Vertical Competition, Systematic Risk, and Expected Returns

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Abstract
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Keywords: Vertical competition; Systematic risk; Cost of equity capital

JEL Classification: L11, L22, G11, G12

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1. Introduction

How industry organizational structure, in particular industry competition, affects firm risk and cost of capital has long intrigued academics and practitioners. Early research provides mixed evidence on the relation between industry competition and the systematic risk of a firm. For example, Sullivan (1978; 1982) documents a negative association between industry concentration and the Capital Asset Pricing (CAPM) beta. In contrast, Melicher, Rush, and Winn (1976), and Curley, Hexter, and Choi (1982) find no significant relation between them. In light of the mixed empirical evidence, Peyser (1994) develops a theoretical model and shows that the relation between CAPM beta and market power is not monotonically negative. It instead depends on many other factors, such as the relative degree of price and wage uncertainty.

Recent literature has not yet arrived at a consensus either. Hou and Robinson (2006) show that firms in concentrated industries are less risky, because the barriers to entry insulate them from undiversifiable distress risk or because they engage in less innovation, and they therefore earn lower expected returns. However, Ali, Klasa, and Yeung (2009) suggest that the results are sensitive to the inclusion of private firms in measuring industry competition. Using a census-based measure of concentration, which includes both private and public firms, they find no significant relation between industry concentration and stock returns. Bustamante and Donangelo (2017) argue that industry aggregate risk serves as a barrier to entry, such that risker industries become more concentrated. They predict and find an overall positive association between expected returns and industry concentration.

Given the mixed and even contradictory evidence, it is unclear whether and how industry organizational structure affects firms' systematic risk and expected returns (or cost of equity capital). In this study, instead of analyzing the effect of peer industry competition, we extend the

literature by examining how vertical competition affects a firm's systematic risk and cost of equity capital. More specifically, we investigate the role of competition intensity of a firm's upstream and downstream industries (i.e., vertical competition) on the determination of its systematic risk and cost of equity capital.

Prior literature has recognized the importance of vertical competition in shaping the competitive advantage and the normal level of a firm's profitability (e.g., Porter, 1979; 2008). Firm profitability is the ultimate outcome of numerous business transactions that often involve bilateral bargaining. Focal industry concentration *per se* cannot unilaterally determine the bargaining outcomes. Competition intensity of a firm's upstream and downstream industries should have a significant influence on its relative bargaining power, and in turn, its fundamental performance.[1]

We posit that vertical competitiveness not only affects the level of a firm's profitability, but also influences its risk exposures. When facing adverse economic shocks (such as an increase in commodity prices or the tax rate), firms have incentives to transfer them to customers (suppliers) via negotiating different output (input) prices and/or changing credit (payment) terms. Favorable output and input prices would help improve their profitability, while favorable credit/payment terms preserve/provide valuable financial liquidity to better combat economic adversity.[2] A pass-through of adverse economic shocks helps insulate a firm from these shocks, which therefore reduces its exposure to macroeconomic risks. A firm's ability to pass on adverse shocks along the supply chain is not only a function of their own industry competition, but is also constrained by the competition landscape of their upstream and downstream industries.[3] Other things being equal,

[1] See, for example, Sorensen (2003), UK Competition Commission (2008), Smith and Thanassoulis (2009), and Ellison and Snyder (2010).

[2] See, for example, Campello, Giambona, Graham, and Harvey (2011), Kahle and Stultz (2010), and Garcia-Appendini and Montoriol-Garriga (2013).

[3] For example, if a firm has a monopolistic supplier, the supplier can easily deny requests to lower input prices by threatening to terminate the relationship and offer assistance to its rivals. When anticipating a slowdown in iPhone demand, Apple attempts to increase its earnings by pushing its suppliers in competitive upstream industries (e.g.,

we expect that a firm with more competitive/less concentrated upstream or downstream industries would have greater ability to pass on adverse shocks through the supply chain, and therefore, have lower risk exposures.[4]

At first glance, the above pass-through argument should also apply to idiosyncratic or firm-specific shocks. However, both economic theories and empirical findings suggest that the pass-through rate of a firm-specific shock is less than an industry/market-wide shock.[5] Consider an example of cost pass-through. A single firm's ability to pass through its firm-specific adverse cost shocks to its consumers by to increasing output price is constrained by the possibility that consumers might switch to rival firms.

To empirically test the relation between vertical competition and a firm's risk exposures, we develop two sets of vertical competition measures based on the Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA Surveys, hereafter), together with industry competition measures over the sample period of 1997 to 2015. BEA Surveys provide information on the amount of goods and services traded among industries, which allows us to identify upstream and downstream industries. The first set of vertical competition measures includes two proxies computed from the U.S. Census four-firm concentration ratio. The four-firm concentration ratio is the percentage of market shares of the largest four firms in an industry. The first proxy, the supply or upstream concentration ratio (*SupCR4*), is the weighted average of the four-firm concentration

Foxconn) to cut prices. However, it appears that Apple does not ask Taiwan Semiconductor (TSMC) and Largan Precision to reduce their quotes, since there are a limited number of players that are able to procure these products (http://www.digitimes.com/news/a20160818PD200.html).

[4] In a much narrower setting, Bodnar, Dumas, and Marston (2002) develop a model of imperfect competition and show that the pass-through of the effect from exchange rate changes reduces a firm's exposure to exchange rate risk and that product substitutability affects the degree of such a pass-through. Allayannis and Ihrig (2001) document similar findings that competition intensity in both the focal and upstream industries affects a firm's exchange-rate exposure.

[5] See, for instance, Ashenfelter, Ashmore, Baker, and McKernan (1998), Gron and Swenson (2000), and OFT Report (2014).

ratios of all upstream industries. The second proxy, the customer or downstream concentration ratio (*CustCR4*), is the weighted average of the four-firm concentration ratios of all downstream industries of a firm.

The second set of measures is based on product similarity, developed by Hoberg and Phillips (2016). Hoberg and Phillips (2016) estimate the product similarity between two industry peers based on a textual analysis of the product descriptions of the two firms. We first compute the mean pairwise product similarity scores of all firms in each of the input-output (IO) industries, and then calculate the average product similarity of all upstream and all downstream industries of a firm, denoted as *SupPairSim* and *CustPairSim,* respectively.

We posit that firms with less concentrated upstream or downstream industries and those with higher upstream or downstream product similarity would have greater ability to pass through adverse economic shocks along the supply chain and therefore have lower risk exposures. Consistent with this prediction, we find that stock returns volatility tends to be lower for these firms. When we decompose stock return volatility into systematic risk (CAPM beta) and idiosyncratic risk, we find consistent evidence that CAMP beta decreases with both upstream and downstream industry competition. For example, mean beta increases from 0.962 for the quintile with the lowest upstream concentration ratio to 1.175 for the quintile with the highest upstream concentration ratio. It also increases from 1.057 for the quintile with the lowest downstream industry concentration to 1.258 for the quintile with the highest downstream industry concentration. We document similar results using product similarity to measure industry competition.

The association between upstream or downstream competition and idiosyncratic volatility is less consistent. We find that upstream industry competition appears to be negatively associated with a firm's idiosyncratic return volatility. In contrast, the relation between downstream industry

competition and idiosyncratic return volatility is either insignificant or positive, suggesting that the pass-through of firm-specific shocks is less pronounced than industry or market-wide shocks. These findings are robust to alternative measures of upstream and downstream competition, such as the fitted Herfindahl-Hirschman index (HHI) (Hoberg and Phillips, 2010), industry-level analysis, and alternative measures of systematic risk, such as the beta estimated from the four-factor model of Fama and French (1993) and Carhart (1997), the value-weighted or equal-weighted beta correcting for nonsynchronous trading using different leads and lags (Scholes and Williams, 1977; Dimson, 1979), the unlevered beta, and upside and downside systematic risks estimated following Ang, Chen, and Xing (2006).

Given the significant association between vertical competition and systematic risk, a natural question is whether vertical competition affects the expected returns of a firm (e.g., Lambert, Leuz, and Verrecchia, 2007; Lintner, 1965; Sharpe, 1964). We examine this question using two *ex-ante* proxies of expected returns.[6] The first proxy is the expected cost of equity capital computed from firm-specific monthly time-series regressions using the three-factor model of Fama and French (1993). The second proxy is the implied cost of equity capital that equates stock price to discounted future expected cash flows. Using these proxies, we find that both upstream and downstream competitions are negatively associated with the expected returns of a firm, even after controlling for measures of focal industry competition. The results suggest that investors perceive firms to be

[6] We refrain from using realized stock returns as a proxy for two reasons. First, extant literature shows that realized stock returns include not only expected returns, but also a cash flow news component and a discount rate news component (e.g., Campbell and Shiller, 1988; Vuolteenaho, 2002; Mao and Wei, 2017). Expected returns only contribute to a small fraction of the cross-sectional variation in realized stock returns (e.g., Richardson, Sloan, and You, 2012). Second, the literature fails to find a positive association between various risk measures and realized stock returns (Fama and French, 1992). In fact, prior studies have documented that both systematic risk and idiosyncratic risk are negatively associated with future stock returns (e.g., Ang, Hodrick, Xing, and Zhang, 2006; Frazzini and Pedersen, 2014).

less risky and require a lower expected return when their upstream or downstream industries are more competitive.

To directly test our prediction that upstream and downstream competitions help insulate firms from adverse economic shocks, we conduct two sets of additional analyses. In the first set of analyses, we document a significantly negative association between earnings volatility and upstream or downstream industry competition. In the second set of analyses, we investigate how upstream or downstream industry competition affects the operating performance of a firm during economic recessions when there are market-wide adverse economic shocks. We observe that while both sales and profitability decline during recessions, firms with more intense upstream or downstream industry competition exhibit smaller decreases in these fundamental performance metrics, providing more direct evidence that these firms might be able to pass through the adverse shocks along the supply chain.

