Peer Competitive Threats, Common Customers, and Strategic News Disclosure

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ABSTRACT

We exploit the vast complex network of supplier-customer relationships to examine the strategic news disclosure behavior of a supplier facing intense competition from peers that supply to the same customers. Results show that competitive threats from customer-connected peers are strongly and positively associated with supplier stock price crash risk beyond other sources of competition, including the level of industry competitiveness, general product market competitive pressure, or threats from non-linked peers. The baseline evidence is further substantiated by three quasi-natural experiments associated with exogenous shocks arising from M&A activity of customers, peer bankruptcies, and peer location disruptions by natural disasters. We find strong cross-sectional differences in information asymmetry (as proxied by institutional ownership breadth, analyst forecast dispersion, and news coverage) on the relation between peer competitive threats and supplier crash risk. Furthermore, supplier firms facing greater peer competitive threats are more likely to receive a larger number of SEC comment letters about their mandatory filings and to produce less readable financial reports. Combined, these results are in line with the strategic information disclosure explanation.

Keywords: Peer Competitive threats, Common Customers, Crash Risk, Information Disclosure
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1. Introduction

The changing competitive environment has brought about the proliferation and significance of interconnected firms in recent years.[1] Corporations can no longer exist as independent entities, but rather are connected through a complex network of customer-supplier relationships. Such firm network structures inevitably increase complexity in information processing and make it more challenging for market participants to analyze the firms. In this study, we exploit this growing network of interconnected firms and examine whether the complicated information environment enables firm managers to make strategic disclosure decisions in the face of intense competition from peers in the same product market.[2] We focus on rival peers or competitors that are linked to the firm through common customers (hereafter customer-connected peers, rivals, or competitors). We hypothesize that supplier managers purposely conceal or delay disclosing adverse information about their firms to mitigate competitive threats from the pool of customer-connected peers. Our analysis of customer-connected peers differentiates itself from the vast literature on peer effects that focuses on firms that are in the same industry or in the same product market.[3] However, such firms may not necessarily be considered rivals of a supplier firm if they do not transact businesses with the same customers; in other words, they do not compete for the same customers. Our study will provide evidence suggesting that non-customer-connected peers from the same industry have no statistically significant effect on a supplier's disclosure behavior, thereby implying that they pose little threat to the supplier.

We argue that in a complex network of supplier-customer relationships, the strategic news disclosure behavior of a supplier is motivated by the supplier's concerns for losing competitive edge and businesses to its peers supplying to the same customers. Such concerns are driven, in part, by the extent of the switching costs faced by its customers. The switching costs are lower if the customers have access to a large pool of alternate suppliers who produce similar products as the focal supplier. The latter, in turn, faces a greater risk of losing its market share to the peers, which in an extreme case, could lead to customer-supplier relationship terminations. Thus, to avoid losing its customers, the supplier is more likely to withhold or delay disclosure of adverse information about the firm. The supplier's concerns also depend on the competitiveness of its connected peers. Peer competitive or predatory threats can take the form of lowering prices or increasing expenditure on non-price competition with the objective of forcing the supplier to exit the market. Intense peer competition, therefore, exacerbates the supplier's risks of losing market share or contractual arrangements with customers to rival peers. Since disclosures may reveal proprietary information to customer-connected peers, who might take advantage of it and prey on the disclosing supplier

[1] See the references in Lavie (2006) for the accumulated evidence of interconnected firms.

[2] See Core (2001), Healy and Palepu (2001), Verrecchia (2001), and Beyer et al. (2010) for reviews of the information disclosure literature.

[3] Substantial empirical evidence of peer effects are shown in corporate policies (e.g., Leary and Roberts, 2014), corporate precautionary cash holdings (e.g., Hoberg, Phillips, and Prabhala, 2014), corporate investment decisions (e.g., Foucault and Fresard, 2014), among others.

in the product market, the supplier likely makes strategic disclosure decisions in part to reduce competitor predation threats.[4] The supplier facing these risks is further incentivized to hoard negative information because of career concerns (Graham, Harvey, and Rajgopal, 2005; Kothari, Shu, and Wysocki, 2009), lower executive compensation, and job termination (Kim, 1999; Kothari, Shu, and Wysocki), among others.

The focus on customer-connected peers in the same product market, as defined by Hoberg and Phillips (2010, 2016), is a distinguishing feature of our study. We exploit the recently available detailed information about US customer-supplier relationships from the Factset Revere (Revere) database and the Compustat's customer segment files to identify the network of a supplier's connected peers. Our expansive data on customer-supplier relationships allow us to construct measures that gauge the focal supplier's competitive pressure from customer-connected peers. Our first construct, *Peer Count*, is the number of other suppliers of customer C_j within the same product market as the focal supplier S_i. The larger the *Peer Count*, the lower is a customer's switching cost and the greater is supplier S_i's likelihood of losing the customer to its competing peers. The second construct, *Peer Sales*, also captures C_j's existing relationships with alternate suppliers in the same industry but further accounts for the extent to which C_j depends on those alternatives by taking the sum of the peers' sales to C_j, scaled by C_j's cost of goods sold. The more reliant is C_j on other suppliers for inputs, the greater is the competitive pressure for S_i. We also employ Hoberg and Phillips's product similarity score to construct *Peer Similarity*, which gauges the scarcity of S_i's products relative to those of the peers who are also supplying to C_j. A large *Peer Similarity* value implies that the products produced by the pool of connected peers are similar to those of the supplier, thereby suggesting that a customer can easily switch to another supplier to source a similar product. Intuitively, the larger the number of relationships that customers are concurrently maintaining with other sources of supply, the greater is the competition faced by a supplier; and this in turn incites the supplier to hoard negative information.

The information hoarding behavior is, unfortunately, unobservable. Following prior studies (e.g., Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009), we employ the formation of a stock price crash as a measure of a supplier's accumulation of bad news. The idea is that when unfavorable news accumulated over an extended period reaches a tipping point beyond which the cost of concealing such news exceeds the benefit, managers are then forced to release the accumulated news at once, thereby causing the stock price to crash. We therefore construct three popular measures of a supplier's crash risk, namely (1) the negative conditional skewness of stock returns (NCSKEW), (2) the log of the standard deviation of Down weekly returns divided by the standard deviation of Up weekly returns (DUVOL);[5] (3) the number of firm-specific weekly returns exceeding 3.09 standard deviation below the mean firm-specific weekly return over the fiscal year (Crash Count).[6] The larger the three measures of crash risk, the greater is the likelihood that a

[4] Beyer et al. (2010) provide an excellent literature review of product market competition effects on firms' voluntary disclosure decisions.

[5] A Down (Up) weekly return is classified as a return below (above) the annual mean weekly return.

[6] Hutton, Marcus, and Tehranian (2009) show that the 3.09 standard deviation is the threshold that the crash

supplier is withholding bad news.

Based on a sample of 28,598 firm-year observations, or of 4,436 unique supplier firms, for the period from 1996 to 2015, our results provide evidence that supports a positive association between supplier stock price crash risk and peer competitive threats, suggesting that supplier firms facing greater threats from customer-connected peers have more motives to withhold negative information. In terms of economic significance, for example, the negative skewness of firm-specific returns increases by 0.029 for a one-standard-deviation increase in *Peer Count*; this magnitude is large compared to the mean $NCSKEW$ of 0.057. Thus, the greater competitive pressure from peers is associated with a larger probability that the supplier will experience large stock price declines in the subsequent year. Additional tests based on our sample of customer-supplier links produce no apparent evidence of other sources of competition, such as the competitiveness of the industry, general competitive environment in which a firm operates (Li and Zhan, 2018), and threats from non-connected-customer peers, on supplier stock price crash risk beyond the competitive pressure from customer-connected rivals. Our baseline evidence is also robust to alternative interpretations that the crash risk is driven by the supplier firm's dependence on a concentrated-customer base (Chen et al., 2018; Kim, Lee, and Song, 2018), or is caused by periods of extreme adverse economic conditions.

Our key evidence of a strong positive association between peer competitive threats and the likelihood of future supplier stock price crashes are subject to endogeneity concerns, such as reverse causality and confounding variables. To allay such concerns, we exploit three different quasi-natural experiments to capture large exogenous shocks to supplier peers. First, we employ the intensity of mergers and acquisitions (M&A) activities of customers as a source of an exogenous increase in the number of peers supplying to the customers and thus the supplier's heightened peer competitive pressure. Next, we exploit an exogenous reduction in peer competitive pressure of a firm due to bankruptcies of customer-connected competitors. Bankrupt firms are inclined to lose substantial market share as customers become less likely to do business with them (Altman, 1984; Opler and Titman, 1994; Chang and McDonald, 1996). When a supplier's connected peer files for bankruptcy, the common customers are expected to rely less on the filing peer for inputs, or to switch away completely, given concerns of the peer's ability to meet its commitments. Finally, we explore exogenous shocks related to major natural disasters that disrupt customer-connected peers' operations of plants and establishments located in disaster-affected areas. Disruptive events caused by natural disasters would reduce the competitiveness of the rival peers, in turn alleviating some of the competitive or predatory threats faced by the firm connected through common customers. Overall, the findings from all three quasi-natural experiments suggest that our baseline results are robust to potential endogeneity issues and that they capture a causal effect of peer competitive pressure on a supplier firm's stock price crash risk.

We next investigate how the relationship dynamics between the supplier firm and its peers play a

incidents account for 0.1% of frequency in the normal distribution.

role in the association between peer competitive threats and supplier price crash risk. One such test focuses on the business partnerships formed between the focal supplier and its peers. We contend that such firm interactions would encourage cooperation among the partners in working toward a common goal and, in turn, reduce the competitive or predatory efforts from those collaborating peers. Consistent with the conjecture, forming business partnership with rival peers mitigates the peers' competitive effects on the supplier's stock price crash risk. A similar test examines whether greater dependence of rival peers on the supplier's innovation would also have a dampening effect on peer competitive threats. First, we expect that the greater the extent to which the peer's innovative output builds on the focal suppler's technological knowledge, the more likely the peers would consider the supplier to be a source of knowledge acquisition rather than competitive rivalry (e.g., Oxley and Sampson 2004; Frankort 2016). Second, suppliers with more valuable inventions, as proxied by the number of citations of a supplier's patents by its peers, can leverage their patents as a competitive advantage over their peers, reducing peer competitive threats. Our results indicate that greater peer citations of a supplier's patents decrease the effect of peer competitive pressure on the supplier, reinforcing the notion that a firm's future crash risks are driven by the competitive dynamics with its peers.

While we have established that the effect of peer competitive threats on crash risk is driven by managers' motivations to hoard negative information from the public, one may argue that it may merely capture the firm's greater exposure to business and cash flow risks associated with its peer competitive environment. It is plausible that firms facing greater business risks are more prone to stock price crashes. To rule out this alternative explanation (i.e., hereafter the business risk hypothesis), we repeat the baseline analysis while controlling for the supplier's contemporary business risk and operating performance. Specifically, we use the supplier's price-cost margin (PCM), the annual standard deviation of quarterly operating return on assets (ROA), and the number of negative news net of positive news on a firm's products and services as measures of the supplier's operating performance. We find that while price crashes are indeed partially driven by the concurrent operating characteristics of the firm, the peer competitive effects on crash risk remain positive and statistically significant. These findings suggest that peer threat effect on crash risk cannot be fully attributed to the firm's business risk characteristics.

Nevertheless, to further substantiate the strategic information disclosure hypothesis, we test the relation between information asymmetry and crash risk. Existing studies argue that firm managers are better able to hoard bad news for an extended period when firms are associated with higher levels of information asymmetry (e.g., Jin and Myers, 2006; Kothari, Shu, and Wysocki, 2009). Hence, the strategic information disclosure hypothesis would imply that the link between peer competitive threats and crash risk is more pronounced for firms with high information asymmetry. Alternatively, the business risk hypothesis would suggest that cross-sectional differences in information asymmetry should have no bearing on the relation between peer competitive threats and crash risk. Using institutional ownership breadth, analyst forecast dispersion, and news coverage as proxies for a firm's level of information asymmetry, our cross-sectional analyses produce a statistically significant effect on the relation between peer competitive pressure and stock price crash risk, consistent with the strategic information disclosure hypothesis.

Finally, if peer competitive threats contribute to supplier managers' information hoarding behavior, we ought to observe similar behavior in their mandatory financial reports. In other words, if supplier managers are impelled to conceal damaging information about the firm that may cause stock price plunges and also jeopardize their careers, they would also attempt to complicate or blur information disclosed in their financial filings. For example, prior studies (e.g., Li, 2008; Rogers, Schrand, and Zechman, 2014) suggest that one way through which managers obfuscate information is to generate more complex financial reports. We therefore ask whether supplier managers' information hoarding behavior associated with peer competitive pressures has any regulatory implications. To address this question, we examine the number of reviews from the Securities and Exchange Commission (SEC) in the form of comment letters relating to different filings (e.g., Form 10-Ks, Form 10-Qs, Form S-1s, and DEF 14A) submitted by supplier firms as well as the readability of the Management Discussion and Analysis (MD&A) section (item 7) of their 10-K filings. We find that more intense peer competitive pressure is associated with a larger number of SEC comment letters and with greater complexity of financial reports, thereby providing direct evidence of the information hoarding behavior.

Two recent similar papers are somewhat related to our study. Both Hu et al. (2018) and Kim, Lee, and Song (2018) also employ information on the customer-supplier relationships, but to examine the relation between corporate customer concentration and stock price crash risk. Hu et al. present competing views on the effect of customer concentration on crash risk. On the one hand, powerful customers may demand supplier managers to account more conservatively and hence, it is less likely that the latter are able to hoard negative information. On the other hand, a concentrated-customer base creates incentives for suppliers to withhold negative information for fear of losing its major customers. Kim, Lee, and Song, however, argue that a major-customer base creates incentives for a supplier to hoard negative information in order to manage customers' expectations on its performance. Despite different arguments, they both reach the same conclusion that corporate customer concentration has a positive impact on stock price crash risk. Unlike these two studies, we employ the identities of both the customers and suppliers to determine each customer's network of suppliers. Such detailed firm-level information allows us to determine the pool of peers that have common customers with the supplier firm of interest, and hence, to construct measures of competitive threats from customer-connected peers. We find that intense peer competition from this linked group of rivals pressures the supplier to strategically withhold bad news to avoid proprietary cost of disclosure and hence, aggravate the risk of stock price plunges, and that our key finding remains unaffected even after controlling for customer concentration.

Our research brings into focus the importance of interconnected firms in today's competitive business environment. We contribute to the growing supply chain literature that recognizes the growing vast network of connected firms. Our study shows that a firm's information disclosures are not independent of its stakeholders or connected firms, and that the firm's crash risk is highly correlated with peer competitive pressure faced by the firm who has common customers, an indication of the nature and extent of firm interdependencies within supply chains. It therefore questions related studies that examine the effect of product market threats on firms' stock crash risk without recognizing the effect of firm connectedness in their analyses (e.g., Li and Zhan, 2018). While competitive pressure from the product market may aggravate managers' desires to strategically withhold unfavorable news, as reported in Li and Zhan, their result perhaps alludes to only competitive pressure from firms which are linked through common customers.

Our work also adds to the accounting literature that offers differing views on the relationship between the customer bargaining power and supplier managers withholding bad news. One view is that a firm's stakeholders (customers or suppliers) that have bargaining advantages over the firm can dictate terms of trade and therefore demand that the firm account more conservatively (i.e., deliver timely unfavorable news disclosures). Hui, Klasa, and Yeung (2012) provide evidence in support of this view that a firm's powerful suppliers and customers are associated with its accounting practices. An alternative view is that conditional conservatism creates a disincentive for firm managers to withhold bad news disclosures (Kim and Zhang, 2016), or that when a supplier faces an extreme litigation risk would induce its managers to hoard bad news (Cen et al., 2018). In contrast, our research expands these studies and shows that suppliers have incentives to hoard unfavorable information when they face a network of peers who are linked to common customers, even powerful customers.

