Contagious Stock Price Crashes along the Supply Chain

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ABSTRACT

Although risk management is widely regarded as an important topic within supply chain (SC) management, little research studies the contagious effect of risk factors along SC networks. By using stock price crashes as an indicator of risk factors, our study reveals that stock price crash risk can be transmitted from major customers to suppliers with a delay of up to two weeks. We show that the information opacity of suppliers is a factor that potentially contributes to the delayed crash contagion. We also find that the contagion effect becomes more pronounced as the importance of customers increases. Moreover, customer operational incidents have a more pronounced contagion effect on suppliers compared to customer financial incidents. Additionally, we find that suppliers tend to take strategic measures following the stock price crashes of their major customers, including diversifying their customer base, enhancing operational efficiency, and improving product quality. However, among these actions, only the improvement of operational efficiency effectively mitigates the adverse impact of customer stock price crashes on suppliers. Overall, our findings provide new insight into the distribution of risk factors across SC networks, highlighting the critical role of operational improvements in bolstering the resilience of firms to SC risks.

Keywords: Supply chain risk, contagion effects, stock price crashes, operational incidents, financial incidents

1. Introduction

Supply chain (SC) risk plays a central role in the literature on SC management. Prior research shows that firms experiencing SC glitches have significantly lower sales growth, higher inventory costs (Hendricks et al., 2005a), and lower shareholder value (Hendricks et al., 2003). Researchers also find that SC risk does not only affect focal firms but is contagious along the supply chain. For example, Lo et al. (2018) find that environmental incidents of a focal firm in China not only significantly affect the stock price of the firm itself but also affect the market value of its overseas customers. Similarly, Kim and Wager (2021) show that the stock market reacts negatively to the corruption risk of upstream suppliers, triggering negative stock price reactions in downstream suppliers. However, little research explicitly investigates whether or how stock price crashes, a key risk factor, are transmitted from major customers to suppliers, and how suppliers respond to the contagious effect of customer crashes.

The supplier–customer relationship often involves important and explicit contractual arrangements, creating an economic bond between two firms (Pandit et al., 2011). Firms in modern economies are increasingly and closely connected via supply chains as a result of production–process specialization. As Levine (2012) explains, for instance, making a Boeing 747 requires more than 6,000,000 parts, the production of each requiring many further operations. Hence, it is reasonable to expect information externalities due to the close connection of firms along the supply chain. An example is Analog Devices, Inc. (ADI), a manufacturer of capacitive touch-screen controllers for the iPhone and Apple Watch. Because ADI is known for being an Apple supplier, its valuation is substantially affected by Apple's business. Triggered by a disappointing earnings report released that day, Apple's stock tumbled nearly 8% on April 27, 2016, wiping out $46 billion in market capitalization. In response, ADI's stock price decreased by nearly 6% over the three subsequent trading days.[1, 2]

Using a large supplier–customer sample of 1,094,638 pair-week observations, we document that the occurrence of significant customer stock price crashes has a reliable predictive power for supplier stock price crashes up to two weeks in the future. In particular, stock price crashes of major customers are not only significantly correlated with the contemporaneous crash risk of suppliers but also more than double the likelihood of suppliers experiencing stock price crashes in the subsequent two weeks. The delayed crash transmission only occurs when the crashed customer is important to the supplier in

[1] The tech giant Apple posted fiscal second-quarter earnings of $1.90 a share on $50.56 billion in revenue, marking its first quarter-over-quarter sales revenue decline since 2003. Apple's stock price subsequently dropped significantly. The stock price crash of Apple dragged down the stocks in its supplier universe. Besides ADI, shares of Skyworks Solutions, Micron Technology, NXP Semiconductors, and Broadcom also dropped significantly afterward.

[2] Another example occurred in 2011 when the earthquake and tsunami hit Japan. The disaster triggered a series of events that led to a shortage of critical components used in the production of automobiles and electronics. The stock price of Toyota, a major player in the automotive industry, declined significantly in the wake of the disaster as the company was forced to halt production due to a parts shortage. This decline in Toyota's stock price also affected its suppliers, such as Denso, which produces electronic components for Toyota's vehicles. The stock price of Denso declined significantly as a result of the production halt, and, in turn, affected the stock prices of other companies in the supply chain, such as semiconductor manufacturers and metal producers.

terms of sales, further validating the supply chain as the conduit of the delayed crash transmission. In addition, we find that the delayed contagion effect of stock price crashes is moderated among suppliers that have a more transparent information environment.

Next, we explore the nature of incidents that may cause the crash contagion effect. Specifically, we identify customer operational shocks (including sales drops, environmental incidents, and product recalls) and customer financial shocks (including negative earnings surprises, lawsuits in which the customer firm is a defendant, and mergers and acquisitions [M&As]). Our results suggest that, in general, operational shocks cause a more significant contagion effect from customers to suppliers, as compared to financial shocks.

We also investigate several potential supplier response strategies following the stock crashes experienced by their customers. Based on relevant literature in operations management (OM), we examine three different actions of suppliers in response to customer crises: (1) diversifying customers (e.g., Leung and Sun, 2021; Jiang et al., 2023), (2) improving operational efficiency (e.g., Yiu et al., 2020), and (3) improving product quality (e.g., Lam et al., 2022). The results show that suppliers tend to adopt all of the above strategies following the stock crashes of their major customers. As a follow-up, we examine the effectiveness of these strategic actions in mitigating the negative impact of stock crashes on suppliers. Interestingly, we find that only operational efficiency improvement, not customer diversification or product quality enhancement, can effectively bolster suppliers' resilience to stock crashes (i.e., enhance the recovery of suppliers' stock prices after crashes).

Last but not least, to alleviate the endogeneity concern that some omitted causes of the customer stock crashes may correlate with unobserved error terms when estimating a supplier's stock crash likelihood, we perform a battery of robustness checks. First, to account for firm-specific news causing stock price crashes, we include customer operational and financial incidents as additional control variables in our baseline regressions and find that our results remain qualitatively unchanged. Furthermore, we interact the customer crash indicator with each of the incident-related indicator variables, respectively. We also include all the interaction terms of the customer crash indicator with the incident-related indicator variables in one regression. Our results remain qualitatively the same. Next, we rerun the baseline regressions using an alternative measure of stock price crash that specifically controls for industry-wide stock price movements. The results are consistent with the baseline findings, suggesting that supply-chain stock price crash contagion is not primarily driven by industry-wide stock price movements. In addition, we find that the delayed transmission of crash risk is essentially confined to the genuine supply chain and does not occur in pseudo-supply chains that are falsely created using firms from the same industries as suppliers or customers. This finding further precludes industry-level lead–lag price co-movement as a potential explanation for delayed crash contagion. Our findings are also robust to controlling for supplier-firm characteristics that are potentially related to stock price crash risks, past supplier stock price crashes, past excess stock returns for both the supplier and its customers, and the year, industry, industry–year, and firm fixed effects.