Compared to focal industry peer competition, upstream or downstream industry competition is less likely to be endogenous when we examine its impact on systematic risk and expected returns of a firm (e.g., Perloff, Karp, and Golan, 2007). Nevertheless, we take advantage of a natural experiment to better establish the causal link from upstream competition to systematic risk and expected returns. Specifically, we use large tariff cuts in firms' major supplier industry from 1981 to 2005 as an exogenous shock to upstream industry competition (Frésard, 2010; Valta, 2012; Frésard and Valta, 2015), and examine its impact on risk exposures and expected returns of the firms. We document that when a firm's upstream industry competition intensifies due to a large tariff cut, there is a significant decrease in stock return volatility, CAPM beta, and expected returns of the firm. The results suggest a significant causal impact of upstream industry competition on systematic risk and expected returns of a firm.

Interestingly, we also find that a large tariff cut in the focal industry increases stock return volatility, CAPM beta, and idiosyncratic volatility of the firms, suggesting that intensified focal industry competition increases firm risk exposures. This exogenous test on the impact of focal industry competition and firm risk indicate that the mixed evidence in prior literature on the relation between industry competition and systematic risk may result from the failure to control for endogeneity bias.

We make several contributions to the literature. First, we are among the first to examine the causal link between vertical completion and risk exposures as well as expected returns of a firm. We find that upstream or downstream competition reduces a firm's risk exposures and expected returns by reducing the firm's fundamental risk, even after controlling for focal industry peer competition. We also contribute to the literature on the relation between focal industry peer competition and risk as well as expected returns. Prior literature finds mixed or even contradictory evidence on the association. The findings might be attributed to the fact that these studies did not control the interactive effects of industry peer competition and vertical competition. We contribute to this strand of literature by documenting that after controlling for vertical competition, focal industry peer concentration is positively associated with expected returns and systematic risk.

The rest of the paper is structured as follows. Section 2 describes the sample selection procedures and variable definitions. Section 3 presents the main empirical results. Section 4 provides robustness checks and additional analysis. Section 5 concludes.

2. Data, Sample, and Definition of Variables

2.1. Data and sample selection

Our primary variables of interest are a firm's upstream and downstream industry competitions. To identify the industrial supply chain structure of the US economy, we rely on the input-output (IO) *USE* tables published by the US Bureau of Economic Analysis (BEA). The tables provide information on the amount of goods and services traded among industries. The BEA reports the industry linkage at both the detail level (six-digit IO industry) and summary level (approximately two-digit IO industry). In our analysis, we rely on the detail-level data, which use finer industry classifications and therefore define a firm's industry membership more precisely.

We combine the industrial supply chain data with two datasets of industry competition to construct our measures of upstream or downstream industry competition. The first dataset of industry competition involves the four-firm concentration ratios (*CR4*) obtained from the Census of Manufactures publications provided by the U.S. Census Bureau. The second dataset involves the product similarity score developed by Hoberg and Phillips (2016).

Since product similarity data are available only after 1996, our sample period starts from year 1997. The BEA input-output tables at the detail level are updated every five years (in years 1997, 2002, and 2007).[7] Hence, we use the 1997, 2002, and 2007 IO tables to estimate our vertical competition measures for years 1997 to 2001, 2002 to 2006, and 2007 to 2015, respectively.

Industry memberships are obtained from Compustat Annual Fundamental data for single segment firms and Compustat Historical Segment data for multi-segment firms (Li, 2010). We also rely on Compustat Annual Fundamental data for financial accounting data. We then merge the data with the Center for Research in Security Prices (CRSP) and the Institutional Brokers' Estimate System (I/B/E/S) to compute the measures of capital market risk and implied cost of

[7] As of November 2017, the 2012 input-output table has not been published yet. The most recent input-output table is the 2007 version.

capital. From the overlapping sample of the above databases, we further exclude penny stocks with stock prices lower than $5 at the end of June each year to obtain our main test sample.

2.2. Measures of competition

We develop two sets of vertical competition measures. The first set of measures is computed with the U.S. census four-firm concentration ratio. The second set of measures is based on product similarity, developed by Hoberg and Phillips (2016). The details of variable definition are as follows.

2.2.1 Industry concentration

The Census of Manufactures publications, provided by the U.S. Census Bureau, report the four-firm concentration ratios (*CR4*) for most industries from 1987. We use the reports in 1997, 2002, 2007, and 2012 for the sample period of 1997-2001, 2002-2006, 2007-2011 and 2012-2015, respectively. Since these reports are based on NAICS industry codes, we map the NAICS industry code to the six-digit IO industry classification of the BEA input-output tables to obtain four-digit industry concentration ratios for each of the IO industries. Specifically, if an IO industry is mapped to an *m-digit* NAICS industry in a one-to-one manner, the IO industry concentration ratio is set as the four-firm concentration ratio of the *m*-digit NAICS industry. In case multiple NAICS industries are mapped to an IO industry, we compute the concentration ratio following an approximation approach suggested by Ali, Klasa, and Yeung (2009).[8]

[8] Specifically, we first determine the component six-digit NAICS industry of a broader six-digit IO industry that has the largest value for the sales of its top four firms. We next divide the sales of the top four firms of this six-digit NAICS industry by the total sales of all component six-digit NAICS industries within the broader six-digit NAICS industry. For instance, in 2007, IO industry 321100 (Sawmills and wood preservation) is mapped to the four-digit NAICS industry of 3211, while IO industry 33351A (Metal cutting and forming machine tool manufacturing) is mapped to the six-digit NAICS industry of 333512 and 333513. The concentration ratio of IO industry 321100 is then

2.2.2 Pairwise similarity

Hoberg and Phillips (2016) estimate pairwise similarity between two industry peers, based on a texture analysis of the product descriptions of the two firms from 1996 to 2015. We construct the pairwise similarity of an IO industry (*PairSim*) as the mean pairwise product similarity score of all firms in the industry.[9,10] For industries with only one firm, the pairwise similarity score is set to zero.

2.3. The measure of vertical competition

Following the prior literature (Lustgarten, 1975; Guth, Schwartz, and Whitcomb, 1977; Ravenscraft, 1983; Scherer and Ross, 1990; Kale and Shahrur, 2007), we use the weighted average of the competition measure of all upstream (downstream) industries to capture upstream (downstream) competitiveness. Specifically, for each firm-segment in the *i-th* industry, the supplier competition measure ($Supplier\ \ Competition_i$) is defined as follows:

$$Supplier\ \ Competition_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} Industry\ \ Competition_j \times Industry\ \ Input\ \ Coefficient_{ji}, \quad (1)$$

computed as the concentration ratio of the four-digit NSICS industry of 3211, while the concentration ratio of IO industry 33351A is computed following the approximation approach.

[9] We alternatively use a measure based on the total similarity score, which is defined as the total similarity (TotSimilarity) between a firm's text product description and its industry (Hoberg and Phillips 2016) and find similar results. We define TotSimilarity at the IO industry level as the median of each firm's total similarity score in the IO industry. To construct TotSimilarity at the IO industry level, we assign a unique IO industry code to each firm.

[10] In case that a firm has multiple segments in different IO industries, we use the IO industry code of the segment with the largest volume of sales to classify the firm into IO industries.

where $Industry\ \ Input\ \ Coefficient_{ji}$ is the ratio of the inputs that industry *i* purchases from industry *j* to the total inputs of industry *i*.[11] $Industry\ \ Competition_j$ is either the four-firm industry concentration ratio or the pairwise product similarity of industry *j*, as defined above. Similarly, for each firm in the *i-th* industry, the customer competition measure is defined as:

$$Customer\ \ Competition_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} Industry\ \ Competition_j \times\ \ Industry\ \ Percentage\ \ Sold_{ij}, \qquad (2)$$

where $Industry\ \ Percentage\ \ Sold_{ij}$ is the ratio of outputs that industry *i* sold to industry *j* to the total outputs of industry *i*.[12] $Industry\ \ Competition_j$ is either the four-firm industry concentration ratio or the pairwise product similarity of industry *j*, as defined above.

For a multi-segment firm that operates in several different industries, we measure the overall upstream or downstream competition of the firm as the sales-weighted average upstream or downstream competition of all its business segments. For vertical competition measured with the four-firm concentration ratio, a higher value of CR4 indicates lower upstream or downstream

[11] We remove scrap, used and secondhand goods, non-comparable imports and adjustment accounts, and value-added accounts from the calculation, since it is difficult to measure the degree of competitiveness of these accounts. It appears that our results are not affected materially if we include these accounts and treat them as the least competitive industry. We also aggregate the government accounts (an IO industry beginning with "S001", "S002", "S005", "S006") as one government sector, and assume that the government sector has large bargaining power over its suppliers or customers. Specifically, we set the concentration ratio of the government industry as the 99% cut-point of the sample distribution, and the similarity score as the 1% cut-point of the sample distribution.

[12] Some industries sell a considerable proportion of outputs to final users, including personal consumption, investment, inventory, imports, exports and government purchases (an IO industry code beginning with "F"). The competition of these industries is difficult to measure. In our main analysis, we assume that final users are highly competitive, i.e., they have low concentration ratio and high product homogeneity. Specifically, we set the concentration ratio (similarity score) of the final user employing the 1% (99%) cut-offs of the sample distribution. In a robustness test, we follow Guth, Schwartz, and Whitcomb (1977) and exclude industries with sales to final users exceeding 25% of total sales, and our results still hold.

competition. In contrast, a higher value of vertical competition measured with pair-wise product similarity (PairSim) indicates higher upstream or downstream competition.

3. Empirical Results

3.1. Summary statistics

Panel A of Table 1 provides summary statistics for our main variables. The average four-firm concentration ratio (CR4) is 26.6%, and the standard deviation is 16.9%, suggesting that there are substantial variations across industries. The upstream (SupCR4) and downstream concentration (CustCR4) ratios are lower than the focal industry concentration ratio because there are many intra-industry transactions, and we also exclude the self-industry concentration ratio from the computation to mitigate the impact of focal industry competition.

Panel B of Table 1 provides the correlation matrix of the key variables of interest. The results show that the concentration ratio and product similarity of both the focal and downstream industries are negatively correlated, while the concentration ratio and product similarity of the upstream industries are positively correlated. The results suggest that industry concentration and product homogeneity might capture different aspects of industry competition. The univariate evidence shows that both upstream and downstream competition measures are significantly associated with systematic risk. The correlation between upstream concentration (pairwise product similarity) and CAPM beta is 0.14 (-0.19). Similarly, the correlation between downstream concentration (pairwise product similarity) and CAPM beta is 0.14 (-0.09).

