Withholding Bad News When Competing Peers Have Common Customers

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Current Version: October 20, 2019

*Dai is from WRDS, The Wharton School, University of Pennsylvania, Philadelphia, USA; Duan and Ng are from the Schulich School of Business, York University, Toronto, Canada. We thank thank Amir Akbari, Peter Cziraki, Itamar Drechsler, Pouyan Foroughi, Haoyu Gao, Jim Goldman, Raymond Kan, Donghyun Kim, Taehyun Kim, Yelena Larkin, Yao Lu, Mohammad Al Mamum, Jordi Mondria, Daniel Taylor, Anjan Thakor, Xu Tian, Kevin, Tseng, Yangru Wu, and participants at the Central University of Finance and Economics, 2019 China International Conference in Finance, La Trobe Business School, Schulich School of Business at York University, Tsinghua University, University of Melbourne, University of Toronto, and WRDS of the Wharton School for their many helpful comments and suggestions. Authors' contact information: Dai: rui.dai.wrds@outlook.com; Duan: Duan: RDuan15@schulich.yorku.ca; Ng: lng@schulich.yorku.ca.

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ABSTRACT

We examine whether the managerial withholding of bad news disclosure is, in part, driven by the intense competition from rivals producing similar products and supplying to common corporate customers. Our study exploits the information on customer-supplier relationships to construct firm-specific competition measures that distinguish between competition from existing rivals (i.e., customer-connected peers) and competition from potential rivals (i.e., non-linked peers). Results show that only competitive pressure from connected peers, while not from potential entrants, is strongly and positively associated with firms' stock price crash risk, a proxy for firm managers' tendency of withholding bad news. Our key 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. Finally, we show that customers, customer-connected peers, and investors play a crucial role in shaping the managerial practice of bad news disclosure.

Keywords: Peer Competitive threats, Common Customers, Crash Risk, Bad News Disclosure

JEL Classification Number: G11, G23, G32

... CFOs argue that they delay bad news in order to further study and interpret the information, or in hopes that the firm's status will improve before the next required information release, perhaps saving the company the need to ever release the bad information ... *Graham, Harvey, and Rajgopal (p. 65, 2005)*

1. Introduction

In their survey of corporate executives, Graham, Campbell, and Rajgopal (2005) report that two-thirds of the respondents agree or strongly agree that firm managers are prone to delay or withhold bad news. This survey evidence is not only intuitive, but also substantiated by a recent strand of empirical literature examining the release of negative news. For example, Kothari, Shu, and Wysocki (2009) contend that because of career concerns, managers have strong incentives to delay bad news release, betting on subsequent improved outcomes that will allow them to conceal the bad news. Bao, Kim, Mian, and Su (2019) further provide reinforcing evidence that managers in general withhold private bad news, as proxied by the level of their firm's residual short interest. Cohen, Lou, and Malloy (2019) find that managers manipulate their conference calls to hide bad news, and that such firms experience consistently predictable negative future returns. In this study, we examine whether firm managers' bad news withholding behavior is, in part, driven by the intense competition from rivals producing similar products and supplying to common corporate customers (hereafter "customer-connected peers"). More importantly, we investigate which stakeholders – customers, connected peers, or investors – play a significant role in shaping the managerial practice of bad news disclosure.

Peer rivals are best identified as those directly competing with a firm for resources from and sales to the same market. In contrast to the extant literature that employs industry-level competition measures,[1] we propose firm-specific competition measures that distinguish between competition from existing rivals (i.e., customer-connected peers) and competition from potential rivals (i.e., non-linked peers). Both groups must be in the same product market, as defined by Hoberg and Phillips (2010, 2016). For example, supplier firms S_1, S_2, S_3, and S_4 produce similar products.

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

S_1 and S_2 supply to customer C_1, whereas S_3 and S_4 supply to customer C_2. While all four suppliers are in the same product space, only S_2 is S_1's direct competitor. S_3 and S_4 are not linked to S_1 in terms of common customers, but are potential rivals of S_1, should C_1 establish a new relationship with either S_3 or S_4, or both. To identify the network of a supplier's connected and non-connected peers, we exploit the recently available firm-level detailed information about customer-supplier relationships, as well as their identities, from the Factset Revere database and Compustat's Customer Segment files that enable us to construct measures of competitive threats from the two groups of competing peers. The advantage of such direct measures is that they require no further validation, as opposed to most existing competition measures. The latter are generally computed based on all firms in the same industry with no information of whether these firms are existing or simply potential competitors of a focal supplier firm.

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. The third measure employs 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 news. In a similar fashion, we construct the *Non-Linked Peer Count* and *Non-Linked Peer Similarity* to identify the number of non-customer-connected peers that are potential competitors of the focal supplier in the product market. The larger the values of *Non-Linked Peer Count* and *Non-Linked Peer Similarity*, the greater is the competitive pressure from potential rivals who are currently not supplying to the focal supplier's customers.

We argue that in a complex network of supplier-customer relationships, a supplier firm's concern is threefold. First, the supplier's concern is partly driven by the extent of 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. It is also plausible that releases of any deterimental news might offer customers a leveraging point to renegotiate existing contracts for more favorable terms. Thus, to avoid losing its customers, the supplier is more likely to withhold or delay disclosure of adverse information about the firm. Second, the supplier is concerned about 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 in the product market, the supplier likely makes strategic disclosure decisions partly to reduce competition pressure. Finally, the supplier facing greater competitive pressure is incentivized to hoard bad news from investors, who have significant influences on firm managers' career perspectives. Career concerns such as employment opportunities, compensation, and potential job termination can motivate managers to withhold bad news given information asymmetry between them and investors (e.g., Graham, Harvey, and Rajgopal, 2005; Kothari, Shu, and Wysocki, 2009). Thus, we predict that customers, connected peers, and investors each plays an important role in firm managers' bad news disclosure decisions.

Drawn from the extant literature (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 bad news hoarding. The rationale is that unfavorable news withheld by managers accumulates over an extended period, until it reaches a tipping point beyond which the cost of concealing it exceeds the benefit. The managers would then be forced to release the accumulated news at once, causing the stock price to crash. We use three popular measures of stock price crash risk, namely (1) the negative conditional skewness of stock returns (*NSCSKEW*); (2) the log of the standard deviation of down weekly returns divided by the standard deviation of up weekly returns ($DUVOL$);[2] and (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*). Critics of crash risk, however, argue that it is but an indirect measure of negative information hoarding and that it may be driven by non-disclosure-related factors such as a firm's operating risk. In addressing such skepticism, our study devotes much effort to validating the crash risk measures by providing complementary evidence of the bad news hoarding behavior.

Based on a sample of 28,598 firm-year observations from 4,436 unique supplier firms over the 1996-2015 period, our baseline analyses 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 incentives to withhold negative information. In terms of the 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. In contrast, we find weak evidence that potential competitor threats, specifically as measured by *Non-Linked Peer Similarity* but not by *Non-Linked Peer Count*, contribute to an increase in future stock price crash risk, but their effect disappears in the presence of those of customer-connected peers, an indication that firm managers' reluctance to release bad news is primarily motivated by the intense pressure from rivals that supply to the same customers. In addition, our analysis finds no evidence that a general industry-level competition measure, such as the product fluidity measure developed in Hoberg, Phillips, and Prabhala (2014) or the traditional Herfindahl-Hirschman Index (HHI), has any effect on stock price crash risk. Combined, these results further substantiate our argument that managers' bad news disclosure incentives are driven by competition among closely-linked supplier peers beyond any other competitive pressure

[2]A down (up) weekly return is classified as a return below (above) the annual mean weekly return.

from potential rivals.

