# THE IMPORTANCE OF INDUSTRY LINKS IN MERGER WAVES*

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# The Importance of Industry Links in Merger Waves


## Abstract

Prior research finds that economic shocks lead to merger waves within an industry. In this paper, we argue that industry merger waves are driven by customer-supplier relations between industries. We construct an industry network using techniques from the graph theory literature, where inter-industry connections are determined by the strength of supplier and customer relations. We find that the strength of industry network connections 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. Finally, we find that economy-wide merger waves are explained in part by the diffusion of merger activity across the economic network to multiple industries simultaneously.

It is well documented that merger waves cluster within industries (Mitchell and Mulherin, 1996; Andrade, Mitchell, and Stafford, 2001; Harford, 2005; Rhodes-Kropf, Robinson, and Viswanathan, 2005). Gort (1969) argues that this phenomenon may be attributed to an efficient reallocation of assets following economic industry shocks, such as new technology, deregulation, or demand and supply shocks. Harford (2005) finds systematic evidence in favor of this argument: economic shocks lead to merger waves within an industry, even controlling for mergers driven by overvalued stock.

In this paper, we build from the economic shocks hypothesis, where our point of departure is a simple, though consequential observation: Industries do not exist in isolation. Instead, product market relationships between customers and suppliers connect multiple industries through a complex network of trade. This observation has at least two important implications for merger waves, one direct, and the other indirect.

First, industry-level economic shocks likely lead to inter-industry mergers. For instance, the merger wave following the Telecom Act of 1996 was dominated by mergers of firms that produce media content (Paramount, Disney, and Time Warner) with firms that distribute the content (Viacom, ABC, and Turner). Since economic industry shocks likely affect customer-supplier relations, it follows that merger waves would occur between industries, rather than solely within industries. For example, Fan (2000) provides empirical evidence that the oil shocks of the 1970s led to a wave of vertical integration in the petrochemical industries. Other examples of industry-specific shocks that could lead to vertical mergers include technology shocks that change an industry's relative demand for its inputs and shocks that alter an industry's costs of making relationship-specific investments which lead to vertical integration (Klein, Crawford, and Alchian, 1978).

Second, the reorganization 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. For example, when radio stations were consolidated following the 1996 Telecom Act, radio playlists became less diverse, which likely influenced the subsequent consolidation of the music industry in the early 2000s (Williams, Brown, and Alexander, 2002). More generally, the countervailing market power theory of Galbraith (1952) predicts that industry consolidation in an upstream (downstream) industry leads to industry consolidation in a downstream (upstream) industry to counteract the monopoly (monopsony) power created through the initial consolidation. In addition, theoretical industrial

organization models predict that changes in the substitutability of products or changes to the cost structure of one industry affect the incentives to merge for firms in vertically related industries (Horn and Wolinsky, 1988; Inderst and Wey, 2003). These theories are not mutually exclusive and for the purposes of this paper, we do not attempt to test any one theory in particular. We simply claim, based on these arguments, that changes in the organization of important customer industries will lead to changes in the organization of supplier industries, and vice versa.

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. This novel network approach allows us to construct a topology of the economy through customer-supplier links which can be analyzed using network techniques that were developed in social networking and graph theory research. This provides important benefits over the analysis of a simple connection between a single supplier and a single customer, typical in prior research. First, the network approach allows us to consider direct and indirect connections between all industries, rather than restricting our attention to industry-pairs involved in a merger, which may produce selection bias. Second, the network approach allows us to analyze higher order effects of the propagation of industry shocks through the economy. For example, using network measures of distance, we can determine if mergers transmit across industries in the economic network in a predictable way, and if so, how fast they move across the network. Third, we can compare the timing of an industry's merger activity, relative to an aggregate merger wave, to the industry's network centrality, a measure of relative importance in the customer-supplier network. This provides a better understanding of how aggregate merger waves develop. These important questions have not yet been addressed in prior research in part because they can only be answered using a network approach, as we do here. In fact, an important contribution of this paper, beyond a new understanding of merger waves, is that it is the first to model product market relationships as a network.

In both static and dynamic settings, we find strong empirical evidence that product market connections play a central role for both the incidence and timing of merger waves. In the static setting, we find that product market relationships strongly predict merger activity across industries in the cross-section. We characterize both the IO network and the merger network and find striking similarities. Both networks exhibit a long right tail in the distribution of connections: many industries

have few connections, but a few industries have a very large number of connections. In addition, both networks are highly interconnected, where only two or three direct connections separate most industry-pairs. Comparing industry-by-industry, we find that the correlation between an industry's centrality in the industry trade network and its centrality in merger activity is 39% to 57%. Results from both ordinary least squares regressions and from more advanced exponential random graph models (ERGM) which account for the entire network structure, show that inter-industry mergers between two industries are more likely when they have stronger supplier-customer relationships, controlling for industry valuation, returns, concentration, and macroeconomic shocks. This effect is present in every year from 1986 to 2008 and is stronger during market booms and aggregate merger waves. The strength of the effect during aggregate merger waves implies that economic fundamentals are more, not less, important during merger waves and that these fundamentals drive merger waves not only within an industry, but also across industries.

Next, we explore the dynamic diffusion of merger activity across the industry network over time. We find strong empirical evidence that unusually high merger activity in one industry is positively correlated with future 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, even excluding the effect of direct merger activity between the two industries.

We also find that the speed that merger activity transmits across the economic network depends upon the direction of product market relationships. In particular, we use graph theory techniques to identify an industry's closely and distantly connected industries, where distance is measured through a sequence of suppliers (up the supply chain) or a sequence of customers (down the supply chain). We then compare the impact of merger activity in close and distant industries accounting for shorter and longer time lags. When we measure distance through customer links (down the supply chain), we find that two-year lagged M&A activity in distant industries and more recent one-year lagged activity in closely connected industries is positively related to mergers in the focal industry. This is consistent with M&As transmitting in a wave-like pattern across the economic network. When we measure distance through supplier links, we find that product market distance

is irrelevant, though the time lags still resemble a wave. These results imply that shocks travel faster up through suppliers than down through customers. This result is consistent with prior research that finds that suppliers are more affected than customers following horizontal mergers (Bhattacharyya and Nain, 2010), changes in industry concentration (Becker and Thomas, 2010), and financial distress (Hertzel, Li, Officer, and Rodgers, 2008). Using the network approach, we are able to identify more nuanced differences in the speed that shocks travel up and down the supply chain.

In the last section of the paper, we present a new explanation for aggregate merger waves. We find that over the last two decades, the industries that were experiencing merger waves during the height of overall economy-wide merger activity were those industries that are most central in the economic network. This is a direct consequence of the highly skewed distribution of inter-industry connections. As merger activity transmits across the network towards more central industries, many overlapping industry waves occur which produce an aggregate merger wave. This evidence addresses a counter argument to the economic shocks hypothesis raised in extant literature. Specifically, the argument is that industry merger waves caused by random industry shocks should not cluster in time and therefore cannot explain economy-wide aggregate merger waves, which are more likely caused by market-wide misvaluation (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004). We find that economic shocks may be random, but aggregate merger waves occur in part because merger waves beget overlapping merger waves, causing many industries to experience waves simultaneously.

Finally, we conduct additional robustness tests to control for the impact of misvaluation for all of our empirical analyses. In each specification we control for the level and dispersion of the prior returns and the market-to-book ratio of each industry, as well as the difference in returns and M/B between industry-pairs. In addition, our results are robust to controls for aggregate market returns, financing liquidity, aggregate merger volume, and industry characteristics. We are careful to note that our goal is not to disentangle misvaluation explanations from economic shock explanations of merger activity as the the initial impetus of a merger wave.[1] Nevertheless, our

[1]We would like to track merger activity backward in time through the network to identify the initial conditions that lead to subsequent mergers. However, because the industry network is extremely inter-connected with many connections to each industry and because most industries have feedback loops after only a few industry connections, our attempts to identify the initial conditions proved infeasible.

results provide strong and consistent evidence that merger activity is transmitted through product market relations, most consistent with the idea that economic fundamentals drive mergers. Even if the reader takes the position that merger waves are caused by the spread of misvaluation across product market relationships, our results imply that it still must be the case that the underlying exogenous product market relationships explain a large portion of the pattern of merger activity across an economy over time.

This paper is related to recent research that investigates the role of industry relations on corporate finance. Bhattacharyya and Nain (2010) study the price effects on suppliers and customers following horizontal mergers. Becker and Thomas (2010) examine how changes in concentration in downstream industries affect concentration in upstream industries, and vice versa. Fee and Thomas (2004) and Shahrur (2005) use vertical relationships to test the effects of horizontal mergers on market power. This work builds from Eckbo (1983) and Stillman (1983), early investigations of industry relations in horizontal M&As. Industry relations have also been studied in samples of distressed firms. 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. Our paper is also related to a strain of recent research on merger waves, including Maksimovic, Phillips, and Yang (2010), Duchin and Schmidt (2010), and Ovtchinnikov (2010).

