to 7,913 in 1997. Though, these data are from Oregon, it is indicative of the effect at the national level, since the forest industry was concentrated in the Pacific Northwest.

The timber supply and price shock led to a large-scale consolidation in timber-related industries. Recall from Figure 1, the timber sector is comprised of a number of industries that are inter-related through trade. Panel (b) of Figure 5 presents the merger activity from 1990 to 2005 in the following industries: 1) sawmills, 2) forest nurseries, forest products, and timber tracts, 3) logging, and 4) pulp mills. To compare merger activity across the industries, for each industry-year, we calculate the percentile of the number of mergers involving firms in each industry over the period 1986 to 2008. We then take the two-year moving-average of the percentile time-series.

First, the sawmill industry (indicated by the solid line in Panel (b) of Figure 5) experienced a large merger wave starting in 1994 and ending in 1999, its largest merger activity over the 23-year sample period. Next, the forest nurseries industry (dashed line) experienced its largest merger wave in our sample period from roughly 1996 to 2001. Following this, both logging (dotted line) and pulp mills (circled line) experienced large merger waves, with merger activity peaking in 1999 and 2000, respectively.

Panel (b) shows a clear time sequence of industry waves in related industries. Notice that all of the waves do not correspond directly with the aggregate merger wave in the late 1990s as shown in Figure 2, since that wave peaked in 1997-1998. Thus the aggregate merger wave is a collection of industry merger waves that begin and die within the overall aggregate wave. Also notice that the pulp mills industry was the last to experience a merger wave. This is consistent with our hypothesis since it is less related to the timber industry than the other three industries.

Panel (c) of Figure 5 presents the same industry time-series of merger activity where the leading industries have been shifted back in time to match the timing of the sawmills industry merger wave. Matching the one-period leading merger activity in the forest nurseries industry, and the three-period leading activity in logging and pulp mills industries to the sawmill industry merger wave presents a striking picture. The duration, intensity, and general shape of all four industry-merger waves are highly comparable. In fact, though the figure shows only the 1990s, the merger activity between the time-shifted industry series over the whole sample period 1986 to 2008 are significantly correlated. For instance, the correlation between the current merger activity in the sawmill industry with the one-period leading merger activity in the forest nurseries industry is 72.8% ($p-$value< 0.001). The correlation between current activity in the sawmill industry and the three-period leading activity in the pulp mills industry is 61.1% ($p-$value$= 0.007$).

The evidence presented on the timber-related industries lends support to the importance of industry links in merger waves. A distinctive economic shock changed the fundamental economic environment in the sawmill and logging industries. Each responded through mergers. This in turn had an affect on forest nurseries and pulp mills, which also responded to the new environment through an industry merger wave. Though these results are consistent with our hypothesis, we still need to show that the results generalize to other industries. We pursue this goal in the next section.

C.2. Formal Tests of Merger Diffusion Across the Industry Network

In this section, we present the results from rigorous tests of the diffusion of merger activity across the industry network. In order to do so, we create a measure of weighted merger activity, where the weights are proportional to the strength of the economic connection to the industry with the merger activity. Intuitively, what this measure captures is the value of merger activity in industries connected to i, not counting merger activity involving i itself, weighted by the strength of the connection. Specifically, for each industry in each year we calculate the total value of deals involving a member of industry j. This includes both intra-industry (horizontal) and inter-industry mergers. Next, we subtract from that total the value of any deals involving industry i. Finally, we multiply the resulting value by one of the measures of IO connection between industry i and industry j and sum this product for all industries $j \neq i$. In mathematical notation, this is:

$$Connected\ M\&A_{it} = \sum_{j \neq i} a_{ij} \left[\sum_{k \neq i} v_{kjt} + \sum_{\substack{k \neq i \\ k \neq j}} v_{jkt} \right] \tag{6}$$

where a_{ij} is the row i, column j entry from the IO network adjacency matrix and v_{kjt} is the row k, column j entry from the directed and valued merger network in year t, where acquirers are on rows and targets on columns and the values are the 2008 dollar values of merger activity.

This measure is central to our question of how merger activity propagates through the economy. One industry may be subject to a specific technological, regulatory or economic shock and respond by reshuffling assets through mergers and acquisitions. That very reshuffling may itself be considered a shock to connected industries, causing them to reorganize assets as well. An example of this is the record industry's reorganization following the merger wave in the media distribution industry discussed in the introduction.

