The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXIX, NO. 2 • APRIL 2014

The Importance of Industry Links in Merger Waves

KENNETH R. AHERN and JARRAD HARFORD*

ABSTRACT

We represent the economy as a network of industries connected through customer and supplier trade flows. Using this network topology, we find that stronger product market connections lead to a greater incidence of cross-industry mergers. Furthermore, mergers propagate in waves across the network through customer-supplier links. Merger activity transmits to close industries quickly and to distant industries with a delay. Finally, economy-wide merger waves are driven by merger activity in industries that are centrally located in the product market network. Overall, we show that the network of real economic transactions helps to explain the formation and propagation of merger waves.

A GROWING BODY OF evidence shows that industry characteristics affect many firm decisions, including financial policy (MacKay and Phillips (2005)), internal capital markets (Lamont (1997)), and corporate governance (Giroud and Mueller (2010)). This line of research emphasizes that strategic interactions between firms and their industry rivals have important implications for fundamental questions in financial economics. We broaden this analysis by making a simple, though consequential, observation: industries do not exist in isolation, but rather are connected through a complex network of customer-supplier relationships. This implies that whole industries may be affected by shocks that are transmitted through the customer-supplier network. In this paper, we investigate how interindustry relations affect the timing and incidence of one of the most important phenomena in corporate finance: merger waves.

*Kenneth Ahern is at the University of Southern California, Marshall School of Business. Jarrad Harford is at the University of Washington, Foster School of Business. We thank two anonymous referees, an anonymous Associate Editor, Cam Harvey (Editor), Sugato Bhattacharyya, Hans Degryse, Ran Duchin, Gerard Hoberg, Jonathan Karpoff, Han Kim, Vojislav Maksimovic, David McLean, Sara Moeller, Gordon Phillips, Ed Rice, Matthew Rhodes-Kropf, David Robinson, Shawn Thomas, Karin Thorburn, and seminar participants at the 2010 Texas Finance Festival, 2010 European Summer Symposium in Financial Markets, First European Center for Corporate Control Studies Workshop in 2010, 2010 Frontiers in Finance Conference, 2011 Washington University Conference on Corporate Finance, 2011 American Finance Association Meetings, 2011 University of British Columbia Winter Finance Conference, Georgia State University, University of Illinois, University of Maryland, University of Michigan, University of North Carolina – Chapel Hill, University of Pittsburgh, and University of Wisconsin for helpful suggestions. We also thank Jared Stanfield for excellent research assistance.

DOI: 10.1111/jofi.12122

The industry network model of an economy has at least three new implications for merger waves. First, industry-level economic shocks could lead to cross-industry vertical merger waves. Though it is well documented that merger waves occur within industries (Mitchell and Mulherin (1996), Maksimovic and Phillips (2001), Rhodes-Kropf, Robinson, and Viswanathan (2005)), vertical merger waves may be just as common. Second, merger waves could propagate through customer and supplier links without direct vertical integration. For instance, the reorganization of a supplier industry could cause a customer industry to reorganize in response. Third, the structure of the industry network could determine how industry-level M&A activity aggregates into an economy-wide merger wave. These implications are important for understanding how economic fundamentals at the industry level influence economy-wide outcomes.

To test these three implications, we empirically model the product market network using input-output (IO) data from the Bureau of Economic Analysis (BEA). These data provide trade flows between 471 industries accounting for all sectors in the economy. Using these industry definitions, we create a network representing cross-industry mergers over the period 1986 to 2010, where the strength of the connection between two industries is proportional to the level of their cross-industry merger activity. Thus, for a comprehensive set of industries, we define two different types of interindustry connections: IO trade flows and cross-industry mergers.

We first characterize the product market and merger networks. We find that both networks are sparse, but highly interconnected through a relatively small set of centralized "hub" industries. To illustrate, more than 95% of industry pairs in the product market network have almost no customer-supplier relations. Similarly, all cross-industry mergers in our sample occur in just 6% of all possible industry pairs. This means that the average industry engages in mergers with a small set of local industries that are closely related through customer-supplier links. We also find that the product market and merger networks both exhibit small-world properties, where the average industry is separated from most other industries by only two or three direct connections, even across 471 different industries. In addition, we find that an industry's centrality in the product market network is correlated with its centrality in the merger network, as are other network characteristics, such as clustering and average distance. Thus, the structure of the merger network is highly similar to the structure of the product market network.

This characterization of the product market and merger networks supports our first finding that vertical mergers are common and highly clustered in a relatively small set of directly linked industry pairs. Of the 51,002 mergers in the sample, 61% are interindustry mergers. Prior research identifies many reasons for vertical mergers.[1] Neoclassical theory proposes that vertical mergers may eliminate an existing inefficiency, such as double price markups in

[1] Comprehensive surveys of the motives for vertical integration can be found in Tirole (1988) and Perry (1989).

successive monopolies (Spengler (1950), Perry (1978b)) or input substitution (Vernon and Graham (1971), Schmalensee (1973), Warren-Boulton (1974)). Another neoclassical motive for vertical mergers is to prevent resale of an input in downstream industries in order to allow price discrimination across different price elasticities of demand (Perry (1978a), Katz (1987)). As an alternative to the neoclassical theory, transaction costs may lead to vertical integration if the net benefits of internal transactions are larger than those of transacting in a market (Coase (1937), Williamson (1979)). The costs of market transactions and the corresponding holdup problems increase with both uncertainty and relationship-specific investments (Klein, Crawford, and Alchian (1978)). Thus, firms with complementary assets may merge with each other to overcome incomplete contracts (Rhodes-Kropf and Robinson (2008)).

We find evidence consistent with transaction cost theories, while showing that IO trade flows predict cross-industry mergers. We estimate exponential random graph models (ERGMs), which are multivariate maximum likelihood regressions developed to allow for simultaneous dependence relations between all nodes in a network. The results show that there are more interindustry mergers between two industries when they have stronger customer-supplier relations, controlling for industry valuation, scope, size, returns, concentration, and macroeconomic shocks. We also find that cross-industry mergers are more likely when industries have greater R&D expenditures and that R&D magnifies the effects of product market links. To the degree that R&D proxies for incomplete contracts, these results are consistent with holdup problems. In addition, we find evidence that cross-industry mergers are positively related to asset complementarity, following Hoberg and Phillips (2010b). We are careful to note that we do not claim to separately identify each motivation for vertical mergers. Instead, we provide evidence that shows that product market trade flows have a first-order effect on the incidence of cross-industry mergers.

The relations between product market links and mergers are economically significant. Industry pairs without a meaningful economic connection have, on average, 0.11 mergers over the sample period. Those with a strong connection have an average of 12.5 mergers. This effect is present in every year from 1986 to 2010 and is stronger during market booms and aggregate merger waves. These results imply that economic fundamentals are more, not less, important during merger waves.

The second implication of the industry network model is that merger waves could propagate through customer and supplier links without direct vertical integration. Galbraith (1952) predicts that industry consolidation in an upstream industry leads to consolidation in a downstream industry to counteract the monopoly power created through the initial consolidation. More recent 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)). Thus, merger activity could be transmitted through economic links between industries, even without vertical integration.

Consistent with this view, we find evidence that mergers propagate across the industry network following a wave-like pattern. We measure each industry's exposure to merger activity in related industries, not including mergers with the industry itself. We use graph theory techniques to identify which industries are close and which are distant in the product market network. Accounting for a number of controls, including industry fixed effects and an industry's own lagged merger activity, we find that mergers in close industries have a strong positive effect on an industry's own merger activity after a one-year delay, while merger activity in distant industries has a positive impact after a delay of two or three years. Thus, merger waves travel across customer-supplier links, even without direct vertical integration. We also find that the impact of mergers in supplier industries is larger and travels faster across the network than the impact of mergers in customer industries. This likely reflects the fact that the supplier network is more densely connected.

In the last section of the paper, we investigate the third implication of the network perspective: the structure of the industry network could determine how industry-level M&A activity aggregates into an economy-wide merger wave. In vector autoregressions (VARs), we find that the industries that experience merger waves during the height of overall economy-wide merger activity are the most central industries in the product market network. This is a direct consequence of the highly skewed distribution of interindustry connections. As merger activity transmits across the network toward more central industries, many overlapping industry waves occur, which produces an aggregate merger wave. This evidence contradicts the idea that industry merger activity caused by random shocks does not cluster in time and therefore cannot explain economy-wide aggregate merger waves (Shleifer and Vishny (2003)). Our evidence suggests that, even if the initial industry shocks are random, aggregate merger waves occur, in part, because of the structure of the industry network.

This paper makes two primary contributions to the literature. First, this paper is related to recent research that investigates the role of industry relations in corporate finance. Bhattacharyya and Nain (2011) 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. Fee and Thomas (2004) and Shahrur (2005) use vertical relations to test the effects of horizontal mergers on market power, building upon Eckbo (1983) and Stillman (1983). Hertzel et al. (2008) find that suppliers to firms that file for bankruptcy suffer negative and significant wealth effects. Our paper is the first to focus on the role of IO connections for cross-industry mergers. Although it is generally accepted 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. Our paper is unique in that we study the determinants of the incidence and timing of interindustry mergers across all industries, rather than the value implications of the mergers that occur. Our paper is also related to a strain of recent research on merger waves, including Maksimovic, Phillips, and Yang (2013), Duchin and Schmidt (2013), Garfinkel and Hankins (2011), and Ovtchinnikov (2013).

The second contribution of this paper is to model the economy as a network of customer and supplier relations. This approach is related to Hoberg and Phillips (2010a, 2010b) (HP), who use network techniques to group firms based on textual product market descriptions. In our paper, we exploit the IO trade flows to model network ties based on exogenous real economic trade flows between industries. The network approach provides key benefits over analysis of single connections between suppliers and customers. In particular, by considering all industries, we alleviate selection bias caused by only considering industry pairs directly involved in mergers. Second, the network approach explicitly accounts for dependencies between all industries, including higher order connections, and allows for tests of the propagation of industry-level shocks from one industry to another across the entire economy. We believe that this approach will have far-reaching applications for understanding the interaction of corporate finance and industrial organization. For the sake of brevity, we present only a fraction of the description of the product market network in the paper, but we provide a comprehensive report in the Internet Appendix, which may be useful for future research.[2]

The rest of the 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 IO network to the merger network in a static setting. In Section III, we present tests of the propagation of merger waves across the industry network over time. Section IV presents tests of aggregate merger waves and network centrality. Section V concludes.

I. Data Sources and Methods

A. Customer-Supplier Trade Network Data

Since 1947, the BEA has provided IO accounts of dollar flows between all producers and purchasers in the U.S. economy. Producers include all industrial and service sectors as well as household production. Purchasers include industrial sectors, households, and government entities. These data therefore cover the entire economy, not just manufacturing industries. The IO tables are based primarily on data from the Economic Census and are updated every five years with a five-year lag. Since our merger data (described below) cover the period 1986 to 2010, we use the IO tables from 1982, 1987, 1992, 1997, and 2002, the most recent report as of July 2012.

The BEA defines industries at two levels of aggregation, detailed and summary. The number of detailed industries, excluding households and government sectors, ranges between 411 and 478 in the different reports. This is slightly

[2] The Internet Appendix is available in the online version of this article on the *Journal of Finance* website.

more narrow than the 416 three-digit 1987 SIC codes, but substantially more coarse than the 1,005 four-digit SIC codes. The detailed IO industries are also closer to the number of four-digit 1997 NAICS codes (313) than to the number of five-digit NAICS codes (721) or six-digit NAICS codes (1,179). The number of summary-level IO industries ranges between 77 and 126, which is similar to two-digit SIC codes (83) and three-digit NAICS codes (96).[3] Thus, the coarseness of the IO industry definitions is roughly equivalent to those of two- and three-digit SIC codes, which are used extensively in prior research.

In each report, the BEA updates the classifications used in the IO tables to reflect changes in the economy. The classifications are designed to group firms into industries that best measure customer and supplier relations, using the most recent standardized industry classifications. Prior to 1997, the IO industries were defined based on 1977 and 1987 SIC codes. In 1997 and 2002, the BEA based the IO industries on 1997 and 2002 NAICS codes, following the policy of most U.S. government agencies to switch from SIC to NAICS codes. Concordance tables between NAICS and SIC codes and IO industry codes are provided by the BEA.

Since our unit of observation is an industry pair, to maintain consistency over the years in our sample we cannot combine data from different BEA reports in the same analysis. Therefore, in the main analysis we present results using the 1997 detail-level IO definitions. We choose the 1997 report because 1997 splits our merger data into two approximately equal time periods. The 1997 report is also concurrent with the largest aggregate merger activity in our sample period. We choose to focus on the detail-level industries in the main analysis because doing so allows for a more granular representation of the economy. Therefore, unless otherwise noted, the results presented in the paper refer to the detail-level industries in 1997. However, for robustness, in the Internet Appendix we run our tests using both detailed and summary-level IO relations from the 1982, 1987, 1992, and 2002 reports.

Each IO report defines "commodity" outputs and producing "industries." A commodity, as defined by the BEA, is any good or service that is produced. An industry may produce more than one commodity, which means that more than one industry may produce the same good or service. However, 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. In the 1997 report, 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.[4] Costs are reported in both purchaser and producer costs (the differences are due to retail and

[3] Internet Appendix Table IA.I reports the number of industries across SIC, NAICS, and BEA IO definitions for various years.