We then conduct an array of empirical tests on other disclosure measures confirming our information hoarding interpretation of crash risk. First, we investigate the information released during conference presentations, earnings calls, earnings announcements, client announcements, product-related announcements, and corporate guidance events to gauge the managers' tendency in disclosing negative news. Classifying these events as negative (positive) news disclosures based on the resulting negative (positive) short-term cumulative abnormal return (CAR) reveals two distinct findings. Specifically, while firms under higher peer competitive pressure are found to have fewer negative-news events in general, these same firms tend to experience more extreme negative-news events that produce large investor reactions. These combined results suggest that managers facing peer threats are incentivized to avoid the release of negative news until it becomes too material to hide, at which point they must release extreme negative information at a cost of large negative CAR. Second, we ask whether supplier managers are impelled to make bad reporting choices in their mandatory filings in order to conceal damaging information about their firms. Such questions can be addressed using *ex post* identification of company filing deficiencies from the Securities and Exchange Commission (SEC) comment letters requesting clarification and from financial restatements of material information. Validating our baseline findings on stock price crash risks, we show that more intense peer competitive pressure is associated with a larger number of SEC comment letters and with a higher probability of restatements. While these constructs have the advantage of directly measuring a firm's disclosure behavior, they are all rare events that cannot be observed on a regular basis and capture the extreme practices of disclosure. Hence, to circumvent the potential issues that arise from extreme observations, our study focuses on stock price crashes and only use the direct disclosure proxies for validation purposes.

Our causal inference of the positive association between peer competitive threats and the likelihood of future supplier stock price crashes are subject to endogeneity concerns. 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. The acquiring customers would mechanically gain new trading partners through consolidation of purchasing accounts, which in turn would add new competitive peers to the existing customer-supplier network. 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 seek for safer alternatives (Altman, 1984; Opler and Titman, 1994; Chang and McDonald, 1996). Thus, we expect that when a supplier's connected peer files for bankruptcy, the common customers would rely less on the filing peer for inputs, or if not, 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 rival peers, thereby 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.

Having established that a firm strategically withholds adverse information when facing peer competitive threats, we now turn to investigating whether such disclosure decisions are driven by three specific types of market players – customers, customer-connected peers, and investors. We contend that firms under peer competitive pressure would be less willing to share negative information with their customers due to increased concerns of the latter switching to alternative suppliers. If this is the case, the effects of peer threats should be mitigated by (i) establishing more cooperative customer-supplier relationships that lower the customers' propensity of switching away; and (ii) reducing the level of information asymmetry between the two counterparts that limits the supplier's ability to conceal information from the customers. Consistent with this conjecture, we find that forming business alliances and having trade credit with its customers reduce peer competitive effects on a firm's stock price crash risk. A similar test is conducted to investigate whether a firm is concerned about revealing information to its closely connected peers given predation threats. We expect that, if there is such a concern, it would be alleviated for the supplier forming business alliances with its peers, curbing the latter's competitive or predatory efforts. Moreover, a close relationship with its peers would hinder the firm's ability to hide negative information from them. Our results provide supportive evidence showing that collaborative relationships with rival peers dampen the effects of peer competition on a firm's information hoarding behavior.[3] Finally, we test whether a supplier facing greater competitive pressure has more incentives to hoard negative information from investors. Using institutional ownership breadth, analyst forecast dispersion, and news coverage as proxies for information asymmetry between a firm and its investors, we examine whether the link between peer competitive threats and crash risk would be more pronounced for firms with greater information asymmetry. Cross-sectional analyses produce results consistent with our prediction, lending support to the notion of hiding information from investors.

Our research brings into focus the importance of interconnected firms in today's competitive business environment. We contribute to the growing disclosure literature by showing that our construct of competitive pressure is useful in identifying the more pressing threats from current competitors that generate strong incentives for managers to conceal negative information beyond other sources of competition. 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, 2019). While competitive pressure from the broadly defined product market may aggravate managers' desires to strategically withhold unfavorable news, as reported in Li and Zhan, our analysis attributes this finding to only competitive pressure from firms which are linked through common customers. Two recent papers are also related to our study. Chen, Hu, Yao, and Zhao (2018) and Kim, Lee, and Song (2018) employ information on the customer-supplier relationships to examine the relation between corporate customer concentration and stock price crash risk. They both reach the same conclusion that corporate customer concentration has a positive impact on stock price crash risk. Unlike these two studies, however, 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

[3] To the extent that connected peers' operating conditions play a role in their predatory intent, the identification tests using peer bankruptcy and natural disaster incidences also indicate that a firm's disclosure behavior is influenced by its incentives to hide information from closely competing rivals.

competitive threats within the customer-supplier network.

Our work also adds to the stock crash literature by going to great length to show that an effect on stock price crash risk corresponds to that on other measures of unfavorable information hoarding. Extant research on agency theory-based arguments of managerial incentives for hoarding information (e.g., Kim, Li, and Zhang, 2011a,b; Kim, Li, and Li, 2014; Kim, Wang, and Zhang, 2016) relies heavily on the prior work by Jin and Myers (2006), Bleck and Liu (2007), and Hutton et al. (2009) to motivate the use of crash risk measures as proxies for information withholding. However, stock price crashes can be driven by many other factors such as the heterogeneity in investors' beliefs (Hong and Stein, 2003) and the nature of firm operations, among others. Our paper exhausts alternative explanations and complements earlier studies in validating stock price crashes as measures of negative news hoarding. Moreover, we contribute to the literature by empirically identifying the stakeholders that have important influences on managers' disclosure incentives.

Finally, our research contributes to the extensive literature that documents 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. Therefore, any firm-level shock is most likely to propagate through the customer-supplier network (Barrot and Saugvanat, 2016). 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 our sample from several data sources: (i) supplier-customer relationship data from both the Factset Revere and Compustat's Customer Segments data, available through the Wharton Research Data Services (WRDS); (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 the SDC Platinum; (v) Chapter 11 bankruptcy filings data from Ma, Tong, and Wang (2017);[4] (vi) county-level disaster data from Federal Emergency Management Agency (FEMA); (vii) firm employment data by establishment from Dun and Bradstreet via Mergent; (viii) firm disclosure events from Capital IQ Key Development; (ix) the SEC comment letter and restatement records from Audit Analytics; (x) institutional holdings data from Thomson Reuters Institutional Holdings (13f); (xi) financial analyst forecast information from the Institutional Brokers Estimate System (IBES); (xii) firm-specific press articles from Ravenpack full package; and (xiii) financial statement data from Compustat. 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 and Customer Segments data to identify customer-supplier relationships. Under SEC Regulation S-K Item 101, all public firms in the United States 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 rev-

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

enues. The Customer Segments data rely 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 this database 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.[5] Unlike Customer Segments data, 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 a more comprehensive supply chain information consisting of both major and minor customers. No manual matching is necessary given that Revere data offers GVKEYs for publicly-listed customers. We complement Revere data, which start coverage from 2003, with Customer Segments data to obtain corporate customer-supplier pairs over our 1996-2015 sample period. For the purpose of illustration, in Figure 1 we show a proportion of the 2014 supply chain network of Texas Instruments Inc. The figure depicts the linkages between Texas Instruments and its competing suppliers as well as its customers. Leveraging such comprehensive information, we construct our key measures of competitive pressure among peer firms who supply to common corporate customers.

2.2. Proxies for peer competitive threats

To construct measures of peer competitive threats, we focus on firms in the same product market that are simultaneously supplying to the same corporate customers. By examining these peer firms connected through existing customer-supplier relationships, we attempt to identify close rivals of a firm that are directly competing for 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 concen-

[5]We thank Ling Cen for providing us his matched Customer Segments data for calibration purposes.

trated product market with few competitors in the industry, our measures gauge the extent to which these few competitors happen to be closely connected firms competing for businesses from the same set of customers. Furthermore, unlike the product market fluidity measure developed by Hoberg, Phillips, and Prabhala (2014) that captures threats from potential entries, our constructs emphasize more pressing threats from current competitors that call for immediate firm actions. Thus, the focus on closely connected rivals through real customer-supplier relationships is a distinguishing feature of our study.

Our proxies for peer competitive threats capture the extent to which 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 robustness and because of the limited availability of information on sales to customers, we construct three different measures of peer competitiveness, as discussed below.

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 C_j's other suppliers within the same product market as S_i. Product markets are defined by Hoberg and Phillips's (2010; 2016) Text-based Network Industry Classifications (TNIC) which are based on the product similarity among firms. 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.[6] The remaining two measures are averaged in the same fashion.

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

where supplier S_i has n_i customers in year t, and each customer C_j has m_j peer suppliers other

[6] Over 70% of the customer-supplier pair observations have 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.

than S_i in the same TNIC 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 the connected peers.