Our research also contributes to the extensive peer effects literature that has documented the pervasive evidence of peer effects not only on individual and household financial decision making and behavior (e.g., Kaustia, and Knüpfer, 2012; Bailey et al., 2016), but also on corporate behavior and policies (e.g., Leary and Roberts, 2014; Kaustia and Rantala, 2015). Our findings perhaps offer an explanation for the widely documented peer effects – these effects may be mainly attributed to the vast network of interconnected firms in the economy. These firms are linked to each other through various relationships of which some are contractual whereas others are implicit. Any shock to one firm is most likely to have a resulting effect on another which is probably linked to the former. Our study adds to this literature by showing that in light of peer pressure or predatory threats faced by firms that are linked to common customers, managerial decisions of one firm are not independent of those of its stakeholders or peers, an implication that future research in peer effects should account for the extent of implicit and explicit interconnectedness among firms and not simply for the fact that firms belong to the same industry.

2. Data and Sample Construction

We construct the sample from several data sources: (i) supplier-customer relationship data from Factset Revere and Compustat's segment customer files; (ii) stock return data from the Center for Research in Security Prices (CRSP); (iii) product market classification and firm relatedness information developed in Hoberg and Phillips (2010; 2016), which is made available via Hoberg and Phillips data library; (iv) information on M&A deals from SDC Platinum; (v) Chapter 11 bankruptcy filings data from Ma, Tong, and Wang (2017); (vi) county-level disaster data from Federal Emergency Management Agency (FEMA); (v) firm employment data by establishment from Dun and Bradstreet via Mergent; (vii) institutional holdings data from Thomson Reuters Institutional Holdings (13f); (viii) financial analyst forecast information from Broker's Estimate System (IBES); (ix) firm-specific press articles from Ravenpack full package; (x) financial statement data from Compustat, and (xi) the SEC comment letter records from Audit Analytics. Our main sample intersects these databases with non-missing values for our main variables of interest. We exclude financial and regulated utility firms (SIC codes 4900-4999 and 6000-6900). This yields a final sample of 28,598 firm-year observations, consisting of 4,436 unique supplier firms over the period between 1996 and 2015. The sample period is bounded by the availability of Hoberg and Phillips' industry classification and firm product relatedness data; their coverage ranges from 1996 to 2015. The actual number of observations varies across analyses given different data availability. The definitions of all the key variables are depicted in Appendix A.

2.1. Customer-supplier networks

We use both the Revere data and Compustat Segment Customer data from Wharton Research Data Services (WRDS) to identify customer-supplier relationships. Under SEC Regulation S-K Item 101, all public firms in the U.S. are required to disclose the existence and identities of major customers representing more than 10% of their sales, while suppliers can also voluntarily disclose minor customers that account for less than 10% of the revenues. The Compustat segment data relies on such regulation to obtain supply chain information from suppliers' annual 10-K filings, and hence contain mainly information on firms' major customers. A critical shortcoming of Compustat is that it does not assign unique company identities (GVKEYs) to publicly-listed customer firms, whose names are as reported in the original filing and are abbreviations or even subsidiary names. To circumvent these data challenges, we closely follow Banerjee, Dasgupta, and Kim (2008) and Cen et al. (2017) in manually matching the customer names with their unique GVKEYs that would allow us to link customer information with other databases.[7] Unlike Compustat, Revere gathers information from multiple sources including corporate quarterly and annual filings (e.g., 8-K, 10-Q, and 10-K), investor presentations, websites, and press releases. The database identifies customer-supplier relationships based on both direct relationships disclosed by the reporting company and indirect relationships disclosed by companies doing business with the reporting company, and thus, offers more comprehensive supply chain information consisting of both major and minor customers. No manual matching is necessary given that Revere data offers GVKEYs for the publicly-listed customers. We complement Revere data, which starts coverage

[7] We thank Ling Cen for providing us his matched Compustat Segment data for calibration purposes.

from 2003, with Compustat segment data to obtain corporate customer-supplier pairs over our sample period 1996-2015. For the purpose of illustration, in Figure 1 we show a proportion of the 2011 supply chain network of Crocs, Inc. The figure depicts the linkages between Crocs and its competing suppliers as well as its customers. Leveraging on such comprehensive information, we construct our key measures of competitive pressure among peer firms who share common corporate customers.

2.2. Proxies for peer competitive threats

To construct measures of peer competitive threats, we focus on customer-connected firms in the same product markets who are simultaneously supplying to the same corporate customers. By examining these peer firms connected through existing customer-supplier relationships, we are essentially capturing the extent to which peer firms are close competitors of resources from and sales to the same customers. The connected-peer-based measures contain unique information incremental to that in other more broadly defined competition variables. For instance, while a high Herfindahl index (HHI) score suggests a concentrated product market with few competitors in the industry, our measures consider the possibility that these few competitors happen to be competing closely for business from the same customers. Furthermore, unlike the product market fluidity measure developed by Hoberg, Phillips, and Prabhala (2014) that captures threats from potential entries, our measures pay more attention to the most pressing threats from current competitors that calls for immediate firm actions. Thus, the emphasis on closely connected rivals through real customer-supplier relationships is a distinguishing feature of our measures.

Our proxies for peer competitive threats capture the extent to which a firm S_i's corporate customers are simultaneously dependent on S_i's rivals. Intuitively, the more relationships that customers are concurrently maintaining with other sources of supply, the greater the competition that S_i would face. First, S_i would likely need to compete with connected peers for additional businesses or collaborative opportunities with the customers. Second, it is easier for customers to switch away from S_i given the established relationship with alternative suppliers, so S_i would also face greater threats of trading relationship termination. For our first measure of customers' dependence on supplier peers, *Peer Count*, we examine each customer C_j of supplier S_i in year t and count the number of other suppliers of C_j within the same industry as S_i, where industries are defined by Hoberg and Phillips's (2010) TNIC industry classification. To obtain an aggregate measure of S_i's competitive threats through its customer network, we take the natural logarithm of the equally-weighted average of the counts across all customers of S_i in year t as shown in Eq. (1) below.[8] The remaining two measures are averaged in the same fashion.

[8]Over 70% of the customer-supplier pair observations are missing sales distribution information. We work with equally-weighted average measures instead of sales-weighted averages to avoid eliminating a large portion of the sample.

$$Peer\ Count_i = \ln\left(\frac{\sum_j^{n_i} m_j}{n_i}\right), \tag{1}$$

where supplier S_i has n_i customers in year t, and each customer C_j has m_j suppliers other than S_i in the same product market. The intuition behind *Peer Count* is illustrated in Figure 2, which exemplifies a scenario where supplier S_1 is, on average, competing with four other industry peers through each of the customers, whereas supplier S_2 is only competing against two other suppliers. Hence, the higher value of *Peer Count* corresponds to a greater competitive threat from connected peers.

Our second measure, *Peer Sales*, similarly captures the C_j's existing relationships with alternative suppliers in the same industry but further accounts for the extent to which C_j depends on those alternatives by taking the sum of the peers' sales to C_j, scaled by C_j's cost of goods sold. The more reliant is C_j on other suppliers for inputs, the greater is the competitive pressure for S_i.

$$Peer\ Sales_i = \sum_j^{n_i}\left(\frac{\sum_k^{m_i} Sales_{j,k}}{COGS_j}\right) \Big/ n_i \tag{2}$$

where $Sales_{j,k}$ is the percentage of peer firm P_k's sales attributed to each customer C_j of supplier S_i in year t, and $COGS_j$ is the cost of good sold of C_j.

For our third measure, we consider the scarcity of S_i's products relative to the peers who are also supplying to C_j. Specifically, we average the product similarity scores of S_i and all other suppliers of C_j belonging to the same industry (*Peer Similarity*). Developed in Hoberg and Phillips (2010; 2016), the product similarity scores measure the relatedness of two firms based on 10-K text-based product market descriptions. The higher the average score, the greater is the substitutability of S_i's products, and the less dependent would C_j be upon S_i.

$$Peer\ Similarity_i = \sum_j^{n_i}\left(\frac{\sum_k^{m_i} Similarity_{i,k}}{m_j}\right) \Big/ n_i \tag{3}$$

where $Similarity_{i,k}$ is the product similarity score between S_i and its peer firm P_k in year t.

2.3. Measures of stock price crash risk

Following prior literature (Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009; and Kim, Li, and Zhang, 2011a, b), we employ three firm-specific measures of stock price risk for each supplier-year. To construct the measures, we first run the following regression for each supplier-year using the weekly returns during the 12-month period earning three months after the supplier's fiscal year end. The three-month lag is used to ensure the availability of financial data to investors, which would in turn be reflected in the stock prices when measuring the crash risk measures (Kim, Li, and Zhang, 2011a).

$$r_{i,\tau} = \alpha_i + \beta_{1,i} r_{m,\tau-2} + \beta_{2,i} r_{m,\tau-1} + \beta_{3,i} r_{m,\tau} + \beta_{4,i} r_{m,\tau+1} + \beta_{5,i} r_{m,\tau+2} + \epsilon_{i,\tau}, \tag{4}$$

where $r_{i,\tau}$ is the return on stock i in week τ, $r_{m,\tau}$ is the return on CRSP value-weighted market index in week τ, and $\epsilon_{i,\tau}$ is the firm-specific residual return in week τ after removing the impact of market fluctuations. The lead and lag market returns are included to account for nonsynchronous trading (Dimson, 1979). We calculate the firm-specific weekly return for supplier i in week τ as natural logarithm of one plus residual return ($W_{i,\tau} = ln(1 + \epsilon_{i,\tau})$) from Eq. (4).

Our first measure of crash risk is the negative skewness of the firm-specific weekly returns ($NCSKEW$) following Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011a, b). It is defined as the negative of the ratio of the third moment to the standard deviation cubed of $W_{i,\tau}$ for each supplier-year. A value of $NCSKEW$ corresponds to a more left-skewed distribution of supplier i's weekly returns, indicating a higher incidence of crash. Specifically, $NCSKEW$ of supplier i's stock returns in year t is computed as:

$$NCSKEW_{i,t} = -\left[n(n-1)^{3/2} \sum W_{i,\tau}^3]/[(n-1)(n-2)(\sum W_{i,\tau}^2)^{3/2} \right] \tag{5}$$

where n is the number of observations of $W_{i,\tau}$ during year t.

The second measure is the down-to-up volatility measure ($DUVOL$) as constructed in Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011a, b). For each supplier-year, we separate all weeks into two groups based on whether the weekly returns are above or below the annual mean. Those returns above the mean are grouped into up weeks, and those below are group into down weeks. We then compute $DUVOL$ as the log ratio of the standard deviation of $W_{i,\tau}$ of the down weeks to that of the up weeks as illustrated in Eq. (6). Similar to $NCSKEW$, a higher value of $DUVOL$ corresponds to a more left skewed distribution of $W_{i,\tau}$, indicating a higher crash risk.

$$DUVOL_{i,t} = \ln \left[\frac{(n_d - 1) \sum_{Down} W_{i,\tau}^2}{(n_u - 1) \sum_{Up} W_{i,\tau}^2} \right] \tag{6}$$

where n_d is the number of down weeks for supplier i in year t, and n_u is the number of up weeks.

As our third measure of crash risk, we count the number of firm-specific weekly returns $W_{i,\tau}$ exceeding 3.09 standard deviations above and below the mean weekly return over the entire fiscal year for each supplier i. The 3.09 standard deviation is chosen following Hutton, Marcus, and Tehranian (2009) so that the crash incidents account for 0.1% of frequency in the normal distribution. The measure $Crash\ Count$ is defined as the difference of downside and upside counts (Callen and Fang, 2015, 2017), so a higher value corresponds to a higher frequency of crashes.

2.4. Control variables

We follow prior studies (Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009; and Kim, Li, and Zhang, 2011a, b) to identify control variables that affect stock price crash risk. Specifically, we control for firm-specific variables including firm size ($Size$), market-to-book ratio of equity (MB), leverage ratio (*Leverage*), profitability (ROA), and cumulative discretionary accrual (*AbAccr*). According to the above studies, the likelihood of future stock price crashes tends to be positively correlated with $Size$, MB, and *AbAccr* and negatively associated with *Leverage*. While ROA is found to have significant effect on crash risk by existing literature, the direction of its effect remains agnostic. The earlier studies conducted by Hutton, Marcus, and Tehranian and Kim, Li, and Zhang find negative relationship between ROA and crash risk, but the more recent studies including Kim and Zhang (2016), Kim, Lee, and Song (2018), Kim et al. (2018), and Li and Zhan (2018) suggest a positive relationship. We also control for stock-specific characteristics including the change in stock turnover ($\Delta Turnover$), firm-specific average weekly return (*Return*), firm-specific weekly return volatility (*Sigma*), and one-year-lagged negative skewness measure ($NCSKEW$), based on the prior findings of Chen, Hong, and Stein that crash risk tends to be higher for stocks with greater heterogeneity in investor opinions and higher past returns, past stock volatility, and past return skewness. The detailed definitions of the control variables are provided in Appendix A.

2.5. Summary statistics

Table 1 presents the summary statistics of the key variables used in our analysis. The mean value of $Peer\ Count$ is 1.015, indicating that a firm's customers are, on average, also trading with about two other competitors simultaneously.[9] Expressed in percentage of inputs, a mean value of $Peer\ Sales$ suggests that, on average, the customers rely on alternative suppliers to produce about 1.6% of their inputs. A supplier has an average product similarity score ($Peer\ Similarity$) of 0.022 with its product market competitors who are also suppliers of its customers. The interquartile range of $Peer\ Similarity$ is between zero and 0.033, with zero implying that none of the other suppliers of the firm's customers are competing within the same product market as the firm. The mean values of $NCSKEW$ and $DUVOL$ are 0.057 and 0.042, respectively. The positive values indicate that, on average, a supplier's weekly returns are left skewed. These statistics are comparable to those reported by Kim et al. (2016a) but, in general, indicate a greater probability of stock price crash than do other prior studies (e.g., Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009; and Kim, Li, and Zhang, 2011a, b), perhaps due to our focus on the supplier sample. The mean value of $Crash\ Count$ is -0.008, suggesting that a supplier firm has, on average, 0.008 more upside weeks than downside crash weeks during a year. The statistic also suggests a greater count of crash weeks than those reported in Callen and Fang (2015, 2017). All control variables are within reasonable ranges and are comparable with the statistics reported in the literature (e.g. Kim, Li,

[9] $Peer\ Count$ is computed as Ln(1 + 1.760) = 1.015.

and Zhang, 2011a, b; Kim, Wang, and Zhang 2016; Kim and Zhang, 2016).

3. Peer Competitive Threats and Supplier Crash Risk

In this section, we begin by examining whether or not peer competitive or predatory threats affect a supplier's bad news disclosure decision, as revealed by the impact of peer effects on supplier stock price crash risk. Our analysis focuses solely on a supplier who faces competitive threats or presssure from a pool of interconnected peers who are also linked to the supplier through common customers. We then conduct a large number of robustness tests to address possible concerns of whether the asssociation between peer threats and stock price crash risk is subject to endogeneity concerns.

3.1. Baseline evidence

To empirically examine the relation between peer competitive pressure and supplier stock price crash risk, we regress stock price crash risk on a proxy for peer competitive threat, firm-level controls, time fixed effects, and industry fixed effects:

$$Crash\ Risk_{i,t+1} = \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \mathrm{FE}_t + \epsilon_{i,t} \tag{7}$$

where $Crash\ Risk_{i,t+1}$ is a measure of one-year-ahead crash risk of supplier i (i.e., $NCSKEW_{i,t+1}$, $DUVOL_{i,t+1}$, and $Crash\ Count_{i,t+1}$); $Peer\ Competitive\ Threat_{i,t}$ captures a proxy for peer competitive threats (i.e., *Peer Count*; *Peer Sales*; *Peer Similarity*) faced by supplier i in year t; $X_{ki,t}$ is a vector of firm-specific control variables defined in an earlier section, measured in year t. We also control for industry (defined by two-digit SIC classification) fixed effects and year fixed effects (FE) in all regressions to account for unmodeled heterogeneity across industries and years.[10] Standard errors are clustered at the supplier firm level.