[4] 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 13 industries or final users in the Use table that are not in the Make table include personal consumption

wholesale markups, taxes, and other transaction costs). Throughout the paper we use producers' prices, but using purchasers' prices makes little difference.

From the Use and Make tables, we create matrices that record flows of inputs and outputs between industries. Following Becker and Thomas (2010) we calculate *SHARE*, an $I \times C$ matrix (Industry $\times$ 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 in column j to the supplier industry in row i. Finally, the *CUST* matrix is *REVSHARE* divided by the sum of all sales for an industry, and the *SUPP* matrix is *REVSHARE* divided by the sum of all purchases 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 inputs that are purchased from industry i. These two matrices describe the relative trade flows between all industries in the economy.

The IO tables treat employee compensation as a commodity input in production. However, there is no corresponding industry that produces compensation. Because of this, employee compensation gets dropped from the industry matrices. Therefore, we create an artificial labor industry to make sure that we account for labor as an input in the industry matrices. If we do not include labor costs, other inputs in labor-intensive industries will appear to be a larger component of total inputs than they actually are, relative to capital-intensive industries. The additional labor industry is used only to account for inputs; we do not include labor as an industry or commodity in our final sample. After excluding household and government industries, as well as exports and imports, and making a few minor adjustments, we are left with 471 industries. A detailed description of the data is reported in Section I of the Internet Appendix.

One of the important features of the IO matrix is that it is largely exogenous to merger activity. This is because the basic input requirements in the production of any good are determined mainly by the good's production function, not by the ownership structure of the firms that produce the inputs.[5] The exogeneity of the product market network, with respect to ownership, mitigates concerns about reverse causality, where merger waves cause product market relations to change. In addition, by using the 1982 IO reports in robustness tests, we ensure that the IO relations are exogenous to merger activity from 1986 to 2010.

expenditures, private fixed investment, change in private inventories, exports and imports, and federal and state government expenditures.

[5] It is possible that vertically integrated firms use substitute inputs based on their ownership of certain supplier segments. However, if input substitution leads to inefficient production, these firms are unlikely to survive, or, alternatively, the input substitution is not important. For this to affect our results, the input substitution would need to occur at an industry level, rather than at the firm level.

B. Merger Network Data

Merger data are from the SDC Thomson Platinum database. We collect data for all mergers that meet the following criteria: (1) announcement dates are between January 1, 1986 and December 31, 2010; (2) both the target and the acquirer are U.S. firms; (3) the acquirer buys 20% or more of the target's shares; (4) the acquirer owns 51% or more of the target's shares after the deal; (5) the merger is completed; and (6) transaction value is 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. The above criteria produce a sample of 51,002 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 NAICS codes of the acquirer and the target. Because SDC records 2007 NAICS codes, 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. In the robustness tests that use IO reports from years other than 1997, we match SIC codes from SDC. This means, for example, that in the tests that use the 1982 IO reports, we first convert 1987 SIC codes reported in SDC to 1977 SIC codes to match to the IO definitions. Section I of the Internet Appendix provides more details on the mapping between industry classifications.

Next, we record merger activity both yearly and cross-sectionally for each directed IO industry-pair of acquirer and target industries, where directed industry pairs differentiate between acquirer and target industries. This produces $471^2 = 221,841$ unique pairs. For each time window (yearly and cross-sectionally), we record the number and dollar value of mergers in which the acquirer is in industry i and the target is in industry j. Therefore, 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 interindustry mergers it is likely that the acquirer could be in either industry, we also record the data in a nondirected way between two industries. This yields $\frac{1}{2} \times 471 \times (471 - 1) = 110,685$ unique industry pairs per window of observation.

In the main analysis, we match firms to IO industries using their primary NAICS code. However, this does not account for diversified firms. As mentioned previously, IO industries are roughly as coarse as three-digit SIC codes. Firms with multiple, but related, segments will tend to be assigned to the same IO industry, regardless of which segment's six-digit NAICS code is used. However, this does not account for firms with multiple unrelated segments that would be assigned to different IO industries, depending upon which industry is listed as its primary segment. Therefore, we use three alternative methods to assign firms to IO industries.

In the first alternative method, we use all industry codes reported in SDC to identify a full set of IO industries per firm. We then assign equal weight to merger counts and dollar volumes for each of these IO industry codes. For instance, if an acquirer is in industries 1 and 2 and a target is in industry 3, we assign 0.5 merger counts to the industry pair (1,3) and 0.5 counts to industry pair (2,3). In the second and third alternatives, we give greater priority to horizontal mergers, followed by vertical mergers, and then unrelated mergers. For each pair of merging firms, we first identify horizontal mergers as any overlaps in all possible IO industry codes. If there are any horizontal matches, we assign an equal fraction of the merger count or dollar volume to the overlapping IO industry codes. If there are no horizontal matches but there is a vertical relation between any of the firms' IO codes, we assign the deal activity equally to those IO industry codes. Vertical relations are defined at two threshold levels. First, we record a vertical relation if two industries exceed a threshold of 1% across any of the following four vertical relations: (1) acquirer industry purchases from target, (2) target industry purchases from acquirer, (3) acquirer industry sells to target, and (4) target industry sells to acquirer. Second, we create a mapping using a 5% threshold of vertical relations. If there are neither horizontal nor vertical industry relations, we assign the deal equally across all of the unrelated industry pairs. This assignment approach ensures that we do not count horizontal mergers as vertical mergers for integrated firms. We describe the industry assignments in more detail in Section I of the Internet Appendix.[6]

C. Other Industry Characteristics

Our aim in this paper is to understand how mergers transmit across industries from a macroeconomic perspective. Therefore, we do not claim to separately identify the various theories of vertical integration empirically. To do so convincingly would require industry case studies. For instance, in a famous paper, Masten (1984) tests for holdup problems using measures of the specificity of design and location for 1,887 aerospace components. Similar papers provide evidence for other industries, such as coal (Joskow (1985, 1987)), aluminum (Stuckey (1983)), chemicals (Lieberman (1991)), and paper industries (Ohanian (1994)), each with unique data. However, we include standardized measures to provide high-level evidence of the importance of possible motives for vertical mergers.

First, as discussed previously, holdup problems associated with incomplete contracts could lead to vertical mergers. To measure the likelihood of holdup problems between two industries, we record the maximum industry R&D/assets for each industry pair. Industry R&D/assets is the median R&D/assets for all firms in the IO industry, using data from Compustat. Though not perfect, investment in R&D proxies for contracting problems because it is a

[6] Though a 1% threshold may seem unimportant, accounting for labor input makes intermediate goods relatively small. In particular, we show later in Table I that over 95% of the inputs in an average industry individually account for less than 1% of total inputs. Of those few industries that supply more than 1%, 46% supply less than 2% of total inputs.

measure of intangible firm-specific knowledge. Larger R&D investments mean that more assets are prone to frictions from incomplete contracts. Following this interpretation, R&D is used in many papers in finance and economics to proxy for difficulty in contracting. These include Denis, Denis, and Atulya (1997), Allen and Phillips (2000), and Fee, Hadlock, and Thomas (2006).[7] We use the maximum of an industry pair's R&D because the presence of contracting problems in one industry is sufficient to create a holdup problem.

Second, cross-industry mergers are more likely when there are asset complementarities between merging firms. Rhodes-Kropf and Robinson (2008) present a search model of mergers based on the property rights theory of the firm (Hart (1995)), in which asset complementarities increase the synergy gains of a merger. Hoberg and Phillips (2010b) provide empirical evidence that firms that are more similar to each other, and also less similar to industry competitors, have greater increases in cash flows and more new product introductions after merging. Furthermore, using a measure of pairwise similarity of product descriptions, Hoberg and Phillips show that SIC and NAICS codes do not adequately capture firm similarity.

To test these theories, we create a measure of interindustry asset complementarity, *HP Similarity*, based on the text-based similarity measure developed by HP, and provided on Jerry Hoberg's website. Hoberg and Phillips's text-based measure identifies firm pairs that have similar product descriptions in their 10-K filings for all firms on Compustat from 1996 to 2008. To aggregate the HP firm-level data to IO industry levels, we record the total number of firms in the HP database that are in a given IO industry pair. Thus, our measure of asset complementarity between two industries is the total number of firm pairs in a given IO industry pair-year that HP identify as similar in a given year. Because these data are only available for roughly half of our sample period, we do not include these measures in the main results, but present them in robustness tests described below.

We also account for the size and scope of industries since both are likely related to merger activity. To measure industry size, we would prefer to have the total number of firms operating in each industry on a yearly basis. However, the available data do not cover our time period, do not have detailed industry classifications, or only cover a limited subset of firms (e.g., public firms in CRSP and Compustat). Instead, we use precise data on the number of establishments from the U.S. Census Bureau's County Business Patterns (CBP) database. Establishments are defined as single physical locations. Thus, larger firms have more establishments. These data are based on the Census Bureau's Business Register, the most complete account of business activities available, and cover the vast majority of industries, including manufacturing and service industries.

[7] One concern with using R&D as a proxy for holdup problems is that R&D could lead to an innovation, or it could fail. Only the ex ante R&D that occurs before an innovation has been discovered should lead to holdup problems (Allen and Phillips (2000), Phillips and Zhdanov (2013)). Given the economy-wide breadth of our study, it is infeasible for us to identify ex ante and ex post R&D.

The data are reported at four-digit SIC and six-digit NAICS code levels. An advantage of establishment-level data is that industry classifications are more precise than firm-level data since establishments are more likely to engage in activities that fall primarily in one industry classification. We aggregate these data to IO industries following the mapping discussed above.

To account for the scope of industries, we record the percent of all NAICS or SIC codes (depending on IO report year) that map to a particular IO industry. Since SIC and NAICS codes are defined to be relatively equal in scope (Economic Classification Policy Committee (1993), Gollop (1994)), this variable provides a measure of the variation in business activities for each IO industry. See Section I of the Internet Appendix for more details. We also control for industry concentration using the eight-firm concentration ratio from the Economic Census of the U.S. Census Bureau. Like the IO data, the Economic Census is conducted every five years, in years ending in two and seven. With the exception of agriculture and public administration, concentration measures are reported for all industries. Since these data cover firms of all sizes and the vast majority of industries, they provide the most comprehensive concentration ratios available. In contrast, concentration ratios calculated using Compustat sales are subject to both a severe size bias and a public listing bias. We map SIC and NAICS codes to IO industries yearly, using the most recent concentration ratios.

To account for valuation-driven mergers, we include various variables, including industry median market-to-book, returns, and standard deviation of returns. We also calculate the difference in these variables between two industries in each industry pair. Finally, we calculate an Industry Economic Shock Index as in Harford (2005). For each industry, we compute 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. All variables are described in detail in Section I of the Internet Appendix.

D. Networks

The primary goal of this paper is to identify the relationship between the IO network and the merger network. To provide a framework for the following analysis, we discuss how networks are defined and measured.

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 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 IO data and merger data as networks. Specifically, each of the networks has the same set of nodes (i.e., the 471 industries from the 1997 IO tables), but the connections between the nodes are either product market relationships in the IO network or interindustry mergers in the merger network. This is easily accomplished by simply treating the IO 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 IO tables and network analysis, to the best of our knowledge this is the first paper to make this connection.

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

Though IO 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 nonlabor inputs in the forest nurseries industry, 64% are purchased from the forestry support industry (a_{21} in Panel B), though of all sales by the forestry support industry, only 14% are purchased by the forest nurseries industry (a_{21} in Panel A). Weighted asymmetric network ties are evident throughout this sector. For example, the forest nurseries 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 the 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 the merger networks, we use techniques from graph theory and social networks. We briefly discuss these techniques next, including the concepts of centrality, clustering, and average shortest paths. Each of these is discussed in greater detail in Section II of the Internet Appendix.

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.

Panel A. Adjacency Matrix Representation of the Timber Network (% of Sales Purchased)

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

Panel B. Adjacency Matrix Representation of the Timber Network (% of Input Supplied)

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

Panel C. Graphical Representation of the Timber Network

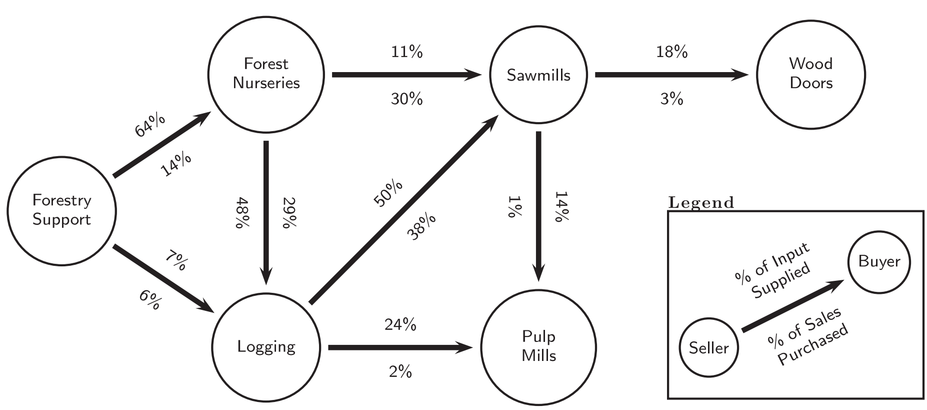

Figure 1. A portion of the timber industry network. This figure presents the adjacency matrices of subsets of the customer and supplier networks from the 1997 U.S. BEA IO tables. The column labels of the adjacency matrices are the transpose of the row labels, and are omitted for brevity. Each entry of 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 nonlabor input costs of the row industry that are purchased by the column industry. Panel C presents both adjacency matrices in graphical representation. For each industry pair, the arrows point from suppliers to customers. The number of the top of the arrow gives the total inputs purchased by the customer from the seller, as a percentage of total inputs purchased from all sources, as reported in Panel B. The number on the bottom of the arrow gives the total sales purchased by the customer industry, as a percetange of the supplier's total sales to all customer industries, as reported in the adjacency matrix in Panel A. The opposite customer-supplier relations exist (e.g., sawmills supply to logging), but they are not reported in this figure.