To test the relationship, we estimate models intended to predict merger activity in industry i in year $t+1$ using a host of industry and macroeconomic characteristics in year t, as well as our measure of weighted connected merger activity in year t. Specifically, we estimate the following logit model:

$$\begin{aligned} \textit{High M\&A}_{i,t+1} = {} & \alpha + \beta_0 \textit{High M\&A}_{i,t} + \beta_1 \textit{Connected M\&A}_{i,t} \\ & + \gamma \textit{Network Measures}_t \\ & + \delta \text{Controls}_t + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where $\textit{High M\&A}_{i,t+1}$ equals 1 if the aggregate value of mergers in industry i in year $t+1$ is in the highest quartile of aggregate merger value across all years for industry i. In addition to the measure of weighted connected merger activity, we include the industry's centrality as well as its centrality multiplied by the scaled total value of merger activity in year t. We also include the annual return on the S&P 500, an indicator variable for deregulatory events affecting the industry from Viscusi, Harrington, and Vernon (2005), the spread between commercial and industrial loans and the federal funds rate (the C&I rate spread), industry-level median market-to-book ratio, mean and standard deviation of returns, industry concentration, and the economic shock index decsribed previously. Table VI summarizes the key data used in the estimations.

The first four columns of Table VII present odds ratios from a logit predicting high merger activity in an industry in year $t+1$ based on whether it had high activity in year t and our measures of connected merger activity in year t. The odds ratios are normalized by subtracting by one, so that a positive coefficient indicates an increase in the odds ratio, and a negative number indicates a decrease. We use each of the four IO networks weighting schemes in the Connected M&A variables.

The four specifications consistently show that the level of merger activity in connected industries increases the likelihood that an industry's own merger activity in the subsequent year will also be unusually high. The odds ratios show that the effects are larger when the connected industries rely on the subject industry either as a key customer (Subject Buys from Connected) or as a key supplier (Subject Sells to Connected).

In the last four columns, we add the rest of the explanatory variables. Again, the columns differ only by the IO measure used to weight connected industry merger activity, though we lose a substantial portion of the data due to Compustat and CRSP limitations. The connected industry merger activity remains significant, as does the relatively greater importance of the two weighting schemes based on the acquirer's sales and purchases. The coefficients on the annual return on the S&P 500, the industry mean return and market-to-book ratio are positive, consistent with prior findings that rising stock markets are correlated with merger activity. Consistent with Harford (2005) and Rhodes-Kropf and Robinson (2008), tighter capital, as indicated by a higher commercial and industrial rate spread, reduces overall merger activity. Surprisingly, the standard deviation of industry returns is negatively related to subsequent merger activity. In unreported results, we include only the macro-economic variables in the regressions in order to maintain the same sample size as in the parsimonious specifications in columns one through four and find the estimates to be qualitatively unchanged.

In further robustness tests, we calculate a measure of connected M&A activity by weighting connected M&A activity by the network distance between the subject industry and every other industry. This approach takes the entire network into consideration. Though the strength of the connected M&A variables are weaker they are still significant and positively related to high merger activity in the subject industry. These results show that controlling for variables that may proxy for growth opportunities, misvaluation, and financing liquidity, the network variables remain positively and significantly related to subsequent merger activity.

The results in Table VII highlight the importance of industry shocks in explaining merger activity. They show that the effect of a shock to a particular industry can travel through the economic network created by input-output relations among industries. In fact, heightened merger activity in connected industries can, by itself, be viewed as a shock to an industry, inducing its own merger activity in response. Viewing merger activity through the lens of industries with interconnections of varying strengths, it is not surprising that more central (more interconnected) industries are less likely to experience peak merger activity outside of an aggregate merger wave. Their very centrality means that intense merger activity in any of the most central industries would be likely to set-off increased merger activity in many other industries, contributing to an aggregate wave.

III. Conclusion

This paper models industries as nodes in a network which are interconnected on multiple dimensions, including industry trade flows and inter-industry merger activity. We hypothesize that economic shocks that affect one industry will also affect the industries that are connected through the network. A shock may lead to mergers in an industry as it adjusts to the new economic environment. We expect to see increased merger activity in the connected industries in direct response to the underlying economic shock which passes through the trade network, or in response to the merger activity in the first industry.

We find strong empirical evidence for our hypothesis. Using input-output data from the U.S. Bureau of Economic Analysis and a very large sample of mergers from SDC over 1986 to 2008, we first show that the network of inter-industry mergers is highly related to the industry trade network. We find this result using the correlation of centrality measures of the two networks, in simple OLS regressions, and in more sophisticated exponential random graph models that account for the complexity of the networks.

We next show that merger waves flow across the industry-trade network. Abnormally high merger activity in one industry leads to subsequently high merger activity in those industries with the strongest connections through the trade network. This result is robust to macroeconomic factors, such as the market return, aggregate merger activity, the cost of debt financing, and regulatory shocks.

The primary innovation of this paper is to model merger waves in a network setting where networks are defined by actual trade flows across industries. Using the well-developed techniques from network and graph theory, we are able to analyze a much more complex dynamic process of merger waves than has been done in prior research. More generally, this is the first paper to model inter-industry trade flows as a network. We believe that this approach will prove to have a multitude of applications in financial economics, beyond merger waves.