Results from our baseline model Eq. (7) are reported in Table 2. The dependent variables are $NCSKEW_{i,t+1}$ in columns (1)-(3), $DUVOL_{i,t+1}$ in columns (4)-(6), and $Crash\ Count_{i,t+1}$ in columns (7)-(9). We regress each measure of crash risk on each proxy for peer competitive threats. All three measures of peer competitive threats generate statistically significant and positive coefficients, indicating that a supplier withstanding greater competitive pressure from peers connected through common customers are more likely to experience stock price crashes in the future. The coefficient on $Peer\ Count$ is 0.029, corresponding to an increase in the negative skewness of supplier returns by 0.029 for each one standard-deviation increase in $Peer\ Count$. This magnitude is large compared to the mean $NCSKEW$ of 0.057. In a similar vein, the coefficients on $Peer\ Sales$ and

[10] Habib, Hasan, and Jiang (2017) suggest that some industries may potentially be more prone to crashes than others due to the fundamental nature of their operations. Industry fixed effects are used to control for such heterogeneity.

Peer Similarity of 0.417 and 1.151 correspond to increases in $NCSKEW$ by 0.016 and 0.031 (i.e., 27.8% and 54.5% of the mean $NCSKEW$), respectively, for a one standard-deviation change in the competition variables.

The results of columns (4)-(9) are qualitatively similar to those of columns (1)-(3). The peer competitive effects on supplier $DUVOL$ and *Crash Count* are sizable and economically significant. For example, one standard-deviation changes in *Peer Count*, *Peer Sales*, and *Peer Similarity* will lead to the corresponding 36.3%, 21.8%, and 40.0% increases relative to their respective crash risk sample means. The findings further suggest that greater competitive pressure from rival peers is associated with a larger probability for a supplier to experience large stock price declines in the subsequent year.

The control variables yield the same sign and similar coefficients to those reported in the prior studies (e.g., Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009; and Kim, Li, and Zhang, 2011a, b). Specifically, the coefficients on *Size*, MB, $\Delta Turnover$, *AbAccr*, $NCSKEW$, *Sigma*, and *Return* are all positive and significant. The coefficients on *Leverage* are negative, but they are statistically insignificant in all regressions. We find the coefficients of ROA to be positive, which is consistent with the more recent studies in the literature (e.g., Kim and Zhang, 2016; Kim, Lee, and Song, 2018; Kim et al., 2018; and Li and Zhan, 2018).

In sum, this subsection provides evidence that lends support to the prediction that firms facing greater threats from closely competing peers have greater incentives to withhold negative information, consistent with the strategic news disclosure hypothesis.

3.2. Robustness tests

One might argue that a suppplier firm not only faces the threat from its linked peers, but also from other sources of competition. For example, Li and Zhan (2018) show that firms facing greater threats from the product market are more likely to experience stock crashes, supporting their hypothesis that competitive pressure instigates managers to withhold negative information. Also, it is plausible that given the nature of the competitive product market environment, the supplier firm may be inclined to withhold adverse information for fear of losing its business not only to linked suppliers but also to potential suppliers. Thus, our baseline results may merely capture these alternative sources of competition. To alleviate such concerns, we conduct extensive robustness tests. First, we consider the possibility that our proxies for peer competitive threats capture the same dimension as the previously defined competition variables broadly accounting for all current and potential competitors. If that is the case, the positive peer competitive effect on supplier stock price crash risk could be driven by the general competitive environment in which a firm operates. To control for a supplier firm's overall competitive environment, we replicate our baseline analysis by adding the supplier firm's industry HHI index and the product fluidity measure developed by Hoberg, Phillips, and Prabhala (2014) as separate controls in our baseline regression model. Results are contained in Panels A and B of Table 3. To rule out the possibility that the competition may be from potential suppliers who produce similar products as the focal supplier but currently have no business with the supplier's customers, we implement additional tests using two measures of non-linked peer threats: *Non-Linked Peer Count* and *Non-Linked Peer Similarity*. Both measures are similar to the manner in which we construct *Peer Count* and *Peer Similiarity*. Results of regressions that control for non-linked peer threats are shown in Panels C and D of the same table.

The coefficients on our key variables remain materially unaffected after controlling for industry HHI, and only some of the coefficients become weaker after controlling for product fluidity. It is important to stress that none of the coefficients associated with supplier industry HHI and product fluidity is statistically significant at conventional levels. We have also conducted several additional tests to reconcile the insignificant effect of *Fluidity* in Panel B and Li and Zhan's (2018) finding of a significant *Fluidity* impact on stock price crash risk, as measured by *NCSKEW*. In particular, we replicate Li and Zhan's results based on their shorter sample period of 1998-2008 as well as on our sample period of 1996-2015 separately, but using our sample of economically-linked firms. We have also examined whether their results are driven by the global crisis period. Untabulated findings show that the coefficient of *Fluidity* is positive and statistically significant, consistent with Li and Zhan's baseline result. The coefficient, however, becomes only marginally significant at the 10% level when using a longer sample period of 1996-2015 and statistically insignficant after removing the crisis period from the sample of observations. The evidence in Panel B remains unaffected even on a shorter sample period of 1996-2008. Combined, while these results imply that Li and Zhan's evidence is specific to their time period employed and is mainly driven by the crisis period, one caveat is that the analysis is based on our sample of firms with customer-supplier relationships. Panels C and D rule out the possibility that our baseline finding captures the competitive pressure from non-linked peers. While their coefficients are all positive, they are not statistically significant. Thus, our connected-peer-competitive threat proxies influence the supplier's crash risk beyond the general effect of the overall competitive environment and the threats from non-linked peers.

Another potential concern is that our peer competitive pressure proxies inevitably capture the supplier firm's dependence on its principal customers as studied by Chen et al. (2018) and Kim, Lee, and Song (2018). We argue, however, that such issues may not be critical because (i) we examine all customer-supplier relationships irrespective of whether the customers are defined as major or minor; and (ii) our proxies do not depend on the number of major customers that a firm has nor do they rely on the percentage of sales attributed to those customers. Nonetheless, we test against such possibilities by controlling for the sum of squared sales percentages to a firm's major corporate customers, a measure of firm dependence on major customers. As shown in Panel A of Table 4, the coefficients on $Customer\ Concentration$ are positive and statistically significant in columns (1)-(6), but not in columns (7)-(9). Chen et al. employ $NCSKEW$ and $CRASH$ as measures of stock price crash risk, whereas Kim, Lee, and Song use $NCSKEW$, $CRASH$, and $DUVOL$. $CRASH$ is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Neither of the two studies construct *Crash Count* as a measure for crash risk. More importantly, the coefficients on all three measures of peer competitive threats remain robust to the additional control variable – *Customer Concentration*, and the level of statistical significance of the former is greater than that of latter, indicating that peer competitive effects differ from the previously defined customer concentration variables.

In our final robustness test, we examine whether our baseline evidence is driven by extreme hard times where there is a high likelihood that suppliers' relationships with customers will be terminated. For instance, Cen et al. (2018) find that faced with greater risk of losing customers, suppliers tend to manage negative news disclosure to avoid losing the customers. To address this issue, our sample excludes the observations that occur during the financial crisis years (2008-2009); this approach removes the influence of excessive bad firm performances. As shown in Panel B of Table 4, the coefficients on all three key measures from the subsample of firms remain statistically significant across all crash risk measures, thereby confirming that the effect of peer competitive threats on supplier stock price crash risk is robust across non-extreme economic conditions.

3.3. Quasi-natural experiments

The results so far underscore a strong relation between competitive threats from supplier peers and the likelihood of future supplier stock price crashes. These estimates are, however, subject to endogeneity concerns such as reverse causality and confounding common factors. For example, customers who anticipate significant business and cash flow risks, which in turn bring high crash risk, of suppliers *ex ante* may immediately seek to establish relationships with alternative suppliers within the same industry producing similar products to reduce their switching costs. Consequently, the sudden increase in the number of peers supplying to the same customers would coincide with future stock price crashes. Similarly, omitted common factors, such as the economic condition of the supplier's industry, may simultaneously affect peers and the supplier, and hence supplier stock price crashes through increased business and cash flow risks. To alleviate these endogeneity concerns, we exploit three quasi-natural experiments to capture large exogenous shocks to supplier peers.

3.3.1. Customer M&A intensity

In our first identification strategy, we use the intensity of M&A activities of customers as a exogenous source of increase in the number of peers supplying to the customers and thus the supplier's peer competitive threats. Through the consolidation of purchasing accounts, the acquiring customers would mechanically gain new trading partners, with some being industry peers of their existing suppliers. Hence, we expect that higher M&A intensity of customer firms would result in greater peer competitive pressure and in turn, can be considered as a valid instrumental variable

(IV) of the competition measures satisfying the relevance condition. We also expect this IV to meet the exclusion restriction. First, customer M&A activities are as good as randomly assigned across the suppliers since they are likely independent of suppliers' corporate decisions. There may be concern that customers undertake M&As to counteract the monopoly power of the suppliers (Galbraith, 1952). To address this issue, our analyses exclude all vertical M&As, which can potentially be motivated by customers' reactions to the market power of upstream firms (Spengler, 1950). Second, it is reasonable to assert that such M&A activity would only affect the supplier's crash risk through its effects on suppliers' peer competitive pressure. One possible concern is that merger waves could have contagion effects through customer industries to supplier industries, and thus, our IV implicitly captures the effect of supplier M&As on its stock price crash risk. While plausible, this argument of M&A propagation along the supply chain industries is less critical in our setting, as Ahern and Harford (2014) show that the effect of customer consolidation on supplier industry is much less than the impact of supplier industry consolidation on customer M&A activity. Nevertheless, we control for the suppliers' industry fixed effects in the IV analyses to address all remaining concerns and to remove any unobserved industry-wide effect of the suppliers that may contaminate the exclusion restriction.

Our empirical procedure is based on a two-stage least-squares estimation. In the first stage, we regress a supplier's peer competitive pressure proxy on the customer M&A intensity measure. The second stage tests the effect of instrumented competitive threats on the stock price crash risk. Formally, we estimate the following two-stage model:

$$Peer\ Competitive\ Threat_{i,t} = \gamma_0 + \gamma_1 Instrumental\ Variable_{i,t} + \sum_{k=1}^{K} \lambda_k X_{ki,t} + \text{FE} + \eta_{i,t}, \quad (8)$$

$$Crash\ Risk_{i,t+1} = \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \quad (9)$$

where $Instrumental\ Variable_{i,t}$ is the average M&A intensity across all customers of firm i, and all other variables are defined as above. To construct the M&A intensity measure, we first obtain M&A deals from the SDC database and apply the following restrictions for each transaction: (i) the deal must be completed; (ii) the acquirer purchases at least 50% of the target during and owns at least 90% after the transaction; (iii) the transaction value is no less than \$1 million; (iv) for each customer-supplier pair, the acquired target of the customer must be in a different 2-digit SIC industry from the supplier.[11] We then exclude all supplier-year observations, where the suppliers are in the same industry as the customers. Taking a similar approach as Campello and Gao (2017), the M&A intensity for each customer is measured as the aggregate M&A transaction values scaled by the customer's total sales in a year and averaged over the last five years.[12] For each supplier,

[11] Restriction (iv) may result in the exclusion of a M&A deal in some customer-supplier pairs but the inclusion of it in other customer-supplier pairs, depending on the 2-digit SIC industry of each supplier firm.

[12] To properly exclude the effects of vertical M&As from each supplier-year observation, we consider a customer M&A as vertical if the target firm is in the same 2-digit SIC industry as the supplier, as long as the supplier-customer

the IV *Customer M&A Intensity* is defined as the weighted average M&A intensity across all its customers, where the weights are determined by the supplier's sales percentage to each customer. Results are shown in Table 5.

Panels A, B, and C of the table present the two-stage least-squares regression results based on each peer competitive threat proxy. In columns (1), (3), and (5), we report the first-stage results where the peer competitive threat proxy is regressed on *Customer M&A Intensity*. The coefficients on the weighted average customer M&A intensity are positive and statistically significant, consistent the notion of increased competitive pressure following intense customer M&A activity. The F-statistics from the first-stage regressions are well above 10, further indicating that the customer M&A intensity is a strong instrument that satisfies the relevance condition. This result is robust across the three different measures of peer competitive threats. The second-stage estimates are shown in columns (2), (4), and (6). Consistent with our baseline results, all the predicted *Peer Count*, *Peer Sales*, and *Peer Similarity* measures have positive and significant effects on all three crash risk measures. Specifically, the instrumented *Peer Count* has a coefficient of 0.288 (significant at the 1% level) for the regression on *NCSKEW*. It indicates that a one-standard-deviation change in the predicted *Peer Count* measure is associated with an increase in *NCSKEW* by 0.047, or an 83% increase relative to the sample mean of 0.057. Similarly, the competition proxy yields coefficients of 0.158 and 0.139 for *DUVOL* and *Crash Count*, respectively. The estimations correspond to increases in the crash risk measures by 0.026 and 0.111 for a one standard-deviation change in the instrumented competition variable, compared to the sample averages of 0.042 and -0.008 for *DUVOL* and *Crash Count*, respectively. Overall, the customer M&A intensity IV approach corroborates our earlier finding and lends support to a causal interpretation of the relationship between peer competitive pressure that a supplier faces and its future stock price crashes. In other words, faced with greater competition from close rivals with common customers, suppliers have a greater tendency to hoard negative information.

3.3.2. Peer firm bankruptcy

Our second identification strategy exploits an exogenous reduction in peer competitive pressure of a firm due to bankruptcies of peer firms with common customers. Bankrupt firms tend to lose substantial market share as customers become less inclined to do business with them (Altman, 1984; Opler and Titman, 1994; Cheng and McDonald, 1996). In the case that a supplier peer files for bankruptcy, we would, therefore, expect the common customers to reduce their reliance on the particular supplier peer for inputs, or switch away completely, given their concerns for the peer's ability to fulfill its commitments. The peer competitive threats that the supplier faces would in turn decline considerably due to reductions in the common customers' dependence on alternative suppliers. We use these exogenous shocks to peer competitive threats in a difference-in-differences framework.

relationship is established within the next 5 years of the merger deal.

A potential concern for this approach is that any relation found between supplier peers' bankruptcies and the supplier's stock price crash risk may be driven by confounding factors. For instance, peers' bankruptcies may reflect adverse conditions within the industry (Warner, 1977) and hence, coincide with higher crash risk of the supplier. Such a concern is less critical in our setting, since our approach predicts a negative treatment effect on the crash risk. The confounding factor would lead to an underestimation of our findings. Nonetheless, we consider the possibility of extremely adverse conditions by controlling for the supplier's own bankruptcy filing. Alternatively, Lang and Stulz (1992) and Cheng and McDonald (1996) suggest that the surviving competitors of bankrupt firms would benefit from increases in demand. Thus, a negative association between the peer bankruptcy events and stock price crashes may reflect a positive effect on the supplier's operational performance rather than a negative effect on the incentives to withhold negative information. To account for such positive effects on firm performance, we control for the supplier's market share in the year the supplier peers have filed for bankruptcy.