Our second measure, *Peer Sales*, similarly captures C_j's existing relationships with alternative suppliers in the same product market as S_i, 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 as a percentage of C_j's costs of goods sold. The more reliant is C_j on peers 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 C_j's cost of good sold.

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*). The product similarity scores measure the relatedness of two firms based on their product market descriptions in their 10-K filings. The higher the average score, the greater is the substitutability of S_i's products, and the less dependent C_j would 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.

In addition, we construct two measures of non-linked peer threats: *Non-Linked Peer Count* and *Non-Linked Peer Similarity* in a similar manner as we construct *Peer Count* and *Peer Similiarity*.[7] These measures are proxies for competitive threats posed by potential suppliers who produce similar products as the focal supplier but currently have no business relationships with the supplier's customers.

[7]Note that we are unable to construct a *Non-Linked Peer Sales*, because these suppliers do not have any sales to the customers.

2.3. *Measures of managers' bad news withholding*

Following the existing 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 crash risk for each supplier-year as proxies for managers' bad news withholding. To construct the measures, we first run the following regression for each supplier-year using weekly returns during the 12-month period ending 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.

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

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 the natural logarithm of one plus residual return ($W_{i,\tau} = ln(1 + \epsilon_{i,\tau})$) from Eq. (4).

The first measure of crash risk is the negative skewness of firm-specific weekly returns ($NCSKEW$). 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:

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

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

The second measure is the down-to-up volatility measure ($DUVOL$). 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 grouped 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.

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

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

The third measure is based on 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 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 also follow the above-mentioned prior studies to identify control variables that affect stock price crash risk. Specifically, our analyses 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*). The above studies show that the likelihood of future stock price crashes tends to be positively correlated with *Size*, MB, and *AbAccr* and negatively associated with *Leverage*. While the existing literature documents a significant ROA effect on crash risk, the direction of its effect remains unclear. For example, Hutton, Marcus, and Tehranian (2009) and Kim, Li, and Zhang (2011a, b) find negative relationship between ROA and crash risk, whereas Kim and Zhang (2016), and Li and Zhan (2019) document a positive relationship. We also control for stock-specific characteristics, including the change in stock turnover ($\Delta Turnover$) computed as the average of the monthly turnover within a fiscal year minus its counterpart in the previous year, firm-specific average weekly return within a fiscal year (*Return*), firm-specific weekly return volatility computed within a fiscal year (*Sigma*), and one-year-lagged negative skewness measure ($NCSKEW$). We expect crash risk 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 summary statistics of the key variables used in our analysis; Panels A, B, and C report the number of observations, mean, standard deviation, as well as the distribution in different percentiles for peer competitive threats, stock price crash risk, and control variables, respectively. 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 (i.e., $\ln(1 + 1.760) = 1.015$). In addition, the mean value of *Peer Sales*, as expressed in percentage of inputs, suggests that, on average, the customers rely on alternative suppliers to produce about 1.6% of their inputs. On average, a supplier has a 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 no other supplier of the firm's customers is competing within the same product market as the firm (i.e., there is no competing peer).

The table also reveals that at least 25% of the sample has a zero value for both *Peer Count* and *Peer Similarity.* A zero *Peer Count* suggests that the focal supplier has no other peer rivals supplying to its customers, and a zero *Peer Similiarity* implies that there is no other peer that produces a product similar to that of the focal supplier.[8] In addition, over 50% of the sample has a zero value for *Peer Sales*; the reason is that many suppliers do not disclose the amount of their sales to individual customers. However, a smaller sample of non-zero *Peer Sales* measure should work against us finding the impact of peer pressure on the likelihood that a firm having competitive rivals would hoard unfavorable information. Nevertheless, our baseline results are robust to all three different peer threat measures. Also, it is important to stress that while *Peer Count* exhibits some variation across time, *Peer Sales* and *Peer Similarity* change very slowly through time. Such stable values may mask peer threat effects on the crash risk measures when firm fixed-effects are incorporated into the model, because of a much smaller within-firm variation than between-firm variation. Furthermore, incorporating firm fixed effects would remove between-firm variation. Hence, for consistency with existing studies and in subsequent analyses, only industry and year fixed effects are reported in all tables throughout this paper.

[8] We repeat our analysis by removing these customer-supplier links with no peer rival, and our unreported results become more pronounced.

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. 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. All control variables are within reasonable ranges and are comparable with the statistics reported in the prior studies mentioned earlier.

3. Peer Competitive Threats and Bad News Hoarding

The first-order question we address is whether peer competitive threats compel a supplier to withhold negative information, as revealed by the impact of peer competition on stock price crash risk. We then conduct a multitude of empirical tests on direct, albeit extreme, measures of managerial disclosure practices in confirming our information hoarding interpretation of the crash risk measures.

3.1. Baseline evidence

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

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

where $Crash\ Risk_{i,t+1}$ is a measure of one-year-ahead crash incidences of supplier i (i.e., $NCSKEW$, $DUVOL$, or $Crash\ Count$); $Peer\ Competitive\ Threat_{i,t}$ captures a proxy for peer competitive threats (i.e., *Peer Count*; *Peer Sales*; or *Peer Similarity*) faced by supplier i in year t; $X_{ki,t}$ is a vector of firm-specific control variables defined earlier, 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.[9] Standard errors are clustered at the supplier firm level.

Results from our baseline model Eq. (7) are reported in Table 2. The dependent variables

[9]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 heterogeneities.

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 facing greater competitive pressure from peers connected through common customers is more likely to experience stock price crashes in the future. For instance, 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 *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. This finding suggests that firm managers are more inclined to withhold unfavorable information as peer pressure intensifies.

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* would lead to the corresponding 36.3%, 21.8%, and 40.0% increases in $DUVOL$ relative to the sample mean of $DUVOL$. These 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 as those reported in previous studies mentioned earlier. Specifically, the coefficients on *Size*, MB, $\Delta Turnover$, *AbAccr*, $NCSKEW$, *Sigma*, ROA, and *Return* are all positive and significant. The coefficients on *Leverage* are negative, but they are statistically insignificant in all regressions.

3.2. Other sources of competitive threats

One might argue that a suppplier firm not only necessarily compete with its linked peers that supply similar products to the same customers, but also face other sources of competitive threats. For example, non-linked suppliers, who produce similar products but are currently not supplying to the focal supplier firm's customers, might also pose as a threat in the next contract negotiation, or serve as alternate suppliers to the customers, thereby lowering the latter's switching cost. Additionally, our proxies for peer competitive threats may capture only some dimension of other commonly employed competition variables broadly accounting for all current and potential competitors, namely, the Hoberg, Phillips, and Prabhala (2014) fluidity measure or traditional measure of market concentration, the Herfindahl-Herfindahl-Hirschman Index (HHI). Fluidity measures similarity between a firm's products and the aggregate changes in its competitors' products; the greater the fluidity measure, the more similar are the focal firm's products to its competitors' and hence the increased intensity of competition. We therefore test whether these plausible sources of threats further aggravate the focal firm's behavior of withholding negative information beyond that already posed by its linked peers.

We replicate our estimates of Eq. (7) with either of the two non-linked peer threats in place of linked peer threats or jointly with the latter. Results are shown in Panel A of Table 3. It is evident that when estimated alone, only *Non-Linked Similarity* has some positive association with the stock price crash risk, but when estimated jointly with *Peer Count* or *Peer Similarity*, its effect is subsumed by that of the latter. This finding suggests that neither *Non-Linked Peer Count* nor *Non-Linked Peer Similarity* has any incremental effect on stock price crash risk beyond that already captured by their customer-connected counterparts, suggesting that non-linked peers present no immediate threat to the supplier. While the coefficients on *Non-Linked Peer Count* and *Non-Linked Peer Similarity* are all positive, they are statistically insignificant. The coefficient estimates of the three peer threat proxies, albeit slightly smaller, are all positive and statistically significant, compared to their counterparts reported in Table 2. For example, the coefficient on *Peer Count* is 0.029 (t =5.45) in Column (1) of Table 2 and is 0.028 (t =4.58) in Panel A of Table 3; correspondingly, the coefficients on *Peer Similarity* are 1.151 (t =5.61) and 1.025 (t =4.35).