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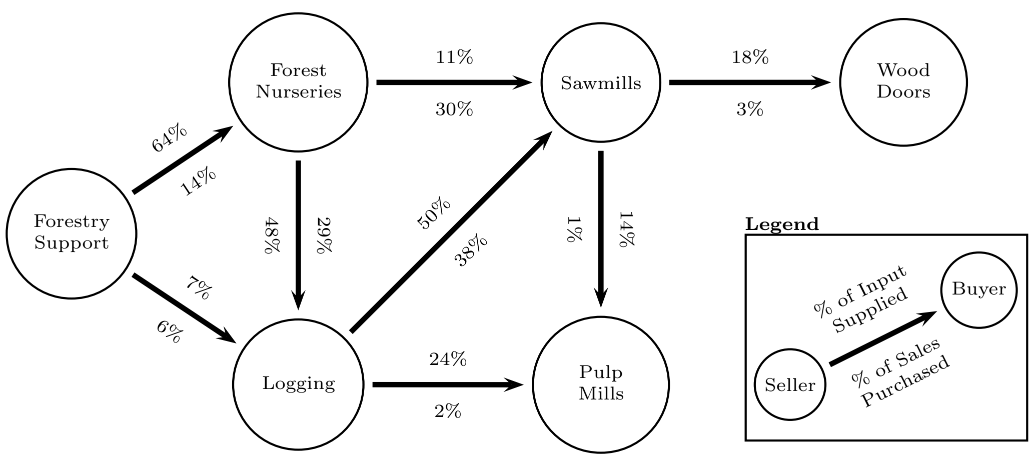
$$\begin{array}{l} \text{Forestry Support} \\ \text{Forest Nurseries} \\ \text{Logging} \\ \text{Sawmills} \\ \text{Pulp Mills} \\ \text{Wood Doors} \end{array} \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 14 & 0 & 0 & 0 & 0 & 0 \\ 6 & 48 & 21 & 0 & 0 & 0 \\ 0 & 30 & 38 & 9 & 0 & 0 \\ 0 & 0 & 2 & 1 & 1 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \end{pmatrix}$$

(a) Adjacency Matrix Representation of the Timber Network (% of Sales Purchased)

$$\begin{array}{l} \text{Forestry Support} \\ \text{Forest Nurseries} \\ \text{Logging} \\ \text{Sawmills} \\ \text{Pulp Mills} \\ \text{Wood Doors} \end{array} \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 64 & 1 & 1 & 0 & 0 & 0 \\ 7 & 29 & 41 & 0 & 0 & 0 \\ 0 & 11 & 50 & 17 & 0 & 0 \\ 0 & 0 & 24 & 14 & 1 & 0 \\ 0 & 0 & 0 & 18 & 0 & 1 \end{pmatrix}$$

(b) Adjacency Matrix Representation of the Timber Network (% of Input Supplied)



(c) Graphical Representation of the Timber Network

Figure 1
The Timber Industry Network
This figure presents the adjacency matrices of subsets of the customer and supplier networks from the 1997 U.S. Bureau of Economic Analysis Input-Output tables. The column labels of the adjacency matrices are the transpose of the row labels, and are omitted for brevity. Each entry of the adjacency matrix in Panel (a) is the percentage of total sales of the column industry that is purchased by the row industry. Each entry in the adjacency matrix in Panel (b) is the percentage of total non-labor input costs of the row industry that are purchased by the column industry. Panel (c) presents both adjacency matrices in a graphical representation. The arrows point from suppliers to customers. The number on the top of the arrow is the percentage of input supplied to the customer industry from the adjacency matrix in Panel (b). The number on the bottom of the arrow is the percentage of sales purchased by the customer industry from the adjacency matrix in Panel (a).