The degree centrality of a given node in a network is simply the number of links that come from it. 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 is considered more central if it is connected to other nodes that are themselves central.[8]

There are other measures of centrality, but we choose to focus on degree centrality and eigenvector centrality because they best reflect how shocks 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 (like a viral infection such as chicken pox would be, since a node is immune after receiving the virus) and that allows 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 that 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 (1998). 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 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 to 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 calculate the shortest path through the network to every other industry in the network using Dijkstra's (1959) algorithm. 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 indicates the closeness of an industry to all others, on average, and at the network level it also indicates how densely connected is the network, or, in our case, the entire economy. For more details, see Albert and Barabási (2002).

[8] 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 λ is a constant. In matrix notation, this is $\mathbf{Ac} = \lambda\mathbf{c}$. Thus, $\mathbf{c}$ is the principal eigenvector of the adjacency matrix.

Table I

Input-Output Summary Statistics

This table presents summary statistics of the IO relationships of industries (IO industries) as defined by the 1997 BEA Input-Output Detail-Level Industry classification. Interindustry pairs include all combinations of the IO industries (excluding own-industry pairs). Interindustry pairs >1% are those observations where either *Customer %* or *Supplier %* is greater than 1%. Intraindustry 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.

	Customer %			Supplier %		
	Interindustry Pairs	Interindustry Pairs> 1%	Intraindustry	Interindustry Pairs	Interindustry Pairs >1%	Intraindustry
Mean	0.220	5.060	3.310	0.270	3.860	4.110
Median	0.010	2.190	1.140	0.010	2.200	1.400
5^{th} percentile	0.000	1.060	0.000	0.000	1.050	0.000
95^{th} percentile	0.620	18.270	12.470	0.980	10.870	16.010
Frequency Percentage						
0% to 1%	96.568	—	47.346	95.131	—	42.675
1% to 2%	1.567	45.644	12.527	2.231	45.816	14.437
2% to 3%	0.615	17.926	6.582	0.810	16.627	5.945
3% to 4%	0.329	9.582	4.246	0.456	9.371	4.246
4% to 5%	0.190	5.528	5.945	0.339	6.959	4.459
>5%	0.732	21.321	23.355	1.034	21.228	28.238

II. The Relation between Product Market and Merger Networks

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 cross-sectional setting.

A. Summary Statistics

Table I presents summary statistics for the 1997 IO relationships. We divide the sample into interindustry pairs, intraindustry pairs, and interindustry pairs that have substantial trade relations. To identify industry pairs with a substantial relationship, we follow Fan and Goyal (2006) and Ahern (2012) and require that either (1) a customer industry buys at least 1% of a supplier industry's total output (Customer %), or (2) 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. As mentioned above, accounting for labor input reduces the share of intermediate inputs considerably. Across all 110,685 interindustry 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 0.27%.

More than 95% of industry pairs have customer and supplier relationships of less than 1%. Considering the breadth of the U.S. economy, it is expected that industries do not have customer-supplier relations with most other industries. For example, we would not expect that firms in the forestry support industry have substantial trade relations with firms in the financial services industry. However, these results indicate that customer-supplier relations are highly clustered in a very small set of industry pairs.

In the interindustry 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 2.2%. Intraindustry 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 1.4%, and close to 50% of industries have supplier and customer relationships of less than 1%.

In Internet Appendix Table IA.II, we provide the same statistics for each IO report year for both detail and summary-level industry definitions. The statistics show that customer-supplier relations remain stable over the 1982 to 2002 period. This likely reflects the fact that vertical relations are persistent and also the fact that the BEA updates its industry definitions to maintain a consistent measurement of IO relations. The statistics for the IO relations at the summary industry level are surprisingly similar to the detail industry level, given that there are only 124 summary-level industries compared to 471 detail-level industries. In particular, across all industry pairs, the average percentage of inputs supplied is roughly 0.80%, but the median is about 0.20%, compared to 0.01% in the detail-level relations. These results are consistent with a product market network composed of few key industries and many less important ones.

Turning to the merger data, Figure 2 summarizes the time series of aggregate merger activity in our sample. This figure primarily establishes that our merger sample is similar to those used in other studies of mergers and of merger clustering in time. As is typical, the 1980s merger wave is small in comparison to the activity in the mid to late 1990s. The most recent wave that began in 2003 to 2004 ends in 2009 due to the financial crisis.

Table II describes the merger data at the industry pair and industry levels. Industry-level observations are aggregates of industry pair observations. For the entire sample across all years, 51,002 mergers and acquisitions represent deal value of \$16.7 trillion in 2010 dollars. Of these, 19,962 are intraindustry, horizontal mergers, representing \$6.6 trillion in deals. The remaining 31,040 deals are interindustry deals, accounting for \$10.1 trillion.

Across all possible pairwise interindustry combinations, the average industry pair has 0.28 mergers over the 25-year sample period and 94% have no mergers at all. This means that, though interindustry mergers are more common than intraindustry mergers in our sample, they are not uniformly distributed across industry pairs, but rather are highly clustered. Only 6% of the 110,685 industry pairs account for all 31,040 interindustry deals. If economic fundamentals drive

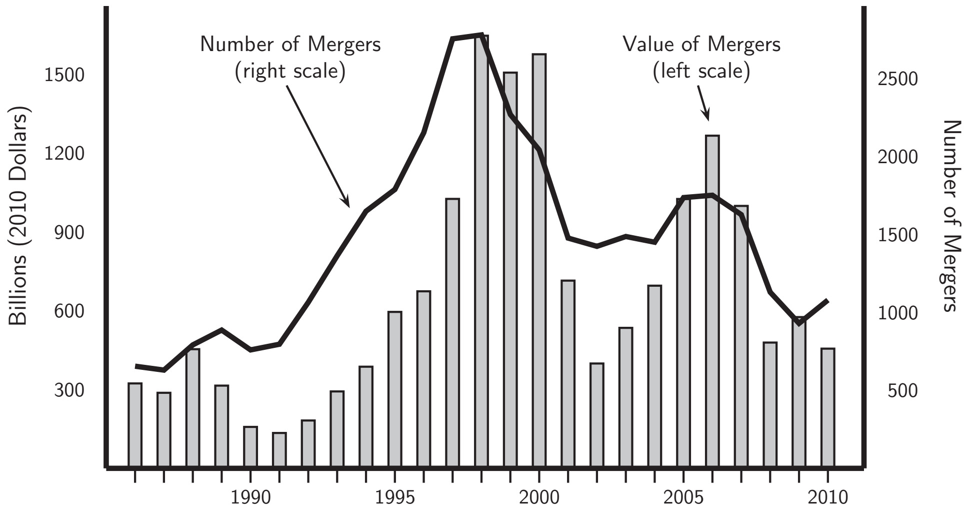

Figure 2. Dollar value and number of mergers, 1986 to 2010. This figure presents aggregate merger volume in 2010-adjusted U.S. dollars and the number of mergers by year. Merger data are from SDC.

merger waves, it is not surprising that they will cluster in a small set of industry pairs given the clustering in the product market network. Looking across all possible interindustry pairings for any given industry, the mean number of cross-industry mergers for a detail-level industry during our 25-year sample period is 65.9 and the median is 15. This compares with an average of 42.4 and median of 4.0 for intraindustry mergers. Eighteen percent of industries have no intraindustry mergers during the sample period, compared with roughly 1% for interindustry mergers.

Summary statistics of merger activity for each of the alternative IO report years (1982, 1987, 1992, and 2002), for both levels of industry aggregation (detail and summary levels), and for each of the alternative industry assignment methods are presented in Internet Appendix Table IA.III. First, the basic patterns of industry clustering and differences between inter- and intraindustry merger activity are relatively stable over the different IO report years. Second, in the 124 summary-level industries, we continue to find that interindustry mergers are highly clustered in a few industry pairs: roughly 60% of industry pairs have no mergers during the 25-year sample period and there are still more interindustry mergers (28,672) than intraindustry mergers (22,330). When we assign firms to industries using all reported SIC or NAICS codes on SDC, the fraction of mergers that are cross-industry mergers increases, and when we give greater priority to horizontal mergers, the opposite holds. However, we still observe highly concentrated interindustry mergers in all of the industry assignment procedures. In particular, even when giving priority to horizontal mergers and in the broad summary-level industries, we still find that roughly a third of all mergers occur across industries.

Table II
Merger Summary Statistics

This table presents summary statistics of the sample of mergers over the period 1986 to 2010 by industry pairs. Merger data are from SDC. Industries are defined by the 1997 BEA Input-Output Detail-Level Industry classifications (IO industries). Interindustry pairs include all combinations of the IO industries (excluding own-industry pairs). Industry-level observations aggregate the industry pair data to a single IO industry. Intraindustry observations include mergers of firms that are in the same IO industry. Interindustry observations at the industry level include all interindustry mergers across all other industries for each of the IO industries divided by two, since each interindustry merger is double-counted at the industry level. Reported in brackets are 2010 millions of U.S. dollars.

		Industry Level	
	Interindustry Pairs	Interindustry	Intraindustry
Observations	110,685	471	471
Total Mergers	31,040	31,040	19,962
	[$10,135,331]	[$10,135,331]	[$6,636,782]
Mean	0.28	65.90	42.38
	[$92]	[$21,519]	[$14,091]
Median	0.00	15.00	4.00
	[$0]	[$2,867]	[$244]
5th Percentile	0.00	1.50	0.00
	[$0]	[$87]	[$0]
95th Percentile	1.00	287.50	200.00
	[$8]	[$75,990]	[$53,046]
Maximum	1,008	3,320	3,118
	[$410,643]	[$1,749,955]	[$1,153,641]
Frequency Percentage			
None	94.16	0.85	18.47
1	3.35	4.46	11.68
2 to 5	1.70	15.29	26.54
6 to 20	0.59	39.28	23.35
21 to 50	0.13	20.38	7.86
>50	0.07	19.75	12.10

B. Comparing Merger and IO Networks: Univariate Evidence

We compare the merger and IO networks to each other in two ways. First, we compare the entire structure of each network. Second, we compare the networks industry by industry.

In Figure 3, we present the degree distributions of the product market and merger networks. Recall that an industry's degree is the number of 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 in the summary statistics, their degree distributions are likely to be skewed. Gabaix (2009) shows that many phenomena in economics and other fields are similarly clustered and many approximate a power law distribution, $p(k) = ck^{-\alpha}$. If the distribution follows a power law, then the

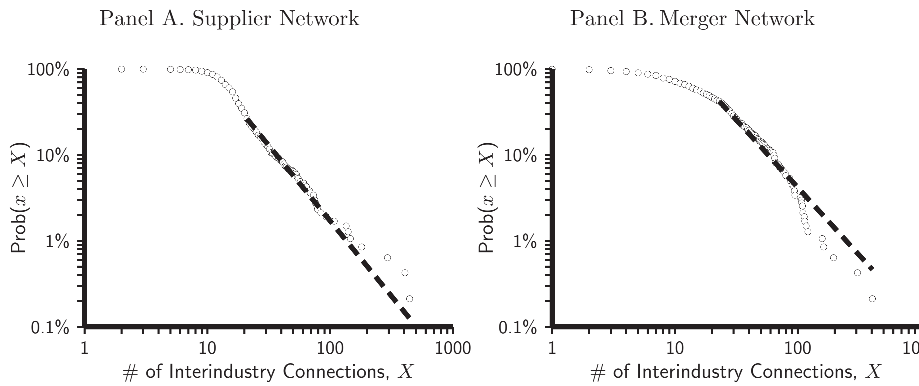

Figure 3. Degree distribution of merger and IO networks. This figure represents the distribution of degree centrality in log-log scale. Circles represent the degree centrality of industries, indicating how many direct connections an industry has to other industries. Dashed lines are from the estimate of the alpha term in the power distribution $P(k) = ck^{-\alpha}$. There are 471 detail-level industries using the 1997 IO tables produced by the U.S. BEA. Supplier network connections occur if an industry supplies more than 1% of the total inputs of a customer industry. Merger network connections occur if there exist any cross-industry mergers. The merger data cover the 1986 to 2010 period and are from SDC.

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 3 reveals that both interindustry mergers and IO connections are characterized by many industries with few connections and few industries with many connections. The circles in the lower right corners of the graphs represent the few rare industries with a very large number of direct connections to other industries. For instance, in the supplier industries, only 0.5% of industries have over 200 connections. In comparison, the fraction of industries with at least 20 connections is about 20%. The degree distributions of the customer-supplier and merger networks are similar. The estimate of α in $p(k) = ck^{-\alpha}$ in the merger network is 3.3. In the supplier network, it is 3.1. Using the more coarse summary-level definitions produces a similar pattern, as shown in Internet Appendix Figure IA.6.

These patterns are important for a number of reasons. First, as mentioned above, if economic fundamentals drive merger waves, it is expected that mergers will cluster in the relatively small set of industries that are connected through IO relations. Second, 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 to occur simultaneously. We discuss this point in more detail in Section IV.