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. Fan and Goyal (2006) report that prior to their paper, even basic facts such as the proportion of mergers that are vertical were unknown. In fact, using 471 industry classifications, we find that cross-industry mergers are more common than are horizontal mergers, and few mergers are truly unrelated. 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. By explicitly examining vertical relations among industries and expanding the analysis to include indirect relations in an economic network setting, we increase our understanding of the important role that product market relationships play in overall merger activity.

The rest of this paper is organized as follows. Section I presents the industry and merger data and describes the construction of the networks we analyze in the paper. Section II presents tests that compare the industry input-output network to the merger network in a static setting. In Section III, we present tests of the dynamic diffusion of merger waves across the industry network over time. Section IV concludes.

## 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. Since our unit of observation is an industry-pair, to maintain consistency over the years in our sample we must choose one of the BEA reports to use throughout our study. We choose to use the 1997 IO definitions because 1997 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.[2] Costs

[2]The six additional commodities that are in the Use table but not in the Make table are, noncomparable imports, used and secondhand goods, rest of world adjustment to final uses, compensation of employees, indirect business tax and nontax liability, and 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.

are reported in both purchaser and producer costs (the differences are due to retail and wholesale markups, taxes, and other transaction costs). 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 (2010) 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 relative 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.

One of the important features of the input-output matrix is that it is exogenous to merger activity in general. This is because the basic input requirements in the production of any commodity are determined by the commodity's production function, not by the ownership structure of the firms that produce the inputs. This is important because we wish to test whether industry merger activity

is influenced by product market relationships. The fact that industry relations are determined exogenously rules out reverse causation, where merger waves cause product market relations to change, or confounding effects from omitted variables. In essence, the elementary nature of the input-output data from the IO tables provides the framework of the economy, upon which mergers may occur.

### *B. Merger Data*

Merger data are from SDC Thomson Platinum database. We collect data for 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
- Transaction values of at least $1 million

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 inter-industry 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.

### *C. Network Definitions*

Any network can be described by an $N \times N$ adjacency matrix, $A$, consisting of $N$ unique 'nodes,' which are connected through 'edges.' Emphasizing the importance of edges in a network, nodes are most generally defined as an endpoint of an edge. 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.

A primary innovation of this paper is to treat the industry input-output data and merger data as networks. Specifically, each of the networks has the same set of nodes – the 471 industries from the IO tables – but the connections between the nodes are either product market relationships in the IO network, or inter-industry mergers in the merger network. This is easily accomplished by simply treating the input-output matrices and the cross-industry merger matrix as adjacency matrices. Thus for the same set of industries we record multiple connections, based either on product market relations or merger activity. Though there is a natural fit between input-output tables and network analysis, to the best of our knowledge, this is the first paper to make this connection. As we show below, using a network approach provides substantial benefits because we can use existing techniques developed in graph theory and networking to answer new questions in financial economics.

To illustrate the network concepts, Figure 1 presents representations of two simple input-output 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. Subfigure (a) presents the network of customers as an adjacency matrix (from the $CUST$ matrix) and subfigure (b) presents the network of suppliers as an adjacency

matrix (from the $SUPP$ matrix). Subfigure (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 highly 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 subfigure (b)), though of all sales by the forestry support industry, only 14% are purchased by the forest nurseries industry ($a_{21}$ in subfigure (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. Increasing the number of nodes to 471 and increasing the number of connections exponentially provides an extremely complex network of industry relations. Therefore, as stated previously, to analyze both the IO and merger networks, we use techniques first developed in graph theory and social networks. We briefly discuss these techniques next.

### *D. Network Measures*

The primary goal of this paper is to identify the relationship between the IO network and the merger network. One way to understand this relationship is to simply compare the networks. To do this, we use a number of key network measures that have been developed in the network literature. In particular, we will compare networks based on the concepts of centrality, clustering, and average shortest paths. Each of these is described below.

Network centrality refers to how important one node in a network is relative to other nodes. Importance is based on how many connections a node has and to which other nodes these connections are made. For our purposes, this means how important an industry is in the flow of inputs and outputs between all industries, or in the number of cross-industry mergers. 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.[3]

There are other measures of centrality, but 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.

The second type of network measure we examine is clustering. Clustering refers to how embedded a node is in the network, or in our case, how embedded an industry is in the economy. More formally, we calculate the clustering coefficient of Watts and Strogatz (1989). Defining a node's neighborhood as the set of nodes to which a particular node is connected, the clustering coefficient is the proportion of observed connections between the nodes in its neighborhood to the total possible connections. Intuitively, the greater is the clustering coefficient of an industry in the customer-supplier network, the more do its customers and/or suppliers also trade with each other. In contrast, the trading partners of industries with low clustering coefficients, trade little with each other. This measure helps us understand how merger activity is likely to transmit across the IO network.

Finally, we measure each industry's average path length. For a given industry, we can calculate the shortest path through the network to every other industry in the network following industry

[3]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 $j \neq i$: $c_i = \frac{1}{\lambda}\sum_{j\in M(i)} c_j = \frac{1}{\lambda}\sum_{j=1}^{N} A_{ij}c_j$ where $M(i)$ is the set of nodes that are connected to node $i$ and $\lambda$ is a constant. In matrix notation, this is $\mathbf{Ac} = \lambda\mathbf{c}$ Thus, $\mathbf{c}$ is the principal eigenvector of the adjacency matrix.

links. We then take the average of the path lengths for each industry. This measure presents another indication of how connected an industry is. This again is important for understanding network dynamics, since it measures the closeness of an industry to all others, on average, and also at the network level it indicates how densely connected is the network, or in our case, the entire economy. For more details, see Albert and Barabási (2002).

## II. The Static Relation of Product Market and Merger Networks

Our hypothesis about the connection between the IO network and merger activity implies that product market connections help explain which mergers happen and when. In particular, aggregate merger waves occur as economic shocks diffuse through the IO network via product market connections. We explore the empirical implications of this hypothesis in this and the next section of the paper.

In this section of the paper, we test whether the IO network of customers and suppliers can explain the merger network of cross-industry mergers in a static setting. To do this, we first compare the network attributes of the merger network to the IO network. We use a battery of formal network statistics common to network analysis, and then supplement them with simple correlation and visual representations of the data that corroborate the network statistics. We conclude this section with a formal test of whether the IO network is a significant determinant of the pattern of cross-industry mergers, controlling for alternative explanations, such as misvaluation.

There are a number of benefits to the first part of our analysis. First, the depth of the relation between product market interactions and merger activity is the foundation of our hypothesis, without which it would be pointless to examine the dynamics of merger activity and waves. Second, the analysis allows us to go well beyond a simple statement that vertical mergers occur. Rather, we can compare the relative importance of intra-industry to inter-industry mergers and within the sample of inter-industry mergers, we can assess the degree of related relative to unrelated activity. We will also be able to test the strength of the product market relationship's effect relative to alternative explanations, such as that firms in high-valued industries buy firms in low-valued industries. Finally, understanding the structure of the IO network will be critical to identification of the dynamic relationship between industry-level and economy-wide merger waves.

In the next section of the paper, we shift to the dynamic implications of the hypothesis. Specifically, can heightened merger activity in one industry explain future heightened merger activity in industries connected to it through the product market? We begin with a logit analysis testing whether the timing of industry-level merger waves can be explained by industry waves in connected industries, controlling for a host of alternative explanations. We then ask whether the strength and directness of the connection between two industries affects how quickly merger activity in one leads to merger activity in the other. Finally, we document when the most economically central industries are undergoing merger waves relative to the peak and trough of aggregate waves. The evidence speaks to how important the diffusion of industry-level shocks is to generating aggregate merger waves.

## *A. Summary Statistics*

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 during our 23-year sample period 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.

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%.

### *B. Comparing Merger and IO Networks*

We compare the merger and IO networks to each other in in two ways. First we compare the entire structure of each network. Second, we compare the networks industry-by-industry. First, 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 subfigure (a), or a higher percentage of customer/supplier relationships in subfigures (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).

Another way to understand the structure of a network is to examine its degree distribution. Recall that degrees are connections between industries. The degree distribution, $P(k)$, is the proportion of industries with $k$ direct connections. Since the merger and IO networks appear highly clustered, we expect that their degree distributions are highly skewed and approximate a power law distribution, $p(k) = ck^{-\alpha}$, as do many phenomena in economics and other fields (Gabaix, 2009b). Therefore, we plot the degree distribution in logarithmic scale for the merger network and the supplier network in Figure 4. If the distribution follows a power law, then the relation between the number of connections and the probability of connections would follow a linear pattern in logarithmic scale. For reference, we plot the estimated power law line using the

maximum likelihood method of Clauset, Shalizi, and Newman (2009), though it is not important for our purposes that the distribution is statistically a power law or not.