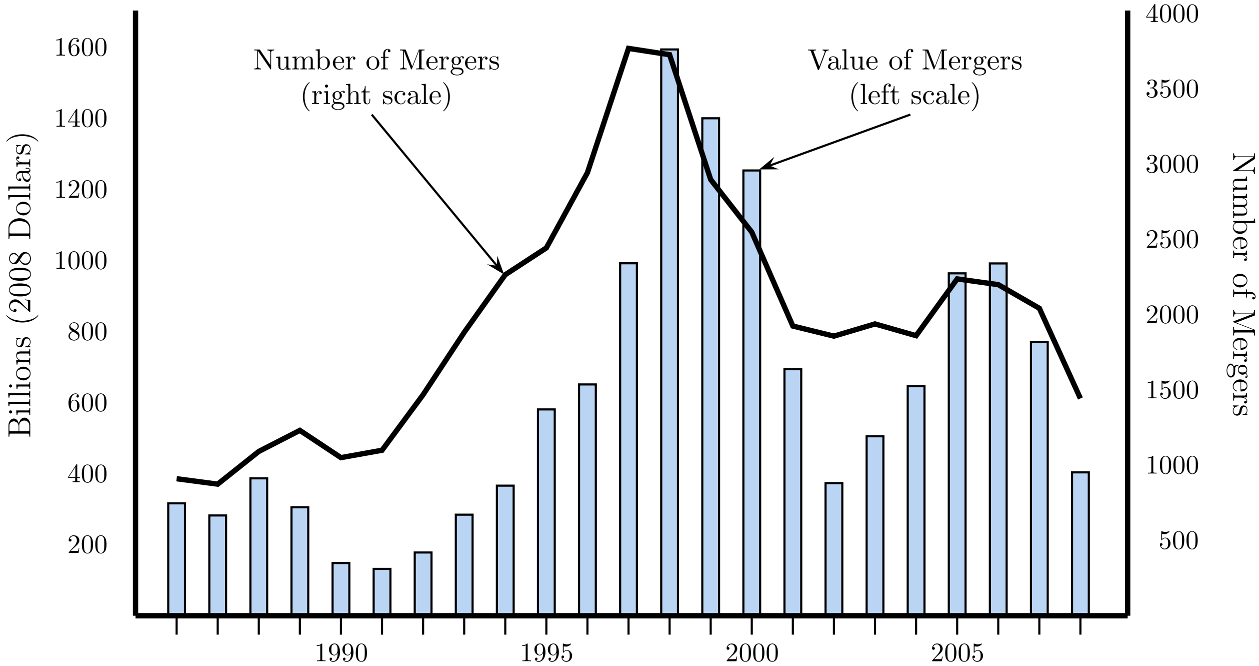
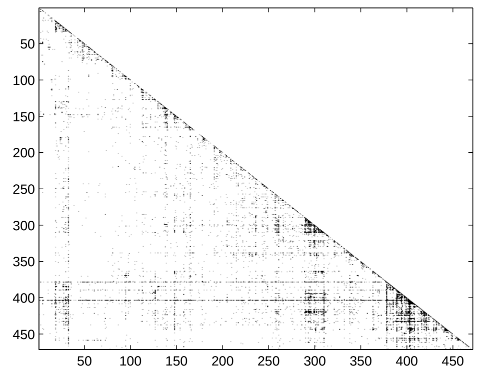
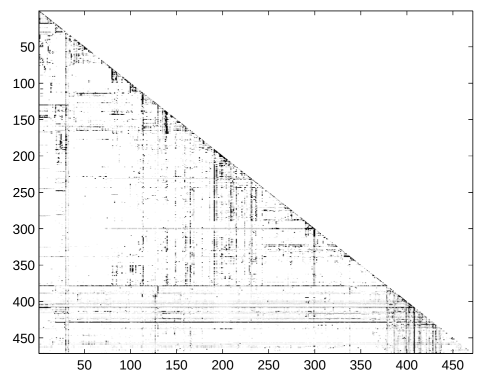


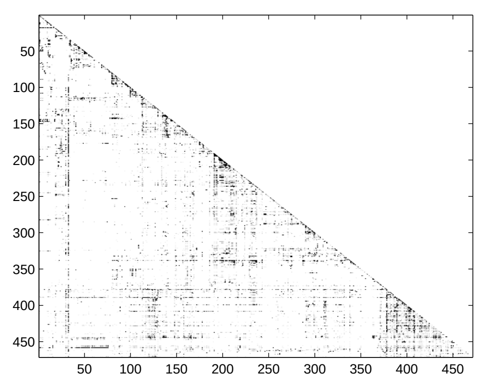
Figure 2
Dollar Value and Number of Mergers, 1986–2008
Aggregate merger volume in 2008 adjusted U.S. dollars and by the number of mergers. Merger data is from SDC.



(a) Mergers



(b) Supplier Relationships



(c) Customer Relationships

Figure 3
Merger and Trade Relations in IO-Industry Space
This figure represents merger activity and industry relations in the 471×471 grid of IO industries. In the merger figure, darker points represent more mergers. In the supplier and customer figures, darker points represent a higher percentage of supplier or customer relationships. The supplier and customer data is from the 1997 IO Tables produced by the U.S. Bureau of Economic Analysis. The merger data is over 1986–2008 from SDC.

