ESSAYS IN CORPORATE FINANCE

by

Mary Joy Becker

B.S.B.A., John Carroll University, 1997

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This dissertation was presented

by

Mary Joy Becker

It was defended on

August 23, 2011

and approved by

Oya Altinkilic, Assistant Professor, Finance

Leonce L. Bargeron, Assistant Professor, Finance

Joseph P.H. Fan, Professor, Finance

Sara B. Moeller, Associate Professor, Finance

Dissertation Advisor: Shawn E. Thomas Associate Professor, Finance

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My dissertation includes two related essays in supply chain and corporate finance. The first is sole authored and entitled "Do merger waves cause ripples in vertically related industries" and the second is co-authored with Shawn Thomas and entitled "Changes in concentration across vertically related industries". In the first, I use a sample of all industries experiencing merger activity between 1980 and 2008 to investigate the relation between customer and supplier horizontal merger waves. I find evidence that a merger wave in a customer (supplier) industry increases the likelihood of a subsequent merger wave in a related industry by 30% (28%), depending on the definition of merger wave used. Additional tests of the data show that industry merger waves are more likely to follow customer merger waves, but not necessarily supplier merger waves, when bargaining power motives are at work. I find that vertically related industry merger waves occur subsequent to supplier and customer industry merger waves, suggesting that merger waves move along the supply chain. Finally, I find that the association between related industry horizontal merger waves is strongest for non-consumer goods industries and industries with little product differentiation.

In the second essay, we investigate the magnitude, timing, and direction of the association between changes in concentration across vertically related industries over the period 1978-2008. We find robust evidence that changes in an industry's level of concentration are significantly positively related to prior and simultaneous changes in the concentration of their customer industries. We find weaker evidence that changes in an industry's level of concentration are related to changes in the concentration of their supplier industries. Thus, the association between changes in concentration across vertically related industries appears stronger in the upstream direction than in the downstream direction. We find that increased concentration across vertically related industries, perhaps reflecting countervailing power effects, explains in part the observed positive association between changes in concentration; however, we also find robust evidence that decreases in concentration, perhaps reflecting the effects of technological innovation in vertically related industries, are also important determinants of the observed association.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

PREFACE

This dissertation is based upon research conducted at the Katz Graduate School of Business, University of Pittsburgh from 2006 through 2011. It could not have been completed without the support and guidance of my committee members and moral support and encouragement from my family and friends.

I am very pleased to thank my dissertation committee chairperson and co-author on the second essay of this dissertation, Shawn Thomas, for providing me with the guidance and training necessary for me to complete this work. The inspiration for this work came in a course he taught and I would like to express my gratitude for his perseverance throughout the time it took to complete this work. I would like to thank all of the members of my dissertation committee; Oya Altinkilic, Leonce Bargeron, Joseph Fan, and Sara Moeller, for generously giving of their time and expertise which greatly improved this work. I would like to thank Kenneth Lehn for his encouragement, excellent instruction and inspiration. I would like to thank the members of the Katz doctoral office, in particular Carrie Woods, for their assistance and optimism. I would like to thank Lindsay Calkins, Jesse Ellis, and Mehmet Yalin for editing, programming support, and general feedback.

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1.0 ESSAY 1: DO MERGER WAVES CAUSE RIPPLES IN VERTICALLY RELATED INDUSTRIES?

1.1 INTRODUCTION

A well-established finding in modern corporate finance is that mergers and acquisitions cluster by industry and over time (see Gort, 1969 and Mitchell and Mulherin, 1996). Researchers have found that industries experiencing higher merger activity have often experienced shifts in regulation, demand, or technology. Moreover, events in one industry may affect, sometimes dramatically, industries connected through trade relations. In fact, prior research shows that financial distress (Hertzel, Li, Officer, and Rodgers, 2008), market returns (Menzly and Ozbas, 2010, and Cohen and Frazzini, 2008), and merger activity (Ahern and Harford, 2011 and Bhattacharyya and Nain, 2010) extend along the supply chain and spread to firms operating in customer and supplier industries. The primary purpose of this paper is to test for an association of horizontal merger waves in vertically related industries.

The evidence in this paper suggests that a merger wave in a supplier industry significantly increases the likelihood of a subsequent horizontal merger wave in the vertically related industry by as much as 28%, depending on the definition of merger wave used. This statistically and economically significant finding is robust to a variety of tests. I also find that the incidence of a merger wave in a customer industry increases the likelihood of a subsequent merger wave in the vertically related industry by 30% again depending on the definition of merger wave used. Testing of the timing of the merger waves shows that supplier merger waves precede vertically related industry merger waves and that customer merger waves occur prior to and concurrent with vertically related industry merger waves. Thus, horizontal merger waves move along the supply chain.

There are several, although not mutually exclusive, reasons why customer or supplier horizontal merger waves may be associated with related industry merger waves. First, firms in both industries could be efficiently reacting to a extraneous shock such as technological improvements or changes in government regulations. Second, operational considerations may be at work in the sense that a merged customer may require that suppliers be able to fulfill larger orders, which may encourage subsequent horizontal supplier mergers. Finally, the hypothesis of countervailing power offered by Galbraith (1952) suggests that a firm may gain bargaining power with customers and/or suppliers by merging horizontally. As a result, trading partners may take actions to neutralize this bargaining power gain by engaging in mergers of their own. Thus, mergers beget mergers.

Through subsequent testing of the data I find some evidence to support Galbraith's theory of countervailing power. Specifically, I find that the association between customer industry horizontal merger waves and vertically related industry horizontal merger waves is strongest when countervailing power motives are most likely to be at work, that is when the customer industry is experiencing higher profits or is increasing in concentration. Other tests show that industries in a weaker bargaining position otherwise, i.e. those with less differentiated products, are more likely to respond to a customer industry merger wave with a merger wave of its own. This association is not as strong for supplier industry merger waves. While I find that industries with less differentiated products are likely to follow supplier merger waves with own horizontal merger waves, this association does not exist when bargaining power motives are most likely to be at work. Thus, there is strong (mixed) evidence that countervailing motives are an important determinant of horizontal industry merger waves that follow customer (supplier) merger waves.

This paper complements two recent papers examining merger activity along the supply chain. Bhattacharyya and Nain (2011) examine the effects of customer mergers on supplier margins and pricing and show that horizontal merger activity (not a merger wave) is associated with prior horizontal merger activity in customer industries.[1] Ahern and Harford (2011) use networking techniques to show that merger waves (for all merger activity, not just horizontal) are related to merger activity in trade-connected industries. This paper extends this analysis and to my knowledge is the first comprehensive large sample test of whether horizontal merger waves in vertically related industries follow horizontal merger waves in customer and supplier industries. In addition, this paper is the first to test which industries are likely to have this association and it provides evidence that in the case of customer merger waves, countervailing power motives are associated with subsequent horizontal merger waves.

The paper proceeds as follows. Section 2 presents related literature and develops the hypothesis. Section 3 provides details about the sample construction, customer and supplier relations, and empirical methodology. Section 4 presents results and Section 5 provides robustness checks. Section 6 concludes.

[1] Bhattacharyya and Nain (2011) test for a relationship between prior supplier industry merger activity and subsequent related industry merger activity and find none.

1.2 RELEVANT LITERATURE AND HYPOTHESIS DEVELOPMENT

This paper draws upon merger wave and financial supply chain literature. Further, motivation for the research question comes from the countervailing power hypothesis explored in the industrial organization and corporate finance literature. Thus, merger wave, supply chain and countervailing power literature, as well as the hypothesis are discussed below.

1.2.1 Merger wave literature

Previous literature has documented that mergers cluster across industries and over time.[2] The neoclassical theory of merger waves posits firms are simultaneously responding to macroeconomic, industrial or competitive shocks using the least-cost method available (Gort, 1969). Empirical efforts to document specific events leading to merger waves have identified industry shocks such as deregulation (Andrade, Mitchell and Stafford, 2001; Harford, 2005; Ovtchinnikov, 2010), changes in demand (Maksimovic and Phillips, 2001), changes in operating performance (Harford, 2005; Mitchell and Mulherin, 1996), and new technologies (Holstrom and Kaplan, 2001) as events precipitating merger waves. Additionally, Harford (2005) shows that favorable overall economic conditions, as measured by the ease of corporate lending, are an important determinant of industry merger waves.[3] Other merger wave research suggests that game theoretic forces (Yan, 2009 and Fridolfsson and Stannek, 2005) or managerial empire building (Goel and Thakor, 2010 and Duchin and Schmidt, 2010) are associated with merger

[2] See Mitchell and Mulherin (1996), Andrade, Mitchell and Stafford (2001), and Mulherin and Boone (2000) regarding waves in the 1980's and 1990's and Alexandridis, Mavrovitis and Travlos (2010) for a description of merger activity in the 2000's.
[3] See also Ditmar and Ditmar (2008) which documents that merger waves are related to growth in GDP.

waves. This paper contributes to merger wave research by exploring an additional trigger that may be associated with merger waves, that of a merger wave in a customer or supplier industry.

1.2.2 Supply chain literature

There is a growing body of research linking events in one industry to the competitive, financing, and operational environment in another. Related to mergers, Becker and Thomas (2011) find evidence that large increases in customer concentration (i.e. consolidation) are associated with subsequent large increases in supplier concentration, consistent with the idea that horizontal mergers in one industry lead to horizontal mergers in another. Ahern and Harford (2011) use networking techniques from graph theory to show that merger waves propagate across industry networks over time. Bhattacharyya and Nain (2011), in a sample of mining and manufacturing firms, find a association between customer merger waves and supplier operating margin and in a larger sample, between customer merger activity and subsequent supplier merger activity. Additionally, researchers have found evidence that financial distress (Hertzel, Li, Officer and Rodgers, 2008), capital structure (Banerjee, Dasgupta and Kim, 2008, and Kale and Shahrur, 2007), and merger gains (Ahern, 2010) may spread along the supply chain. This paper adds to previous research and provides further evidence that industries do not exist in isolation and decisions made by managers in one industry have effects that extend to vertically related industries.

1.2.3 Countervailing power literature and hypothesis development

The idea that customer and supplier merger waves may be associated with vertically related industry merger waves stems from the theory of countervailing power first offered by Galbraith (1952). When first presented, Galbraith used the term countervailing power to describe the ability of large buyers in concentrated markets to gain more favorable pricing from suppliers (Snyder, 2005). He extended this notion to include the supposition that merging firms create a measure of monopoly (or monopsony) power which buyers (or sellers) are encouraged to counteract. Because larger negotiating partners garner more bargaining power, Stigler (1954) notes that according to this theory, mergers beget mergers. Although the countervailing power hypothesis was originally criticized (Stigler, 1954), recent evidence supports it (Bhattacharyya and Nain, 2011).

Below I explain why merging suppliers may encourage subsequent customer mergers and then why the converse may be true. To start, suppliers engage in horizontal mergers for efficiency or empire building reasons and subsequently experience higher profits.[4] Customers, realizing there are larger gains to bargain for, may engage in merger activity of their own to obtain better pricing from sellers (see Stigler, 1964).[5] Snyder's (1998) model supports this conclusion and shows that suppliers engage in more aggressive price competition after customers merge. In this scenario, the larger customers simulate a boom in demand and as a result sellers are willing to deviate from collusive pricing.

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[4] We are agnostic as to why the suppliers are merging and how they subsequently gain higher profits.
[5] Empirical studies by Lustgarten (1975), Chipty (1995), and Scherer and Ross (1990) also support the idea that larger customers enjoy greater bargaining power.

Working in an auction setting, Snyder (1996) also suggests that merging customers may obtain better pricing due to intensified supplier competition. In this model, firms engaging in horizontal mergers use their purchasing power to induce suppliers to compete in a "winner-take-all" tournament (see also Fee and Thomas, 2004). In the same vein, Inderst and Shaffer (2007) show that, following a merger, retailers (customers) can enhance bargaining power vis-à-vis suppliers by committing to a single source purchasing strategy. Thus, following supplier mergers, customers are encouraged to engage in mergers themselves to foster price competition amongst the remaining suppliers.

In addition to bargaining power considerations, larger customers may be able to secure lower prices from suppliers due to lower distribution or production costs if the production function exhibits increasing returns to scale (Snyder, 2005). Taken together, past research suggests that supplier merger waves may induce subsequent customer industry merger waves as customers grow in order to better bargain with suppliers or to take advantage of production efficiencies.

Past research also suggests that the converse may be true; supplier mergers may follow customer mergers. One reason suppliers may merge is to better negotiate with larger customers. Horn and Wolinski (1988) show that merged suppliers can gain power vis-à-vis customers through more credible bargaining. Bargaining gains in this case come from the material commitment that makes any price concession more costly for the merged versus stand alone supplier. Suppliers may also merge to take advantage of scale economies provided by larger orders from merged customers (Lambrecht, 2004). Lambrecht's model also shows that the takeover premium in hostile deals is increasing in product market uncertainty. Larger customers provide more product market uncertainty because the loss of any one customer is costlier, even if the probability that any one customer may leave is unchanged (Snyder, 1998). This greater uncertainty leads to higher takeover premiums and increases the likelihood that a supplier industry takeover offer will be made and accepted.

Empirical support that customer mergers may be associated with subsequent supplier mergers come from Fee and Thomas (2004) who find that suppliers experience significant declines in cash flow margins immediately subsequent to downstream mergers. The margin deterioration is not permanent, however, suggesting that suppliers may undertake actions of their own to offset customer bargaining gains. Bhattacharyya and Nain (2011) find evidence that suppliers may engage in acquisitions to off-set any adverse bargaining power effects resulting from previous customer merger activity.[6]

This leads to the following hypothesis:

H0: A horizontal merger wave in a customer or supplier industry increases the likelihood of a horizontal merger wave in a vertically related industry.

There is the possibility, however, that a common shock exogenous to both industries is the cause for merger waves occurring subsequently in vertically related industries. In order to test if the merger wave association between customer and supplier industries is related to the shock of the prior merger wave versus an exogenous shock, I control for other factors previously found to be associated with industry merger waves. Further, I examine if the association is stronger for industries that are more closely related (see Fee and Thomas, 2004 and Shahrur, 2005) and in cases where bargaining power motives are more likely to be at work. Finally, I examine the timing between the customer or supplier merger wave and the related industry merger wave.

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[6] See also Chipty and Snyder, 1999 and Gal-Or and Dukes, 2006 for additional consideration of merger effects on a customer's bargaining position.

1.3 DATA AND METHODOLOGY

To determine whether merger waves in an industry are associated with prior customer or supplier merger waves, I use customer and supplier relations drawn from Bureau of Economic Analysis (BEA) input-output (I-O) tables to generate two samples; one where each industry is matched with its significant suppliers and the second where each industry is matched with its significant customers. The samples are called Industry & Suppliers and Industry & Customers, respectively. When discussing the Industry & Suppliers sample I use the term “suppliers” to refer to the matched suppliers and “related industries” to refer to the set of industries. The terminology is analogous for the Industry & Customers sample. Because there is no clear consensus on what constitutes a merger “wave”, I use past research as a guide to generate two definitions of merger waves which are used in the empirical analysis. The process of matching industries with customers and suppliers and the methodology for identifying merger waves are discussed below.

1.3.1 Industry classifications and relations

I classify industries based on the industry codes (IO-codes) used in the 2002 Make and Use tables published by the BEA.[7] The Make table details commodities produced and the Use table details commodities used as production inputs by each industry. The most important source of information for the Make and Use tables is the US Census Bureau’s Economic Census which is an establishment-by-establishment survey of businesses operating inside the United States

[7] Using BEA tables from only one year is advisable because BEA updates industry codes with each new set of detailed tables. Tables from different time periods are not directly comparable and using multiple tables precludes me from creating a panel of data extending more than five years. As a robustness test I perform the same analysis using the 1992 BEA tables and find similar if not stronger results. See 1.5.3 Industry relationship tests for a discussion of these results.

conducted every five years. There are 439 industries and other categories in the Make and Use tables.[8] My sample includes the 387 private (non-governmental) industries with at least one merger during the entire sample period of 1980-2008.

Following the methodology outlined in Appendix A, I use the Make and Use tables to create an industry by industry production-consumption matrix. Using this matrix I match the 387 industries with supplier industries providing at least 5% of the industry's inputs.[9] This is the basis for the first sample, which I call the Industry & Suppliers sample. On average, an industry has 4.3 related suppliers and purchases 10.5% (median is 8.0%) of its commodity inputs from a related supplier.[10] In total, I identify 38,852 relationship-years from which I build the Industry & Suppliers sample. Additionally, I match each of the 387 industries with customer industries consuming at least 3% of the industry's outputs.[11] This is the basis for the second sample, which I call the Industry & Customers sample. On average, an industry has 5.9 related customers and sells 9.2% (median is 5.9%) of its commodity outputs to a related customer.[12] Eighty-five

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[8] Other categories include scrap, imports, exports and government activities.

[9] Statistics for industries and their top 10 suppliers show that the median (mean) percentage of inputs supplied to the industry is 5.9% (3.9%). 5% is between these two figures and has been used in prior research (Shahrur, 2005). See 1.5.3 Industry relationship tests for results where the cut-off is reduced to 3%.

[10] As an example, the industry with the most matched suppliers is the rubber and plastics hoses and belting manufacturing industry. The suppliers to the industry and percent of commodities supplied are: other rubber product manufacturing (13.0%) knit fabric mills (11.8%), plastics material and resin manufacturing (8.0%), management of companies and enterprises (6.6%), wholesale trade (5.7%) other basic organic chemical manufacturing (5.5%), synthetic rubber manufacturing (5.5%), and hardware manufacturing (5.2%).

[11] Statistics on industries and their top 10 customers show that median (mean) percentage of inputs supplied to the industry is 4.0% (1.9%). 3% is between these two figures and has been used in prior research (Shahrur, 2005). Further, household consumption is an important non-industrial customer in the sample. 41% of the industries' most important customer is private households, and on average (the median) private households purchase 30.1% (8.2%) of an industry's output. Consumption by governmental agencies further lowers the percentage of output sold to private industry. This explains a lower 3% cut-off in sample 2 versus sample 1. See 1.5.3 Industry relationship tests for results where the cut-off is increased to 5%.

[12] As an example, the industry with the most matched customers is the electronic capacitor, resistor, coil, transformer, and other inductor manufacturing industry. The customers of this industry and percent of output purchased are: software publishing (8.4%) motor vehicle parts manufacturing (6.9%), semiconductor and related device manufacturing (6.2%), printed circuit assembly manufacturing (5.6%) electronic computer manufacturing (5.2%), bare printed circuit board manufacturing (4.9%), electro medical and electrotherapeutic apparatus manufacturing (4.3%), telecommunications (3.7%), search, detection, and navigation instruments manufacturing

industries have no industry customers consuming over 3% of its outputs. These industries have a majority of the output sold to personal households or to the government.[13] In total, I identify 34,260 relationship-years from which I build the Industry & Customers sample. The similar sample sizes and trade relation averages (10.5% percent of inputs supplied and 9.2% percent of outputs consumed) indicate that the samples are comparable.

1.3.2 Merger data and merger wave definitions

I collect merger and acquisition data using Security Data Corp.'s (SDC) Mergers & Acquisitions database and include all completed horizontal mergers and tender offers of U.S. targets meeting the following criteria: (1) the announcement date is between January 1, 1980 and December 31, 2008, (2) the percent of acquired shares is greater than 50% and (3) the acquirer owns at least 95% of the target's shares upon completion of the transaction.14 For each deal I also obtain transaction value (where available) which is defined as the total value of the consideration paid by the acquirer less fees associated with the deal. Because SDC reports an industry NAICS code with each target and acquirer, I use the IO-code to NAICS code translation table published by the BEA to assign IO-codes to all companies used in the study.15,16 Mergers are deemed to be

(3.6%), other electronic component manufacturing (3.2%), audio and video equipment manufacturing (3.0%), and telephone apparatus manufacturing (3.0%).

[13] Examples include personal care services; amusement parks, arcades, and gambling industries; offices of physicians, dentists, and other health practitioners; retail; ammunition manufacturing; bowling centers; automotive repair and maintenance, except car washes; and automobile manufacturing.

[14] Because I do not rely on data available only from publicly traded firms I am able to include many transactions that are traditionally dropped from other datasets. See Netter, Stegemoller and Wintoki (2010) for a discussion of how data screens on the size and characteristics of transactions in the SDC database can significantly influence results.

[15] SDC uses 2007 NAICS codes for all companies, regardless of the year of the deal. First, therefore, I map the 2007 NAICS codes to the 2002 NAICS codes.

[16] There are 1,146 different 6-digit NAICS codes that are matched to 439 IO-codes. Some mappings are direct. Often, however, two or three NAICS codes are mapped to one IO-code. A typical example is the IO-code 311810, bread and bakery product manufacturing, which has three NAICS codes, 311811, retail bakeries, 311812,

horizontal if the two merging entities have the same IO-code. There are 54,349 horizontal transactions representing $7.9 trillion in 2008 dollars worth of deals that fit the above description. Figure 1 shows the number of horizontal transactions and total transaction value for all industries by year. The figure shows a pattern of mergers similar to those examined in other studies with aggregate merger wave periods in the late 1980's, late 1990's and the middle of the first decade of the 2000's. On an industry basis, there are a total of 387 industries with zero to 609 horizontal mergers per year.[17] On average (median) an industry is involved in 4.7 (0.0) mergers per year. Of those industries reporting a deal with a disclosed transaction value in a year, the average (median) reported annual transaction value in an industry year is $2,074 million ($123 million).

Using the transaction data described above, I measure adjusted acquisition activity for each IO-code as total annual industry transaction value divided by fiscal year-end market value of industry assets.[18] I identify a merger wave using two methods. In the first, an industry merger wave occurs if the 2-year moving average of adjusted acquisition activity is in the top 20% *of the sample*, there are at least three horizontal mergers in the year, and if neither of the previous two years are considered a wave.[19] These restrictions make certain that the acquisition activity is high relative to all industries, is not driven by one or two extremely large transactions, and ensures

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commercial bakeries, and 311813, frozen cakes, pies, and other pastries manufacturing mapped to it. In some cases, many NAICS codes are mapped to one IO-code. Two examples are the wholesale and retail industries where 71 and 75 NAICS 6-digit NAICS codes industries are mapped each IO-codes industry, respectively.