We next test whether our measures of peer competitive threats are subsumed by the product fluidity measure or perhaps by HHI. We repeat our analysis of Panel A by replacing measures of non-linked peer threats by *Fluidity* or HHI; their results are reported in Panels B and C. The coefficients on our key variables remain materially unaffected after adding industry HHI to our baseline model, and only some of the coefficients become weaker after factoring in product fluidity. Importantly, none of the coefficients associated with supplier industry HHI and product fluidity is statistically significant at conventional levels. Thus, 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.

We also conduct additional robustness tests, whose results are reported in Appendix Table A.1. A potential concern is that our peer competitive pressure proxies inevitably capture a source of significant cash flow and business risk for supplier firms, as measured by customer concentration (Chen et al., 2018; 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 A.1, the coefficients on *Customer Concentration* are positive and statistically significant in Columns (1)-(6), but not in Columns (7)-(9). More importantly, the coefficients on all three measures of peer competitive threats remain robust to the additional control variable – *Customer Concentration*, indicating that peer competitive effects differ from the previously defined customer concentration variables. In another 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, 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 extreme economic conditions. [10]

[10] We also replicate Li and Zhan's (2019) study by constructing a sample similar to theirs and find that their

3.3. *Managerial strategic disclosure behavior*

While we have established the effect of peer competitive threats on crash risk, one may criticize that crash risk is merely an indirect measure of negative information hoarding based on the prior argument that managers stockpile bad news until the point of a sudden release, leading to a large stock price decline (Jin and Myers 2006; Bleck and Liu 2007; and Hutton et al. 2009). Price crashes can also be driven by many other factors such as the fundamental nature of a firm's operations, irrespective of whether its managers are withholding bad news. In this section, we aim to address such skeptical views of crash risk measures by examining other, more direct, measures of managerial information disclosure behavior.

First, we exploit corporate disclosure events, including conference presentations, earnings calls, earnings announcements, client announcements, product-related announcements, and corporate guidance, to construct three measures capturing managers' tendencies in releasing bad news. Each of these events is classified as a positive-news (negative-news) disclosure event if the cumulative abnormal return CAR(-1,1) during the 3-day window surrounding the event is positive (negative). *All News*, defined as the ratio of the number of negative-news events to the number of positive-news events, gauges firm managers' overall propensity to release negative information, incorporating both material and immaterial information. In contrast, *5% Significant News* and *10% Significant News* are intended to only capture the propensity of disclosing material news that result in large investor reactions. Specifically, *5% Significant News* (*10% Significant News*) is the ratio of the number of negative-news events with CAR(-1,1) less than -5% (-10%) to positive-news events with CAR(-1,1) more than 5% (10%). We replicate our baseline analysis using these three proxies measured one-year ahead as the outcome variables. Results are shown in Panel A of Table 4.

The panel reveals two distinct findings. The coefficients on *All News*, as shown in Columns (1)-(3), are negative and statistically significant across all peer competition measures, indicating that firms under higher peer competitive pressure tend to release less negative news in general. For instance, the coefficients on *Peer Count*, *Peer Sales*, and *Peer Similarity* are -0.022 ($t = -4.60$),

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evidence based on *Fluidity* as a measure of product market competition is specific to their time period employed, but we find that *Fluidity* becomes statistically insignificant when the crisis period is removed from the sample.

-0.393 ($t = -3.18$), and -0.439 ($t = -2.17$). On the other hand, the coefficients on extreme news ratios tend to be positive, suggesting that firms under peer competitive threats tend to expose more material negative information. Columns (4)-(9) show that the coefficients are mostly statistically significant. For example, the coefficient on *Peer Count* is 0.017 ($t = 3.20$) in Column (4) and 0.020 ($t = 4.16$) in Column (7). Taken together, these findings suggest that when the intensity of peer pressure is high, managers would have stronger incentives to avoid revealing any negative news until it stockpiles to material information, at which point they must be disclosed at the cost of large negative investor reactions.

Second, we examine whether supplier managers are impelled to make bad reporting choices in their mandatory filings in order to conceal damaging information about their firms. Managers intending to hide negative information would have a strong motivation to be less transparent or even manipulative in their manadatory reporting. One *ex post* identification of company filing deficiencies is the comment letters sent by SEC. 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) to ensure compliance with "the applicable disclosure and accounting requirements." The Division conducts three levels of reviews: (i) a complete review of all of a firm's filings; (ii) a financial statement review that involves financial statements, notes, and related disclosure such as the management discussion and analysis or 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. Due to limited time and resources, the Division only conducts reviews on a chosen subset of firms registered with the SEC.

We utilize 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 firms, we expect their required financial filings to lack clarity and trigger SEC feedback. The comment letters are obtained from the Audit Analytics for the 2005-2015 period, from which we define the number of SEC comment letters as the number of different corporate filings from a firm that triggered a comment letter. Firm-year observations not receiving any comment letters would have a value of zero. We conduct two sets of regressions using the number of SEC comment letters as the dependent variable and report the results in Columns (1)-(6), Panel B of Table 4. The first set analyzes the full sample in this study regardless of whether a firm has received a review from the SEC, whereas the second set focuses on only the sample of firm-years reviewed by the SEC. The coefficients on all the different measures of peer competitive threats are positive and strongly significant at the 1% level, consistent with the notion of strategic information disclosure under peer competitive pressure.

As another measure of supplier managers' deliberate information hoarding behavior, we examine the material restatements of a firm's financial reporting.[11] Effective 2004, the SEC requires all firms to disclose restatements of any SEC filing via Item 4.02 in Form 8-K filing. Compared to those disclosed in other filings (i.e., stealth restatements filed in other forms such as 10-K or 10-Q), restatements filed through 8-Ks are associated with significant negative market reactions, suggesting the materiality of the latter (Irani and Xu, 2011). Using restatements information from Audit Analytics, we conduct logit regressions with an indicator variable to denote the occurrence of material restatements as the dependent variable and using the same specification as that in Eq. (7). Columns (7)-(9) of Panel B report our findings. The positive and strongly statistically significant coefficients indicate that managers' increased intention to hoard adverse information and ultimately precipitate financial restatements.

Additionally, we also perform several tests to rule out the possibility that our key results might be driven by firms that are more prone to crashes due to the fundamental nature of their operations. We therefore construct three proxies to capture a focal supplier's operating and business risks, namely, (i) the price-cost margin scaled by the supplier's sales, which captures the supplier's market power; (ii) the annual standard deviation of the firm's operating income before depreciation over total assets as a measure of operating risk; and (iii) the contemporaneous operating performance

[11]We also conduct several additional robustness tests that examine the impact of peer pressure on firms' mandatory and voluntary disclosures. Prior research suggests that when managers tacitly collude to withhold bad news, their financial report readability measures are low, or their management earnings forecasts are less precise or exhibit more dispersion (e.g., Beyer et al., 2010; Huang, Jennings, and Yu, 2017). Unreported results show positive associations between our constructs of peer competitive pressure and three popular measures of financial report readability, namely, the Flesch-Kincaid index, the Gunning Fog index, and the Gobbledygook index. Furthermore, peer competition pressure is negatively (positively) related to the precision (dispersion) of managment earnings forecasts. Hence, managers' deliberate hoarding of negative information also manifests in their mandatory and voluntary disclosures.

of the supplier. For (iii), 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. We repeat our baseline regressions by controlling for the three constructs separately. Results shown in Panels A-C of Table A.2. suggest that the peer competitive effects on crash risk remain substantially unchanged in terms of magnitude and statistical significance. Thus, our main results are not driven by a firm's business or operating risk.

The overall evidence validates the bad news hoarding nature of crash risk measures. While these constructs have the advantage of directly measuring a firm's disclosure behavior over the crash risk proxies, they suffer important drawbacks. For instance, the disclosure events with large negative investor reactions are rare in occurrence, and the likelihood of identifying them is highly dependent on the overall number of events that held by a firm. Firms exhibit large heterogeneity in the number of communication events, and the decisions of holding them may be endogenously determined, potentially confounding our causal inferences of the relationship. Similarly, SEC reviews, let alone comment letters, are rarely found in our sample, and SEC's decisions to review may be endogenous. Furthermore, material restatements also capture extreme practices of disclosure that cannot be observed on a regular basis. Thus, to circumvent the potential issues that arise from extreme observations and endogeneity, our study focuses on stock price crashes and only use these direct disclosure proxies for validation purposes.