3.2. Capital market risk

We begin our analysis by examining the association between the upstream or downstream competition of a firm and its overall capital risk, proxied by total stock return volatility (*Volatility*). We compute *Volatility* as the annualized standard deviation of stock returns in a one-year window, starting from July 1st of the following year (t+1). We use the natural logarithm of stock return volatility as the dependent variable to mitigate concerns that the skewness of stock return volatility might introduce bias in statistical inference (e.g., Goyal and Santa-Clara, 2003; Xu and Malkiel, 2003). We control for a set of covariates following Pástor and Veronesi (2003), Gaspar and Massa (2006), and Dhaliwal, Judd, Serfling, and Shaikh (2016). Specifically, we include the concentration ratio of sales to major customers (*MajorCustHHI*, major customer concentration hereafter) to control for concentration risk, as documented by Dhaliwal et al. (2016).[13] Moreover, we include stock returns in the prior year (*Mom*), return on assets (*ROA*), market-to-book ratio (*MTB*), and the forecast long-term growth rate of earnings (*Ltg*) to control for past performance and growth opportunities. We also include in the ratio of long-term debt to total assets (*Leverage*) to control for indebtedness that might contribute to shareholder risk (Black, 1976), analyst forecast dispersion (*Dispersion*) to control for information uncertainty (Barry and Brown, 1985; Diether, Malloy, and Scherbina, 2002; Cen, Wei, and Yang, 2017), the logarithm of stock price (*LnPrice*)

[13] One major difference between our measure of downstream industry concentration and major customer concentration risk is that the downstream industry concentration of a firm reflects the organizational structure of upstream and downstream industries that are largely exogenous to the firm, while the major customer concentration is the outcome of the firm's endogenous choices. Even if a firm's downstream industries have many firms (i.e., low downstream concentration), the firm may still choose to deal with a small number of customers (i.e., high major customer concentration). Due to this reason, while the two measures are positively correlated, the magnitude of the correlation is not particularly high with a correlation coefficient of 0.17.

to control for the impact of microstructure noise on the estimation of volatility for low-priced stocks, and dividend-paying firms to control for the impact of learning uncertainty on volatility (Pástor and Veronesi, 2003).[14] Lastly, we control for the year fixed effects and cluster the standard errors at the firm level.

Columns (1) to (2) of Table 2 present the regression results. As predicted, we find that stock return volatility is positively associated with upstream concentration ratio (*SupCR4*) and is statistically significant at the 1% level with a *t*-statistic of 8.67. Although stock return volatility is also positively associated with downstream concentration ratio (*CustCR4*), the coefficient is statistically insignificant (*t*-statistic = 1.46). Using the product similarity-based vertical competition measures, we observe that stock returns tend to be less volatile when the degree of the product similarity of their upstream industries (*SupPairSim*) are higher, i.e., when firms in their supplier industries selling more homogenous products. While we also find that downstream product similarity (*CustPairSim*) is negatively associated with stock return volatility, the coefficient is not statistically significant. The result suggests that whether or not a firm in the customer industry which sells homogenous products does not have a significant impact on the total risk of the firm's stock.

We next decompose overall risk into systematic risk (CAPM beta) *and* idiosyncratic risk (*IdioVol*). The CAPM beta is the beta estimated from a market model estimated using the value-

[14] We also use a model specification excluding analyst earnings forecast dispersion and the forecast long-term growth rate of earnings, and estimate the model specification in a sample with and without the measure of the implied cost of capital. A benefit of this approach is that we can establish the relation between firm risk and supplier and/or customer competition for firms with and without analyst coverage. The sample size increases from 23,959 to 41,216. Results are consistent both quantitatively and qualitatively.

weighted daily market returns in the one-year window starting from July 1st in the following year, correcting for nonsynchronous trading (Scholes and Williams, 1977). Idiosyncratic risk is estimated as the natural logarithm of the annualized standard deviation of the residual from the market model. Columns (3) and (4) of Table 2 present the results from the regression of CAPM beta on vertical competition measures, as well as control variables. The results show that systematic risk is significantly associated with both upstream and downstream concentration ratios. The coefficients on *SupCR*4 and *CustCR*4 are both positive and statistically significant at the 1% level with *t*-statistics of 10.06 and 8.68, respectively. Panel B of Table 2 shows that CAPM beta increases from 0.962 for the quintile with the lowest upstream concentration ratio to 1.175 for the quintile with the highest upstream concentration ratio. The CAPM beta is 1.057 for the quintile with the lowest downstream concentration ratio, while it is 1.258 for the quintile with the highest downstream concentration ratio. We find qualitatively similar results using the upstream or downstream industry competition measures based on product similarity. Overall, the results in Columns (3) and (4) of Panel A and in Panel B suggest that firms with their suppliers or customers in more completive industries have lower systematic risk.

Columns (5) and (6) present the regression results with idiosyncratic volatility as the dependent variable. The regression results show that idiosyncratic volatility has a significantly positive association with *SupCR*4 (coefficient = 0.512; *t*-statistic = 6.51), and a significantly negative association with *SupPairSim* (coefficient = -3.346; *t*-statistic = -8.27), suggesting that upstream industry competition is negatively associated with a firm's idiosyncratic risk. In contrast, the relation between downstream industry competition and idiosyncratic return volatility is rather

mixed. The regression analysis shows that idiosyncratic volatility has a negative and insignificant association with *CustCR*4 (coefficient = -010; *t*-statistic = -2.81), and a significantly positive association with *CustPairSim* (coefficient = 0.303; *t*-statistic=3.80). Overall, we find contradictory results in Columns (4) and (5) of Panel A for idiosyncratic volatility. On one hand, firms with their suppliers in more completive industries have lower systematic risk. On the other hand, firms with their customers in more completive industries have higher systematic risk.

The result also shows a positive association between focal industry concentration (CR4) and CAPM beta, after controlling for vertical competition. The result is consistent with Bustamante and Donangelo's (2017) argument that industry aggregate risk serves as a barrier to entry, such that risker industries become more concentrated. Idiosyncratic volatility also decreases with focal industry concentration (CR4), which is consistent with prior literature, such as Gaspar and Massa (2006) and Abdoh and Varela (2017). However, the association between idiosyncratic volatility and focal industry product similarity (PairSim) is insignificant. Finally, firms with higher major customer concentration (*MajorCustHHI*) have a lower CAPM beta, but higher idiosyncratic volatility. The result suggests that having large and stable companies as major customers might help firms lower their systematic risk. However, the idiosyncratic risk of major customers may also influence the firms because of the concentrated customer base. Hence, the influence of major customer concentration on firm risk, as documented by Dhaliwal et al. (2016), is very different from the effect of vertical competition.

3.3. The cost of equity capital

Given the significant association between vertical competition and systematic risk, a natural question is whether vertical competition affects the expected returns of a firm (Lambert, Leuz and Verrecchia, 2007; Lintner, 1965; Sharpe, 1964). We test this prediction by using two *ex-ant*e proxies of expected returns. The first measure is the expected cost of capital (*ECC*) estimated following Barth, Konchitchki, and Landsman (2013), which is computed from firm-specific monthly time-series regressions using the three-factor model of Fama and French (1993).[15] We require the estimates to be positive to enter the sample. The second measure is the implied cost of capital (*ICC*), which is estimated as the discount rate that equates the stock price and discounted future expected cash flows based on four models introduced by Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). Since there is little consensus as to which model performs the best (Botosan and Plumlee, 2005; Gode and Mohanram, 2003; Guay, Kothari, and Shu, 2011), we follow the prior literature and set *ICC* as the mean of the estimates from the four models (e.g., Hail and Leuz, 2006; Li, 2010; Chen, Chen, and Wei, 2011). Appendix B provides detailed information of the estimates.

Table 3 presents the regression results of *ECC* and *ICC* on various vertical competition measures and other control variables. We include a set of covariates following Dhaliwal et al. (2016), and variables that are likely to affect firm risk, as discussed in the previous section.[16] Consistent with our predictions, we find that *ECC* has a significant and positive association with both upstream and downstream industry concentration measures (*SupCR*4 and *CustCR*4), even

[15] We also estimate the cost of equity based on the four-factor model of Fama and French (1993) and Carhart (1997). The results remain similar both qualitatively and quantitatively.

[16] In untabulated results, we also control for CAPM beta and idiosyncratic volatility and find similar results.

after controlling for the focal industry concentration, as well as other control variables.[17] The results are similar when we use vertical competition measures based on product similarity. We document a significantly negative association between *ECC* and the product similarity of both upstream and downstream industries. We observe similar results using the implied cost of capital (*ICC*) as a proxy for expected returns. Specifically, Columns (3) and (4) of Table 3 show that ICC is significantly positively associated with upstream and downstream concentration ratio, while it is significantly negatively associated with upstream and downstream similarity. However, the association between the cost of equity and focal industry concentration or product similarity is ambiguous in the presence of vertical competition measures and other control variables.

Consistent with Dhaliwal et al. (2016), we find a significantly positive association between major customer concentration and the implied cost of equity (*ICC*). Our finding that downstream concentration, after controlling for major customers concentration, increases the cost of equity capital suggests that vertical competition and major customer concentration affect the cost of equity via different channels. Indeed, downstream competition affects firm risk via systematic risk, while major customer concentration affects firm risk mainly via idiosyncratic risk.

3.4. Empirical results from pass-through of adverse economic shocks

To directly test our prediction that upstream and downstream competition help insulate firms

[17] We also use a model specification excluding analyst forecast dispersion and the forecast long-term growth rate of earnings, and estimate the model in a sample with and without the measure of the implied cost of capital (*ICC*). The sample size increases to 34,418. *ECC* is positively associated with upstream concentration ratio (coefficient = 8.22; *t*-statistic = 4.79) and downstream concentration ratio (coefficient = 3.93; *t*-statistic = 4.42), while is negatively associated with upstream similarity (coefficient = -20.56; *t*-statistic = -2.27) and downstream similarity (coefficient = -11.36; *t*-statistic = -5.56).

from adverse economic shocks, we conduct two sets of additional analyses.