Our work contributes to the literature on supply chain management. The extant literature has documented the effect of supplier-customer relationships on a variety of factors, such as mergers and acquisitions (e.g., Fee and Thomas, 2004), bankruptcy (e.g., Yang et al., 2015), capital structure (e.g., Banerjee et al., 2008), information sharing (e.g., Pandit et al., 2011), financial analysts (e.g., Luo and Nagarajan, 2015), innovation (e.g., Chu et al., 2019). The literature does not investigate whether or how a firm's stock price crash risk is affected by the stock price crashes of other SC members or the factors that influence the efficiency of such transmission along the supply chain. We contribute to the literature by documenting that the transmission of stock price crashes from a firm's major customers can face a significant delay of up to two weeks and that the information opacity of supplier firms plays a key role in the delayed crash contagion effect.

Our results show that operational incidents of major customers, which could be indicators for future cash flows or the economic performance of upstream suppliers, are the main causes of stock crash spillover in the supply chain. Our findings highlight the significance of operational incidents that cause stock crashes along the supply chain and document novel evidence showing that a fundamental improvement of operations and firm efficiency is an effective way to mitigate the negative impact transmitted from customers' stock crashes.

The rest of this paper is organized as follows: Section 2 reviews the relevant literature and develops our hypotheses; Section 3 describes the data and variables; Section 4 presents the main findings; Section 5 discusses the results of further empirical analyses; and Section 6 concludes the paper. Variable definitions and additional empirical results are available in the E-Companion.

2. Research Background and Hypotheses Development

2.1 Research on supply chain contagion

Researchers in OM have long been interested in how various supply chain practices affect firms' operational effectiveness and the subsequent changes in shareholder value (Hendricks et al., 2005b). Despite the difficulty in measuring "supply chain practices" (Fan et al., 2022), researchers find that harmful incidents in supply chain management—such as product delay, shortage of parts, and supply–demand mismatch—adversely affect shareholder value. Researchers realize that firms' operational incidents not only negatively impact the focal firm but also their SC partners (Lo et al., 2018). Various studies provide empirical evidence as to the contagious effect of SC risk. For stance, focusing on natural disasters, Hendricks et al. (2020) show that the Great East Japan Earthquake (GEJE) had a significant negative effect on firms whose operations were not directly affected by the earthquake. Instead, the negative effects were transmitted through the propagation from upstream customers who were directly impacted by the GEJE. Jacobs et al. (2022) find that, upon the sanction of the US government on a Chinese telecommunication equipment manufacturer, both tier-one and tier-two US suppliers of the Chinese manufacturer reacted negatively. Several other studies have focused on negative stock price reactions of suppliers to specific corporate events of their customers, including emissions scandals

(Jacobs and Singhal, 2020), corruption practices (Wang et al., 2023) and environmental incidents (Lo et al., 2018).

Another stream of research examines the propagation of credit shocks from customers to suppliers, with a focus on how investors of suppliers incorporate the information from the credit default swap (CDS) market of customers (Agca et al., 2022; Ağca et al., 2023; Fang et al. 2023). For example, using CDS spread (i.e., the insurance cost of a company's debt) as a measure, Agca et al. (2022) find that credit shocks do not transmit in inactive supply chain, but are amplified if supply chain partners are followed by the same stock analysts. More generally, other studies examine how financial distress is transmitted within industries (Dontoh et al. 2021) and across supply chains (Aral et al., 2021; Di Giovanni and Hale, 2022). For example, Di Giovanni and Hale (2022) find that nearly 70% of the stock market spillovers across countries are channelled through supply chain networks.

Despite our knowledge of the contagious effect of SC risk (e.g., Lo et al., 2018; Aral et al., 2022), the research in this area is still in its infancy. There is little research on the underlying incidents behind the stock price crashes and how different types of events are transmitted in the supply chain. Specifically, little is known on how the underlying operational and financial incidents of major customers behind stock price crashes influence the contagious effect in supply chains and the relative impact of these two event types on the performance of suppliers (Agca et al., 2022; Shen and Sun, 2023). There is also little research into the response strategies of suppliers after stock crashes. We seek to understand the underlying events that contribute to these transmissions and potential remedies or strategies that make firms more resilient to customer–supplier stock price crash contagion.

2.2 Hypotheses development

In a supplier-customer relationship, both parties have a stake in each other's operations, creating economic interdependence (Olsen and Dietrich, 1985; Banerjee et al., 2008). This interdependence results in externalities between SC partners, implying that stock price crashes experienced by major customers could impact the likelihood of stock price crashes for the supplier. When a major customer firm's stock price crashes, investors revise their expectations downward regarding the customer's future earnings and cash flows. This, in turn, affects expectations about the supplier's future earnings and cash flows, potentially leading to stock price crashes throughout the supply chain. We develop the first hypothesis as follows.

H1*: Customer stock price crashes increase the stock price crash risk of suppliers.*

Much research in operations and supply chain management has examined how customer dependency makes firms more vulnerable to supply chain risks and how over-reliance on a few major customers affects suppliers' performance (e.g., Kim and Zhu, 2018). Leung and Sun (2021) show that firms strategically diversify their customer base during periods of increasing economic policy risk and uncertainty, resulting in improved profitability through new opportunities beyond existing customer-supplier relationships. Firms with a concentrated customer base normally devote a large amount of effort to establish deep relationships, which lead to highly embedded relationships (Özer et al., 2014; Kim and Henderson, 2015), reduced transaction costs (Lee et al., 2018) and increased productivity gains (Serpa and Krishnan, 2018). However, there are also potential issues with high customer dependency. Kim and Zhu (2018) reveal that suppliers with high customer dependency tend to reduce their R&D expenditures due to the threat of high switching costs. With a highly concentrated customer base, any financial difficulty faced by the customers can have an immediate impact on the supplier's revenue and cash flow. As a result, operational difficulties of customers are directly transferred to supplier's business (Donohue et al., 2020), especially when the supplier has tailored their operations to meet the specific needs of the customer.

The bargaining power view of buyer-supplier relationships also highlights the negative consequences and risks associated with dealing with a small number of major customers (Ak and Patatoukas, 2016; Handley et al., 2019) and the importance of trust (Özer et al., 2014; Brinkhoff et al., 2015). When facing powerful customers, suppliers may be compelled to accept less favourable contract terms, such as higher trade credits (e.g., Lee et al., 2018), making them more vulnerable to financial shocks and risk events. With the risks of powerful customers, suppliers have less control over their continuous and smooth operations in the supply chain (Kim and Zhu, 2018; Chang et al., 2022). This can lead to inventory fluctuations, increased costs, and reduced resilience. In summary, the power unbalance with dominant customers enables buyers to shift more risk to suppliers, thereby intensifying risk transmission to upstream supply chains (Lanier et al., 2010; Ak and Patatoukas, 2016; Chang et al., 2022). Accordingly, we formulate the second hypothesis as follows.