[17] The monetary authorities and depositary credit intermediation industry in year 1995 accounts for the 609 transactions in one year.

[18] Market value of assets data is from Compustat and is calculated as the sum of net debt (total of long term debt plus capitalized lease obligations less cash), market value of preferred stock and the number of common shares outstanding times price per share.

[19] This measure is similar to the measure of liquidity of corporate assets used by Schlingemann, Stultz and Walkling (2002). I chose the two year moving average because past merger wave studies treat industry merger waves as a two-year phenomena. See Mitchell and Mulherin (1996), Harford (2005), Duchin and Schmidt (2008), and Gorton, Kahl and Rosen (2009).

that I identify the start of the merger wave. There are 557 identified waves using this methodology, which I refer to as Top20_Wave.

For the second measure, merger activity is considered a wave if the one year adjusted acquisition activity level is at least one standard deviation above *own industry mean* measured over the sample period. All years which meet this criterion are considered wave years.[20] There are 776 waves identified using this methodology which I refer to as STD_Wave. Figure 2 depicts the number of Top20_Waves and STD_Waves by year and shows greater year over year variation of STD_Waves as compared to Top20_Waves. I combine merger wave information with the industry-customer and industry-supplier relations described above to form the two samples. See Table 1 and Table 2 for descriptive statistics on each sample. Panel A contains statistics for the industries and Panel B contains statistics for the related supplier (or customer) industry. Because each sample starts with the same set of industries and differ only in the matched customer or supplier industries, I expect and find that the statistics in Panel A are similar for both samples. Panel B shows that supplier industries are larger and on average involved in more transactions (on a dollar basis) than are the customer industries.

1.3.3 Economy and industry control variables

Certain economic and industry factors have been found in past empirical research to positively affect merger rates over time. One is the ease with which managers can obtain funds to finance investment projects. As a proxy I use the spread of the average commercial and industrial loan rate over the federal funds rate which Lown, Morgan, and Rohatgi (2000) find is highly

[20] Measure based on the variable used in a recent working paper by Maksimovic, Phillips and Yang (2010).

negatively correlated with ease of commercial lending (see also Harford, 2005, and Maksimovic, Phillips, and Yang, 2010). A higher spread implies tighter lending standards and is expected to be negatively related to merger wave activity.

Harford (2005) and Mitchell and Mulherin (1996) find that deregulatory events are a catalyst for industry merger waves and Andrade et al. (2005) find that over half of the merger activity in the 1990s is associated with deregulation. In this study I use a dummy variable to indicate an industry has experienced a deregulatory event in year t= 0 and expect that this variable is positively related to the likelihood of industry merger waves. I obtain information on deregulation from Economic Reports to the President and specific industry sources.[21]

A negative relation between initial levels of concentration and the likelihood that concentration will increase further is documented in the literature (see Curry and George, 1983) for a review). In addition, anti-trust policies may make it difficult for a highly concentrated industry to consolidate further. Therefore, the industry Herfindahl Index which is the sum of squared market shares is included as a control variable.[22] In an effort to control for industry shocks other than deregulation, I follow Harford (2005) and include a variable to take into account several correlated factors that may influence an industry's decision to consolidate. The industry shocks variable is the first principal component of the one year absolute change in following variables: profitability, asset turnover, capital expenditures, employee growth, return on assets and sales growth.[23]

[21] Viscusi, Vernon, and Harrington (2000) contains a list of deregulatory events obtained from an Economic Report to the President. Deregulation events are found in the Economic Report to the President for years 1989, 1995, 1999, 2001, 2003, and 2005. Specific industry sources include www.consumerreports.org and www.naturalgas.org.

[22] Industry sales data is from Compustat.

[23] Because principal component analysis is heavily influenced by outliers I Winsorize the variables at the 5% level.

If investment opportunities are high and internal growth is time consuming, firms may prefer to acquire other firms in the industry rather than rely on organic growth. To capture the aggregate level of investment opportunities I follow Maksimovic et al. (2010) and use the one year return on the S&P500 as a control variable. If managerial motives are a significant catalyst of merger waves, those industries with more cash would be more likely to engage in merger activity. To capture the managerial motive for merger waves I use industry cash divided by assets as a control variable (See Jensen, 1986). See Table 3 Panel A for a summary of the above discussion.

1.4 EMPIRICAL RESULTS

1.4.1 Industry & Suppliers results

This section examines the likelihood of merger waves in relation to previous supplier industry merger waves. In a univariate setting, I find that on average an industry experiences 0.054 Top20_Waves and 0.079 STD_Waves per year when a matched supplier industry does not experience the start of a merger wave two years prior. The averages increase to 0.079 Top20_Waves and 0.095 STD_Waves per year when the supplier industry does experience the start of a merger wave two years prior, increases of 46% and 20%, respectively. The difference in means is significant at the 1% level for both merger wave measures.

To determine whether the univariate results hold after controlling for certain economic and industry factors previously found to affect merger rates over time, I estimate several logistic regression models. The sample is the Industry & Suppliers supplier sample for years 1980 – 2008 and the first and last years of the sample are dropped due to leads and lags in the data. The logistic equations are as follows:

$$Logit(p_{Top20\_Wave=+1}) = \beta_0 + \beta_1 SupTop20\_Wave_{t=-1} + \beta_2 Spread_{t=-1,0} + \beta_3 Deregulation_{t=0} + \beta_4 Herfindahl_{t=0} + \beta_5 Principal\ component_{t=0} + \beta_4 Industry\ cash_{t=0} + S\&P\ one\ year\ return_{t=-1,0} \quad (1)$$

$$Logit(p_{STD\_Wave=+1}) = \beta_0 + \beta_1 SupSTD\_Wave_{t=-1} + \beta_2 Spread_{t=-1,0} + \beta_3 Deregulation_{t=0} + \beta_4 Herfindahl_{t=0} + \beta_5 Principal\ component_{t=0} + \beta_4 Industry\ cash_{t=0} + S\&P\ one\ year\ return_{t=-1,0} \quad (2)$$

where Top20_Wave$_{t=+1}$ (STD_Wave$_{t=+1}$) is a dummy variable equal to one if the related industry experiences a merger wave beginning in year t= +1 and SupTop20_Wave$_{t=-1}$ (SupSTD_Wave$_{t=-1}$) is a dummy variable equal to one if the related supplier industry experiences a merger wave beginning in year t= -1. Panels A and B of Table 3 contain definitions and descriptive statistics, respectively, for Spread$_{t=-1,0}$, Deregulation$_{t=0}$, Herfindahl$_{t=0}$, Principal component$_{t=0}$, Industry cash$_{t=0}$, and S&P one year return$_{t=-1,0}$. The table shows that deregulation is a infrequent event and that the industries are, on average, highly concentrated.[24]

Table 4 presents the results of the logistic regression model estimating merger waves.[25] Columns (1) and (4) contain results for the logistic model including control variables only. Columns (2) and (5) contain results including the supplier merger wave variable. As is consistent with the hypothesis, the supplier Top20_Wave (column 5) variable is positive and significant at the 5% level, indicating that an industry is more likely to undergo a merger wave in year t= +1 if a supplier industry has undergone a merger wave beginning in year t= -1. The supplier STD_Wave variable is positive but has a p-value of 14%. The odds ratio of 1.31 (1.14) for the supplier Top20_Wave (supplier STD_Wave) variable indicates that the odds of an industry

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[24] The Department of Justice considers an industry to be highly concentrated if the Herfindahl is above 0.18.
[25] P-values are based on White standard errors clustered at the industry level.

experiencing a merger wave beginning in year t= 1 increase by a factor of 1.31 (1.14) if the supplier has experienced a merger wave in year t= -1, holding all other variables constant. Further, when the Top20_Wave variable changes from 0 to 1 the probability of observing a Top20_Wave in an industry increases from 0.044 to 0.057, an increase of 28.0%, holding all other variables at their mean. The higher Chi-squared test for model (2) as compared to model (1) (114.50 vs. 112.50) and for model (5) as compared to model (4) (74.81 vs. 72.21) indicates that the models including supplier merger wave variables improve our ability to explain the likelihood of the occurrence of an industry merger wave.

As is consistent with previous research, the coefficient on the average spread variable is negative and significant at the 1% level for all models indicating that an industry is less likely to experience a merger wave when spreads are high. The deregulation coefficient has an expected positive sign but is not significant in any specification. For all specifications, the coefficient on the industry Herfindahl is negative and significant at the 1% level indicating that an already concentrated industry is less likely to undergo a merger wave.[26] Coefficients on principal component variables are difficult to interpret. The coefficient on the first principal component is positive in the first three specifications and negative in the last three specifications and is never significant. Industry cash is positive and significant indicating that those industries with more cash as a percentage of assets are likely to engage in a merger wave. Consistent with the idea that periods of higher investment opportunities are associated with acquisitions, the S&P one year

[26] The results are similar when I use the residuals from an OLS equation where the dependent variable is the Herfindahl at t=0 and the independent variables are Herfindahl measured at t=-1 and t=-2 as the measure of concentration. Results are also similar for a specification including Herfindahl at t=0 and Herfindahl at t=0 squared. Results are similar if I include the number and percent of medium sized firms in an industry, where a medium-sized firm is defined as one with total assets between 5% and 30% of total assets of the industry's largest firm (see Gorton et al., 2009).

return is positively associated with industry merger waves the following year for the Top20_Wave variable. This variable is positive but not significant for the STD_Wave measure.[27]

To test if the relation between industry and supplier merger waves is stronger when the supplier is a relatively more important one, I generate a dummy variable equal to one if the supplier is the top supplier to the industry as measured by percent of inputs provided. The interaction term (supplier wave dummy times top supplier dummy) is positive and jointly significant with the supplier Top20_Wave variable at the 5% level in specification (3). This suggests that a merger wave in a more versus less important supplier industry increases the probability that the related industry will experience a subsequent merger wave. This relation is not found in the STD_Wave model. Therefore I find evidence with the Top20_Wave measure that the effect a supplier industry merger wave has on the likelihood of a subsequent related industry merger wave is increasing in supplier importance.

1.4.1.1 Industry & Suppliers evidence of market power motivation

If bargaining power is a motivating factor for industry merger waves following supplier merger waves, I expect this relation is strongest when the supplier is experiencing higher profits (i.e. when the margin for which the parties bargain is greatest). To proxy for high profits, I create a dummy variable equal to one if the operating margin for the supplier industry in year t=0 is higher than the industry median operating profit over the entire sample period. Results from regressions including this variable and an interaction term equal to the high profit dummy times the supplier wave dummy are presented in columns (1) and (3) in Table 5. In specifications (1) and (3), the supplier high profit dummy is positive with a p-value of 22.4% and 6.2%,

[27] Results are also similar with industry market-to-book added as control variable. The market-to-book variable is not significant and does not add to the explanatory power of the model.

respectively, indicating that an industry is more likely to undergo a merger wave when the supplier is experiencing higher profits but no merger wave. The supplier wave times high profit interaction term is negative in both specifications, suggesting that supplier high profits do not increase the likelihood an industry will experience a merger wave subsequent to a supplier merger wave.

According to the bargaining power hypothesis, a merger wave in a supplier industry resulting in fewer competitors or higher concentration should be more likely to induce subsequent industry merger waves than one where the supplier industry remains less concentrated. To test this idea, specifications (2) and (4) in Table 5 include results for a regression which include a dummy variable equal to one if the supplier change in Herfindahl over the period t= -2 to t= 0 is greater than the two-year median change (0.03%) for all suppliers and an interaction term equal to the supplier merger wave dummy times the high change in Herfindahl dummy. As is consistent with results from Becker and Thomas (2011) the change in Herfindahl dummy is positive and significant in both specifications. This indicates that a high increase in the supplier Herfindahl, absent a supplier merger wave, is associated with a subsequent merger wave in the industry. The interaction term in regression (2) is small and negative, suggesting that given a supplier industry merger wave, supplier changes in concentration do not add to the likelihood of a subsequent industry merger wave. The only support for the bargaining power hypothesis is in specification (4), where the interaction term is positive and jointly significant with the supplier wave variable, suggesting that only supplier merger waves associated with increases in concentration are associated with subsequent industry merger waves. Taken together, the results offer little support for the bargaining power hypothesis of merger waves.

1.4.1.2 Industry & Suppliers type of industry considerations

Past literature suggests that competitive forces other than size may affect bargaining amongst related industries. I expect industry participants that cannot credibly bargain using forces other than size to be more likely to respond to supplier industry mergers with mergers of their own. Past research suggests that positions of market power are found in the consumer goods industries (Galbraith, 1952) and firms with greater product differentiation (Porter, 1974).[28] I therefore expect that non-consumer goods industries and industries with lower product differentiation are more likely to respond to a supplier merger wave with a subsequent merger wave. To test this assumption I create three dummy variables. The first is equal to one if an industry is not in a consumer goods industry. The other two proxy for low product differentiation and are separately equal to one if the industry advertising to sales ratio (Schmalensee, 1982) and R&D to sales ratio (Anderton, 1999) are in the bottom half of the sample. Results including these variables and interaction terms are given in Table 6. The last row of the table, which contains the sum of the coefficients and joint significance of the supplier merger wave variable and interaction term, is the basis of the discussion below. In specifications (1) and (5) the supplier wave variable and non-consumer goods interaction term are jointly positive and significant suggesting that given a supplier industry merger wave, non-consumer goods industries are more likely to experience a subsequent merger wave vs. consumer goods industries. In specifications (2) and (6) the low advertisement spending interaction term is jointly significant with the supplier merger wave measures. The low R&D interaction is not jointly significant with the supplier merger wave variable but is positive in specification (3). The unreported p-value for the joint significance in (3) is 10.5%. This is weak evidence that given a supplier merger wave, industries with low R&D

[28] Porter (1974) finds that retailers with greater differentiation have more bargaining power.

are more likely to experience a merger wave. Taken together, the evidence implies that those industries with weaker positions of market power initially are more likely to experience a merger wave to gain bargaining power with suppliers subsequent to supplier merger waves. This result is consistent across both measures of merger wave.

The unionization rate of an industry's workforce may also influence its bargaining position with customers and suppliers. Specifically, an industry without a unionized workforce may be more likely to engage in merger activity for bargaining power motives because gains from merging will not have to be surrendered to the union.[29] To control for industry unionization rates I include a dummy variable equal to one if the unionization rate for the industry year is less than the sample median (14.5%) and an interaction variable equal to the low industry dummy times the supplier merger wave dummy.[30] Results are given in columns (4) and (8) of Table 6. A joint test of the low industry unionization dummy and interaction variable for both measures of merger wave indicate that given a weakly-unionized industry, an industry is more likely to undergo a merger wave subsequent to a supplier industry merger wave. This is evidence that following a supplier industry merger wave, industry merger waves are more likely if gains from merging do not have to be surrendered to another party, namely the union.

1.4.1.3 Tests on the timing of merger activity

I test if industry merger activity is sensitive to the timing of the supplier merger activity. I repeat the original regression equation except that my independent variable of interest is changed to indicate supplier merger waves beginning in years t= -3, t= -2, t= -1 (original specification), t= 0,

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[29] See Matsa (2010), Klasa, Maxwell, and Ortiz-Molina (2009) and DeAngelo and DeAngelo (1991) for union bargaining studies.
[30] Industry unionization rates are from www.unionstats.com. See Hirsh and Macpherson (2003).

and t= +1. See Table 7 for results. Specifications (1) through (5) refer to Top20_Waves and indicate that if a supplier industry experiences a wave beginning in year -1 (specification 3) the industry has increased probability of experiencing a merger wave beginning in year t= +1. This supports the idea that the industry merger waves occur subsequent to the supplier merger wave. Specifications (6) through (10) refer to waves measured as STD_Waves and indicate that if the supplier experiences a wave in years t= -2 or t= 0, (specifications 7 and 9) then the industry has increased probability of experiencing a merger wave in year t= +1. These results are also suggestive that the supplier merger wave occurs prior to the industry merger wave, and that horizontal merger waves produce a ripple effect moving along the supply chain from suppliers to customers. For both measures of merger wave, the results in specifications (5) and (10) where the supplier and industry merger wave are both measured at t= +1 (concurrent merger waves) suggest that the supplier and industry merger waves do not occur simultaneously.

1.4.2 Industry & Customers results

To examine the likelihood of industry merger waves in relation to previous customer industry merger waves I use the Industry & Customers sample and perform tests similar to those conducted previously. I find that on average, when a customer industry does not experience a merger wave two years prior, an industry experiences 0.047 (0.073) Top20_Waves (STD_Waves) per year. This increases to 0.058 (0.102) Top20_Waves (STD_Waves) per year when the customer industry does experience a merger wave two years previously. The difference in means is significant at the 5% (1%) level. To determine whether the results hold in a multivariate setting, I estimate several logistic regression models in which the dependent variable is the probability that the industry experiences a merger wave in year t= +1. The logistic equations are as follows:

$$Logit(p_{Top20\_Wave=+1}) = \beta_0 + \beta_1 CustTop20\_Wave_{t=-1} + \beta_2 Spread_{t=-1,0} + \beta_3 Deregulation_{t=0} + \beta_4 Herfindahl_{t=0} + \beta_5 Principal\ component_{t=0} + \beta_4 Industry\ cash_{t=0} + S\&P\ one\ year\ return_{t=-1,0} \quad (3)$$

$$Logit(p_{STD\_Wave=+1}) = \beta_0 + \beta_1 CustSTD\_Wave_{t=-1} + \beta_2 Spread_{t=-1,0} + \beta_3 Deregulation_{t=0} + \beta_4 Herfindahl_{t=0} + \beta_5 Principal\ component_{t=0} + \beta_4 Industry\ cash_{t=0} + S\&P\ one\ year\ return_{t=-1,0} \quad (4)$$

where $Top20\_Wave_{t=+1}$ ($STD\_Wave_{t=+1}$) is a dummy variable equal to one if the industry experiences a merger wave beginning in year t= +1 and $CustTop20\_Wave_{t=-1}$ ($CustSTD\_Wave_{t=-1}$) is a dummy variable equal to one if the customer industry experiences a merger wave beginning in year t= -1. The other variables are described in Panel A of Table 3 and descriptive statistics are in Panel C. Descriptive statistics are similar to those for the Industry & Suppliers sample.

Table 8 presents the results of the logistic regression model estimating merger waves.[31] Columns (1) and (4) contain results of control variables only. Columns (2) and (5) contain results including the customer merger wave variable. The customer wave dummy variable is positive and significant in specification (5) but not (2), indicating that an industry is more likely to undergo an STD_Wave (but not a Top20_Wave) in year t= +1 if a related customer industry has undergone a similarly-measured merger wave beginning in year t= -1. The odds ratio of 1.34 for the customer STD_Wave variable indicates that the odds of an industry experiencing a merger wave beginning in year t= 1 increase by a factor of 1.34 if the supplier has experienced a merger wave in year t= -1, holding all other variables constant. When all variables are held at their mean,

[31] P-values are based on White standard errors clustered at the industry level.

the probability of observing an STD_Wave in an industry is 7.4% when the customer STD_Wave variable is 0. This probability increases to 9.6% when the customer STD_Wave variable changes to 1, an increase of 29.9%. The higher Chi-squared test of all coefficients in model (5) as compared to model (4) (64.36 versus 53.67) indicates that the model including the customer STD_Wave variable improves the ability to explain the likelihood of an industry STD_Wave. However, the Chi-squared result for model (1) as compared to model (2) indicates that the customer Top20_Wave has little power to explain the probability of a subsequent industry Top20_Wave beyond what the control variables explain. In sum I find strong support that a customer industry merger wave increases the likelihood of a subsequent industry merger wave when the merger wave is measured as an STD_Wave. I reject the hypothesis that customer industry merger activity increases the likelihood of a subsequent industry merger wave when the merger wave is measured as an Top20_Wave. The control variables in all specifications behave similarly to their counterparts in the other sample with the exception of industry cash, which is positive but not significant, and S&P one year return, which is significant in the first three specifications only.[32]

To test if the relation of industry and customer merger waves is increasing in the importance of the customer, I generate a dummy variable equal to one when the customer is the top industrial customer for the industry, as measured by percent of output purchased. Results including this variable and an interaction term equal to customer merger wave times top customer dummy are in columns (3) and (6) of Table 8. The interaction term is positive and

[32] Results are similar if I use the residuals from an OLS equation where the dependent variable is the Herfindahl at t=0 and the independent variables are Herfindahl measured at t=-1 and t=-2 as the measure of concentration. Results similar to the specification including Herfindahl at t=0 and Herfindahl at t=0 squared. Results are robust to the inclusion of the number and percent of medium sized firms in an industry, where a medium-sized firm is defined as one with total assets between 5% and 30% of total assets of the industry's largest firm (see Gorton et al., 2009). Results are also similar if industry market-to-book is included. The market-to-book variable is not significant.

jointly significant with the customer STD_Wave variable in specification (6) suggesting that given a customer merger wave, the industry is more likely to undergo a merger wave if the customer is the most important one. No such relation exists for the Top20_Wave measure. Thus I find that, for the STD_Wave measure, the relation between the customer and related industry merger waves is increasing in customer importance.

1.4.2.1 Industry & Customers evidence of market power motivation

If bargaining power motives are at work, the relation between customer and related industry merger waves will be strongest when the customer is experiencing higher profits or is more highly concentrated. To proxy for high customer profits I use a dummy variable equal to one if the operating margin for the customer industry in year t= 0 is higher than the industry median operating profit over the entire sample period. Results are presented in columns (1) and (3) in Table 9. The customer wave times high profit interaction term is positive and jointly significant with the customer wave variable in specification (3) suggesting that given a customer STD_Wave the industry is more likely to experience a subsequent STD_Wave if the customer industry is experiencing higher profits. To proxy for high customer concentration in specifications (2) and (4) I include a dummy variable equal to one if the customer change in Herfindahl over the period t= -2 to t= 0 is greater than the two-year median change for all customers. Similar to results for the high profit dummy, the positive customer high change in Herfindahl dummy supports the idea that an industry STD_Wave is more likely to occur subsequent to a customer STD_Wave when market power motivations are most likely to be at work. A relation between customer and industry merger waves does not exist when market power motives are at work for the Top20_Wave measure.

