

## The Spillover Effects of Changes in Industry Concentration

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This draft: December 1, 2008

### **Abstract:**

This paper examines the importance of “spillover” effects of changes in industry concentration among vertically related industries over the period 1978-2006. Specifically, we investigate the timing, magnitude, and direction of the relation between changes in industry concentration across vertically related industries. We document that changes in customer industry concentration are positively related to subsequent changes in supplier industry concentration consistent with the existence of significant spillover effects. While we find evidence that countervailing power motives explain in part the observed relation, we find robust evidence that new entry in vertically related industries is also an important determinant of the observed relation. We also document several interesting patterns in the data regarding the timing and direction of spillover effects.

*Keywords:* Industry Concentration; Countervailing Power; Merger Waves; IPO Waves;

*JEL classification:* G34, L11

We thank Jesse Ellis for helpful comments and suggestions. Any errors remain our own.

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**\*\* VERY PRELIMINARY; Please do not cite without permission. Comments welcomed.**

## 1. Introduction

Research in industrial organization and financial economics has long considered the potential for changes in concentration in one industry to prompt changes in concentration in vertically related industries, i.e., customer and supplier industries. Perhaps the most well-known and controversial conjecture that predicts such “spillover” effects of changes in concentration 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.<sup>1</sup> 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 relation between changes in industry concentration and subsequent changes in customer and/or supplier industry concentration.<sup>2</sup>

It should be noted that we might expect to observe a positive relation between changes in industry concentration and subsequent changes in customer and/or supplier industry concentration even absent “countervailing” horizontal mergers and acquisitions in the customer and supplier industries. 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

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<sup>1</sup> 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), Chitty and Snyder (1999), and Inderst and Wey (2003).

<sup>2</sup>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. 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.

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 who 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 increase in concentration for the merging firms' industry and a likely subsequent increase in concentration in the supplier firms' industry as the market shares of the winning and losing supplier firms change to reflect the outcome, i.e., an increase in market share for the winner and a decrease in market share for the loser and, all else equal, an overall increase in supplier industry concentration as measured by a Herfindahl-Hirschman Index (HHI).<sup>3</sup>

While the horizontal merger literature examines industry consolidation, theories of how entry in a particular industry might be associated with entry in vertically related industries are much less well developed. However, there are some seemingly plausible conjectures that one could make. If the presence of recent entrants is indicative of increased demand for an industry's product, then this might also indicate that supplying the inputs for manufacturing such a product has also become more attractive prompting entry in the supplier industry as well, absent significant natural or regulatory barriers.

The initial public offering (IPO) literature examines entry waves, at least in terms of entry into the population of firms with public securities outstanding.<sup>4</sup> Non-behavioral explanations for why IPO activity clusters by time and industry generally appeal to two

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<sup>3</sup> 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.

<sup>4</sup> Backfilling by Compustat often results in several years of financial data for firms prior to going 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 IPO on August 19<sup>th</sup>, 2004 and Compustat has financial data for Google starting in fiscal year 2002.

possible explanations. First, if firms prefer to issue stock when their cash flows are high and the cash flows of firms in the same industry are more highly correlated than in the general cross section of firms, then firms in the same industry will often find it optimal to issue stock in the same time period. Insofar as firms in vertically related industries have correlated cash flows, this explanation extends to customers and suppliers of an industry experiencing an IPO wave. Second, Benveniste et al. (2002) and Benveniste et al. (2003) suggest that IPO clustering by industry could be related to efforts by investment banks to minimize or share information costs. Given the likely commonalities it would therefore seem reasonable that after incurring the costs of information gathering for one industry it would be relatively less costly for investment banks to gather information on vertically related industries. Venture capitalists may face similar incentives in deciding on which nascent firms to fund resulting in vertical spillovers in early stage financing. In sum these explanations suggest that there could be proximity in entry and IPO waves across vertically related industries. This proximity naturally implies a pattern of decreased concentration in one industry being followed by decreased concentration in an upstream or downstream industry.

The countervailing power, supplier tournament, and entry stories described above all predict a positive relation between changes in industry concentration and *subsequent* changes in the concentration of supplier and customer industries. Thus, observing such a pattern in the data can generally be interpreted as evidence consistent with the existence of spillover effects of changes in concentration. Alternatively, if changes in concentration among firms in vertically related industries reflect only reactions to common shocks (but are not due to significant spillover effects), then we would generally

expect to observe a positive relation between *simultaneous* changes in concentration among vertically related industries. As we discuss further in section 2, there is clearly the possibility that both spillover and common shocks effects will be evident in the data as they are not mutually exclusive. However, observing a positive relation between changes in industry concentration and subsequent changes in the concentration of supplier and customer industries would provide the strongest possible indication of the presence of spillover effects.

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 a relative paucity of empirical research examining the validity of this notion, owing perhaps mostly to perceived data limitations. This paper examines the importance of “spillover” effects of changes in industry concentration among vertically related industries over the period 1978-2006. Specifically, we investigate the timing, magnitude, and direction of the relation between changes in industry concentration across vertically related industries.

We use the benchmark input-output (IO) tables published by the Bureau of Economic Analysis at the U.S. Department of Commerce to identify industries with significant vertical relationships. Specifically, we use the IO tables to identify the particular industry (top customer) that purchases the largest percentage of the output of another industry (supplier). We refer to this sample of relationships as the supplier-top customer sample. We also use the IO tables to identify the particular industry (top supplier) that provides the largest percentage of the inputs used by another industry (customer). We refer to this sample of relationships as the customer-top supplier sample.

In both samples, the individual observations represent customer-supplier relationship years.

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 comprised more than 10% of a firm's consolidated yearly sales. Thus, our measures of industry concentration are at the business segment level (and not the consolidated firm level).

Results from the supplier-top customer sample indicate that top customer changes in concentration are positively and significantly related to subsequent changes in the concentration of supplier industries but are not related to simultaneous changes in the concentration of supplier industries. That supplier changes in concentration occur subsequent to and in the same direction as changes in customer concentration is strongly consistent with the existence of spillover effects in changes in concentration. The observed relation between top customer changes in concentration and subsequent changes in supplier concentration persists even after controlling for those factors expected to influence suppliers' own-industry changes in concentration.

We also find that, on average, decreases in concentration (entry) in top customer industries are more strongly related to subsequent decreases in concentration (entry) in supplier industries than are increases in concentration (consolidation).<sup>5</sup> This result suggests that the spillover effects of new entry are at least as important as countervailing power or supplier tournament outcomes in explaining the observed positive relation

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<sup>5</sup> 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. 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.

between changes in concentration across vertically related industries. However, we also find evidence that particularly large increases in top customer concentration are related to large subsequent increases in supplier concentration consistent with the presence of countervailing power effects. Finally, we demonstrate that the positive relation that we observe between changes in top customer and subsequent supplier concentration does not simply reflect a secular increase in concentration over time in the industries represented in our sample and is robust to a variety of changes in sampling criteria and regression specifications.

Results from the customer-top supplier sample indicate that changes in top supplier concentration are unrelated to simultaneous and subsequent changes in customer concentration. In short, we find little systematic evidence the changes in top supplier concentration spillover to their customer industries. The differing results across the two samples are consistent with spillover effects traveling up the supply chain but not down the supply chain. This finding is consistent with several previous papers examining the effects of major corporate events on customers and suppliers which generally find evidence that only suppliers are significantly affected by these events, e.g., financial distress (Hertzel et al. (2008)), horizontal mergers (Fee and Thomas (2004)), and leveraged buyouts (Brown et al. (2008)).