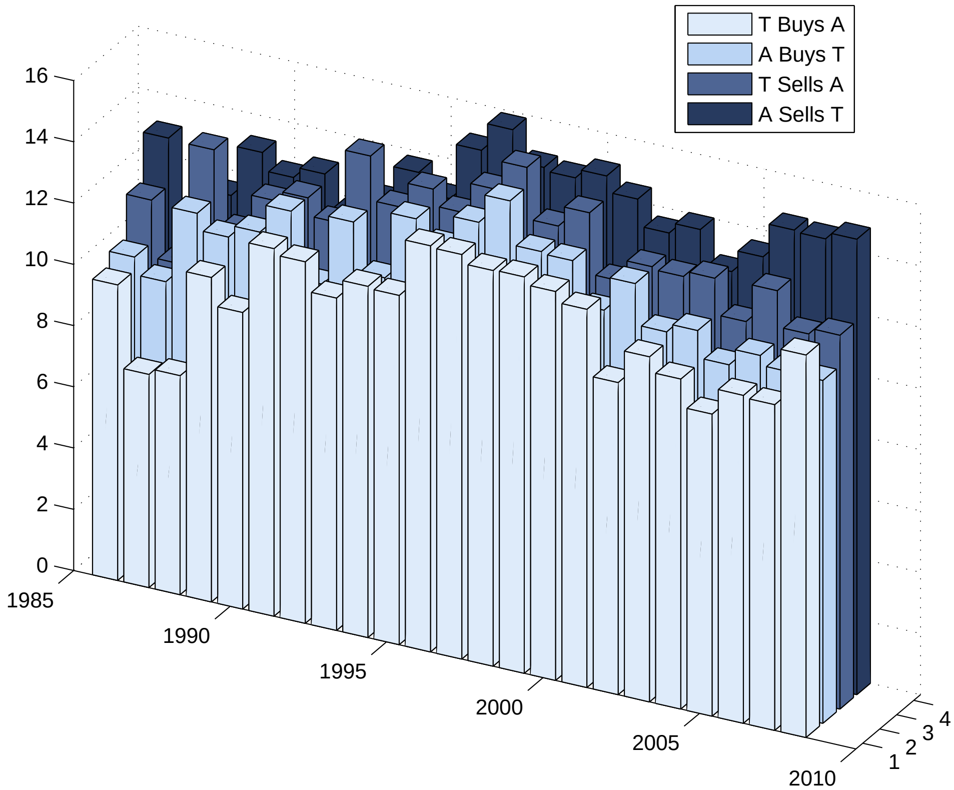
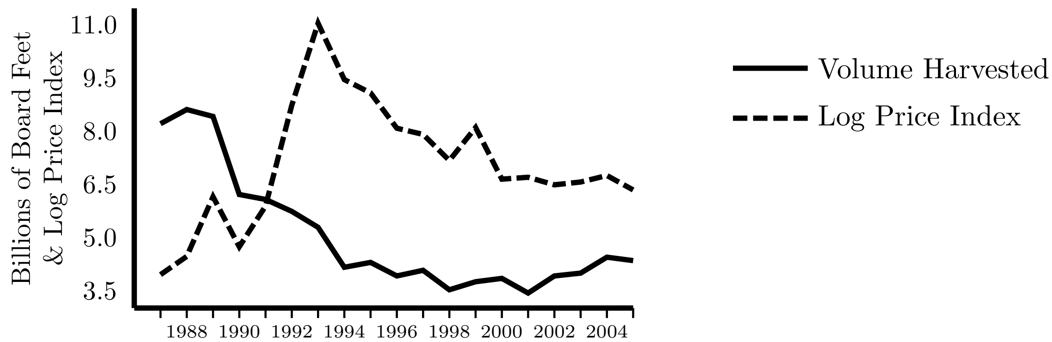
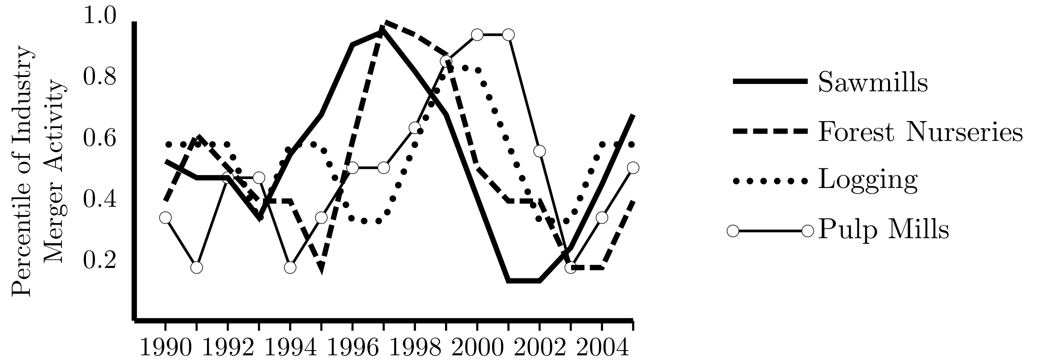


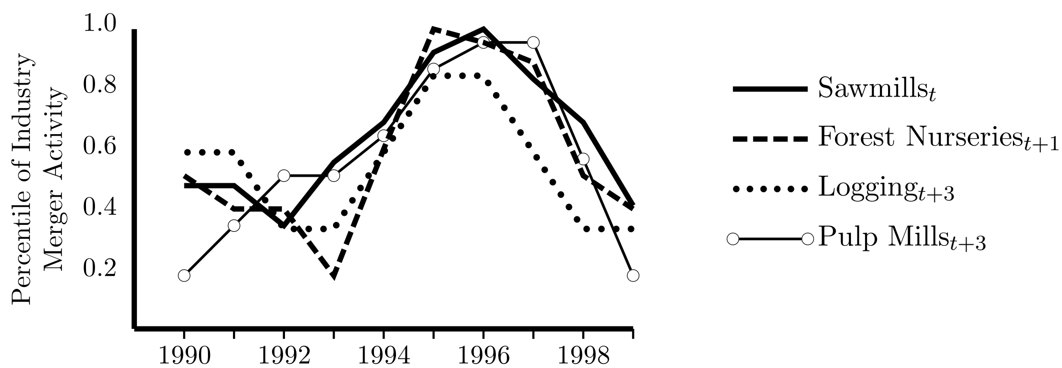
Figure 4
$t-$Statistics from Yearly ERGM Tests
This figure represents the $t-$statistic on each of the four IO networks (T Buys A, A Buys T, etc.) from yearly ERGM tests from 1986 to 2008.