1.4.2.2 Industry & Customers type of industry considerations

Similar to the results for the Industry & Suppliers sample, I expect industry participants that cannot credibly bargain using forces other than size to be more likely to respond to supplier industry mergers with mergers of their own. To test this assumption as I did with the previous sample, I create three dummy variables. The first is equal to one if an industry does not compete in a consumer goods industry. The other two are separately equal to one if the industry advertising to sales ratio and R&D to sales ratio are in the bottom half of the sample. Results including these dummy variables and interaction terms equal to the customer wave times the industry dummy are given in Table 10. The last row contains results for the joint significance of the customer merger wave interaction term. In specification (5) the customer wave variable and interaction term are jointly significant suggesting that given a customer merger wave, non-consumer goods industries are more likely to experience a subsequent STD_Wave vs. consumer goods industries. In specification (6), however, the low advertisement interaction variable is negative, indicating that industries with low advertisement spending are not more likely to experience merger waves subsequent to customer merger waves. In specification (7) the low R&D spending interaction term is jointly significant with the customer STD_Wave variable. Taken together, the results offer some evidence that those industries with initially weaker positions of market power are more likely to use merger activity to gain bargaining power subsequent to customer merger waves than are those industries with stronger positions of market power.

Because those industries with a highly unionized workforce may have to surrender higher profits gained from bargaining to the union, I expect that industries with low unionization rates are more likely to engage in mergers subsequent to customer mergers versus industries that are highly unionized. I control for industry unionization rates as I did with the previous sample by including a dummy variable equal to one if the unionization rate for the industry year is less than the sample median (14.5%) and an interaction variable equal to the low industry dummy times the customer merger wave dummy.[33] The results are given in columns (4) and (8) of Table 10. A joint test of the customer STD_Wave and low union interaction variable suggests that industry merger waves are less likely to occur subsequent to customer merger waves if the industry is not highly unionized, lending support to the bargaining power hypothesis for merger waves.

1.4.2.3 Tests on the timing of merger activity

I test if industry merger activity is sensitive to the timing of the customer merger activity. I repeat the original regression equation except that I include customer merger waves beginning in years t= -3, t= -2, t= -1 (original specification), t= 0, and t= +1. See Table 11 for results. Specifications (1) through (5) refer to waves measured as Top20_Waves and indicate that customer waves are not associated with subsequent or concurrent industry merger waves. Specifications (6) through (10) refer to waves measured as STD_Waves and indicate that if the customer experiences a wave in years t= -1, or t= +1 then the industry has increased probability of experiencing a merger wave in year t= +1. This gives some evidence that past customer waves increase the probability of subsequent industry merger waves and that customer and industry merger waves may occur simultaneously.

[33] Industry unionization rates are from www.unionstats.com. See Hirsh and Macpherson (2003).

1.5 ROBUSTNESS TESTS

I have conducted a variety of robustness tests on both samples. The results of these tests are given below. Unless otherwise indicated, the results are for both samples.

1.5.1 Single segment and frequent supplier tests

The general results rely on Compustat annual data to identify industry merger waves and calculate control variables. In this database, Compustat reports only one NAICS code for the entire company. For firms reporting multiple segments, therefore, assets not in the company's primary line of business are wrongly classified. As a robustness test, I perform my analysis using only single segment firm data. Results using single segment firm data to calculate merger waves as well as all industry control variables rely on fewer observations (22,400 for the Industry & Suppliers sample and 21,491 for the Industry & Customers sample) and are stronger for the Industry & Suppliers sample. Specifically, the supplier STD_Wave is positive and significant with a p-value of 6.1% for the single segment results versus 14.0% for the general results. The Industry & Customers results remain qualitatively unchanged.

In the Industry & Suppliers sample, some industries appear many times as a significant supplier. For example, the top two suppliers, wholesale trade and real estate, are a significant supplier in 21.4% and 5.9% of industry-matched supplier years, respectively. When observations that include wholesale or real estate as the matched supplier are dropped from the sample the results for the Top20_Wave variable are similar.[34] In the Industry & Customers sample, food

[34] Wholesale and retail trade industries are defined in the BEA tables very generally and include all wholesalers and

service and residential construction are most often named as a significant customer (4.5% and 4.3% of the observations, respectively). When these are removed from the sample results are qualitatively unchanged.[35]

1.5.2 Randomly matched samples test

To ensure it is the merger wave in the supplier (or customer) industry and not just any industry which significantly influences the likelihood an industry merger wave, I construct 1,000 samples where the industry is matched with a random industry as its supplier (or customer).[36] For the Industry & (Random) Supplier sample, the logistic regressions produce a significant coefficient at the 5% level on the randomly-matched supplier wave variable only 62 times for the Top20_Wave measure. This rejects the null hypothesis at the 10% level that a merger wave in any industry is a predictor of a merger wave in another industry. For the Industry & (Random) Customer sample, the logistic regressions produce a significant coefficient at the 5% level on the randomly-matched customer STD_Wave variable 86 times, again providing evidence that a merger wave in any industry is not a predictor of a merger wave in another industry. Further, the average coefficient on the randomly-matched supplier industry is 0.056, which is much lower than the 0.292 coefficient for the Industry & Suppliers sample. Considering that industry merger waves cluster to form economy-wide merger waves, it is expected that a randomly matched sample would sometimes generate significant results. Therefore, these statistics provide assurance that for both samples, it is the supplier or customer merger wave that is associated with

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retailers across many product lines. Therefore I exclude observations where wholesale, retail, or real estate is the top supplier industry and find quantitatively similar results to those where just wholesale and real estate are excluded.

[35] I exclude observations where wholesale, retail, food service or residential construction is the top customer industry and find quantitatively similar results to those where just wholesale and real estate are excluded.

[36] The randomly matched supplier or customer could be the industry's actual supplier or customer.

the likelihood of a subsequent vertically related industry merger wave, not a merger wave in any industry.

1.5.3 Industry relation tests

To ensure that my results are not influenced by the way the industry-supplier and industry-customer relations are formed, I test my results using different percentages and a different BEA table. For general results pertaining to the Industry & Suppliers sample, industries are matched with suppliers providing at least 5.0% of its inputs. When this percentage is reduced to 3.0% the number of observations grows to 46,891 and the supplier Top20_Wave variable continues to be significant with a p-value of 0.3%. The STD_Wave, which is not significant for the general results, is significant at the 10% level in this sample. For the Industry & Customers sample general results are based on customers purchasing at least 3.0% of an industry's outputs. When this percentage is increased to 5.0% the number of observations falls to 14,671 and results are similar to the main results although with slightly larger p-values.[37]

Heretofore, the results are based on industry relations that are drawn using the BEA tables available for 2002. Although the changing industry definitions preclude me from using different BEA tables to draw relations throughout the dataset, I can test if my results are robust to another BEA table. When I use the BEA table from 1992 to develop my industry definitions and merger waves for the Industry & Suppliers sample I find that the STD_Wave definition results are much stronger than they are for the 2002 definitions (coefficient of 0.418 and significant at the 1% level). However, I find no relation between supplier merger waves and industry merger

[37] Results are qualitatively similar for a sample composed of each industry's top five suppliers (customers) where each supplier provides (customer purchases) at least 1% of industry inputs (outputs).

waves for the Top20_Wave definition. The supplier Top20_Wave variable is significant, however, if the supplier cut-off is reduced from the 5% used in the general results to 1%, which has been used in previous research (Shahrur, 2005).

For the Industry & Customers sample, I find the results for the STD_Wave measure are similar to those presented in the main analysis. The Top20_Wave measure results, however, are markedly different. Specifically, the a customer merger wave and subsequent industry merger wave is positive and significantly related (coefficient of 0.527 and p-value of 0.8%). Therefore, the association between supplier (customer) merger waves and subsequent industry merger waves appears to be slightly weaker (stronger) for relations drawn using the 1992 BEA tables.

1.6 CONCLUSION

Using a large sample of all industries experiencing mergers and acquisitions from 1980 through 2008, I find that the existence of a merger wave in a customer industry increases the likelihood of a merger wave in a vertically related industry by as much as 30%, depending on the definition of merger wave. Consistent with the theory of countervailing market power, this association appears strongest in cases where bargaining power motives are present. Additionally, the association is strongest in industries with less product differentiation and in industries not related to consumer goods. Also, the findings are robust to a variety of tests which provide empirical support that it is the special relation between the customer and the vertically related industry that is responsible for the association of merger waves, rather than aggregate economic conditions or common economic shocks. This is consistent with findings by Ahern and Harford (2011) and

Bhattacharyya and Nain (2011) both of which find evidence of customer merger and acquisition activity preceding supplier merger activity.

I also find a positive association between merger waves in supplier industries and subsequent merger waves in the vertically related industry. Further testing suggests this association is not dependent on bargaining power motives, however, it is more likely to exist for industries offering undifferentiated products. This result is not consistent with results by Bhattacharyya and Nain (2011) which finds no association between supplier merger activity and customer merger activity. This research offers additional confirmation for the idea that merger waves travel along the supply chain and adds to the literature exploring how decisions made by managers in a customer or supplier industry affect vertically related industries. In sum, the results provide evidence that a customer or supplier merger wave is a significant shock associated with subsequent merger waves.

Future research may explore more reasons why certain industries, such as low R&D and low advertising industries are able or willing to respond to supplier and customer merger waves with own industry merger waves. Perhaps governance factors, economies of scale or scope, or the importance of bargaining power in these relations make merger activity the preferred response to supplier merger activity. Further, there are other efficient actions managers may take in response to merger waves in related industries that are not tested here. Testing of these responses, such as recapitalizations, asset sales, or joint ventures, is left for future research. Finally, because I employ two separate measures of merger wave in the analysis, this paper demonstrates that conclusions drawn using merger wave data are sensitive to the way a merger wave is measured. Future research may explore how different measures of merger waves may lead to different empirical conclusions.

2.0 ESSAY 2: CHANGES IN CONCENTRATION ACROSS VERTICALLY RELATED INDUSTRIES

2.1 INTRODUCTION

The perception that a change in concentration in one industry will "spill over" into other vertically related industries appears to be widely held in the business press. For instance, a recent Wall Street Journal article notes that "as the retail industry continues a wave of consolidation, apparel manufacturers are poised to accelerate their (own) acquisition activity as a way to increase their negotiating clout with the new retail giants." Along this same line of reasoning, another article states that "the suppliers of the gear used in the world's communications networks are facing a new challenge: the sudden and rapid consolidation of their customers. A wave of acquisition activity among U.S. wireless and traditional fixed-line carriers… is forcing the telecommunications-equipment companies to ponder their futures, including whether to do deals of their own."38 Anecdotes describing similar effects frequently appear in articles reporting on disparate industries suggesting that these effects are perceived as rather widespread.[39]

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[38] Mike Esterl, "Apparel Firms Gird for Possible Merger Wave," The Wall Street Journal, June 16, 2005. Christopher Roads, "Telecom-gear mergers may start to heat up – phone-sector consolidation may challenge survival of some equipment firms," The Wall Street Journal, February 11, 2005.
[39] Also, see for example, Paul Glader, "Deal Would Create No. 1 Steelmaker," The Wall Street Journal, October 26, 2004, which states, "The combination of the Mittals' Ispat International NV and LNM Holdings NV with ISG of

While the potential implications of changes in concentration in one industry being associated with changes in concentration in other vertically related industries are wide-reaching, there is little empirical research examining the validity of this notion. This paper examines the importance of such an association between changes in concentration across vertically related industries over the period 1978-2008. Specifically, we investigate the magnitude, timing, and direction of the association between changes in concentration across vertically related industries with an aim towards providing stylized facts on which future empirical and theoretical work can be based. To the best of our knowledge, no previous paper has examined changes in concentration across vertically related industries in a large sample setting.[40]

To identify industries with significant vertical relationships, we use the benchmark input-output (IO) tables published by the Bureau of Economic Analysis at the U.S. Department of Commerce. For every industry i, we use the IO tables to identify the particular industry, j, (top customer) that purchases the largest percentage of industry i's (supplier) output. We refer to this sample of vertical relationships as the supplier-top customer sample. Similarly, for each industry, i, we use the IO tables to identify the particular industry, k, (top supplier) that provides the largest percentage of the inputs used by industry i (customer). We refer to this sample of vertical relationships as the customer-top supplier sample. Note that the industries referred to as the supplier industries in the supplier-top customer sample are nearly identical to the industries referred to as the customer industries in the customer-top supplier sample. Figure 1 illustrates the sample nomenclature that we use throughout the paper.

Richfield, Ohio, ... if successful and if followed, as expected, by further consolidation, ... could provide the surviving steelmakers with more consistent pricing power over raw-materials suppliers and customers."

[40] For a review of papers examining concentration and changes in concentration, see Curry and George (1983). Our paper is perhaps closest in approach to Lustgarten (1975) which relates the level of seller industry concentration with the level of buyer industry concentration.

We obtain annual measures of industry concentration from the Compustat Business Information File which includes sales revenues for any business segment (4-digit Standard Industrial Classification (SIC) Code) that comprises more than 10% of a firm's consolidated yearly sales.[41] Thus, our measures of industry concentration are at the business segment level (and not the consolidated firm level) which minimizes issues associated with aggregation across unrelated activities and aggregation across vertically integrated activities.

Analysis of the supplier-top customer sample indicates that top customer changes in concentration are positively and significantly related to not only simultaneous but also subsequent changes in the concentration of supplier industries. The observed relation between top customer changes in concentration and changes in supplier concentration persists even after controlling for those factors expected to influence suppliers' own-industry changes in concentration. We demonstrate that the positive association we observe between changes in top customer and supplier concentration is greatly diminished when we randomly match top customer industries with supplier industries. Finally, we demonstrate the relation is robust to a variety of changes in sampling criteria, concentration measures, and regression model specifications.

We find that, on average, decreases in concentration in top customer industries are more strongly related to decreases in concentration in supplier industries than are increases in concentration. However, we also find some evidence that particularly large increases in top customer concentration are related to large simultaneous and subsequent increases in supplier concentration perhaps consistent with the presence of countervailing power effects.

[41] The Compustat segments database, like the Compustat annual consolidated database, contains information for nearly all firms in the U.S. and Canada with public securities (debt or equity) outstanding as well as international firms with American Depository Receipts traded in the U.S.

Results from the customer-top supplier sample indicate that changes in top supplier concentration are not strongly related to simultaneous and subsequent changes in customer concentration. The differing results across our two samples are consistent with the association between changes in concentration across vertically related industries being stronger in the upstream direction than the downstream direction. This finding is consistent with several recent papers examining the effects of major corporate events on firms' customers and suppliers which generally find evidence that suppliers but not customers are significantly affected by these events, e.g., financial distress (Hertzel, Li, Officer, and Rodgers (2008)), horizontal mergers (Fee and Thomas (2004), Shahrur (2005), and Bhattacharya and Nain (2011)), and leveraged buyouts (Brown, Fee, and Thomas (2009)).

This paper proceeds as follows. In section 2, we describe several empirical predictions from economic theory regarding an association between changes in concentration across adjacent industries and the implications of such predictions for our empirical approach. In section 3, we provide details of our sample construction and our methodology to identify vertically related industries. In section 4, we present results for a sample of supplier and top customer relationship years. In section 5, we present results for a sample of customer and top supplier relationship years. In section 6, we summarize our findings and provide some concluding remarks.

2.2 PREDICTIONS FROM THEORY AND IMPLICATIONS FOR EMPIRICAL RESEARCH

Industrial organization theory has long considered the potential for changes in concentration in one industry to be associated with changes in concentration in vertically related industries, i.e., customer and supplier industries. Perhaps the most well-known and controversial conjecture that predicts such a relation is the so-called theory of countervailing power first articulated in Galbraith (1952). Galbraith contends that if an industry undertakes consolidation to increase its degree of monopolistic or monopsonistic power, then those industries to which it sells or from which it buys will defend against or countervail this power by also undertaking consolidation.[42] Stigler (1954) maintains that this notion translates approximately into the hypothesis that market power begets market power. Thus, the countervailing power theory predicts that we should observe a positive association between changes in industry concentration and changes in customer and/or supplier industry concentration.[43]

It should be noted that we might expect to observe a positive relation between changes in industry concentration and changes in customer and/or supplier industry concentration even absent "countervailing" horizontal mergers and acquisitions in the customer and supplier industries, e.g., see Bhattacharya and Nain (2011) and Ahern and Harford (2010). For instance, Snyder (1996) demonstrates that, in an infinitely repeated procurement auction setting, firms undertaking horizontal mergers are able to use their newly combined purchasing power to induce their respective suppliers to compete on price in a winner-take-all tournament to determine who will be selected to sell to the merged firm. Fee and Thomas (2004) document that supplier firms which win these tournaments subsequently experience significant gains in market share relative to those firms that lose. Thus, under the supplier tournament scenario, we would observe an

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[42] See Stigler (1954) and Hunter (1958) for criticisms of the theory of countervailing power. For more recent theoretical treatment of countervailing power, see for example Horn and Wolinsky (1988), Stole and Zwiebel (1996), Snyder (1996), Chipty and Snyder (1999), Inderst and Wey (2003), and Chen (2003).

[43] It is important to point out that the emergence of large customers may be followed by the emergence of large suppliers and vice versa for reasons unrelated to market power, e.g., see Coase (1937). For instance, it may simply be most efficient in terms of distribution costs for large customers to be served by large suppliers, e.g., bilateral oligopoly is the market structure that minimizes transactions costs regardless of how the cost savings are divided up among market participants. For instance, see "P&G's Gillette Edge: The Playbook it Honed at Wal-Mart," The Wall Street Journal, January 31, 2005.

increase in concentration for the merging firms' industry and a change in concentration in the supplier firms' industry as the market shares of the winning and losing supplier firms change to reflect the tournament outcome. Assuming that more efficient suppliers have larger market shares and more frequently win these tournaments than less efficient suppliers, then we will observe an overall increase in supplier industry concentration as measured by a Herfindahl-Hirschman Index (HHI).[44]

While the countervailing power literature examines industry consolidation, formal theories of how decreases in concentration in a particular industry might be associated with decreases in concentration in vertically related industries are not as well developed. However, there are some seemingly plausible conjectures that one could make. For instance, it is often hypothesized that larger firms in fast growing industries will find it difficult to take advantage of all of the available opportunities for expansion. Thus, opportunities for smaller firms will be greater resulting in increased relative market shares for smaller firms and decreased industry concentration, e.g., see Mueller and Hamm (1975) and Caves and Porter (1977). If the presence of recent entrants or rapid growth in market shares for smaller firms in an industry is indicative of increased demand for an industry's product, then this might also indicate that supplying the inputs for producing such a product has also become more attractive prompting entry or rapid growth in market share for smaller firms in the supplier industry as well.[45] Technological innovation in an industry is also hypothesized to result in decreases in concentration stemming

[44] There are scenarios where supplier industry HHI could fall as well. However, assuming that the more efficient suppliers have larger market shares and more frequently win these tournaments than less efficient suppliers, the result would generally be an increase in HHI in the supplier industry as HHI satisfies the principle of transfers condition for measures of concentration.

[45] For ease of exposition, we often refer to increases in concentration as consolidation and decreases in concentration as entry. Clearly, these changes could be entirely due to changes in the market shares of a constant set of competitors, e.g., see Davies and Geroski (1997). We provide some evidence below on how frequently increases in concentration are accompanied by a decrease in the number of competitors (consolidation) and how frequently decreases in concentration are accompanied by an increase in the number of competitors (entry).

from cost savings or reductions in minimum efficient scale, e.g., see Demsetz (1973) and Geroski and Pomroy (1990). To the extent that related industries overlap in certain technologies, innovation could lead to corresponding decreases in concentration across adjacent industries. Deregulation of an industry is often associated with significant subsequent entry, e.g., see Whinston and Collins (1992) or Zingales (1998). To the extent that deregulation or simply an erosion of non-regulatory barriers to entry prompts decreases in concentration in one industry, then we might also observe decreases in concentration in adjacent industries.

Note that, in general, a positive association would be expected if the changes in concentration are due to either a common shock affecting vertically related industries or to a shock specific to one industry that prompts a change in concentration which then prompts reactionary changes in vertically related industries, i.e., spillover effects.[46] If we observe no significant association between changes in concentration across industries, then this suggests that changes in one industry occur largely independently of changes in concentration in vertically related industries. Observing an insignificant association could also be due to low power in the tests due to noise introduced either by the inability to identify industries that share a significant trading relationship or a lack of timely measures of changes in industry concentration at a sufficient level of disaggregation. Finally, it would be possible to observe a negative association; however, while observing such an association might be somewhat difficult to interpret under existing economic theory, it would prompt further work investigating such an association.

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[46] We consider a common shock any economic, technological, or deregulatory event that directly affects both industries who share a trading relationship, e.g., the passage of the North American Free Trade Agreement or a labor strike by the United Auto Workers Union members that affects the motor vehicle manufacturing industry and the automotive stamping industry. We consider a spillover effect as a situation in which an economic, technological, or deregulatory event directly affects one party to a trading relationship but not the other. Thus, any effect of the event on the industry not directly affected is a spillover effect, e.g., deregulation of the commercial banking industry results in consolidation and greater bargaining power that prompts consolidation by the blankbook and looseleaf binder industry to countervail customers' gains in bargaining power.

Given that none of the potential explanations for a significant relation between changes in concentration across adjacent industries predicts a particular timeframe in which the respective changes in concentration should occur, our approach will be to report results for several time windows intended to capture a relation, i.e., simultaneous and subsequent time windows, e.g., see Caves and Porter (1980).

While the primary purpose of our analysis is to determine if changes in concentration are correlated across vertically related industries, we also make initial efforts at determining which of the possible channels for this association might be in play. For instance, we investigate the relation between increases in concentration vs. decreases in concentration. Given the countervailing power theory suggests significant consolidation in one industry should be followed by significant consolidation in another, we run logistic regressions where the variables of interest take a value of one for large positive changes in concentration and zero otherwise. Finally, by contrasting the results across our two samples, we may be able to determine if there are asymmetric reactions to changes in concentration depending on whether the initial change in concentration originates with top customers or top suppliers. In other words, we can determine whether the association between changes in concentration is stronger primarily upstream, primarily downstream, or in both directions along the supply chain.