Next, in Table III we present averages and medians of industry-level network statistics for the supplier, customer, and merger networks. The average

Table III
Mean and Median Network Statistics by Network

Degree centrality is an industry's number of interindustry connections. IO degree centrality is measured using the binary connections in the 1997 U.S. BEA Input-Output Networks (Customer or Supplier) at the detail level. 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 interindustry mergers, where a binary connection is defined as any interindustry mergers between two industries over 1986 to 2010. See the text for definitions of eigenvector centrality, average shortest path, clustering coefficient, and max(shortest distance). Top cells are means and bottom cells are medians, in brackets.

	Network		
	Supplier	Customer	Merger
Degree Centrality	22.883	16.132	27.444
	[16.000]	[13.000]	[18.000]
Eigenvector Centrality	0.037	0.033	0.046
	[0.033]	[0.025]	[0.045]
Average Shortest Path	1.966	2.537	2.075
	[1.971]	[2.467]	[2.032]
Clustering Coefficient	0.461	0.275	0.422
	[0.462]	[0.250]	[0.400]
Max(Shortest Distance)	3.000	6.000	5.000

(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 27 different industries in our sample period and the median is 18. The average shortest path across industries is about two for all networks, which reveals the "small-world" nature of these networks: across 471 industries, a typical industry is only 2 to 2.5 connections away from any other industry. In fact, the maximum shortest path length between any two industries, known as the diameter of the network, is three 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. Overall, we find that, at an aggregate network level, the industries exhibit similar features. The most notable difference is that the average industry in the merger network is more clustered and more central than it is in the IO networks. Internet Appendix Table IA.IV presents these statistics for each IO report year, for each of the algorithms for assigning firms to IO industries, and for summary-level industry definitions.

Next, we examine industry-by-industry relationships between the IO and merger networks. In Table IV, we present the 10 most central industries in the supplier, customer, and merger networks according to degree centrality. Many of the most central industries in the IO network are also among the most central in the merger network, including wholesale and retail trade industries,

Table IV

The Most Central Industries in the IO and Merger Networks

Degree centrality is an industry's number of interindustry connections. IO degree centrality is measured using the binary connections in the 1997 U.S. BEA Input-Output Networks at the detail level. 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 interindustry mergers, where a binary connection is defined as any interindustry merger between two industries over 1986 to 2010. * indicates a merger industry also in the top 10 IO industries

Rank	Supplier Network	Customer Network	Merger Network
1	Wholesale trade	Construction	Securities, commodity contracts, & investments
2	Mgmt. of companies & enterprises	Wholesale trade	Wholesale trade*
3	Truck transp.	Retail trade	Retail trade*
4	Power generation & supply	Motor vehicle parts manuf.	Construction*
5	Real estate	Real estate	Funds, trusts, & other financial vehicles
6	Iron & steel mills	Food srvcs. & drinking places	Software reproducing
7	Paperboard container manuf.	Hospitals	Motor vehicle parts manuf.*
8	Plastics plumbing fixtures & all other plastics products	Telecommunications	Information srvcs.
9	Monetary auth. & depository credit intermed.	Iron & steel mills	All other electronic component manufacturing
10	Lessors of nonfinancial intangible assets	Power generation & supply	Mgmt. consulting srvcs.

construction, motor vehicle parts, and administrative support services. These industries have interindustry mergers with the largest number of industries, not necessarily the most mergers overall, as well as many connections in the product market. The substantial overlap indicates that industries that are economically central as customers or suppliers are also central in the merger network.[9] Internet Appendix Table IA.V provides these same results for each IO report year and for data at the summary level.

In Table V, we present correlations of the industry-by-industry network characteristics. 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 53.3%. 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 24.1%. We find that the correlations are equivalent or stronger in the summary-level networks (see Internet Appendix Tables IA.VI and IA.VII).

[9] As discussed below, we drop retail and wholesale industries in robustness tests.

Table V

Correlations between Industry Characteristics across Networks

Centrality is an industry's number of interindustry connections. IO degree centrality is measured using the binary connections in the 1997 U.S. BEA Input-Output Networks (Customer or Supplier) at the detail level. 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 centrality is measured using the binary network of interindustry mergers, where a binary connection is defined as any interindustry mergers between two industries over 1986 to 2010. See the text for definitions of average shortest path and clustering coefficient. *p*-values are reported in parentheses. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels.

	Customer Centrality	Supplier Centrality	Merger Centrality	Customer Avg. Path	Supplier Avg. Path	Merger Avg. Path	Customer Clustering	Supplier Clustering
Supplier Centrality	0.556***							
	(<0.001)							
Merger Centrality	0.533***	0.393***						
	(<0.001)	(<0.001)						
Customer Avg. Path	−0.568***	−0.316***	−0.271***					
	(<0.001)	(<0.001)	(<0.001)					
Supplier Avg. Path	−0.447***	−0.790***	−0.163***	0.260***				
	(<0.001)	(<0.001)	(<0.001)	(<0.001)				
Merger Avg. Path	−0.302***	−0.225***	−0.578***	0.241***	0.108**			
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.020)			
Customer Clustering	−0.225***	−0.135***	−0.129***	−0.123***	0.104**	0.077*		
	(<0.001)	(0.004)	(0.005)	(0.008)	(0.026)	(0.097)		
Supplier Clustering	−0.449***	−0.528***	−0.330***	0.342***	0.444***	0.234***	0.230***	
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	
Merger Clustering	−0.207***	−0.152***	−0.293***	0.180***	0.137***	−0.155***	0.008	0.164***
	(<0.001)	(0.001)	(<0.001)	(<0.001)	(0.003)	(<0.001)	(0.863)	(<0.001)

The univariate results in this section 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. In the next section, we control for additional factors that could be related to industry structure, such as market valuations, industry concentration, or industry size.

C. Comparing Merger and IO Networks: Multivariate Evidence

Our final cross-sectional analysis of the relation between the IO and merger networks uses a network analysis technique called ERGM. Just as a logit regression produces maximum likelihood estimates (MLEs) 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. The key difference between ERGM and logit or ordinary least squares (OLS) regressions is that ERGM explicitly accounts for higher order dependence between industries by modeling the entire network outcome, rather than single industry or industry pair outcomes. Since the core of our argument is that industry connections affect the incidence of mergers, ERGM is a necessary tool to account for dependence between industry nodes. In Section III of the Internet Appendix, we provide a detailed description of the theory and implementation of ERGM, as well as citations to the papers that originally developed ERGM.

The results of the ERGM analysis are presented in Table VI. The coefficient values are the estimates of the marginal effect of the explanatory variable on the conditional log-odds that two industries will have an additional interindustry merger. Explanatory variables describe both intraindustry characteristics, such as an industry's concentration ratio, and interindustry relations, such as customer-supplier relations. For example, *Target Buys from Acquirer* is the interindustry percentage of the target's industry's purchases from the acquirer's industry. The coefficient estimate of the variable *Number of Connections* is unique to ERGM and measures the marginal change on the M&A network from adding a random connection.

The results in Table VI show that the IO networks significantly help to 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. This result implies that cross-industry merger activity is related to the strength of the customer-supplier relationship between industries.

In column (6) of Table VI, we add industry characteristics as additional explanatory variables to account for possible holdup problems, overvaluation, and economic characteristics of the industries. These additional control variables are defined at both the industry pair level, including the absolute differences in returns, volatility, market-to-book, and concentration, and the industry level,

Table VI
Exponential Random Graph Model to Explain the M&A Network

This table reports coefficient estimates from exponential random graph models. The coefficient estimates are the marginal effect of the explanatory variable on the conditional log-odds that two industries will have an additional interindustry merger. The connections in the merger network are the dependent variables, where the merger network is constructed as the number of interindustry mergers between two industries using SDC merger data over 1986 to 2010. 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. BEA. *Target Buys from Acquirer* is the network where each connection is the percentage that the target industry buys of the acquirer industry's output. The connections in *Target Sells to Acquirer* are the percentage of inputs supplied by the target industry to the acquirer industry. The coefficient on *Number of Connections* is the marginal effect of an additional random connection on the conditional log-odds ratio of two industries having an additional merger in the merger network. $|\Delta$ *Variable* $|$ is the absolute difference between two industry nodes' value of *variable*. AIC is the Akaike Information Criterion. 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)
Number of Connections	−3.519***	−3.523***	−3.545***	−3.549***	−3.596***	−3.480***	−3.468***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Target Buys from Acquirer	6.564***				3.328***	5.239***	5.093***
	(<0.001)				(<0.001)	(<0.001)	(<0.001)
Acquirer Buys from Target		8.092***			4.680***	4.465***	3.763***
		(<0.001)			(<0.001)	(<0.001)	(<0.001)
Acquirer Sells to Target			16.208***		13.922***	21.301***	19.590***
			(<0.001)		(<0.001)	(<0.001)	(<0.001)
Target Sells to Acquirer				17.585***	14.790***	16.793***	18.423***
				(<0.001)	(<0.001)	(<0.001)	(<0.001)
max{Industry R&D}						4.933***	4.871***
						(<0.001)	(<0.001)
$|\Delta$ Industry M/B$|$						−0.113**	−0.115**
						(0.016)	(0.015)
$|\Delta$ Industry Mean Returns$|$						−0.697***	−0.696***
						(<0.001)	(<0.001)
$|\Delta$ Std Dev of Returns$|$						−0.149	−0.149
						(0.238)	(0.240)
$|\Delta$ Concentration Ratio$|$						0.003**	0.003**
						(0.013)	(0.014)

(*Continued*)

Table VI—*Continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T Buys from A× max{Industry R&D}							12.402
							(0.557)
A Buys from T× max{Industry R&D}							53.284**
							(0.024)
A Sells to T× max{Industry R&D}							73.437**
							(0.020)
T Sells to A× max{Industry R&D}							−74.823***
							(0.008)
Industry Economic Shock Index						−0.241***	−0.241***
						(<0.001)	(<0.001)
Industry Median M/B						−0.057*	−0.057*
						(0.086)	(0.086)
Industry Median R&D						0.510	0.441
						(0.538)	(0.597)
Industry Mean Return						0.253	0.253
						(0.119)	(0.119)
Industry Std Dev of Returns						2.259***	2.259***
						(<0.001)	(<0.001)
Concentration Ratio						−0.011***	−0.012***
						(<0.001)	(<0.001)
Industry Size						0.000	0.000
						(0.285)	(0.276)
Industry Scope						0.419	0.364
						(0.855)	(0.874)
AIC	58,158	58,034	57,791	57,691	56,938	25,563	25,551
Number of Industries	471	471	471	471	471	214	214

including industry median market-to-book, median R&D, and others described previously. The industry-level variables describe characteristics of one industry node in the network, whereas the industry pair variables describe connections between industries.

We find that adding the additional controls does not affect the strong predictive power of the IO connections. In fact, three of four coefficient estimates of the IO connections increase after adding the controls. This result is particularly strong since the data limitations of the control variables reduce the size of the network in the analysis, and hence the expected predictive power of the industry connection variables. These results show that a first-order determinant of cross-industry mergers is the economic trade flows between industries.

We also find that greater differences in market-to-book and average returns between industries lead to a lower likelihood of a cross-industry merger, consistent with Rhodes-Kropf and Robinson (2008). However, we find that industries with greater median market-to-book and smaller variance in returns are less likely to be involved in a merger. We also do not find any strong evidence of overvaluation-driven mergers, based on our control variables.

The results in Table VI also show that greater R&D expenditures is related to increased merger likelihood, consistent with holdup problems. In column (7), we include interactions of the maximum R&D variable with the four IO relation variables to test whether stronger customer-supplier relations magnify holdup problems. The results indicate that, when an acquirer is an important customer or supplier to the target, greater holdup problems as proxied by R&D, are associated with more mergers on the margin. In contrast, when a target is an important customer or supplier to the acquirer, greater holdup problems are associated with fewer mergers. An alternative way to characterize these results is that, when holdup problems are larger, the firm that has stronger IO connections becomes the acquirer, rather than the target. This result is consistent with one of the predictions of the property rights theory of the firm (Grossman and Hart (1986), Hart and Moore (1990), Hart (1995)). The theory predicts that, of two merging firms, the one that would have greater investment distortions if the merger did not happen will be the acquirer (Grossman and Hart (1986)). We find that, in industry pairs where holdup problems are larger, the acquiring firm tends to be the firm that is a large customer or supplier and the firm that is the target has weaker IO relations. Assuming that potential distortions in investments are related to the strength of the IO connections, these results provide further evidence that holdup problems help to explain not only the occurrence of cross-industry mergers, but also which firm is the ultimate owner of the combined assets.

The impact of stronger IO connections on the likelihood of cross-industry mergers is economically important. Using the coefficient estimates from the specification with the most controls, we find that for a one standard deviation increase in IO relations, the odds of an additional merger between two industries increases by 6% to 20%. However, this calculation understates the effect because it estimates the effect of changing one customer-supplier connection strength while holding the others constant. In reality, the strengths of the connections are correlated so that, when one is higher, the other measures are higher as well. To estimate the economic significance of customer-supplier relations on merger incidence, we compare the average incidence of mergers in industry pairs where all IO measures are below 1% to those where there is a strong IO connection. We consider a strong connection as occurring when industry i buys 5% or more of industry j's output and industry j supplies at least 5% of industry i's total inputs. The average merger incidence for industry pairs with IO measures below 1% is 0.11. The average for an industry pair with a strong connection is 12.5. These results imply not only that vertical mergers occur, but, more interestingly, that stronger IO connections are associated with more vertical mergers.