The Chapter 11 bankruptcy filings data are from Ma, Tong, and Wang (2017) that cover all US public firms from 1980 to 2016.[13] We define our treated group as suppliers whose connected peers have filed for Chapter 11 bankruptcy in year $t+1$, where the peers are linked to the suppliers through customer-supplier relationships identified in year t. Our sample of Chapter 11 cases is not confined to any particular type of bankruptcy outcomes such as liquidation, acquisition, or reorganization, because we anticipate that all bankruptcies would have almost immediate adverse effects on the bankrupt firm's ability to compete in the product market irrespective of the final court decisions. All other suppliers without bankrupt peers are considered as our control group. The treatment period is defined as the one-year period during which bankruptcies are filed by supplier peers, allowing us to test the immediate effects of the shocks in the supplier's competitive threats. Formally, we estimate the following regression model:

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_{i,t+1} + \alpha_3 Treat_i \times Post_{i,t+1} \\ & + \text{Additional Controls} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \end{aligned} \tag{10}$$

where $Treat_i$ is a dummy variable indicating whether supplier i's connected peers have filed for bankruptcy that changes the extent of peer competitive pressure; $Post_{i,t+1}$ is a dummy variable covering the one-year period during which the bankruptcies are filed;[14] and $X_{i,t}$ includes the same set of firm-level controls as Eq. (7) and two additional controls, $Bankruptcy_{i,t+1}$ and $MktShare_{i,t+1}$. A detailed definition of all variables is provided in Appendix A. As in our baseline regressions, we include industry and year fixed effects (FE) and cluster standard errors at the firm level.

The estimation results are reported in Table 6. Consistent with our *prior*, the two additional

[13]We thank Wei Wang for generously sharing the bankruptcy data with us.

[14]The variable *Post* is dropped from the actual regression estimation due to its perfect collinearity with the year fixed effect dummies.

controls, $Bankruptcy_{i,t+1}$ and $MktShare_{i,t+1}$, bear the expected signs. Specifically, the supplier's own bankruptcy filing as captured by the *Bankruptcy* dummy has positive effects on the stock price crash risk, whereas the firm market share has negative effects. These coefficients are statistically significant at the 1% level. Controlling for potential confounding factors, the resulting coefficients on the interaction term, $Treat \times Post$, are negative and statistically significant across all crash risk measures. According to the estimations, peer bankruptcies lead to reductions in $NCSKEW$, $DUVOL$, and *Crash Count* by 0.155, 0.132, and 0.096, respectively, or threefold to elevenfold increases relative to their correponding means. A negative treatment effect of supplier peers' bankruptcies lends further support to the causal interpretation of the relation between peer competitive threats and supplier stock price crash risk.

3.3.3. Peer firm disruptions by natural disasters

Our third main source of identification explores the effect of major natural disasters on supplier peer operations. Similar to bankruptcies, natural disasters represent disruptions to firm production if they occur in areas where the firm's plants and establishments are located. However, we expect such disruptive events to differ from bankruptcies in an important way – disruptions of firm operations caused by natural disasters tend to be temporary in nature, and hence would have, if any, limited effects on the relationship with its customers. Thus, it is unlikely for disaster events to induce a sizeable shift in customer dependence to alternative suppliers as would bankruptcies.[15] Instead, we use disaster events on supplier peers to capture the temporary exogenous reductions in the supplier peers' competitiveness through adverse effects on firm performance and disruptions on their competitive actions against others. We conjecture that, for any given level of customer dependence on the supplier peers, the competitive threats that such troubled supplier peers pose to the supplier firm would decline considerably. Hence, we test whether the effects of our three key variables on crash risk would be less pronounced when the connected peers are suffering from natural disasters. Our analysis has the same spirit as the difference-in-differences approach, with the exception that the treatment is a continuous function of our key peer competitive threat variables.

We obtain information on all federally declared disasters within the U.S. from Federal Emergency Management Agency (FEMA). The database includes information on the incident start and end dates as well as the Federal Information Processing Standards (FIPS) code of all counties. Following Barrot, Noel, and Julien (2016) and He (2018), we focus on major disasters that occurred after 1996. The major disasters are identified by manually matching the FEMA data with the list of major disasters provided in Barrot, Noel, and Julien and He, who have restricted the disasters to those lasting less than 30 days with total estimated damages above $1 billion. The remaining 28 major disaster events include hurricanes, blizzards, floods, and wildfires.

[15] Barrot, Noel, and Julien (2016) provide evidence supporting this argument. The authors find that the disaster-induced disruptions of a supplier do not result in increases in the sales growth of other suppliers servicing the same customer.

Crucial to our analysis is the identification of affected firms by the disasters. We first collect plant- and establishment-level data from Mergent Data Explr database, which is an annual snapshot data directly from Dun and Bradstreet. Data Explr contains annual information on employment and location by plant and establishment for all US firms from 1985 to 2017. We then match the FEMA and Data Explr datasets by the location of each firm and measure the impact of natural disasters on the firm based on the percentage of the firm's employees in the disaster area. Specifically, we consider a firm's operations to be disrupted by a disaster if at least 20% of the firm's total employees reside in the affected county.

We use the following model to test the differential effects of peer competitive threats when the peers are adversely affected by natural disasters.

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times Peer\ Disaster_{i,t+1} + \alpha_2 Peer \\ & Competitive\ Threat_{i,t} + \alpha_3 Peer\ Disaster_{i,t+1} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t} \end{aligned} \quad (11)$$

where $Peer\ Disaster_{i,t+1}$ is a dummy variable taking a value of one for firm i in year $t+1$ if its connected peers are affected by a disaster occurred in $t+1$.[16] In addition to the same set of control variables as Eq. (7), we also include a dummy variable indicating whether the supplier firm i itself is adversely affected by a disaster in $t+1$ ($Disaster_{i,t+1}$). It accounts for the possibility that supplier i is located close to its peers, and hence are also affected by the same disasters.

Results, as reported in Table 7, reveal the heterogeneous effects of peer competitive threats under different conditions for the peers. The coefficients on all three key peer competitive pressure variables are positive and significant, consistent with the notion that, for suppliers with peers unaffected by disasters, the peer competitive pressure remains strong and so is its effect on the supplier's stock price crash risk. In contrast, the coefficients on the interaction term are negative and statistically significant in all but one specification (column (6)), implying that the effects of our key competition variables become less pronounced when supplier peers are affected by disasters.

For instance, as shown in column (1), a one standard-deviation change in $Peer\ Count$ leads to an increase by 0.033 ($= 0.033 \times 1.015$) for firms competing against unaffected supplier peers. However, a negative coefficient on the interaction term suggests that the positive effect from $Peer\ Count$ is decreased by a magnitude of 0.046 ($= 0.045 \times 1.015$) following disaster events that affect supplier peers. Taken together, these findings suggest that for suppliers competing against affected peers, a one standard-deviation increase in $Peer\ Count$ ultimately leads to a 21.4% ($= (0.033 - 0.045) \times 1.015/0.057$) reduction in $NCSKEW$ relative to the sample mean. Interestingly, an exogenous shock to supplier peers' locations of operations weakens their competitive threats to the extent that it reduces supplier stock price crash risk. Similar observations can be made for all but two tests. As illustrated in columns (3) and (6), while the peer disaster events are associated with a

[16] The connected peers are those who serve the same customers as supplier i as reported at the end of year t.

marginal decline in the positive effects of *Peer Similarity* on crash risk, they do not ultimately lead to a reduction in the crash risk. The findings are consistent with our *prior* that an exogenous shock to supplier peers' own conditions weakens their competitive threats and, in turn, leads declines in stock price crashes.

Overall, the evidence from all three quasi-natural experiments suggests that our baseline results are robust to potential endogeneity concerns and that peer competitive pressure has causal effects on a supplier firm's crash risk.

4. Dynamics of Peer Relationships

In the preceding section, we provide empirical evidence that a supplier firm's stock price crash risk is related to the competitive pressure of its peers that are connected to the supplier through common customers. We argue that such pressure arises from (i) the fear of losing customers who incur lower switching costs given their access to alternative suppliers; and (ii) the predatory or competitive efforts of the rival peers. In this section, we investigate whether the relationship dynamics between the focal supplier and its peers play a role in moderating the competitive or predatory threats from the peers. Specifically, our tests focus on business partnerships formed between the supplier and its peers as well as the dependence of the peers on the supplier's innovative efforts. Evidence supporting a dampening effect on the link between our key competition measures and supplier crash risk would further corroborate our baseline evidence and reinforce the notion that a firm's future crash risk can be attributed to the competitive dynamics with its peers.

4.1. Business partnership

When two or more firms form business partnership, they aim for mutual benefits. Their objective is to combine their efforts for various reasons including, but not limited to, sharing knowledge, expertise, expenses, as well as to gain a competitive advantage in the product market. Berg and Friedman (1981) suggest that alliances are formed for learning and knowledge acquisition, whereas Gomes-Casseres, Hagedoorn, and Jaffe (2006) show that alliances promote cooperation in the development of new technology. We test whether such collaborative interactions among the partners would reduce the peers' competitive or predatory efforts and, in turn, attenuate the effects of peer competitive pressure on stock price crash risk.

To conduct the test, we construct three alliance measures (*Alliance Peer Competitive Threat*) similar to our proxies for peer competitive threats: (i) *Alliance Peer Count* – the number of supplier peers who have formed a business partnership with the supplier, where business partnership is defined as pairs of firms committed to any of the following forms of business relationships: research collaboration; integrated product offering; joint venture; cross-ownership in equity stakes; products, patents, and intellectual property licensing; and use of each other's manufacturing, marketing, and distribution services; (ii) *Alliance Peer Sales* – the proportion of *Peer Sales* from supplier peers who have formed a business partnership with the supplier; (iii) *Alliance Peer Similarity* – *Peer Similarity* computed on those supplier peers who have formed a business partnership with the supplier. The information on whether supplier peers have established an alliance with a peer is obtained from the Revere database. With these *Alliance Peer Competitive Threat* constructs, we run the following panel regression.

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Alliance\ Peer\ Competitive\ Threat_{i,t} + \alpha_2 Peer\ Competitive \\ & Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \mathrm{FE} + \epsilon_{i,t}, \end{aligned} \tag{12}$$

In Eq. (12), the coefficient of α_1 captures the incremental effect of *Alliance Peer Competitive Threat* beyond that explained by the proxy for *Peer Competitive Threat*. We also consider an alternative specification of testing the effect of alliances where we decompose the measure *Peer Competitive Threat* into *Alliance Peer Competitive Threat* and *Non-Alliance Peer Competitive Threat*, and obtain qualitatively similar results. To conserve space, we only report regression results of Eq. (12) in Table 8.

The coefficients on all *Alliance Peer Competitive Threat* measures are negative and statistically significant for *Alliance Peer Count* and *Alliance Peer Similarity*. Consistent with our prior that collaborative relationships reduce peer competitive and predatory threats, the results indicate that alliances formed between the supplier and its peers reduce the overall peer competitive pressure on supplier stock price crash risk. For instance, a one-standard-deviation increase in *Alliance Peer Similarity* would lower $NCSKEW$ by 17.2% (= $(-1.653 + 1.29) \times 0.027/0.057$; see column (3)) of its sample mean (0.057), or would decrease $DUVOL$ by 21.9% (= $(-1.079 + 0.738) \times 0.027/0.042$; see column (6)) based on its sample mean (0.042).

4.2. Peer cross citations

We are also interested in whether a supplier's patents cited by its peers provide another mechanism through which peer competitive threats may exhibit a lesser impact on supplier stock price crash risk. The reasons are twofold. First, the more dependent is the peers' innovative output on the focal supplier's technological knowledge, the more likely the peers would consider the supplier as a source of knowledge acquisition rather than competitive rivalry (e.g., Oxley and Sampson, 2004; Frankort, 2016). Thus, we contend that dependent peers would commit less competitive efforts against the supplier. Second, patents can be employed in anti-competitive strategies, whose aim is to exclude competitors from the market. We contend that innovative suppliers can leverage their technological knowledge to gain competitive advantage over their peers. When used in the production of new products and processes, valuable inventions would stregthen the competitive position of oneself relative to its peers.

Economic research employs the number of times a patent is cited by subsequent patents as a proxy for the value of inventions (Gittelman, 2012; Sampat and Ziedonis, 2005). Accordingly, our analysis employs the average number of citations of a supplier's patents by its peers, *Peer Cross Cites*, as a means to gauge the dampening effect on peer competitive threats through the two channels. If supplier patents can be used to reduce the peer competitive pressure, we predict that peer cross citations would mollify the association between competitive pressure and the supplier crash risk. To test our prediction, we conduct a panel regression analysis by regressing each crash risk measure on the interaction of *Peer Cross Cites* with peer competitive threats variables as follows:

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times Peer\ Cross\ Cites_{i,t} + \alpha_2 Peer \\ & Competitive\ Threat_{i,t} + \alpha_3 Peer\ Cross\ Cites_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} \\ & + \mathrm{FE} + \epsilon_{i,t}, \end{aligned} \tag{13}$$

Regression results are shown in Table 9. Consistent with our prediction, *Peer Cross Cites* has attenuating effects on the relation between peer competitive pressure and the supplier crash risk. The coefficient on the interaction between *Peer Cross Cites* and *Peer Competitive Threat* is negative and statistically significant in a majority of the specifications.

Overall, we show that the relationship dynamics between the focal supplier and its peers play an important role in the effects of peer competitive pressure on the supplier's stock price crash risk. By reducing the peer competition intensity, collaborative efforts and knowledge sharing with the peers serve a moderating effect on the baseline relationship. Such findings further corroborate our conjecture that a firm's future crash risks are driven by the competitive dynamics with its peers.

5. Strategic News Hoarding or Business Risk?

While we have established that the effect of peer competitive threats on crash risk is driven by managers' motivations to hoard negative information from the public, one may argue that it merely captures the firm's greater exposure to business and cash flow risks associated with its peer competitive environment. Firms may potentially be more prone to crashes due to the fundamental nature of the firms' operations, irrespective of the information disclosure behavior. In this section, we aim to rule out this alternative explanation that hinges on firm business risk – the business risk hypothesis. First, we repeat the baseline analysis while controlling for the supplier's contemporary business risk and operating performance. If business risk and not adverse information hoarding is the underlying driver of the relationship between crash risk and peer pressure, then we should not find any peer threat effect on crash risk after accounting for the supplier's operating characteristics. Second, we investigate the relation between information asymmetry and crash risk as an indirect test against the business risk hypothesis. We contend that the effects of peer threats should be more pronounced for firms with high information asymmetry under the strategic disclosure hypothesis. Alternatively, if the business risk is the underlying driver of our key findings, then we should not find any differential peer pressure effects on the crash risk of firms with high vs. low information asymmetry.

5.1. Contemporaneous operating performance

We construct three proxies to capture the focal supplier's operating performance and business risk under the influence of peer competitive pressure, all of which are measured in year $t+1$. The first proxy we construct is the supplier's price-cost margin (PCM), which captures the supplier's market power (*Supplier Market Power*). Gaspar and Massa (2006) suggest that product market power works as a natural hedge that smooths out cash flow fluctuations, thereby reducing the idiosyncrative volatility of a firm. Thus, we contend that the greater the firm's PCM, the lower is its business risk. Following Peress (2010), we define PCM as the firm's operating profit margin demeaned by the industry average to account for the industry-specific attributes unrelated to competition intensity. The second proxy is the annual standard deviation of the firm's operating income before depreciation over total assets (*Supplier Operating Risk*). The third proxy variable is the contemporaneous operating performance of the firm (*Supplier Operating Performance*). We capture the incidence of negative operating performance using the number of negative news net of positive news on the firm's products and services. In particular, we use news articles from Ravenpack that are related to the focal supplier's demand-guidance, demand, production-outlook, supply-guidance, supply, market-guidance, and market-share, all of which are topics relevant for product market competition considerations. News with below the median event sentiment score is considered as negative news and the rest as positive news. Results using these three different proxies for a firm's business risk are shown in Panels A-C of Table 10, respectively.