2.3 SAMPLE CONSTRUCTION AND DESCRIPTION

2.3.1 Identifying vertical relationships

We use the benchmark input-output tables published in 1992 by the Bureau of Economic Analysis (BEA) at the U.S. Department of Commerce to identify industries with significant vertical relationships.[47] The IO tables consist of a make and a use table. The make table is an industry by commodity matrix which gives the value in producer's prices of each commodity produced by each industry. The use table is a commodity by industry matrix which gives the value of each commodity that is used as an input by each industry. The make and use tables can be combined to construct an industry by industry matrix which details how much of each industry's output is purchased by other industries and also how much of an industry's inputs are provided by other industries.

For every industry i, we use this industry by industry matrix to identify the particular industry, j, (top customer) that purchases the largest percentage of industry i's (supplier) output. We refer to this sample of vertical relationships as the supplier-top customer sample. Similarly, for each industry, i, we use the matrix to identify the particular industry, k, (top supplier) that provides the largest percentage of the inputs used by industry i (customer). We refer to this

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[47] Lawson (1997) provides a detailed description of the BEA input-output tables. The BEA reports benchmark (detailed) make and use tables every five years. We chose the 1992 tables because 1992 represents the midpoint of our sample period. As a check on the potential for this choice to influence our results, we calculated the correlation between relationships identified using the 1992 table and those identified using tables from earlier editions of the BEA reports. Relationships identified using the 1992 tables are highly correlated with the relationships identified in prior tables perhaps owing to the stability of vertical relationships between industries in general. Since we use leading and lagged data in the tests below, it is difficult to allow identified relationships to vary over intervals within the sample period corresponding to different editions of the BEA reports, hence, we are in effect assuming that relationships identified using the 1992 table were present prior to that year and persist after that year. To the extent that we misidentify parties to vertical relationships, we largely bias against finding evidence of relation between changes in concentration across industries as the power of our tests will be reduced.

sample of vertical relationships as the customer-top supplier sample.[48] Note that the industries referred to as the supplier industries in the supplier-top customer sample are nearly identical to the industries referred to as the customer industries in the customer-top supplier sample. Figure 1 describes the nomenclature that we use for the respective samples. See Appendix A Identifying vertically related industries for further details of how the make and use tables are utilized to identify vertical relationships.

2.3.2 Supplier-top customer sample relationships

Table 12 reports information regarding the supplier-top customer sample relationships. While there are 419 relationships included in this sample, we list in panel A the ten relationships where the identified top customers purchase the largest percentage of supplier output to provide a sense of the relationships in the sample.[49] In panel B, we provide summary statistics on the percentage of supplier output that is purchased by its top customer. The average (median) percentage of a supplier's output purchased by the identified top-customer industry is 19.9% (12.5%). Thus, our sample construction procedure seems successful in identifying industries with significant trading relationships.

While we only match each supplier with its top customer in our sample, we are able to observe other customer industries that purchase less supplier output than the top customer. To

[48] When the top customer or top supplier is identified as an industry for which we can obtain no Compustat data (i.e. personal consumption expenditures or government), we then use the industry with the next most significant trading relationship as the top customer until an industry with Compustat data available is reached.
[49] In order to gauge domestic supply, some final use accounts, including but not limited to inventory, fixed capital, scrap and imports, may be negative. As a result, there are two cases where it appears that one industry is consuming more than 100% of another industry's output. In these cases, we winsorize the percent bought by the top customer and the percent bought by the top four customers at 100%.

gauge the relative concentration of the output market for supplier goods, we also report in panel B the percentage of supplier output purchased by its top four customer industries. The average (median) percentage of a supplier's output purchased by its top four customer industries is 34.6% (27.4%). Thus, on average, the top customer industry accounts for more of the suppliers' sales volume than the next three largest customer industries combined. Note that each supplier has only one top customer, although the same top customer may be matched to multiple supplier industries. Panel C shows the ten industries that are most frequently identified as the top customer industries.

2.3.3 Customer-top supplier sample relationships

Table 13 reports information regarding the customer-top supplier sample relationships. There are 421 relationships included in this sample and we list in panel A the ten relationships where the top suppliers supply the largest percentage of customer inputs. In panel B, we provide summary statistics on the percentage of customer inputs that are supplied by the top supplier. The average (median) percentage of a customer's inputs supplied by the identified top-supplier industry is 12.4% (8.6%). We also report in panel B the percentage of customer inputs purchased from its top four supplier industries. The average (median) percentage of customer inputs supplied by its top four supplier industries is 25.8% (22.4%). Panel C shows the ten industries that are most frequently identified as the top suppliers of other industries.

2.3.4 Comparison of supplier-top customer and customer-top supplier samples

We conduct the same empirical analysis on both of our samples. However, Table 12 and Table 13 do reveal several differences in the samples that might be expected to impact what we observe in the respective results. For instance, suppliers are, on average, more dependent on their top customers for sales revenues than customers are dependent on their top suppliers for inputs. As an example, the commercial fishing industry sells 68% of its output to the prepared seafood industry, its top customer, whereas the prepared seafood industry purchases 38% of its inputs from commercial fishing, its top supplier.[50] Given that prepared seafood purchases some of its inputs from other industries, e.g., fish hatcheries and aquaculture, it could be argued that changes in the prepared seafood industry will affect commercial fishing more so than changes in commercial fishing will affect prepared seafood.

It might also be expected that suppliers are more affected by their top customers' actions even absent their customers' ability to potentially substitute among inputs as in the prepared seafood industry. Moving downstream along the supply chain towards the products bought by ultimate consumers is generally associated with value added at each step. Thus, customer firms are often purchasing inputs from more supplier industries at each step potentially rendering the customer firms less dependent on any particular supplier industry.[51]

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[50] Fifty-seven of the identified relationship pairs are common to both samples.

[51] This reasoning is consistent with the accounting rules regarding the required disclosures by firms regarding their customers and suppliers. Firms are required to report certain information about any individual customer that accounts for more than 10% of sales revenues. Presumably the basis for this disclosure is so that investors can assess the possible revenue consequences of losing a large customer. However, firms are not required to report any information regarding the identity and amount purchased from their suppliers perhaps consistent with the accounting standards bodies viewing information about a firm's customers as more value-relevant for investors than information about a firm's suppliers. From 1978 to 1998, customer disclosure rules were defined in FASB 14. From 1998-present, customer disclosure rules are defined in SFAS 131.

Table 12 and Table 13 also reveal that for 22.5% of customer-top supplier relationship years, the "wholesale trade" industry is identified as the top supplier, as opposed to 7.8% of relationship years in the supplier-top customer sample where "wholesale trade" is the top customer. Unfortunately, the IO tables classify wholesale trade at a high level of aggregation. Specifically, wholesale trade includes SIC codes 5000-5199 which essentially encompass the wholesaling activities of most individual industries. In effect, changes in concentration for a specific wholesale trade activity are largely unobservable since they are lumped in with the changes in every other wholesaling activity. Thus, a difference in results across the two samples might stem from the relative inability of the customer-top supplier sample to identify top suppliers at a reasonable level of specificity which reduces variation in changes in concentration and biases against finding a relation.[52]

Clearly, there are valid counterarguments to the reasoning above. However, for the reasons outlined, as well as for ease of exposition, we report results for the supplier-top customer sample first and in full, and we report results for the customer-top supplier sample second and in abbreviated form. We discuss where and why the results differ across the two samples in Section 5 when we describe results for the customer-top supplier sample.

2.3.5 Measures of concentration

We obtain annual measures of industry concentration from the Compustat database which reports financial information for nearly all firms in the U.S. with public securities (debt or equity) outstanding. Specifically, we use the Compustat Business Information File which includes sales

[52] The classification of "retail trade, except eating and drinking" is subject to a similar issue in that it includes SIC codes 5200-5799 and 5900-5999.

revenues for any business segment (4-digit Standard Industrial Classification (SIC) Code) that comprised more than 10% of a firm's consolidated yearly sales.[53] Thus, our measures of industry concentration are calculated at the business segment level rather than the consolidated firm level. This approach allows us to develop measures of industry concentration that are more representative than if we were to assign the consolidated sales of firms with multiple unrelated segments or multiple vertically-related segments to one SIC code.[54] There are a total of 237,435 segment years used to calculate concentration measures in our sample or approximately 7,770 distinct segments per year on average.

Since the IO tables classify industries by IO codes and Compustat classifies segments by SIC codes, we use the SIC-IO code conversion tables published by Fan and Lang (2000) to

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[53] The Compustat segments database, like the Compustat annual consolidated database, contains information for nearly all firms in the U.S. and Canada with public securities (debt or equity) outstanding as well as international firms with American Depository Receipts traded in the U.S. Regulated utilities (SIC 4900-4999) and financial institutions (SIC 6000-6999) are not regularly included in the segment data since firms in these industries generally do not report segment level data. To ensure consistency, any reported segments with the SIC codes listed above are dropped from the sample as are segments of firms incorporated outside of the U.S. The segments database is also susceptible to occasional instances of double counting of segments. These instances arise when Compustat records historic segment data for newly-formed public companies that were previously segments of other public firms, i.e., spin-offs or carve-outs. Compustat may also assign multiple permanent identifiers (gvkeys) to one company if the company has multiple classes of securities outstanding. Thus, we investigate all instances where segments report the same exact sales revenues and SIC code for a given year and remove observations that are duplicates. There are a total of 2,390 duplicate observations removed from the dataset.

[54] Using Compustat segment data as the source of our measures of industry concentration offers several advantages and disadvantages relative to alternatives such as the Census of Manufacturers publications produced by the Center for Economic Studies at the Bureau of the Census, e.g., see Davis and Duhaime (1992) and Ali, Klasa, and Yeung (2009). The Census surveys establishments only every five years which makes measuring changes in industry concentration over shorter periods impossible. The Census publications only include data on manufacturing firms whereas Compustat is much more comprehensive in its industry coverage. The Census publications do however include private firms, although concentration ratios are only available for the largest 50 companies in an industry or all firms in the industry if less than 50. Compustat offers no such limitation on the number of segments in an industry. Compustat, strictly speaking, does not include private firms. However, as we note elsewhere, Compustat backfills data for private firms that complete IPOs and leveraged buyout (LBO) targets often continue to report financial data as a result of having public debt outstanding. Given that (at least within the manufacturing sector) the biggest difference between Compustat and Census data are the inclusion of private firms, we also examine results using four-firm concentration ratios since these ratios are likely to be the least affected by excluding private firms given the strong tendency for the largest firms in an industry to have accessed public capital. While the Business Information Tracking Series (BITS) data might appear to be a viable alternative to the Census of Manufacturers, BITS does not report sales data by establishment and must be merged with Compustat to obtain sales figures. Further, BITS only becomes available in 1989, see Villalonga (2004). Trinet establishment data were also considered, e.g., see Liebskind, Opler, and Hatfield (1996); however, this data series ends in 1989.

assign each segment from the Compustat dataset an IO code. Once each segment has an assigned IO code, we combine data within each IO-code year to generate industry data. The IO code classification system generates industries that are slightly more general than four-digit SIC codes but importantly does not include both producers and consumers in the same code.[55]

As our primary measure of concentration we use the annual Herfindahl-Hirschman Index (HHI). HHI is calculated as the sum of the squares of each segment's sales as a proportion of the industry's total sales. Thus, for industry i in year t, HHI is measured as

$$HHI_{it} = \sum_{j=1}^{N_{it}} \left(\left(SALES_{jit} \Big/ \sum_{j=1}^{N_{it}} SALES_{jit} \right) * 100 \right)^2$$

where N_{it} is the number of segments in industry i at time t and $Sales_{jit}$ are the net sales attributable to segment j of industry i at time t. Changes in HHI are calculated as the ratio of HHI at one point in time over HHI at another point in time, minus one, e.g., the one year ahead change in HHI is calculated as $(HHI_{t=+1}/HHI_{t=0})$-1. HHI is increasing in the concentration level of an industry and positive changes in HHI over time indicate an industry is becoming increasingly concentrated whereas negative changes in HHI over time indicate that an industry is becoming less concentrated. In robustness tests, we also use four-firm concentration ratios calculated as the fraction of total industry sales accounted for the by the four firms with the largest sales.

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[55] While every SIC code has an IO code, not all IO codes are matched by Fan and Lang (2000) with an SIC code. For the supplier- top customer sample, if a supplier industry has no associated SIC code, then that relationship is dropped. Likewise for the customer- top supplier sample, if a customer industry has no assigned SIC code, then that relationship is also dropped. However, for relationships where an identified top customer or top supplier IO code is not matched with an SIC code, we use the industry with the next most significant trading relationship as the top customer or top supplier provided that it also has an IO-SIC code correspondence in Fan and Lang. Results for subsequent time windows when these "secondary" relationship pairs are excluded are very similar to those reported. However, results for simultaneous time windows are weaker.

2.4 RESULTS FOR SUPPLIER-TOP CUSTOMER SAMPLE

2.4.1 Summary statistics

Table 14 reports descriptive statistics for concentration and changes in concentration within the supplier-top customer sample. The average supplier industry year is populated with 19.6 distinct segments and has a mean (median) HHI of 4,583.8 (3,848.9). Consistent with the findings of most prior studies of changes in concentration, the supplier industries in our sample experienced an average increase in concentration over each of the windows reported. For instance, the average annual percentage change in supplier industry HHI is an increase of 4.3% across all relationship years. Changes in concentration over longer time windows are increasing in the number of years that elapse. The average annual change in the number of segments in a supplier industry when the one-year change in HHI is positive (negative) is a decrease (increase) of 1.1 (0.7) segments, i.e., approximately an exit of one segment (entry of seven tenths of a segment).[56]

The average top customer industry year is populated with 100.5 distinct segments and has a mean (median) HHI of 2,231.2 (1,230.2). Thus, identified top customer industries tend to have more participants than the supplier industries and, consequently, top customer industries are less concentrated as well. The average top customer industry experienced an increase in concentration over each of the windows reported. For instance, the average annual percentage change in top customer industry HHI is an increase of 3.2% across all relationship years. The average annual change in the number of segments in a top customer industry when the one-year change in HHI is positive (negative) is a decrease (increase) of 3.4 (0.5) segments, i.e., an exit of

[56] For evidence on patterns of entry and exit in the U.S., see, e.g., Dunne, Roberts, and Samuelson (1988).

over three segments (entry of one half of a segment). Aggregate sales (in 2008 dollars) of top customer industries are larger than aggregate sales of supplier industries; however, there are generally more segments in the customer industries relative to the supplier industries.

Given that there is no a priori guide to the precise timing of changes in concentration across industries, we will report abbreviated results for a number of different time windows, e.g., see Caves and Porter (1980). However, we initially report full results of a multivariate regression explaining changes in supplier concentration over the period from t=0 to t=+3, which we use as a candidate regression. Table 15 reports summary statistics for the independent variables that will be included in the candidate regression. To be included in this particular specification, the relationship pairs must have change in HHI data available for the period t=0 to t=+3 for the suppliers and for the period t=-3 to t=0 for the top customers.

Panel A reports summary statistics for factors specific to the individual supplier industries. We calculate the growth rate of inflation adjusted total industry sales from t=-2 to t=0. We construct a deregulation dummy variable that is set equal to one if the supplier industry experienced deregulation from t=-1 to t=0. Most of the data on deregulation events are obtained from Economic Reports to the President.[57] Import market share is the customs value (in dollars) of products imported into the US with the same IO code as the supplier industry divided by the supplier industry's total sales at t=0. If import data are missing from the NBER-CES Manufacturing Industry Database for a particular industry, then this variable is set to zero.[58] Missing imports flag is a dummy variable equal to one if the import data are missing for a particular industry. Median industry advertising to sales is the industry median advertising to

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[57] Specifically, sources include the Economic Report to the President for years 1989, 1995, 1999, 2001, 2003, and 2005, www.consumerreports.org, www.naturalgas.org and Viscusi, Vernon, and Harrington (1995).
[58] See Feenstra, Romalis, and Schott (2002) for details.

sales ratio at t=0. The median is calculated using data from all single segment firms in each industry since advertising expenditures are not reported at the segment level. If there are no single segment firms, then we use data from all two-segment firms operating in the industry.

The first principal component is the first principal component of the absolute value of the two year change (from t=-2 to t=0) of the following supplier industry ratios: asset turnover (total sales/assets), earning power (operating income/assets), profit margin (operating income/sales), and capital expenditures (capital expenditures/assets). The statistic is calculated as the median value for all the segments in the industry. We include the first principal component in the regression rather than the individual ratios since including all of the ratios in the regression would lead to problems with multicollinearity. The first principal component is set equal to zero if data required to calculate it are missing. The missing principal component flag is a dummy variable that takes a value of one if the first principal component is missing and zero otherwise.

Panel B reports summary statistics for the macroeconomic variables. Harford (2005) finds that the timing of merger waves, i.e., significant increases in concentration within an industry, is associated with not only economic shocks to that industry but also the availability of financing to undertake transactions. Thus, we include in our regressions the commercial and industrial loan rate spread above the intended Federal funds rate as of December t=0. Data to calculate spread are obtained from the survey of terms of business lending published quarterly by the Federal Reserve.[59] Prior research has found that both entry (decreased concentration) and merger (increased concentration) activity follow increases in stock prices. Thus, we include the

[59] The intended Federal funds rate is available from 1986 to the present. Before 1986 we use the actual Federal funds rate to estimate the intended rate. The commercial and industrial loan rate spread is available quarterly from 1977 to the present.

S&P 500 2-year return which is the 2-year compounded annual return on the S&P 500 for the period ending at t=0. S&P 500 levels are obtained from finance.yahoo.com.

2.4.2 Multivariate regressions explaining changes in supplier concentration

Table 16 reports the results of a multivariate regression explaining changes in supplier concentration over the period from t=0 to t=+3. Consistent with Petersen (2008), we cluster standard errors by supplier industry code.[60] Changes in supplier concentration are positively and significantly associated with lagged changes in top customer concentration. We include supplier industry HHI at t=0 as an explanatory variable to control for the initial level of concentration in the industry as well as perhaps to correct for the boundedness in changes in concentration. Initial HHI enters the regression with a small but highly significant negative coefficient suggesting that industries with higher initial levels of concentration are less likely to experience a further increase in concentration and are more likely to experience a decrease in concentration, e.g., see Curry and George (1983). Higher sales revenues (greater market size) are associated with subsequent reductions in supplier industry concentration. We also include the growth rate of inflation adjusted supplier industry sales from t=-2 to t=0. If in faster growing industries large established firms find it more difficult to take advantage of all the opportunities for expansion, then opportunities for small firms will be greater, resulting in a reduction in concentration.

[60] Our reasons are twofold. First, for the regression specifications that measure supplier concentration changes over a period greater than one year, there is some overlap from observation to observation, i.e., the change from t=0 to t=+3 in one relationship year is measured over two-thirds of the same years as the change from t=0 to t=+3 in the subsequent relationship year. Note that in specifications where the dependent variable is measured over a one year window, the overlap in adjacent observations is not an issue. Our reported results are very similar when we cluster standard errors by both year and IO code. Further, our results are similar, but more significant, when we do not cluster standard errors and only correct for heteroskedasticity. Second, unidentified factors that affect each industry similarly may exist. For these two reasons observations may not be entirely independent. Thus, clustering standard errors by industry represents a conservative approach to evaluating statistical significance relative to not clustering standard errors by industry.

However, the coefficient on sales growth is positive although very small and not significantly different from zero.

The deregulation dummy enters the regression with a negative but insignificant coefficient. The imports market share variable is positive and significant consistent with industries which face greater competition from imports increasing concentration. The dummy variable for missing imports data enters the regression with a negative and significant coefficient. Given that imports data from the Census is generally missing for non-manufacturing industries, the negative coefficient on this variable can be interpreted as indicating that changes in concentration are more generally negative for industries that are not part of the broad manufacturing classification, e.g., service industries.

Product differentiation created via advertising could act as a barrier to entry, e.g., see Mueller and Rogers (1980) and Sutton (1991). Thus, we include supplier-industry median advertising to sales; however, advertising expenditures enter the regression with a negative and marginally significant coefficient. The principal component variable is positive and significant consistent with industry shocks leading to increases in concentration as in Harford (2005).[61]

The coefficient on the spread variable is negative and significant suggesting that higher spreads are associated with smaller increases in concentration. This result is consistent with Harford (2005) in that higher spreads indicate less financing is available on favorable terms to fund acquisitions and observed changes in concentration are smaller given fewer firms undertaking horizontal acquisitions. The coefficient on the 2-year return on the S&P 500 is positive but not significant at conventional levels in this specification. The positive coefficient is

[61] In addition to the four ratios that we use to extract the first principal component variable, Harford (2005) also includes the changes in employees and research and development expense; however, these additional measures are not required disclosures for business segments.

consistent with recent positive stock returns being associated with greater future merger activity and an increase in industry concentration.

In sum, at least for the particular time windows examined in Table 16, a significantly positive relation between changes in top customer concentration and subsequent changes in supplier concentration is apparent even when including other variables expected to explain changes in supplier industry concentration. The R-squared reported in Table 16 is not large, as is generally the case for studies of changes in concentration. However, we note that the windows over which we are examining changes in concentration are considerably shorter than those in previous studies, e.g., Mueller and Hamm (1974), Wright (1978), and Pryor (1994).

Table 17 presents the results of 15 multivariate regressions where the dependent variable is the change in supplier industry HHI over the indicated time window and the independent variable of interest is the change in top customer industry HHI over the indicated time window. The coefficients on the change in top customer industry HHI variables are reported along with their p-values in brackets and the number of relationship years included in the particular regression specification in italics. Additional control variables as identified in Table 16 are also included in each specification but results for these additional variables are not reported to conserve space. The top nine cells of the table correspond to regressions of top customer changes in concentration on subsequent changes in supplier concentration. In six out the nine specifications, changes in supplier concentration are positively and significantly associated with lagged changes in top customer concentration. The bottom three rows of the table correspond to regressions of simultaneous changes in top customer concentration on changes in supplier concentration. In four out the six specifications, the change in top customer concentration is significantly positively associated with a simultaneous change in supplier concentration. Thus, the results indicate that changes in the level of concentration of supplier industries generally occur both subsequent to and simultaneous with changes in concentration in top customer industries.