H2: *The strength of the contagious effect of stock price crashes increases with the importance of customers*

It is important to differentiate between the specific types of incidents that contribute to customer stock crashes and subsequently transfer to suppliers. Specifically, we focus on two key dimensions of business functions: the operational and financial aspects of firms. We then examine their impact on contagious stock crashes in the supply chain. We focus on three types of customer operational incidents that are widely recognized as common concerns in the literature and are frequently observed within our sample, including (1) demand uncertainty (measured as sales drop) (e.g., Hendricks and Singhal, 2014; Sting and Huchzermeier, 2014), (2) environmental incidents (e.g., Lo et al., 2018), and (3) product recalls (e.g., Wowak et al., 2015; Ball et al., 2018). For financial incidents, we focus on three types of events that are extensively documented to have a significant impact on capital markets, including (1) negative earnings surprises (Ak et al., 2016; Li and Zhan, 2019), (2) lawsuits in which the customer firm is a defendant (e.g., Gande and Lewis, 2009), and (3) M&As (e.g., Moeller et al., 2005).

It is well-documented that operational incidents, such as demand uncertainty, product quality, and environmental problems, have a highly significant negative effect on firm profitability (Ho et al., 2015; Lo et al., 2018), negatively affecting both the future cash flows of the customer and the prospect of its suppliers. Firms facing sales loss (e.g., due to product introduction delay) may experience a significant decline in profitability, as noted by Hendricks and Singhal (2008). Additionally, there is ample evidence that operational mishaps like environmental violations and product recalls have an immediate and noteworthy effect on both the financial performance and public perception of firms. This impact not only diminishes the financial prospects of the focal firm but also affects the suppliers reliant on that firm, as highlighted by Ball et al. (2018) and Lo et al. (2018). We develop the following hypothesis.

H3: *Relative to the stock price crashes of customers unrelated to operational incidents, stock price crashes related to operational incidents have a stronger contagion effect on supplier firms.*

Financial incidents may also have a significant contagious effect in the supply chain due to their potential damages to the customer firm. Negative earnings surprises of a customer can indicate weakened profitability and issues such as reduced demand and high operational costs for the customer firm (Skinner and Sloan 2002; Ak et al. 2016)), implying decreased business opportunities for its suppliers. Lawsuits in which the customer firm is a defendant may cause a negative perception among investors and shareholders, damaging the firm's reputation and market value, affecting both the customer and their dependent firms (e.g., Kim and Wagner, 2021). Similarly, customer M&As may lead to integration challenges, unforeseen costs, and market disruptions, resulting in an uncertain outlook in the supply chain and risks in buyer-supplier relationships (Moeller et al., 2005). We have the following hypothesis.

H4: *Relative to the stock price crashes of customers unrelated to financial incidents, stock price crashes related to financial incidents have a stronger contagion effect on supplier firms.*

Overall, the above hypotheses suggest that a stock price crash can result from either operational incidents or financial incidents. Intuitively, customer stock price crashes related to customer operational incidents may have a more direct impact on supplier firms' business operations through supply-chain linkages, compared to customer stock price crashes related to customer financial incidents. This is because customer operational incidents can directly affect the operations of supplier firms through the supply chain. In contrast, customer financial incidents may initially influence the customer firm's own operations before potentially influencing supplier firms through supply-chain relations.[3] The contagion of the stock price crash from customers to suppliers is also more likely to occur when the importance of customers to suppliers is high. The E-Companion Figure A1 illustrates the contagion process.

3. Sample, Variables, and Summary Statistics

3.1 Sample

We begin by constructing the supplier–customer sample. Both SFAS 14 (1976) and SFAS 131 (1997) require public firms to disclose customers who account for more than 10% of their total sales in

[3] To illustrate the differentiation between operational and financial incidents, we provide a few examples of operational-incident-related stock price crash contagion and financial-incident-related stock price crash contagion within our sample. These examples can be found in Appendix C of the E-Companion of the revised manuscript.

their interim financial reports, allowing us to identify the major customers of a given supplier firm. We initially obtain a preliminary sample of 550,907 observations between 1989 and 2019 from the Compustat segment files. Our sample ends in 2019 to avoid any potential confounding effects of the COVID-19 pandemic, which emerged in the United States in early 2020 and resulted in widespread stock price crashes. To be included in our dataset, we require the customer to be classified as a company and the name of the customer to be neither missing nor stated as "customers." After removing duplicate observations, we are left with 172,211 supplier–customer-year observations. These observations include the supplier firm's identity, the names of customer firms, and the U.S. dollar value of sales to each customer each year.

One practical difficulty is that the Compustat segment files list only abbreviated names of customers without any other identifiers. To tackle this problem, we use a method in line with that of Fee and Thomas (2004) and Chu et al. (2019). Specifically, we generate a list of potential matches for the customer's name, first using a string-matching algorithm that compares the number and order of the letters in the abbreviated names with those in the company names listed in Compustat. We then manually check for potential matches to ensure match accuracy, taking a conservative approach and eliminating eliminated all matched pairs with uncertain matching accuracy. After this procedure, we have a sample of 58,128 supplier–customer pair-year observations.

We then merge the supplier–customer sample with stock price crash data. Following the literature, we construct weekly stock price crash data using daily stock returns from the Center for Research in Security Prices (CRSP). In addition, we obtain financial data from Compustat annual files and analyst earnings forecast data from the Thomson Reuters IBES database. After excluding financial firms (SIC codes 6000–6999) and observations with missing control variables, our final regression sample contains 1,094,638 pair-week observations (covering 21,234 pair-year observations) which originate from 2,917 unique suppliers and 1,213 unique customers.

3.2 Variable measurement

3.2.1 Measuring a stock price crash

Following the literature (e.g., Kim et al., 2011a,b), we compute the firm-specific weekly returns using the following model:

$$r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-2} + \beta_{2,j} r_{m,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{m,\tau+1} + \beta_{5,j} r_{m,\tau+2} + \varepsilon_{j,\tau}, \quad (1)$$

where $r_{j,\tau}$ is the return on stock j in week τ, and $r_{m,\tau}$ is the return on the CRSP value-weighted market index. Following Kim et al. (2011a,b), we allow for nonsynchronous trading by including lead and lag market returns. The firm-specific return on stock j in week τ ($W_{j,\tau}$) is measured as the natural logarithm of 1 plus the residual $\varepsilon_{j,\tau}$ from Eq. (1). Following Hou and Moskowitz (2005), we define weekly returns as the compounded daily returns from Wednesday close to the following Wednesday close.