In Internet Appendix Table IA.VIII, we present ERGM tests using the summary-level industry definitions and the different IO report years. We find a similar pattern for each of the IO report years from 1982 to 2002. In all specifications, the IO variables are positive and significant. In addition, the coefficient on the interaction between maximum R&D and the intensity of the acquirer as a customer or supplier is positive and significant in the large majority of specifications. The summary-level results are largely consistent with the detail-level tests, where stronger customer-supplier connections lead to a greater likelihood of cross-industry mergers. The results for the control variables are less robust.

These results are robust to other controls. In tests reported in Internet Appendix Table IA.IX, we first control for asset complementarities using the *HP Similarity* variable described above. Our main results are unchanged, with strong positive associations between the customer-supplier relations and cross-industry merger volume. Consistent with Hoberg and Phillips (2010b), we find that greater asset complementarities are associated with greater cross-industry merger flows. Next, in Internet Appendix Table IA.X we calculate ERGM tests as in our main tests, but match firms to industries using the three alternative methods discussed previously: (1) using all industry codes, (2) giving priority to horizontal mergers then vertical mergers at the 1% relations level, and (3) giving priority to horizontal mergers then vertical mergers at the 5% level. Using these alternative assignment procedures, we find results that are consistent with our main tests, showing a positive relation between IO connections and merger activity.

To further ensure that our results are not driven by overvaluation-driven mergers, in Internet Appendix Table IA.XI we present correlations between the strength of customer-supplier relations and average three-day abnormal announcement returns for the acquirer and for the size-weighted combined returns of the acquirer and target. On average, we find positive but small correlations for both the acquirer and the combined returns. In addition, we do not find any strong relations between the average fraction of cash used in mergers and the IO relations. These results show that the IO variables do not

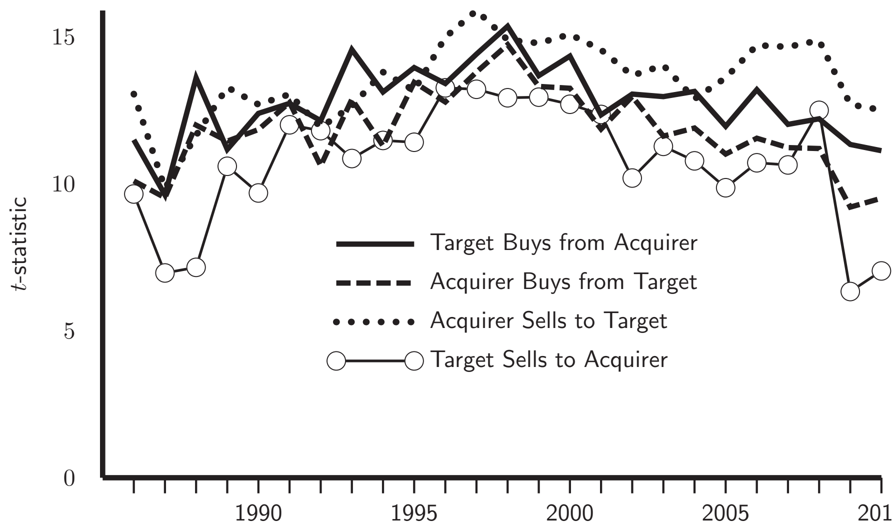

Figure 4. *t*-statistics from yearly ERGM tests. This figure represents the *t*-statistic on each of the four IO networks (Target Buys from Acquirer, Acquirer Buys from Target, Acquirer Sells to Target, and Target Sells to Acquirer) from yearly ERGM tests from 1986 to 2010. See Table VI for variable definitions and data sources.

proxy for misvaluation, and, if anything, stronger IO connections are associated with greater acquirer gains and total synergies.[10]

Though these tests account for an average effect of the control variables, 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 4 presents the *t*-statistics from each of the four explanatory IO networks in ERGM tests that are run using yearly M&A network data. The edge covariance coefficients are highly significant in each year, as in the overall sample.

Although ERGM analysis is the best way to analyze our research 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 and retail trade industries from our analysis, following Acemoglu, Johnson, and Mitton (2009), and find that our results are unchanged.

[10] Tests of announcement returns are complicated by truncated distributions since we only observe returns where mergers actually occurred. Our focus in this paper is the pattern of merger incidence across industries. Therefore, we leave a more in-depth investigation of the value implications of mergers across the IO network for future research.

D. Summary of Cross-Sectional Tests

In this section, we present a number of related results. First, we show that the structures of the IO and merger networks are highly similar. Second, we show that industry-level network characteristics are highly correlated between the IO and merger networks. Finally, we show in multivariate tests controlling for a host of variables that IO relations predict cross-industry merger activity and that these relations are more important when holdup problems are more likely. In contrast, we could have found that many mergers were in unrelated industries, or that they only occurred in high valuation industries or industries with more complementary assets, independent of the strength of the IO connection. Taken together, our results provide consistent evidence that merger activity follows fundamental economic relations on multiple dimensions.

III. Propagation of Mergers across the Industry Network

In this section, we consider the dynamic aspects of mergers across industries over time. In particular, we predict that the likelihood that an industry experiences a merger wave is 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, or is driven by some other forces, such as misvaluation or asset complementarity.

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 that led to an industry reorganization. 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 toward the South where timber tracts were privately owned. However, protection of the old-growth timber led to a severe and long-lasting supply shock.

Panel A of Figure 5 presents the time series of the volume and price of timber in Oregon from 1986 to 2008. The volume of timber harvested dropped precipitously from about 8.5 billion board feet in 1989 to about 4 billion board feet in 1997. This supply shock caused the price index of timber to rise from

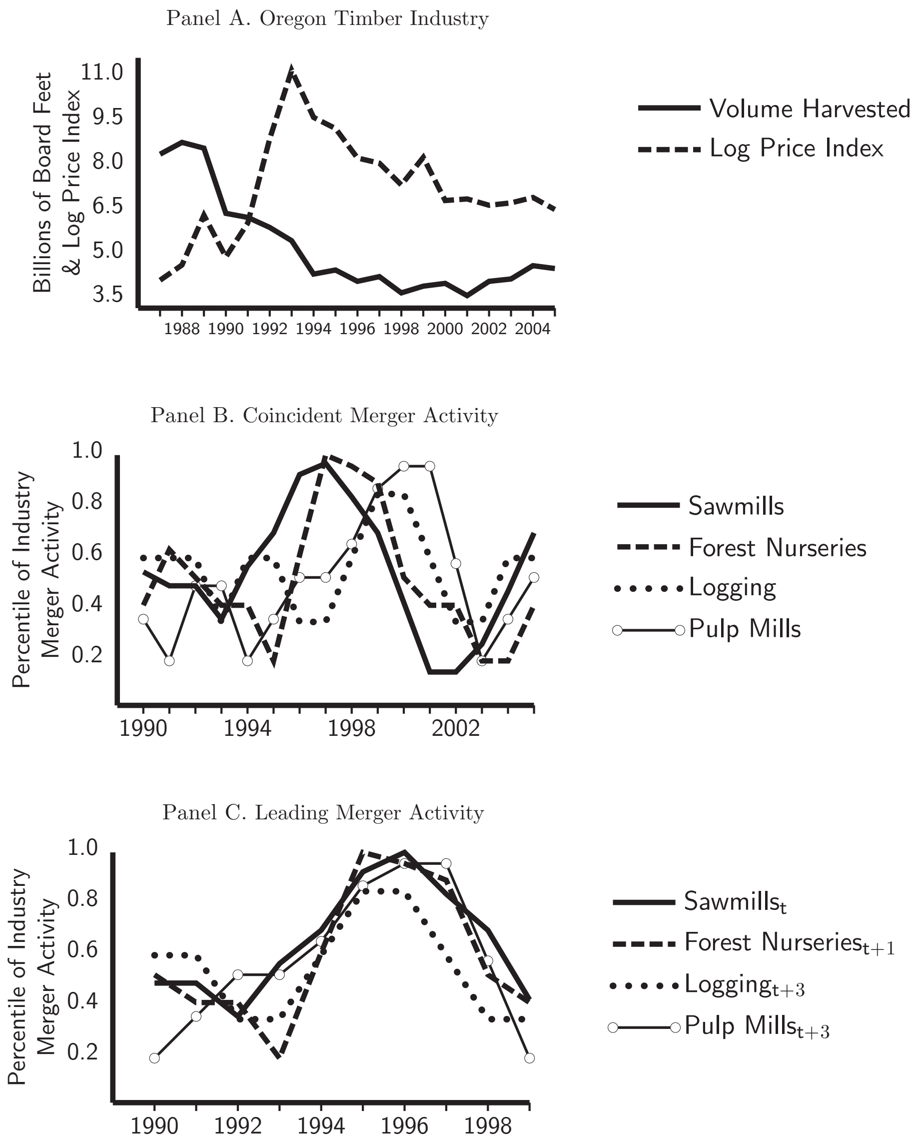

Figure 5. Diffusion of merger activity in timber-related industries. Panel A presents the volume (in billions of board feet) and log price index for Oregon timber. Data are from the Oregon Department of Forestry, Annual Timber Harvest Reports. Panel B presents industry merger activity in BEA IO industry classifications: (1) Sawmills, (2) Forest nurseries, forest products, and timber tracts, (3) Logging, and (4) Pulp Mills. For each industry-year, figures present the two-year moving-average of the percentile of the number of mergers involving firms in each industry over the period 1986 to 2008. Panel C uses one-year leading data for Forest nurseries, and three-year leading data for Logging and Pulp Mill mergers.

6,155 in 1989 to 11,047 in 1993, after which it declined to 7,913 in 1997. Though these data are from Oregon, they are 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, that the timber sector comprises a number of industries that are interrelated through trade. Panel B of Figure 5 presents the merger activity from 1990 to 2005 in the following industries: (1) Sawmills, (2) Forest nurseries, forest products, and timber tracts, (3) Logging, and (4) Pulp Mills. To compare merger activity across 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 Panel B of Figure 5) experienced a large merger wave starting in 1994 and ending in 1999, its greatest 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. Overall, Panel B shows a clear time sequence of industry waves in related industries.

Panel C of Figure 5 presents the same industry time series of merger activity where the leading industries have been shifted back in time to match the timing of the sawmills industry merger wave. Matching the one-period-leading merger activity in the forest nurseries industry and the three-period-leading activity in logging and pulp mills industries to the sawmill industry merger wave presents a striking picture. The duration, intensity, and general shape of all four industry merger waves are highly comparable. In fact, though the figure shows only the 1990s, the merger activity between the time-shifted industry series over the entire 1986 to 2008 sample period is 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. We next test whether these results generalize to other industries.

B. Closeness-Weighted M&A Activity in Connected Industries

In this section, we present results from tests of the diffusion of merger activity across the industry network. We first create a measure of an industry's exposure to merger activity that does not include the industry itself. For each industry, we calculate a weighted exposure to high levels of M&As in all other industries, where the weights are the inverse of the shortest distance from the subject industry to each other industry. Specifically, for each industry-year we calculate

$$\textit{Closeness-Weighted M\&A Activity}_{it} = \sum_{j \neq i} \frac{1}{dist_{ij}} \sum_{k \neq i} v_{jkt}, \tag{1}$$

where $dist_{ij}$ is the shortest path between industries i and j, and v_{jkt} is a measure of M&As between industries j and k in year t. We compute the shortest path in two ways: the first uses the network defined by customer links greater than 1%, and the second uses supplier links. This allows us to differentiate the importance of exposure to mergers in upstream versus downstream industries.

To account for cross-sectional differences in average merger activity across industry pairs, we measure v_{jkt} as an indicator variable for industry pair-years with high merger activity. The indicator takes the value of one if the log of the inflation-adjusted dollar volume between industries j and k in year t is greater than or equal to the 75$^{\text{th}}$ percentile of the industry pair's time series of dollar volumes from 1986 to 2010. This measure controls for the fact that the volume of mergers between two related industries is normally higher than between two unrelated industries. Thus, $\sum_{k \neq i} v_{jkt}$ records for each industry j the total number of industry pairs that experience high merger activity with industry j in year t, including intraindustry mergers in industry j itself, but excluding merger activity between i and j directly. This sum for industry j is then weighted by the inverse of the discrete number of customer or supplier connections between industries i and j. An industry that is a direct customer or supplier to industry i is one step away. Intuitively, this measure captures an industry's exposure to high merger activity in more closely connected industries, not counting merger activity involving the industry itself.

Alternatively, an industry's merger activity may be part of aggregate merger activity driven by macroeconomic shocks or widespread technological changes. In addition, an industry's position in the network will affect its distance from other industries, and hence its likelihood of exposure to industries that are experiencing merger waves. Compared to an industry on the periphery of the network, a central industry will naturally be exposed to more industries that are experiencing merger waves, simply because it is more connected. Thus, if we observe that the central industry also experiences more mergers, it could be caused by its centrality, rather than its exposure to mergers in other industries.