2.4.3 Robustness tests and additional results

We also conducted our analysis when changes in concentration were measured as raw changes in HHI over each time period as well as the natural logarithm of the ratio of beginning and ending HHI. The multivariate results using raw changes and log changes are very similar to those reported for percentage changes. We also repeated our analysis using four-firm concentration ratios. Results using changes in four-firm concentration ratios are similar to those reported. Given that the largest four firms in an industry are relatively more likely to all have public securities outstanding, results for this measure are less sensitive to the exclusion of private firms by Compustat than are HHIs, e.g., see Ali et al. (2009). In sum, our reported results for suppliers and top customers are not particularly sensitive to the definition or functional form of our measures of changes in concentration.

Our industry concentration measures are obtained from Compustat and Compustat has increased its coverage over the time period of our sample. Thus, if Compustat is adding firms across all industries which reduces our HHI measures, we might expect to observe a positive correlation between supplier and top customer changes in concentration. Note that the summary statistics in Table 14 suggest that the average supplier and top customer industries in Compustat experienced increased concentration which is inconsistent with expanded coverage perhaps accounting for the positive relation that we observe in Table 17. However, we investigate in

Table 18 whether any secular trends in Compustat might account for, at least in part, the observed positive relation between supplier and top customer changes in concentration.

Table 18 presents the results of multivariate regressions where the dependent variable is the change in supplier industry HHI over the indicated time period and the independent variable of interest is the change in top customer industry HHI over the indicated time period. The change in top customer HHI is for a *randomly* assigned industry which cannot be the top customer industry identified from the benchmark IO tables. For each time period considered, we construct 1,000 samples where the customer industries are assigned randomly (with replacement) to the supplier industries. The reported coefficients are the average coefficients obtained from the 1,000 regressions run on these samples. The frequency with which the coefficient on the change in random top customer HHI is significant at the 5% level in the 1,000 individual regressions is reported in the second row. We also test whether the frequency of significant coefficients on the random top customer change in HHI is significantly greater than 0.050 at the 5% level using a one-sided binomial test. Additional control variables as identified in Table 16 are also included in each specification but results for these additional variables are not reported to conserve space.

The coefficients on the randomly assigned top customer change in HHI are uniformly positive and in 11 cases significantly more than 50 of the individual coefficients from each 1,000 regressions were significant at the 5% level. However, most important for our purposes is that the magnitude of the coefficients in Table 18 are generally between 3.3 and 8.8 times smaller than the significant coefficients reported in Table 17 where suppliers were matched with their actual top customers. Thus, there is little evidence that the positive relation in Table 17 is due primarily to secular trends in changes in concentration among industries in Compustat.

Segments generally have to be part of a firm with publicly traded securities and represent at least 10% of total firm sales to be reported by the firm and included in Compustat. Therefore, going private transactions, reverse leveraged buyouts, initial public offerings, acquisitions of private firms or their assets by public acquirers, or growth in a distinct business line to greater than 10% of the consolidated sales of a firm will affect our measures of industry concentration.[62] We therefore used data from Thomson Financial's New Issues and Mergers and Acquisitions databases to determine if any firms in an industry were involved in a going private transaction, initial public offering, or an acquisition of a private target for each year of our sample. We constructed dummy variables that take a value of one if any firm in the industry was involved in an IPO, going private transaction, or an acquisition of a private target, respectively in year t=0 and included these dummies in the multivariate regressions of Table 17. The coefficients on the IPO and acquisition of private target variables each enter the regressions with significant negative coefficients while the going private variable is generally, but not always, negative and significant. Again, the coefficients on changes in customer concentration when these variables where included are very similar to those reported in Table 17.

As a more general check on how our results are affected by firms with significant market shares either entering or exiting (for whatever reason) the industries in our sample, we repeated the analysis of Table 17 and included, respectively, dummy variables indicating whether a firm with market share greater than 15% or 25% or simply the firm with the largest market share either enters or exits the supplier industry in the time window examined. The coefficients on the

[62] Note that entry in our data does not require an IPO; entry only requires that an operating segment grow to represent 10% of consolidated revenue for a firm with public debt or equity outstanding. Backfilling of data by Compustat often results in several years of financial data for firms prior to issuing securities to the public so that changes in our measures of industry concentration are better indicators of entry than they might first appear. For instance, Google Inc. conducted its equity IPO on August 19th, 2004 and Compustat has financial data for Google starting in fiscal year 2002. See Liebeskind, Opler, and Hatfield (1996) for evidence regarding concentration levels and corporate restructuring activity.

dummies indicating the exit (entry) of a firm with significant market share are uniformly positive (negative) and highly significant. The coefficients on changes in customer concentration when these variables where included are in all cases very similar to or of greater significance than those reported in Table 17. In short, this is strong evidence that our results are not driven merely by changes in our concentration measures resulting from changes in firms' public/private status or Compustat-assigned SIC codes.

To further assess the robustness of our results, we rerun our tests on various subsamples of the data. Specifically, to investigate whether the change in segment reporting standards in 1998 affects our results, we rerun our tests on the sample for years 1978 through 1998 and find significant results in four of the subsequent time windows. Given that this period largely predates the growth in internet firms, it appears that our results are not driven by either changes in segment reporting or the internet entry wave of the late 1990s. We also split the sample into two subperiods at roughly the midpoint, i.e., 1978 through 1992 and 1993 through 2008. Results for the 1978 to 1992 subperiod are significant in simultaneous windows only and results for the 1993 to 2008 are largely insignificant.

We also rerun our tests on the subsamples where top customers purchase at least 1%, 5%, or 10% of supplier output. Results for the 1% and 5% subsamples are similar to those reported and stronger in the subsequent windows than reported. Statistically significant coefficients for the subsample where the top customers purchase at least 10% of supplier output are found only in the subsequent windows and the significance is slightly lower. However, the number of observations drops considerably with this screen in place.[63] We also rerun our tests on the

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[63] As mentioned earlier, if the BEA make and use tables identify an industry's top customer as something other than an industry (i.e. the government, or personal consumption) we use the industry with the highest purchases from the supplier industry as the top customer. Although this practice may bias us against finding results, we run our tests on

subsamples of relationships where the supplier and top customer industries each had a minimum of four segments. Given there may be antitrust restrictions that limit changes in concentration in industries with few competitors, this screen should result in a sample where an increase in concentration is perhaps feasible. The results are similar but slightly weaker than those reported.

2.4.4 Changes in supplier concentration when top customer industries consolidate

As discussed in Section 2, the positive relation between changes in supplier and top customer concentration could reflect consolidation in one industry being associated with consolidation in another and/or decreased concentration in one industry being associated with decreased concentration in another. To better assess the source of the positive relation, we augment the multivariate specifications of Table 17 with a term interacting the change in top customer HHI with a dummy variable that is equal to one if the change in top customer HHI is positive. This piecewise linear specification allows us to contrast the relation between supplier and top customer changes in concentration when the change in customer concentration is negative (decreased concentration) vs. positive (increased concentration). Table 19 reports, for the indicated time windows, the coefficient on the change in top customer HHI in the top row and the coefficient on the interaction term in the second row. The third row presents the p-value, in brackets, from an *F* test of the null hypothesis that the sum of the coefficients on the change in top customer HHI and the interaction term is zero. In other words, we test whether the slope of

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a subsample of the data where suppliers are excluded if the actual top customer is not an industry. The results are similar to those reported in the subsequent time windows. There is no significant relationship found in the simultaneous time windows.

the relation between changes in top customer and supplier concentration is different from zero over the range where changes in top customer concentration are positive.

In general, the coefficients on changes in top customer HHI are positive and most often significant for those windows where supplier changes in concentration are subsequent to top customer changes. Hence, there is generally a significant positive relation between decreases in customer concentration and subsequent decreases in supplier concentration. The coefficients on the interaction term are uniformly negative and in several instances significant; however, when we test the hypothesis that the two coefficients sum to zero, we fail to reject this hypothesis for these windows. Thus, it appears as if the positive relation between changes in customer concentration and subsequent changes in supplier concentration is driven substantially by decreases in concentration in customer industries being followed by decreases in supplier industries perhaps as a result of technological innovation, e.g., see Blair (1972) and Geroski and Pomroy (1990).

There are no simultaneous windows where the coefficients on the change in customer HHI and the interaction term are significant. This suggests that, in the case of simultaneous changes in concentration, the observed positive relation between changes in customer and supplier concentrations is not driven by decreases in concentration. Rather, both the increases and decreases in concentration account for the general results.

As an additional check of the ability of the countervailing power story to, in part, explain the positive relation that we observe between changes in top customer concentration and subsequent changes in supplier concentration, we examine the association of large positive changes in top customer concentration with large positive changes in supplier concentration. Specifically, we run a multivariate logistic regression where the dependent variable is a dummy variable that takes a value of one if the change in supplier HHI over a given period is above the 75th percentile of all changes in supplier HHI. We similarly transform the change in top customer HHI to be a dummy variable that takes a value of one if the change in top customer HHI is above the 75th percentile of changes in customer HHI. Additional control variables as identified in Table 16 are also included in each specification but results for these additional variables are not reported to conserve space.

Table 20 presents the results of these regressions.[64] There are one subsequent and three simultaneous time windows in which large increases in top customer concentration are positively and significantly related to subsequent large increases in supplier industry concentration as predicted by countervailing power story. Bhattacharyya and Nain (2011) and Ahern and Harford (2010) document increased acquisition activity in supplier industries following mergers in customer industries. Our results are consistent with the net effects of these transactions being significant simultaneous and subsequent increases in concentration in adjacent industries.

2.5 RESULTS FOR CUSTOMER TOP-SUPPLIER SAMPLE

2.5.1 Summary statistics

Table 21 reports descriptive statistics for concentration and changes in concentration within the customer-top supplier sample. Not surprisingly, the summary statistics for customer industries

[64] We also performed similar regressions for large decreases in concentration, i.e., dummy variable that takes a value of one if the change in supplier HHI over a given period is below the 25th percentile of all changes in supplier HHI over the same period. The customer change in concentration coefficient is significant in eight of the nine subsequent time windows and two of the six simultaneous time windows. These results are therefore slightly stronger than those reported in the Table 19 piecewise linear regressions.

are very similar to those reported for supplier industries in Table 14 since these are very nearly the same industries. The average top supplier industry year is populated with 136.0 distinct segments and has a mean (median) HHI of 1,985.9 (925.2). Thus, identified top supplier industries tend to have more participants than the customer industries and, consequently, the top supplier industries are less concentrated as well. Also, the average supplier industry experienced an increase in concentration over each of the windows reported. For instance, the average annual percentage change in top supplier industry HHI is an increase of 4.1% across all relationship years. We note that the average annual percentage change in customer industry HHI is an increase of 4.3% across all relationship years. The average annual change in the number of segments in a customer industry when the one-year change in HHI is positive (negative) is a decrease (increase) of 1.1 (0.7) segments, i.e., the exit of approximately one segment (entry of seven tenths of a segment). The average annual change in the number of segments in a top supplier industry when the one-year change in HHI is positive (negative) is a decrease (increase) of 4.7 (0.9) segments, i.e., the exit of four and seven tenths segments (entry of approximately one segment).

2.5.2 Multivariate regressions explaining changes in customer concentration

Table 22 presents the results of multivariate regressions where the dependent variable is the change in customer industry HHI over the indicated time period and the independent variable of interest is the change in top supplier industry HHI over the indicated time period. Additional control variables as identified in Table 16 are also included in each specification but results for these additional variables are not reported. The coefficients are uniformly smaller than those from Table 17 and much less frequently significant. However, there is a sizeable coefficient which is significant at the 5% level in the three-year simultaneous window.

2.5.3 Robustness tests and additional results

While most of the results reported above for the customer-top supplier sample are insignificant, we have conducted the same additional analysis and robustness tests that were described for the supplier-top customer sample. There are several instances where this analysis revealed interesting results. First, results using changes in four-firm concentration ratios are generally positive and significant for nearly all of the windows. Second, for the subsample of non-manufacturing industries, there are several instances where changes in top supplier HHI are positively and significantly related to subsequent changes in customer HHI. Third, we do find that, when the sample relationships are restricted to those where the top supplier provides a minimum of 5% of customer inputs, changes in top supplier concentration are positively and significantly related to subsequent changes in customer concentration in two time windows in the multivariate analysis. Specifically, the change in top supplier concentration from t=-1 to t=0 is significantly related to the change in customer concentration from t=0 to t=+2 and the change in top supplier concentration from t=-2 to t=0 is significantly related to the change in customer concentration from t=0 to t=+1.

Taken together, the results using the alternative measure of concentration and from the two subsamples indicate the existence of a relation between top supplier changes in concentration and changes in customer concentration. However, the fact that results from the entire sample as well as most of the other subsamples and specifications reveal only limited evidence of such effects offers a caveat to this conclusion.

2.5.4 Differences in results across the samples

The results in the supplier-top customer sample are much stronger than those for the customer-top supplier sample. As mentioned above, the differing results across the two samples are potentially informative subject to the caveat that there are differences in the samples as detailed in section 3.4. The results for the respective samples are strongly consistent with changes in concentration traveling from customers to suppliers but there is much weaker evidence consistent with changes in concentration traveling from suppliers to customers. In other words, we find evidence consistent with changes in buyer market power being more important than changes in seller market power.

2.6 CONCLUSION

This paper investigates the timing, magnitude, and direction of the association between changes in industry concentration across vertically related industries over the period 1978-2008. We find that changes in industry concentration in top customer industries are positively associated with subsequent and simultaneous changes in concentration in supplier industries. Further, we find that the positive observed relation is due in part to decreases in concentration in top customer industries being associated with decreases in concentration in supplier industries. We also find some evidence consistent with countervailing power motives as a factor in changes in concentration. On balance, we find limited evidence that changes in concentration in top supplier industries are associated with changes in concentration in customer industries. Our results suggest that additional theoretical and empirical investigation is warranted to increase our understanding of the mechanisms whereby a change in concentration in one industry translates into a change in concentration in a vertically related industry.

APPENDIX A

IDENTIFYING VERTICALLY RELATED INDUSTRIES

This Appendix describes the benchmark input-output (IO) tables published by the Bureau of Economic Analysis at the U.S. Department of Commerce and explains how I use these tables to match each industry with customers and suppliers.

The make table is an industry by commodity matrix which gives the value in producer's prices of each commodity produced by each industry. Every industry is designated as a primary producer for a certain commodity, and is often a secondary producer for other commodities. For example, industry 240400, envelopes, is the primary producer of commodity 240400, envelopes, and a secondary producer of eight other commodities including scrap (81001), die-cut paper and paperboard and cardboard (240703), and stationary, tablets and related products (240706).

The use table is a commodity by industry matrix which gives the value of each commodity c that is used by each industry j, or final non-industry consumer (government or personal consumption expenditures) in producer prices. For example, the top consumers of commodity 240400, envelopes, in order of significance, are personal consumption expenditures (910000), banking (700100), state and local government consumption, wholesale trade (690100), federal government consumption (980021) and retail trade except eating and drinking establishments (690200).

I begin with the make table to determine the percentage of each commodity that each industry makes, or each industry k's market share of commodity c. The market share of industry k's production of commodity c is defined as

$$share_{k,c} = \frac{make_{k,c}}{\sum_{k=1}^{K} make_{k,c}},$$

where $make_{k,c}$ is the amount of industry k's output of commodity c from the make table. The summation in the denominator is the total output of a commodity produced by all industries. I use a constant market share assumption to derive the amount that each consumer purchases from each industry. That is if industry i produces 90% of commodity one then a consumer industry j will purchase 90% of its commodity one inputs from industry k.

Using the market share number and the use table, I then calculate the dollar value that each buyer industry contributes to each producing industry. I call this revenue share. Thus for supplier industry k and customer industry j

$$revshare(k, j) = \sum_{c=1}^{C} (share_{k,c} * use_{c,j}),$$

where $use_{c,j}$ is the amount of the commodity c used by industry j. Revshare is a producer industry by consumer industry matrix that can be used to find a top customer and a top supplier for each industry. Finally, to generate the percentage of each producer industry k's output consumed by customer industry j, I define

$$CUST\_percent_{k,j} = \frac{revshare_{k,j}}{output_i},$$

where

$$output_k = \sum_{c=1}^{C} make_{k,c} = use_k = \sum_{c=1}^{C} use_{c,k}.$$

I use this CUST_percent as the guide to match customers with each industry. Additionally, each industry's customers are ranked by the percentage purchased from the supplying industry. The customer industry (excluding government and personal consumption) that purchases the most from the supplying industry is the top customer.

Similarly, to find top suppliers I define

$$SUPP\_percent_{j,k} = \frac{revshare_{k,j}}{output_j},$$

where

$$output_j = \sum_{c=1}^{C} make_{j,c} = use_j = \sum_{c=1}^{C} use_{c,j}.$$

I use this SUPP_percent as a guide to match each industry with suppliers. Additionally, I rank each industry's suppliers by percentage supplied to the customer industry. The top supplier is the supplier with the highest ranking and this forms the customer–top supplier pair.

REFERENCES

Ahern, K. R., 2010. Bargaining power and industry dependence in mergers. Unpublished working paper, University of Michigan.

Ahern, K., and Harford, J., 2011. The importance of industry links in merger waves. Unpublished working paper, University of Michigan.

Alexandridis, G., Mavrovitis, C.F., and Travlos, N.G., 2010. How have M&As changed? Evidence from the sixth merger wave. Unpublished working paper, ALBA Graduate School of Business.

Ali, A., Klasa, S., and Yeung, E., 2009. The limitations of industry concentration measures constructed with Compustat data: Implications for finance research. The Review of Financial Studies 22, 3839-3871.

Anderton, B., 1999. Innovation, product quality, variety, and trade performance: an empirical analysis of Germany and the UK. Oxford Economic Papers 51, 152-167.

Andrade, G., Mitchell, M., and Stafford, E., 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives 15, 103-120.

Banerjee, S., Dasgupta, S., and Kim, Y., 2008. Buyer-supplier relationships and the stakeholder theory of capital structure. Journal of Finance 63, 2507-2552.

Becker, M. J., and Thomas, S., 2011. Changes in Concentration Across Vertically Related Industries. Unpublished working paper, University of Pittsburgh.

Bhattacharyya, S., and Nain, A., 2011. Horizontal acquisitions and buying power: A product market analysis. Journal of Financial Economics, 99, 97-115.

Blair, J., 1972. Economic Concentration; Structure, Behavior and Public Policy. New York. Harcourt, Brace, Jovanovich, Inc.

Brown, D.T., Fee, C.E., and Thomas, S.E., 2009. Financial leverage and bargaining power with suppliers: evidence from leveraged buyouts. Journal of Corporate Finance 15, 196-211.

Caves, R.E., and Porter, M.E., 1977. From entry barriers to mobility barriers: Conjectural decisions and contrived deterrence to new competition. The Quarterly Journal of Economics 91, 241-262.

Caves, R.E., and Porter, M.E., 1980. The dynamics of changing seller concentration. Journal of Industrial Economics 29, 1-31.

Chen, Z., 2003. Dominant retailers and the countervailing-power hypothesis. Rand Journal of Economics 34, 612-625.

Chipty, T., 1995. Horizontal integration for bargaining power: evidence from the cable television industry. Journal of Economics & Management Strategy 4, 375-397.

Chipty, T. and Snyder, M., 1999. The role of firm size in bilateral bargaining: A study of the cable television industry. The Review of Economics and Statistics 81, 326-340.

Coase, R., 1937. The nature of the firm. Economica 4, 33-55.

Cohen, L. and Frazzini, A., 2008. Economic links and predictable returns. Journal of Finance 63, 1977-2011.

Curry, B. and George, K., 1983. Industrial concentration: A survey. Journal of Industrial Economics 31, 203-255.

Davies, S.W., and Geroski, P., 1997. Changes in concentration, turbulence and the dynamics of market shares. The Review of Economics and Statistics 79, 383-391.

Davis, R., and Duhaime, I., 1992. Diversification, vertical integration, and industry analysis: new Perspectives and measurement. Strategic Management Journal 13, 511-524.

DeAngelo, Harry, and Linda DeAngelo, 1991. Union negotiations and corporate policy: A study of labor concessions in the domestic steel industry during the 1980s. Journal of Financial Economics 30, 3–43.

Demsetz, H., 1973. Industry structure, market rivalry, and public policy. Journal of Law and Economics. Journal of Law and Economics 16, 1-9.

Dittmar, A.K. and Dittmar, R. F., 2008. The timing of financing decisions: An examination of the correlation in financing waves. Journal of Financial Economics 90, 59-83.

Duchin, R., and Schmidt, B., 2010. Riding the merger wave. Unpublished working paper, University of Michigan.

Dunne, T., Roberts, M.J., and Samuelson, L., 1988. Patterns of firm entry and exit in U.S. manufacturing industries. RAND Journal of Economics 19, 495-515.

Fan, J.P.H., and Lang, L.H.P., 2000. The measurement of relatedness: an application to corporate diversification. Journal of Business 73, 629-660.

Fee, C.E. and Thomas, S.E., 2004. Sources of gains in horizontal mergers: evidence from customer, supplier, and rival firms. Journal of Financial Economics 74, 423-460.

Feenstra, R.C., Romalis, J., and Schott, P.K., 2002. U.S. imports, exports and tariff data, 1989-2001. NBER Working Paper No. 9387.

Fridolfsson, S. O. and Stennek, J., 2005. Why mergers reduce profits and raise share prices—a theory of preemptive mergers. Journal of the European Economic Association 3, 1083-1104.

Galbraith, J.K., 1952. American Capitalism; The Concept of Countervailing Power, M. E. Sharpe, Inc.

Gal-Or, E., and Dukes, A., 2006. On the profitability of media mergers. Journal of Business 79,489-525.

Geroski, P.A., and Pomroy, R., 1990. Innovation and the evolution of market structure. Journal of Industrial Economics 38, 299-314.

Goel, A.M. and Thakor, A.V., 2010. Do envious CEOs cause merger waves? Review of Financial Studies 23, 487-517.

Gort, M., 1969. An economic disturbance theory of mergers. Quarterly Journal of Economics 83, 624-642.