This paper proceeds as follows. In section 2, we describe the empirical implications of spillover effects and discuss how our results contribute to previous research where elements of financial economics and industrial organization overlap. In section 3, we provide details of the sample construction and our methodology to identify vertically related firms. 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. Empirical implications and related literature**

### *2.1. Empirical implications of spillover effects in changes in concentration*

Table 1 describes the different outcomes we might observe in the data when analyzing the relation between changes in concentration across vertically related industries. The table also describes the particular interpretations that we place on each possible outcome. There are two dimensions upon which the outcomes vary. First, the sign of any observed relation could be positive, negative, or insignificantly different from zero. Second, the “timing” of the relation may be evident over simultaneous time windows only, subsequent time windows only, or both simultaneous and subsequent time windows. Thus, the possible timing outcomes are not entirely mutually exclusive. However, there are instances where patterns of results across the sign and time window combinations do have substantially differing implications. As we describe below, we exploit this fact to help distinguish among the possible explanations for any observed relation, i.e., reactions to common shocks and/or spillover effects.

A positive relation indicates that changes in concentration across vertically related industries move in similar directions, i.e., increased (decreased) concentration in one industry is associated with increased (decreased) concentration in customer or supplier industries. Note that, in general, a positive relation is expected in the presence of either reactions to common shocks or spillover effects. No significant relation (zero) suggests

that changes in concentration in one industry occur largely independently of changes in concentration in vertically related industries. Observing an insignificant relation 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 relation; however, such a relation would be difficult to interpret under existing economic theory.<sup>6</sup>

As indicated in Table 1, a positive relation between *only simultaneous* changes in concentration across vertically related industries would be most consistent with industries responding to common shocks.<sup>7</sup> Observing that changes in concentration in one industry are associated with *only subsequent* changes in concentration in an adjacent industry would represent the most compelling evidence in support of spillover effects.<sup>8</sup> Observing simultaneous and subsequent effects could be evidence of both reactions to common shocks and spillover effects.

The interpretations that we place on each of the possible outcomes in Table 1 are, in part, predicated on the respective vertically related industries not differing greatly in terms of the speed with which they can respond to common shocks. For instance, if the industries that we identify as top customers are on average industries that can respond

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<sup>6</sup> As described in footnote 3, there are some supplier tournament outcomes that could account for a negative relation. However, on average, a positive relation is generally expected under the supplier tournament scenario.

<sup>7</sup> 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.

<sup>8</sup> 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 subsequently prompts consolidation by the blankbook and looseleaf binder industry to countervail their customers' gains in bargaining power.

more quickly to common shocks than the industries we identify as suppliers, then we could observe changes in supplier industries' concentration occurring subsequent to changes in top customer concentration as a result of common shocks. Hence, finding a positive and subsequent relation could not reliably be interpreted as evidence of spillover effects as asserted in Table 1. Thus, we investigate several proxies for the speed of adjustment in our sample industries as detailed below. In short, we find no evidence that differences in speed of adjustment meaningfully confound the interpretations we place on the respective outcomes in Table 1.

While the primary purpose of our analysis is to determine if spillover effects are present in changes in concentration, we also make an effort at determining which of the possible channels for spillover effects appear relevant. For instance, we investigate the relation between changes in concentration when the changes are positive (consolidation) vs. negative (entry). 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 spillover effects travel primarily upstream, primarily downstream, or in both directions along the supply chain.

## *2.2. Related literature and contribution to the literature*

Our results have implications primarily for the academic literature where elements of financial economics and industrial organization overlap. For instance, there are several papers documenting that mergers and acquisitions cluster by time and industry in so called merger waves, e.g., see Gort (1969), Mitchell and Mulherin (1996), Andrade, Mitchell, and Stafford (2001), Rhodes-Kropf, Robinson, and Viswanathan (2005), and Harford (2005). Harford (2005) reports the results of news searches intended to determine the impetus of observed merger waves in 28 industries over the period 1981-2000. He finds anecdotal evidence that in several cases merger waves in an industry were prompted by prior consolidation in an upstream or downstream industry.<sup>9</sup> Bhattacharyya and Nain (2006) find that, subsequent to periods of abnormally high downstream horizontal merger activity, there is increased merger activity among supplier industries perhaps motivated by a desire to countervail the effects of the downstream mergers.

Prior research documents that IPO activity tends to cluster in time and by industry, e.g., for theoretical treatment see Persons and Warther (1997), Stoughton, Wong, and Zechner (2001), and Benninga, Helmantel, and Sarig (2005), and for

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<sup>9</sup> The perception that a change in concentration in one industry will “spillover” into other vertically related industries appears to be widely held in the business press. For instance, a recent article in the Wall Street Journal 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.” See Mike Esterl, “Apparel Firms Gird for Possible Merger Wave,” The Wall Street Journal, June 16, 2005. Anecdotes describing similar effects can be found in articles reporting on industries as disparate as steel production and telecommunications-gear manufacturing. See for example, 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, which states, “Having survived a three-year bust, 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.” 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 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.”

empirical treatment see Ritter (1984), Lowry and Schwert (2002), and Pastor and Veronesi (2005). If firms prefer to issue stock when their cash flows are high, then firms in the same industry will often find it optimal to issue stock in the same time period given significant positive correlation in the cash flows of firms in the same industry.

Alternatively, Benveniste et al. (2002) and Benveniste et al. (2003) suggest that IPO clustering by industry could be related to efforts by investment banks to share or minimize information costs. It would seem reasonable that after incurring the costs of information gathering for one industry, it would be less costly for investment banks and venture capitalists to gather information on vertically related industries given the likely commonalities. Thus, these explanations suggest that there could be proximity in entry and IPO waves across vertically related industries.

To the best of our knowledge, no previous paper has examined the spillover effects of changes in concentration in a large sample setting.<sup>10</sup> Our results complement the merger wave literature by indicating that changes in concentration in up or downstream industries are important factors in own industry changes in concentration even outside periods of extreme merger and acquisition activity. Additionally, our results suggest that the spillover effects of entry are also significant which could be used to motivate new research on this topic in the venture capital and IPO literatures.

Our results also have implications for those papers that examine the association between the level of industry concentration and important corporate finance policy choices, e.g., capital structure decisions (Kale and Shahrur (2007)), payout policy (Massa, Rehman, and Vermaelen (2007) and Grullon and Michaely (2007)), and

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<sup>10</sup> For a review of papers examining concentration and changes in concentration, see Curry and George (1983).

corporate governance (Aggrawal and Samwick (1999) and Giroud and Mueller (2007)). To the extent that these papers find that the level of concentration in an industry influences corporate decision-making, it seems reasonable to expect that changes in concentration (perhaps brought about as a spillover effect of a change in concentration in an up or downstream industry) should also play an important role in corporate decision-making. The results of this paper contribute to this literature by increasing our understanding of what factors prompt changes in industry concentration and, thus, how these factors might also be expected to impact corporate decisions through their effect on concentration.

As one example of how the results in this paper might have specific implications for prior research, consider the following. Hou and Robinson (2006) demonstrate that industry concentration is a priced factor in stock returns even when size, book-to-market, momentum, and other return determinants are considered. Specifically, they find that firms in concentrated industries earn significantly lower returns. The authors attribute the returns differences to innovation and distress risk. Namely, innovation and distress risk are conjectured to be lower in concentrated industries than in competitive industries, hence, lower returns. Our results that changes in industry concentration in one industry are associated with subsequent changes in concentration in upstream industries suggests that changes in concentration in one industry might also be associated with changes in expected stock returns for firms in vertically related industries via anticipated spillover effects.<sup>11</sup>

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<sup>11</sup> Cohen and Frazzini (2008) find evidence of a “customer momentum” effect whereby the stock returns of customer firms predict subsequent supplier firms’ returns. This suggests that supplier returns may not rapidly incorporate the relevant information in customer returns even when the vertical relationship is readily apparent to investors via required disclosures.