First, we investigate the channel through which vertical competition affects the risk of a firm by examining the relation between upstream or downstream competition and firms' earnings volatility. If firms are able to transfer negative economic shocks to their upstream and downstream industries, their fundamental performance should be less volatile (Gaspar and Massa, 2006). We use the standard deviation of realized future earnings as a proxy for the fundamental volatility (Kothari, Laguerre, and Leone, 2002). Specifically, it is defined as the standard deviation of per-share earnings before extraordinary items and discontinued operations from year t+1 to year t+3, scaled by the stock price at the beginning of the period of year t+1.[18] We limit our sample to the sample period from 1997 to 2013 due to data requirement.

Following Kothari, Laguerre, and Leone (2002), we control for the leverage ratio (*Leverage*), asset tangibility (*Tangibility*), ROA, R&D intensity (*R&D*), and firm size (*Size*). *Tangibility* is measured as the ratio of property, plant, and equipment to total assets, while *R&D* is the ratio of R&D expenditures to sales. We also include analysts' long-term growth forecast (*Ltg*) to control for growth and investment opportunities. The results in Table 4 suggest that both the upstream and downstream concentration ratios are positively associated with future earnings volatility, and both upstream and downstream product similarity measures are negatively associated with future

[18] This requirement on the existence of earnings data in the consecutive three years is not innocuous in terms of testing our hypothesis. Firms facing higher systematic risk are likely to experience economic and financial distress, and thus might not survive in the future three years. To mitigate such a potential sample selection issue, we follow Kothari, Laguerre, and Leone (2002) and replace the missing value of the standard deviation of realized future earnings with the median value of firms that have a similar default risk. Specifically, we classify firms into deciles in each year, according to Altman's (1968) Z-score. We then assign the median earnings variability of the Z-score decile to which a firm with missing future earnings data belongs. In untabulated results, we show that our conclusions are not affected materially if we exclude non-surviving firms from the analysis.

earnings volatility. All four coefficients are statistically significant at the 1% percent level. The result indicates that the channel through which vertical competition affects the capital market risk of a firm comes from fundamental risk.

Second, we investigate how upstream or downstream industry competition affects the operating performance of a firm during economic recessions when there are market-wide adverse economic shocks. Firms with more competitive upstream or downstream industries should be able to transfer more of the shocks to their suppliers and/or customers. They therefore should be less affected by adverse economic shocks. To test this prediction, we regress firms' one-year-ahead operating performance, including sales growth, change in ROA, and change in profit margins, on an indicator capturing economic recessions, upstream and downstream competition, and their interaction terms.[19] We classify upstream or downstream competitiveness into quintiles, and define a binary variable *High SupCR*4 (*High CustCR*4) that equals one, if the firm is the quintile with the highest upstream (downstream) concentration ratio. We similarly define a binary variable *High SupPairSim* (*High CustPairSim*) that equals one, if the firm is the quintile with the highest upstream (downstream) product similarity.

Table 5 presents the results. Columns (1) and (2) report results using firms' sales growth as the dependent variable. The point estimate of *Recession* in Column (1) is -0.072 (*t*-statistic = -14.33), implying that the sales growth rate of average firms decreases by 0.072% during recession periods, corresponding to 51% of the sample average (14.2%). The interaction term of *High*

[19] The definition of a recession is based on the NBER-based Recession Indicators. Since we use one-year-ahead operating performance as the dependent variable, the binary variable, *Recession*, is set to one if the NBER-based Recession indicator in any month of the following year equals one and zero otherwise.

*SupCR*4 and *Recession* is negative and statistically significant at the 5% level (coefficient = -0.022; *t*-statistic = -2.27). The interaction term of *High CustCR*4 and *Recession* is negative and statistically significant at the 1% level (coefficient = -0.036; *t*-statistic = -3.20). The results suggest that firms with highly concentrated upstream or downstream industries experience a significantly larger decrease in sales during recession periods.

Column (2) of Table 5 reports results using vertical competition measures based on product similarity. The coefficient on *Recession* is -0.102, and the coefficient on the interaction term of *Recession* and *High SupPairSim* (*High CustPairSim*) is 0.053 (0.038) with all significant at the 1% level. The results are consistent with the prediction that firms exhibit a significantly decrease in sales during recession periods, but less so for firms with highly competitive upstream or downstream industries. The results are similar when we use the change in return on assets (ΔROA) or the change in profit margins ($\Delta Profit$) as the dependent variable. Overall, the results suggest that while both sales and profitability decrease during recession periods, firms with more intense upstream or downstream industry competition exhibit a smaller decrease in these fundamental performance metrics. The results provide more direct evidence that these firms might be passing through the adverse shocks along the supply chain.

3.4. A causality test: Empirical results from a natural experiment

Compared to focal industry competition, upstream or downstream industry competition is less likely to be endogenous when we examine their impact on systematic risk and expected returns of a firm (e.g., Perloff, Karp, and Golan, 2007). Nevertheless, we still take advantage of a natural

experiment to better establish the causal link between upstream competition and systematic risk and expected returns.

Following Frésard (2010), Valta (2012), and Frésard and Valta (2015), we use large import tariff cuts in firms' major supplier industry as an exogenous shock to upstream industry competition. Import tariffs represent a significant proportion of trade costs to enter the U.S. product market. The reduction of import tariffs facilitates the penetration of foreign rivals into domestic markets. A tariff cut in the supplier industry increases the competition of the industry, as foreign firms can compete with domestic players more equally.[20]

Our test starts with the tariff data for manufacturing industries (four-digit SIC) from 1981 to 2005, compiled by Frésard and Valta (Frésard, 2010; Valta, 2012; Frésard and Valta, 2016). The sample begins in 1981 because the I/B/E/S data required to estimate the cost of capital are incomplete before 1981. To define large tariff cuts, we require a reduction in import tariffs of the four-digit SIC industry in the year to be greater than three times the average change in import tariffs (both in absolute values) in the same industry over the whole sample period. Due to the change in the coding of imports in 1989, we neglect the change in the import tariffs in this year. We exclude large tariff cuts followed by equivalently large increases in tariffs over the subsequent two years to ensure that the large tariff cuts are non-transitory. We also exclude large tariff cuts if the ex-ante tariff rates were less than 1%, since the import restrictions in these industries were likely to be minimum ex-ante. Lastly, if an industry experience more than one large tariff cut

[20] In contrast, we do not expect the import tariff cuts to significantly stimulate exports by U.S. firms. Thus, it is less likely that a U.S. firm will significantly expand its customer base abroad following import tariff cuts in downstream industries.

during the sample period, we use the largest one as the event. We identify 62 large tariff cuts in 52 unique four-digit SIC industries over the sample period, with 1995 as the year having the largest number of events, followed by 1982 and 1986.

To identify tariff cuts in a firm's supplier industry, we rely on the 1992 IO table at the detail industry level, which splits our sample in half.[21] For the competition in the supplier industry to affect firms' risk, it is necessary for the purchase from the supplier industry to constitute a large fraction of firms' overall purchases. We thus focus only on the tariff cuts in the major supplier industry. Specifically, for each manufacturing IO industry (the first digit of an IO industry code is 2 or 3), we define its major supplier industry as the manufacturing IO industry from which the industry purchases the most. Moreover, we require the purchase from the major supplier industry to constitute at least 1% of firms' total purchases.[22] We then define an IO industry as a treatment industry that experiences a decrease in supplier industry competition if its major supplier industry experiences a large tariff cut.[23]

The test results appear in Table 6. *Supplier Cut* is a binary variable that equals one if the firm's major supplier industry has experienced a large tariff cut, as defined above, and zero otherwise. *Tariff Cut* is a binary variable that equals one if the firm's own industry has experienced a large tariff cut and zero otherwise. We control for year and firm fixed effects throughout the tests. Column (1) of Table 6 shows that total return volatility decreases significantly (coefficient = -

[21] Prior to 1997, IO industries were defined based on the 1987 SIC codes.
[22] We also use 10% as the threshold to define the major supplier industry, and our results continue to hold.
[23] In case that an IO industry is mapped to multiple SIC industries, we code it as experiencing a tariff cut if any of these SIC industries experience a large tariff cut in the year.

0.073; *t*-statistic = -2.21) after a tariff cut in the supplier industry. Columns (2) and (3) decompose total return volatility into the CAPM beta and idiosyncratic volatility. We find that the CAPM beta decreases significantly after a tariff cut in the supplier industry. Specifically, the coefficient on *Supplier Cut* is -0.305 and is statistically significant at the 1% level (*t*-statistic = -3.93). In contrast, although the correlation between *Supplier Cut* and idiosyncratic is negative (coefficient = -0.017), the coefficient is insignificant at the conventional level (*t*-statistic = -0.51). Results are consistent with our prior findings that the upstream industry competition of a firm mainly affects its systematic risk rather than idiosyncratic risk. Finally, we investigate the impact of tariff cuts in the major supply industry on the cost of equity capital, and we report the results in Columns (4) and (5) of Table 6. We document a significantly negative relation between *Supplier Cut* and the expected cost of capital (*ECC*) or the implied cost of capital (*ICC*). The coefficient on *Supplier Cut* is -3.625 (*t*-statistic = -3.33) for *ECC* and -1.047 (*t*-statistic = -1.72) for *ICC*, implying that investors require lower expected returns to hold the equity of a firm if its upstream industry becomes more competitive.[24]

4. Robustness Checks

4.1. Alternative measures of systematic risk

This section provides robustness tests using several alternative measures of systematic risk.

[24] Interestingly, we also find that the stock return volatility, CAPM beta, and idiosyncratic volatility increase following a large tariff cut in the focal industry, implying that intensified industry competition increases firm risk. This exogenous test indicates that the mixed evidence of the prior literature on the relationship between industry competition and systematic risk may result from failure to control for endogeneity bias.