4. Identification strategies: quasi-natural experiments

Thus far, the results underscore a strong relation between competitive threats from customer-connected 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 customer-connected peers.

4.1. Customer M&A intensity

In our first identification strategy, we use the intensity of M&A activities of customers as an 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 suppliers since they are likely independent of suppliers' corporate decisions. There may be a 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 the 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:

$$\begin{aligned} Peer\ Competitive\ Threat_{i,t} &= \gamma_0 + \gamma_1 Instrumental\ Variable_{i,t} + \sum_{k=1}^{K} \lambda_k X_{ki,t} + \text{FE} + \eta_{i,t}, \quad (8) \\ Crash\ Risk_{i,t+1} &= \alpha_0 + \alpha_1 \widehat{Peer\ Competitive\ Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \quad (9) \end{aligned}$$

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 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.[12] 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.[13] For each supplier, 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 4.

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

[12] Restriction (iv) may result in the exclusion of an 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.

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

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 with 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.

4.2. 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 customer-connected peer files for bankruptcy, we would, therefore, expect 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 captured by the three measures 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.

A potential concern for this approach is that any relation found between customer-connected 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 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 its 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. 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 shocks on 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 $X_{ki,t}$ includes the same set of firm-level controls as that in 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 5. Consistent with our *prior*, the two additional 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 decreases 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.

4.3. 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

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

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 of shocks to the three competitive threats measures, the disaster events capture the temporary exogenous reductions in their 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 as measured by Peer Count, Peer Sales, and Peer Similarity, the competitive threats that such troubled supplier peers pose to the supplier firm would decline considerably. Thus, we test whether the effects of our three key variables on crash risk would be less pronounced, *ceteris paribus*, when the connected peers are suffering from natural disasters. Our analysis has the same spirit as the difference-in-differences approach. However, in order to emphasize the key feature that the treatment does not directly affect the peer competitive threat variables but rather captures nonlinearity in the impact of the key competitive variables, we interact the treatment indicator variable with our key peer competitive threat variables.

We obtain information on all federally declared disasters within the United States 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 and Saugvanat (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 the two studies that 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.

Crucial to our analysis is the identification of affected firms by disasters. We first collect plant- and establishment-level data from the Mergent Data Explr database, which is an annual snapshot data directly from Dun and Bradstreet. Data Explr contains annual information on employment

[15] Barrot and Saugvanat (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.

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 its 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 peers are adversely affected by natural disasters.

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

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 is also affected by the same disaster.

Results, as reported in Table 6, 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 mainly statistically significant at the 5% level, implying that the effects of our key competition variables become less pronounced when customer-connected 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 customer-connected 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 customer-connected peers. Taken together, these findings suggest that for suppliers competing against affected peers, a one-standard-deviation increase in *Peer Count* ultimately gives

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

rise 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. These findings are consistent with our *prior* that an exogenous shock to supplier peers' own conditions weakens their competitive threats and, in turn, results in 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.

5. Stakeholders and Managerial Withholding of Bad News

Having established that a firm strategically withholds adverse information when facing peer competitive threats, we now investigate, in this section, whether such disclosure decisions are driven by three specific types of stakeholders – customers, customer-connected peers, and investors.

5.1. Disclosure to customers

We posit that suppliers under peer competitive pressure would be less willing to share negative information with their customers. The three key competitive threat measures inherently incorporate the customer switching costs dimension. The switching costs are lower if the customers have access to a larger pool of alternate suppliers who produce similar products as the focal supplier. Hence, greater peer competitive pressure is associated with increased managerial concerns of the common customers switching to peer competitors. If such is the case, we expect the negative information hoarding incentives to be mitigated by a closer, cooperative business relationship between the firm and its customers. The effects are two fold: (i) collaborative relationships increase the dependence of customers on the firm, thereby reducing the former's propensity to switch away; and (ii) more intense customer-supplier business transactions both lower the information asymmetry between the the counterparties and increase the customers' attention to the firm, limiting the its ability to conceal information.

5.1.1. *Trade credit*

To test whether maintaining a closer customer-supplier business relationship plays a role in the strategic information disclosure, we first examine trade credit a firm offers to its corporate customers. The more benefits that customers enjoy from the focal firm through advanced products and delayed payments, the higher the likelihood for the former to maintain a stable relationship with the firm and the more information exchange between the two. The proxy we construct is *AccRec*, defined as the natural logarithm of one plus accounts receivable, and we predict that a higher *AccRec* is associated with a dampening effect on the positive association between peer competitive threats and stock price crash risks. We conduct a panel regression analysis by regressing each crash risk measure on the interaction of *AccRec* with peer competitive threats variables as follows:

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Peer\ Competitive\ Threat_{i,t} \times AccRec_{i,t} + \alpha_2 Peer\ Competitive \\ & Threat_{i,t} + \alpha_3 AccRec_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \mathrm{FE} + \epsilon_{i,t}, \end{aligned} \tag{12}$$

Regression results are shown in Table 9. Consistent with our prediction, *AccRec* has attenuating effects on the relation between peer competitive pressure and the supplier crash risk. The coefficients on the interaction term, α_1, are negative and statistically significant across all but one regression analyses.

5.1.2. *Customer-supplier business alliance*

Another aspect of customer-supplier relationship we focus on is the business alliance established between a firm and its customers. 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 trading partners would facilitate their relationship maintenance and information sharing, reducing both the incentive and the ability for the supplier firm to hide negative information from its customers.

For each supplier firm, we reestimate the three measures of peer competitive threats from a subset of its common customers who have formed a least one type of business alliance with it (hereafter $CusAl$), including 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. The identification of $CustAl$ is conducted using the relationship information obtained from Revere database. With these *Peer Competitive Threat (CusAl)* constructs, we run the following panel regression.

$$\begin{aligned} Crash\ Risk_{i,t+1} \quad &= \quad \alpha_0 + \alpha_1 Peer\ Competitive\ Threat(CusAl)_{i,t} + \alpha_2 Peer\ Competitive \\ &\quad\quad Threat_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \end{aligned} \tag{13}$$

where $Peer\ Competitive\ Threat(CusAl)$ is either (i) *Peer Count (CusAl)*, defined as the log average of the number of supplier peers connected through $CusAl$; (ii) *Peer Sales (CusAl)*, the proportion of *Peer Sales* from $CusAl$-connected supplier peers; and (iii) *Peer Similarity (CustAl)* computed as the average product similarity score of $CusAl$-conncted peers. In Eq. (13), the coefficient of α_1 captures the incremental effect of peer competitive threats from a customer in alliance beyond that explained by an average common customer. Results are reported in Table 9.

The coefficients on all *Peer Competitive Threat (CusAl)* measures are negative and statistically significant for all but one regression. Consistent with our *prior* that collaborative customer-supplier relationships reduce manageral concerns on releasing information to customers, the results indicate that peer competitive threats from $CusAl$-connected peers dampen the overall competitive effects on supplier stock price crash risk. For instance, a one-standard-deviation increase in *Peer Sales (CusAl)* would lead to an increase in $NCSKEW$ by 0.020, a significant reduction from a 0.039 increase associated with a one-standard-deviation change in *Peer Sales*. Both effects are large in economic magnitude compared to the mean $NCSKEW$ of 0.057.

In sum, we find that forming business alliances and having trade credit with its customers have moderating effects on the positive relation between peer competitive threats and crash risk, supporting the notion that strategic information disclosure is at least partially driven by managerial concerns on the information released to corporate customers.

5.2. Disclosure to connected peers

We contend that firms under peer competitive pressure would also be concerned about the predatory actions that connected peers would take against them. Peers can compete agressively by lowering prices or increasing expenditure on non-price competition with the objective of forcing the supplier out of the market, and releasing proprietary information to these customer-connected peers may be costly for the supplier under competitive environment. To test whether a firm is concerned about revealing information to its closely connected peers given predation threats, we examine the role supplier-peer business alliance plays in the association between peer competitive threats and crash risk. We expect that a collaborative relationship between a firm and its connected peers would curb both the latter's competitive and predatory efforts and the former's ability to hide material information from the counterparty. Hence, if disclosure behavior is in part influenced by connected peers, supplier-peer alliance would have attenuating effects of the baseline relation.