Measures of the likelihood of crashes or jumps are constructed based on the presence of firm-specific weekly returns exceeding 3.2 standard deviations below or above, respectively, the mean value over the entire fiscal year. Specifically, *CRASH* is an indicator variable that equals 1 if the firm-specific weekly return is at least 3.2 standard deviations below the mean weekly firm-specific return over that fiscal year, and 0 otherwise, while *JUMP*, in contrast, is equal to 1 if the return is at least 3.2 standard deviations above the mean. Following the existing studies, we choose 3.2 standard deviations to generate a frequency of 0.1 percent in the normal distribution (e.g., Kim et al., 2011a,b; Li and Zhan, 2019). Since stock price crashes are defined based on weekly stock returns over a fiscal year, it is not possible to use a cutoff of 0.1 percent of the empirical distribution for a year because each year consists of only 52 trading weeks. Even the lowest weekly return in a year will exceed 0.1 percent of the empirical distribution (as 1/52 = 0.0192 or 1.92%). In Table B1 in the E-Companion of the revised manuscript, we show that the results remain qualitatively unchanged when we define crashes based on a cutoff of 0.1 percent of the empirical distribution of a supplier firm's weekly stock returns over our entire sample period. These definitions of a crash or a jump capture an extreme decrease or increase in firm-specific stock returns. Weekly crash and jump indicators help mitigate market microstructure biases from daily frequencies and also allow us to examine potential contagion delays.

3.2.2 Measuring control variables

Following prior literature (e.g., Jin and Myers, 2006; Kim et al., 2011a,b), we control for a vector of common firm characteristics that may affect a firm's stock price crash risk: *firm size* (natural logarithm of the market value of a firm's equity), *market-to-book ratio* (the market value of equity divided by the book value of equity), *leverage* (total long-term debt scaled by total assets), *return on assets (ROA)* (income before extraordinary items divided by total assets), *discretionary accruals (DACC)* (the absolute value of discretionary accruals estimated based on the performance-matched modified Jones model following Kothari et al. [2005]), *sigma* (the standard deviation of firm-specific weekly returns over a fiscal year), and *returns* (the average firm-specific weekly returns over a fiscal year multiplied by 100). These control variables are measured at the fiscal-year end prior to the year of stock price crashes. Finally, we control for Fama and French's 48 industry fixed effects and year fixed effects. Our results remain qualitatively unchanged whether the industry fixed effects are defined by two-digit or four-digit SIC codes.

3.2.3 Measuring conditional variables

We include multiple conditional variables to examine cross-sectional variations in crash contagion. These conditional variables, measured at the end of the last fiscal or calendar year before the crash year, consist of the *percentage of sales to customer* (the total sales made to the major customer by the supplier divided by the supplier's total sales over a fiscal year), *analyst following* (the number of unique analysts providing current fiscal-year earnings-per-share forecasts for the supplier), *dispersion of analyst forecasts* (the inter-analyst standard deviation of analyst earnings-per-share forecasts for the current fiscal-year scaled by the current-fiscal-year-end stock price of the supplier), *probability of informed trading (PIN)* (an estimate of the probability that a particular trade order originates from a privately informed investor, measured for the supplier firm based on the EKOP market microstructure model developed by Easley et al. [1996]), *bid–ask spread* (the supplier firm's average of daily bid–ask spreads scaled by stock prices over the calendar year), and *idiosyncratic volatility* (the standard deviation of residuals from a regression of its daily excess stock returns on the daily excess market factor). Detailed variable definitions may be found in E-Companion Table A1.

3.2.4 Summary statistics

Table 1 presents summary statistics for the variables used in this study. The suppliers have, on average, a 0.4% unconditional likelihood of encountering both stock price crashes and jumps in any given week. This is consistent with returns demonstrating fat tails and the crash and jump measures capturing extreme stock price movements. The average unconditional probability of crashes and jumps for customer firms is 0.4% and 0.3%, respectively. These numbers are much lower than those reported in previous studies on stock price crashes, likely due to higher measurement frequencies. For example, the unconditional mean of the annual crash and jump indicator variables reported by Kim et al. (2011a,b) are 16.1% and 17.2%, respectively. The crash variable in prior literature is measured on an annual basis (i.e., *CRASH* as an indicator variable equals 1 if the firm experiences at least one crash week during the entire fiscal year). By contrast, our crash variable is measured on a weekly basis, which substantially decreases the average crash risk through an increased total number of observations for which the indicator variable is 0.

Our control variables are generally comparable to those reported in current studies. For example, in line with Chu et al. (2019), customer firms are much larger than supplier firms (mean of firm size: 9.763 vs. 5.974) and, on average, customers outperform their suppliers (mean of *ROA*: 0.048 vs. -0.031). Interestingly, we found that the average earnings management of suppliers is greater than that of customers (*DACC*: 0.463 vs. 0.300).

4. Empirical Results

4.1 Baseline specification and results

To test the existence of the contagion effect of customer firms' stock price crashes on their supplier firms, we estimate the following logistic model:

$$Supp\_Crash_{i,t} = \alpha + \sum_{\tau=0}^{4} \beta_\tau Cust\_Crash_{i,t-\tau} + \gamma' X_{i,t-1yr} + Year\ and\ Industry\ FE + \varepsilon_{it}, \quad (2)$$

where, for firm i and week t, *Supp_Crash* is the stock price crash indicator variable for supplier firms, *Cust_Crash* is the crash indicator variable for customer firms, and X is a vector of supplier characteristics, including *SIZE*, *M/B*, *LEVERAGE*, *ROA*, *DACC*, *SIGMA*, and *RETURNS*. We further control for year and industry fixed effects (Fama and French's 48 industries). If contemporaneous and/or delayed contagion effects of stock price crashes exist, then we should observe significant positive coefficient estimates on the contemporaneous and/or lagged customer crash indicator variables.