The first measure is the market beta estimated with equal-weighted daily market returns (instead of value-weighted market returns). The second measure is corrected for nonsynchronous trading, following Dimson (1979). Specifically, we regress the daily stock returns on contemporaneous value-weighted market returns, together with the five leads and lags of the market return. The market beta is then computed as the sum of the beta of the contemporaneous market return and the betas of the five leads and lags of the market return. The third beta measure is based on the four-factor model of Fama and French (1993) and Carhart (1997). Systematic risk is defined as the coefficient (beta) on the value-weighted market returns. We also replicate our main findings using unlevered beta as the dependent variable. We follow Baker, Hoeyer, and Wurgler (2017) and compute the unlevered beta as the CAPM beta times one minus net market leverage.[25] Finally, we investigate upside versus downside systematic risk. Following Ang, Chen, and Xing (2006), we regress the four-factor model of Fama and French (1993) and Carhart (1997) for only observations in which excess market returns are negative, and define downside systematic risk as the beta on market returns estimated from the regression. Similarly, we define upside systematic risk as the beta on market returns estimated from the model for only observations in which excess market returns are positive

Table 7 presents the results that are all consistent with those reported in Table 2. Across all measures of beta, the upstream and downstream industry concentration ratios are positively correlated with systematic risk, with *t*-statistics ranging from 3.40 to 11.40. In contrast, measures

[25] We also compute unlevered beta as $CAPM\ beta/(1+(1-tax\ rate)\times(\frac{Debt}{Book}equity)$ and find consistent results.

of upstream and downstream product similarity are negatively correlated with systematic risk, with *t*-statistics ranging from -3.65 to -9.90. Overall, upstream and downstream competition reduces all alternative measures of systematic risk, as well as both upside and downside systematic risk.

4.2. An alternative measures industry competition: The fitted Herfindahl-Hirschman index

In this section, we replicate our main findings using an alternative measure of supplier or customer competition: the Herfindahl-Hirschman index (HHI). Since the census HHI is available only for manufacturing industries, we follow Hoberg and Phillips (2010) and estimate the fitted HHI for all industries based on the information of the census HHI and Compustat HHI.[26] The fitted HHI captures the influence of both public and private firms, and thus should better reflect the industry structure than the Compustat public firm-only HHI (Hoberg and Phillips, 2010).[27] We rank the fitted HHI into quintiles and use the ranking of the fitted HHI to calculate the upstream fitted HHI (*Sup Fitted HHI*) and downstream fitted HHI (*Cust Fitted HHI*). A larger value of *Sup Fitted HHI* (*Cust Fitted HHI*) indicates lower upstream (downstream) competition.

Regression results are tabulated in Table 8. Total stock return volatility is positively correlated with both *Sup Fitted HHI* and *Cust Fitted HHI,* and both coefficients are statistically significant at the 1% level. Moreover, both *Sup Fitted HHI* and *Cust Fitted HHI* are positively associated with CAPM beta and both coefficients (0.077 and 0.083) are statistically significant the

[26] Specifically, we collect the census HHI of manufacturing industries at the six-digit NAICS level, and regress the census HHI on the following three variables: the Compustat public firm-only HHI, the census average number of employees per firm in the industry, and the average number of employees per firm in the industry for public firms in Compustat. We next use the estimated coefficients to compute the fitted HHI for all six-digit NAICS industries.

[27] While the correlation between the Compustat HHI and the census HHI of manufacturing industries is only 19.00%, the correlation between the fitted HHI and the census HHI is 46.15%.

1% level. Finally, we find consistent results that the expected cost of capital (*ECC*) and implied cost of capital (*ICC*) are positively and significantly associated with *Sup Fitted HHI* and *Cust Fitted HHI*. Specifically, the coefficients on *Sup Fitted HHI* are 0.910 (*t*-statistic = 4.28) for *ECC* and 0.346 (*t*-statistic = 5.10) for *ICC*, while coefficients on *Cust Fitted HHI* are 0.632 (*t*-statistic = 5.19) for *ECC* and 0.188 (*t*-statistic = 6.09) for *ICC*. Overall, our results are robust to an alternative measure of product market competition measured by the Herfindahl-Hirschman index.

4.3. Industry-level analysis

We further check whether our results are robust if we conduct the analysis at the industry level. In this test, we assign only one IO industry to each firm based on its segment sales, and then aggregate our firm-year data into IO industry-year panel data. We then repeat our main analysis using the industry-year panel data. The results are presented in Table 9. We observe that the results from industry-level analysis are consistent with those from firm-level analysis. Specifically, across all measures of upstream and downstream competition, we find a significant negative relation between upstream or downstream competition and systematic risk and cost of equity capital.

4.4. Sales to final use

As discussed in the prior section, the measure of downstream industry competition might be noisy because certain industries sell a large proportion of their outputs to final users, including personal consumption, investment and inventory, imports, exports, and government purchases. It is difficult to measure the bargaining power of final users. In our main analysis, we retain such

industries by assuming that final users have little bargaining power. In this section, we provide robustness tests by excluding industries that sell a large proportion of outputs to final users. Specifically, we follow Guth, Schwartz and Whitcomb (1977) and exclude industries whose sales to final users exceed 25% of total sales. This leads to a 17% reduction in the sample size. Table 10 displays the results. Our conclusion that downstream competitiveness is negatively associated with systematic risk continues to hold after correcting the bias of the measure of downstream competition.

4.5. Tests at the primary industry level

Throughout the paper we conduct tests based on the weighted-average of the upstream or downstream competition of all segments of a firm. The benefit of this measure is its ability to reflect upstream or downstream competitiveness in different markets where the firm operates. We also check whether our results still hold, if we use only the firm's primary industry to measure vertical competition. Results in Table 11 shows that the results are similar, both qualitatively and quantitatively, using this alternative measure of vertical competition.

5. Conclusion

There have been considerable debates on whether and how industry organizational structure affects firm risk and its cost of equity capital. The existing literature provides mixed evidence on the relation between focal industry competition and firms' systematic risk, and expected returns. We revisit this research question from a different angle by examining how vertical competition

affects firms' systematic risk and expected returns.

Using vertical competition measures estimated from the concentration and product differentiation of a firm's upstream and downstream industries, we find compelling evidence that the systematic risk of a firm decreases with its upstream and downstream competition. We also find that firms with more competitive upstream or downstream industries tend to have lower earnings volatility. The fundamental performance of these firms also deteriorates less during economic recessions. Moreover, we find that the cost of equity capital of a firm decreases with its upstream or downstream competition. These results suggest that upstream and downstream competition help firms pass on adverse economic shocks to their customers or suppliers, which, in turn, reduces their non-diversifiable systematic risk. Investors also perceive these firms as being less risky and demand lower expected returns to hold the stocks. Our paper highlights the importance of the industry supply chain in determining the risk and expected returns of a firm.

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Appendix A: Definition of Variables

Variable	**Definition**
SupCR4	The average of four-firm concentration ratios of all upstream industries weighted by the amount of input purchased from each of the upstream industries.
CustCR4	The average of four-firm concentration ratios of all downstream industries weighted by the amount of output sold to each of the downstream industries.
CR4	Four-firm concentration ratio of the focal IO industry.
SupPairSim	The average of pairwise product similarity scores of all upstream industries weighted by the amount of input purchased from each of the upstream industries.
CustPairSim	The average of pairwise product similarity scores of all downstream industries weighted by the amount of output sold to each of the upstream industries.
PairSim	Pairwise product similarity of the focal IO industry. Pairwise product similarity is the average of pairwise product similarity scores of all firms in the industry.
Volatility	The annualized standard deviation of stock returns in a one-year window starting from July 1 of year t+1.
Beta	The CAPM beta estimated from a market model using the value-weighted daily market returns in a one-year window starting from July 1 of year t+1, correcting for nonsynchronous trading (Scholes and Williams, 1977).
IdioVol	The annualized standard deviation of residuals from the market model in a one-year window starting from July 1 of year t+1, correcting for nonsynchronous trading (Scholes and Williams, 1977).
ECC	The expected cost of equity capital based on the firm-specific monthly time-series regression using the Fama and French (1993) three-factor model.
ICC	The median of the implied cost of equity capital that equates the stock price at the end of June of year t+1 to discounted analysts' earnings forecast based on four prominent residual income models.
ΔRevenue	The percentage of sales growth from year t to year t+1.
ΔROA	The change of ROA from year t to year t+1. ROA is defined as the ratio of operating income before depreciation to total assets.
ΔProfit	The change of profit margins from year t to year t+1. Profit margin is defined as the ratio of sales minus cost of goods sold to sales.
EarnVol	The standard deviation of per-share earnings before extraordinary items and discontinued operations from years t+1 to t+3, scaled by the stock price at the beginning of the period of year t+1. The per-share earnings are adjusted for dividend payouts and stock splits.

Supplier Cut	A dummy variable that equals one if the firm's major supplier industry has experienced a large import tariff cut and zero otherwise.
Tariff Cut	A dummy variable that equals one if the firm's focal industry has experienced a large import tariff cut and zero otherwise.
MajorCustHHI	The Herfindahl-Hirschman index (HHI) of sales to major customers that contribute to more than 10% of the firm's total sales.
LnPrice	The natural logarithm of the stock price at the end of June.
Size	The quintile rankings of market capitalization in the IO industry. Firms are classified into quintiles, according to the market capitalization at the end of June.
MTB	The market-to-book equity ratio.
Leverage	The leverage ratio, defined as the ratio of total long-term debt to total assets.
Mom	The cumulative stock returns in the lagged-one year.
DivPayer	A dummy variable that equals one if the firm pays dividends in the year and zero otherwise.
Dispersion	The standard deviation of analyses' per share earnings forecasts for year t+1, scaled by the stock price at the end of June of year t+1.
Ltg	The census analysts' forecast long-term growth rate (%) as of June of year t+1.
ROA	The ratio of operating income before depreciation to total assets.
Tangibility	The ratio of property, plant, and equipment to total assets.
R&D	The ratio of R&D expenditures to sales.

Appendix B: The Estimation of the Implied Cost of Capital

We estimate the implied cost of equity capital based on the stock price and analysts' per-share earnings forecasts at the end of June of year *t*+1. We follow prior literature and outline different methodologies to estimate the cost of capital (Chen et al., 2011; Dhaliwal et al., 2016). We first describe the variables that are used in the following four models.