Figure 4 reveals that both inter-industry mergers and IO connections are characterized by many industries with few connections and a few industries with many connections. The circles in the lower right corners of both graphs represent the few rare industries with a very large number of direct connections to other industries. These patterns are important for a number of reasons. First, if economic fundamentals drive merger waves, it is not surprising that they will cluster in certain industries given that many connections in the IO network are clustered in a few industries. Second, it suggests that if merger activity follows the industry network over time, we should not expect to see random unrelated merger waves, but rather we would expect many merger waves occurring simultaneously. We discuss this point in more detail in Section III.

Next, in Panel A of Table III we present averages and medians of industry-level network statistics for the supplier, customer, and merger networks, as well as statistical tests of their differences. The average (median) industry has about 22 (16) connections to suppliers and 16 (13) connections to customers, where connections are substantial relations, as defined previously. The average industry has cross-industry mergers with 25 different industries in our sample period and the median is 16. The average shortest path across industries is about two for all networks, which confirms the 'small-world' nature of these networks: across 471 industries, a typical industry is only 2 to 2.5 connections away from every other industry. In fact, the maximum shortest path length between any two industries, known as the diameter of the network, is four in the supplier network, six in the customer network, and five in the merger network. These results indicate that though the networks are sparse, they are still highly connected through central 'hub' industries. The tests of differences in Panel A also reveals that the networks are statistically different from each other. In particular, the average industry is more clustered and is more central in the merger network than it is in the IO networks.

Next, we examine industry-by-industry relationships between the IO and merger networks. In Table IV, we present the 15 most central industries in the supplier 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.

In unreported tabulations, similar overlaps between the IO networks and the merger network occurs for the most clustered industries and for the industries with the shortest average path. Take the tobacco industry as an example. Tobacco related industries are highly clustered in the customer network. This means that the customers of the tobacco industry are also likely to be customers of each other. Tobacco is also one of the most clustered industries in the merger network. Firms that make cross-industry mergers with tobacco firms, are also likely to merge with each other. This relation is replicated for average shortest path lengths. Tobacco industries have high average path lengths to other industries in the IO networks. This means they are isolated from other industries, on average. Tobacco firms are also isolated in the merger network as the path length of cross-industry connections to all other industries through mergers is among the highest of all industries. Combining the clustering coefficient with the shortest path length reveals that the tobacco industry is relatively isolated from most other industries, but highly clustered with a few other tobacco related industries. For our purposes, these results also suggest that the structure of the IO network is similar to the structure of the merger network, at an industry-by-industry level.

To generalize these findings, we present a traditional correlation analysis of the industry network characteristics. Panel B of Table III presents the correlation matrix for centrality, average

path length, and clustering for each industry in each network. First, the centrality measures are correlated across networks, so that central industries in the IO networks are likely to be central industries in the merger network. The correlation between the centrality of the customer and merger industries is a significant 56.5%. Similarly, the correlation of an industry's average path length in the merger network with its average path length in the customer network is a significant 26.4%. The only insignificant correlation is the clustering coefficient of the merger network with the customer industry, though the merger network is positively correlated with the supplier network clustering coefficient.

These results provide strong evidence that the industries that are important in the IO network in terms of centrality, path lengths, and clustering, are also important in the merger network. However, these findings do not control for additional factors that could be related to industry structure, such as market valuations or industry concentration. Therefore, the final analysis of the relation between the IO networks and the merger network uses a network analysis technique called Exponential Random Graph Models (ERGM). Just as a logit regression produces maximum likelihood estimates (MLE) of a single dependent variable, ERGM produces MLE estimates of the entire network, including node characteristics and the strength of connections between nodes. Importantly, like a multivariate regression, ERGM allows multiple variables to jointly explain the observed network. See the appendix for more details on ERGM.

The results of the ERGM analysis are presented in Table V. The dependent network that the model attempts to explain is the cross-industry merger network and the explanatory variables are the network connections in the 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 other IO network variables are analogous. 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 coefficient estimate of the variable 'Number of Connections,' measures the marginal change on the M&A network from adding a random connection.

It is clear from the results in Table V that the IO networks explain the merger network. Each of the four IO network connections has a positive and significant effect on the likelihood of merger

connections, both separately in columns (1) through (4), and jointly in column (5), each incrementally contributing to an understanding of the occurrence and intensity of merger activity between industries. 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.

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 variables related to misvaluation, including 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.

Adding the industry-level valuation controls does not affect the strong predictive power of the IO connections. 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 expected predictive power of the industry connection variables. Most of the valuation variables affect the likelihood of mergers as one would expect. High market-to-book, greater variation in firm returns, and low average returns leads to more mergers. In addition, as expected, more concentrated industries experience fewer mergers. These control variables are at the industry-level, while our main variables of interest are at the industry-pair level. To properly control for valuation effects, we next include as control variables the absolute value of industry-pair differences in market-to-book ratios, average and standard deviations of returns, and concentration ratios. Like the IO connections, these variables measure the relations between industry pairs, rather than the characteristics of the industry alone.

Column 7 of Table V presents the results of ERGM coefficients after including the industry-pair control variables. Greater inter-industry differences in M/B ratios and the standard deviation of returns are positively related to the likelihood of inter-industry mergers. However, after including these control variables we find that the industry connections are still positively and significantly related to merger activity. As stated previously, since the IO network connections are exogenous, these results provide clear evidence that the pattern of cross-industry merger activity is driven by fundamental economic links.

Though these tests account for an average effect of the control variables, the interpretation of their effect on merger activity is unclear since they may change over time. Therefore, we separately estimate ERGMs for each year in the sample period. Figure 5 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.[4] 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. In addition, for robustness we drop the "wholesale trade" and "retail trade" industries from our analysis following Acemoglu, Johnson, and Mitton (2009) and find the inferences from our ERGM analysis are unchanged.

### *C. Summary of Static Tests*

In this section, we have presented a number of related results. First, we have shown that cross-industry mergers are more common than horizontal mergers at the IO industry level. Second, we

[4]The consistently high $t-$statistics over time also justifies using the 1997 IO matrix for all years in our sample.

have shown that the pattern of cross-industry mergers is determined by product market relations. Thus, though the majority of mergers are vertical, we can say something more important: stronger vertical IO relations predict more vertical mergers. In contrast, we could have found that many mergers were in unrelated industries. Or alternatively, we could have found that vertical mergers were common, but only in high valuation industries, independent of the strength of the IO connection. Instead we find that the network structure of the merger network matches closely the IO networks' structures. Industries that are highly connected in the IO network also experience cross-industry merger activity in the same set of connected industries. Industries that are isolated and clustered together in the IO network also share similarly isolated and clustered merger connections.

Taken together, these results provide consistent evidence that merger activity follows fundamental economic relations on multiple dimensions. Given that product market relationships determine cross-industry merger patterns in the cross-section, we next want to understand the dynamics of merger waves. In the following section, we ask exactly that question: whether we can dynamically explain merger activity in a given industry with merger activity in connected industries.

## III. 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 industries following economic shocks. A separate line of research suggests that market misvaluation leads to merger waves, as firms use overvalued equity to purchase other firms (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf, Robinson, and Viswanathan, 2005). However, both lines of research share a common goal: to identify the important sources of variation that explain the static cross-section of merger activity at an industry-level.

In contrast, our goal in this paper is to understand *cross*-industry patterns of mergers in both static and dynamic settings. Our first results show that IO networks have a strong influence on cross-industry merger patterns in a static setting. In this section, we consider the dynamic aspects of mergers across industries. In particular we investigate a dynamic model of merger activity within an industry based on heightened merger activity in all industries that are connected through product

market relations. We predict that the likelihood that an industry experiences a merger wave will be greater if its customer and/or supplier industries recently experienced merger waves. Thus, under this hypothesis, merger waves beget merger waves across the IO network. The alternative hypothesis is that merger activity in an industry is unrelated to its customer and supplier industries' merger activity, but instead is driven by some other forces, such as misvaluation.

First, to illustrate how the diffusion of merger activity across related industries occurs, we present an example from the forest industry we discussed above.

### *A. 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 long-lasting supply shock.

Subfigure (a) of Figure 6 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. Subfigure (b) of Figure 6 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 time-series 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 subfigure (b) of Figure 6) 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.

Subfigure (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. Instead, an 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.

Subfigure (c) of Figure 6 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.

### *B. 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:

$$Connected\ M\&A_{it} = \sum_{j \neq i} a_{ij} \left[ \sum_{k \neq i} v_{kjt} + \sum_{\substack{k \neq i \\ k \neq j}} v_{jkt} \right] \tag{1}$$

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:

$$\begin{aligned} \textit{High M\&A}_{i,t+1} = \alpha &+ \beta_0 \textit{High M\&A}_{i,t} + \beta_1 \textit{Connected M\&A}_{i,t} \\ &+ \gamma \textit{Network Measures}_t \\ &+ \delta \text{Controls}_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

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 described previously. Table VI summarizes the key data used in the estimations.

The first four columns of Table VII present odds ratios from a logit model 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.