### 3. Sample construction and description

#### 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.<sup>12</sup> 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. See Appendix A for further details of how the make and use tables are utilized to identify the supplier top-customer relationships.

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

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<sup>12</sup> Lawson (1997) provides a detailed description of the BEA input-output tables. The BEA reports 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 both earlier and later editions of the BEA reports. Relationships identified using the 1992 tables are highly correlated with the relationships identified in prior or later 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 spillover effects of changes in concentration as the power of our tests will be reduced.

particular industry,  $k$ , (top supplier) that provides the largest percentage of the inputs used by industry  $i$ . We refer to this sample of vertical relationships as the customer-top supplier sample.<sup>13</sup> 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.<sup>14</sup>

### *3.2. Supplier-top customer sample relationships*

Table 2 reports information regarding the supplier-top customer sample relationships. While there are 427 relationships included in this sample, we list in Panel A the ten relationships where the identified top customers purchase the largest percentage of suppliers output to provide a sense of the relationships in the sample.<sup>15</sup> 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 17.2% (9.7%). Thus, our sample construction procedure seems successful in identifying firms 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 gauge the relative concentration of the output market for supplier goods,

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<sup>13</sup> When the top customer or is identified as personal consumption expenditures or government, then we use the industry with the next most significant trading relationship as the top customer.

<sup>14</sup> There are 427 relationships in the supplier-top customer sample and 432 relationships in the customer-top supplier sample. All 427 of the supplier industries in the supplier-top customer sample are also customer industries in the customer-top supplier sample. There are five industries for which we can identify top suppliers but not top customers.

<sup>15</sup> 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%.

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% (27.3%). Thus, on average, the top customer industry accounts for about as much of the suppliers' sales volume as 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 of another industry.

### *3.3. Customer-top supplier sample relationships*

Table 3 reports information regarding the customer-top supplier sample relationships. While there are 432 relationships included in this sample, we list in Panel A the ten relationships where the identified 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 12.6% (9.2%). 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.

### *3.4. Comparison of supplier-top customer and customer-top supplier samples*

Since economic theory suggests no a priori reasons to expect dramatically

differing results across our two relationship samples, we conduct the same analysis on both samples. However, Tables 2 and 3 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.<sup>16</sup> 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 often 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. This reasoning is consistent with the accounting rules regarding the required disclosures by firms of their customers and suppliers. Firms are required to report certain information about any individual customer that accounts for more than 10% of sales revenues.<sup>17</sup> 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

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<sup>16</sup> Fifty-three of the identified relationships are common to both samples.

<sup>17</sup> From 1978 to 1998, customer disclosure rules were defined in FASB 14. From 1998-present, customer disclosure rules are defined in SFAS 131.

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.

Tables 2 and 3 also reveal that for 20.1% of customer-top supplier relationship years the "wholesale trade" industry is identified as the top supplier as opposed to 5.9% 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.<sup>18</sup>

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 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

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<sup>18</sup> 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. As a robustness check, we have conducted our analysis excluding observations where wholesale trade or retail trade are identified as part of a relationship pair. The results are very similar to those reported.

supplier sample.

### *3.5. Concentration measure*

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 comprised more than 10% of a firm's consolidated yearly sales.<sup>19</sup> 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 segments to one SIC code. 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 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 SIC codes but importantly never include

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<sup>19</sup> 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 Ali et al. (2008). 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. In robustness tests described below, we investigate the potential for firms changing their public status to private, e.g., going private transactions, to explain our results.

both producers and consumers in the same code.<sup>20</sup>

As our measure of industry 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

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

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.

## 4. Results for supplier-top customer sample

### 4.1. Summary statistics

Table 4 reports descriptive statistics for concentration and changes in concentration within the supplier-top customer sample. The average supplier industry year is populated with 26.004 distinct segments and has a mean (median) HHI of 4,159.4

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<sup>20</sup> 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 that relationship is dropped. Likewise for the customer-top customer sample, if a customer industry has no assigned SIC code 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.

(3,331.0). Also, the supplier industries 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 4.1% across all relationship years. Changes in concentration over longer time windows are increasing in the number of years that elapse.

The average top customer industry year is populated with 114,268 distinct segments and has a mean (median) HHI of 1,908.8 (1,263.1). 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 2.1% across all relationship years.<sup>21</sup> Aggregate sales (in 2006 dollars) of top customer industries are larger than aggregate sales of supplier industries; however, there are generally many more segments in the customer industries relative to the supplier industries.

As discussed in Section 2, systematic differences in how quickly supplier and top customer industries can respond to common shocks has the potential to confound our interpretations of any observed relation. In particular, there is a concern that if the industries identified as top customers can, on average, respond more rapidly than the industries identified as suppliers, then a relation between changes in top customer concentration and subsequent supplier concentration could be due to common shocks rather than spillover effects. Figure 1 reports the distributions of one year changes in

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<sup>21</sup> The average annual change in the number of segments in a supplier industry when the one-year change in HHI is positive (negative) is an increase (decrease) of 0.9 (1.0) segments, i.e., approximately one new entrant (an exit of one segment). 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 an increase (decrease) of 0.09 (2.6) segments, i.e., approximately one tenth of a new entrant (an exit of nearly three segments).

HHI for supplier and top customer industries. As can be seen in the figure, the distributions of changes in HHI over the shortest time horizon we can observe are not dramatically different across the industries we identify as suppliers and top customers. If anything, supplier industries more frequently experience large annual changes in HHI than do the top customer industries which is inconsistent with top customer industries being able to respond more quickly to common shocks.

The summary statistics for changes in concentration reported in Table 4 also do not appear consistent with speed of adjustment being more rapid in top customer industries than supplier industries. For instance, when we compare the mean and median signed changes in HHI over the same time windows including the one year window, supplier industries' changes in HHI are significantly larger than the top customer industries' changes (all differences are significant at the 1% level, test statistics not reported) again suggesting that suppliers' changes are not occurring at a slower rate than those of top customers. Thus, it does not appear as if speed of adjustment differences meaningfully impact our ability to reliably interpret a positive relation between changes in top customer and subsequent supplier concentration as evidence of spillover effects.

#### *4.2. Univariate regressions explaining changes in supplier concentration*

Rather than report simple correlations between changes in supplier and top customer concentration, we report the results of univariate regressions explaining changes in supplier concentration with lagged and simultaneous changes in top customer concentration. Consistent with Petersen (2008), we cluster standard errors by supplier industry code for two main reasons. 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.<sup>22</sup> 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.

Table 5 presents the results of 12 univariate regressions where the dependent variable is the change in supplier industry HHI over the indicated time window and the independent variable is the change in top customer industry HHI over the indicated time window. The coefficients on the independent variables are reported along with their p-values in brackets and the number of relationship years included in the particular regression specification in italics. The top nine cells of the table correspond to regressions of top customer changes in concentration on subsequent changes in supplier concentration. In seven 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 no case is the change in top customer concentration significantly associated with a simultaneous change in supplier concentration. Thus, the results indicate that changes in the concentration of supplier industries generally occur

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<sup>22</sup> 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.

subsequent to changes in concentration in top customer industries consistent with the presence of significant spillover effects.