We report the regression results in Table 2. Column 1 includes only the contemporaneous and lagged customer crash indicators; Column 2 controls for supplier-firm characteristics; and Column 3 further controls for lagged supplier crash indicators. Industry and year fixed effects are included throughout. The coefficient estimates for *Cust_Crash* in week t (i.e., the T0 week) are all positive and statistically significant at the 1% level, indicating a contemporaneous contagion effect. The coefficient estimates on *Cust_Crash* in weeks t-1 and t-2 are also significantly positive at the 1% level, suggesting a positive delayed contagion effect of customer crash risk on supplier future crash risk, in addition to the contemporaneous effects. Column 4 reports the marginal effect based on Column 3: customer stock price crashes increase supplier stock price crash risk over the next one and two weeks by 0.24% and 0.27%, respectively. The economic magnitude is sizable given that the unconditional crash likelihood is 0.4% (i.e., customer stock price crashes more than double the likelihood of a supplier firm's crash within the next two weeks, ignoring the trivial likelihood that a price crash occurs in each of these two consecutive weeks). The results in Table 2 suggest that the delayed transmission effect of customer crashes on the supplier crashes disappears as the length of time since the customer crash increases. This suggests that, while there is a delayed crash contagion, it is no longer than two weeks on average.[4]

Overall, our baseline results support hypothesis H1. The results show that the stock price crashes of major customers have strong predictability for the crash risk of suppliers in the near future—i.e., up to two weeks. Because stock price crashes are classically salient attention-grabbing events (e.g., Barber and Odean, 2008), the efficient-market hypothesis suggests that the information embedded in major customer stock price crashes should be instantaneously impounded into a supplier's own stock price through investor trading. Thus, this finding of a delay in crash contagion of up to two weeks is intriguing.

4.2 Importance of customers to suppliers

To test our hypothesis H2, we partition the sample according to the importance of customers to their suppliers. Following the prior literature (e.g., Luo and Nagaragan, 2015; Pandit et al., 2011), we measure the importance of customers to suppliers using the *percentage of sales to the customer*, calculated as a supplier's total sales to its major customer divided by the supplier's total sales in a given year. Initially, a customer is deemed more important to its supplier when the supplier's percentage of annual sales to that customer is more than 10%. We then repeat the regression using 25% in place of 10%. We choose 10% as a cutoff value because FAS 131 defines major customers as those who account for greater than or equal to 10% of a firm's total sales. The cutoff value of 25% is chosen following Itzkowitz's (2013) subsample analysis, where the author divides the sample into quartiles based on the percentage of sales to major customers. Table 3 presents the regression results.

As seen in both Columns 1 and 2, the coefficient estimates on $Cust\_Crash_{T}$ are significant at the 1% level in both columns, regardless of sales percentage, but the coefficient estimates on $Cust\_Crash_{T\text{-}1}$ and

[4] In E-Companion Table B2, we perform a subsample analysis by splitting our sample into two subperiods: 1989–2014 and 2015–2019. We find that the delayed crash contagion within the supply chain exists in both periods, indicating that the market is no more efficient in recent years with the application of big data and AI. Several possible reasons exist. First, while big data can provide investors with access to a rich set of information, it can also lead to information overload, making it difficult to identify relevant and actionable insights. Second, the use of complex algorithms and models to analyze big data can introduce new sources of error and bias, which can further reduce market efficiency.

Cust_Crash$_{T-2}$ are positive and significant at least at the 5% level only when the customers contribute more than 10% of sales to the suppliers. These coefficient estimates are insignificant when the *percentage of sales to the customer* is less than 10%. Likewise, in Columns 3 and 4, the coefficient estimates on *Cust_Crash*$_{T-1}$ and *Cust_Crash*$_{T-2}$ are positive and significant at the 5% and 10% level, respectively, when the customer contributes more than 25% of sales to the suppliers. In contrast, the significance of those coefficients disappears when a customer accounts for 25% or less of sales to the supplier. Taken together, consistent with the hypothesis H2, these findings suggest that the delayed contagion effect of customer stock price crashes on a supplier firm's crash risk is more likely to occur when a supplier has greater economic dependence on its major customers.

The results of Table 3 show the importance of customers to suppliers exacerbates the transmission of stock crashes in the supply chain. In the OM literature, the importance of customers, relative power, and bilateral dependency are commonly discussed in supply chain management (Fan et al., 2022; Jiang et al., 2023). An understanding of SC relationships and mutual dependency is critical to building an effective supply chain (Brinkhoff et al., 2015; Bhardwaj and Ketokivi, 2021). While previous studies show the negative effects of high customer dependency and power unbalance on SC coordination, this stream of research does not approach this issue from a risk transmission perspective. Our findings support the notion that power unbalance (i.e., concentrated dependence on a customer) is not only harmful to SC relationships but also increases the risk transmission to firms. That is, high dependency and customer concentration increase the vulnerability of suppliers in crises such as customer stock crashes. Our results reveal another dark side of high dependency and power unbalance, where the unfavorable incidents of customers transmit through the supply chain with a delay.

4.3 The nature of incidents causing stock price crashes

We obtain the data on firm sales from the Compustat database. To capture information on environmental incidents, we utilize the RepRisk database. For data on product recalls, we access records from the U.S. Consumer Product Safety Commission (CPSC), the U.S. Food and Drug Administration (FDA), and the Factiva news service. Data to measure earnings surprises are obtained from the IBES database, data on lawsuits are from the Audit Analytics database, and M&A data are from the Refinitiv SDC Platinum database. We measure customer operational incidents using customers' annual sales growth, environmental incidents (ENV) and their severity (SEV), and the number of product recalls announced in the most recent five weeks (including week *t*). Similarly, customer financial incidents are measured using customers' quarterly earnings surprises, the number of lawsuit cases, and the number of M&A deals announced in the most recent five weeks.

We then partition our full customer-supplier-week sample into different subsamples according to whether the customer firm experienced a certain type of operational or financial shocks in the most recent five weeks. With each subsample, we then rerun the baseline logit regressions predicting supplier stock price crash in week *t* using the customer stock price crash indicators in week *t*-4 through week *t*, with control variables and both industry and year fixed effects. Tables 4 and 5 present the results.

Table 4 shows that relative to the stock price crashes of customers unrelated to the operational incidents, stock price crashes related to the three investigated operational incidents can all cause stronger stock crash contagion (both contemporaneous and delayed contagion) to supplier firms. These results support hypothesis H3.

By contrast, as shown in Table 5, among the three types of customer financial shocks, only the crashes related to negative earnings surprises cause stronger stock price crash contagion to supplier firms. These results suggest that customer stock crashes related to operational incidents lead to stronger stock crash contagion to supplier firms than customer stock crashes related to financial incidents (e.g., M&As and lawsuits). The results only partially support hypothesis H4.

The findings in this section hence imply that supply chain and operational managers should consider potential negative externalities of customer operational incidents to suppliers, as well as potential ripple effects that can cause supply chain disruptions (Agca et al., 2022; Aral et al., 2022) and destroy the firm value of the supply chain (Hendricks et al., 2005a; Lo et al., 2018). Operational managers at supplier firms need to pay particular attention to stock crashes related to customers' operational incidents, which have a stronger contagious effect within the supply chain.

5. Further Analyses and Robustness Checks

In this section, we explore the underlying mechanism of delayed crash transmission along the supply chain and possible strategic actions for suppliers after the stock crashes of their major customers. We further perform a bundle of sensitivity analyses to ensure the robustness of our results.