The impact of connected industries' merger activity on a subject industry's merger activity is economically substantial. For a one standard deviation increase in "Connected Buys from Subject," or in "Connected Sells to Subject," the odds of a subject industry being in the high merger state increase by 7.7 percent or 8.6 percent. For a one standard deviation increase in "Subject Buys from Connected," or "Subject Sells to Connected," the odds increase by 23 percent or 30 percent. Since these variables are the product of the merger activity in a connected industry and the strength of the IO connection to the subject industry, either increases in M&As or in the strength of the IO connection can produce these large changes in the likelihood of increased merger activity in the subject industry. For comparison, a one standard deviation increase in an industry's current merger state yields a 17 percent increase in odds of a high merger state in the next year. A one standard deviation increase in median industry market to book ratios yields a 29 percent increase in odds. Thus the network effects are large and significant even when compared to other known factors.

In unreported tests, we run similar tests using Tobit models where the dependent variable is the total aggregate value of mergers in a subject industry in a given year. The effects are similarly large and significant. Between 21 percent and 51 percent of the dollar values in connected industries

'spills over' into the subject industry in the following period. We also include longer lag lengths and find that there is typically a drop off in the effect, where the second lag has an effect that is roughly two thirds the size of the first lag's effect.

## C. The Effect of Industry Closeness and Time Lags on Diffusion

In this section, we investigate how the distance between two industries across the IO network affects the diffusion of merger activity at different time lags. If merger activity is diffusing across an economy, we would expect that the the current merger activity in closely connected industries would have a greater impact on an industry's future merger activity than would distantly connected industries' M&A activity. In addition, if merger activity diffuses as a wave, we may observe a positive relationship between time and distance, such that M&A activity in more distantly-connected industries may have a delayed effect on a subject industry's future merger activity. The following equation captures these effects:

$$\begin{aligned} \textit{High M\&A}_{i,t+1} = \alpha &+ \beta_0 \textit{High M\&A}_{i,t} + \beta_1 \textit{High M\&A}_{i,t-1} \\ &+ \beta_2 \textit{Closely Connected M\&As}_{i,t} + \beta_3 \textit{Closely Connected M\&As}_{i,t-1} \\ &+ \beta_4 \textit{Distantly Connected M\&As}_{i,t} + \beta_5 \textit{Distantly Connected M\&As}_{i,t-1} + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

To measure closeness in the merger network we incorporate the entire network, not only the directly connected industries as in Equation 1. We use Dijkstra's (1959) algorithm to calculate the minimum distance between every possible industry pair by either moving upstream or downstream in the IO network using the weighted and directed connections between industries. In particular, if we take a subject industry as a customer, we can define the first degree of distance to every supplier by the subject industry's purchases as a percent of total supplier sales (from the $CUST$ matrix). The greater is the fraction of total sales accounted for by the subject industry, the closer are the two industries. Thus the first degree of distance measures how important the subject industry is as a customer. Then, for each of these supplier industries, we can measure the distance to each of its suppliers using the same measure. The distance between the subject industry and one of the supplier's suppliers (the supplier that is two degrees of separation away from the subject industry)

is the sum of the distances from each step in the chain. Intuitively, this is the distance measured by tracing a path through each industry's most important customers. Distance can also be defined using the $SUPP$ matrix, where distance is the fraction of total inputs supplied by the connected industries. Larger fractions again imply a shorter distance. In this case, the distance would be the path through each industry's most important suppliers. For each of these two measures, Dijkstra's algorithm finds the shortest distance between two industry pairs.

For each industry, we compute the vector of distances to every other industry. We define *Closely Connected M&As* as the total value of deals in the industries that are closer than the median distance, excluding any mergers with the subject industry, as before. The *Distantly Connected M&As* variable is computed using only the industries that are further than the median distance from the subject industry. Thus, these variables distinguish merger activity by distance in the product market network. We then use the current and lagged values as explanatory variables in Equation 3. Since our prior results were unchanged after including the additional valuation control variables, we omit them from these tests to maintain a sample that includes the entire network.

In our first tests, we focus on the case where the subject industry is the customer and the connected industries are the suppliers. In column 1, we measure distance by the subject industry's purchases as a fraction of the connected industries' total sales (the path through the most important customers). In column 2, we measure distance using a supplier's fraction of the subject's total input costs (the path through the most important suppliers). In both cases, the subject industry is the customer, but the way distance is measured to its suppliers is different.

Columns one and two of Table VIII present the odds ratio estimates (minus one) from logit regressions of Equation 3. Positive coefficients indicate that the odds of high M&A activity in the subject industry are positively related to the explanatory variable. As before, the results in Table VIII show that if an industry is experiencing high merger activity currently, then it is more likely to continue to experience high merger activity next year. However, the two-year lagged industry merger activity is not significantly related to current merger activity. Thus merger waves appear to last no more than two years, on average, consistent with the findings in Mitchell and Mulherin (1996) and Harford (2005).

When we distinguish between closely and distantly connected suppliers, we find that the two methods of measuring distance (through important customers, or through important suppliers) produce different results. First, in column 1, when distance is measured using the importance of the customer to the supplier, we find that one-year lagged M&A activity in closely connected industries is positively and significantly related to current merger activity, but two-year lagged activity in closely connected industries is negatively and significantly related to high merger activity. This result is quite interesting because it indicates that mergers do follow a wave-like pattern over time and over the network topology. Similar to the illustration of the timber industry, high merger activity in distant industries takes two years before it affects the subject industry. Once a closely connected industry is affected it takes just one year before the subject industry is affected. Thus, as predicted, the results in column 1 of Table VIII suggest that there is a positive relation between time lags and distance in the industry network.

In column 2, where distance is measured using the importance of the supplier to the customer, we do not observe the effect of distance across the industry network, but the effect of the time lags remains. Merger activity with a one year lag in both closely and distantly connected industries is positively related to the likelihood of high merger activity in a subject industry. Similarly, merger activity in both closely and distantly connected industries with a two year lag is negatively related to the likelihood of higher merger activity. Thus we still observe the wave pattern in time, but the distance across the IO network is unimportant.

The different effect between the two ways of measuring distance from a customer industry up a supply chain to its suppliers may suggest that the relative importance of the customer or the supplier affects the speed with which mergers diffuse across the network. When distance is measured by tracing the path through the most important suppliers, even the merger activity in distantly connected industries has an immediate effect. In contrast, when distance is measured by tracing the path from a supplier through the most important customers along the supply chain, the merger activity in distantly-connected industries affects a customer industry after a longer time delay. Thus, consistent with the results that indicate that shocks are more *likely* to travel upward through a supply chain than downward (Hertzel, Li, Officer, and Rodgers, 2008), we find that merger shocks travel *faster* upward through suppliers than they travel downward through customers.

Columns 3 and 4 of Table VIII report the estimates of the effect of time and distance from Tobit regressions on the value of mergers in a subject industry. The direction of the coefficients is identical to the logit tests. We find that for a one dollar increase in an industry's current year aggregate merger transaction value, its next year's merger values increase by 0.56 dollars and as before, the two-year lagged values are insignificant. For a one dollar increase in the value of merger activity in closely connected industries, a subject industry's next year's merger values increase by 0.02 dollars, compared to 0.003 dollars from an increase in merger values in distantly connected industries.

The results in this section 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. In the next section, we present evidence on the relation between industry centrality and peak merger activity.

### *D. Network Centrality and The Timing of Industry Merger Activity*

Figure 7 overlays aggregate merger activity from Figure 2 with the average centrality of industries experiencing high merger years. The figure shows that the centrality of high merger industries increases as the aggregate wave continues. There is also a noticeable jump in average centrality during each wave. Indeed, in unreported t-tests, we find that the centrality measures of those industries with merger waves at the aggregate peak are statistically higher than those industries experiencing mergers at the aggregate trough.

The relation between centrality and aggregate merger waves is consistent with a diffusion model of merger activity. Recall that industries in both the IO and merger networks have highly skewed

distributions of connections, which approximate power law distributions. A few 'hub' industries have many direct connections and many industries have relatively few direct connections. Shocks that follows the IO network will move towards the center of the network, branching out in parallel to other industries. At the center of the network, the shocks will branch out even more, though they will die out as more and more industries have already been affected. Thus we observe a positive relationship between centrality and the number of industries experiencing merger waves. In particular, our results show that merger waves transmit towards more central industries which leads to aggregate merger waves.

These results provide a new explanation for why aggregate merger waves occur. A criticism of prior research that argued that economic industry shocks produced merger waves was that random industry shocks could not explain why overall merger activity in an economy was also not randomly distributed over time. We argue that the initial economic industry shocks may be random, but the subsequent 'after-shocks' follow the IO links, which are not random. Instead, the pattern of aggregate merger waves is likely driven by the fat-tailed nature of IO links. A similar argument is made by Gabaix (2009a) regarding productivity shocks. He argues that since the distribution of firm sizes is also approximately a power law distribution, idiosyncratic shocks to small firms do not average out idiosyncratic shocks to large firms.