#### *4.3. Multivariate regressions explaining changes in supplier concentration*

Given that our univariate regressions do not control for other factors that might affect changes in supplier industry concentration that are independent of, but perhaps correlated with, changes in top customer industry concentration, we next turn our attention to multivariate analysis. Table 6 reports summary statistics for the independent variables that will be included in multivariate regressions explaining changes in supplier concentration over the period from  $t=0$  to  $t=+2$ , which we use as a candidate regression rather than report summary statistics for all 12 time-window permutations. To be included in this particular specification, the relationship pair must have change in HHI data available for the period  $t=0$  to  $t=+2$  for the suppliers and for the period  $t=-2$  to  $t=0$  for the top customers.

Panel A 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.<sup>23</sup> Prior research has found that both new issues (entry) and mergers (consolidation) activity follow

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<sup>23</sup> 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.

increases in stock prices. Thus, we include the 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](http://finance.yahoo.com).

Panel B reports summary statistics for factors specific to the individual supplier industries. We include a deregulation dummy variable that is set equal to one if the supplier industry experienced deregulation in  $t=0$  or  $t=-1$ . Most of the data on deregulation events are obtained from Economic Reports to the President.<sup>24</sup> 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 from the NBER-CES Manufacturing Industry Database for a particular industry this variable is set to zero.<sup>25</sup> Missing imports flag is a dummy variable equal to one if the import data are missing for a particular industry. 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 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. 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 was missing and zero otherwise. We include the first principal component in the regression rather than the individual ratios since including all of the

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<sup>24</sup> Specifically, sources include the Economic Report to the President for years 1989, 1995, 1999, 2001, 2003, and 2005, [www.consumerreports.org](http://www.consumerreports.org), [www.naturalgas.org](http://www.naturalgas.org) and Viscusi, Vernon, and Harrington (1995).

<sup>25</sup> See Feenstra, Romalis, and Schott (2002) for details.

ratios in the regression would lead to problems with multicollinearity.

Table 7 reports the results of multivariate regressions explaining changes in supplier concentration over the period from  $t=0$  to  $t=+2$ . The macroeconomic variables are introduced in column (1). 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 and not quite significant at conventional levels in this specification. The positive coefficient is consistent with recent positive stock returns being associated with greater future merger and acquisition activity and an increase in industry concentration. Most important for our purposes, the coefficient on top customer change in HHI continues to be positive and highly significant.

In column (2), we add the deregulation and import activity variables. The deregulation dummy enters the regression with a negative and significant coefficient consistent with deregulation resulting in a subsequent decrease in concentration perhaps via new entrants. The imports market share variable is not significant; however, 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 generally smaller for industries that are not part of the broad manufacturing classification, e.g., service industries. Again, the

coefficient on top customer change in HHI remains positive and significant.

In column (3), we add variables measuring prior operating performance of supplier industries. Higher sales revenues are associated with reduced supplier industry concentration as might be expected if higher revenues proxy for the presence of supernormal profits which should attract new entrants absent barriers to entry. The principal components variables are not significant in the presence of sales revenues.<sup>26</sup> In column (4), we replace the principal components variables with an individual measure of operating performance, change in asset turnover. The coefficient is negative and highly significant suggesting that increased asset productivity in the supplier industry is associated with a subsequent reduction in concentration perhaps due to entry or, alternatively, that industries consolidate in response to decreases in sales relative to assets. In sum, at least for the particular time period examined in Table 7, the observed relation between changes in top customer concentration and subsequent changes in supplier concentration appears robust to including additional variables expected to explain changes in supplier industry concentration.

Table 8 presents the results for the full set of 12 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 periods are reported along with their p-values in brackets and the number of relationship years included in the particular regression

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<sup>26</sup> In addition to the five 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. Thus, our principal component variable includes fewer ratios which may account for the lack of significance relative to Harford.

specification in italics. Additional control variables as identified in column (4) of Table 7 are also included in each specification but results for these additional variables are not reported to conserve space. The multivariate results are very similar in terms of coefficient sign, magnitude, and significance to those reported in the univariate analysis suggesting that the observed relation between top customer changes in concentration and subsequent changes in supplier concentration persists even after controlling for those factors expected to influence suppliers' own-industry changes in concentration.

#### *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 entry in one industry being associated with entry in another. To better assess the source of the positive relation, we augment the multivariate specifications of Table 8 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 (entry) vs. positive (consolidation). Table 9 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 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 (entry) and subsequent decreases in supplier concentration. The coefficients on the interaction term are generally negative but not often significant; however, when we test the hypothesis that the two coefficients sum to zero, we fail to reject this hypothesis in all cases. Thus, it appears as if the positive relation between changes in customer concentration and subsequent changes in supplier concentration is driven substantially by entry in customer industries being followed by entry in supplier industries.

There is one simultaneous window ( $t=0$  to  $t=+3$ ) where the coefficients on the change in customer HHI and the interaction term are significant. This represents some evidence of common shocks but, again, the positive relation between changes in supplier and top customer concentration is stronger for decreases in concentration than for increases in concentration.

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 over the same period. 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 75<sup>th</sup> percentile of changes in customer HHI. Additional control variables as identified in column (4) of Table 7 are also included in each specification but results for these additional variables are not reported to conserve space.

Table 10 presents the results of these regressions. There are three 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 (2006) document increased acquisition activity in supplier industries following mergers in customer industries. Our results demonstrate that the net effects of these transactions are often significant increases in concentration in adjacent industries.

#### *4.5. Robustness tests and additional results*

Our industry concentration measures are obtained from Compustat and industry segments generally have to be part of a firm with publicly traded securities to be included in Compustat. Therefore, going private transactions will, in some cases, affect our measures of industry concentration.<sup>27</sup> Note that since we observe suppliers' changes in concentration as subsequent to changes in top customer concentration, it would have to be the case that going private waves occur first in top customer industries and then later

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<sup>27</sup> While firms generally must have public equity to be in Compustat, there are some firms with only public debt that are also covered by Compustat. For example, Brown et al. (2008) document that about 51% of the total market capitalization of firms undertaking leveraged buyouts between 1980 and 2001 continued to report financial statements and file with the SEC since they had public debt outstanding.

in supplier industries to account for the positive relation that we observe. Nonetheless, we used data from Thomson Financial's Mergers and Acquisitions database to determine if any firms in an industry were involved in a going private transaction for each year of our sample. When a dummy variable that takes a value of one if any firm in the industry was involved in a going private transaction in year  $t=0$  is included in the multivariate regressions of Table 8, the coefficient on the going private variable is very small and is not significant in any case. Therefore, our results do not seem to be explained by going private activity over the sample period.

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 4 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 8. However, we investigate 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 11 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 top customer industry which should generally not 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.<sup>28</sup> 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 0.05 at the 5% level using a one-sided binomial test. Additional control variables as identified in column (4) of Table 7 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. In 3 out of 12 time windows examined, there were significantly more than 50 of the individual coefficients from each 1,000 regressions significant at the 5% level suggesting that there is a general positive relation between changes in concentration among all industries that are suppliers and customers and not necessarily among just those that are actually vertically related to one another. However, the time windows for which significantly more than 50 of the coefficients were significant are all simultaneous windows for which we find no such relation in Table 8. Most important for our purposes is that the magnitude of the coefficients in Table 11 are generally between five and fifteen times smaller than the significant coefficients reported in Table 8 where suppliers were matched with their actual top customers. Thus, there is no evidence that the positive relation in the “subsequent” windows in Table 8 is due to secular trends in changes in concentration among industries in Compustat. In other words, the observed

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<sup>28</sup> We do not constrain the resulting relationship pairs to not be actual relationships identified in the supplier-top customer sample. Thus, there are certainly some instances where actual relationship pairs are included in the analysis.

effect is due to changes in actual top customer concentration influencing changes in supplier concentration, i.e., spillover effects.