P_t: The stock price of firm's common stock at time *t*, which is measured as the stock price as of June of year *t*+1 reported by I/B/E/S.

B_t: Book value of equity at time *t*, which is derived from the most recent available financial statement on Compustat before the end of June of year *t*+1.

$FEPS_{t+i}$: Market expectation of the firm's earnings per share (EPS) in the i^{th} year after time *t*.

$FROE_{t+i}$: Market expectation of the firm's earnings to book equity ratio (ROE) in the i^{th} year after time *t*.

$POUT$: Forecast dividend payout ratio, which is the ratio of the indicated annual dividend from I/B/E/S to $FEPS_{t+1}$. Negative $FEPS_{t+1}$ is replaced by assuming a return on assets of 6% to calculate earnings. $POUT$ is winsorized to be within 0 and 1.

1. Gebhardt, Lee, and Swaminathan (2001)

$$P_t = B_t + \frac{\Sigma_{i=1}^{T-1}(FROE_{t+1} - R_{GLS}) \times B_{t+i-1}}{(1+R_{GLS})^i} + \frac{(FROE_{t+T} - R_{GLS}) \times B_{t+T-1}}{(1+R_{GLS})^{T-1} \times R_{GLS}} \quad .$$

We use analysts' forecasts on EPS to proxy for the market expectation of a firm's earnings for the next three years. We thereafter compute FROE by assuming that the future ROE declines linearly to an equilibrium level from year *t*+4 to year *T*. The equilibrium level is assumed to be the Fama and French (1997) 48 industry-median ROE in the past 10 years, where ROE is defined as the ratio of income available for common shareholders to the lagged total book value of equity. Firms with negative ROEs are retained while computing the industry ROE (Botosan and Plumlee, 2005), and the industry ROE that is less than the risk-free rate is replaced with the risk-free rate (Liu et al., 2002). The risk-free rate is the yield on 10-year Treasury bonds at the end of June in each year. The future book value of equity B_{t+i} is estimated by assuming a clean surplus, i.e., $B_{t+i} = B_{t+i-1} + EPS_{t+i} - EPS_{t+i} \times POUT$. We assume that T = 12. We

use the numerical approximation program to solve R_{GLS} such that the left- and right-hand sides of the equation are within a difference of \$0.001.

2. Claus and Thomas (2001)

$$P_t = B_t + \frac{\Sigma_{i=1}^{5} FEPS_{t+i} - R_{CT} \times B_{t+i-1}}{(1+R_{CT})^i} + \frac{(FROE_{t+5} - R_{CT} \times B_{t+4})(1+g_{lt})}{(R_{CT} - g_{lt})(1+R_{CT})^5}.$$

We use analysts' forecast on EPS to proxy for the market expectation of firms' earnings for the next three years. The market expectations of earnings in year *t*+4 and year *t*+5 are derived from $FEPS_{t+3}$ and the long-term earnings growth rate. The long-term earnings growth rate is missing, we derive it from $FEPS_{t+3}$ and $FEPS_{t+2}$. The long-term abnormal earnings growth rate (g_{lt}) is computed as the risk-free rate minus 3%. Other variables are defined above. We use the numerical approximation program to solve R_{CT} such that the left- and right-hand sides of the equation are within a difference of \$0.001.

3. Ohlson and Juettner-Nauroth (2005) and implemented by Gode and Mohanram (2003)

$$R_{OJ} = \frac{1}{2}\left(g_{lt} + \frac{FEPS_{t+1} \times POUT}{P_t}\right) + \sqrt{\frac{1}{4}\left(g_{lt} + \frac{FEPS_{t+1} \times POUT}{P_t}\right)^2 + \frac{FEPS_{t+1}}{P_t}(g_{st} - g_{lt})}.$$

We compute the average short-term growth rate (g_{st}) as the average of the growth rate implied in $FEPS_{t+1}$ and $FEPS_{t+2}$ and the analysts' forecast long-term growth rate. We require that $FEPS_{t+1} > 0$ and $FEPS_{t+2} > 0$ to implement the calculation. Other variables are defined above.

4. Easton (2004)

$$P_t = \frac{FEPS_{t+1}}{R_{MPEG}} + \frac{FEPS_{t+1}(g_{st} - R_{MPEG} \times (1 - POUT))}{R_{MPEG}^2}.$$

Variables are defined above. We require that $FEPS_{t+2} > FEPS_{t+1} > 0$ to implement the calculation. We use the numerical approximation program to solve R_{MPEG} such that the left- and right-hand sides of the equation are within a difference of \$0.001.

Table 1. Summary statistics and correlation matrix

Panel A of this table presents the means, standard deviations (Std), and the 10th, 25th, 50th, 75th, and 90th percentiles of variables. SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry, respectively. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. Volatility, CAPM beta, and IdioVol, are the total return volatility, CAPM beta, and idiosyncratic volatility, respectively, estimated from a market model. ECC (ICC) is the expected (implied) cost of equity capital based on the Fama and French three-factor model (the residual income models). Price is stock price, MV is market cap, Size is the ranking of market cap in the focal IO industry, MTB is market-to-book equity, leverage is the leverage ratio, Mom is past one-year cumulative return, DivPayer is a dummy variable that equals one if the firm pays dividends, Dispersion is the dispersion of analysts' earnings forecasts, Ltg is the long-term growth rate of forecast earnings, and ROA is returns on assets. MajorCustomer_HHI is the HH index of sales to major customers. Detailed definitions of variables are provided in Appendix A. Panel B presents the pairwise correlations between main variables. The Pearson correlations are reported below the diagonal and the Spearman correlations above the diagonal. All correlations are significant at the 10% level or better except those in *italic* marked by +.

Panel A: Summary statistics

	N	Mean	Std	P10	P25	P50	P75	P90
SupCR4	23,958	0.188	0.047	0.134	0.166	0.187	0.211	0.242
CustCR4	23,958	0.146	0.097	0.040	0.066	0.128	0.209	0.301
CR4	23,958	0.266	0.169	0.075	0.112	0.254	0.389	0.520
SupPairSim	23,958	0.035	0.010	0.024	0.029	0.034	0.039	0.045
CustPairSim	23,958	0.103	0.042	0.042	0.067	0.109	0.143	0.156
PairSim	23,958	0.043	0.021	0.023	0.031	0.040	0.050	0.069
Volatility	23,958	0.454	0.234	0.214	0.287	0.396	0.556	0.781
CAPM beta	23,958	1.109	0.613	0.384	0.687	1.048	1.453	1.904
IdioVol	23,958	0.405	0.222	0.178	0.246	0.351	0.504	0.719
ECC	23,958	5.481	2.369	2.759	3.880	5.220	6.764	8.590
ICC	23,958	15.676	10.959	3.076	7.301	13.783	21.919	30.288
LnPrice	23,958	7.249	1.639	5.279	6.079	7.093	8.252	9.469
LnMV	23,958	3.236	0.707	2.251	2.745	3.262	3.734	4.139
Size	23,958	6.962	1.697	4.821	5.717	6.833	8.082	9.340
MTB	23,958	2.261	1.615	1.036	1.262	1.732	2.612	4.084
Leverage	23,958	0.176	0.166	0.000	0.004	0.152	0.290	0.408
Mom	23,958	0.173	0.510	-0.352	-0.139	0.096	0.358	0.724
DivPayer	23,958	0.429	0.495	0.000	0.000	0.000	1.000	1.000
Dispersion	23,958	0.068	0.088	0.010	0.020	0.040	0.080	0.150
Ltg	23,958	16.631	8.837	7.500	10.750	15.000	20.000	27.500
ROA	23,958	0.148	0.081	0.062	0.097	0.139	0.191	0.251
MajorCustomer_HHI	23,958	0.049	0.113	0.000	0.000	0.000	0.043	0.156

Table 1 -continued

Panel B: Correlation matrix

		1	2	3	4	5	6	7	8	9	10
1	SupCR4		0.13	0.03	0.05	-0.09	-0.13	-0.03	0.15	-0.05	0.06
2	CustCR4	0.10		0.22	-0.06	-0.89	-0.14	-0.08	0.13	-0.11	0.04
3	CR4	0.06	0.19		-0.24	-0.19	-0.08	-0.03	0.11	-0.04	-0.08
4	SupPairSim	-0.01	-0.04	-0.18		0.07	0.10	0.07	-0.20	0.10	-0.07
5	CustPairSim	-0.08	-0.84	-0.14	0.03		0.11	0.07	-0.08	0.10	-0.06
6	PairSim	-0.08	-0.12	-0.05	0.15	0.10		-0.06	-0.11	-0.04	0.00
7	Volatility	-0.01	-0.06	-0.01	-0.04	0.06	-0.03		0.27	0.97	0.07
8	CAPM beta	0.14	0.14	0.12	-0.19	-0.09	-0.07	0.32		0.19	0.07
9	IdioVol	-0.03	-0.10	-0.03	*-0.02*$^{+}$	0.09	*-0.01*$^{+}$	0.97	0.24		0.06
10	ICC	0.06	0.06	-0.05	-0.04	-0.08	*0.01*$^{+}$	0.09	0.04	0.08	

Table 2. Vertical Competition and Firm Risk

Panel A of this table presents results from the OLS regression of firm risk measures (Volatility, CAPM beta, or IdioVol) on supplier and customer competitions. Volatility, CAPM beta, and IdioVol, are the total return volatility, CAPM beta, and idiosyncratic volatility. SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. MajorCustomer_HHI is the HH index of sales to major customers. Price is stock price, Size is the ranking of market cap in the focal IO industry, MTB is market-to-book equity, Leverage is the leverage ratio, Mom is past one-year cumulative return, DivPayer is a dummy variable that equals one if the firm pays dividends, Dispersion is the dispersion of analysts' earnings forecasts, Ltg is the long-term growth rate of forecast earnings, and ROA is returns on assets Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. Panel B presents the average of CAPM beta for quintile portfolios sorted by measures of concentration or similarity. H – L is the difference between the top and bottom quintiles, The *t*-statistics are in parentheses.