To control for both time-varying economy-wide factors and industry-specific fixed factors, we estimate

$$\log(1 + v_{i,t}) = \alpha + \rho \log(1 + v_{i,t-1}) + \beta \, \textit{Closeness-Weighted M\&A Activity}_{i,t-1} + \gamma_i + \tau_t + \varepsilon_{i,t}, \tag{2}$$

where $v_{i,t} = \sum_j v_{ijt}$ is the number of industry pairs involving industry i that experience high merger activity in year t, as above. The industry fixed effects, γ_i, control for all time-invariant industry characteristics, such as centrality and scope. They also account for much of the cross-sectional differences in industry size, valuation, and returns, which are persistent over time, though we explicitly control for these variables in later tests. The year fixed effects, τ_t, capture any macroeconomic shocks, such as the market return and the economy-wide availability of financing, among other possible factors. To account for persistence in mergers, equation (2) also includes lagged merger activity in industry i. Thus, this empirical model isolates the impact of within-industry time-series variation in exposure to mergers while controlling for macroeconomic time-series changes and persistence in merger activity.

To estimate equation (2), we follow Arellano and Bond (1991) to account for the endogeneity created by using lagged dependent variables in a fixed effects model. Table VII presents the coefficient estimates. The first three columns define distance using customer relations. The last three columns use supplier relations. In column (1), we find a positive and significant effect of customer-based closeness-weighted M&A activity in time $t-1$ on industry merger activity at time t. This implies that, when the customers of an industry are engaged in more mergers, the industry's own merger activity increases the following year. In column (4), we find a similar positive and significant effect for supplier connections. However, the magnitude of the effect is doubled, indicating that exposure to mergers from supplier industries has a bigger impact on future merger activity.

In columns (2) and (5), we include three additional lags of the closeness measure and the subject industry's own merger activity to control for delayed responses. The coefficient on the one-year lag is unchanged for both customers and suppliers. The two-year lag is negative and significant and the three- and four-year lags have small negative effects. This time-series pattern is consistent with a large shock in year $t-1$ leading to future merger activity in connected industries.

The prior results present predictive regressions, using only information available in prior years to predict merger activity in the current year. A concern with this approach is that the one-year lagged exposure to M&As may simply proxy for current activity because of persistence in M&A activity. If current activity in connected industries has a positive impact, we could not distinguish whether the diffusion of mergers happens within one year or whether there was simply an omitted variable driving both subject and connected industries' mergers. To address this concern, in columns (3) and (6) we include concurrent exposure to merger activity. For customers, the coefficient is insignificant. For suppliers, it is negative and significant. In both cases, the effect of one-year lagged exposure remains positive and significant. These results provide further evidence that a wave-like peak of M&As in connected industries occurs one year before the subject industries' increased merger activity. In Internet Appendix Table IA.XII, we present the same analysis using the summary-level industry definitions. We find a similar pattern as in the detailed-level industries.

Table VII

The Dynamic Impact of Mergers in Close Industries

This table reports results from Arellano and Bond (1991) GMM regressions to estimate the effect of mergers that occur in industries connected through customer-supplier links, but do not include mergers that involve the subject industry itself. Observations are from 1986 to 2010 for detail-level IO industries defined in the 1997 IO reports, where firms are matched to industries based on primary SIC or NAICS codes. The dependent variable is the log of one plus the number of industry pairs involving industry i that experience high merger activity in year t. High merger activity equals one if the log of the inflation-adjusted dollar volume between industries j and k in year t is greater than or equal to the 75[th] percentile of the industry pair's time series of dollar volume from 1986 to 2010. *Closeness-Weighted M&A Activity*$_t$ is $\sum_{j \neq i} \frac{1}{dist_{ij}} \sum_{k \neq i} v_{jkt}$, where $dist_{ij}$ is the shortest path between industries i and j, and v_{jkt} is an indicator variable for high merger activity in industry pair-years. The shortest path is measured using the network based on either discrete customer links (columns (1) to (3)) or supplier links (columns (4) to (6)), where links are defined as customer or supplier flows greater than 1%. *Own M&A Activity*$_{t-1}$ is the lagged dependent variable at $t-1$. *Own Industry Fixed Effects* are accounted for through first-differencing. Lagged levels of the independent variables are used as instruments for the endogenous first differences. Numbers in parentheses are p-values based on standard errors that are robust to general cross-section and time-series heteroskedasticity and within-group autocorrelation. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels.

	Dependent Variable: Industry Merger Activity$_t$					
	Closeness through Customer Links			Closeness through Supplier Links		
	(1)	(2)	(3)	(4)	(5)	(6)
Closeness-Weighted M&A Activity$_t$			−0.024			−0.556***
			(0.665)			(<0.001)
Closeness-Weighted M&A Activity$_{t-1}$	0.615***	0.680***	0.445***	1.230***	1.251***	1.011***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Closeness-Weighted M&A Activity$_{t-2}$		−0.323***	−0.259***		−0.416***	−0.442***
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
Closeness-Weighted M&A Activity$_{t-3}$		−0.051	−0.105		−0.080	−0.197*
		(0.425)	(0.101)		(0.406)	(0.052)
Closeness-Weighted M&A Activity$_{t-4}$		0.017	0.002		−0.091	−0.112
		(0.781)	(0.974)		(0.430)	(0.296)
Own M&A Activity$_{t-1}$	13.505***	20.035***	21.119***	14.930***	20.617***	23.589***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

(Continued)

Table VII—*Continued*

	Dependent Variable: Industry Merger Activity$_t$					
	Closeness through Customer Links			Closeness through Supplier Links		
	(1)	(2)	(3)	(4)	(5)	(6)
Own M&A Activity$_{t-2}$		9.066***	10.326***		7.890***	10.342***
		(<0.001)	(<0.001)		(<0.001)	(<0.001)
Own M&A Activity$_{t-3}$		6.657***	7.283***		5.789***	7.423***
		(<0.001)	(<0.001)		(0.001)	(<0.001)
Own M&A Activity$_{t-4}$		2.790*	3.122*		1.858	3.034*
		(0.090)	(0.057)		(0.260)	(0.061)
Own Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	302.732	393.583	402.453	280.762	381.718	417.524
p-value	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	10,833	9,420	9,420	10,833	9,420	9,420

One-year lagged closeness-weighted M&A activity is positive and significant in all cases. This result is robust to the inclusion of longer time lags and to concurrent M&A activity in connected industries, as in the detail-level results.

While these tests show a positive effect on merger activity related to one-year lagged merger activity in connected industries, they also show negative effects in the concurrent year and in year $t-2$. This means that, controlling for the large positive effect in year $t-1$, merger activity in related industries leads to fewer mergers in the subject industry. This may be caused by multicollinearity from persistence in the *Closeness-Weighted M&A Activity* variable. To investigate this possibility, in Internet Appendix Table IA.XIII we include each of the closeness-weighted activity variables from t to $t-3$ separately. We find the strongest effects at $t-1$, and smaller positive or no effects at t, $t-2$, and $t-3$. We only find small negative effects at $t-3$ in a few specifications, when we control for four lags of own-industry M&A activity. These tests provide further evidence in support of the idea that merger waves travel across industries, with the peak of M&As in connected industries occurring one year in advance of the subject industry's M&A wave.

The impact of M&A activity in close industries is economically meaningful. A one standard deviation change in lagged customer closeness-weighted M&A activity implies an increase of 0.380 in the number of industry pairs that experience high merger activity. This is a substantial increase compared to the average of 0.323. This means that the number of cross-industry merger waves doubles following high merger activity in customer and supplier industries. Moreover, the marginal effect for supplier links is even stronger, with double the impact of the customer links.

While the industry fixed effects account for time-invariant determinants of M&A activity, there may be time-varying factors that are correlated with the closeness-weighted M&A activity variables, such as misvaluation, holdup problems, and asset complementarity. Therefore, in Internet Appendix Table IA.XIV, we run additional tests that include the industry economic shock index, an indicator for a deregulatory shock, industry median market-to-book, median R&D, and the yearly average stock return and standard deviation of returns for firms in the industry.[11] Though the sample size is reduced, we still find positive and significant coefficients on the lagged closeness-weighted M&A activity variable, and negative coefficients for longer lags. Industry R&D is positively related to M&A activity, though the other variables are insignificant. The insignificance likely occurs because the time-series variation in market-to-book and returns is small relative to the cross-sectional variation, which is captured by industry fixed effects. In other unreported tests, we find positive though insignificant interactions between close merger activity and industry R&D expenditures. We also verify that these results are robust to assigning firms to

[11] In these panel tests, we include industry fixed effects, which subsume all time-invariant industry-level variables, including concentration, size, and scope (which are calculated at the IO-year and hence are fixed). However, we include the time-varying rate spread and deregulatory shock variables because they are meaningful in the panel setting.

IO industries using all listed NAICS and SIC codes in Internet Appendix Table IA.XV.

Next, in Internet Appendix Table IA.XVI, we study the effect of closeness-weighted M&A activity on a subject industry's horizontal mergers, excluding cross-industry mergers. This test examines whether exposure to other industries experiencing heightened M&A activity causes internal reallocation of assets within an industry, as opposed to vertical mergers. We find a positive and significant effect on lagged closeness-weighted M&A activity in all specifications, consistent with our main results. The economic significance relative to the average is the same or stronger than that in the main results. These results indicate that the diffusion of M&As can happen indirectly as industries move assets internally to more efficient ownership arrangements, rather than directly through cross-industry mergers with other vertically integrating industries.

In a series of robustness checks, we control for the influence of mergers that flow across industries through asset complementarities, rather than customer-supplier links. Similar to our definition of *Closeness-Weighted M&A Activity*, for each industry we calculate the exposure to high levels of M&As in industries that share asset complementarities, based on the measure of HP. In particular, we calculate

$$\textit{HP-Weighted M\&A Activity}_{it} = \sum_{j \neq i} HP_{ijt} \sum_{k \neq i} v_{jkt},$$

where HP_{ijt} is an indicator variable that equals one if two IO industries have any firms that Hoberg and Phillips identify as similar in a given year, using their text-based similarity scores.[12] High merger activity, v_{jkt}, is recorded as above. Thus, this variable measures the amount of merger activity in close industries, where closeness is based on asset complementarity rather than direct product market relations. In Internet Appendix Tables IA.XVII, IA.XVIII, and IA.XIX, we run robustness tests that include the HP-based measure as an explanatory variable for both detail and summary-level industry definitions, controlling for additional variables such as R&D. We find that merger activity in close industries, based on asset complementarity, has a positive though not always significant effect on a subject industry's merger activity. This means that merger activity transmits across industries connected through similar product offerings. At the same time, we find that the transmission of merger activity across the customer-supplier network remains strongly significant and positive, as in our main tests. These results show that mergers propagate through multiple economic links between industries.

To provide more evidence on the effect of misvaluation-driven mergers, we follow the same methodology as in the previous tests to calculate closeness-weighted acquirer returns and lags of own-industry returns. In Internet Appendix Table IA.XX, we find that one-year lagged closeness-weighted returns

[12] Similar results are obtained if we use a continuous variable to measure the number or fraction of firms that are similar according to HP.

are positively and significantly related to an industry's own acquirer returns. This means that acquirers are more likely to have high returns (above the 75th percentile of the industry pair time series) if acquirers in closely connected industries had unusually high returns in the prior year. Though we view this evidence as supportive of an efficiency motivation for mergers that flow through the customer-supplier network, as we note before our focus is on the incidence of mergers, not their value implications, which are beyond the scope of this paper.

C. The Effect of Close versus Distant M&As

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. In contrast to the prior section, we separately identify the timing of the impact of mergers in close versus distant industries. If merger activity is diffusing across an economy, we would expect the merger activity in closely connected industries to have a greater impact on an industry's merger activity in the near future than the merger activity in distantly connected industries. In addition, if merger activity diffuses in a wave-like pattern, we expect to observe a positive relationship between time and distance, such that M&A activity in more distantly connected industries has a delayed positive effect on a subject industry's future merger activity. The following equation captures these effects:

$$\log(1+v_{i,t}) = \alpha + \sum_{s=1}^{4} \rho_s \log(1+v_{i,t-s}) + \sum_{s=1}^{4} \theta_s v_{Close,t-s} + \sum_{s=1}^{4} \phi_s v_{Distant,t-s} + \gamma_i + \tau_t + \varepsilon_{i,t}, \tag{3}$$

where $v_{i,t}$ is as defined above, and $v_{Close,t}$ and $v_{Distant,t-s}$ are the aggregate merger activity in close and distant industries, not including mergers with firms in industry i. Close industries are defined as industries that are directly connected to the subject industry through a customer or supplier link above the 1% threshold. Distant industries are those that have the maximum shortest path from the subject industry. In the supplier network, this is three connections away. In the customer network, it is four connections.[13]

One concern with the empirical model is the potential for multicollinearity in the variables. Internet Appendix Table IA.XXI shows that there is persistence in merger activity in terms of both time and network distance. We therefore use only the closest and most distant industries, as opposed to the full set of discrete distances from one to the maximum, to avoid multicollinearity. Thus, in contrast to the weighted measure of closeness used previously, this model

[13] The maximum shortest distance is six in the customer network, but the number of mergers in industries more than four steps away is orders of magnitude less than in the closer industries. This reflects the fact that industries in the periphery do not make many mergers. Thus, to make sure our results are not driven by outliers, we use industries that are four steps away as our Distant industries. If anything, this will make our results biased toward zero.

separately identifies the impact of mergers in the closest industries compared to the most distant industries.

Table VIII presents the coefficient estimates of equation (4). First, in columns (1) and (5), we include only the merger activity in close industries to avoid multicollinearity in the explanatory variables. Similar to the results in Table VII, we find a strong positive relation between lagged merger activity in close industries and current merger activity in the subject industry.