5.1 Underlying mechanism

During the contagion of stock price crashes, information transparency can play a crucial role (Li and Tang, 2016; Ried et al., 2021). A lack of transparency in a supplier's information environment can make it difficult for investors to receive timely and accurate information about disruptions, risks, or stock price crashes in the supply chain, thereby hampering the speed of stock price information transmission from major customers to the supplier firm. Motivated by the prior literature (e.g., Jin and Myers, 2006; Hutton et al., 2009; Kothari et al., 2009), we expect that the time between customer stock market reaction and supplier stock market reaction might be influenced by the information opaqueness of the supplier firm. Specifically, when the information environment of a supplier firm is opaque, it is more difficult for investors to understand the degree of economic dependence among the supply chain partners, process information effectively, and grasp the effect of customer stock price crashes on the supplier firm, potentially leading to a delayed contagion effect of the crash.

We empirically examine this conjecture by employing a set of common proxies to measure suppliers' information opacity, as per the extant literature (e.g., Leuz, 2003; Brown et al., 2004; Chan and Hameed, 2006): analyst following, dispersion of analyst earnings forecasts, probability of informed trading (PIN), stock bid–ask spread, and idiosyncratic stock return volatility. Lower analyst following, higher dispersion of analyst earnings forecasts, higher PIN, higher stock bid–ask spread, and/or higher idiosyncratic stock return volatility indicate greater opaqueness in the information environment of a supplier firm. Table 6 reports the results of these analyses.

When we partition the sample based on analyst following, Columns 1 and 2 in Table 6 show that both $Cust\_Crash_{T-1}$ and $Cust\_Crash_{T-2}$ are statistically significant in the low-following subsample but not in the high-following subsample. A similar pattern holds when the other information asymmetry proxies (i.e., dispersion of analyst forecasts, PIN, stock bid–ask spread, and idiosyncratic return volatility) are used, as shown in Columns 3 to 10. In sum, these results offer empirical support for the information opacity explanation of the delayed crash transmission—supplier information opacity hampers the speed of stock price information transmission from customers to suppliers.[5]

5.2 Strategic actions of suppliers after customer stock crashes

Considering that stock price crashes are attention-grabbing events and that U.S. stock markets are generally quite efficient (Fama, 1998), one might expect spontaneous customer-supplier crash contagions without delay. However, our findings suggest that even in relatively efficient stock markets with ample investor attention, delayed crash contagions along the supply chain occur when the information environments of supplier firms are opaque. This potential delay emphasizes the need for operations managers to remain highly vigilant when major customers experience stock price crashes, even if their own firms' stock prices remain stable. Quick measures to enhance operational efficiency (e.g., imposing hiring freezes, halting unnecessary purchases of goods and services, etc.) may need to be adopted to address potential delayed crash contagions.

We next examine several possible strategic actions that may be taken by suppliers after stock crashes of their customers. Based on prior OM literature, we examine three different actions of suppliers in response to the crisis of their customers, which include (1) diversifying customer base (e.g., Leung and Sun, 2021; Jiang et al., 2023), (2) improving operational efficiency (e.g., Yiu et al., 2020), and (3) improving product quality (e.g., Lam et al., 2022). These actions are considered to be common strategic operational actions in response to a crisis (D'Aveni and MacMillan, 1990; Ittner 1994; Ross and Droge, 2004; Hendricks et al., 2009). We regress the supplier firm's future operational efficiency (measured using data envelopment analysis of relative efficiency within specific industries as per Demerjian et al. [2012]), number of customers, and product quality score (measured using MSCI KLD product quality data) in year t+1 or year t+2 on the stock crash indicators of the supplier firm and its customer firms in

[5] The literature on limited investor attention (e.g., Barber and Odean, 2008; Cohen and Frazzini, 2008) suggests that stock prices may fail to promptly incorporate all publicly available news about related firms due to investor inattention, which results in significant stock return predictability. In our context, this explanation of limited attention may account for the delayed crash contagion in the supply chain. We conduct several analyses to examine whether the delayed crash contagion can be explained by investor inattention to suppliers. Specifically, we partition the full sample into subsamples using three different types of measures that reflect or affect investor attention to supplier firms: 1) Google search volume, 2) supplier earnings announcements, and 3) market conditions. We find only limited support for this explanation, as shown in E-companion Table B3. This is likely because firm-specific stock crashes are salient, attention-grabbing events. Hence, investor inattention plays a limited role in explaining the uncovered delayed crash contagion in the supply chain.

year t, as well as industry and year fixed effects, using a supplier-year sample. Our results, reported in Table 7, show that suppliers diversify their customer base (i.e., increasing the number of customers), enhance their operational efficiency, and improve product quality following the stock crashes of major customers. Interestingly, we also find that suppliers' own stock crashes actually harm their future operational efficiency and product quality.

Next, we evaluate the effectiveness of these strategic operational actions in mitigating the negative impact of customer stock crashes on suppliers (i.e., the resilience or recovery of suppliers after stock crashes). We include only the supplier firms that experienced stock price crashes in this analysis. We gauge the resilience of suppliers to stock crashes by measuring the level of stock bounce back, or stock price recovery, after the stock crash (e.g., Jiang et al., 2023). Specifically, we regress the cumulative abnormal stock returns (monthly abnormal returns are calculated using a market-adjusted model and CRSP value-weighted stock market index) of the supplier firm over the next 12 or 24 months following the stock crash week on the change in firm efficiency, the number of customers, or product quality over the same period of either 12 or 24 months, while controlling for industry and year fixed effects. Table 8 reports the results.

Interestingly, we find that diversifying customers and product quality enhancement do not have a significant impact on the stock recovery or resilience of suppliers after crashes. Only the improvement of operational efficiency has a significant positive effect. This result is consistent with our argument that the contagious effect of customer stock crashes on suppliers is due to the anticipated impact on the operations and business fundamentals of suppliers resulting from the economic linkages. Accordingly, a fundamental improvement of operations and firm efficiency is the only way to mitigate the transmitted negative impact; diversifying customers and enhancing product quality do not appear to be effective strategies, although they are common supplier responses.

5.3 Robustness checks

We conduct several robustness checks on our findings. A first potential concern is that the omission of certain causes of customer stock crashes in our regression model may result in an omitted-variable bias. We construct the indicator variables to indicate the various types of customer operational incidents (i.e., sales drops, environmental incidents, and product recalls) and customer financial incidents (i.e., negative earnings surprises, lawsuits in which the customer firm is a defendant, and M&A) that occurred in the window of week t-4 to week t. We then include these operational and financial incident indicators as additional control variables in our baseline logit regressions as a robustness check. The results, as reported in E-Companion Table B4, show that the baseline regression results remain qualitatively unchanged. In other words, the customer stock crash indicators in week t-2 to week t are still significantly and positively related to supplier stock crashes in week t.