(a) Oregon Timber Industry



(b) Coincident Merger Activity



(c) Leading Merger Activity

Figure 5
Diffusion of Merger Activity in Timber-Related Industries
Panel (a) presents the volume (in billions of board feet) and log price index for Oregon timber. Data is from the Oregon Department of Forestry, Annual Timber Harvest Reports. Panel (b) presents the industry merger activity in four Bureau of Economic Analysis IO industry classifications: 1) Sawmills, 2) Forest nurseries, forest products, and timber tracts, 3) Logging, and 4) Pulp Mills. For each industry-year, we calculate the percentile of the number of mergers involving firms in each industry over the period 1986 to 2008. We then take the two-year moving-average of the percentile time-series. Panel (c) presents the same data, but using the one-year leading data for Forest nurseries, and the three-year leading data for Logging and Pulp Mill mergers. Merger data is from SDC.

Table I
Merger Summary Statistics
This table presents summary statistics of the sample of mergers over the period 1986 to 2008 by industry pairs. Merger data is from SDC. Industries are defined by the 1997 Bureau of Economic Analysis Input-Output (IO) Detailed Industry classification. Inter-industry pairs include all combinations of the 471 industries (excluding own-industry pairs). Industry-level observations are observations at the IO Industry level. Intra-industry observations include mergers of firms that are in the same IO industry. Inter-industry observations at the industry-level includes all inter-industry mergers across all other industries for each of the 471 industries divided by two, since each inter-industry merger is double-counted at the industry-level. 2008 millions of US dollars are reported in brackets.

			Industry-Level	
	Inter-Industry Pairs		Inter-Industry	Intra-Industry
Observations	110,685		471	471
Total mergers	25,267		25,267	20,428
	[$7,424,778]		[$7,424,778]	[$6,862,942]
Mean	0.23		53.65	43.37
	[$67.08]		[$15,763.86]	[$14,571.00]
Median	0.00		13.00	4.00
	[$0.00]		[$2,086.60]	[$225.04]
5th Percentile	0.00		1.00	0.00
	[$0.00]		[$31.04]	[$0.00]
95th Percentile	1.00		251.45	170.80
	[$2.88]		[$62,223]	[$43,927]
Maximum	507.00		2,605.50	3,471.00
	[$259,601]		[$1,277,891]	[$1,223,366]
Frequency Percentage				
None	94.74%	None	2.55%	20.38%
1	3.00	1	2.55	11.68
2	0.85	2–5	16.56	26.54
3	0.37	6–20	37.79	21.44
4	0.22	21–50	15.71	8.70
> 4	0.82	> 50	19.11	11.25

Table II
Input-Output Summary Statistics

This table presents summary statistics of the Input-Output relationships of industries as defined by the 1997 Bureau of Economic Analysis Input-Output (IO) Detailed Industry classification. Inter-industry pairs include all combinations of the 471 industries (excluding own-industry pairs). Inter-industry pairs > 1% are only those observations where either Customer % or Supplier % is greater than 1%. Intra-industry observations include relations of firms that are in the same IO industry. Customer % is the percentage of industry i's sales that are purchased by industry j. Supplier % is the percentage of industry i's inputs that are purchased from industry j. All numbers, except observations, are in percentages.

	Inter-Industry Pairs		Inter-Industry Pairs > 1%		Intra-Industry	
	Customer %	Supplier %	Customer %	Supplier %	Customer %	Supplier %
Observations	110,685	110,685	3,799	5,279	471	471
Mean	0.22	0.26	5.06	3.92	3.31	4.51
Median	0.01	0.01	2.19	2.09	1.14	1.47
5th percentile	0.00	0.00	1.06	1.06	0.00	0.00
95th percentile	0.62	0.96	18.26	11.90	12.46	17.19
Frequency Percentage						
0%–1%	96.57	95.23	—	—	47.35	41.83
1%–2%	1.57	2.26	45.64	47.32	12.53	14.44
2%–3%	0.62	0.85	17.93	17.83	6.58	5.73
3%–4%	0.33	0.45	9.58	9.43	4.25	4.03
4%–5%	0.19	0.30	5.53	6.31	5.94	3.40
> 5%	0.73	0.91	21.32	19.11	23.35	30.57

Table III

The Most Central Industries in the IO and Merger Networks

Degree centrality is an industry's number of inter-industry connections. IO degree centrality is measured using the binary connections in the Input-Output Network using data from the U.S. Bureau of Economic Analysis for 1997. A binary connection is defined as a connection where one industry either supplies at least 1% of the connected industry's inputs, or buys at least 1% of the connected industry's output. Merger degree centrality is measured using the binary network of inter-industry mergers, where a binary connection is defined as any inter-industry mergers between two industries over 1986 to 2008.