In columns (2) and (6), we include only distant industry variables. When distance is measured through customer relations in column (2), we find a positive effect for distant M&As that occurred two years prior. For the supplier network, we find positive relations in distant industries at a lag of three and four years. Columns (3) and (7) include close and distant industries in the same model, with little change in results. These results are consistent with a wave-like diffusion process, where merger activity in distant industries spills over into industries connected through the customer-supplier network. These results could also shed light on the channel through which shocks spread through customer-supplier relations. Though we imagine that the strongest effect of the supply chain follows from reorganizations in the close industry, this is not the only way that reorganization in the supply chain can matter. For example, mergers in distant industries could lead to changes in trade relations of close industries, without industry restructuring, which could then lead to industry restructuring in the subject industry. Alternatively, following merger waves in more distant industries, a subject industry may anticipate changes to close industries and preemptively reorganize, without close industries experiencing a merger wave. The degree to which distant M&A activity matters, after controlling for close M&A activity, provides evidence that shocks travel through the IO network, but not necessarily in the form of direct reorganization in the close industries.

Finally, as before, we include concurrent merger activity to account for any spurious correlation caused by an omitted variable that drives current and lagged activity. For customer links, one-year lagged close merger activity remains positive and significant, though distant merger activity becomes insignificant. For supplier links, both one-year lagged close merger activity and the three-year lag of distant activity remain positive and significant. In addition, we find that distant activity at the one-year lag is also positive and significant. Because of concerns of multicollinearity, we view the positive effect of distant mergers with a three-year lag as the most robust result for suppliers.

In Internet Appendix Table IA.XXII, we present robustness tests using the summary-level industry definitions. We find consistent results though with weaker significance levels. In Internet Appendix Table IA.XXIII, we control for time-varying industry characteristics and find similar or stronger results, including a positive and significant effect of one-year lagged close M&A activity and positive and significant effects for three- and four-year lagged distant M&A activity. R&D expenditures are positively related to merger activity. Next, in Internet Appendix Table IA.XXIV, we find a positive and significant effect for lagged close M&A activity on horizontal mergers, but the impact of distant

Table VIII

The Diffusion of Merger Activity across Close and Distant Industries

This table reports results from Arellano and Bond (1991) GMM regressions to estimate the effect of mergers that occur in industries connected through customer-supplier links, but do not include mergers that involve the subject industry itself. Observations are from 1986 to 2010 for detail-level IO industries defined in the 1997 IO reports, where firms are matched to industries based on primary SIC or NAICS codes. The dependent variable is the log of one plus the number of industry pairs involving industry i that experience high merger activity in year t. High merger activity equals one if the log of the inflation-adjusted dollar volume between industries j and k in year t is greater than or equal to the 75th percentile of the industry pair's time series of dollar volume from 1986 to 2010. *Close M&A Activity*$_t$ is aggregate merger activity in close industries, not including mergers with firms in industry i. Merger activity is defined by the number of industry pairs that experience high merger activity. *Distant M&A Activity*$_t$ is defined analogously. Close industries are defined as the industries that are directly connected to the subject industry through a customer or supplier link above the 1% threshold. Distant industries are those that have the maximum shortest path from the subject industry. In the supplier network, this is three connections away; in the customer network, it is four connections. *Own M&A Activity*$_{t-1}$ is the lagged dependent variable at $t-1$. *Own Industry Fixed Effects* are accounted for through first-differencing. Lagged levels of the independent variables are used as instruments for the endogenous first differences. Numbers in parentheses are p-values based on standard errors that are robust to general cross-section and time-series heteroskedasticity and within-group autocorrelation. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels.

	Dependent Variable: Industry Merger Activity$_t$							
	Closeness through Customer Links				Closeness through Supplier Links			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Close M&A Activity$_t$				0.432***				0.433***
				(<0.001)				(<0.001)
Close M&A Activity$_{t-1}$	0.470***		0.454***	0.111**	0.572***		0.588***	0.231***
	(<0.001)		(<0.001)	(0.046)	(<0.001)		(<0.001)	(0.004)
Close M&A Activity$_{t-2}$	−0.159***		−0.153***	−0.133**	−0.228***		−0.202***	−0.202***
	(0.005)		(0.008)	(0.017)	(<0.001)		(0.002)	(0.002)
Close M&A Activity$_{t-3}$	−0.072		−0.075	0.013	−0.057		−0.021	0.018
	(0.243)		(0.237)	(0.839)	(0.328)		(0.716)	(0.761)
Close M&A Activity$_{t-4}$	−0.076		−0.060	−0.019	−0.110*		−0.088	−0.044
	(0.166)		(0.288)	(0.742)	(0.072)		(0.170)	(0.509)
Distant M&A Activity$_t$				−0.010				−0.170***
				(0.816)				(0.004)

(*Continued*)

Table VIII—*Continued*

	Dependent Variable: Industry Merger Activity$_t$							
	Closeness through Customer Links				Closeness through Supplier Links			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distant M&A Activity$_{t-1}$		−0.236***	−0.123**	−0.015		−0.074	0.098*	0.118**
		(<0.001)	(0.032)	(0.779)		(0.201)	(0.080)	(0.021)
Distant M&A Activity$_{t-2}$		0.081*	0.088**	−0.014		0.061	0.068	−0.007
		(0.070)	(0.048)	(0.751)		(0.257)	(0.210)	(0.889)
Distant M&A Activity$_{t-3}$		0.040	−0.021	0.057		0.173***	0.096*	0.092*
		(0.477)	(0.705)	(0.315)		(0.001)	(0.059)	(0.068)
Distant M&A Activity$_{t-4}$		0.078	0.058	0.019		0.126**	0.086	0.006
		(0.239)	(0.376)	(0.770)		(0.039)	(0.164)	(0.923)
Own M&A Activity$_{t-1}$	18.808***	22.319***	18.803***	17.777***	18.635***	22.415***	18.257***	17.198***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Own M&A Activity$_{t-2}$	9.733***	11.758***	9.753***	9.230***	9.427***	11.947***	9.152***	8.641***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Own M&A Activity$_{t-3}$	6.955***	7.599***	6.966***	6.512***	6.878***	7.936***	6.768***	6.212***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Own M&A Activity$_{t-4}$	3.065*	2.938*	3.111*	2.635	2.837	3.370**	2.817	2.352
	(0.070)	(0.066)	(0.066)	(0.125)	(0.105)	(0.036)	(0.108)	(0.178)
Own Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
χ^2	416.227	401.270	421.617	412.450	413.673	394.583	413.417	401.866
p-value	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Observations	9,420	9,420	9,420	9,420	9,420	9,420	9,420	9,420

M&As becomes insignificant. This suggests that the indirect effect of M&As in related industries on internal industry reorganization is driven by mergers in close industries, not distant industries. Finally, Internet Appendix Table IA.XXV presents tests based on acquirer returns and finds patterns similar to the patterns of merger incidence, where returns in close industries have a positive effect after one year and returns in distant industries have a positive effect after two years.

The results in this section provide evidence that mergers follow a wave-like pattern across the IO network topology. Similar to the illustration of the timber industry, high merger activity in close industries affects the subject industry's merger activity with a one-year delay, whereas merger activity in distant industries takes a longer time to impact the subject industry.

It is also interesting to note that the effects of related industry mergers differ between customer and supplier links. First, exposure to M&As through supplier links has a stronger effect than that through customer links. Second, the diffusion of mergers through supplier links occurs more rapidly than through customer links. Consistent with prior research that indicates that economic shocks are more likely to travel upward through a supply chain than downward (Hertzel et al. (2008), Bhattacharyya and Nain (2011)), we find that merger shocks travel faster upward through suppliers than they travel downward through customers. Our network approach identifies one possible reason for this phenomenon. As we show in Table I, the supplier network is denser and more interconnected than the customer network. Given this structural difference, it is not surprising that shocks travel faster through the denser supplier network.

IV. Network Centrality and Aggregate Merger Waves

In this section, we investigate how industry-level diffusion of merger activity relates to the time series of economy-wide aggregate merger waves. One possibility is that aggregate merger waves occur as merger activity transmits toward central industries. 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, while many industries have relatively few direct connections. Shocks that follow the IO network will move toward the center of the network, branching out in parallel to other industries.

An alternative possibility is that aggregate merger waves consist of industries on the periphery of the network. While central industries have more product market connections to other industries than do peripheral industries, their diversity of connections could reduce the impact of any one shock in a connected industry. In addition, firms in central industries could have merger options across a greater diversity of connected industries, raising the threshold for selecting a merger partner. Under this scenario, the limited but relatively important local connections of peripheral industries could lead to their participation in aggregate merger waves. Ultimately, whether having more connections or

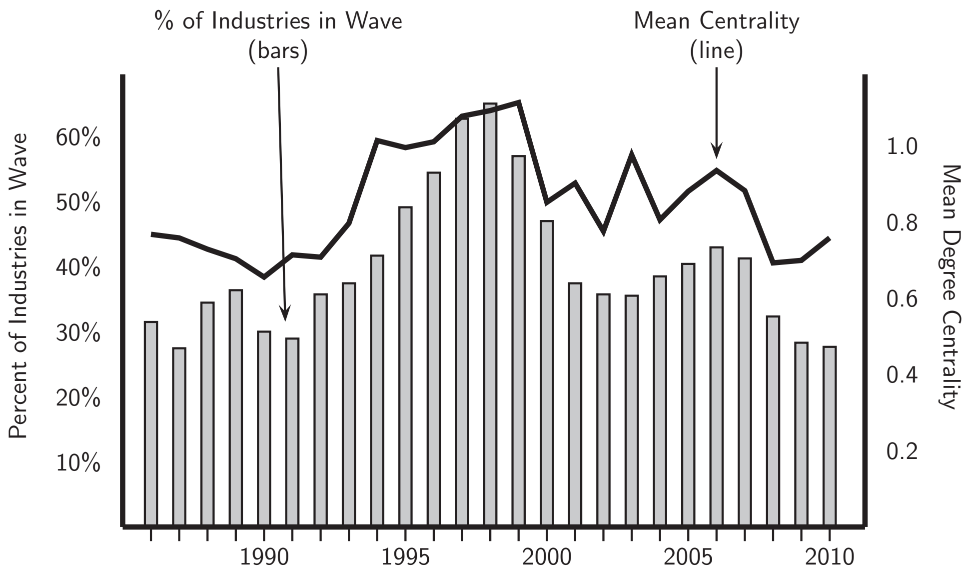

Figure 6. Network centrality and industry merger waves. Vertical bars represent the percentage of all 471 industries in year t that experience a merger wave. A merger wave is when an industry has more mergers than the 75^{th} percentile of mergers, relative to the industry's time series of mergers from 1986 to 2010. The black line represents the average degree centrality of the industries that are experiencing a merger wave, where centrality is computed from the weighted and directed network of supplier links between industries in the 1997 detailed-level IO network. Merger firms are classified into industries based on their primary NAICS code as reported in SDC.

stronger connections determines whether an industry will experience merger waves during economy-wide aggregate merger waves is an empirical question.

Figure 6 compares the time series of the percentage of total industries that are experiencing a merger wave in a given year to the time series of the average IO centrality of those industries experiencing a merger wave. Merger waves are defined as above, as industry-years in which the number of mergers of firms in an industry is greater than the 75^{th} percentile of the number of yearly mergers over 1986 to 2010. Thus, the greater the fraction of industries merging in a given year, the greater is the aggregate merger wave. During the peak in 1998, 65% of the 471 industries in our main sample experience a merger wave.

The figure shows a strong correlation between the two time series, indicating that firms in central industries are more likely to merge during aggregate merger waves. In Table IX, we test this relationship statistically. First, in Panel A, we run time-series regressions of the current and lagged percentages of industries in a merger wave on the average centrality of the wave industries. Standard errors are corrected for heteroskedasticity and autocorrelation following the procedure of Newey and West (1987) and using the automatic lag selection model of Newey and West (1994). We find a strong statistically significant relation between current aggregate merger activity and centrality

Table IX

Aggregate Merger Activity and Centrality

This table presents coefficients for time-series regressions from 1988 to 2010. The dependent variable in Panel A is $Centrality_t$, the average degree centrality of the industries experiencing a merger wave, where centrality is computed from the weighted and directed network of supplier links between industries in the IO network. *Industry Merger Waves (%)*$_t$ is the percent of all industries in year t experiencing a merger wave. A merger wave is when an industry has more mergers than the 75th percentile of mergers in a given year, relative to the industry's time series of mergers from 1986 to 2010. Supplier networks are based on the 1997 BEA IO Report, using the detailed level of industries. Merger firms are classified into industries based on their primary SIC or NAICS code, or using all industry codes reported in SDC, as indicated in the column heading. Panel B presents vector autoregressions with two endogenous variables: $Centrality_t$ and *Industry Merger Waves*$_t$. p-values are reported in parentheses from standard errors corrected for heteroskedasticity and autocorrelation using the procedure of Newey and West (1987) and the automatic lag selection of Newey and West (1994). Granger causality tests are reported of the null hypothesis that centrality does not Granger cause market merger waves and that merger waves do not Granger cause average centrality. We report the χ^2 and p-value for each test. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels.