We construct three new measures of peer competitive threats (*Alliance Peer Competitive Threat*) similar to those based on *CustAl*, with the key distinction that *Alliance Peer Competitive Threat* variables are computed on the subset of connected peers who have formed business alliance with the focal supplier. We reestimate Eq. (13) with *Alliance Peer Competitive Threat* replacing *Peer Competitive Threat (CusAl)* and report our findings in Table 10.

The coefficients are negative and statistically significant for *Alliance Peer Count* and *Alliance Peer Similarity*. Consistent with our *prior*, 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). The results provide supportive evidence showing that collaborative relationships with rival peers mitigate the effects of peer competition on a firm's information hoarding behavior, and in turn suggest that supplier's strategic disclosure behavior is influenced by managerial concerns on the information released to close competitors.

5.3. Disclosure to investors

Finally, we test whether a supplier facing greater competitive pressure has more incentives to hoard negative information from investors. Existing literature (e.g., Jin and Myers, 2006; Kothari, Shu, and Wysocki, 2009) suggests that managers are better able to conceal bad news from investors when there is high information asymmetry between the firm and investors. Hence, a firm's intent to hide information from investors can be tested by examining changes in information asymmetry. Specifically, we look for any cross-sectional impact of (i) institutional ownership breadth, (ii) analyst forecast dispersion, and (iii) news coverage on the link between competitive threats and stock price crash risks.

5.3.1. 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. (12) using $No.Inst$ in place of *AccRec* and report our findings in Panel A of 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.

5.3.2. *Analyst forecast dispersion*

Another measure we construct to proxy for information asymmetry between a firm and its investors 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 IBES data, 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. (12) using $High\ Dispersion_{i,t}$ in place of *AccRec*, and results are presented in Panel B of Table 11. 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 Panel A and support the notion that crash risk is driven by the strategic hoarding of negative information to investors.

5.3.3. 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 investors 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 the previous two panels, Panel C of Table 11 presents results from the estimation of Eq. (12) using $Media\ Coverage_{i,t}$. 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 between a firm and its investors, 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 and suggest that our main findings are driven by managers' intentions to withhold negative news from investors.

6. Conclusion

We exploit the vast complex network of supplier-customer links to provide insights on the strategic bad news disclosure behavior of firm managers facing intense competition from peers that supply to the same customers. We find that our firm-specific measures of customer-connected peer competitive pressure play an important role in supplier stock price crash risk, a proxy for a supplier's accumulation of bad news. This evidence suggests that supplier managers strategize to withhold or delay disclosing bad news that may have a detrimental effect on their stock price. Our analyses also show that non-linked peers, or potential competitors, do not affect managers' behavior to withhold or delay bad news disclosure, nor does our study find evidence that industry-level competition explains such behavior. To alleviate possible endogeneity concerns associated with our 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 connected-peer competitive pressure has a causal effect on supplier stock price crash risk. Finally, we show that firms' bad-news disclosure decisions are driven by their stakeholders, namely their customers, customer-connected peers, and investors.

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Figure 1: A Snapshot of Texas Instruments Inc's Network of Suppliers

This graph contains a proportion of the supply-chain network of Texas Instruments Inc in 2014. It includes corporate customers and 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 a focal supplier, Texas Instruments Inc, the blue nodes represent corporate customers of Texas Instruments Inc, and the orange nodes represent suppliers of the customers, which are connected peers to Texas Instruments, according to Hoberg and Phillips's (2010) TNIC classification. In addition, the figure also show the number of non-customer-connected peers of the focal firm to reduce the number of nodes.

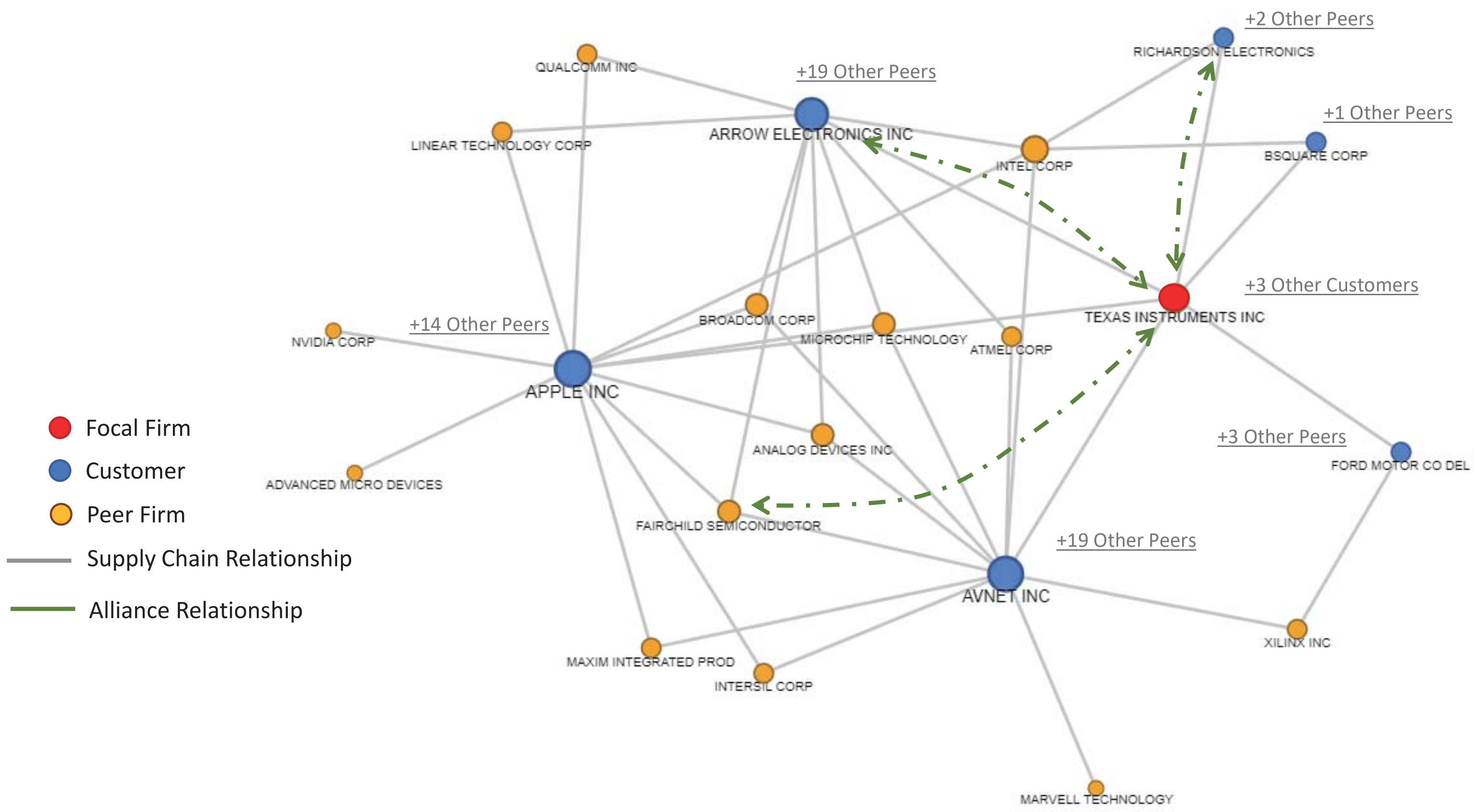

Figure 2: A Supplier's Customer Network and Peer Firms

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.