As a further robustness check, we perform an interaction test by interacting the customer crash indicator in the T0 week with incident-related indicator variables. In Columns (1)-(7) of E-Companion Table B5, we interact the customer crash indicator in the T0 week with each of the six incident-related indicator variables respectively. In the last column of Table B5, we further include all the interaction terms of the customer crash indicator in the T0 week with the six incident-related indicator variables in one regression. Our results remain qualitatively unchanged as the main effect of customer crashes in the T0 week remains statistically significant at the 1% level across all regression models.

In particular, Column (7) of Table B5 shows that the coefficient estimates of the interaction terms between the customer crash indicator in the T0 week and the three operational-incident-related indicators are all significantly positive. These results indicate that customer stock price crashes associated with customer demand uncertainty, environmental incidents, and product recalls can all increase the risk of stock price crashes for supplier firms. Nevertheless, the results also suggest that customer stock price crashes related to customer sales drops and environmental incidents are more likely to lead to supplier stock crashes than customer stock price crashes related to customer product recalls. This reflects the greater anticipated impact of customer sales drops and environmental incidents on the operations and business fundamentals of the supplier firms. In contrast, none of the coefficient estimates of the interaction terms between the customer crash indicator in T0 week and the three financial-incident-related indicators are statistically significant. This finding hence suggests that customer stock price crashes related to customer operational incidents are indeed more likely to lead to supplier stock price crashes, likely because they can directly affect supplier firms' business operations through the supply-chain relations.

Second, we rerun the baseline regressions using a version of the stock price crash definition that specifically controls for industry-wide stock price movements. Specifically, we regress weekly individual stock returns on market returns and industry returns to obtain the residuals (i.e., the idiosyncratic returns orthogonalized to market returns and industry returns) and then define stock price crashes using the obtained residuals. The results, reported in E-Companion Table B6, are qualitatively similar to the baseline findings, suggesting that our findings of supply-chain stock price crash contagion are not driven primarily by industry-wide stock price movements.

Third, we conduct a series of placebo tests. In the first test, for each supplier-customer-year observation in our sample, we take the customer as given and replace the supplier with a pseudo-supplier randomly selected from the same industry as the genuine supplier (classified using Fama and French's 48 industries) in that fiscal year. We repeat this process 1,000 times resulting in 1,000 pseudo-samples. We then reestimate Eq. (2) with the pseudo-suppliers and report the summary statistics of the 1,000 sets of coefficient estimates of the contemporaneous and lagged customer crash indicators in Panel A of E-Companion Table B7. The results reveal that both the magnitudes and significance levels of the coefficient estimates are significantly diminished when the pseudo-supplier–customer samples are used. The coefficient estimates of the contemporaneous and lagged customer crashes, for example, are reduced by 30% to 60%.

In the second placebo test, we take the supplier as given and replace the customer with a pseudo-customer randomly picked from the same fiscal year and the same industry as the customer. We rerun the regressions, estimating Eq. (2) with the pseudo-customers, and report the results in Panel B of E-Companion Table B7. The results again show that when the genuine customer–supplier relationships are broken, both the magnitudes and significance levels of the coefficient estimates are significantly reduced.[6] The results of these placebo tests show that our baseline findings primarily reflect delayed contagion effects along the supply chain, rather than mere industry-level, lead–lag price co-movements.

We also conduct several other sensitivity tests to check the robustness of the results. In Panel A of E-Companion Table B8, we first repeat our baseline results (i.e., the results reported in Column 3 of Table 2) as a benchmark in Column 1. Next, we include the lagged weekly customer portfolio excess returns (*XRET*) in the past four weeks as additional control variables to control for the influence of customer momentum. Customer portfolio excess returns are constructed as sales-weighted portfolios of customer returns in excess of the CRSP value-weighted market returns, following Cohen and Frazzini (2008). As shown in Column 2, our results remain qualitatively unchanged. In Column 3, we control for the lagged weekly excess returns of the supplier firm in the past four weeks, and in Column 4, we include both lagged weekly customer portfolio excess returns and lagged weekly supplier excess returns. Again, our results are robust to these controls, indicating that the delayed crash contagion effect uncovered in our paper exists beyond known customer and supplier momentum effects.

In Panel B of E-Companion Table B8, we conduct the regressions using a supplier-week panel dataset and redefine the crash indicator variables as being equal to 1 if the supplier firm experienced at least one customer crash in a given week. The results remain qualitatively unchanged. In the supplier-week panel dataset, we then replace the crash indicator variables with the actual number of customer stock price crashes in a given week. The results, as reported in Panel C of E-Companion Table B8, imply that the likelihood of a supplier crash is associated with the number of crashes of related customers one and two weeks prior. Lastly, we control for industry–year fixed effects to account for shocks common to all firms in an industry at a particular time. We further control for firm fixed effects to remove the effect of time-invariant firm characteristics. The results, as reported in Panel D of E-Companion Table B8, show that our findings remain qualitatively unaffected.[7]

5.4 The effect of customer stock price jumps

We focus on stock price crash transmission in our main analysis. A natural subsequent question is whether customer stock price jumps can also predict future supplier stock price jumps. We examine this question and report the results, showing that a contemporaneous relationship exists between stock price

[6] It is worth noting that the significant coefficients on contemporaneous customer crash measures are likely due to industry co-movement. When an industry suffers, related industries are also likely to suffer due to the common economic shocks. Moreover, large firms such as Apple may have many suppliers. Even if our method to identify supplier–customer pairs did not indicate that pair was linked in the supply chain, they could still actually be linked (albeit not detected by our identification method), which can also explain the significant effect.

[7] As a further robustness check, we control for a set of customer-firm characteristics (i.e., firm size, market-to-book ratio, leverage, ROA, discretionary accruals, sigma, and returns). Our main findings continue to hold after including these additional controls (not tabulated).

jumps of suppliers and customers, in E-Companion Table B9. The coefficient estimates on the customer jump indicator in week t-1 are marginally significant at the 10% level while the coefficient estimates on the other (lagged) customer jump indicators are not significantly different from zero. Overall, these results suggest that the good news embedded in customer stock price jumps is less likely to be transmitted with a delay to suppliers than the bad news embedded in stock price crashes. This is consistent with the argument that firms have no incentive to hide good news.[8]

6. Discussion and Concluding Remarks

This paper shows that the occurrence of major customer stock price crashes has significant and robust predictive power for supplier stock price crashes up to two weeks in the future. The delayed crash contagion can be moderated by the information transparency of the affected suppliers. Our results further suggest that customer operational incidents have a more significant contagion effect from customers to suppliers than customer financial incidents. Finally, we find that following customer stock price crashes, supplier firms tend to diversify their customer base, enhance their operational efficiency, and improve product quality. However, improvement of operational efficiency is the only effective way to mitigate the negative crash impact transmitted from customers; diversifying the customer base and improving product quality do not have a significant positive impact on stock recoveries.