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 very similar results. Given that this period also 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 1991 and 1992 through 2006. Results for the 1978 to 1991 subperiod are largely insignificant and the results for the 1992 to 2006 subperiod are very similar to those reported. Thus, it appears that the spillover effects we document for the entire sample period were more prevalent in the latter half of the sample period.

We also rerun our tests on the subsamples where top customers purchase at least 1%, 5%, or 10% of supplier output. Results for each of these subsamples are similar to those reported. It does appear that the statistical significance of the results is slightly lower in the subsample requiring top customers to purchase a minimum of 10% of supplier output, but the number of observations drops considerably with this screen in place. We also rerun our tests on the subsamples of relationships where the supplier and top customer industries each had a minimum of five 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 again very similar to those reported. We also included

supplier industry HHI at  $t=0$  as an explanatory variable to control for the initial level of concentration in the industry as well as to perhaps 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 decline in concentration. The coefficients on the change in customer concentration are nearly identical to those reported.

## **5. Results for customer top-supplier sample**

### *5.1. Summary statistics*

Table 12 reports descriptive statistics for concentration and changes in concentration within the customer-top supplier sample. Not surprisingly, the summary statistics for customer industries are very similar to those reported for supplier industries in Table 4 since, with the exception of five industries, these are the same industries. The average top supplier industry year is populated with 154.201 distinct segments and has a mean (median) HHI of 1,811.4 (1,036.6). 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 customer industry HHI is an increase of 2.7% across all relationship years. We note that the average annual percentage change in customer industry HHI is an increase of 4.0% across all relationship years which is significantly larger (at the 1% level) than the 2.7% reported for top suppliers suggesting

top supplier industries do not systematically respond faster to common shocks than our customer industries.<sup>29</sup>

### *5.2. Univariate regressions explaining changes in customer concentration*

Table 13 presents the results of 12 univariate regressions where the dependent variable is the change in customer industry HHI over the indicated time window and the independent variable is the change in top supplier industry HHI over the indicated time window. The coefficients are all quite small and in no instances are the coefficients significant. Thus, there is little indication from the results in Table 13 of spillover effects of top supplier changes in concentration on customers.

### *5.3. Multivariate regressions explaining changes in customer concentration*

Table 14 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 column (4) of Table 7 are also included in each specification but results for these additional variables are not reported to conserve space. As in the univariate cases, there are no instances where the coefficients of interest are significant. Thus, there is little indication from the results in Tables 13 and 14 of spillover effects of top supplier changes in concentration on customers.

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<sup>29</sup> The average annual change in the number of segments in a customer industry when the one-year change in HHI is positive (negative) is an increase (decrease) of 0.9 (1.0) segments, i.e., approximately one new entrant (the exit of one 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 an increase (decrease) of 0.5 (3.6) segments, i.e., approximately one half of a new entrant (the exit of nearly four segments).

#### *5.4. Robustness tests and additional results*

While all 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 only two instances where this analysis revealed interesting results. First, we do find that, when the sample relationships are restricted to those where the top supplier provides a minimum of 10% of customer inputs, changes in top supplier concentration are positively and significantly related to subsequent changes in customer concentration in three time windows. Specifically, the change in top supplier concentration from  $t=-3$  to  $t=0$  is significantly related to the change in customer concentration from  $t=0$  to  $t=+2$  and from  $t=0$  to  $t=+3$  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  $t=+3$ .

Second, when the sample is restricted to only those relationships for which the top supplier industry and the customer industry had a minimum of five segments, changes in top supplier concentration are positively and significantly related to subsequent changes in customer concentration in five time windows. Specifically, the change in top supplier concentration from  $t=-3$  to  $t=0$  is significantly related to the change in customer concentration from  $t=0$  to  $t=+2$  and from  $t=0$  to  $t=+3$ ; 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  $t=+1$  and from  $t=0$  to  $t=+2$ ; and 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  $t=+2$ .

Taken together, the results from these two subsamples indicate the existence of spillover effects from top supplier changes in concentration to subsequent changes in customer concentration. However, the fact that results from the entire sample as well as all of the other subsamples and specifications reveal no evidence of such effects offers a strong caveat to this conclusion.

#### *5.5. 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 spillover effects traveling from customers to suppliers but there is much weaker evidence consistent with spillover effects traveling from suppliers to customers. In other words, we find evidence consistent with spillover effects of changes in buyer market power but not of changes in seller market power.

Recent empirical papers in finance have documented that some corporate actions by trading partners significantly affect suppliers but not customers. For instance, Fee and Thomas (2004) observe that horizontal mergers are significantly negatively associated with supplier abnormal returns and subsequent operating performance whereas customers of the merging firms are relatively unaffected, including those customers that appear particularly dependent on the merging firms for inputs. Similarly, Hertz et al. (2008) find contagion effects of financial distress extend to firms' suppliers but not to their customers. Perhaps in light of these results, at least two recent papers have restricted

their analysis to suppliers when customer data could have been obtained, e.g., Bhattacharya and Nain (2006) and Brown et al. (2008).

## **6. Conclusion**

This paper examines the importance of “spillover” effects of changes in industry concentration among vertically related industries over the period 1978-2006. Specifically, we investigate the timing, magnitude, and direction of the relation between changes in industry concentration across vertically related industries. We find that changes in industry concentration in top customer industries are positively associated with subsequent changes in concentration in supplier industries consistent with the existence of spillover effects in changes in concentration. Further, we find that the positive observed relation is due in part to decreases in concentration in customer industries being followed by decreases in concentration in supplier industries. In other words, entry begets entry. We also find evidence consistent with countervailing power motives as a factor in changes in concentration. Specifically, we find that large positive changes in concentration among top customer industries are followed by large positive changes in concentration among supplier industries. On balance, we find little evidence that changes in concentration in top supplier industries spillover into changes in concentration in customer industries consistent with spillover effects traveling up the supply chain but not down the supply chain. These results have implications for the literature where elements of financial economics and industrial organization overlap.

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## 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 we use these tables to match each industry with a top customer and top supplier.

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  $i$ , 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).

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

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

where  $make_{i,c}$  is the amount of industry  $i$ '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. We 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  $i$ .

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

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

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  $i$ 's output consumed by customer industry  $j$ , we define

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

$$\text{where } output_i = \sum_{c=1}^C make_{i,c} = use_i = \sum_{c=1}^C use_{c,i}.$$

We use this CUST\_percent to generate rankings for each industry. 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 becomes the top customer in the supplier-top customer relationship. Note that each supplier has only one top customer, although more than one

supplier industry can have the same top customer.

Similarly, to find top suppliers we define

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

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

We use this SUPP\_percent to 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. Note that each customer has only one top supplier, although more than one customer industry can have the same top supplier.