Panel A: Regression results

	Volatility		CAPM beta		IdioVol	
	(1)	(2)	(3)	(4)	(5)	(6)
SupCR4	0.647***		1.252***		0.512***	
	(0.075)		(0.124)		(0.079)	
CustCR4	0.049		0.584***		-0.101***	
	(0.034)		(0.067)		(0.036)	
CR4	-0.020		0.119***		-0.037*	
	(0.021)		(0.040)		(0.022)	
SupPairSim		-3.287***		-4.105***		-3.346***
		(0.381)		(0.619)		(0.404)
CustPairSim		-0.041		-1.246***		0.303***
		(0.075)		(0.150)		(0.080)
PairSim		-0.215		-0.754***		-0.085
		(0.158)		(0.255)		(0.173)
MajorCustHHI	0.123***	0.094***	-0.135***	-0.128***	0.183***	0.144***
	(0.024)	(0.025)	(0.045)	(0.046)	(0.026)	(0.026)
LnPrice	-0.216***	-0.218***	-0.107***	-0.113***	-0.246***	-0.248***
	(0.006)	(0.006)	(0.010)	(0.010)	(0.006)	(0.006)
Size	-0.019***	-0.018***	0.033***	0.036***	-0.030***	-0.031***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
MTB	0.033***	0.030***	0.062***	0.060***	0.033***	0.030***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)
Leverage	-0.139***	-0.119***	-0.148***	-0.133***	-0.120***	-0.097***
	(0.020)	(0.020)	(0.035)	(0.036)	(0.021)	(0.021)
Mom	0.101***	0.103***	0.201***	0.205***	0.099***	0.101***
	(0.004)	(0.004)	(0.009)	(0.009)	(0.004)	(0.004)
DivPayer	-0.160***	-0.154***	-0.132***	-0.128***	-0.182***	-0.174***
	(0.007)	(0.007)	(0.013)	(0.013)	(0.008)	(0.008)
Dispersion	0.737***	0.759***	0.940***	0.980***	0.762***	0.785***
	(0.040)	(0.040)	(0.071)	(0.072)	(0.043)	(0.042)
Ltg	0.012***	0.012***	0.013***	0.013***	0.013***	0.013***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
ROA	-0.127***	-0.117***	-0.792***	-0.799***	-0.040	-0.031
	(0.040)	(0.038)	(0.076)	(0.075)	(0.042)	(0.040)
Intercepts	-0.514***	-0.258***	0.746***	1.406***	-0.470***	-0.305***
	(0.024)	(0.022)	(0.041)	(0.041)	(0.025)	(0.024)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23,958	23,958	23,958	23,958	23,958	23,958
Adjusted R^2	0.687	0.688	0.289	0.281	0.693	0.694

Panel B: Average beta of sorted portfolios

	CAPM beta					
Rank	SupCR4	SupPairSim	CustCR4	CustPairSim	CR4	PairSim
1 (L)	0.962	1.171	1.057	1.252	1.105	1.164
2	1.122	1.151	1.160	1.170	1.026	1.223
3	1.222	1.162	1.088	0.969	1.083	1.136
4	1.130	1.117	1.099	1.146	1.132	1.038
5 (H)	1.175	0.994	1.258	1.104	1.280	1.083
H – L	0.213	-0.177	0.201	-0.148	0.174	-0.081
(*t*-stat)	(4.90)	(-6.39)	(4.30)	(-3.97)	(3.38)	(-3.07)

Table 3. Vertical Competition and the Implied Cost of Capital

This table presents results from the OLS regression of implied cost of capital (ECC or ICC) on supplier and customer competitions. ECC (ICC) is the expected (implied) cost of equity capital based on the Fama and French three-factor model (the residual income models). SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. MajorCustomer_HHI is the HH index of sales to major customers. Price is stock price, MV is market cap, MTB is market-to-book equity, Leverage is the leverage ratio, Mom is past one-year cumulative return, DivPayer is a dummy variable that equals one if the firm pays dividends, Dispersion is the dispersion of analysts' earnings forecasts, Ltg is the long-term growth rate of forecast earnings, and ROA is returns on assets. Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	ECC		ICC	
	(1)	(2)	(3)	(4)
SupCR4	6.842***		1.613***	
	(1.943)		(0.476)	
CustCR4	3.530***		0.686***	
	(0.990)		(0.235)	
CR4	-0.092		-0.250*	
	(0.562)		(0.152)	
SupPairSim		-48.547***		-12.842***
		(9.503)		(2.190)
CustPairSim		-7.488***		-1.370***
		(2.258)		(0.530)
PairSim		-3.397		-2.266**
		(4.406)		(0.993)
MajorCustHHI	0.039	-0.179	0.729***	0.640***
	(0.831)	(0.823)	(0.164)	(0.164)
LnPrice	-2.023***	-2.038***	-1.182***	-1.182***
	(0.164)	(0.164)	(0.038)	(0.038)
LnMV	0.071	0.070	-0.054***	-0.060***
	(0.072)	(0.072)	(0.016)	(0.016)
MTB	0.125	0.091	-0.471***	-0.483***
	(0.082)	(0.080)	(0.016)	(0.016)
Leverage	0.839	1.056*	1.210***	1.312***
	(0.593)	(0.599)	(0.141)	(0.140)
Mom	1.568***	1.607***	-0.749***	-0.741***
	(0.178)	(0.179)	(0.030)	(0.030)
DivPayer	-1.438***	-1.385***	0.393***	0.408***
	(0.198)	(0.199)	(0.045)	(0.045)
Dispersion	9.263***	9.468***	5.872***	5.953***
	(0.967)	(0.960)	(0.293)	(0.290)
Ltg	0.110***	0.108***	0.087***	0.087***
	(0.014)	(0.014)	(0.003)	(0.003)
ROA	-1.234	-1.248	4.909***	4.984***
	(1.301)	(1.280)	(0.277)	(0.271)
Intercepts	17.950***	22.444***	7.343***	8.381***
	(0.639)	(0.671)	(0.147)	(0.152)
Year FE	Yes	Yes	Yes	Yes
Obs.	20,298	20,298	23,958	23, 958
Adjusted R^2	0.387	0.387	0.484	0.486

Table 4. Vertical Competition and Earnings Volatility

This table presents results from the OLS regression of earnings volatility (EranVol) on supplier and customer competitions. SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. Leverage is the leverage ratio, Ltg is the long-term growth rate of forecast earnings, Tangibility is asset tangibility, ROA is returns on assets, R&D is R&D intensity, and Size is the ranking of market cap in the focal IO industry. Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Earnings volatility (EarnVol)	
	(1)	(2)
SupCR4	0.044***	
	(0.016)	
CustCR4	0.026***	
	(0.009)	
CR4	0.009*	
	(0.005)	
SupPairSim		-0.315***
		(0.090)
CustPairSim		-0.067***
		(0.019)
PairSim		0.090**
		(0.037)
Leverage	0.049***	0.047***
	(0.005)	(0.005)
Ltg	-0.000	-0.000
	(0.000)	(0.000)
Tangibility	-0.019***	-0.017***
	(0.004)	(0.004)
ROA	-0.149***	-0.157***
	(0.009)	(0.009)
R&D	-0.016	-0.019*
	(0.012)	(0.011)
Size	-0.007***	-0.007***
	(0.001)	(0.001)
Intercept	0.075***	0.104***
	(0.005)	(0.005)
Year FE	Yes	Yes
Obs.	20,800	20,800
Adjusted R^2	0.086	0.086

Table 5. Pass-through of Adverse Economic Shocks

This table presents results from the OLS regression of changes in accounting performance (ΔRevenue, ΔROA, or ΔProfit) during recession period. ΔRevenue, ΔROA, and ΔProfit are sales growth, change in ROA, and change in profit margin from year *t* to year *t*+1, respectively. Recession is a dummy variable that equals one if the following year is a recession year and zero otherwise, according to the NBER recession indicator index. SupCR4 and CustCR4 are the average concentration ratio of all upstream industries and all downstream industries. SupPairSim and CustPairSim are defined similarly and measure pairwise product similarity. High SupCR4 is a dummy variable that equals one if a firm is in the top SupCR4 quintile and zero otherwise. High CustCR4, High SupPairSim, and High CustPairSim are defined similarly. Controls are control variables, including Size, Tangibility, Ltg, ROA, MTB, MajorCustHHI, DivPayer, and R&D. Tangibility is asset tangibility and R&D is R&D intensity. Detailed definitions of other variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	ΔRevenue		ΔROA		ΔProfit	
	(1)	(2)	(3)	(4)	(5)	(6)
Recession	-0.072***	-0.102***	-0.009***	-0.015***	-0.009***	-0.019***
	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)	(0.002)
Recession × High SupCR4	-0.022**		-0.005*		-0.006**	
	(0.010)		(0.003)		(0.003)	
Recession × High CustCR4	-0.036***		-0.009***		-0.019***	
	(0.011)		(0.003)		(0.003)	
Recession × High SupPairSim		0.053***		0.009***		0.010***
		(0.011)		(0.002)		(0.003)
Recession × High CustPairSim		0.038***		0.010***		0.013***
		(0.009)		(0.002)		(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23,934	23,934	23,934	23,934	23,934	23,934
Adjusted R^2	0.154	0.156	0.020	0.019	0.021	0.019

Table 6. Tests of Causality: Evidence from Large Tariff Cuts

This table presents results from the OLS regression of firm risk (Volatility, CAPM beta, and IdioVol) and expected returns (ECC and ICC) on tariff cuts in the supplier industry. Volatility, CAPM beta, and IdioVol, are the total return volatility, CAPM beta, and idiosyncratic volatility estimated from a market model. ECC (ICC) is the expected (implied) cost of equity capital based on the Fama and French three-factor model (the residual income models). Supplier Cut is a dummy variable that equals one if the firm's major supplier industry has experienced a large tariff cut and zero otherwise. Tariff Cut is a dummy variable that equals one if the firm's own industry has experienced a large tariff cut. Controls are control variables, including MajorCustHHI, LnPrice, Size, MTB, Leverage, Mom, DivPayer, Dispersion, Ltg, and ROA Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Volatility	Beta	IdioVol	ECC	ICC
	(1)	(2)	(3)	(4)	(5)
Supplier Cut	-0.073**	-0.305***	-0.017	-3.625***	-1.047*
	(0.033)	(0.078)	(0.032)	(1.089)	(0.610)
Tariff Cut	0.054***	0.079*	0.049**	1.405*	0.054
	(0.020)	(0.041)	(0.021)	(0.803)	(0.205)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	15,184	15,184	15,184	14,049	15,184
Adj. R2	0.760	0.517	0.760	0.498	0.424