IO Degree Centrality		Merger Degree Centrality	
1	**Management of companies and enterprises**	1	Securities, commodity contracts, investments
2	**Wholesale trade**	2	**Wholesale trade**
3	Power generation and supply	3	**Retail trade**
4	Construction, maintenance and building repair	4	Business support services
5	**Real estate**	5	Management consulting services
6	**Retail trade**	6	Architectural and engineering services
7	Iron and steel mills	7	**Motor vehicle parts manufacturing**
8	Plastics plumbing fixtures and all other plastics products	8	**Real estate**
9	Paperboard container manufacturing	9	Waste management and remediation services
10	**Motor vehicle parts manufacturing**	10	Scientific research and development services
11	**Telecommunications**	11	Computer systems design services
12	Monetary authorities and depository credit intermediation	12	**Management of companies and enterprises**
13	Food services and drinking places	13	Other ambulatory health care services
14	Petroleum refineries	14	**Telecommunications**
15	Other basic organic chemical manufacturing	15	Software publishers

Table IV
Correlation Between IO and Merger Network Centrality Measures
Degree centrality is an industry's number of inter-industry connections. IO degree centrality is measured using the binary connections in the Input-Output Network using data from the U.S. Bureau of Economic Analysis for 1997. A binary connection is defined as a connection where one industry either supplies at least 1% of the connected industry's inputs, or buys at least 1% of the connected industry's output. Merger degree centrality is measured using the binary network of inter-industry mergers, where a binary connection is defined as any inter-industry mergers between two industries over 1986 to 2008. Eigenvector centrality is the principal eigenvector of the network's adjacency matrix. $p-$values are reported in parantheses. Statistical significance is indicated by ***, **, and *, for the 0.01, 0.05, and 0.10 levels.

	IO Degree Centrality	IO Eigenvector Centrality	M&A Degree Centrality
IO Eigenvector Centrality	0.4026***		
	($<$ 0.0001)		
M&A Degree Centrality	0.2632***	0.4279***	
	($<$ 0.0001)	($<$ 0.0001)	
M&A Eigenvector Centrality	0.2594***	0.3515***	0.8545***
	($<$ 0.0001)	($<$ 0.0001)	($<$ 0.0001)

Table V
Exponential Random Graph Model to Explain the M&A Network
This table reports the coefficient estimates from an exponential random graph model. The coefficient estimates are the marginal effect of the explanatory variable on the conditional log-odds that two industries will have inter-industry mergers, where the connections are weighted by the aggregate dollar value of merger transactions between the two industries. The connections in the merger network are the dependent variables, where the merger network is constructed as in the text using SDC merger data over 1986 to 2008. The explanatory variables are the connections in the IO network constructed as in the text using data from the 1997 Input-Output tables from the U.S. Bureau of Economic Analysis. 'T buys A' is the network where each connection is the dollar value that the Target industry buys of the Acquirer industry's output. The connections in 'T sells A' are the dollar values of inputs supplied by the Target industry to the Acquirer industry. The coefficient on 'Connections' is the marginal effect of an additional random connection on the conditional log-odds ratio of two industries having a transaction-valued connection in the merger network. AIC is the Akaike's Information Criterion. $t-$statistics are reported in parentheses. Statistical significance is indicated by ***, **, and *, for the 0.01, 0.05, and 0.10 levels.

	Dependent Network: M&A Network					
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Connections	−3.406***	−3.408***	−3.430***	−3.426***	−3.487***	−4.314***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Target Buys from Aacquirer	10.042***				5.939***	13.126***
	(0.000)				(0.000)	(0.000)
Acquirer Buys from Target		10.599***			6.625***	12.495***
		(20.575)			(0.000)	(0.000)
Acquirer Sells to Target			18.540***		14.952***	25.537***
			(0.000)		(0.000)	(0.000)
Target Sells to Acquirer				17.144***	13.317***	22.218***
				(0.000)	(0.000)	(0.000)
Industry Economic Shock Index						−0.225***
						(0.000)
Industry Median M/B						0.286***
						(0.000)
Industry Mean Return						−0.599***
						(0.000)
Industry Std Dev of Returns						2.010***
						(0.000)
Concentration Ratio						−0.008***
						(0.000)
AIC	63438	63393	63047	63158	61878	16477
Number of industries	471	471	471	471	471	214

Table VI
Logit Variables Summary Statistics
This table presents summary statistics of the variables used in the logit regressions. High M&A equals one if the aggregate merger values in an industry-year is in the highest quartile of all values for the industry over 1986 to 2008. Connected M&A: Connected Buys from Subject is a measure of merger activity over all industries except industry i, weighted by the IO network connection (Connected Buys from Subject, etc.) between industry i and all other industries. Subject refers to the observation industry and connected refers to the other industries. Aggregate M&As is the dollar values of all M&As in year t divided by the total value of all mergers in all years (1986–2008). IO Degree Centrality (Centrality) is an industry's number of inter-industry connections. IO degree centrality is measured using the binary connections in the Input-Output Network using data from the U.S. Bureau of Economic Analysis for 1997. A binary connection is defined as a connection where one industry either supplies at least 1% of the connected industry's inputs, or buys at least 1% of the connected industry's output. Deregulatory Shock equals one if there was a change in regulation in the industry-year. C&I Rate Spread is the difference between commercial and industrial loans and the federal funds rate. The S&P 500 Return is an annual return.