Gorton, G., Kahl, M. and Rosen, R. J., 2009. Eat or be eaten: a theory of mergers and firm size. Journal of Finance 64, 1291-1344.

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

Hertzel, M. G., Li, Z., Officer, M.S., and Rodgers, K.J., 2008. Inter-firm linkages and the wealth effects of financial distress along the supply chain. Journal of Financial Economics 87, 374–387.

Hirsch, Barry T., and David A. Macpherson, 2003. Union membership and coverage database from the current population survey: Note. Industrial and Labor Relations Review 56, 349–354.

Holmstrom, B., and Kaplan, S., 2001. Corporate governance and merger activity in the U.S.: making sense of the 80's and the 90's. Journal of Economic Perspectives 15, 121–144.

Horn, H., and Wolinsky, A., 1988. Bilateral monopolies and incentives for merger. Rand Journal of Economics 19, 408-419.

Hunter, A., 1958. Countervailing power. In K.W. Rothschild (ed.), Power in Economics—Selected Readings. Harmondsworth, UK: Penguin. 255–274.

Inderst, R., and Shaffer, G., 2007. Retail mergers, buyer power and product variety. The Economic Journal 117, 45-67.

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

Jensen, M.C., 1986. Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. The American Economic Review 76. 323-329.

Kale, J. R., and Shahrur, H., 2007. Corporate capital structure and the characteristics of suppliers and customers. Journal of Financial Economics 83, 321-365.

Klasa, S., Maxwell, W.F., and Ortiz-Molina, H. 2009. The strategic use of corporate cash holdings in collective bargaining with labor unions. Journal of Financial Economics 92, 421-442.

Lambrecht, B. M., 2004. The timing and terms of mergers motivated by economies of scale. Journal of Financial Economics 72, 41-62.

Lawson, A.M., 1997, Benchmark input-output accounts for the U.S. economy, 1992. Survey of Current Business, 1997 - Bureau of Economic Analysis, US Department of Commerce.

Liebskind, J., Opler, T., and Hatfield, D., 1996. Corporate restructuring and the consolidation of US industry. Journal of Industrial Economics 44, 53-68.

Lown, C. S., Morgan, D. P., and Rohatgi, S., 2000. Listening to loan officers: The impact of commercial credit standards on lending and output. FRBNY Economic Policy Review, July.

Lustgarten, H., 1975. The impact of buyer concentration in manufacturing industries. The Review of Economics and Statistics 57, 125-132.

Maksimovic V. and Phillips, G., 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, V., Phillips, G., and Yang, L., 2010. Public and private merger waves. Unpublished working paper, University of Maryland.

Matsa, D.A., 2010. Capital Structure as a strategic variable: Evidence from collective bargaining. Journal of Finance 65, 1197-1232.

Menzly, L., and Ozbas, O., 2010. Market segmentation and cross-predictability of returns.

Journal of Finance 65, 1555-1580.

Mitchell, M. L., and Mulherin, J. H., 1996. The impact of industry shocks on takeover and restructuring activity. Journal of Financial Economics 41, 193-229.

Mueller, W.F., and Hamm, L.G., 1975. Trends in industrial market concentration, 1947-1970. Review of Economics and Statistics 56, 511-520.

Mueller, W.F., and Rogers, R.T., 1980. The role of advertising in changing concentration of manufacturing industries. The Review of Economics and Statistics 62, 89-96.

Mulherin, J. H., and Boone, A.L., 2000. Comparing acquisitions and divestitures. Journal of Corporate Finance 6, 117-139.

Netter, J., Stegemoller, M., and Wintoki, J., 2010. Implications of data screens on merger and acquisition analysis: A large sample study of mergers and acquisitions from 1992-2009. Unpublished working paper, University of Georgia.

Ovtchinnikov, A. V., 2010. Merger waves following industry deregulation. Unpublished working paper, Vanderbilt University.

Petersen, M.A., 2008. Estimating standard errors in finance panel data sets: Comparing approaches. The Review of Financial Studies 22, 435-480.

Porter, M.E., 1974. Consumer behavior, retailer power, and market performance in consumer goods industries. The Review of Economics and Statistics 56, 419-436.

Pryor, F.L., 1994. The evolution of competition in U.S. manufacturing. Review of Industrial Organization 9, 695-715.

Scherer, F. M., and Ross, D., 1990. Industrial Market Structure and Economic Performance. Rand McNally.

Schlingemann, F. P., Stulz, R. M., and Walkling, R. A., 2002. Divestitures and the liquidity of the market for corporate assets. Journal of Financial Economics 64,117-144.

Schmalensee, R., 1982. Product differentiation advantages of pioneering brands. The American Economic Review 72, 349-365.

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

Snyder, C. M., 2005, Countervailing power. Contribution to the New Palgrave Dictionary.

Snyder, C. M., 1998. Why do larger buyers pay lower prices? Intense supplier competition. Economics Letters 58, 205-209.

Snyder, C., 1996. A dynamic theory of countervailing power. RAND Journal of Economics 27, 747-769.

Stigler, G. J., 1964. A theory of oligopoly. The Journal of Political Economy 72, 44-61.

Stigler, G.J., 1954. The economist plays with blocs. American Economic Review 44, 7-14.

Stole, L.A., and Zwiebel, J., 1996. Intra-firm bargaining under non-binding contracts. Review of Economic Studies 63, 357-410.

Sutton, J., 1991. Sunk cost and market structure: Price competition, advertising, and the evolution of concentration. Cambridge, Mass. MIT Press.

Villalonga, B., 2004. Diversification discount or premium: new evidence from the Business Information Tracking Series. The Journal of Finance 59, 479-506.

Viscusi, W. K., Vernon, J. M. and Harrington, J. E., 2000. Economics of Regulation and Antitrust. Cambridge, Mass. MIT Press.

Whinston, M.D., and Collins, S.C., 1992. Entry and competitive structure in deregulated airline markets: an event study analysis of People Express. Rand Journal of Economics 23, 445-462.

Wright, N.R., 1978. Product differentiation, concentration, and changes in concentration. Review of Economics and Statistics 60, 628-631.

Yan, J., 2009. Merger waves: theory and evidence. Unpublished working paper, University of Pennsylvania.

Zingales, L., 1998. Survival of the fittest or the fattest? Exit and financing in the trucking industry. The Journal of Finance 53, 905-938.

Figure 1: Horizontal mergers

The bars are the number of horizontal mergers (left axis) by year and the line is the total transaction value of horizontal mergers in billions of 2008 dollars (right axis) per year.

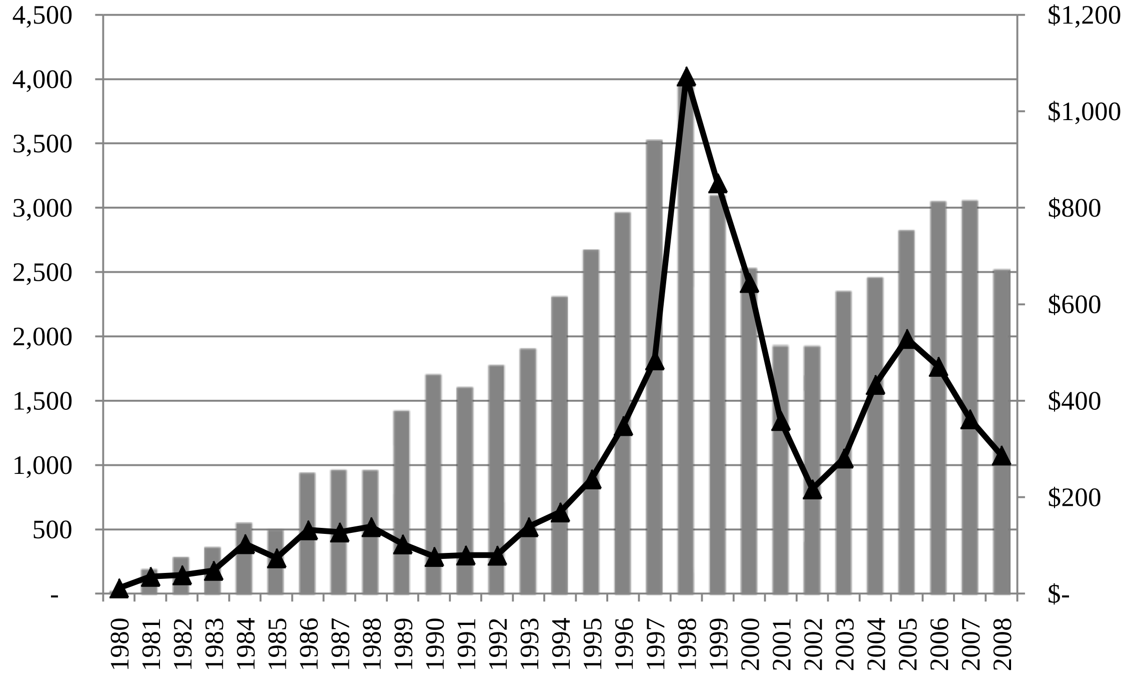

Figure 2: Number of merger waves

Figure depicts the number of industry merger waves by year. Top20_Wave, dashed line, is equal to one if the industry experienced an Top20_Wave and zero otherwise. An industry experiences an Top20_Wave if the two year moving average of adjusted acquisition activity is in the top 20% of the sample, the industry had at least three mergers in the first year of the wave, and the previous two years did not contain a wave. STD_Wave, solid line, is equal to one if the industry experienced an STD_Wave and zero otherwise. An industry experiences an STD_Wave if the one year adjusted acquisition activity is at least one standard deviation above the industry mean measured over the sample period.

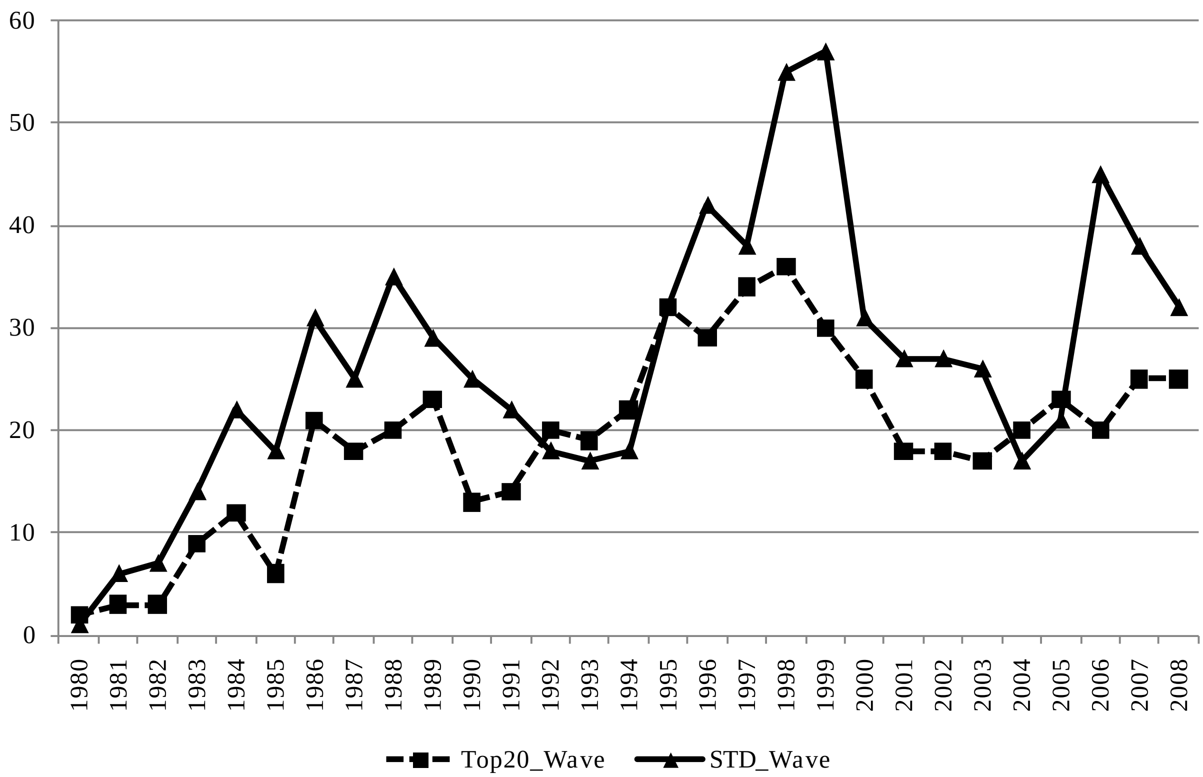

Figure 3: Sample nomenclature

For every industry i, we use the benchmark input-output (IO) tables published by the Bureau of Economic Analysis at the U.S. Department of Commerce to identify the particular industry, j, (top customer) that purchases the largest percentage of industry i's (supplier) output. We refer to this sample of vertical relationships as the supplier-top customer sample. Similarly, for each industry, i, we use the IO tables to identify the particular industry, k, top supplier) that provides the largest percentage of the inputs used by industry (customer). We refer to this sample of vertical relationships as the customer-top supplier sample.

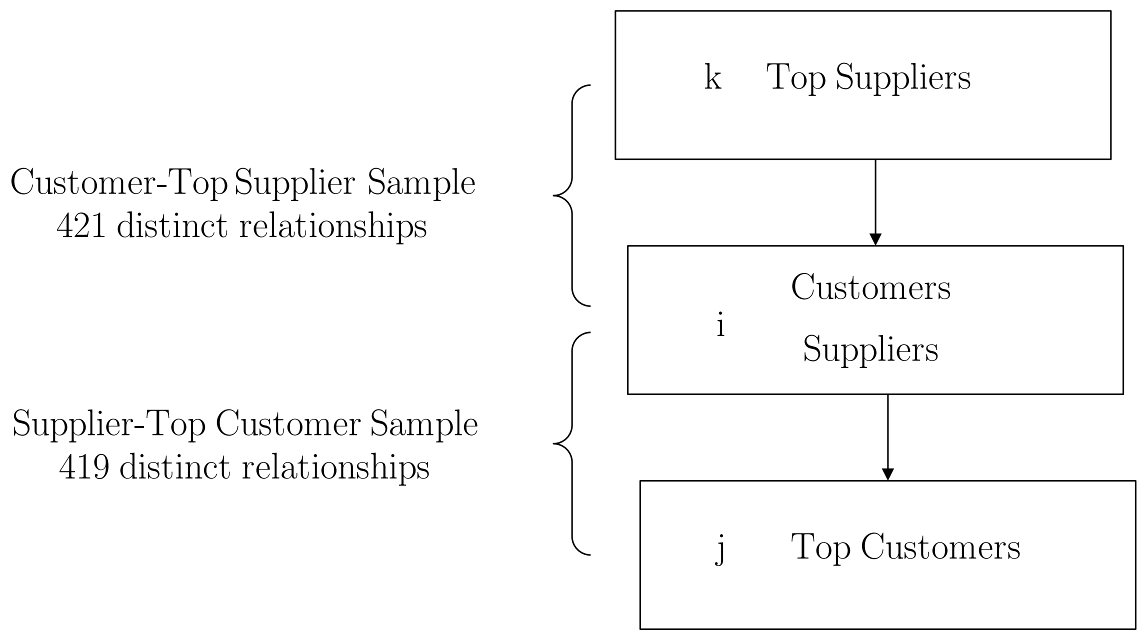

Table 1: Industry & Suppliers merger descriptive statistics

Panel A: Industry descriptive statistics

Table contains descriptive statistics for the industries in the Industry & Suppliers sample. Horizontal mergers is the number of horizontal mergers in an industry year. Transaction value is the sum of transaction values of all mergers in the industry in the year in billions of 2008 dollars. Market value assets is the total market value of assets in the industry at fiscal yearend in billions of 2008 dollars. Adjusted acquisition activity is the total transaction value of all deals in the industry in the year divided by the sum of industry total market value of assets. Top20_Wave (STD_Wave) is equal to one if the industry experienced a Top20_Wave (STD_Wave) and zero otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Adjusted acquisition activity is Winsorized at the 1% level.

	Num Obs	Mean	Median	Std. Dev.	Min.	Max.
Horizontal mergers	38,852	4.252	1.000	19.056	0.000	609.000
Transaction value	38,852	0.572	0.000	4.431	0.000	243.279
Market value assets	38,852	32.886	2.973	159.550	0.000	3,394.906
Adjusted acquisition activity	38,852	0.030	0.000	0.131	0.000	1.093
Top20_Wave	38,852	0.051	0.000	0.220	0.000	1.000
STD_Wave	38,852	0.075	0.000	0.264	0.000	1.000

Panel B: Related supplier descriptive statistics

Table contains descriptive statistics for the related suppliers in the Industry & Suppliers sample. Percent supplied is the percent of commodity inputs supplied to the industry by the supplier industry. All other variables are as defined in Panel A.

	Num Obs	Mean	Median	Std. Dev.	Min.	Max.
Horizontal merger	38,497	29.451	3.000	63.864	0.000	609.000
Transaction value	38,497	3.150	0.069	12.503	0.000	243.279
Market value assets	31,167	163.478	34.476	308.440	0.000	3,394.906
Adjusted acquisition activity	30,704	0.020	0.005	0.049	0.000	0.360
Top20_Wave	30,704	0.097	0.000	0.296	0.000	1.000
STD_Wave	30,704	0.108	0.000	0.310	0.000	1.000
Percent supplied	38,852	0.104	0.080	0.073	0.050	0.731

Table 2: Industry & Customers merger descriptive statistics

Panel A: Industry descriptive statistics

Table contains descriptive statistics for the industries in the Industry & Customers sample. Horizontal mergers is the number of horizontal mergers in an industry year. Transaction value is the sum of transaction values of all mergers in the industry in the year in billions of 2008 dollars. Market value assets is the total market value of assets in the industry at fiscal yearend in billions of 2008 dollars. Adjusted acquisition activity is the total transaction value of all deals in the industry in the year divided by the sum of industry total market value of assets. Top20_Wave (STD_Wave) is equal to one if the industry experienced a Top20_Wave (STD_Wave) and zero otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Adjusted acquisition activity is Winsorized at the 1% level.

	Num Obs	Mean	Median	Std. Dev.	Min.	Max.
Horizontal mergers	34,260	3.652	0.000	15.942	0.000	609.000
Transaction value	34,260	0.444	0.000	3.838	0.000	243.279
Market value assets	34,260	24.378	2.293	130.737	0.000	3,155.370
Adjusted acquisition activity	34,260	0.037	0.000	0.187	0.000	1.600
Top20_Wave	34,260	0.044	0.000	0.205	0.000	1.000
STD_Wave	34,260	0.070	0.000	0.256	0.000	1.000

Panel B: Related customer descriptive statistics

Table contains descriptive statistics for the related customers in the Industry & Customers sample. Percent purchased is the percent of industry outputs purchased by the customer industry. All other variables are as defined in Panel A.

	Num Obs	Mean	Median	Std. Dev.	Min.	Max.
Horizontal merger	32,058	17.096	2.000	40.643	0.000	609.000
Transaction value	32,058	2.654	0.036	13.149	0.000	243.279
Market value assets	30,344	120.921	18.639	314.568	0.000	3,394.906
Adjusted acquisition activity	29,952	0.026	0.003	0.078	0.000	0.575
Top20_Wave	29,952	0.098	0.000	0.297	0.000	1.000
STD_Wave	29,952	0.100	0.000	0.300	0.000	1.000
Percent consumed	34,260	0.091	0.059	0.100	0.030	1.000

Table 3: Control variables descriptive statistics

Panel A: Control variables listed and described

Table contains the expected sign, definition, sources and references for the control variables used in the logistic regression equations.

Variable name (Expected Sign)	Definition (Sources)	References
Spread (-)	The average of the commercial and industrial loan rate minus the federal funds rate measured at December t= 0 and t= -1. (Federal Reserve)	Harford (2005), Lown et al. (2002)
Deregulation (+)	Dummy variable equal to one if the industry underwent deregulation in year t= 0. (Viscusi et al., 2000; Economic Reports to the President)	Mitchell and Mulherin (1996), Andrade et al. (2005)
Herfindahl (-)	Industry sum of squared market shares measured as of yearend t= 0. (Compustat)	Becker and Thomas (2011), Curry and George (1983)
Principal component (+)	First principal component of the industry median value of the one year absolute change in profitability, asset turnover, capital expenditures, employee growth, ROA and sales growth. (Compustat)	Harford (2005)
Industry cash (+)	Industry cash divided by book value of industry assets, year t=0. (Compustat)	Jensen (1986)
S&P one year return (+)	Return on the S&P500, measured from end of year t=-1 to t=0 (yahoo.finance.com)	Ahern and Harford (2011), Maksimovic et al. (2010)

Panel B: Industry & Suppliers control variables descriptive statistics

Table contains descriptive statistics for the industries in the Industry & Suppliers sample. The variables are defined in Panel A. Herfindahl and industry cash are Winsorized at the 1% level.

	Num. Obs.	Mean	Median	Std. Dev.	Min.	Max.
$\text{Spread}_{t=-1,0}$	38,852	2.064	2.050	0.596	0.300	4.170
$\text{Deregulation}_{t=0}$	38,852	0.004	0.000	0.061	0.000	1.000
$\text{Herfindahl}_{t=0}$	38,852	0.466	0.406	0.300	0.016	1.000
$\text{Principal component}_{t=0}$	35,075	0.027	0.078	1.512	-5.556	5.196
$\text{Industry cash}_{t=0}$	38,852	0.052	0.031	0.059	0.000	0.309
S&P one year return $_{t=-1 \text{ to } t=0}$	38,852	0.092	0.124	0.170	-0.385	0.341

Panel C: Industry & Customers control variables descriptive statistics

Table contains descriptive statistics for the industries in the Industry & Customers sample. Variable definitions are given in Panel A. Herfindahl and industry cash are Winsorized at the 1% level.