Table 7. Robustness Checks: Alternative Measures of Systematic Risk

Panel A of this table presents results from the OLS regression of alternative measures of firm systematic risk measures on supplier and customer competitions. Columns (1) and (2) estimate the market beta using the equal-weighted daily market returns correct nonsynchronous trading following Scholes and Williams (1977). Columns (3) to (4) correct beta for nonsynchronous trading following Dimson (1979). Columns (5) to (6) estimate beta based on the four-factor model of Fama and French (1993) and Carhart (1997). Columns (7) to (8) estimate the unlevered beta as the CAPM beta times one minus net market leverage. Columns (9) to (10) estimate beta based on the four-factor model of Fama and French (1993) and Carhart (1997) for observations in which excess market returns are negative. Columns (11) to (12) estimate beta based on the four-factor model of Fama and French (1993) and Carhart (1997) for observations in which excess market returns are positive. SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. Controls are control variables identical to those in Table 2. Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Equally-weighted		Five leads/lags		Four-factor model		Unlevered beta		Upside beta		Downside beta	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SupCR4	1.51***		1.50***		0.44***		0.37***		0.54***		0.90***	
	(0.133)		(0.149)		(0.079)		(0.086)		(0.102)		(0.131)	
CustCR4	0.656***		0.60***		0.31***		0.21***		0.43***		0.61***	
	(0.069)		(0.080)		(0.042)		(0.047)		(0.054)		(0.074)	
CR4	0.11***		0.11**		0.01		-0.03		0.04		0.34***	
	(0.042)		(0.047)		(0.025)		(0.026)		(0.031)		(0.045)	
SupPairSim		-4.33***		-4.79***		-1.66***		-1.37***		-1.75***		-5.85***
		(0.650)		(0.708)		(0.377)		(0.403)		(0.480)		(0.590)
CustPairSim		-1.42***		-1.31***		-0.66***		-0.45***		-0.97***		-1.30***
		(0.154)		(0.179)		(0.099)		(0.108)		(0.127)		(0.166)
PairSim		-0.94***		-1.17***		-0.01		-0.04		-0.10		-0.57**
		(0.279)		(0.326)		(0.169)		(0.192)		(0.224)		(0.283)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23,958	23,958	23,958	23,958	23,958	23,958	23,958	23,958	23,958	23,958	23,958	23,958
Adjusted R^2	0.290	0.280	0.179	0.175	0.085	0.082	0.046	0.045	0.059	0.057	0.405	0.398

Table 8. Robustness Check: Evidence form the Fitted the Herfindahl-Hirschman Index

This table presents results from the OLS regression of firm risk (Volatility, CAPM beta, and IdioVol) and expected returns (ECC and ICC) on an alternative measure of competition (i.e., the fitted Herfindahl-Hirschman index). Volatility, CAPM beta, and IdioVol, are the total return volatility, CAPM beta, and idiosyncratic volatility estimated from a market model. ECC (ICC) is the expected (implied) cost of equity capital based on the Fama and French three-factor model (the residual income models). The fitted HHI is the ranking of the fitted HHI at the IO industry level (e.g., Hoberg and Phillips, 2012). Controls are control variables identical to those in Table 2. Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Volatility	Beta	IdioVol	ECC	ICC
SUPP Fitted HHI	0.031***	0.077***	0.021***	0.910***	0.346***
	(0.007)	(0.013)	(0.008)	(0.213)	(0.051)
CUST Fitted HHI	0.016***	0.083***	-0.002	0.632***	0.188***
	(0.004)	(0.009)	(0.004)	(0.122)	(0.031)
Fitted HHI	-0.016***	-0.003	-0.017***	-0.083	0.044***
	(0.003)	(0.005)	(0.003)	(0.075)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	23,602	23,602	23,602	19,981	23,602
Adjusted R^2	0.687	0.285	0.693	0.389	0.493

Table 9. Robustness Check: Evidence at the Industry Level

This table presents results from the OLS regression of risk (Volatility, CAPM beta, and IdioVol) and expected returns (ECC and ICC) at the industry level on upstream and downstream competitions. Volatility, CAPM beta, and IdioVol, are the total return volatility, CAPM beta, and idiosyncratic volatility estimated from a market model. ECC (ICC) is the expected (implied) cost of equity capital based on the Fama and French three-factor model (the residual income models). SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. We aggregate the yearly firm-level variables into an industry-year panel and conduct the test at the industry level. Controls are control variables identical to those in Table 2. Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Volatility		Beta		IdioVol		ECC		ICC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SupCR4	0.32***		1.14***		0.11*		4.14**		1.64***	
	(0.066)		(0.126)		(0.068)		(2.024)		(0.419)	
CustCR4	0.10***		0.52***		-0.04		3.65***		0.50**	
	(0.035)		(0.068)		(0.037)		(1.075)		(0.224)	
CR4	0.03		0.02		0.06***		1.62***		0.88***	
	(0.019)		(0.037)		(0.020)		(0.590)		(0.122)	
SupPairSim		-0.59		-2.50***		-0.63		-37.16***		-18.68***
		(0.383)		(0.739)		(0.398)		(11.740)		(2.433)
CustPairSim		-0.32***		-1.33***		0.004		-8.04***		-1.20**
		(0.078)		(0.150)		(0.081)		(2.366)		(0.493)
PairSim		0.36***		0.13		0.440***		4.73		-1.47**
		(0.117)		(0.225)		(0.121)		(3.588)		(0.742)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,898	3,898	3,898	3,898	3,898	3,898	3,666	3,666	3,898	3,898
Adjusted R^2	0.753	0.753	0.387	0.379	0.762	0.762	0.569	0.569	0.558	0.558

Table 10. Robustness Check: Excluding Industries with Large Sales to Final Users

This table presents results from the OLS regression of firm risk (Volatility, CAPM beta, and IdioVol) and expected returns (ECC and ICC) on upstream and downstream competitions excluding industries with large sales to final users. Volatility, CAPM beta, and IdioVol, are the total return volatility, CAPM beta, and idiosyncratic volatility estimated from a market model. ECC (ICC) is the expected (implied) cost of equity capital based on the Fama and French three-factor model (the residual income models). SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. We aggregate the yearly firm-level variables into an industry-year panel and conduct the test at the industry level. Controls are control variables identical to those in Table 2. Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Volatility		Beta		IdioVol		ECC		ICC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SupCR4	0.581***		1.216***		0.441***		6.513***		1.330***	
	(0.077)		(0.129)		(0.082)		(2.122)		(0.495)	
CustCR4	0.068*		0.679***		-0.088**		3.242***		0.668***	
	(0.036)		(0.071)		(0.038)		(1.083)		(0.243)	
CR4	-0.011		0.146***		-0.027		0.085		-0.338**	
	(0.022)		(0.043)		(0.023)		(0.601)		(0.157)	
SupPairSim		-3.371***		-4.322***		-3.366***		-49.815***		-12.872***
		(0.386)		(0.624)		(0.410)		(10.339)		(2.254)
CustPairSim		-0.101		-1.528***		0.269***		-7.088***		-1.225**
		(0.080)		(0.162)		(0.085)		(2.486)		(0.551)
PairSim		-0.247		-0.778***		-0.127		-2.441		-2.370**
		(0.162)		(0.263)		(0.179)		(4.668)		(1.032)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	19,949	19,949	19,949	19,949	19,949	19,949	16,772	16,772	19,949	19,949
Adjusted R^2	0.669	0.670	0.291	0.283	0.679	0.681	0.384	0.385	0.491	0.493

Table 11. Robustness Checks: Primary Industry Analysis

This table presents results from the OLS regression of firm risk (Volatility, CAPM beta, and IdioVol) and expected returns (ECC and ICC) on upstream and downstream competitions measured at the firm's primary industry level. A firm's primary industry is defined as the IO industry with the largest sales. Volatility, CAPM beta, and IdioVol, are the total return volatility, CAPM beta, and idiosyncratic volatility estimated from a market model. ECC (ICC) is the expected (implied) cost of equity capital based on the Fama and French three-factor model (the residual income models). SupCR4, CustCR4, and CR4 are the average concentration ratio of all upstream industries, all downstream industries, and the focal IO industry. SupPairSim, CustPairSim, and PairSim are defined similarly and measure pairwise product similarity. Controls are control variables identical to those in Table 2. Detailed definitions of variables are provided in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. Standard errors are in parentheses and are clustered at the firm level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Volatility		Beta		IdioVol		ECC		ICC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SupCR4	0.006***		0.012***		0.005***		0.065***		0.015***	
	(0.001)		(0.001)		(0.001)		(0.018)		(0.005)	
CustCR4	0.001*		0.005***		-0.001**		0.033***		0.007***	
	(0.000)		(0.001)		(0.000)		(0.010)		(0.002)	
CR4	-0.000		0.001***		-0.000		0.001		-0.002	
	(0.000)		(0.000)		(0.000)		(0.005)		(0.001)	
SupPairSim		-3.106***		-3.871***		-3.168***		-47.087***		-12.471***
		(0.361)		(0.581)		(0.382)		(8.816)		(2.054)
CustPairSim		-0.042		-1.161***		0.278***		-7.156***		-1.356***
		(0.072)		(0.144)		(0.077)		(2.161)		(0.505)
PairSim		-0.235		-0.646***		-0.132		-3.364		-1.876**
		(0.150)		(0.244)		(0.164)		(4.210)		(0.947)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23,958	23,958	23,958	23,958	23,958	23,958	20,074	20,298	23,958	23,958
Adjusted R^2	0.688	0.688	0.290	0.281	0.693	0.694	0.385	0.387	0.487	0.486