	Mean	Median	Std. Dev.	N
High M&A State	0.215	0.000	0.411	9,891
Connected M&A: Connected Buys from Subject	0.054	0.008	0.336	9,891
Connected M&A: Subject Buys from Connected	0.029	0.014	0.054	9,891
Connected M&A: Subject Sells to Connected	0.039	0.026	0.057	9,891
Connected M&A: Connected Sells to Subject	0.054	0.006	0.266	9,891
IO Degree Centrality	0.002	0.001	0.005	9,891
Centrality × Scaled Network-wide M&A Activity	0.089	0.021	0.271	9,891
Deregulatory Shock	0.013	0.000	0.111	9,891
C&I Rate Spread	1.615	1.640	0.244	9,891
S&P 500 Return	0.127	0.109	0.159	9,891

Table VII
Logit Regression on High Industry Merger Activity

This table presents the coefficient estimates of a logit regression where the dependent variable is the M&A Activity State of an Industry. This variable equals one if the aggregate merger value in an industry-year is in the highest quartile of all values for the industry over 1986–2008. Coefficient estimates are the log odds ratio minus one. Aggregate M&As is the dollar values of all M&As in year t divided by the total value of all mergers in all years (1986–2008). Connected M&A: Connected Buys from Subject is a measure of merger activity over all industries except industry i, weighted by the IO network connection (Connected Buys from Subject, etc.) between industry i and all other industries. Subject refers to the observation industry, connected to the other industries. IO Degree Centrality (Centrality) is an industry's number of inter-industry connections. IO degree centrality is measured using the binary connections in the Input-Output Network using data from the U.S. Bureau of Economic Analysis for 1997. A binary connection is defined as a connection where one industry either supplies at least 1% of the connected industry's inputs, or buys at least 1% of the connected industry's output. Deregulatory Shock equals one if there was a change in regulation in the industry-year. C&I Rate Spread is the difference between commercial and industrial loans and the federal funds rate. The S&P 500 Return is an annual return. $p-$values are reported in parantheses. Statistical significance is indicated by ***, **, and *, for the 0.01, 0.05, and 0.10 levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged High M&A State	0.409***	0.396***	0.385***	0.400***	0.282**	0.259**	0.242*	0.264**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.035)	(0.050)	(0.069)	(0.047)
Connected M&A: Connected Buys from Subject	0.230***				0.144***			
	(0.000)				(0.000)			
Connected M&A: Subject Buys from Connected		4.383**				5.610*		
		(0.023)				(0.075)		
Connected M&A: Subject Sells to Connected			5.332***				6.301**	
			(0.000)				(0.023)	
Connected M&A: Connected Sells to Subject				0.322***				0.218***
				(0.001)				(0.000)
IO Degree Centrality					−1.000	−1.000	−1.000	−1.000
					(0.603)	(0.688)	(0.695)	(0.627)
IO Degree Centrality × Aggregate M&As					0.294	0.176	0.219	0.274
					(0.541)	(0.717)	(0.631)	(0.568)
C&I Rate Spread					−0.592***	−0.590***	−0.591***	−0.591***
					(0.000)	(0.001)	(0.001)	(0.000)
S&P 500 Return					2.392***	2.248***	2.294***	2.416***
					(0.000)	(0.000)	(0.000)	(0.000)
Industry Economic Shock Index					0.013	0.015	0.022	0.012
					(0.825)	(0.805)	(0.712)	(0.843)
Econ Shock × High C&I Spread					−0.100	−0.105	−0.102	−0.099
					(0.197)	(0.175)	(0.186)	(0.204)
Deregulatory Shock					−0.087	−0.065	−0.069	−0.077
					(0.784)	(0.840)	(0.831)	(0.810)
Industry Median M/B					0.609***	0.609***	0.597***	0.619***
					(0.000)	(0.000)	(0.000)	(0.000)
Industry Mean Return					0.391**	0.424**	0.419**	0.396**
					(0.023)	(0.016)	(0.016)	(0.024)
Industry Std Dev of Returns					−0.264**	−0.275**	−0.266**	−0.270**
					(0.024)	(0.018)	(0.021)	(0.022)
Industry Concentration					−0.003**	−0.003**	−0.004***	−0.003**
					(0.020)	(0.021)	(0.010)	(0.019)
Observations	9,891	9,891	9,891	9,891	2,862	2,862	2,862	2,862
Pseudo R^2	0.005	0.005	0.006	0.005	0.033	0.345	0.036	0.034