	Num. Obs.	Mean	Median	Std. Dev.	Min.	Max.
Spread$_{t=-1,0}$	34,260	2.064	2.050	0.602	0.300	4.170
Deregulation$_{t=0}$	34,260	0.003	0.000	0.057	0.000	1.000
Herfindahl$_{t=0}$	34,260	0.495	0.440	0.305	0.023	1.000
Principal component$_{t=0}$	30,816	0.026	0.081	1.587	-5.556	5.196
Industry cash$_{t=0}$	34,260	0.051	0.031	0.055	0.000	0.283
S&P one year return $_{t=-1 \text{ to } t=0}$	34,260	0.093	0.124	0.170	-0.385	0.341

Table 4: Industry & Suppliers logistic regression results

Table contains results for logistic regression models estimated for merger wave starts. The sample is the Industry & Suppliers sample for years 1980-2008, although the first and last years are lost due to data leads and lags. The dependent variable is equal to 1 in specifications (1), (2), and (3) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (4), (5), and (6) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Supplier Top20_Wave and supplier STD_Wave are defined similarly to Top20_Wave and STD_Wave except that the wave is measured beginning in year t= -1 and refers to the supplier industry. Spread, deregulation, Herfindahl, principal component, industry cash and S&P one year return are defined in Table 3. Top supplier dummy is equal to one if the supplier industry provides the highest percent of inputs to the industry and 0 otherwise. Herfindahl is Winsorized at the 1% level. Robust p-values clustered at the industry level are in brackets. Odds ratios are in italics. The symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

	Industry Top20_Wave$_{t=+1}$			Industry STD_Wave$_{t=+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier Top20_Wave$_{t=-1}$		0.266**	0.213*			
		[0.026]	[0.089]			
		1.305	*1.238*			
Supplier STD_Wave$_{t=-1}$					0.110	0.146*
					[0.140]	[0.078]
					1.117	*1.158*
Top supplier dummy			0.010			-0.02
			[0.892]			[0.549]
			1.010			*0.980*
Supplier wave$_{t=-1}$			0.189			-0.173
*(Top supplier dummy)[a]			[0.406]			[0.310]
			1.208			*0.841*
Spread$_{t=-1,0}$	-0.358**	-0.345**	-0.347**	-0.629***	-0.623***	-0.622***
	[0.015]	[0.019]	[0.018]	[0.000]	[0.000]	[0.000]
	0.699	*0.708*	*0.707*	*0.533*	*0.536*	*0.537*
Deregulation$_{t=0}$	0.749	0.756	0.759	0.864	0.857	0.861
	[0.234]	[0.228]	[0.226]	[0.130]	[0.132]	[0.130]
	2.116	*2.130*	*2.137*	*2.374*	*2.356*	*2.365*
Herfindahl$_{t=0}$	-3.065***	-3.044***	-3.044***	-1.019***	-1.018***	-1.020***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	0.047	*0.048*	*0.048*	*0.361*	*0.361*	*0.361*
Principal component$_{t=0}$	0.001	0.001	0.001	-0.030	-0.030	-0.03
	[0.975]	[0.973]	[0.972]	[0.290]	[0.301]	[0.299]
	1.001	*1.001*	*1.001*	*0.970*	*0.971*	*0.971*
Industry cash$_{t=0}$	2.009**	1.933**	1.939**	1.680**	1.659**	1.653**
	[0.032]	[0.039]	[0.038]	[0.020]	[0.021]	[0.022]
	7.456	*6.913*	*6.949*	*5.368*	*5.256*	*5.22*
S&P one year return$_{t=-1 \text{ to } t=0}$	0.612*	0.618*	0.616*	0.340	0.324	0.324
	[0.056]	[0.054]	[0.055]	[0.239]	[0.260]	[0.261]
	1.843	*1.855*	*1.852*	*1.405*	*1.383*	*1.383*
Constant	-1.173***	-1.231***	-1.230***	-0.839***	-0.860***	-0.856***
	[0.000]	[0.000]	[0.000]	[0.008]	[0.007]	[0.008]
Observations	26,298	26,298	26,298	26,298	26,298	26,298
Chi Squared Statistic	112.50	114.50	118.10	72.21	74.81	76.69

(a) p-value for joint significance with Supplier Wave$_{t=-1}$ is 0.065 for regression (3) and 0.861 for regression (6)

Table 5: Industry & Suppliers evidence of market power motivations

Table contains results for logistic regression models estimated for merger wave starts. The sample is for the Industry & Suppliers sample for years 1980-2008, although the first and last year are lost due to data leads and lags. The dependent variable is equal to 1 in specifications (1) and (2) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (3) and (4) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Supplier Top20_Wave and supplier STD_Wave are defined similarly to Top20_Wave and STD_Wave except that they are measured at year t= -1 and refer to the supplier industry. Control variables are the same as in Table 4 but are omitted to conserve space. Supplier high profit is a dummy variable equal to one if the supplier's operating profits in year t= 0 were greater than the median for that industry for the entire sample period. Supplier high change in Herfindahl is a dummy variable equal to one if the supplier change in Herfindahl from year t= -2 to year t= 0 was greater than the median for all supplier industries and 0 otherwise. Herfindahl is Winsorized at the 1% level. Robust p-values clustered at the industry level are in brackets. Odds ratios are in italics. The symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

	Industry Top20_Wave$_{t=+1}$		Industry STD_Wave$_{t=+1}$	
	(1)	(2)	(3)	(4)
Supplier Top20_Wave$_{t=-1}$	0.286**	0.255*		
	[0.014]	[0.087]		
	1.331	*1.291*		
Supplier STD_Wave$_{t=-1}$			0.113	-0.064
			[0.140]	[0.623]
			1.119	*0.938*
Supplier high profit dummy	0.064		0.091*	
	[0.224]		[0.062]	
	1.066		*1.096*	
Supplier Wave$_{t=-1}$	-0.032		-0.053	
*(Supplier high profit)[a]	[0.849]		[0.280]	
	0.968		*0.949*	
Supplier high change in Herfindahl dummy		0.161***		0.122**
		[0.004]		[0.020]
		1.174		*1.129*
Supplier Wave$_{t=-1}$		-0.004		0.211
*(Supplier high change in Herfindahl)[b]		[0.980]		[0.180]
		0.996		*1.235*
Observations	26,271	26,298	26,206	26,298
Chi Squared Statistic	117.00	119.40	77.96	82.78

a P-value for joint significance with supplier Top20_Wave is 0.141 and with supplier STD_Wave is 0.538

b P-value for joint significance with supplier Top20_Wave is 0.068 and with supplier STD_Wave is 0.095

Table 6: Industry & Suppliers industry characteristic considerations

Table contains selected results for logistic regression models estimated for merger wave starts. The sample is for the Industry & Suppliers sample for years 1980-2008, although the first and last year are lost due to data leads and lags. The table presents coefficients for the regression variables specified, with significance indicated with symbols. The dependent variable is equal to 1 in specifications (1) through (4) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (5) through (8) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Supplier Top20_Wave and supplier STD_Wave are defined similarly to Top20_Wave and STD_Wave except that they are measured beginning in year t= -1 and refer to the supplier industry. Non-consumer goods is a dummy equal to one if the industry is not a maker of consumer durable or consumer non-durable goods. Low ads spending is a dummy variable equal to one if advertising expenditures divided by sales is less than the sample median. Low R&D spending is a dummy variable equal to one if R&D expenses divided by sales is less than the sample median. Low industry unionization is a dummy variable equal to one if the unionization rate for the industry year is less than the sample median (14.5%). The interaction variable is the supplier wave variable times the respective industry dummy. Joint supp wave and interaction is the sum of supplier wave and interaction coefficients and significance is based on a test of joint significance for the supplier wave and interaction variable. Control variables are the same as those used in the regression equations presented in Table 4 and the results are omitted to conserve space. The symbols ***, **, and * indicate significance at 1%, 5% and 10% levels respectively.

	Industry Top20_Wave$_{t=+1}$				Industry STD_Wave$_{t=+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Supplier Top20_Wave$_{t=-1}$	0.009	0.259	0.140	0.181				
Supplier STD_Wave$_{t=-1}$					0.102	-0.010	0.176	0.004
Non-consumer goods	-0.040				0.016			
Low Ads spending		0.060				0.071		
Low R&D spending			0.610***				0.179**	
Low Industry Unionization				0.341***				-0.045
Interaction	0.274	0.007	0.103	0.082	0.116	0.207	-0.116	0.188
Joint supp wave and interaction	0.283**	0.266*	0.245	0.262*	0.218**	0.197**	0.059	0.192*

Table 7: Industry & Suppliers timing of merger waves

Table contains results for logistic regression models estimated for merger wave starts. The sample is for the industry-matched supplier sample for years 1980-2008. The dependent variable is equal to 1 in specifications (1) through (5) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (6) through (10) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Supplier Top20_Wave and supplier STD_Wave are defined similarly to Top20_Wave and STD_Wave except that they refer to the supplier industry. Supplier merger wave starts are measured at year t= -3 for specifications (1) and (6), t= -2 for specifications (2) and (7), t= -1 for specifications (3) and (8), t= 0 for specifications (4) and (9) and t= +1 for specifications (5) and (10). Control variables are the same as in Table 4 but are omitted to conserve space. Robust p-values clustered at the industry level are in brackets. The symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

	Industry Top20_Wave$_{t=+1}$				
	(1)	(2)	(3)	(4)	(5)
Supplier Top20_Wave$_{t=-3}$	0.154				
	[0.198]				
Supplier Top20_Wave$_{t=-2}$		0.080			
		[0.483]			
Supplier Top20_Wave$_{t=-1}$			0.266**		
			[0.026]		
Supplier Top20_Wave$_{t=-0}$				0.079	
				[0.500]	
Supplier Top20_Wave$_{t=+1}$					-0.016
					[0.886]
Observations	25,199	26,210	26,298	26,393	26,295
Chi Squared Statistic	110.39	112.90	114.53	112.52	112.82

	Industry STD_Wave$_{t=+1}$				
	(6)	(7)	(8)	(9)	(10)
Supplier STD_Wave$_{t=-3}$	-0.036				
	[0.664]				
Supplier STD_Wave$_{t=-2}$		0.147**			
		[0.044]			
Supplier STD_Wave$_{t=-1}$			0.110		
			[0.140]		
Supplier STD_Wave$_{t=0}$				0.169**	
				[0.021]	
Supplier STD_Wave$_{t=+1}$					0.017
					[0.821]
Observations	31,930	33,146	26,298	26,393	33,146
Chi Squared Statistic	66.38	75.14	74.81	78.62	73.32

Table 8: Industry & Customers logistic regression results

Table contains results for logistic regression models estimated for merger wave starts. The sample is the Industry & Customers sample for years 1980-2008, although the first and last years are lost due to data leads and lags. The dependent variable is equal to 1 in specifications (1), (2), and (3) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (4), (5), and (6) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Customer Top20_Wave and customer STD_Wave are defined similarly to Top20_Wave and STD_Wave except that the wave is measured beginning in year t= -1 and refers to the customer industry. Spread, deregulation, Herfindahl, principal component, industry cash and S&P one year return are defined in Table 3. Top customer dummy is equal to one if the customer is the industry's most important customer in terms of percent of output purchased and 0 otherwise. Herfindahl is Winsorized at the 1% level. Robust p-values clustered at the industry level are in brackets. Odds ratios are in italics. The symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

	Industry Top20_Wave$_{t=+1}$			Industry STD_Wave$_{t=+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Customer Top20_Wave$_{t=-1}$		0.064	0.035			
		[0.570]	[0.806]			
		1.067	*1.035*			
Customer Top20_Wave$_{t=-1}$					0.292***	0.290***
					[0.000]	[0.001]
					1.339	*1.336*
Top customer dummy			0.075			0.053
			[0.428]			[0.216]
			1.078			*1.054*
Customer Wave$_{t=-1}$			0.083			0.007
*(Top customer dummy)[a]			[0.716]			[0.959]
			1.087			*1.007*
Spread$_{t=-1,0}$	-0.407**	-0.405**	-0.406**	-0.619***	-0.612***	-0.612***
	[0.042]	[0.044]	[0.043]	[0.000]	[0.000]	[0.000]
	0.666	*0.667*	*0.666*	*0.538*	*0.542*	*0.542*
Deregulation$_{t=0}$	0.281	0.279	0.278	-0.044	-0.044	-0.046
	[0.696]	[0.697]	[0.700]	[0.945]	[0.945]	[0.943]
	1.325	*1.322*	*1.320*	*0.957*	*0.957*	*0.955*
Herfindahl$_{t=0}$	-2.865***	-2.862***	-2.852***	-1.058***	-1.055***	-1.050***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	0.057	*0.057*	*0.058*	*0.347*	*0.348*	*0.350*
Principal component$_{t=0}$	-0.011	-0.011	-0.011	-0.021	-0.020	-0.020
	[0.807]	[0.812]	[0.812]	[0.535]	[0.563]	[0.563]
	0.989	*0.990*	*0.990*	*0.979*	*0.981*	*0.981*
Industry cash$_{t=0}$	2.294	2.279	2.297	1.313	1.250	1.259
	[0.120]	[0.124]	[0.119]	[0.181]	[0.204]	[0.200]
	9.915	*9.770*	*9.939*	*3.716*	*3.491*	*3.522*
S&P one year return$_{t=-1 \text{ to } t=0}$	0.576	0.574	0.574	0.664*	0.642*	0.643*
	[0.197]	[0.200]	[0.199]	[0.066]	[0.073]	[0.073]
	1.780	*1.775*	*1.775*	*1.943*	*1.901*	*1.902*
Constant	-1.237**	-1.250**	-1.270**	-0.907**	-0.951**	-0.966***
	[0.014]	[0.014]	[0.011]	[0.013]	[0.010]	[0.009]
Observations	25,713	25,713	25,713	25,713	25,713	25,713
Chi Squared Statistic	77.73	78.13	81.34	53.67	64.36	69.21

(a) p-value for joint significance with Supplier Wave$_{t=-1}$ is 0.518 for regression (3) and 0.025 for regression (6)

Table 9: Industry & Customers evidence of market power motivations

Table contains results for logistic regression models estimated for merger wave starts. The sample is for the industry-matched customer sample for years 1980-2008, although the first and last year are lost due to data leads and lags. The dependent variable is equal to 1 in specifications (1) and (2) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (3) and (4) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Customer Top20_Wave and customer STD_Wave are defined similarly to wave except that they are measured at year t= -1 and refer to the customer industry. Control variables are the same as in Table 8 but are omitted to conserve space. Customer high profit is a dummy variable equal to one if the customer's operating profits in year t= 0 were greater than the median for that industry for the entire sample period. Customer high change in Herfindahl is a dummy variable equal to one if the customer change in Herfindahl from year t= -2 to year t= 0 was greater than the median for all customer industries and 0 otherwise. Herfindahl is Winsorized at the 1% level. Robust p-values clustered at the industry level are in brackets. Odds ratios are in italics. The symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

	Industry Top20_Wave$_{t=+1}$		Industry STD_Wave$_{t=+1}$	
	(1)	(2)	(3)	(4)
Customer Top20_Wave$_{t=-1}$	0.255**	0.131		
	[0.049]	[0.344]		
	1.290	*1.139*		
Customer STD_Wave$_{t=-1}$			0.291***	0.213*
			[0.000]	[0.067]
			1.338	*1.237*
Customer high profit dummy	0.045		0.058	
	[0.453]		[0.310]	
	1.046		*1.060*	
Customer Wave$_{t=-1}$	-0.378**		0.099	
*(Customer high profit)[a]	[0.015]		[0.315]	
	0.685		*1.104*	
Customer high change in Herfindahl dummy		0.065		-0.006
		[0.308]		[0.906]
		1.067		*0.994*
Customer Wave$_{t=-1}$		-0.127		0.123
*(Customer high change in Herfindahl)[b]		[0.493]		[0.359]
		0.881		*1.131*
Observations	25,690	25,713	25,690	25,713
Chi Squared Statistic	82.47	80.05	69.56	66.04

a P-value for joint significance with supplier Top20_Wave is 0.400 and with supplier STD_wave is 0.001

b P-value for joint significance with supplier Top20_Wave is 0.980 and with supplier STD_Wave is 0.000

Table 10: Industry & Customers industry characteristic considerations

Table contains selected results for logistic regression models estimated for merger wave starts. The sample is for the Industry & Customers sample for years 1980-2008, although the first and last year are lost due to data leads and lags. The table presents coefficients for the regression variables specified, with significance indicated with symbols. The dependent variable is equal to 1 in specifications (1) through (4) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (5) through (8) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Customer Top20_Wave and customer STD_Wave are defined similarly to Top20_Wave and STD_Wave except that they are measured beginning in year t= -1 and refer to the customer industry. Non-consumer goods is a dummy equal to one if the industry the industry is not a maker of consumer durable or non-durable goods. Low ads spending is a dummy variable equal to one if industry advertising expenditures divided by sales is less than the sample median. Low R&D spending is a dummy variable equal to one if industry R&D expenses divided by sales is less than the sample median. Low industry unionization is a dummy variable equal to one if the unionization rate for the industry year is less than the sample median (14.5%). The interaction variable is the customer wave variable times the respective industry dummy. Joint cust wave and interaction is the sum of customer wave and interaction coefficients and significance is based on a test of joint significance for the customer wave and interaction variable. Control variables are the same as those used in the regression equations presented in Table 8 and the results are omitted to conserve space. The symbols ***, **, and * indicate significance at 1%, 5% and 10% levels respectively.

	Industry Top20_Wavet=+1				Industry STD_Wavet=+1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer Top20_Wavet=-1	-0.301	-0.079	0.075	0.044				
Customer STD_Wavet=-1					-0.076	0.303***	0.222**	0.216**
Non-consumer goods	0.073				-0.043			
Low Ads spending		0.009				-0.027		
Low R&D spending			0.768***				0.116	
Low Industry Unionization				0.232				-0.092
Interaction	0.394	0.302	-0.083	0.009	0.410	-0.022	0.124	0.152
Joint cust wave and interaction	0.093	0.224	-0.008	0.052	0.334***	0.282**	0.346***	0.368***

Table 11: Industry & Customers timing of merger waves

Table contains results for logistic regression models estimated for merger wave starts. The sample is for the industry-matched customer sample for years 1980-2008. The dependent variable is equal to 1 in specifications (1) through (5) if the industry experienced a Top20_Wave beginning in year t= +1 and 0 otherwise. The dependent variable is equal to 1 in specifications (6) through (10) if the industry experienced a STD_Wave beginning in year t= +1 and 0 otherwise. Top20_Wave and STD_Wave are defined in Figure 2. Customer Top20_Wave and customer STD_Wave are defined similarly to Top20_Wave and STD_Wave except that they refer to the customer industry. Customer merger wave starts are measured at year t= -3 for specifications (1) and (6), t= -2 for specifications (2) and (7), t= -1 for specifications (3) and (8), t= 0 for specifications (4) and (9) and t= +1 for specifications (5) and (10). Control variables are the same as in Table 8 but are omitted to conserve space. Robust p-values clustered at the industry level are in brackets. The symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels respectively.

	Industry Top20_Wave$_{t=+1}$				
	(1)	(2)	(3)	(4)	(5)
Customer Top20_Wave$_{t=-3}$	0.154				
	[0.129]				
Customer Top20_Wave$_{t=-2}$		0.140			
		[0.163]			
Customer Top20_Wave$_{t=-1}$			0.064		
			[0.570]		
Customer Top20_Wave$_{t=0}$				0.112	
				[0.270]	
Customer Top20_Wave$_{t=+1}$					0.071
					[0.479]
Observations	24,629	25,614	25,713	25,852	25,710
Chi Squared Statistic	88.15	81.59	78.13	79.22	79.16

	Industry STD_Wave$_{t=+1}$				
	(6)	(7)	(8)	(9)	(10)
Customer STD_Wave$_{t=-3}$	0.039				
	[0.639]				
Customer STD_Wave$_{t=-2}$		0.058			
		[0.460]			
Customer STD_Wave$_{t=-1}$			0.292***		
			[0.000]		
Customer STD_Wave$_{t=0}$				0.036	
				[0.649]	
Customer STD_Wave$_{t=+1}$					0.174**
					[0.014]
Observations	24,629	25,614	25,713	25,852	27,512
Chi Squared Statistic	43.92	55.33	64.36	54.28	67.55

Table 12: Supplier-top customer sample description of relationships and the frequency that certain industries are identified as top customers

We use the benchmark input-output tables published in 1992 by the Bureau of Economic Analysis at the U.S. Department of Commerce to identify industries with significant vertical relationships. Panel A lists the ten relationships where the identified top customer industries purchase the largest percentage of supplier industry output. Panel B provides summary statistics on the percentage of supplier output that is purchased by the top customer and by the top four customer industries, respectively. Panel C reports the number of relationship years (N = 11,713) for which the named industry is identified as the top customer.

Panel A: Relationship description

Supplier description	Top customer description	Percent purchased
Maintenance and repair of petrol. and nat. gas wells	Crude petroleum and natural gas	100.0%
Electrometallurgical products, except steel	Blast furnaces and steel mills	100.0%
Fine earthenware table and kitchenware	Eating and drinking places	100.0%
Sugar crops	Sugar	95.6%
Malt	Malt beverages	93.8%
Iron and ferroalloy ores and misc. metal ores, n.e.c.	Blast furnaces and steel mills	89.1%
Wood television and radio cabinets	Household audio and video equip.	88.0%
Fasteners, buttons, needles, and pins	Apparel made from purchased material	77.8%
Poultry and eggs	Poultry slaughtering and processing	76.9%
Steel springs, except wire	Motor vehicle and passenger car bodies	76.8%

Panel B: Percentage of supplier output purchased by top customers

	Relationships	Mean	Median	Std. Dev.	Min.	Max.
Percent purchased by top customer	419	19.9%	12.5%	20.6%	0.0%	100.0%
Percent purchased by top 4 customers	419	34.6%	27.4%	27.8%	0.0%	100.0%

Panel C: Frequency named industry is identified as the top customer

Top customer industry	Number of relationship-years named as top customer	Fraction of all relationship-years named as top customer
Motor vehicles and passenger car bodies	1,231	10.5%
Eating and drinking places	1,223	10.4%
Maintenance and repair of farm and nonfarm residential structures	944	8.1%
Wholesale trade	909	7.8%
Retail trade, except eating and drinking	486	4.2%
Motor vehicle parts and accessories	305	2.6%
Blast furnaces and steel mills	299	2.6%
Aircraft	277	2.4%
Apparel made from purchased materials	210	1.8%
Miscellaneous repair shops	182	1.6%

Table 13: Customer-top supplier sample description of relationships and the frequency that certain industries are identified as top suppliers

We use the benchmark input-output tables published in 1992 by the Bureau of Economic Analysis at the U.S. Department of Commerce to identify industries with significant vertical relationships. Panel A lists the ten relationships where the identified top supplier industries supply the largest percentage of customer industry inputs. Panel B provides summary statistics on the percentage of customer inputs that are supplied by the top supplier and by the top four supplier industries, respectively. Panel C reports the number of relationship years (N = 11,744) for which the named industry is identified as the top supplier.