If aggregate merger waves are a result of the structure of the IO network, then we can draw direct relationships between networks and characteristics of merger waves. For instance, the speed with which the central industries are affected depends on how highly connected the central industries are to the rest of the network. In a dense network, the central industries are highly connected to most of the other industries and will be affected quickly when any industry undergoes a merger wave. In a sparser network, merger activity will propagate to the center more slowly. As we showed in Table II, the input-output network is sparse, with more than 95 percent of industry pairs barely connected or not at all. When the shock spreads to a central industry, it will quickly spread to other central industries, creating the observed jump pattern in average centrality (although the lower average centrality in 1994 is unexplained).

Of course, the other major determinant of the speed of diffusion to the center is where the activity starts. If it starts in a central industry, additional industries will quickly be affected. If

we had a long enough time series of aggregate merger waves, we would expect to see one where the initial shock occurred in a central industry, quickly spread to other central industries and then outward. In the two aggregate merger waves studied here, the evidence is more consistent with shocks initially hitting non-central industries and then moving to the center. Though our sample of merger waves is too small to provide rigorous tests, future research may be able to exploit this idea to explain international differences in merger waves using the cross-sectional differences in domestic IO networks.

## IV. 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 the attributes of the 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, as well as measures of misvaluation. Moreover, mergers travel in waves over the industry network. We document a positive and significant relationship of the effect of M&A activity in connected industries by the distance across the industry network and the time lag between the

observation of heightened merger activity in each industry. Finally, we provide a new explanation for aggregate merger waves based on the structure of the customer-supplier network.

One of the primary innovations 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. To our knowledge, 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.

# Appendix A. Exponential Random Graph Models

This appendix provides additional details on exponential random graph models (ERGM). 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,

$$P_\theta(G = g) = \frac{\exp\{\theta' s(g)\}}{\sum_{\text{all graphs } h} \exp\{\theta' s(h)\}} \tag{4}$$

where

$$\theta \equiv \text{An unknown vector of parameters} \tag{5}$$

$$s(g) \equiv \text{A known vector of network statistics on } g \tag{6}$$

Similar to the maximum-likelihood estimator of a limited-dependent variable model, ERGM estimates $\theta$, the unknown parameters of the model class, which are the coefficients on the $s(g)$, by finding the $\theta$ that provide the closest network to the observed network $g$ by maximizing the log-likelihood function. The $s(g)$ include both node (industry)-specific variables as well as variables that describe the edges that connect the nodes.

The key difference between ERGM and a common limited-dependent variable model, such as a logistic regressions is that the objective function of the maximization problem is a single outcome variable, whereas in ERGM, it is an entire network, including the strengths of connections between nodes. The complexity of estimating all possible random graphs is computationally challenging. Therefore, simulated random graphs are computed using Markov Chain Monte Carlo simulations.

In our context, we focus on edge covariance. This measure considers the network as a whole and takes into account the strength of the connection. Therefore, it is assessing more than just whether an economic IO connection predicts a merger connection. Rather, we use ERGM to assess whether strong economic connections predict high rather than low merger activity. 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).

## REFERENCES


Acemoglu, Daron, Simon Johnson, and Todd Mitton, 2009, Determinants of vertical integration: Financial development and contracting costs, *The Journal of Finance* 64, 1251–1290.

Albert, Réka, and Albert-László Barabási, 2002, Statistical mechanics of complex networks, *Review of Modern Physics* 74, 47–97.

Andrade, Gregor, Mark Mitchell, and Erik Stafford, 2001, New evidence and perspectives on mergers, *The Journal of Economic Perspectives* 15, 103–120.

Becker, Mary J., and Shawn Thomas, 2010, The spillover effects of changes in industry concentration, *University of Pittsburgh Working Paper*.

Bhattacharyya, Sugato, and Amrita Nain, 2010, Horizontal acquisitions and buying power: A product market analysis, *Journal of Financial Economics, forthcoming*.

Bonacich, Philip, 1972, Factoring and weighting approaches to status scores and clique identification, *Journal of Mathematical Sociology* 2, 113–120.

Borgatti, Stephen P., 2005, Centrality and network flow, *Social Networks* 27, 55–71.

Clauset, Aaron, Cosma R. Shalizi, and M.E.J. Newman, 2009, Power-law distributions in empirical data, *SIAM Review* 51, 661–703.

Dijkstra, E. W., 1959, A note on two problems in connexion with graphs, *Numerishce Mathematik* 1.

Duchin, Ran, and Breno Schmidt, 2010, Riding the merger wave, *University of Michigan and Emory University Working Paper*.

Eckbo, B. Espen, 1983, Horizontal mergers, collusion, and stockholder wealth, *Journal of Financial Economics* 11, 241–273.

Fan, Joseph P.H., and Vidhan K. Goyal, 2006, On the patterns and wealth effects of vertical mergers, *Journal of Business* 79, 877–902.

Fan, Joseph P.H., 2000, Price uncertainty and vertical integration: An examination of petrochemical firms, *Journal of Corporate Finance* 6, 345–376.

Fee, C. Edward, and Shawn Thomas, 2004, Sources of gains in horizontal mergers: Evidence from customer, supplier, and rival firms, *Journal of Financial Economics* 74, 423–460.

Ferris, Ann, 2009, Environmental regulation and labor demand: The Northern Spotted Owl, *University of Michigan, Working Paper*.

Gabaix, Xavier, 2009a, The granular origins of aggregate fluctuations, *New York University Working Paper*.

———, 2009b, Power laws in economics and finance, *Annual Review of Economics* 1, 255–293.

Galbraith, John Kenneth, 1952, *American Capitalism: The Concept of Countervailing Power* (M. E. Sharpe, Inc.).

Gort, Michael, 1969, An economic disturbance theory of mergers, *The Quarterly Journal of Economics* 83, 624–642.

Harford, Jarrad, 2005, What drives merger waves?, *Journal of Financial Economics* 77, 529–560.

Hertzel, Michael G., Zhi Li, Micah S. Officer, and Kimberly J. Rodgers, 2008, Inter-firm linkages and the wealth effects of financial distress along the supply chain, *Journal of Financial Economics* 87, 374–387.

Horn, Henrick, and Asher Wolinsky, 1988, Bilateral monopolies and incentives for merger, *The RAND Journal of Economics* 19, 408–419.

Hunter, David R., Mark S. Handcock, Carter T. Butts, Steven M. Goodreau, and Martina Morris, 2008, ergm: A package to fit, simulate and diagnose exponential-family models for networks, *Journal of Statistical Software* 24.

Inderst, Roman, and Christian Wey, 2003, Bargaining, mergers, and technology choice in bilaterally oligopolistic industries, *The RAND Journal of Economics* 34, 1–19.

Kedia, Simi, S. Abraham Ravid, and Vicente Pons, 2008, Vertical mergers and the market valuation of the benefits of vertical integration, *Rutgers Business School Working Paper*.

Klein, Benjamin, Robert G. Crawford, and Armen A. Alchian, 1978, Vertical integration, appropriable rents, and the competitive contracting process, *Journal of Law and Economics* 21, 297–326.

Maksimovic, Vojislav, Gordon M. Phillips, and Liu Yang, 2010, Private and public merger waves, *University of Maryland and UCLA Working Paper*.

Mitchell, Mark L., and J. Harold Mulherin, 1996, The impact of industry shocks on takeover and restructuring activity, *Journal of Financial Economics* 41, 193–229.

Ovtchinnikov, Alexei V., 2010, Merger waves following industry deregulation, *Vanderbilit University Working Paper.*

Rhodes-Kropf, Matthew, and David Robinson, 2008, The market for mergers and the boundaries of the firm, *Journal of Finance* 62, 1169–1211.

Rhodes-Kropf, Matthew, David T. Robinson, and S. Viswanathan, 2005, Valuation waves and merger activity: The empirical evidence, *Journal of Financial Economics* 77, 561–603.

Rhodes-Kropf, Matthew, and S. Viswanathan, 2004, Market valuation and merger waves, *The Journal of Finance* 59, 2685–2718.

Robins, Garry, and Martina Morris, 2007, Advances in exponential random graph ($p^\star$) models, *Social Networks* 29, 169–172.

Shahrur, Husayn, 2005, Industry structure and horizontal takeovers: Analysis of wealth effects on rivals, suppliers, and corporate customers, *Journal of Financial Economics* 76, 61–98.

Shleifer, Andrei, and Robert W. Vishny, 2003, Stock market driven acquisitions, *Journal of Financial Economics* 70, 295–311.

Stillman, Robert, 1983, Examining antitrust policy towards horizontal mergers, *Journal of Financial Economics* 11, 225–240.

Viscusi, W. Kip, Joseph E. Harrington, and John M. Vernon, 2005, *Economics of Regulation and Antitrust* (MIT Press: Cambridge, Mass.) 4th edn.

Watts, Duncan J., and Steven H. Strogatz, 1989, Collective dynamics of 'small-world' networks, *Nature* 393, 440–442.