Firm-Level Industry Classification:	Primary	All
Panel A: Concurrent and Lagged Time-Series Regressions		
Dependent Variable:	Average Degree Centrality of Wave Industry$_t$	
Industry Merger Waves (%)$_t$	1.288***	1.160***
	(<0.001)	(<0.001)
Industry Merger Waves (%)$_{t-1}$	−0.256	−0.757***
	(0.262)	(<0.001)
Industry Merger Waves (%)$_{t-2}$	0.205	0.429***
	(0.313)	(<0.001)
Constant	0.353***	0.699***
	(<0.001)	(<0.001)
Adjusted R^2	0.709	0.513
Observations	23	23
Panel B: Predictive Vector Autoregressions and Granger Causality		
Dependent Variable:	Centrality$_t$	Waves$_t$
Average Centrality$_{t-1}$	0.244	0.262***
	(0.391)	(0.009)
Average Centrality$_{t-2}$	0.077	−0.033
	(0.783)	(0.767)
Industry Merger Waves (%)$_{t-1}$	1.231***	1.111***
	(0.009)	(<0.001)
Industry Merger Waves (%)$_{t-2}$	−0.693	−0.627***
	(0.154)	(<0.001)
Constant	0.364**	0.015
	(0.031)	(0.828)
Adjusted R^2	0.544	0.851

(*Continued*)

Table IX—*Continued*

Firm-Level Industry Classification:	Primary		All
Dependent Variable:	Centrality$_t$		Waves$_t$
Observations	23		23
Granger Causality			
H_0: Centrality $\nRightarrow$ Waves			
χ^2		6.316**	
p-value		(0.043)	
H_0: Waves $\nRightarrow$ Centrality			
χ^2		7.958**	
p-value		(0.019)	

regardless of whether we assign firms to industries based on their primary NAICS codes or based on all of their NAICS codes. These results show that more central industries experience merger waves concurrently with aggregate merger waves.

In Panel B, we run predictive VARs of the percentage of industries in merger waves and their centrality. Standard errors are again corrected using the Newey-West procedures. We find that lagged aggregate merger activity is positively related to current centrality. The results in Panel B also show that an increase in aggregate merger activity Granger causes an increase in the average centrality of the industries in merger waves. There is weak evidence of reverse Granger causation as well. In Internet Appendix Tables IA.XXVI, IA.XXVII, and IA.XXVIII, we show that these results are robust to using the 1982 IO industry relations, the summary-level industry definitions, and merger waves defined using a 50$^{\text{th}}$ percentile threshold, and to excluding the tech bubble years 1997 through 2002. These results confirm that there is a strong positive time-series relation between aggregate merger waves and the centrality of the firms in the waves.

The distinction between the tests in Panels A and B is that Panel A includes concurrent effects whereas Panel B is a forward-looking predictive regression and also includes two equations that are simultaneously estimated. In Panel A, we find that, in years when more industries have a merger wave, those industries are more central, relative to the average year. In Panel B, we find that, when more industries are experiencing a merger wave in a given year, the centrality of the industries experiencing a merger wave next year is higher, relative to the average year. However, this does not imply that the centrality of industries this year is also not high compared to an average year, as in Panel A. This is simply not tested in Panel B. More generally, the tests in Panel A of Table IX show that aggregate merger waves comprise central industries. The predictive tests in Panel B show that waves propagate toward the center, rather than away from the center, over time. In addition, evidence from these tests supports the idea that the number of connections is more important than the strength of connections for the transmission of merger shocks.

These results provide a new explanation for why aggregate merger waves occur. A criticism of prior research that argues that economic industry shocks produce merger waves is that random industry shocks cannot explain why overall merger activity in an economy is also not randomly distributed over time. We argue that the initial economic industry shocks may be random, but the subsequent "after-shocks" follow IO links, which are not random. The pattern of aggregate merger waves is thus likely driven by the fat-tailed nature of product market connections. A similar argument is made by Gabaix (2011) regarding productivity shocks. He argues that, since the distribution of firm size 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 network and merger wave characteristics. 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. When the shock spreads to a central industry, it will quickly spread to other central industries, creating the observed jump pattern in average centrality. In addition, we show in Tables I and VIII that the supplier network is denser than the customer network and that mergers tend to diffuse faster through supplier networks than through customer networks. These results imply that aggregate merger waves are more likely to be caused by the transmission of shocks through suppliers toward central industries.

V. Conclusion

Using detailed data from the BEA, this paper models the U.S. economy as a network of industries connected through customer-supplier trade flows. Larger trade flows represent stronger interindustry connections. We hypothesize that economic shocks travel across the economy through this network in a predictable way. We investigate one type of economic shock: merger waves. Neoclassical theory argues that mergers represent efficient reallocations of resources. This argument suggests that the timing and incidence of cross-industry merger waves is influenced by the real economic linkages in the industry network. We test three hypotheses: (1) interindustry mergers cluster in industry pairs with strong trade flows (2) merger waves propagate across industries through customer-supplier links and (3) the structure of the customer-supplier network influences which industries are involved in economy-wide merger waves.

First, we find that cross-industry mergers are highly clustered in a small number of industry pairs. Of all possible industry pairs, 94% experience no mergers at all during 1986 to 2010. This means that every cross-industry merger in our sample occurs in just 6% of industry pairs. This pattern is almost identical for cross-industry trade flows, where 95% of industry pairs have almost zero or no trade flows at all. Using network techniques from graph theory, we find that the pattern of cross-industry mergers and the customer-supplier network are similar in other ways. Both exhibit small-world properties, where an average industry is just two or three links away from every other industry. Industries that are more central and clustered in the customer-supplier network are also more central and clustered in the network of interindustry mergers.

Second, we find that industry merger activity travels in a wave-like pattern through customer-supplier links. We measure the distance between all industries in the customer-supplier network, where distance is calculated based on the strength of trade flows. For each industry, we measure the intensity of merger activity in all other industries, excluding mergers with the industry itself. We find that an industry that is exposed to mergers in close industries experiences increased merger activity in the following year. Merger activity in distant industries leads to increased merger activity in two or three years. Thus, mergers propagate through the customer-supplier network in a predictable, wave-like pattern. We also find that these effects are stronger and the delay is smaller when shocks travel through supplier links, compared to customer links. This likely reflects the fact that the network of suppliers is more densely connected than the network of customers.

Third, we show that the industries that experience merger waves in concert with an aggregate merger wave are more central in the product market network. Our evidence suggests that merger waves travel through the customer-supplier links toward central industries, which then diffuse merger activity outward across many different industries. These results show that, even if industry-level merger waves are motivated by random industry shocks, the structure of the customer-supplier network leads to aggregate economy-wide merger waves.

The results in this paper show that merger waves are driven, in part, by economic fundamentals of product market relations. Our results are robust to proxies for overvaluation-driven mergers. Even if merger waves are caused by the spread of misvaluation across product market relations, our results imply that it still must be the case that the underlying exogenous product market relations explain a large portion of merger activity across an economy over time. Finally, though we do not claim to conduct rigorous tests of competing theories of vertical integration, we find evidence consistent with an incomplete contracts model, where asset complementarity and holdup problems motivate vertical mergers.

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 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 studied in prior research. To our knowledge, this is the first paper to model interindustry trade flows as a network. We believe that this approach will prove to have a multitude of applications in economics, beyond merger waves.

Initial submission: July 17, 2010; Final version received: September 9, 2013
Editor: Campbell Harvey

REFERENCES

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

Ahern, Kenneth R., 2012, Bargaining power and industry dependence in mergers, *Journal of Financial Economics* 103, 530–550.

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

Allen, Jeffrey W., and Gordon M. Phillips, 2000, Corporate equity ownership, strategic alliances, and product market relationships, *Journal of Finance* 55, 2791–2815.

Arellano, Manuel, and Stephen Bond, 1991, Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies* 58, 277–297.

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

Bhattacharyya, Sugato, and Amrita Nain, 2011, Horizontal acquisitions and buying power: A product market analysis, *Journal of Financial Economics* 99, 97–115.

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.

Coase, R. H.,1937, The nature of the firm, *Economica* 4, 386–405.

Denis, David J., Diane K. Denis, and Atulya Sarin, 1997, Agency problems, equity ownership, and corporate diversification, *Journal of Finance* 52, 135–160.

Dijkstra, E. W., 1959, A note on two problems in connexion with graphs, *Numerishce Mathematik* 1, 269–271.

Duchin, Ran, and Breno Schmidt, 2013, Riding the merger wave, *Journal of Financial Economics* 107, 69–88.

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

Economic Classification Policy Committee, 1993, Criteria for determining industries, Discussion Paper 4, Bureau of Economic Analysis, U.S. Department of Commerce.

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

Fee, C. Edward, Charles J. Hadlock, and Shawn E. Thomas, 2006, Corporate equity ownership and the governance of product market relationships, *Journal of Finance* 61, 1217–1251.

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, Working paper, University of Michigan.

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

Gabaix, Xavier, 2011, The granular origins of aggregate fluctuations, *Econometrica* 79, 733–772.

Galbraith, John Kenneth, 1952, *American Capitalism: The Concept of Countervailing Power* (Houghton Mifflin, Boston).

Garfinkel, Jon A., and Kristine Watson Hankins, 2011, The role of risk management in mergers and merger waves, *Journal of Financial Economics* 101, 515–532.

Giroud, Xavier, and Holger M. Mueller, 2010, Does corporate governance matter in competitive industries? *Journal of Financial Economics* 95, 312–331.

Gollop, Frank M., 1994, The heterogeneity index: A quantitative tool to support industrial classification, Discussion Paper 2, Bureau of Economic Analysis, U.S. Department of Commerce.

Grossman, Sanford J., and Oliver D. Hart, 1986, The costs and benefits of ownership: A theory of vertical and lateral integration, *Journal of Political Economy* 94, 691–719.

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

Hart, Oliver, 1995, *Firms, Contracts, and Financial Structure* (Clarendon Press, Oxford, England).

Hart, Oliver, and John Moore, 1990, Property rights and the nature of the firm, *Journal of Political Economy* 98, 1119–1158.

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.

Hoberg, Gerard, and Gordon Phillips, 2010a, Dynamic text-based industry classifications and endogenous product differentiation, Working paper, University of Maryland and University of Southern California.

Hoberg, Gerard, and Gordon Phillips, 2010b, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.

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

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

Joskow, Paul L.,1985, Vertical integration and long term contracts: The case of coal-burning electric generating stations, *Journal of Law, Economics, and Organization* 1, 33–80.

Joskow, Paul L., 1987, Contract duration and relationship specific investments, *American Economic Review* 77, 168–175.

Katz, Michael L., 1987, The welfare effects of third-degree price discrimination in intermediate good markets, *American Economic Review* 77, 154–167.

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.

Lamont, Owen, 1997, Cash flow and investment: Evidence from internal capital markets, *Journal of Finance* 52, 83–109.

Lieberman, Marvin, 1991, Determinants of vertical integration: An empirical test, *Journal of Industrial Economics, Special Issue on Vertical Relationships* 39, 451–466.

MacKay, Peter, and Gordon M. Phillips, 2005, How does industry affect firm financial structure? *Review of Financial Studies* 18, 1433–1466.

Maksimovic, Vojislav, and Gordon Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains? *Journal of Finance* 56, 2019–2065.

Maksimovic, Vojislav, Gordon M. Phillips, and Liu Yang, 2013, Private and public merger waves, *Journal of Finance* 68, 2177–2217.

Masten, Scott E., 1984, The organization of production: Evidence from the aerospace industry, *Journal of Law and Economics* 27, 403–417.

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.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Newey, Whitney K., and Kenneth D. West, 1994, Automatic lag selection in covariance matrix estimation, *Review of Economic Studies* 61, 631–653.

Ohanian, Nancy Kane, 1994, Vertical integration in the U.S. pulp and paper industry, 1900-1940, *Review of Economics and Statistics* 76, 202–207.

Ovtchinnikov, Alexei V., 2013, Merger waves following deregulation, *Journal of Corporate Finance* 21, 51–76.

Perry, Martin K., 1978a, Price discrimination and forward integration, *Bell Journal of Economics* 9, 209–217.

Perry, Martin K., 1978b, Vertical integration: The monopsony case, *American Economic Review* 68, 561–570.

Perry, Martin K., 1989, Vertical integration: Determinants and effects, in Richard Schmalensee and Robert D. Willig, eds.: *Handbook of Industrial Organization* (North Holland, Amsterdam).

Phillips, Gordon M., and Alexei Zhdanov, 2013, R&D and the incentives from merger and acquisition activity, *Review of Financial Studies* 26, 34–78.

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.

Schmalensee, Richard, 1973, A note on the theory of vertical integration, *Journal of Political Economy* 81, 442–449.

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.

Spengler, Joseph J., 1950, Vertical integration and antitrust policy, *Journal of Political Economy* 58, 347–352.

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

Stuckey, John A., 1983, *Vertical Integration and Joint Ventures in the Aluminum Industry* (Harvard University Press, Cambridge, MA).

Tirole, Jean, 1988, *The Theory of Industrial Organization* (The MIT Press, Cambridge, MA).

Vernon, John M., and Daniel A. Graham, 1971, Profitability of monopolization by vertical integration, *Journal of Political Economy* 79, 924–925.

Warren-Boulton, Frederick R., 1974, Vertical control with variable proportions, *Journal of Political Economy* 82, 783–802.

Watts, Duncan J., and Steven H. Strogatz, 1998, Collective dynamics of "small-world" networks, *Nature* 393, 440–442.

Williamson, Oliver E., 1979, Transaction-cost economics: The governance of contractual relations, *Journal of Law and Economics* 22, 233–261.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Appendix S1: Internet Appendix.