Panel A: Relationship description

Customer description	Top supplier description	Percent supplied
Meat packing plants	Meat animals	79.1%
Soybean oil mills	Oil bearing crops	61.6%
Petroleum refining	Crude petroleum and natural gas	56.6%
Creamery butter	Fluid milk	51.3%
Fluid milk	Dairy farm products	51.0%
Poultry slaughtering and processing	Poultry and eggs	48.4%
Malt	Feed grains	47.2%
Sausages and other prepared meat products	Meat packing plants	47.0%
Cottonseed oil mills	Cotton	46.2%
Poultry and eggs	Prepared feeds, n.e.c.	42.1%

Panel B: Percentage of customer inputs supplied by top suppliers

	Relationships	Mean	Median	Std. dev.	Min.	Max.
Percent supplied by top supplier	421	12.4%	8.6%	10.6%	0.6%	79.1%
Percent supplied by top 4 suppliers	421	25.8%	22.4%	13.3%	3.4%	84.8%

Panel C: Frequency named industry is identified as the top supplier

Top supplier industry	Number of relationship-years named as top supplier	Fraction of all relationship-years named as top supplier
Wholesale trade	2,647	22.5%
Blast furnaces and steel mills	868	7.4%
Paper and paperboard mills	466	4.0%
Miscellaneous plastics products, n.e.c.	450	3.8%
Industrial inorganic and organic chemicals	434	3.7%
Petroleum refining	394	3.4%
Broadwoven fabric mills and fabric finishing	381	3.2%
Other electronic components	337	2.9%
Trucking and courier services, except air	327	2.8%
Sawmills and planing mills, general	278	2.4%

Table 14: Supplier-top customer descriptive statistics

The statistics below are reported by supplier - top customer relationship year. The Herfindahl-Hirschman Index (HHI) is calculated as the sum of the squares of each segment's sales as a proportion of the industry's total sales. Thus, for industry i in year t, HHI is measured as $HHI_{it}= \sum_{j=1}^{N_{it}}\left(\left(SALES_{jit} \Big/ \sum_{j=1}^{N_{it}} SALES_{jit}\right)*100\right)^2$, where N_{it} is the number of segments in industry i at time t and $Sales_{jit}$ are the net sales attributable to segment j of industry i at time t. Changes in HHI are calculated as the ratio of HHI at one point in time over HHI at another point in time minus one, e.g., the one year ahead change in HHI is calculated as $(HHI_{t=+1}/HHI_{t=0})$-1. Industry sales are reported in billions of 2008 dollars. Changes in HHI and industry sales are Winsorized at the 1% and 99% level.

	Rel. years	Mean	Median	Std. Dev.	Min.	Max.
Supplier						
Number of segments per industry	11,713	19.629	6.000	53.411	1.000	1,200.000
Hirschman-Herfindahl Index ($HHI_{t=0}$)	11,713	4,583.8	3,848.9	3,029.5	137.9	10,000.0
3-year change HHI, ($HHI_{t=+3}/HHI_{t=0}$)-1	10,304	0.124	0.030	0.400	-0.583	1.644
2-year change HHI, ($HHI_{t=+2}/HHI_{t=0}$)-1	10,745	0.084	0.010	0.322	-0.546	1.317
1-year change HHI, ($HHI_{t=+1}/HHI_{t=0}$)-1	11,204	0.043	0.000	0.226	-0.471	0.974
Industry sales	11,713	15.610	2.779	47.038	0.005	366.422
Top Customer						
Number of segments per industry	11,713	100.548	38.000	141.432	1.000	1,200.000
Hirschman-Herfindahl Index ($HHI_{t=0}$)	11,713	2,231.2	1,230.2	2,287.2	137.9	10,000.0
3-year change HHI, ($HHI_{t=0}/HHI_{t=-3}$)-1	10,493	0.094	0.039	0.324	-0.496	1.307
2-year change HHI, ($HHI_{t=0}/HHI_{t=-2}$)-1	10,899	0.064	0.024	0.257	-0.460	1.107
1-year change HHI ,($HHI_{t=0}/HHI_{t=-1}$)-1	11,297	0.032	0.004	0.169	-0.378	0.713
1-year change HHI, ($HHI_{t=+1}/HHI_{t=0}$)-1	11,329	0.032	0.004	0.168	-0.377	0.713
2-year change HHI, ($HHI_{t=+2}/HHI_{t=0}$)-1	10,954	0.063	0.024	0.254	-0.460	1.073
3-year change HHI, ($HHI_{t=+3}/HHI_{t=0}$)-1	10,233	0.093	0.039	0.323	-0.491	1.303
Industry sales	11,713	158.089	60.619	249.072	0.026	1,407.643

Table 15: Summary statistics for variables in multivariate regressions explaining changes in supplier concentration

This table reports summary statistics for the independent variables in multivariate regressions explaining changes in supplier concentration over the period from t=0 to t=+3. To be included in this regression the relationship pair must have change in HHI data available for the period t=0 to t=+3 for the suppliers and for the period t=-3 to t=0 for the top customers. Panel A reports summary statistics for factors specific to the individual supplier industries. Sales growth is the change in inflation adjusted total industry sales from t=-2 to t=0. The deregulation dummy is equal to one if the supplier industry experienced deregulation in t=0 or t=-1. Import market share is the customs value (in dollars) of products imported into the US with the same IO code as the supplier industry divided by the supplier industry's total sales at t = 0, where import data are missing for a particular industry this variable is set to zero. Missing imports flag is a dummy variable equal to one if the import data are missing for a particular industry. Advertising to sales is the industry median advertising to sales ratio at t=0. The first principal component is first principal component of the absolute value of the two year change (from t=-2 to t=0) of the following supplier ratios: asset turnover (total sales/assets), earning power (operating income/assets), profit margin (operating income/sales), and capital expenditures (capital expenditures/assets). The statistic is calculated as the median value for all the segments in the industry. The first principal component is set equal to zero if data required to calculate it are missing. The missing principal component flag is equal to one if the first principal component was missing. Panel B reports summary statistics for macroeconomic variables. Spread is the commercial and industrial loan rate spread above the Federal funds rate as of December t=0. The S&P 500 2-year return is the 2-year compounded annual return on the S&P 500 for the period ending at t=0.

Panel A: Supplier industry variables

	Rel. years	Mean	Median	Std. dev.	Min.	Max.
Sales growth	8,983	0.269	0.035	1.343	-0.936	10.360
Deregulation dummy	9,127	0.005	0.000	0.068	0.000	1.000
Import market share	9,127	1.316	0.134	5.478	0.000	51.999
Missing imports flag	9,127	0.218	0.000	0.413	0.000	1.000
Advertising to sales	9,127	0.022	0.010	0.038	0.000	0.226
First principal component	9,127	-0.014	-0.177	0.857	-0.865	21.029
Missing principal components flag	9,127	0.044	0.000	0.206	0.000	1.000

Panel B: Macroeconomic variables

	Rel. years	Mean	Median	Std. dev.	Min.	Max.
Spread	27	2.017	2.000	0.607	0.297	4.173
S&P 2-year return	27	0.233	0.189	0.235	-0.334	0.659

Table 16: Multivariate regressions explaining changes in supplier concentration from t=0 to t=+3

This table reports regression results explaining changes in supplier concentration over the period from t=0 to t=+3. To be included in this regression the relationship pair must have change in HHI data available for the period t=0 to t=+3 for the suppliers and for the period t=-3 to t=0 for the top customers. Supplier $HHI_{t=0}$ is the supplier industry HHI at t=0. Supplier industry sales is the net inflation adjusted sales volume for the supplier industry as of t=0. Supplier sales growth is the change in inflation adjusted total industry sales from t=-2 to t=0. The deregulation dummy is equal to one if the supplier industry experienced deregulation in t = 0 or -1. Import market share is the customs value (in dollars) of products imported into the US with the same IO code as the supplier industry divided by the supplier industry's total sales at t = 0, where import data are missing for a particular industry this variable is set to zero. Missing imports flag is a dummy variable equal to one if the import data are missing for a particular industry. Advertising to sales is the industry median advertising to sales ratio at t=0. The first principal component is first principal component of the absolute value of the two year change (from t=-2 to t=0) of the following supplier ratios: asset turnover (total sales/assets), earning power (operating income/assets), profit margin (operating income/sales), and capital expenditures (capital expenditures/assets). The first principal component is set equal to zero if data required to calculate it are missing. The missing principal component flag is equal to one if the first principal component was missing. Spread is the commercial and industrial loan rate spread above the Federal funds rate as of December t=0. The S&P 500 2-year return is the 2-year compounded annual return on the S&P 500 for the period ending at t=0. Reported p-values are based on White standard errors clustered by supplier industry. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Coefficient	p-value
Top customer HHI change, $(HHI_{t=0}/HHI_{t=-3})$ -1	0.035**	[0.039]
Supplier $HHI_{t=0}$	-0.000***	[0.000]
Supplier industry sales	-0.767***	[0.000]
Supplier sales growth	0.000	[0.928]
Deregulation dummy	-0.075	[0.279]
Import market share	0.002**	[0.029]
Missing imports flag	-0.051***	[0.001]
Advertising to sales	-0.231*	[0.089]
First principal component	0.015***	[0.004]
Missing principal component flag	0.018	[0.386]
Spread	-0.025***	[0.007]
S&P 2-year return	0.033	[0.145]
Constant	0.379***	[0.000]
Observations	8,983	
Adjusted R-squared	0.083	
F-statistic	36.58	

Table 17: Multivariate regressions explaining changes in supplier concentration

This table presents the results of multivariate regressions where the dependent variable is the change in supplier industry HHI over the indicated time window and the independent variable of interest is the change in top customer industry HHI over the indicated time window. The coefficients on the change in top customer industry HHI over the indicated time windows are reported along with their p-values in brackets and the number of relationship years included in the particular regression specification in italics. Additional control variables as identified in Table 16 are also included in each specification but results for these additional variables are not reported to conserve space. Reported p-values are based on White standard errors clustered by supplier industry. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Supplier		
Top customer	$(HHI_{t=+3}/HHI_{t=0})$-1	$(HHI_{t=+2}/HHI_{t=0})$-1	$(HHI_{t=+1}/HHI_{t=0})$-1
$(HHI_{t=0}/HHI_{t=-3})$-1	0.035**	0.026**	0.014**
	[0.039]	[0.024]	[0.025]
	8,983	9,385	9,811
$(HHI_{t=0}/HHI_{t=-2})$-1	0.027	0.028*	0.012
	[0.135]	[0.052]	[0.149]
	9,380	9,784	10,212
$(HHI_{t=0}/HHI_{t=-1})$-1	0.044*	0.034*	0.010
	[0.052]	[0.070]	[0.488]
	9,368	9,772	10,200
$(HHI_{t=+1}/HHI_{t=0})$-1	0.042*	0.022	0.005
	[0.061]	[0.245]	[0.721]
	9,348	9,752	10,180
$(HHI_{t=+2}/HHI_{t=0})$-1	0.042**	0.028*	
	[0.029]	[0.062]	
	9,340	9,744	
$(HHI_{t=+3}/HHI_{t=0})$-1	0.036**		
	[0.029]		
	9,324		

Table 18: Multivariate regressions explaining changes in supplier concentration using changes in top customer concentration when top customers are assigned randomly

This table presents the results of multivariate regressions where the dependent variable is the change in supplier industry HHI over the indicated time window and the independent variable of interest is the change in top customer industry HHI over the indicated time window. The change in top customer HHI is for a randomly assigned top customer industry. For each time window considered, we construct 1,000 samples where the customer industries are assigned randomly (with replacement) to the supplier industries. The reported coefficients are the average coefficients obtained from the 1,000 regressions run on these samples. The frequency that the coefficient on the change in random top customer HHI is significant at the 5% level in the 1,000 individual regressions is reported in the second row. * denotes that the observed frequency of significant coefficients on the random top customer change in HHI is significantly greater than 0.05 at the 5% level using a one sided binomial test. Additional control variables as identified in Table 16 are also included in each specification but results for these additional variables are not reported to conserve space.

	Supplier		
Top customer	$(HHI_{t=+3}/HHI_{t=0})$-1	$(HHI_{t=+2}/HHI_{t=0})$-1	$(HHI_{t=+1}/HHI_{t=0})$-1
$(HHI_{t=0}/HHI_{t=-3})$-1	0.004	0.005	0.003
Frequency significant at 5% level	0.050	0.076*	0.087*
$(HHI_{t=0}/HHI_{t=-2})$-1	0.006	0.006	0.004
Frequency significant at 5% level	0.057	0.067*	0.072*
$(HHI_{t=0}/HHI_{t=-1})$-1	0.008	0.007	0.004
Frequency significant at 5% level	0.074*	0.075*	0.048
$(HHI_{t=+1}/HHI_{t=0})$-1	0.009	0.007	0.004
Frequency significant at 5% level	0.077*	0.074*	0.046
$(HHI_{t=+2}/HHI_{t=0})$-1	0.010	0.007	
Frequency significant at 5% level	0.092*	0.079*	
$(HHI_{t=+3}/HHI_{t=0})$-1	0.011		
Frequency significant at 5% level	0.094*		

Table 19: Multivariate regressions explaining changes in supplier concentration when top customer industries consolidate

This table presents the results of multivariate regressions where the dependent variable is the change in supplier industry HHI over the indicated time window and the independent variables are: the change in top customer industry HHI over the indicated time window; a term interacting the change in top customer HHI and a dummy variable that is equal to one if the change in top customer HHI is positive; and the additional control variables identified in Table 16. The change in top customer HHI coefficient is presented in the top row, the coefficient on the interaction term is in the second row, and the third row presents the p-value, in brackets, from an *F* test that the sum of the coefficients on the change in top customer HHI and the interaction term is zero. Significance of the individual coefficients as well as the significance of the results of the *F* test is indicated. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Supplier		
Top customer	$(HHI_{t=+3}/HHI_{t=0})$-1	$(HHI_{t=+2}/HHI_{t=0})$-1	$(HHI_{t=+1}/HHI_{t=0})$-1
$(HHI_{t=0}/HHI_{t=-3})$-1	0.107**	0.084**	0.061***
Interaction term	-0.095*	-0.076*	-0.061***
	[0.577]	[0.591]	[0.996]
$(HHI_{t=0}/HHI_{t=-2})$-1	0.118**	0.101***	0.047**
Interaction term	-0.122**	-0.099**	-0.047*
	[0.872]	[0.893]	[0.992]
$(HHI_{t=0}/HHI_{t=-1})$-1	0.107*	0.039	0.041
Interaction term	-0.089	-0.008	-0.045
	[0.596]	[0.226]	[0.836]
$(HHI_{t=+1}/HHI_{t=0})$-1	0.040	0.039	-0.028
Interaction term	0.003	-0.025	0.046
	[0.201]	[0.606]	[0.311]
$(HHI_{t=+2}/HHI_{t=0})$-1	0.055	0.006	
Interaction term	-0.018	0.030	
	[0.147]	[0.083*]	
$(HHI_{t=+3}/HHI_{t=0})$-1	0.051		
Interaction term	-0.019		
	[0.140]		

Table 20: Multivariate logistic regressions explaining large increases in supplier concentration

This table presents the results of multivariate logistic regressions where the dependent variable is a dummy variable that takes a value of one if the change in supplier industry HHI over the indicated time window is above the 75th percentile and a zero otherwise. The independent variable of interest is a dummy variable that takes a value of one if the change in top customer industry HHI over the indicated time window is above the 75th percentile and zero otherwise. The coefficients on the change in top customer industry HHI dummy variables over the indicated time windows are reported along with their p-values in brackets and the number of relationship years included in the particular regression specification in italics. Additional control variables as identified in Table 16 are also included in each specification but results for these additional variables are not reported to conserve space. Reported p-values are based on White standard errors clustered by supplier industry. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Supplier		
Top customer	$(HHI_{t=+3}/HHI_{t=0})$-1	$(HHI_{t=+2}/HHI_{t=0})$-1	$(HHI_{t=+1}/HHI_{t=0})$-1
$(HHI_{t=0}/HHI_{t=-3})$-1	-0.036	-0.006	0.054
	[0.632]	[0.926]	[0.358]
	8,983	9,385	9,811
$(HHI_{t=0}/HHI_{t=-2})$-1	-0.017	0.061	0.103*
	[0.797]	[0.357]	[0.065]
	9,380	9,784	10,212
$(HHI_{t=0}/HHI_{t=-1})$-1	0.044	0.070	0.023
	[0.479]	[0.234]	[0.678]
	9,368	9,772	10,200
$(HHI_{t=+1}/HHI_{t=0})$-1	0.090	0.042	0.095*
	[0.138]	[0.464]	[0.080]
	9,348	9,752	10,180
$(HHI_{t=+2}/HHI_{t=0})$-1	0.133**	0.062	
	[0.049]	[0.310]	
	9,340	9,744	
$(HHI_{t=+3}/HHI_{t=0})$-1	0.131*		
	[0.059]		
	9,324		

Table 21: Customer-top supplier sample descriptive statistics

The statistics below are reported by customer – top supplier relationship year. The Herfindahl-Hirschman Index (HHI) is calculated as the sum of the squares of each segment's sales as a proportion of the industry's total sales. Thus, for industry i in year t, HHI is measured as $HHI_{it}= \sum_{j=1}^{N_{it}}\left(\left(SALES_{jit} \Big/ \sum_{j=1}^{N_{it}} SALES_{jit}\right)*100\right)^2$, where N_{it} is the number of segments in industry i at time t and $Sales_{jit}$ are the net sales attributable to segment j of industry i at time t. Changes in HHI are calculated as the ratio of HHI at one point in time over HHI at another point in time minus one, e.g., the one year ahead change in HHI is calculated as $(HHI_{t=+1}/HHI_{t=0})$-1. Industry sales are reported in billions of 2008 dollars. Changes in HHI and industry sales are Winsorized at the 1% and 99% level.

	Rel. years	Mean	Median	Std. dev.	Min.	Max.
Customer						
Number of segments per industry	11,744	20.056	6.000	53.662	1.000	1,200.000
Hirschman-Herfindahl Index ($HHI_{t=0}$)	11,744	4,557.6	3,804.8	3,043.6	137.9	10,000.0
3-year change HHI, ($HHI_{t=+3}/HHI_{t=0}$)-1	10,325	0.124	0.030	0.399	-0.584	1.648
2-year change HHI, ($HHI_{t=+2}/HHI_{t=0}$)-1	10,771	0.083	0.010	0.322	-0.549	1.323
1-year change HHI, ($HHI_{t=+1}/HHI_{t=0}$)-1	11,230	0.043	0.000	0.225	-0.472	0.974
Industry sales	11,744	15.714	2.785	46.872	0.004	366.422
Top supplier						
Number of segments per industry	11,744	136.020	42.000	182.188	1.000	1,200.000
Hirschman-Herfindahl Index ($HHI_{t=0}$)	11,744	1,985.9	925.2	2,369.6	137.9	10,000.0
3-year change HHI, ($HHI_{t=0}/HHI_{t=-3}$)-1	10,511	0.122	0.042	0.393	-0.510	1.589
2-year change HHI, ($HHI_{t=0}/HHI_{t=-2}$)-1	10,920	0.083	0.021	0.306	-0.471	1.264
1-year change HHI ,($HHI_{t=0}/HHI_{t=-1}$)-1	11,328	0.041	0.005	0.198	-0.370	0.848
1-year change HHI, ($HHI_{t=+1}/HHI_{t=0}$)-1	11,362	0.041	0.005	0.198	-0.370	0.848
2-year change HHI, ($HHI_{t=+2}/HHI_{t=0}$)-1	10,977	0.084	0.021	0.306	-0.469	1.264
3-year change HHI, ($HHI_{t=+3}/HHI_{t=0}$)-1	10,253	0.122	0.042	0.395	-0.510	1.589
Industry sales	11,744	157.958	46.373	223.155	0.019	856.547

Table 22: Multivariate regressions explaining changes in customer concentration

This table presents the results of multivariate regressions where the dependent variable is the change in customer industry HHI over the indicated time window and the independent variable of interest is the change in top supplier industry HHI over the indicated time window. The coefficients on the change in top supplier industry HHI over the indicated time windows are reported along with their p-values in brackets and the number of relationship years included in the particular regression specification in italics. Additional control variables identified Table 16 (with appropriate changes so they reflect customer industry characteristics) are also included in each specification but results for these additional variables are not reported to conserve space. Reported p-values are based on White standard errors clustered by customer industry. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Customer		
Top supplier	$(HHI_{t=+3}/HHI_{t=0})-1$	$(HHI_{t=+2}/HHI_{t=0})-1$	$(HHI_{t=+1}/HHI_{t=0})-1$
$(HHI_{t=0}/HHI_{t=-3})-1$	0.009	0.010	0.004
	[0.516]	[0.287]	[0.542]
	8,994	9,403	9,829
$(HHI_{t=0}/HHI_{t=-2})-1$	0.012	0.017	0.012
	[0.447]	[0.177]	[0.107]
	9,390	9,801	10,229
$(HHI_{t=0}/HHI_{t=-1})-1$	0.014	0.023	0.003
	[0.505]	[0.162]	[0.771]
	9,385	9,796	10,224
$(HHI_{t=+1}/HHI_{t=0})-1$	0.017	0.004	0.002
	[0.407]	[0.807]	[0.884]
	9,363	9,773	10,202
$(HHI_{t=+2}/HHI_{t=0})-1$	0.019	0.012	
	[0.236]	[0.316]	
	9,345	9,755	
$(HHI_{t=+3}/HHI_{t=0})-1$	0.031**		
	[0.022]		
	9,330		