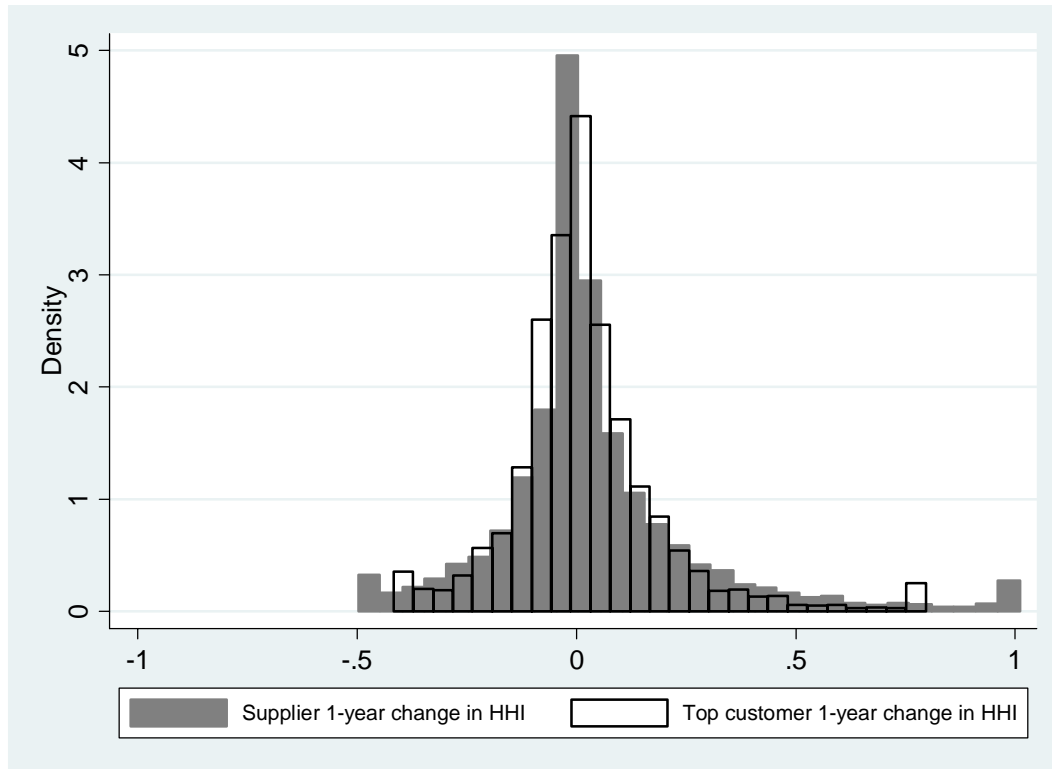
**Figure 1: Distributions of one year changes in HHI for supplier and top customer industries**

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

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

, 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  $t=+1$  to HHI at  $t=0$ , minus one, i.e., the one year change in HHI is calculated as  $(HHI_{t=+1}/HHI_{t=0})-1$ . Changes in HHI are Winsorized at the 1% and 99% level.



**Table 1: Possible relations between and timing of changes in concentration across vertically related industries and their respective likely interpretations**

This table describes the possible relations that we might observe in the data between changes in concentration across vertically related industries. The table also describes the possible time windows in which we might observe the relations. The interpretations of the various combinations of relation sign and time windows are also delineated.

Observed relation between changes in concentration of vertically related industries	Time windows in which relation between changes in concentration of vertically related industries are observed		
	Simultaneous only	Subsequent only	Simultaneous and Subsequent
Positive	Evidence consistent with common shocks <sup>1</sup>	Evidence consistent with spillover effects <sup>2,3</sup>	Evidence consistent with both common shocks and spillovers
Zero	Evidence consistent with changes in concentration being independent	Evidence consistent with changes in concentration being independent	Evidence consistent with changes in concentration being independent
Negative	Uncertain interpretation	Uncertain interpretation	Uncertain interpretation

1. We consider a common shock any economic, technological, or deregulatory event that directly affects both industries which 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.

2. 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 subsequently prompts consolidation by the blankbook and looseleaf binder industry to countervail their customers' gains in bargaining power.

3. Spillover effects are possible outcomes of mergers and acquisitions motivated by countervailing power incentives, supplier tournaments initiated when their customers engage in horizontal mergers, or entry waves. The countervailing power, supplier tournaments, and entry stories all predict a positive relation between changes in concentration in one industry and subsequent changes in concentration in another industry. However, the entry story predicts that decreased concentration in one industry will be associated with decreased concentration in another industry, the countervailing power, supplier tournament, and contagion stories predict that increased concentration in one industry will be associated with increased concentration in another industry.

**Table 2: 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 = 11,562) for which the named industry is identified as the top customer.

*Panel A: Relationship description*

Supplier description	Top customer description	Percent bought
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%
Insurance agents, brokers, and services	Insurance carriers	99.6%
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 equipment	88.0%
Fasteners, buttons, needles, and pins	Apparel made from purchased material	77.8%
Poultry and eggs	Poultry slaughtering and processing	76.9%

*Panel B: Percentage of supplier output bought by top customers*

	Relationships	Mean	Median	Standard deviation	Min.	Max.
Percent bought by top customer	427	17.2%	9.7%	20.0%	0.0%	100.0%
Percent bought by top four customers	427	34.6%	27.3%	27.9%	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
Eating and drinking places	1,134	9.8%
Motor vehicles and passenger car bodies	1,129	9.8%
Maintenance and repair of farm and nonfarm residential structures	929	8.0%
Wholesale trade	680	5.9%
Retail trade, except eating and drinking	485	4.2%
Banking	312	2.7%
Motor vehicle parts and accessories	288	2.5%
Aircraft	261	2.3%
Real estate agents, managers, operators	256	2.2%
Blast furnaces and steel mills	236	2.0%

**Table 3: 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 = 11,651) 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%
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%
Natural gas distribution	Crude petroleum and natural gas	44.6%
Poultry and eggs	Prepared feeds, n.e.c.	42.1%

*Panel B: Percentage of customer inputs supplied by top suppliers*

	Relationships	Mean	Median	Standard deviation	Min.	Max.
Percent supplied by top supplier	432	12.6%	9.2%	10.2%	1.4%	79.1%
Percent supplied by top four suppliers	432	25.8%	22.4%	13.4%	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	2,338	20.1%
Blast furnaces and steel mills	830	7.1%
Real estate agents, managers, operators	813	7.0%
Miscellaneous plastics products, n.e.c.	437	3.8%
Paper and paperboard mills	436	3.7%
Broad-woven fabric mills and fabric finish	366	3.1%
Industrial inorganic and organic chemic	360	3.1%
Other electronic components	315	2.7%
Electric services (utilities)	305	2.6%
Petroleum refining	288	2.5%

**Table 4: 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

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

, 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 2006 dollars. Changes in HHI and industry sales are Winsorized at the 1% and 99% level.

	Relationship years	Mean	Median	Standard deviation	Min.	Max.
<i>Supplier</i>						
Number of segments per industry	11,572	26.004	8.000	67.540	1.000	1,375.000
Hirschman-Herfindahl Index ( $HHI_{t=0}$ )	11,572	4,159.4	3,331.0	3,006.2	127.9	10,000.0
3-year change in HHI, $(HHI_{t=3}/HHI_{t=0})-1$	10,135	0.116	0.021	0.422	-0.614	1.824
2-year change in HHI, $(HHI_{t=2}/HHI_{t=0})-1$	10,586	0.080	0.008	0.344	-0.576	1.498
1-year change in HHI, $(HHI_{t=1}/HHI_{t=0})-1$	11,055	0.041	0.000	0.238	-0.493	1.010
Industry sales	11,572	25.984	3.795	80.898	0.004	613.276
<i>Top Customer</i>						
Number of segments per industry	11,572	114.268	48.000	150.890	1.000	1,375.000
Hirschman-Herfindahl Index ( $HHI_{t=0}$ )	11,572	1,908.8	1,263.1	2,132.0	127.9	10,000.0
3-year change in HHI, $(HHI_{t=0}/HHI_{t=3})-1$	10,310	0.059	0.011	0.317	-0.610	1.0366
2-year change in HHI, $(HHI_{t=0}/HHI_{t=2})-1$	10,727	0.040	0.009	0.256	-0.510	1.093
1-year change in HHI, $(HHI_{t=0}/HHI_{t=1})-1$	11,138	0.021	0.000	0.177	-0.410	0.826
1-year change in HHI, $(HHI_{t=1}/HHI_{t=0})-1$	11,153	0.020	0.000	0.176	-0.410	0.796
2-year change in HHI, $(HHI_{t=2}/HHI_{t=0})-1$	10,750	0.039	0.009	0.255	-0.509	1.091
3-year change in HHI, $(HHI_{t=3}/HHI_{t=0})-1$	10,076	0.058	0.011	0.318	-0.610	1.312
Industry sales	11,572	206.586	68.180	320.368	0.029	1,528.328

**Table 5: Univariate regressions explaining changes in supplier concentration**

This table presents the results of univariate regressions where the dependent variable is the change in supplier industry HHI over the indicated time window and the independent variable is the change in top customer industry HHI over the indicated time window. The coefficients on the independent variables are reported along with their p-values in brackets and the number of relationship years included in the particular regression specification in italics. 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.