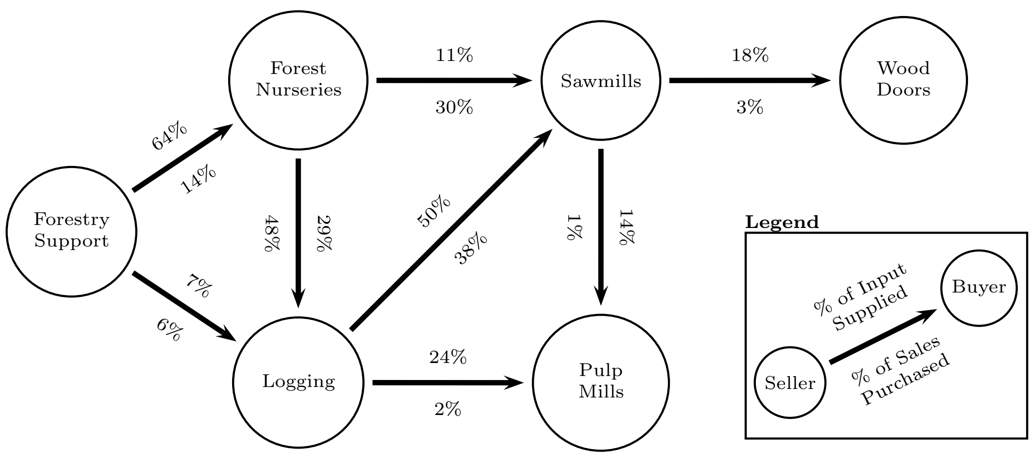
Williams, George, Keith Brown, and Peter Alexander, 2002, Radio market structure and music diversity, *Federal Communications Commission: Media Bureau Staff Research Paper.*

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

**(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).

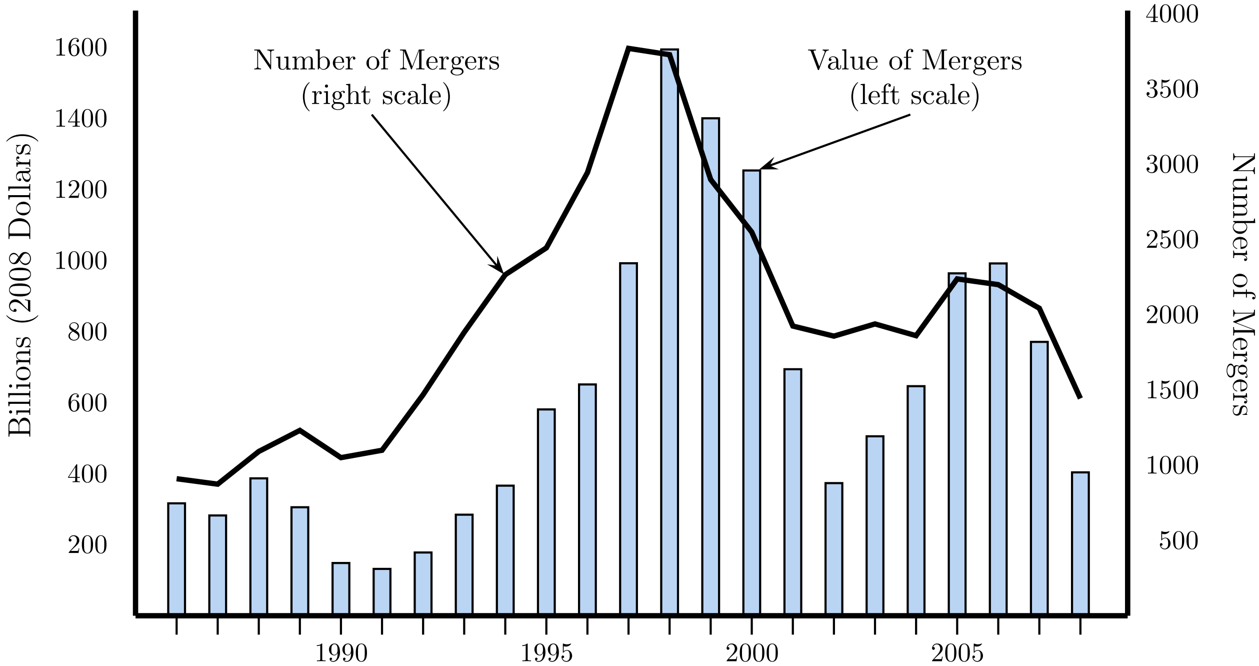
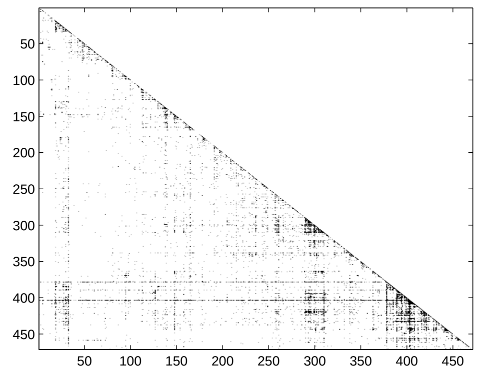
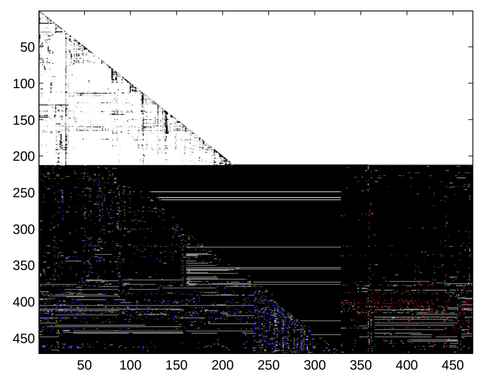


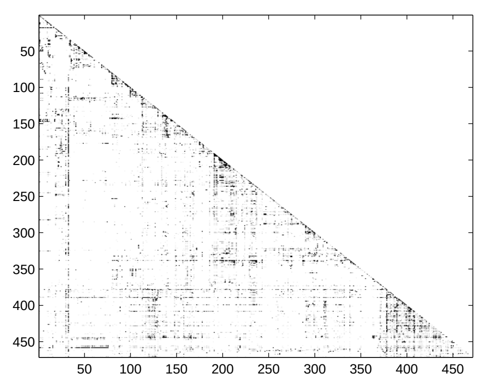

**Figure 2**
**Dollar Value and Number of Mergers, 1986–2008**
Aggregate merger volume in 2008 adjusted U.S. dollars and by the number of mergers. Merger data is from SDC.




**(a)** Mergers

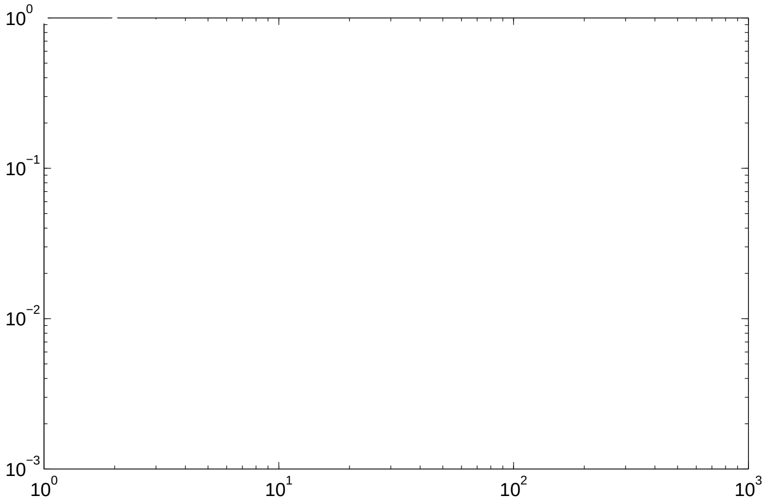



**(b)** Supplier Relationships




**(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.




Degree kp(k)