The panels reveal two distinct findings suggesting that it is negative news hoarding rather than business risk that is the channel through which peer competitive threats affect stock price crash risk. First, while the coefficients on *Supplier Market Power* are not statistically significant, those on *Supplier Operating Risk* and *Supplier Operating Performance* are positive and mainly statistically significant at the conventional level. These findings suggest that the greater the business risk, the larger is a supplier's stock price crash risk. Second, comparing to those of Table 2, the coefficients on the three proxies for peer competitive threats remain substantially unchanged in terms of magnitude and statistical significance. The implication is that the proxies for business risk do not subsume the effect of peer threats on crash risk, therefore suggesting that business risk is not the driving force behind the impact of peer pressure on crash risk.

5.2. *Information asymmetry*

Existing literature (e.g., Jin and Myers, 2006; Kothari, Shu, and Wysocki, 2009) suggests that managers are better able to conceal bad news for an extended period when firms have high information asymmetry. Hence, one empirical implication of the strategic information disclosure explanation is that the link between peer competitive threats and crash risk would be stronger for firms with high information asymmetry. The operating risk explanation, on the other hand, makes no such prediction. Under this alternative hypothesis, crash risk is driven by the underlying operational performance of a firm, so cross-sectional differences in information asymmetry should not have any sizeable effect on the relation between peer competitive threats and crash risk. We employ these differences in prediction to indirectly test our strategic information disclosure hypothesis. Specifically, we examine the role of information asymmetry by investigating the cross-sectional impacts of (i) institutional ownership breadth; (ii) analyst forecast dispersion; and (iii) news coverage.

5.2.1. *Institutional ownership breadth*

Prior work demonstrates that as sophisticated investors, institutional owners trade on superior information and in turn, accelerate the incorporation of such information into stock prices (El-Gazzar, 1998; Jiambalvo, Rajgopal, and Venkatachalam, 2002; Piotroski and Roulstone, 2004). Thus, greater institutional presence should improve the information environment of a firm and reduce the impact of peer competitive threats on crash risk, due to fewer opportunities afforded to firm managers to hoard bad news. To test our prediction, we use institutional breadth, $No.Inst_{i,t}$, defined as the natural log of the number of institutions holding shares of firm i's stock in year t, as a proxy for institutional presence in a firm.

We rerun Eq. (13) using $No.Inst_{i,t}$ in place of $Peer\ Cross\ Cites_{i,t}$ and report our findings in Table 11. Peer competitive threats on supplier stock price crash risk continue to exhibit a positive impact on firms with low institutional presence. The coefficients on the peer competitive pressure measures are strongly significant at the 1% level for all crash risk proxies. For example, the coefficient on *Peer Count* is from 0.037 ($t = 3.08$) in column (4) to 0.080 ($t = 4.41$) in column (1). However, this positive effect is substantially weakened for firms with high level of institutional breadth; the coefficient on the interaction term is negative and statistically significant at the 5% level across different measures of crash risk and peer competitive threats. For example, a one-standard-deviation rise in *Peer Count* would result in a reduction of the likelihood of stock price crash risk by about 25% ($= -0.014 \times 1.015/0.057$) for suppliers with greater institutional breadth. The evidence is in line with the strategic information disclosure hypothesis.

5.2.2. *Analyst forecast dispersion*

Another measure we construct to proxy for information asymmetry is analyst forecast dispersion. Firm opacity impairs the ability of analysts to interpret the current-period information and reach consensus on their predictions of the firm's future performance. Analysts covering firms with greater information asymmetry tend to generate more dispersed opinions. Using the data obtained from the Institutional Brokers' Estimate System (IBES), we compute analyst forecast dispersion as the standard deviation of annual earnings per share (EPS) forecasts for fiscal year t, scaled by the stock price at the beginning of the fiscal year. Following Lang and Lundholm (1996) and Gu and Wang (2005), we take the one-year-ahead consensus forecasts at six months prior to the fiscal year-end to ensure that all analysts have access to the financial information from the previous fiscal year and have the same forecast horizons. We then define a binary variable $High\ Dispersion$, which equals 1 if analyst dispersion is above the fourth quartile of all firms in the same industry-year, and 0 if it is below the first quartile.

We re-estimate Eq. (13) using $High\ Dispersion_{i,t}$ in place of $Peer\ Cross\ Cites_{i,t}$, and results are presented in Table 12. The coefficients on the key competition variables indicate that competitive pressure is not statistically related to crash risk for highly transparent firms. However, the coefficients on the interaction term are positive and significant for most of the specifications, suggesting that when faced with greater peer competitive pressure, high opaque firms tend to have significantly higher crash risk. The findings are consistent with those of Table 11 and support the notion that crash risk is driven by the strategic hoarding of negative information by supplier managers.

5.2.3. *News coverage*

Bushee et al. (2010) find that greater news coverage reduces the information asymmetry of a firm. Through the timely dissemination of firm-initiated information as well as the packaging of information from multiple sources, the business press provides information to the market participants incremental to firm disclosures and other information intermediaries. Thus, news coverage is another appropriate measure of information environment that we use to conduct the cross-sectional tests.

We obtain data on press articles from Ravenpack full package, which includes articles from over 150,000 press releases, regulatory disclosures, web aggregators, and blog sites. We utilize the log of the number of unique Ravenpack news sources covering each firm over its fiscal year as a proxy for news coverage breadth. Similar to Tables 11-12, Table 13 presents results from the estimation of Eq. (13) using $Media\ Coverage_{i,t}$ in place of$Peer\ Cross\ Cites_{i,t}$. The coefficients on the interaction term are all negative but statistically significantly only for both $NCSKEW$ and $Crash\ Count$. It is apparent that the lower the information asymmetry, the less likely the supplier managers are able to withhold negative news. Combined, these results suggest that the effect of peer competitive threats on supplier stock price crash risk is more pronounced for firms with high information asymmetry.

In summary, the multitude of cross-sectional tests on information asymmetry complement one another in suggesting that our main findings are driven by managers' intentions to withhold negative news as opposed to the business and cash flow risks of the suppliers.

6. Regulatory Implications

Our empirical evidence, thus far, seems consistent with the information story that peer competitive pressure contributes to managers' motives to conceal negative information. In this section, we explore the regulatory implications associated with such information hoarding behavior. In particular, we ask whether this type of behavior manifests itself in the managers' mandatory disclosure of financial reporting to regulatory authorities, such as the SEC. Corporations disclose mandatory financial information through regulated financial reports, including financial statements, 10-K footnote disclosures, MD&A, and other regulatory filings. Disclosure allows firm managers to provide information to different stakeholders, regulators and government agencies, as well as the general public.

Our analysis focuses only on mandatory disclosure so as to circumvent the typical self-selection concern associated with voluntary communication, such as management forecasts, press releases, internet sites, analysts' presentations and conference calls, and other corporate reports. We implement several empirical tests of the disclosure quality of the mandatory financial reporting of supplier firms. The first set of tests looks at the number of SEC comment letters on different corporate filings with the SEC, whereas the other set examines the complexity of the financial reports.

6.1. SEC comment letters

The SEC frequently reviews corporate filings and such reviews have traditionally been a main source of uncovering irregularities and significant deficiencies in disclosure. The reviews are, however, time consuming and require considerable resources. Prior to the Sarbanes-Oxley Act of 2002 (SOX), the SEC reviewed the financial filings of about 20 percent of all public firms yearly (Johnston and Petacchi, 2017). Following the Enron accounting scandal, one main criticism against the SEC was that it failed to review any of Enron's post 1997 financial statements, missing its opportunity to find red flags in the company's gross misstatements.[17] Subsequently, Section 408 of SOX was instituted that requires the SEC to conduct some level of review of each publicly listed company at least once every three years.

[17] "Systemic Failure by SEC Is Seen in Enron Debacle," by Jonathan Weil and John Wilke Staff Reporters of The Wall Street Journal, Oct. 7, 2002.

The SEC's Division of Corporation Finance has an oversight role of financial reporting through its review of company filings (e.g., Form 10-Ks, Form 10-Qs, Form S-1s, and DEF 14A). Their mission is to ensure compliance with "the applicable disclosure and accounting requirements." The SEC staff conducts three levels of reviews: (i) a complete review of all of a firm's filings; (ii) a financial statement review that involves the financial statements, notes, and related disclosure such as the MD&A; or (iii) a targeted review examining particular issues in a filing. If a review flags potential deficiencies, the SEC sends a comment letter to the firm requesting clarification, additional information, or disclosure adjustments in the filing or future filings. A majority of SEC comment letters relate to annual and quarterly financial reports, material news disclosures, proxy statements, and registration and prospectus filings. While the SEC comment letters reflect the SEC staff positions and have no legal implications, corporate executives could perceive them differently and be concerned about the market participants' response to the SEC comment letter correspondence. The SEC released their comment letters and companies' response letters, starting 2005, and releases of such letters have prompted a plethora of studies in this area. For example, Dechow, Lawrence, and Ryans (2016) find that insiders engage in substantial sales of their shares prior to the public disclosure of revenue recognition-related SEC comments. Cassell, Dreher, and Myers (2013) show that firms incur high associated remediation costs in response to SEC comment letters.

We exploit these comment letters to evaluate the quality of suppliers' mandatory financial reporting in response to peer competitive threats. If such threats incite supplier managers to hide negative information of their firm, we expect their required financial filings to lack clarity and trigger SEC reviews. SEC comment letters are obtained from the Audit Analytics comment letter database, which records the disclosure date and transcribes and codes the issues identified in the comment letters. We employ the number of SEC comment letters (*No. Comment Letters*) a supplier firm receives each year as a testament of the supplier managers' deliberate information hoarding behavior. We reestimate Eq. (7) by replacing the dependent variable, *Crash Risk*, with *No. Comment Letters* and report the results in Table 14. We find the coefficients on all the different measures of peer competitive threats to be positive and strongly significant at the 1% level. Mandatory financial reports filed by supplier managers might have reflected their intention to hoard information and ultimately, precipitated the SEC reviews, consistent with the strategic information disclosure explanation.

6.2. *Financial report readability*

Prior research finds that firms with weak performance tend to disclose harder to read financial information and that those with better performance are likely to produce readable financial statements (e.g., Li, 2008). Such findings are consistent with management obfuscating the truth about their firms. Others show that when managers tacitly collude to withhold bad news, their financial report readability measures are low, consistent with the hypothesis that managers strategically hoard negative information (e.g., Rogers, Schrand, and Zechman, 2014). A recent study by Li and Zhan (2018) suggests that one adverse outcome of product market competition is that faced with intense competition, firms tend to produce more obscure financial disclosures, making it harder for investors to analyze their firm's information. Following this strand of literature, we examine the readability of the MD&A section of supplier firms' annual and quarterly financial reporting

As required by the SEC and the Financial Accounting Standards Board (FASB), all US public firms must include the MD&A section in their annual report to shareholders. According to FASB, "MD&A should provide a balanced presentation that includes both positive and negative information about the topics discussed." Hence, in the MD&A section, firm management will provide a narrative disclosure of the firm's performance over the past year using qualitative and quantitative performance measures. Firm management also will comment on financial statements, current and future challenges faced by the firm, goals and projections, and the extent of its exposure to market risks. The MD&A represents the management's opinions and provides a forecast of future operations, and therefore these statements cannot typically be falsified. Market participants view this section as a vital source of information to evaluate the firm's financial fundamentals and management performance.

Given that the MD&A section is qualitative, text-based, and narrative in nature, we utilize text analysis and language processing algorithm to construct three popular measures of financial report readability for these narrative disclosures, namely the Flesch-Kincaid index (*Flesch-Kincaid*), the Gunning Fog index (*Fog*), and the Gobbledygook index (*SMOG*),[18] to gauge the extent of financial report readability. Therefore, the three readability indexes measure the complexity of these narrative financial disclosure; the index values increase with complexity of financial reporting. We test whether proxies for peer competitive threats are associated with the three measures of financial report readability. Results, as reported in Table 15, show robust evidence that more peer competitive threats are associated with greater complexity of financial reports (i.e., larger *Flesch-Kincaid*, *Fog*, and *SMOG* indexes), suggesting that when faced with greater peer competitive threats, supplier managers are more likely to withhold adverse information through obscure financial reports.

7. Conclusion

We exploit the vast complex network of supplier-customer links to examine the strategic news disclosure behavior of a supplier facing intense competition from peers that supply to the same customers. We find that our measures of customer-connected peer competitive pressure play an important role in supplier stock price crash risk, a proxy for the supplier's accumulation of bad news, suggesting that supplier managers strategize to withhold or delay disclosing bad news that may have

[18] We have also employed two alternative measures, such as the Flesch reading-ease score and automated readability index, and the unreported results are substantially similar to those reported using the three more popular measures adopted in the accounting and finance literature.

a detrimental effect on their stock price. This finding is robust to other sources of competition, as measured by the level of industry competitiveness, or the level of non-linked peer competitiveness, as well as to the customer concentration base and extreme economic crisis period that might influence future stock price crash risk. To alleviate possible endogeneity concerns associated with this baseline evidence, we investigate three quasi-natural experiments that capture large exogenous shocks to linked peers: (i) the M&A activities of customers as an exogenous source of an increase in the number of peers supplying to the same group of customers, thereby intensifying peer competitive threats to the supplier; (ii) the exogenous reduction in peer competitive pressure due to peer bankruptcies; and (iii) locations of peers' business operations affected by natural disasters. Results from these three quasi-natural experiments corroborate our evidence that peer competitive pressure has a causal effect on supplier stock price crash risk.

While our findings have established a positive relation between peer competitive pressure and supplier stock price crash risk, such a relationship is consistent with two competing views – the strategic news disclosure hypothesis and the business risk hypothesis. For the strategic news disclosure hypothesis, the link between peer competitive threats and crash risk would be more pronounced for firms with high information asymmetry. Intuitively, it is easier for managers of firms with have high information asymmetry to conceal bad news for an extended period than their counterparts with low information asymmetry. On the other hand, for the business risk hypothesis, crash risk is explained by the firm's underlying operational performance. If the result is consistent with this hypothesis, then the peer competitive threat effect on stock price crash risk should reflect the underlying impact of business risk on crash risk. Furthermore, if the business risk of a firm is, indeed, driving the peer pressure effect on crash risk, any cross-sectional variation in information asymmetry should not have any pronounced effect on the relation between peer competitive threats and crash risk. Our tests using different proxies for business risk yield results suggesting that business risk is not the driving force behind our key finding. Our further analysis explores the role of information asymmetry in the link between peer competitive pressure and crash risk and provides confirming indirect evidence consistent with the strategic information disclosure hypothesis. Finally, we also find that a supplier firm's mandatory financial filings are more inclined to trigger a greater number of SEC reviews of their financial information and that their financial reports are more complex and less readable. The overall results therefore suggest that our key findings are consistent with the strategic information disclosure hypothesis that in the face of intense peer competitive pressure, supplier managers strategically withhold or delay releases of negative news.

Our results have significant implications for disclosure policies of supplier information. While prior studies (e.g., Hui, Klasa, and Yeung, 2012) suggest that customer bargaining power promotes transparency of supplier firms, our findings indicate that such transparency between customers and suppliers does not necessarily reduce the information asymmetry between the suppliers and their investors. Unlike Chang et al. (2015) that claim a positive relationship between customer bargaining power and corporate governance, our results reveal a dark side to the power imbalance of trading relationships. Regulators should keep in mind that interconnectedness of firms through trading relationships can adversely affect the information environment of these firms.