Top Customer	Supplier		
	$(HHI_{t=+3}/HHI_{t=0})-1$	$(HHI_{t=+2}/HHI_{t=0})-1$	$(HHI_{t=+1}/HHI_{t=0})-1$
$(HHI_{t=0} / HHI_{t=-3})-1$	0.028 [0.155] <i>8,902</i>	0.029** [0.040] <i>9,347</i>	0.017** [0.017] <i>9,809</i>
$(HHI_{t=0}/HHI_{t=-2})-1$	0.044** [0.040] <i>9,313</i>	0.049*** [0.005] <i>9,759</i>	0.025*** [0.005] <i>10,217</i>
$(HHI_{t=0}/HHI_{t=-1})-1$	0.063*** [0.010] <i>9,716</i>	0.056*** [0.004] <i>10,158</i>	0.018 [0.148] <i>10,625</i>
$(HHI_{t=+1}/HHI_{t=0})-1$			-0.011 [0.435] <i>11,022</i>
$(HHI_{t=+2}/HHI_{t=0})-1$		-0.007 [0.644] <i>10,541</i>	
$(HHI_{t=+3}/HHI_{t=0})-1$	0.006 [0.736] <i>10,076</i>		

**Table 6: 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  $t=+2$ . To be included in this regression the relationship pair must have change in HHI data available for the period  $t=0$  to  $t=+2$  for the suppliers and for the period  $t=-2$  to  $t=0$  for the top customers. Panel A 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 B reports summary statistics for factors specific to the individual supplier industries. 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 4-digit SIC 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. 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. Supplier change in asset turnover is the change in asset turnover from  $t=-2$  to  $t=0$  and is Winsorized at the 1% and 99% level.

*Panel A: Macroeconomic variables*

	Relationship years	Mean	Median	Standard deviation	Min.	Max.
Spread	25	2.010	2.000	0.630	0.297	4.173
S&P 2-year return	25	0.240	0.189	0.243	-0.334	0.659

*Panel B: Supplier industry variables*

	Relationship years	Mean	Median	Standard deviation	Min.	Max.
Deregulation dummy	9,759	0.009	0.000	0.093	0.000	1.000
Import market share	9,759	1.042	0.620	4.776	0.000	42.530
Missing imports flag	9,759	0.304	0.000	0.460	0.000	1.000
First principal component	9,759	-0.004	0.000	0.801	-0.940	25.851
Missing principal components flag	9,759	0.267	0.000	0.442	0.000	1.000
Supplier change in asset turnover	9,550	0.090	-0.010	0.634	-0.801	4.520

**Table 7: Multivariate regressions explaining changes in supplier concentration from t=0 to t=+2**

This table reports regression results explaining changes in supplier concentration over the period from t=0 to t=+2. To be included in this regression the relationship pair must have change in HHI data available for the period t=0 to t=+2 for the suppliers and for the period t=-2 to t=0 for the top customers. Spread is the commercial and industrial loan rate spread above the Federal funds rate as of December 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 4-digit SIC 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. 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. Supplier industry sales is the net sales volume for the supplier industry as of 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. Supplier change in asset turnover is asset turnover from t=-2 to 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.

	(1)	(2)	(3)	(4)
Top customer HHI change, $(HHI_{t=0}/HHI_{t=-2}) - 1$	0.050*** [0.004]	0.051*** [0.003]	0.050*** [0.003]	0.050*** [0.004]
Spread	-0.010** [0.037]	-0.010** [0.045]	-0.009** [0.047]	-0.009* [0.052]
S&P 2-year return	0.032 [0.111]	0.031 [0.112]	0.032 [0.111]	0.035* [0.084]
Deregulation dummy		-0.083* [0.073]	-0.070 [0.134]	-0.069 [0.125]
Import market share		-0.001 [0.134]	-0.001 [0.121]	-0.001 [0.584]
Missing imports flag		-0.026*** [0.000]	-0.021*** [0.002]	-0.021*** [0.002]
Supplier industry sales			-0.146*** [0.002]	-0.152*** [0.001]
First principal component			-0.003 [0.469]	
Missing principal component flag			-0.001 [0.902]	
Supplier change in asset turnover				-0.027*** [0.000]
Constant	0.090*** [0.000]	0.099*** [0.000]	0.101*** [0.000]	0.104*** [0.000]
Observations	9,759	9,759	9,759	9,550
Adjusted R-squared	0.002	0.004	0.005	0.007
F-statistic	6.24	6.57	5.75	8.99

**Table 8: 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 column (4) of Table 7 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.

Top customer	Supplier		
	$(HHI_{t=+3}/HHI_{t=0})-1$	$(HHI_{t=+2}/HHI_{t=0})-1$	$(HHI_{t=+1}/HHI_{t=0})-1$
$(HHI_{t=0} / HHI_{t=-3})-1$	0.031 [0.115] 8,729	0.032** [0.026] 9,143	0.017** [0.018] 9,577
$(HHI_{t=0}/HHI_{t=-2})-1$	0.046** [0.037] 9,136	0.050*** [0.004] 9,550	0.025*** [0.006] 9,979
$(HHI_{t=0}/HHI_{t=-1})-1$	0.059** [0.017] 9,152	0.051*** [0.010] 9,561	0.014 [0.272] 9,996
$(HHI_{t=+1}/HHI_{t=0})-1$			-0.008 [0.596] 9,999
$(HHI_{t=+2}/HHI_{t=0})-1$		-0.006 [0.688] 9,553	
$(HHI_{t=+3}/HHI_{t=0})-1$	0.004 [0.834] 9,124		

**Table 9: 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 control variables presented in column (4) of Table 7. 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.

Top customer	Supplier		
	$(HHI_{t=+3}/HHI_{t=0})-1$	$(HHI_{t=+2}/HHI_{t=0})-1$	$(HHI_{t=+1}/HHI_{t=0})-1$
$(HHI_{t=0} / HHI_{t=-3})-1$	0.047	0.049	0.040**
Interaction term	-0.022	-0.024	-0.032
	[0.316]	[0.186]	[0.449]
$(HHI_{t=0}/HHI_{t=-2})-1$	0.080*	0.104***	0.056***
Interaction term	-0.050	-0.078	-0.045*
	[0.306]	[0.304]	[0.409]
$(HHI_{t=0}/HHI_{t=-1})-1$	0.135**	0.085**	0.032
Interaction term	-0.114	-0.051	-0.026
	[0.555]	[0.234]	[0.743]
$(HHI_{t=+1}/HHI_{t=0})-1$			0.016
Interaction term			-0.036
			[0.330]
$(HHI_{t=+2}/HHI_{t=0})-1$		0.036	
Interaction term		-0.061	
		[0.248]	
$(HHI_{t=+3}/HHI_{t=0})-1$	0.083*		
Interaction term	-0.111**		
	[0.221]		

**Table 10: 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 75<sup>th</sup> 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 75<sup>th</sup> 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 column (4) of Table 7 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.