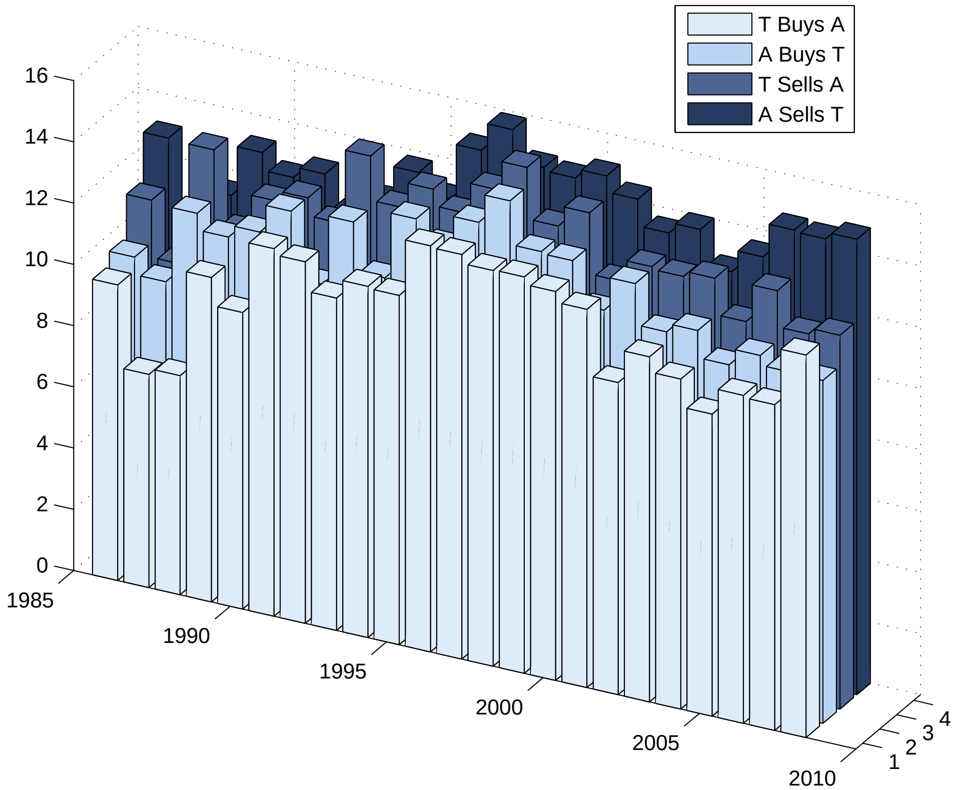
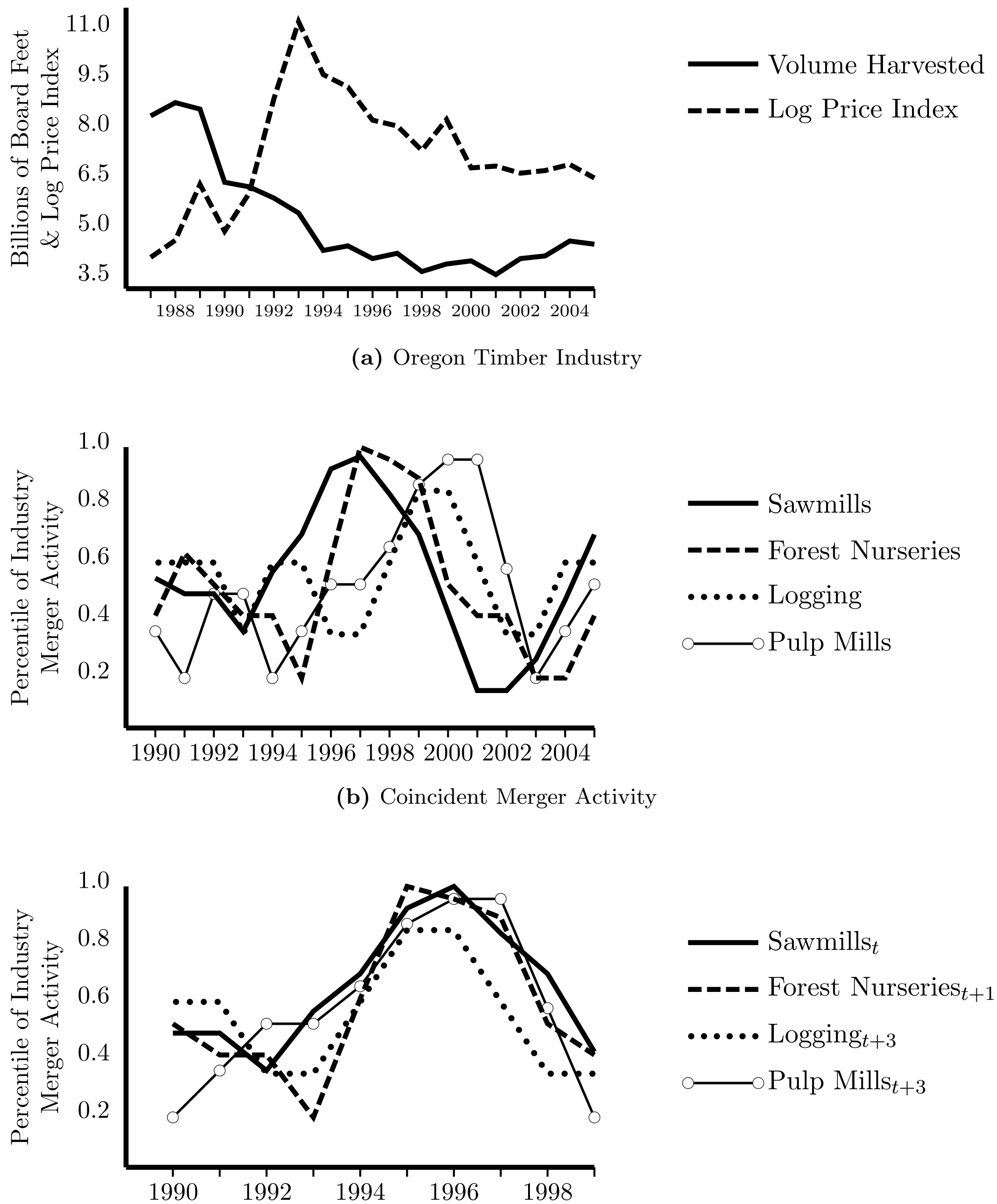



**Figure 5**
**$t-$Statistics from Yearly ERGM Tests**
This figure represents the $t-$statistic on each of the four IO networks (T Buys A, A Buys T, etc.) from yearly ERGM tests from 1986 to 2008.




**(a)** Oregon Timber Industry

**(b)** Coincident Merger Activity

**(c)** Leading Merger Activity

**Figure 6**
**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.

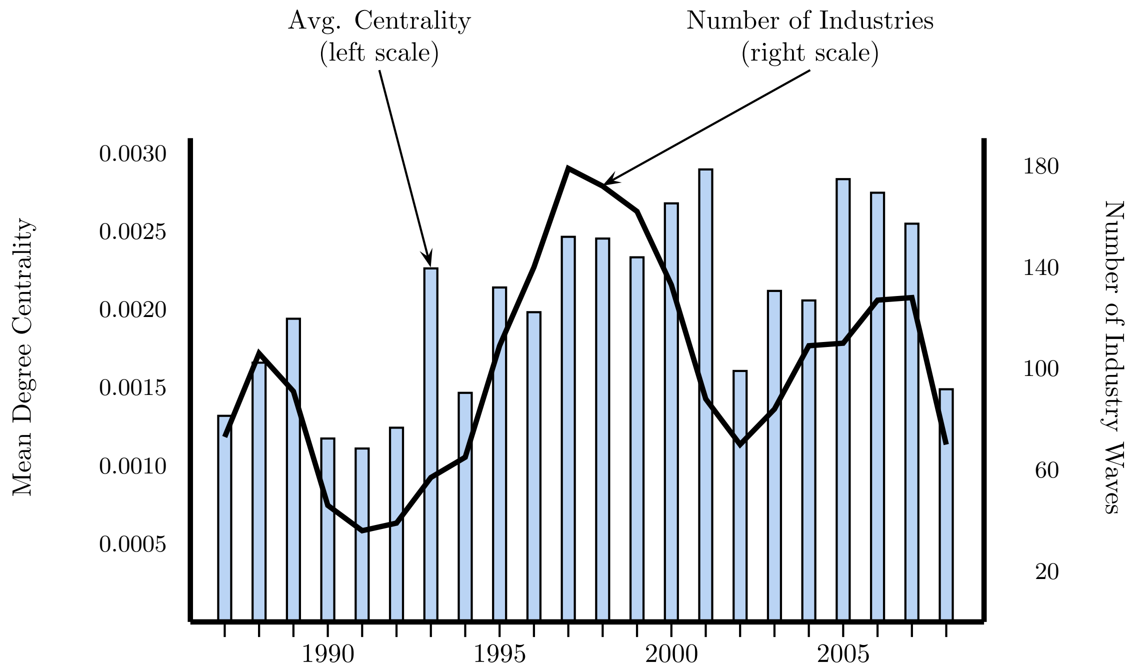



**Figure 7**
**Network Centrality and Industry Merger Waves**
Vertical bars represent the average eigenvector centrality across the industries that are experiencing abnormal merger volumes. Centrality is over the supplier input-output network where nodes are each of the 471 IO industries from the U.S. Census Bureau data from 1997. The black line represents the number of industries experiencing high merger activity (75th percentile of the number of mergers, based on the within-industry time series variation from 1986–2008). 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

**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
## Univariate Relationships Between 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 Networks (Customer or Supplier) 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. See text for definitions of avg. shortest path and clustering coefficient. In Panel A, top cells are means and bottom cells are medians, in brackets. $p-$values from t-tests and rank tests are reported in parentheses. Statistical significance is indicated by ***, **, and *, for the 0.01, 0.05, and 0.10 levels.