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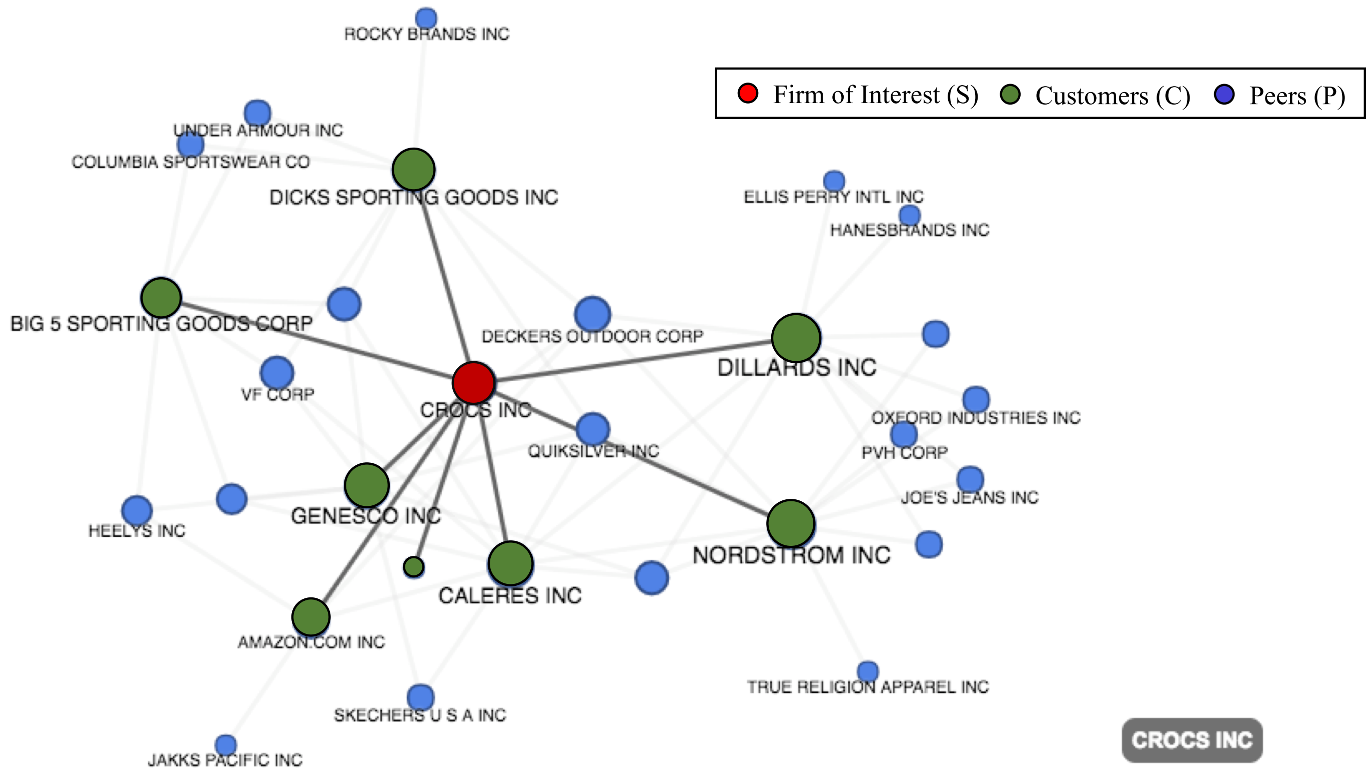
Figure 1: A Snapshot of Crocs Inc's 2011 Network of Suppliers

This graph contains a proportion of the supply-chain network of Crocs, Inc in 2011. It includes all corporate customers and other peer suppliers to those customers that could be identified by Revere and Compustat supply-chain data. We restrict all the firms in this graph to be a part of CRSP and Compustat universe. The red node indicates Crocs, Inc, the green nodes represent the corporate customers of Crocs, Inc, and the blue nodes represent the suppliers to those customers, which are industry peers to Crocs, Inc according to Hoberg and Phillips's (2010) TNIC classification. All the layout and label are generated by Fusiontables, a Google data visualization application.



Firm (S_i) has n_i customers; each customer (C_j) has m_j suppliers, including S_i and S_i's industry peer P_k, where industry is defined in Hoberg and Phillips (2010).

$$Peer\ Count_i = ln\left(\frac{\sum_{j=1}^{n_i} m_j}{n_i}\right) \qquad Peer\ Sales_i = \sum_{j=1}^{n_i}\left(\sum_{k=1}^{m_j}\frac{Sales_{j,k}}{COGS_j}\right)\Big/ n_i \qquad Peer\ Similarity_i = \sum_{j=1}^{n_i}\left(\sum_{k=1}^{m_j}\frac{Similarity_{i,k}}{m_j}\right)\Big/ n_i$$

where $Sales_{j,k}$ is the sales from P_k to C_j, $COGS_j$ is the cost of goods sold of C_j, and $Similarity_{i,k}$ is Hoberg-Phillips industry similarity between S_i and P_k.

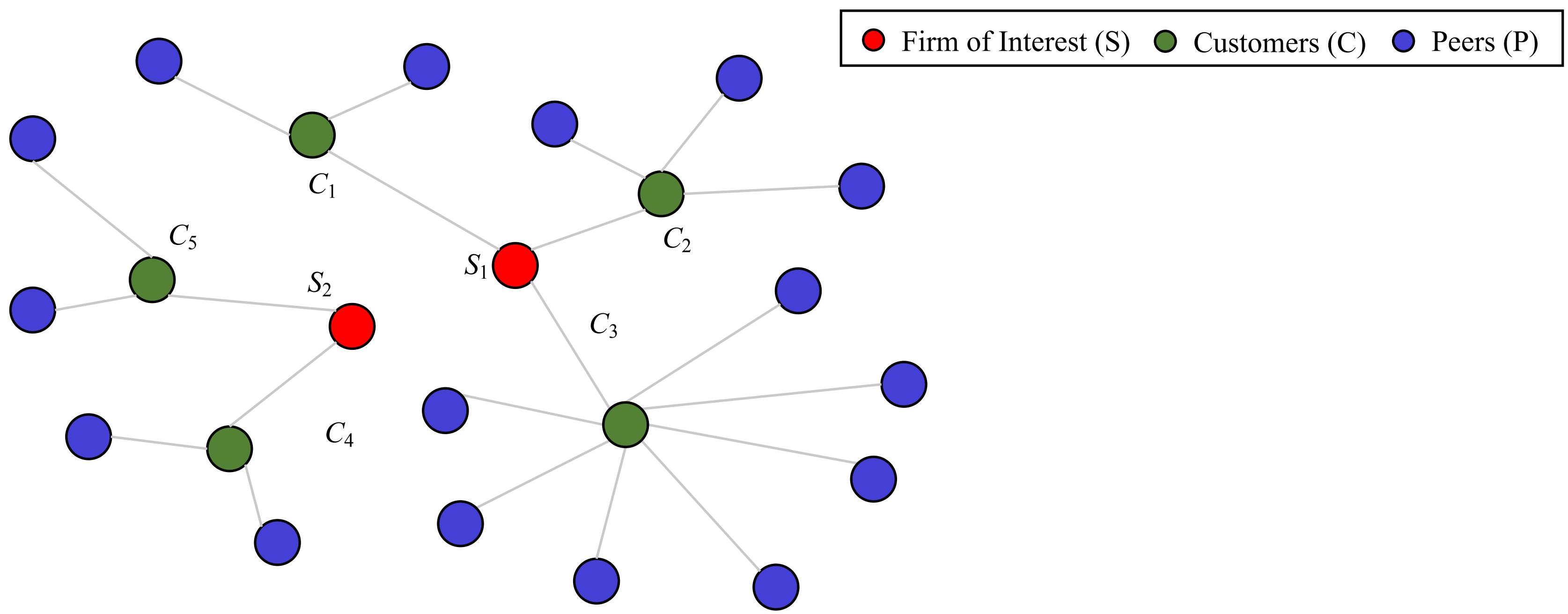


Table 1

Summary Statistics

This table reports the number of observations (N), the mean and standard deviation of the variable, as well as the distribution in different percentiles of 5%, 25%, 50% (median), 75%, and 95%. Panel A contains the summary statistics of four proxies for the peer competitive threats, namely (1) the log of number of other suppliers in the same industry of the customer (Peer Count); (2) the sum of the ratio of a supplier's sales to customer's cost of goods sold across all other suppliers of the customer (Peer Sales); (3) the averge product similarity with other suppliers of the customer (Peer Similarity). Panel B shows the summary statistics of three measures of stock price crash risk: (1) the negative conditional skewness of stock returns (NCSKEW); (2) the log of the standard deviation of down weeks' returns divided by the standard deviation of weekly returns in the up weeks (DUVOL); (3) the number of firm-specific weekly returns exceeding 3.09 standard deviation below the mean firm-specific weekly return over the fiscal year (Crash Count). Panel C contains summary statistics of firm-specific control variables such as size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), and past stock return. Construction of the variables is presented in Appendix A. Sample period is from 1990 to 2015.

				Percentiles				
Variable	N	Mean	Std Dev	5%	25%	Median	75%	95%
Panel A: Peer Competitive Threats								
Peer Count$_t$	28,598	1.015	1.015	0.000	0.000	0.693	1.792	2.952
Peer Sales$_t$	27,136	0.016	0.038	0.000	0.000	0.000	0.014	0.086
Peer Similarity$_t$	28,598	0.022	0.027	0.000	0.000	0.013	0.033	0.079
Panel B: Measures of Stock Price Crash Risk								
NCSKEW$_{t+1}$	28,585	0.057	0.849	-1.294	-0.426	0.019	0.480	1.589
DUVOL$_{t+1}$	28,585	0.042	0.542	-0.840	-0.320	0.024	0.380	0.982
Crash Count$_{t+1}$	28,598	-0.008	0.656	-1.000	0.000	0.000	0.000	1.000
Panel C: Control Variables								
Size$_t$	28,598	6.551	2.176	3.074	4.981	6.452	8.022	10.398
MB$_t$	28,598	3.307	3.983	0.676	1.338	2.168	3.649	9.371
Leverage$_t$	28,598	0.153	0.164	0.000	0.000	0.109	0.257	0.480
ROA$_t$	28,598	-0.003	0.167	-0.338	-0.018	0.038	0.078	0.159
ΔTurnover$_t$	28,598	-0.003	0.070	-0.116	-0.038	-0.005	0.029	0.122
AbAccr$_t$	28,598	0.216	0.184	0.038	0.090	0.160	0.277	0.604
Sigma$_t$	28,598	0.057	0.031	0.020	0.034	0.049	0.071	0.119
Return$_t$	28,598	-0.205	0.249	-0.702	-0.249	-0.118	-0.055	-0.020

Table 2

Peer Competitive Threats and Supplier Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for peer competitive threats as follows:

$$Crash\ Risk_{i,t+1} = \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \mathrm{FE}_t + \epsilon_{i,t}.$$

where $X_{ki,t}$ is a vector of controls, such as size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). The three proxies for the peer competitive threats include Peer Count; Peer Sales; and Peer Similarity, whereas the three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count_t	0.029***			0.015***			0.019***		
	(5.45)			(4.28)			(4.64)		
Peer Sales_t		0.417***			0.241***			0.197*	
		(2.92)			(2.72)			(1.87)	
Peer Similarity_t			1.151***			0.622***			0.562***
			(5.61)			(4.83)			(3.57)
Size_t	0.039***	0.039***	0.038***	0.023***	0.023***	0.023***	0.027***	0.027***	0.027***
	(11.25)	(11.03)	(11.10)	(10.58)	(10.36)	(10.43)	(10.25)	(10.13)	(10.24)
MB_t	0.005***	0.004***	0.005***	0.004***	0.004***	0.004***	0.002*	0.002	0.002*
	(3.24)	(2.95)	(3.23)	(3.90)	(3.76)	(3.89)	(1.80)	(1.58)	(1.81)
Leverage_t	-0.032	-0.028	-0.042	-0.019	-0.019	-0.024	-0.012	-0.009	-0.018
	(-0.91)	(-0.78)	(-1.19)	(-0.85)	(-0.82)	(-1.08)	(-0.46)	(-0.34)	(-0.67)
ROA_t	0.267***	0.255***	0.272***	0.153***	0.145***	0.156***	0.193***	0.185***	0.193***
	(7.38)	(6.92)	(7.56)	(6.70)	(6.27)	(6.87)	(7.20)	(6.76)	(7.21)
$\Delta\text{Turnover}_t$	0.500***	0.540***	0.506***	0.308***	0.328***	0.311***	0.326***	0.359***	0.329***
	(5.78)	(6.19)	(5.85)	(5.66)	(5.95)	(5.72)	(4.87)	(5.33)	(4.92)
AbAccr_t	0.079**	0.096***	0.079**	0.056***	0.065***	0.056***	0.049**	0.057**	0.050**
	(2.48)	(2.97)	(2.49)	(2.82)	(3.24)	(2.82)	(1.99)	(2.26)	(2.05)
NCSKEW_t	0.013*	0.017**	0.013*	0.005	0.008*	0.005	0.014***	0.016***	0.014***
	(1.84)	(2.45)	(1.90)	(1.18)	(1.76)	(1.23)	(2.63)	(3.00)	(2.70)
Sigma_t	5.347***	5.475***	5.317***	3.012***	3.049***	2.985***	2.872***	3.076***	2.908***
	(7.99)	(7.99)	(7.93)	(7.12)	(7.02)	(7.05)	(5.58)	(5.81)	(5.64)
Return_t	0.611***	0.622***	0.610***	0.332***	0.333***	0.331***	0.369***	0.390***	0.373***
	(8.19)	(8.20)	(8.16)	(6.95)	(6.84)	(6.91)	(6.40)	(6.59)	(6.47)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.017
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3

Peer Competitive Threats vs. Other Sources of Competition

This table reports results from regressing supplier stock price crash risk on each proxy for peer competitive threats as well as a proxy for other source of competition, as follows:

$$Crash\ Risk_{i,t+1} = \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \text{Other Source of Competition} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE}_t + \epsilon_{i,t},$$

where $X_{ki,t}$ is a vector of controls, such as size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). Panels A-D replicate the analysis as Table 2 in the presence of a proxy for other source of competition, namely supplier industry HHI, supplier fluidity measure, non-linked peer count and non-linked peer similarity, respectively. The three proxies for the peer competitive threats include Peer Count; Peer Sales; and Peer Similarity, whereas the three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Proxy for Product Market Environment: Supplier Industry Concentration (HHI)									
Peer Count_t	0.030***			0.015***			0.020***		
	(5.48)			(4.32)			(4.69)		
Peer Sales_t		0.421***			0.245***			0.202*	
		(2.94)			(2.76)			(1.91)	
Peer Similarity_t			1.157***			0.627***			0.569***
			(5.63)			(4.86)			(3.60)
Supplier Industry HHI_t	0.239	0.204	0.226	0.193	0.189	0.188	0.259	0.234	0.241
	(0.90)	(0.75)	(0.85)	(1.15)	(1.09)	(1.12)	(1.35)	(1.18)	(1.25)
NObs	28,582	27,120	28,582	28,582	27,120	28,582	28,595	27,133	28,595
R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Proxy for Product Market Environment: Supplier Fluidity Measure									
Peer Count_t	0.018***			0.009**			0.011**		
	(2.76)			(2.04)			(2.22)		
Peer Sales_t		0.289*			0.169*			0.104	
		(1.92)			(1.80)			(0.94)	
Peer Similarity_t			0.814***			0.457***			0.274
			(3.46)			(3.09)			(1.51)
Fluidity_t	0.002	0.003	0.001	0.001	0.002	0.000	0.001	0.002	0.001
	(0.77)	(1.34)	(0.51)	(0.54)	(1.12)	(0.20)	(0.63)	(1.14)	(0.81)
NObs	24,111	22,664	24,111	24,111	22,664	24,111	24,121	22,674	24,121
R^2	0.027	0.027	0.028	0.030	0.029	0.030	0.020	0.020	0.020
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 – Continued