Top customer	Supplier		
	$(HHI_{t=+3}/HHI_{t=0})-1$	$(HHI_{t=+2}/HHI_{t=0})-1$	$(HHI_{t=+1}/HHI_{t=0})-1$
$(HHI_{t=0} / HHI_{t=-3})-1$	0.085 [0.224] <i>8,729</i>	0.053 [0.390] <i>9,143</i>	0.107** [0.030] <i>9,577</i>
$(HHI_{t=0}/HHI_{t=-2})-1$	0.013 [0.842] <i>9,136</i>	0.048 [0.447] <i>9,550</i>	0.153*** [0.003] <i>9,979</i>
$(HHI_{t=0}/HHI_{t=-1})-1$	0.034 [0.525] <i>9,152</i>	0.086 [0.117] <i>9,561</i>	0.097** [0.040] <i>9,996</i>
$(HHI_{t=+1}/HHI_{t=0})-1$			0.008 [0.889] <i>9,999</i>
$(HHI_{t=+2}/HHI_{t=0})-1$		-0.081 [0.177] <i>9,553</i>	
$(HHI_{t=+3}/HHI_{t=0})-1$	0.034 [0.612] <i>9,124</i>		

**Table 11: 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 (which should generally not be the top customer industry identified from the benchmark IO tables). 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 column (4) of Table 7 are also included in each specification but results for these additional variables are not reported to conserve space.

Top customer	Supplier		
	$(HHI_{t+3}/HHI_{t=0})-1$	$(HHI_{t+2}/HHI_{t=0})-1$	$(HHI_{t+1}/HHI_{t=0})-1$
$(HHI_{t=0} / HHI_{t=-3})-1$	0.001	0.003	0.002
Frequency significant at 5% level	0.031	0.043	0.045
$(HHI_{t=0}/HHI_{t=-2})-1$	0.003	0.004	0.003
Frequency significant at 5% level	0.034	0.042	0.059
$(HHI_{t=0}/HHI_{t=-1})-1$	0.006	0.006	0.004
Frequency significant at 5% level	0.039	0.056	0.058
$(HHI_{t+1}/HHI_{t=0})-1$			0.005
Frequency significant at 5% level			0.063*
$(HHI_{t+2}/HHI_{t=0})-1$		0.008	
Frequency significant at 5% level		0.072*	
$(HHI_{t+3}/HHI_{t=0})-1$	0.011		
Frequency significant at 5% level	0.087*		

**Table 12: 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

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

, 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 2006 dollars. Changes in HHI and industry sales are winsorized at the 1% and 99% level.

	Relationship years	Mean	Median	Standard deviation	Min.	Max.
<i>Customer</i>						
Number of segments per industry	11,662	25.985	8.000	67.293	1.000	1,375.000
Hirschman-Herfindahl Index ( $HHI_{t=0}$ )	11,662	4,156.2	3,326.6	3,013.9	127.9	10,000.0
3-year change in HHI, $(HHI_{t=+3}/HHI_{t=0})-1$	10,212	0.116	0.020	0.422	-0.614	1.824
2-year change in HHI, $(HHI_{t=+2}/HHI_{t=0})-1$	10,667	0.079	0.007	0.344	-0.575	1.497
1-year change in HHI, $(HHI_{t=+1}/HHI_{t=0})-1$	11,139	0.040	0.000	0.238	-0.493	1.008
Industry sales	11,662	25.717	3.782	80.360	0.004	612.633
<i>Top supplier</i>						
Number of segments per industry	11,662	154.201	61.000	191.231	1.000	1,375.000
Hirschman-Herfindahl Index ( $HHI_{t=0}$ )	11,662	1,811.4	1,036.6	2,158.7	127.9	10,000.0
3-year change in HHI, $(HHI_{t=0}/HHI_{t=-3})-1$	10,379	0.083	0.015	0.408	-0.684	1.861
2-year change in HHI, $(HHI_{t=0}/HHI_{t=-2})-1$	10,803	0.055	0.013	0.321	-0.617	1.543
1-year change in HHI, $(HHI_{t=0}/HHI_{t=-1})-1$	11,225	0.027	0.000	0.216	-0.465	1.059
1-year change in HHI, $(HHI_{t=+1}/HHI_{t=0})-1$	11,237	0.028	0.000	0.217	-0.469	1.059
2-year change in HHI, $(HHI_{t=+2}/HHI_{t=0})-1$	10,822	0.056	0.013	0.321	-0.612	1.543
3-year change in HHI, $(HHI_{t=+3}/HHI_{t=0})-1$	10,143	0.083	0.015	0.409	-0.684	1.861
Industry sales	11,662	207.062	52.204	294.264	0.014	1,258.832

**Table 13: Univariate regressions explaining changes in customer concentration**

This table presents the results of univariate regressions where the dependent variable is the change in customer industry HHI over the indicated time window and the independent variable is the change in top supplier industry HHI over the indicated time window. The coefficients on the independent variables are reported along with their p-values in brackets and the number of relationship years included in the particular regression specification in italics. 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.

Top supplier	Customer		
	$(HHI_{t=+3}/HHI_{t=0})-1$	$(HHI_{t=+2}/HHI_{t=0})-1$	$(HHI_{t=+1}/HHI_{t=0})-1$
$(HHI_{t=0} / HHI_{t=-3})-1$	0.005 [0.776] <i>8,962</i>	0.005 [0.675] <i>9,409</i>	-0.001 [0.885] <i>9,871</i>
$(HHI_{t=0}/HHI_{t=-2})-1$	0.008 [0.687] <i>9,377</i>	0.006 [0.680] <i>9,826</i>	0.000 [0.962] <i>10,287</i>
$(HHI_{t=0}/HHI_{t=-1})-1$	0.006 [0.763] <i>9,789</i>	0.007 [0.669] <i>10,264</i>	-0.002 [0.871] <i>10,705</i>
$(HHI_{t=+1}/HHI_{t=0})-1$			-0.007 [0.499] <i>11,105</i>
$(HHI_{t=+2}/HHI_{t=0})-1$		-0.003 [0.808] <i>10,614</i>	
$(HHI_{t=+3}/HHI_{t=0})-1$	0.007 [0.605] <i>10,143</i>		

**Table 14: 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 as identified in column (4) of Table 7 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.

Top supplier	Customer		
	$(HHI_{t=+3}/HHI_{t=0})-1$	$(HHI_{t=+2}/HHI_{t=0})-1$	$(HHI_{t=+1}/HHI_{t=0})-1$
$(HHI_{t=0} / HHI_{t=-3})-1$	0.015 [0.386] <i>8,785</i>	0.013 [0.270] <i>9,202</i>	0.003 [0.637] <i>9,635</i>
$(HHI_{t=0}/HHI_{t=-2})-1$	0.017 [0.398] <i>9,195</i>	0.014 [0.338] <i>9,612</i>	0.004 [0.622] <i>10,042</i>
$(HHI_{t=0}/HHI_{t=-1})-1$	0.011 [0.610] <i>9,215</i>	0.009 [0.583] <i>9,628</i>	-0.001 [0.906] <i>10,063</i>
$(HHI_{t=+1}/HHI_{t=0})-1$			-0.001 [0.907] <i>10,068</i>
$(HHI_{t=+2}/HHI_{t=0})-1$		0.003 [0.824] <i>9,614</i>	
$(HHI_{t=+3}/HHI_{t=0})-1$	0.011 [0.394] <i>9,180</i>		