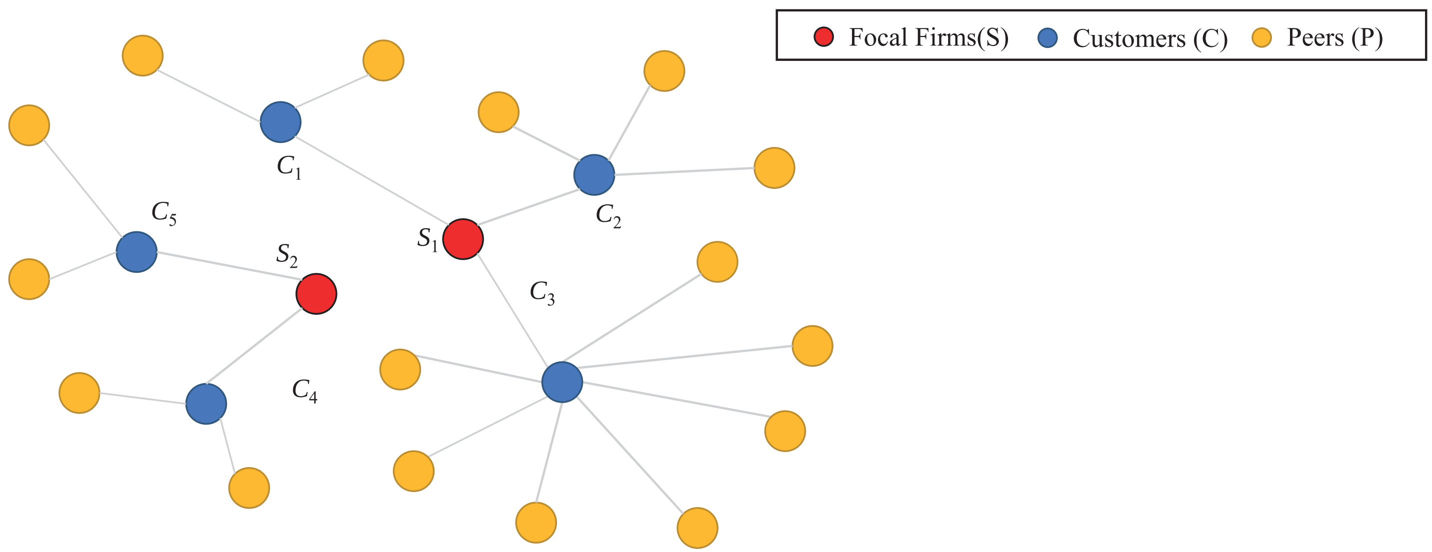

Table 1

Summary Statistics

This table reports the number of observations (NObs), 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 summary statistics of the three proxies for 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 average product similarity with other suppliers of the customer (Peer Similarity). Panel B shows summary statistics of three measures of stock price crash risk, which are proxies for managers' bad news withholding: (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); (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	NObs	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 Negative News Hoarding

This table reports results from regressing supplier stock price crash risk, a proxy for supplier negative news hoarding, on each measure of peer competitive threats and firm-specific controls 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 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 parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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$_t$	0.029***			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)
ΔTurnover$_t$	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
Adj-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

Customer-Connected Peer Competitive Threats vs. Other Sources of Competitive Threats

This table reports results from regressing supplier stock price crash risk, a proxy for supplier negative news hoarding, on each measure of peer competitive threats as well as on proxies for other sources of competitive threats, while controlling for firm-specific variables as follows:

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

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-C replicate the analysis in Table 2 in the presence of a proxy for other sources of competition, namely, Non-Linked Peer Count as well as Non-Linked Peer Similarity, supplier Fluidity measure, and supplier industry concentration HHI, respectively. The three proxies for 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 parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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)	(10)	(11)	(12)
	Panel A: Competition from Non-Linked Peer Threats											
Non-Linked Peer	0.013	0.005			0.008	0.004			0.014	0.008		
Count$_t$	(0.82)	(0.28)			(0.79)	(0.38)			(1.22)	(0.69)		
Peer Count$_t$		0.028***				0.013***				0.019***		
		(4.58)				(3.35)				(4.13)		
Non-Linked Peer			0.359**	0.201			0.204*	0.117			0.205*	0.134
Similarity$_t$			(2.04)	(1.13)			(1.91)	(1.08)			(1.68)	(1.07)
Peer Similarity$_t$				1.025***				0.566***				0.460**
				(4.35)				(3.82)				(2.55)
NObs	22,904	22,904	22,904	22,904	22,904	22,904	22,904	22,904	22,915	22,915	22,915	22,915
Adj-R^2	0.017	0.018	0.017	0.018	0.020	0.021	0.020	0.021	0.011	0.012	0.011	0.011
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 – Continued

Peer Competitive Threats vs. Other Sources of Competitive Threats

	$NCSKEW_{t+1}$				$DUVOL_{t+1}$				Crash $Count_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: Fluidity – Product Market Competitive Environment												
$Fluidity_t$	0.004	0.002	0.003	0.001	0.002	0.001	0.002	0.000	0.002	0.001	0.002	0.001
	(1.64)	(0.77)	(1.34)	(0.51)	(1.24)	(0.54)	(1.12)	(0.20)	(1.34)	(0.63)	(1.14)	(0.81)
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Supplier Industry Concentration (HHI)												
Supplier Industry	0.076	0.239	0.204	0.226	0.136	0.193	0.189	0.188	0.056	0.259	0.234	0.241
HHI_t	(0.40)	(0.90)	(0.75)	(0.85)	(1.09)	(1.15)	(1.09)	(1.12)	(0.40)	(1.35)	(1.18)	(1.25)
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)
NObs	32,107	28,582	27,120	28,582	32,107	28,582	27,120	28,582	32,107	28,595	27,133	28,595
Adj-R^2	0.026	0.025	0.024	0.025	0.026	0.027	0.026	0.027	0.026	0.018	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4

Negative News, SEC Comment Letters, and Restatements

Panel A of this table reports results from regressing the ratio of negative-news associated CAR(-1,1) to positive-news associated CAR(-1,1) on each proxy for peer competitive threats. CAR(-1,1) is a 3-day cumulative return in market reaction to news of management-involved events in year $t+1$. Number of 5% (10%) Significant News$_{t+1}$ counts only key events with $|CAR(-1,1)| > 5\%(10\%)$. Panel B reports panel regression results from regressing the number of SEC comment letters on mandatory disclosures 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), or on the occurrence of material restatements on the different filings submitted by a supplier in year $t+1$ on each proxy for peer competitive threats. In all regressions, we control 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). The three measures of peer competitive threats include Peer Count, Peer Sales, and Peer Similarity. In Columns (1)-(6), the analysis is based on a sample period from 2004 to 2015, because SEC comment letters are available starting 2005. $t-$statistics are shown in parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted R^2† (adj R^2 in Columns (1)-(6) and pseudo-R^2 in Columns (7)-(9)) are reported. Construction of the variables is presented in Appendix A.

	All News$_{t+1}$			5% Significant News$_{t+1}$			10% Significant News$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Negative-Over-Positive Management Disclosure at $t+1$									
Peer Count$_t$	-0.022***			0.017***			0.020***		
	(-4.60)			(3.20)			(4.16)		
Peer Sales$_t$		-0.393***			0.219			0.201*	
		(-3.18)			(1.58)			(1.74)	
Peer Similarity$_t$			-0.439**			0.754***			0.674***
			(-2.17)			(3.54)			(3.69)
NObs	23,556	22,216	23,556	23,556	22,216	23,556	23,556	22,216	23,556
R^2	0.016	0.017	0.016	0.050	0.050	0.050	0.108	0.107	0.108
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
	SEC Comment Letters at $t+1$								
	Full Sample			Firms with Comment Letters			Occurrence of Restatements$_{t+1}$		
Panel B: Comment Letters and Material Restatements $t+1$									
Peer Count$_t$	0.053***			0.067***			0.007***		
	(6.27)			(6.36)			(4.97)		
Peer Sales$_t$		0.870***			0.907***			0.105***	
		(3.86)			(3.46)			(2.86)	
Peer Similarity$_t$			1.804***			2.121***			0.242***
			(5.52)			(5.36)			(3.75)
NObs	19,055	17,941	19,055	8,757	8,283	8,757	23,154	21,816	23,154
Adj-R^2†	0.063	0.060	0.063	0.098	0.094	0.097	0.026	0.025	0.025
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 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).