Peer Competitive Threats vs. General Product Market Environment

Variable	$NCSKEW_{t+1}$ (1)	(2)	(3)	$DUVOL_{t+1}$ (4)	(5)	(6)	Crash $Count_{t+1}$ (7)	(8)	(9)
Panel C: Proxy for Product Market Environment: Non-Linked Peer Count									
Peer $Count_t$	0.028***			0.013***			0.019***		
	(4.58)			(3.35)			(4.13)		
Peer $Sales_t$		0.392**			0.219**			0.208*	
		(2.51)			(2.23)			(1.81)	
Peer $Similarity_t$			1.087***			0.600***			0.486***
			(4.65)			(4.09)			(2.72)
Non-Linked Peer $Count_t$	0.005	0.013	0.003	0.004	0.006	0.002	0.008	0.015	0.009
	(0.29)	(0.78)	(0.18)	(0.42)	(0.59)	(0.25)	(0.68)	(1.27)	(0.79)
NObs	22,904	21,580	22,904	22,904	21,580	22,904	22,915	21,591	22,915
R^2	0.018	0.017	0.018	0.021	0.020	0.021	0.012	0.011	0.011
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel D: Proxy for Product Market Environment: Non-Linked Peer Similarity									
Peer $Count_t$	0.026***			0.012***			0.019***		
	(4.34)			(3.12)			(4.02)		
Peer $Sales_t$		0.372**			0.209**			0.204*	
		(2.37)			(2.12)			(1.77)	
Peer $Similarity_t$			1.024***			0.565***			0.461**
			(4.35)			(3.81)			(2.55)
Non-Linked Peer $Similarity_t$	0.242	0.290	0.203	0.152	0.149	0.121	0.120	0.144	0.134
	(1.36)	(1.56)	(1.14)	(1.41)	(1.31)	(1.11)	(0.97)	(1.14)	(1.07)
NObs	22,904	21,580	22,904	22,904	21,580	22,904	22,915	21,591	22,915
R^2	0.018	0.017	0.018	0.021	0.020	0.021	0.012	0.011	0.011
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4

Additional Robustness Tests

This table reports additional robustness results from regressing supplier stock price crash risk on each proxy for peer competitive threats, and additional controls, as follows:

$$\textit{Crash Risk}_{i,t+1} = \alpha_0 + \alpha_1 \textit{Peer Competitive Threat}_{i,t} + \alpha_2 \text{Additional Control} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE}_t + \epsilon_{i,t},$$

where $X_{ki,t}$ is a vector of controls, such as size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). Panels A and B conduct the same analysis as Table 2 with additional controls. Panel A controls for customer concentration, whereas Panel B replicates the panel regressions of Table 2, except the sample excludes the global financial crisis years of 2007-2008. The three proxies for the peer competitive threats include Peer Count; Peer Sales; and Peer Similarity, whereas the three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Control for Customer Concentration									
Peer Count_t	0.027***			0.014***			0.019***		
	(5.04)			(3.96)			(4.52)		
Peer Sales_t		0.366**			0.214**			0.184*	
		(2.55)			(2.40)			(1.74)	
Peer Similarity_t			1.068***			0.580***			0.551***
			(5.14)			(4.45)			(3.43)
Customer	0.110**	0.140***	0.104**	0.058*	0.074**	0.053*	0.012	0.035	0.015
Concentration_t	(2.22)	(2.76)	(2.08)	(1.94)	(2.42)	(1.77)	(0.32)	(0.93)	(0.40)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Exclude Global Financial Crisis Years 2007 and 2008									
Peer Count_t	0.027***			0.014***			0.017***		
	(4.72)			(3.87)			(3.92)		
Peer Sales_t		0.391***			0.229**			0.198*	
		(2.59)			(2.42)			(1.76)	
Peer Similarity_t			1.145***			0.659***			0.520***
			(5.25)			(4.82)			(3.10)
NObs	25,241	23,948	25,241	25,241	23,948	25,241	25,252	23,959	25,252
R^2	0.024	0.024	0.025	0.027	0.026	0.027	0.018	0.018	0.017
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5

Customer M&A and Supplier Stock Price Crash Risk

The table conducts the two-stage least squares analysis using M&A as an instrumental variable, and the reported weak ID $F-$ test. Similar to Table 2, each measure of the supplier stock price crash risk is regressed on a proxy for peer competitive threats, while controlling for firm-specific variables, such as size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned} Peer\ Competitive\ Threat_{i,t} &= \gamma_0 + \gamma_1 Instrumental\ Variable_{i,t} + \sum_{k=1}^{K} \lambda_k X_{ki,t} + \text{FE} + \eta_{i,t}, \\ Crash\ Risk_{i,t+1} &= \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}. \end{aligned}$$

The three proxies for the peer competitive threats include Peer Count; Peer Sales; and Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and weak ID $F-$statistics are reported. Construction of the variables is presented in Appendix A.

	First-Stage	NCSKEW$_{t+1}$	First-Stage	DUVOL$_{t+1}$	First-Stage	Crash Count$_{t+1}$
Variable	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Peer Count			
Customer M&A Intensity$_t$	1.355***		1.355***		1.359***	
	(6.23)		(6.23)		(6.25)	
Peer Count$_t$		0.288***		0.158**		0.139*
		(2.81)		(2.49)		(1.84)
NObs	25,089	25,089	25,089	25,089	25,100	25,100
Weak ID F-stat		38.87		38.87		39.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
			Panel B: Peer Sales			
Customer M&A Intensity$_t$	0.042***		0.042***		0.042***	
	(5.53)		(5.53)		(5.53)	
Peer Sales$_t$		9.117***		4.950**		4.481*
		(2.64)		(2.36)		(1.75)
NObs	23,901	23,901	23,901	23,901	23,912	23,912
Weak ID F-stat		30.53		30.53		30.60
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
			Panel C: Peer Similarity			
Customer M&A Intensity$_t$	0.020***		0.020***		0.021***	
	(4.15)		(4.15)		(4.16)	
Peer Similarity$_t$		19.097**		10.474**		9.170*
		(2.51)		(2.27)		(1.74)
NObs	25,089	25,089	25,089	25,089	25,100	25,100
Weak ID F-stat		17.24		17.24		17.34
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6

Difference-in-differences Analysis: Peer Bankruptcy

The table presents a difference-in-differences analysis of a measure of stock price crash risk of the supplier with and without peer bankruptcy. The independent variables are Post, Treatment firms (Treat), supplier peer bankruptcy (Bankruptcy), supplier's market share (MktShare) in the product market, as well as firm-specific controls.

$$\begin{aligned} Crash\ Risk_{i,t+1} &= \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_{i,t+1} + \alpha_3 Treat_i \times Post_{i,t+1} \\ &\quad + \text{Additional Controls} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}. \end{aligned}$$

Treat is an indicator equal to one if any of the supplier peers files for Chapter 11 bankruptcy, and 0 otherwise. Post_{t+1} is an indicator that equals one during the year in which the supplier peer files for bankruptcy, and 0 otherwise. Bankruptcy_{t+1} is an indicator that equals one if the supplier files bankruptcy in $t+1$ and 0 otherwise. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. Firm-specific variables include size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW_{t+1}	DUVOL_{t+1}	Crash Count_{t+1}
	(1)	(2)	(3)
$\text{Post}_{t+1} \times \text{Treat}_{t+1}$	-0.155***	-0.132***	-0.096**
	(-2.91)	(-3.38)	(-2.40)
Treat_{t+1}	0.027	0.019	0.023
	(1.10)	(1.18)	(1.23)
Bankruptcy_{t+1}	0.843***	0.508***	0.445***
	(3.40)	(2.84)	(2.66)
MktShare_{t+1}	-0.644***	-0.408***	-0.403***
	(-3.68)	(-3.72)	(-3.12)
NObs	19,222	19,222	19,227
R^2	0.022	0.027	0.014
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 7

Peer Disaster and Supplier Stock Price Crash Risk

This table reports panel regression results from regressing a measure of supplier stock price crash risk on a measure of peer competitive threats, Peer Disaster indicator, and the interaction between the latter two variables, while controlling for firm-specific variables ($X_{ki,t}$), such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE), as follows.

$$
\begin{aligned}
Crash\ Risk_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times Peer\ Disaster_{i,t+1} + \alpha_2 Peer \\
& Competitive\ Threat_{i,t} + \alpha_3 Peer\ Disaster_{i,t+1} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t},
\end{aligned}
$$

The three proxies for peer competitive threats include Peer Count, Peer Sales, Peer Similarity. The Peer Disaster indicator takes a value of one if a major disaster occurred in the county where the supplier's peer had at least 20% of their employees and zero otherwise. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count_t	-0.045**			-0.024*			-0.028*		
$\times$ $\text{Peer Disaster}_{t+1}$	(-2.00)			(-1.65)			(-1.70)		
Peer Count_t	0.033***			0.020***			0.022***		
	(3.63)			(3.36)			(3.11)		
Peer Sales_t		-0.588*			-0.388*			-0.396*	
$\times$ $\text{Peer Disaster}_{t+1}$		(-1.81)			(-1.82)			(-1.71)	
Peer Sales_t		0.455**			0.315***			0.205	
		(2.53)			(2.75)			(1.57)	
Peer Similarity_t			-1.051*			-0.283			-0.955**
$\times$ $\text{Peer Disaster}_{t+1}$			(-1.69)			(-0.71)			(-2.10)
Peer Similarity_t			1.061***			0.603***			0.436**
			(3.91)			(3.56)			(2.13)
$\text{Peer Disaster}_{t+1}$	0.073	0.014	0.034	0.032	0.005	0.002	0.043	0.009	0.034
	(1.42)	(0.64)	(1.15)	(1.00)	(0.37)	(0.12)	(1.13)	(0.55)	(1.50)
Disaster_{t+1}	0.018	0.014	0.019	0.014	0.008	0.014	0.014	0.012	0.013
	(0.67)	(0.49)	(0.68)	(0.83)	(0.43)	(0.84)	(0.67)	(0.56)	(0.63)
NObs	19,230	17,768	19,230	19,230	17,768	19,230	19,235	17,773	19,235
R^2	0.022	0.020	0.022	0.026	0.024	0.026	0.014	0.013	0.014
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8

Alliance Peer Competitive Threat and Supplier Stock Price Crash Risk

This table reports panel regression results from regressing a measure of supplier stock price crash risk on each proxy for alliance peer competitive threats, while controlling for firm-specific variables, such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$Crash\ Risk_{i,t+1} = \alpha_0 + \alpha_1 Alliance\ Peer\ Competitive\ Threat_{i,t} + \alpha_2 Peer\ Competitive\ Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}.$$

The three measures of peer competitive threats include Peer Count, Peer Sales, and Peer Similarity, whereas the three proxies for the alliance peers include Alliance Peer Count, Alliance Peer Sales, Alliance Peer Similarity; the three alliance peer constructs are measured in an identical way as the peer competitive threat proxies to capture the formation of alliances between rival peers and the supplier. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alliance Peer Count$_t$	-0.120**			-0.077**			-0.112***		
	(-2.46)			(-2.57)			(-2.91)		
Peer Count$_t$	0.033***			0.016***			0.024***		
	(5.20)			(4.06)			(4.98)		
Alliance Peer Sales$_t$		-0.031			-0.041			-0.034	
		(-0.49)			(-0.99)			(-0.59)	
Peer Sales$_t$		0.416***			0.239**			0.238**	
		(2.59)			(2.36)			(2.00)	
Alliance Peer Similarity$_t$			-1.653***			-1.079***			-1.461***
			(-2.58)			(-2.69)			(-2.97)
Peer Similarity$_t$			1.290***			0.738***			0.683***
			(5.31)			(4.85)			(3.68)
NObs	22,904	21,554	22,904	22,904	21,554	22,904	22,915	21,565	22,915
R^2	0.018	0.017	0.018	0.021	0.020	0.021	0.012	0.011	0.012
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9

Peer Cross Citation and Supplier Stock Price Crash Risk

This table reports panel regression results from regressing a measure of supplier stock price crash risk on each proxy for peer competitive threats, peer cross citation (Peer Cross Cites), and the interaction between the latter two variables, while controlling for firm-specific variables, such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned} Crash\ Risk_{i,t+1} &= \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times \text{Peer Cross Cites}_{i,t} + \alpha_2 Peer \\ &\quad Competitive\ Threat_{i,t} + \alpha_3 \text{Peer Cross Cites}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}. \end{aligned}$$

The three measures of peer competitive threats include Peer Count, Peer Sales, and Peer Similarity, and the three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count$_t$	-0.009***			-0.004*			-0.012***		
× *Peer Cross Cites$_t$*	(-2.94)			(-1.80)			(-4.43)		
Peer Count$_t$	0.032***			0.019***			0.023***		
	(3.57)			(3.24)			(3.40)		
Peer Sales$_t$		-0.134**			-0.042			-0.182***	
× *Peer Cross Cites$_t$*		(-2.30)			(-1.19)			(-2.93)	
Peer Sales$_t$		0.388**			0.260**			0.200	
		(2.31)			(2.48)			(1.60)	
Peer Similarity$_t$			-0.283			-0.037			-0.356**
× *Peer Cross Cites$_t$*			(-1.60)			(-0.31)			(-2.09)
Peer Similarity$_t$			1.029***			0.551***			0.403*
			(3.16)			(2.74)			(1.67)
Peer Cross Cites$_t$	0.006	-0.003	0.000	0.000	-0.004*	-0.004	0.013**	0.001	0.004
	(1.13)	(-0.87)	(0.08)	(0.13)	(-1.75)	(-1.07)	(2.48)	(0.16)	(0.74)
NObs	15,138	14,341	15,138	15,138	14,341	15,138	15,143	14,346	15,143
R^2	0.022	0.021	0.021	0.026	0.025	0.026	0.015	0.015	0.014
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10

Supplier Business Risk and Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for peer competitive threats as well as on a proxy for a supplier's product market pricing power, as follows::

$$Crash\ Risk_{i,t+1} = \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \alpha_2 Business\ Risk + \sum_{k=1}^{K} \beta_k X_{ki,t} + \mathrm{FE}_t + \epsilon_{i,t},$$

where $X_{ki,t}$ is a vector of controls, such as size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). Business Risk of a suppiler is proxied by: (i) Supplier market power is measured as the price-cost margin scaled by sales; (ii) Supplier operating risk is measured as annual standard deviation of a firm's quarterly operating income before depreciation over total assets; (iii) Supplier operating performance is measured by subtracting the number of positive product market news from the number of negative product market news occurred in a calendar year. The three proxies for the peer competitive threats include Peer Count; Peer Sales; and Peer Similarity, whereas the three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Supplier Market Power_{t+1}									
Peer Count_t	0.029***			0.015***			0.018***		
	(5.29)			(4.27)			(4.34)		
Peer Sales_t		0.431***			0.234**			0.203*	
		(2.93)			(2.57)			(1.81)	
Peer Similarity_t			1.033***			0.535***			0.500***
			(4.84)			(4.03)			(3.01)
Supplier Market Power_{t+1}	-0.002	-0.004	-0.002	-0.002	-0.003	-0.001	-0.002	-0.003	-0.002
	(-0.76)	(-1.26)	(-0.54)	(-0.92)	(-1.47)	(-0.74)	(-0.86)	(-1.28)	(-0.75)
NObs	26,987	25,618	26,987	26,987	25,618	26,987	26,991	25,622	26,991
R^2	0.027	0.026	0.027	0.030	0.029	0.030	0.018	0.018	0.018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Supplier Operating Risk_{t+1}									
Peer Count_t	0.029***			0.014***			0.019***		
	(5.32)			(4.16)			(4.50)		
Peer Sales_t		0.408***			0.235***			0.190*	
		(2.85)			(2.66)			(1.80)	
Peer Similarity_t			1.130***			0.610***			0.546***
			(5.50)			(4.74)			(3.46)
Supplier Operating Risk_{t+1}	0.821**	0.940**	0.786**	0.641***	0.712***	0.623***	0.124	0.190	0.115
	(2.11)	(2.38)	(2.02)	(2.69)	(2.92)	(2.61)	(0.43)	(0.64)	(0.40)
NObs	25,320	23,973	25,320	25,320	23,973	25,320	25,324	23,977	25,324
R^2	0.025	0.024	0.025	0.028	0.027	0.028	0.017	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10 – Continued