*Panel A: Mean and Median Network Statistics by Network*

| | Network | | | $p-$values of difference | | |
|---|---|---|---|---|---|---|
| | Supplier | Customer | Merger | | | |
| | (1) | (2) | (3) | (1) − (2) | (1) − (3) | (2) − (3) |
| Degree Centrality | 22.416 | 16.132 | 24.743 | 0.000*** | 0.240 | 0.000*** |
| | [16.000] | [13.000] | [16.000] | 0.000*** | 0.095* | 0.000*** |
| Eigenvector Centrality | 0.037 | 0.033 | 0.046 | 0.003*** | 0.000*** | 0.000*** |
| | [0.033] | [0.025] | [0.045] | 0.000*** | 0.000*** | 0.000*** |
| Average Shortest Path | 2.021 | 2.537 | 2.117 | 0.000*** | 0.000*** | 0.000*** |
| | [2.002] | [2.467] | [2.052] | 0.000*** | 0.000*** | 0.000*** |
| Clustering Coefficient | 0.386 | 0.275 | 0.416 | 0.000*** | 0.005*** | 0.000*** |
| | [0.382] | [0.250] | [0.400] | 0.000*** | 0.011** | 0.000*** |

*Panel B: Correlations Between Industry Characteristics Across Networks*

| | Customer Centrality | Supplier Centrality | Merger Centrality | Customer Avg. Path | Supplier Avg. Path | Merger Avg. Path | Customer Clustering | Supplier Clustering |
|---|---|---|---|---|---|---|---|---|
| Supplier Centrality | 0.532*** | | | | | | | |
| | (0.000) | | | | | | | |
| Merger Centrality | 0.565*** | 0.393*** | | | | | | |
| | (0.000) | (0.000) | | | | | | |
| Customer Avg. Path | −0.565*** | −0.334*** | −0.300*** | | | | | |
| | (0.000) | (0.000) | (0.000) | | | | | |
| Supplier Avg. Path | −0.275*** | −0.575*** | −0.127*** | 0.188*** | | | | |
| | (0.000) | (0.000) | (0.007) | (0.000) | | | | |
| Merger Avg. Path | −0.311*** | −0.228*** | −0.556*** | 0.264*** | 0.174*** | | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | | |
| Customer Clustering | −0.227*** | −0.144*** | −0.125*** | −0.121*** | 0.064 | 0.061 | | |
| | (0.000) | (0.002) | (0.008) | (0.010) | (0.170) | (0.192) | | |
| Supplier Clustering | −0.412*** | −0.519*** | −0.258*** | 0.327*** | 0.268*** | 0.160*** | 0.226*** | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | |
| Merger Clustering | −0.203*** | −0.179*** | −0.291*** | 0.151*** | 0.101** | −0.150*** | 0.005 | 0.146*** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.031) | (0.001) | (0.922) | (0.002) |

**Table IV**
**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 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. $|\Delta$ *Variable* $|$ is the absolute difference between two industry nodes' value of *variable*. AIC is the Akaike's Information Criterion. $p-$values 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) | (7) |
| Number of Connections | −3.406*** | −3.408*** | −3.430*** | −3.426*** | −3.487*** | −4.314*** | −4.328*** |
| | (0.000) | −3.408*** | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Target Buys from Acquirer | 10.042*** | (0.000) | | | 5.939*** | 13.126*** | 12.926*** |
| | (0.000) | | | | (0.000) | (0.000) | (0.000) |
| Acquirer Buys from Target | | | | | 6.625*** | 12.495*** | 12.301*** |
| | | 10.599*** | | | (0.000) | (0.000) | (0.000) |
| Acquirer Sells to Target | | (20.575) | 18.540*** | | 14.952*** | 25.537*** | 25.553*** |
| | | | (0.000) | | (0.000) | (0.000) | (0.000) |
| Target Sells to Acquirer | | | | 17.144*** | 13.317*** | 22.218*** | 22.197*** |
| | | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Industry Econ Shock Index | | | | | | −0.225*** | −0.220*** |
| | | | | | | (0.000) | (0.000) |
| Industry Median M/B | | | | | | 0.286*** | 0.265*** |
| | | | | | | (0.000) | (0.000) |
| Industry Mean Return | | | | | | −0.599*** | −0.586*** |
| | | | | | | (0.000) | (0.000) |
| Industry Std Dev of Returns | | | | | | 2.010*** | 2.034*** |
| | | | | | | (0.000) | (0.000) |
| Concentration Ratio | | | | | | −0.008*** | −0.008*** |
| | | | | | | (0.000) | (0.000) |
| $\mid \Delta$ Industry M/B$\mid$ | | | | | | | 0.229** |
| | | | | | | | (0.030) |
| $\mid \Delta$ Industry Mean Returns $\mid$ | | | | | | | −0.512 |
| | | | | | | | (0.107) |
| $\mid \Delta$ Std Dev of Returns $\mid$ | | | | | | | 0.661** |
| | | | | | | | (0.011) |
| $\mid \Delta$ Concentration Ratio $\mid$ | | | | | | | 0.004 |
| | | | | | | | (0.217) |
| AIC | 63,438 | 63,393 | 63,047 | 63,158 | 61,878 | 16,477 | 16,453 |
| Number of Industries | 471 | 471 | 471 | 471 | 471 | 214 | 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. 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. Scaled Network-wide M&A Activity is the dollar values of all M&As in year $t$ divided by the total value of all mergers in all years (1986–2008). 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. Industry Economic Shock Index equals one in industry years where 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 is in the top quartile. Deregulatory Shock equals one if there was a change in regulation in the industry-year. Industry concentration is the 8-firm concentration ratio of sales.

| | 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 |
| IO Degree Centrality × Scaled Network-wide M&A Activity | 0.089 | 0.021 | 0.271 | 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 |
| Industry Economic Shock Index | −0.415 | −0.741 | 1.140 | 2,862 |
| Deregulatory Shock | 0.021 | 0.000 | 0.144 | 2,862 |
| Industry Median M/B | 1.392 | 1.274 | 0.481 | 2,862 |
| Industry Mean Return | 0.157 | 0.107 | 0.412 | 2,862 |
| Industry Standard Deviation of Returns | 0.564 | 0.432 | 0.522 | 2,862 |
| Industry Concentration | 47.006 | 46.400 | 20.413 | 2,862 |

**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. 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. See Table VI for the definition of other variables. $p-$values are reported in parentheses. 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 | 0.035 | 0.036 | 0.034 |

**Table VIII**
**The Effect of Network Closeness and Time Lags on Connected Industry Merger Activity**

This table presents the coefficient estimates of a logit regression in columns 1 and 2, where the dependent variable is the M&A Activity State of an Industry in year $t+1$. 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, and zero otherwise. Coefficient estimates are the log odds ratio minus one. Columns 3 and 4 present coefficient estimates of Tobit regressions where observations are left censored at zero. The dependent variable is the aggregate dollar value of the subject industry mergers in year $t+1$. Subject refers to the observation industry, connected to the other industries. Network connection indicates whether the distance of industry connections to the subject industry is measured as the percentage of all inputs that the connected industry buys from the subject industry (Connected Buys from Subject) or the percentage of all sales accounted by connected industry purchases (Subject Sells to Connected). Closely (Distantly) Connected M&A is a measure of merger activity over the industries with above (below)-median distance network measures (excluding mergers with the subject industry $i$). $p-$values are reported in parentheses. Standard errors are clustered at the industry level. Statistical significance is indicated by $^{***}$, $^{**}$, and $^{*}$, for the 0.01, 0.05, and 0.10 levels.

| | Logit | | Tobit | |
|---|---|---|---|---|
| Dependent Variable | M&A Activity State$_{t+1}$ | | Industry Merger Value$_{t+1}$ | |
| Network Connection | Connected Sells to Subject | Subject Buys from Connected | Connected Sells to Subject | Subject Buys from Connected |
| | (1) | (2) | (3) | (4) |
| Subject Industry M&A$_t$ | 0.278$^{***}$ | 0.341$^{***}$ | 0.557$^{***}$ | 0.558$^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Closely Connected M&A$_t$ | 0.075$^{***}$ | 0.006$^{***}$ | 0.018$^{**}$ | 0.000 |
| | (0.000) | (0.000) | (0.035) | (0.571) |
| Distantly Connected M&A$_t$ | −0.005$^{***}$ | 0.007$^{***}$ | −0.001 | 0.002$^{**}$ |
| | (0.001) | (0.000) | (0.295) | (0.044) |
| Subject Industry M&A$_{t-1}$ | 0.047 | 0.076 | 0.035 | 0.032 |
| | (0.468) | (0.240) | (0.228) | (0.279) |
| Closely Connected M&A$_{t-1}$ | −0.045$^{***}$ | −0.003$^{*}$ | −0.020$^{***}$ | −0.001$^{*}$ |
| | (0.000) | (0.094) | (0.007) | (0.063) |
| Distantly Connected M&A$_{t-1}$ | 0.006$^{***}$ | −0.003$^{***}$ | 0.003$^{***}$ | −0.001 |
| | (0.002) | (0.008) | (0.004) | (0.200) |
| Constant | | | −0.384$^{**}$ | −0.362$^{**}$ |
| | | | (0.037) | (0.027) |
| Observations | 9,400 | 9,380 | 9,870 | 9,849 |
| Pseudo $R^2$ | 0.022 | 0.010 | 0.092 | 0.091 |