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

The three proxies for peer competitive threats are 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 parentheses 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's peers files for Chapter 11 bankruptcy, and 0 if otherwise. Post_{t+1} is an indicator that equals one during the year in which the supplier peer files for bankruptcy, and 0 if otherwise. Bankruptcy_{t+1} is an indicator that equals one if the supplier files bankruptcy in $t+1$ and 0 if 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 parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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)
$\text{Post}_{i,t+1} \times \text{Treat}_i$	-0.155***	-0.132***	-0.096**
	(-2.91)	(-3.38)	(-2.40)
Treat_i	0.027	0.019	0.023
	(1.10)	(1.18)	(1.23)
$\text{Bankruptcy}_{i,t+1}$	0.843***	0.508***	0.445***
	(3.40)	(2.84)	(2.66)
$\text{MktShare}_{i,t+1}$	-0.644***	-0.408***	-0.403***
	(-3.68)	(-3.72)	(-3.12)
NObs	19,222	19,222	19,227
Adj-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.

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

The three proxies for peer competitive threats include Peer Count, Peer Sales, Peer Similarity. The Peer Disaster indicator takes the 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 if otherwise. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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*		
× 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*	
× 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**
× 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)
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
Adj-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

Customer Trade Credit, Peer Competitive Threats, 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, customer trade credit as proxied by a supplier's accounts receivable (*AccRecs*), 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.

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

$AccRecs_t$ is defined as $\ln(1+RecTr)$, where *RecTr* is the accounts receivable through trading activities from Compustat at year t. The three proxies for peer competitive threats include Peer Count, Peer Sales, 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 parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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)
$Peer\ Count_t$	-0.006**			-0.003			-0.004*		
$\times AccRecs_t$	(-2.34)			(-1.58)			(-1.91)		
$Peer\ Count_t$	0.048***			0.024***			0.031***		
	(4.20)			(3.12)			(3.56)		
$Peer\ Sales_t$		-0.170**			-0.090**			-0.094*	
$\times AccRecs_t$		(-2.55)			(-2.10)			(-1.91)	
$Peer\ Sales_t$		1.103***			0.604***			0.604**	
		(3.38)			(2.91)			(2.51)	
$Peer\ Similarity_t$			-0.248***			-0.109*			-0.175**
$\times AccRecs_t$			(-2.75)			(-1.88)			(-2.57)
$Peer\ Similarity_t$			1.983***			1.003***			1.154***
			(4.50)			(3.60)			(3.53)
$AccRecs_t$	-0.013***	-0.018***	-0.012**	-0.007**	-0.010***	-0.006**	-0.008**	-0.012***	-0.008**
	(-2.71)	(-4.03)	(-2.52)	(-2.14)	(-3.24)	(-2.00)	(-2.17)	(-3.47)	(-2.09)
NObs	26,379	24,936	26,379	26,379	24,936	26,379	26,392	24,949	26,392
Adj-R^2	0.023	0.022	0.023	0.026	0.025	0.026	0.015	0.015	0.015
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

Customer Alliances 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).

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

The three measures of peer competitive threats (i.e., Peer Count, Peer Sales, and Peer Similarity) are constructed in the following manner. We construct three measures where peers are connected to common customers that form alliances with the focal supplier firm, and another three similar measures where peers are connected to common customers that form no alliances with the focal firm. To distinguish the two groups of constructs, we add the expression "(*CusAl*)" to the former. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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(CusAl)$_t$	-0.018**			-0.012**			-0.013**		
	(-2.51)			(-2.50)			(-2.32)		
Peer Count$_t$	0.038***			0.020***			0.025***		
	(6.13)			(5.06)			(5.28)		
Peer Sales(CusAl)$_t$		-0.060**			-0.054***			-0.023	
		(-2.35)			(-3.11)			(-1.02)	
Peer Sales$_t$		0.454***			0.275***			0.211**	
		(3.14)			(3.06)			(1.98)	
Peer Similarity(CusAl)$_t$			-0.471*			-0.353**			-0.312*
			(-1.95)			(-2.30)			(-1.67)
Peer Similarity$_t$			1.370***			0.786***			0.708***
			(6.05)			(5.56)			(3.99)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
Adj-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

Table 10

Peer Alliances 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).

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

The three measures of peer competitive threats (i.e., Peer Count, Peer Sales, and Peer Similarity) are constructed in the following manner. We construct three measures where peers do not establish any alliances with the focal supplier firm, and another three similar measures where peers form an alliance with the focal firm. To distinguish the two groups of constructs, we add the expression "Peer Alliance" to the latter. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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 Alliance 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)		
Peer Alliance 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)	
Peer Alliance 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
Adj-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 11

Information Asymmetry and Supplier Bad News Hoarding

This table reports panel regression results from regressing a measure of supplier bad news hoarding (proxied by stock price crash risk) on a measure of peer competitive threats, a proxy for information asymmetry (i.e., the number of institutional investors (*No.Inst*); high dispersion in analyst opinions (*High Dispersion*; *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).

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

The three proxies for peer competitive threats include Peer Count, Peer Sales, Peer Similarity, whereas the three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. The proxies for information asymmetry are: (i) No.Inst captures the log of the number of 13F filers of suppliers in the quarter prior to fiscal year end of the supplier; (ii) 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; (iii) 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. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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: Breadth of Institutional Ownership									
Peer Count_t	-0.014***			-0.006**			-0.009***		
$\times\ \text{No.Inst}_t$	(-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**	
$\times\ \text{No.Inst}_t$		(-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***
$\times\ \text{No.Inst}_t$			(-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
Adj-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 11 – Continued

Information Asymmetry and Supplier Bad News Hoarding

Variable	NCSKEW$_{t+1}$ (1)	NCSKEW$_{t+1}$ (2)	NCSKEW$_{t+1}$ (3)	DUVOL$_{t+1}$ (4)	DUVOL$_{t+1}$ (5)	DUVOL$_{t+1}$ (6)	Crash Count$_{t+1}$ (7)	Crash Count$_{t+1}$ (8)	Crash Count$_{t+1}$ (9)
Panel B: Dispersion in Analyst Opinions									
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
Adj-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
Panel C: Media Coverage									
Peer Count$_t$	-0.006**			-0.003			-0.006**		
× 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*	
× 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***
× 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
Adj-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

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 average 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 the Revere Relationship database (FactSet Revere) and within the same Hoberg and Phillip's (2010) TNIC industry as a supplier. (FactSet Revere; Hoberg and Phillips, 2010)
Non-Linked Peer Similarity	The average 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)

Appendix A - Continued

Variable Definition and Data Source

Variable	**Definition and Data Source**
Variables relating to Tests of Economic Consequences	
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)
Fog	The Gunning Fog index measures the readability of the 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 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).
Restatement	An indicator equal to one if any of the supplier have a material restatement in a given year, and 0 otherwise.(Audit Analytics)
Precision	Management forecast precision(EPS) in a given year, measured as the averaged absolute difference between the upper- and lower-end estimates, scaled by mean estimates of management. (IBES Guidance)
Dispersion	Management forecast dispersion(EPS) in a given year, measured as the averaged absolute difference between the management and Analyst Estimate Consensus, scaled by mean estimates of management.(IBES Guidance)
Disclosure Ratio	Management negative-over-positive disclosure ratio, measured by ratio of number of negative disclosure over positive disclosure in a given year. The sign of disclosure is determined by the cumulative abnormal return from the Fama-French 4-factor model at the announcement. The disclosure events are earnings announcements, conference presentations, client announcements, earnings calls, product-related announcements, and corporate guidance events from Capital IQ Key Development. The firm and year observations with less than 4 events are removed (Capital IQ).

Appendix A - Continued

Variable Definition and Data Source

Variable	**Definition and Data Source**
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 monthly stock turnover within a fiscal year minus that of the previous year. (CRSP)
AbAccr	The prior three years' moving sum of the absolute 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)

Table A.1

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:

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

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 2008-2009. 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 parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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 Concentration_t	0.110**	0.140***	0.104**	0.058*	0.074**	0.053*	0.012	0.035	0.015
	(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
Adj-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 2008 and 2009									
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
Adj-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 A.2

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 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 parentheses and are computed based on standard errors clustered at the supplier firm level. The number of observations (NObs) and adjusted 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
Adj-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

Table A.2 – 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 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
Adj-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
				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
Adj-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