Supplier Business Risk and Stock Price Crash Risk

	$NCSKEW_{t+1}$			$DUVOL_{t+1}$			Crash $Count_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel C: Supplier Operating $Performance_{t+1}$									
Peer $Count_t$	0.029***			0.014***			0.019***		
	(5.32)			(4.16)			(4.50)		
Peer $Sales_t$		0.408***			0.235***			0.190*	
		(2.85)			(2.66)			(1.80)	
Peer $Similarity_t$			1.130***			0.610***			0.546***
			(5.50)			(4.74)			(3.46)
Supplier Operating $Performance_{t+1}$	0.016**	0.017***	0.017**	0.010**	0.010**	0.010**	0.013**	0.014**	0.013**
	(2.47)	(2.59)	(2.52)	(2.12)	(2.21)	(2.14)	(2.33)	(2.52)	(2.47)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11

Institutional Ownership Breadth and Supplier Stock Price Crash Risk

This table reports panel regression results from regressing a measure of supplier stock price crash risk on a measure of peer competitive threats, the number of institutional investors ($No.Inst$), and the interaction between the latter two variables, while controlling for firm-specific variables, such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad &= \quad \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times No.Inst_{i,t} + \alpha_2 Peer \\ &\quad Competitive\ Threat_{i,t} + \alpha_3 No.Inst_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \mathrm{FE} + \epsilon_{i,t}, \end{aligned}$$

The three proxies for peer competitive threats include Peer cCunt, Peer Sales, Peer Similarity. $No.Inst$ captures the log of the number of 13F filers of suppliers in the quarter prior to fiscal year end of the supplier. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count$_t$	-0.014***			-0.006**			-0.009***		
× No.Inst$_t$	(-3.42)			(-2.34)			(-3.07)		
Peer Count$_t$	0.080***			0.037***			0.053***		
	(4.41)			(3.08)			(3.78)		
Peer Sales$_t$		-0.403***			-0.222**			-0.211**	
× No.Inst$_t$		(-3.00)			(-2.51)			(-2.15)	
Peer Sales$_t$		2.203***			1.230***			1.103**	
		(3.36)			(2.83)			(2.32)	
Peer Similarity$_t$			-0.521***			-0.221**			-0.409***
× No.Inst$_t$			(-3.30)			(-2.14)			(-3.32)
Peer Similarity$_t$			3.175***			1.456***			2.145***
			(4.35)			(3.05)			(3.76)
No.Inst$_t$	0.051***	0.049***	0.050***	0.026***	0.026***	0.025***	0.038***	0.037***	0.040***
	(7.65)	(7.84)	(7.75)	(6.16)	(6.61)	(6.19)	(7.51)	(7.82)	(8.04)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
R^2	0.027	0.026	0.027	0.028	0.027	0.028	0.019	0.019	0.019
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12

Dispersion in Analyst Opinions and Supplier Stock Price Crash Risk

This table reports panel regression results from regressing a measure of supplier stock price crash risk on a measure of peer competitive threats, High Dispersion indicator, and the interaction between the latter two variables, while controlling for firm-specific variables, such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned} Crash\ Risk_{i,t+1} &= \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times \text{High Dispersion}_{i,t} + \alpha_2 Peer \\ &\quad Competitive\ Threat_{i,t} + \alpha_3 \text{High Dispersion}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \end{aligned}$$

The three proxies for peer competitive threats include Peer cCunt, Peer Sales, Peer Similarity. The High Dispersion indicator takes a value of one if the dispersion of analysts' opinion of the supplier's quarterly earnings is above 75% percentile of those of all CRSP/Compustat firms and zero otherwise. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count$_t$	0.025**			0.015**			0.016		
× High Dispersion$_t$	(2.25)			(2.35)			(1.49)		
Peer Count$_t$	0.007			0.001			-0.001		
	(0.60)			(0.19)			(-0.05)		
Peer Sales$_t$		0.861**			0.463*			0.509**	
× High Dispersion$_t$		(2.65)			(2.03)			(2.12)	
Peer Sales$_t$		-0.030			-0.059			-0.101	
		(-0.11)			(-0.34)			(-0.45)	
Peer Similarity$_t$			0.591*			0.358*			0.145
× High Dispersion$_t$			(1.81)			(2.07)			(0.42)
Peer Similarity$_t$			0.496			0.195			0.184
			(1.58)			(1.17)			(0.65)
High Dispersion$_t$	-0.050*	-0.037	-0.039*	-0.020	-0.010	-0.014	-0.031	-0.020	-0.019
	(-1.87)	(-1.69)	(-1.76)	(-1.09)	(-0.64)	(-0.96)	(-1.53)	(-1.23)	(-1.05)
NObs	10,685	10,106	10,685	10,685	10,106	10,685	10,687	10,108	10,687
R^2	0.017	0.015	0.017	0.020	0.020	0.020	0.011	0.010	0.011
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 13

Media Coverage and Supplier Stock Price Crash Risk

This table reports panel regression results from regressing a measure of supplier stock price crash risk on a measure of peer competitive threats, media coverage, and the interaction between the latter two variables, while controlling for firm-specific variables, such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times \text{Media Coverage}_{i,t} + \alpha_2 Peer \\ & Competitive\ Threat_{i,t} + \alpha_3 \text{Media Coverage}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \end{aligned}$$

The three proxies for peer competitive threats include Peer cCunt, Peer Sales, Peer Similarity. The media coverage measures the log of the number of news covering the supplier in public media and web sources in a fiscal year t. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count$_t$	-0.006**			-0.003			-0.006**		
$\times$ Media Coverage$_t$	(-2.08)			(-1.33)			(-2.50)		
Peer Count$_t$	0.048***			0.023***			0.036***		
	(4.93)			(3.58)			(4.69)		
Peer Sales$_t$		-0.187**			-0.079			-0.107*	
$\times$ Media Coverage$_t$		(-2.28)			(-1.56)			(-1.74)	
Peer Sales$_t$		0.973***			0.479***			0.514**	
		(3.36)			(2.69)			(2.41)	
Peer Similarity$_t$			-0.214**			-0.065			-0.252***
$\times$ Media Coverage$_t$			(-2.17)			(-1.02)			(-3.21)
Peer Similarity$_t$			1.782***			0.821***			1.292***
			(5.17)			(3.70)			(4.69)
Media Coverage$_t$	-0.004	-0.002	-0.003	-0.005	-0.003	-0.005	0.002	0.003	0.003
	(-0.57)	(-0.28)	(-0.49)	(-1.18)	(-0.76)	(-1.23)	(0.33)	(0.53)	(0.60)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 14

SEC Comment Letters and Peer Competitive Threats

This table reports panel regression results from regressing the number of SEC comment letters on the different filings submitted by a supplier in year $t+1$, on each proxy for peer competitive threats, while controlling for firm-specific variables, such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$No.\ Comment\ Letters_{i,t+1} = \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \mathrm{FE} + \epsilon_{i,t},$$

The three measures of peer competitive threats include Peer Count, Peer Sales, and Peer Similarity. Panels (1)-(3) are the total number of supplier firms in the sample with the available variables for the respective tests, whereas Panels (4)-(6) focus on those that receive SEC comment letters on SEC filings, including annual and quarterly financial reports (Form 10-Ks, Form 10-Qs), material news disclosures (Form 8-Ks), registration and prospectus filings (e.g., Form S-1), and proxy filings (e.g., Def 14A). The sample period is from 2004 to 2015, as SEC comment letters are available starting from 2005. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	Number of SEC Comment Letters in Year $t+1$					
	All Sample			Received SEC Comment Letters		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Count$_t$	0.053***			0.067***		
	(6.27)			(6.36)		
Peer Sales$_t$		0.870***			0.907***	
		(3.86)			(3.46)	
Peer Similarity$_t$			1.804***			2.121***
			(5.52)			(5.36)
NObs	19,055	17,941	19,055	8,757	8,283	8,757
R^2	0.063	0.060	0.063	0.098	0.094	0.097
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 15

Supplier Financial Report Readability and Peer Competitive Threats

This table reports panel regression results from regressing a measure of the readability of the Management Discussion and Analysis section of a supplier's 10-K filing, on each proxy for peer competitive threats, while controlling for firm-specific variables, such as size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$Readability_{i,t+1} \quad = \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t},,$$

The three measures of peer competitive threats include Peer Count, Peer Sales, and Peer Similarity.The three measures of supplier Readability are *Flesch-Kincaid*, *Fog*, and *SMOG* indexes. $t-$statistics of the regression coefficients are shown in parenthesis and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix A.

	Flesch-Kincaid$_{t+1}$			Fog$_{t+1}$			SMOG$_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count$_t$	0.123**			0.094*			0.057**		
	(2.37)			(1.93)			(2.22)		
Peer Sale$_t$		2.304**			2.169**			1.286***	
		(2.24)			(2.34)			(2.59)	
Peer Similarity$_t$			4.501**			3.948**			2.916***
			(2.48)			(2.34)			(3.35)
NObs	20,224	19,022	20,224	20,224	19,022	20,224	20,224	19,022	20,224
R^2	0.029	0.030	0.029	0.032	0.034	0.032	0.055	0.057	0.055
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix A

Variable Definition and Data Source

Variable	Definition and Data Source
Measures of Stock Price Crash Risk	
NCSKEW	Negative of the ratio of the third moment to standard deviation cubed of firm-specific abnormal weekly returns during a fiscal year. (CRSP)
DUVOL	Log ratio of the standard deviation of firm-specific abnormal weekly returns of the down weeks to that of the up weeks. Down (up) is defined as the return above (below) the annual mean. (CSRP)
Crash Count	The number firm-specific weekly returns exceeding 3.09 standard deviation below the mean firm-specific weekly return over the fiscal year. (CRSP)
Proxies for Peer Competitive Threats	
Peer Count	The number of supplier peers servicing each customer of the supplier, averaged across all customers of the supplier, and tranformed to natural log value. Peers are defined as those firms within the same Hoberg and Phillip's (2010) text-based network industry classification (TNIC) industry as a supplier. (FactSet Revere; Hoberg and Phillips, 2010)
Peer Sales	The sum of the supplier peers' sales to each customer of the supplier, scaled by customer's cost of goods sold, averaged across all customers of the supplier. (FactSet Revere; Compustat)
Peer Similarity	The averge product similarity with all supplier peers servicing each customer of the supplier, averaged again across all customers of the supplier. (FactSet Revere)
Non-Linked Peer Count	The logarithmic number of total supplier peers without sharing a common customer with a supplier. Non-Linked Peers are identified as mutual competitors of a supplier in Revere Relationship database (FactSet Revere) and within the same Hoberg and Phillip's (2010) text-based network industry classification (TNIC) industry as a supplier. (FactSet Revere; Hoberg and Phillips, 2010)
Non-Linked Peer Similarity	The averge product similarity with all supplier peers without sharing a common customer with a supplier. (FactSet Revere)
Identification Strategy Variables	
Customer M&A Intensity	The prior five years' moving average of total customer M&A transaction values divided by the customer's total sales, weighted averaged across all customers of the supplier, where the weights are the percentage of supplier's sales to each customer. (SDC)
Post× Treat	A interaction dummy variable equal to one if the connected peers of a firm file for Chapter 11 bankruptcy during the year, and zero otherwise. (Ma, Tong, and Wang, 2019)
Peer Disaster	A dummy variable equal to one if the connected peers of a firm are hit by a major natural disaster during the year, and zero otherwise. (FEMA; Dun and Bradstreet)
Mechanism Variables	
Alliance Peer Count	Peer Count computed on those supplier peers who have formed a strategic partnership with the supplier, where strategic partnership is defined as pairs of firms committed to any of the following forms of business relationship: (i) research collaboration; (ii) integrated product offering; (iii) joint venture; (iv) cross-ownership in equity stakes; (v) products, patents, and intellectual property licensing; (vi) use of each other's manufacturing, marketing, and distribution services. (Factset Revere)
Alliance Peer Sales	Peer Sales computed on those supplier peers who have formed a strategic partnership with the supplier. (Factset Revere)
Alliance Peer Similarity	Peer Similarity computed on those supplier peers who have formed a strategic partnership with the supplier. (Factset Revere)
Peer Cross Cites	The average number of supplier's patents cited by supplier peers. (Patstat)
Flesch-Kincaid	The Flesch-Kincaid index measures the readability of the Management Discussion and Analysis section (MD&A) of a firm's 10-K filing, computed as (0.39×words per sentence)+(11.8×syllables per word)-15.59. A higher index value corresponds to a greater complexity in the text. (SEC)

Appendix A - Continued

Variable Definition and Data Source

Variable	Definition and Data Source
Fog	The Gunning Fog index measures the readability of the Management Discussion and Analysis section (MD&A) of a firm's 10-K filing, computed as 0.4×(words per sentence + 100×percent of polysyllables words), where polysyllables words are words with three syllables or more. A higher index value corresponds to a greater complexity in the text. (SEC)
SMOG	The Simple Measure of Gobbledygook index measures the readability of the Management Discussion and Analysis section (MD&A) of a firm's 10-K filing, computed as 1.043×square root (number of polysyllables per sentence×30)+3. A higher index value corresponds to a greater complexity in the text. (SEC)
High Dispersion	A dummy variable equal to one if analyst forecast dispersion is above the fourth quartile of all firms in the same industry-year, and zero if it is below the first quartile. Analyst forecast dispersion defined as the standard deviation of annual EPS forecasts, scaled by the stock price at the beginning of the fiscal year. (IBES)
No.Inst	The log number of institutional owners of the firm. (13f)
Media Coverage	The log number of unique news sources covering a firm over its fiscal year. (Ravenpack)
Supplier Market Power	Sales minus the sum of COGS and SG&A (sales, general and administrative expenses) and then divided by sales. The value is then industry-adjusted by subtracting sales-weighted price-cost margin of all firms within the same Fama French 30 industry classifications (Compustat).
Supplier Operating Risk	The standard deviation of the ratio of the quarterly operational income before depreciation to total assets within a year. (Compustat).
Supplier Operating Performance	The difference in the number between supplier's negative and positive product market news in a year. (Ravenpack).
Control Variables	
Size	The log of market price multiplied by the number of oustanding shares outstanding. (Compustat)
MB	Market value of common equity divided by book value of common equity. (Compustat)
Leverage	Long-term debt divided by total assets. (Compustat)
ROA	Income before extraordinary items divided by total assets. (Compustat)
Δ Turnover	Average weekly stock turnover within a fiscal year minus that of the previous year. (CRSP)
AbAccr	The prior three years' moving sum of the absoluate value of discretionary accruals, where discretionary accruals are estimated from the modified Jones model (Dechow, Sloan, and Sweeney, 1995). (Compustat)
Sigma	The standard deviation of firm-specific weekly returns over the fiscal-year period. (CRSP)
Return	The mean of firm-specific weekly returns over the fiscal-year period. (CRSP)
MktShare	The proportion of a fimr's sales in the 2-digit SIC industry. (Compustat)
HHI Index	The sum of squared market shares of all firms in the same 2-digit SIC industry. (Compustat)
Fluidity	A "cosine" similarity between a firm's products and the changes in the rivals' products, scaled between 0 and 1. (Hoberg, Phillips, and Prabhala, 2014)
Customer Concentration	The sum of the squared sales percentages to all major corporate customers of a firm, where major corporate customers are those accounting for at least 10% of the firm's total revenue. (Compustat)
Bankruptcy	A dummy variable equal to one if a firm files for Chapter 11 bankruptcy during the year, and zero otherwise. (Ma, Tong, and Wang, 2019)
Disaster	A dummy variable equal to one if a firm is hit by a major natural disaster during the year, and zero otherwise. (FEMA; Dun and Bradstreet)