Previous research shows that stock crashes are primarily driven by information, particularly macroeconomic news, which causes a spillover effect in different markets (Bongaerts et al., 2022). Such spillover effects can be caused by crisis-related illiquidity (Dontoh et al., 2021) and supply chain contagion (McFarland et al., 2008), resulting in sector-wide downturns and economic recessions (Dontoh et al., 2021). Extending the previous research, we show in more detail how and why company news, information, and economic outlooks are transmitted in the supply chain. We explicitly demonstrate how customers' operational incidents, which can be indicators for the future cash flow or economic performance for upstream suppliers, cause spillover in the supply chain. McFarland et al. (2008) demonstrate a supply chain contagion effect in firm behavior (but not stock price crashes) due to institution and imitation motives, while Dontoh et al. (2021) examine sector-wide stock crash effects across markets. In contrast to these previous studies, we show that stock price crash contagion in the supply chain is not merely a sector-wide effect. Instead, there can be supply chain stock price crash contagion due specifically to economic links between supply chain players. In other words, the economic prospects of suppliers can be impacted by the operational incidents of downstream customers, causing stock price crashes to spillover to suppliers, sometimes with a delay of up to two weeks. We further demonstrate that such a delay in supply chain stock price crash contagion can be moderated by supply chain information transparency.

[8] Kothari et al. (2009) present empirical evidence showing that managers tend to hide bad news but immediately reveal good news to investors. Likewise, Hutton et al. (2009) suggest that better performance encourages greater and timelier revelation of good news.

Different from the previous literature on supply chain contagion, our paper focuses on and compares two major types of incidents (i.e., financial incidents vs. operational incidents). We show that not all causes (i.e., incidents) behind stock crashes have an equal impact on suppliers. Stock price crashes with significant implications on business functions, operational incidents in particular, tend to have a stronger transmission effect within the supply chain. Thus, it is the operational implications and underlying business fundamentals that primarily transmit through the supply chain, rather than stock price per se.

Importantly, we further explore suppliers' responses to customer crashes and the effectiveness of these remedy actions which enhance resilience. While there is extensive literature on risk contagions within supply chains, very few studies have investigated the specific responses of suppliers to stock crashes of customers. Agca et al. (2023) have recently examined several supplier firms' characteristics, including financial positions, cash holdings, credit ratings, financial leverage, and others, on their resilience in the face of customer crises. On the policy level, Aral et al. (2022) show that the Supplier Protection Act in the US is an effective way to reduce the risk of suppliers in the face of financially distressed buyers, reducing the contagion of credit risks along supply chain. Different from these two previous studies, we take an OM perspective to investigate the possible strategic actions that firms can undertake to reduce risk contagion from customers to suppliers. Unlike Agca et al. (2023), who focus on firm financial characteristics, and Aral et al. (2022), who examine government policy, our study focuses on firm-specific strategic actions taken after crises to minimize adverse contagion effects. Our results suggest that fundamental improvements in operational efficiency, rather than customer diversification and product quality improvement, are the primary effective ways for supplier firms to reduce the negative impact and enhance resilience.

Our findings have implications for operations and supply chain managers in several ways. First, operational managers of supplier firms should pay particular attention to customer stock price crashes related to customer operational incidents, because these types of shocks have been found to have a stronger and delayed contagion to supplier firms compared to stock price crashes unrelated to customer operational incidents. When a customer experiences an operational shock, such as a sales drop, environmental incident, or product recall, it can have a significant, negative impact on the supplier's stock price in the future. Operations managers should scrutinize the operational performance of their customers and take proactive measures to mitigate any potential negative impacts on their own firm's performance. Second, the finding that improved operating efficiency helps suppliers recover from contagious shocks implies that operational managers at supplier firms may want to prioritize initiatives aimed at a fundamental enhancement of efficiency enhancement within their operations to better position their firm for recovery from contagious SC stock price crash incidents.

Our study also has implications for academics, regulators, and investors. For academics, the findings provide a valuable addition to the literature on stock price crash risk by showing that, in addition to the documented bad-news-hoarding behavior of crashed firms, stock price crashes can also be transmitted through the supply chain from customer firms to supplier firms with a delay. Our results may also indicate that the highly interrelated economic and transaction relationships in SC networks are less understood by the investor community or the public as a whole, despite the large volume of related research that has been conducted by OM scholars. Given the considerable information externalities between customers and suppliers, regulators may find it important to require firms to adequately disclose information about their upstream and downstream trading partners. This could facilitate the information processing of investors and reduce their informational costs. For investors, our results indicate that stock market investors might have underestimated the contagious effect of stock crash risk along the supply chain, leading to a less efficient market environment. This may reflect a lack of complete information on the SC network and knowledge of the interdependent relationships between network members. This is particularly the case when the information transparency of a member of the supply chain is weak and the relationships of SC partners are opaque, as shown in our study.

Apart from the supplier firm's information opaqueness, other factors such as firm characteristics and industry affiliations can influence the time gap between customer and supplier stock market reactions. In addition, the nature of the supplier-customer relationship further affects the time gap. Collaborative partnerships with established communication channels enable faster alignment of stock market reactions. In contrast, transactional relationships with limited interaction may result in a more pronounced time gap. Exploring these factors can be an interesting avenue for future research and may provide further insights into stock market dynamics.

Appendices

The Appendices with variable definitions and additional results are available online as an E-companion.

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TABLE 1: Summary Statistics

This table reports the summary statistics for the variables used in the main analyses. Definitions of all variables are in E-Companion Table A1.

	N	Mean	Std. Dev.	P25	Median	P75
Supplier						
Crash	1,094,638	0.004	0.064	0.000	0.000	0.000
Jump	1,094,638	0.004	0.065	0.000	0.000	0.000
Firm size	1,094,638	5.974	2.191	4.453	5.971	7.394
Market/book	1,094,638	4.389	49.695	1.294	2.123	3.676
Leverage	1,094,638	0.163	0.177	0.000	0.110	0.279
ROA	1,094,638	-0.031	0.256	-0.049	0.031	0.074
DACC	1,094,638	0.463	1.938	0.044	0.114	0.299
Sigma	1,093,549	0.065	0.037	0.039	0.057	0.083
Returns	1,093,549	-0.279	0.439	-0.336	-0.160	-0.076
Customer						
Crash	1,094,638	0.004	0.062	0.000	0.000	0.000
Jump	1,094,638	0.003	0.053	0.000	0.000	0.000
Firm size	1,094,638	9.763	1.879	8.622	9.955	11.131
Market/book	1,094,638	4.794	30.766	1.717	2.718	4.044
Leverage	1,094,638	0.181	0.125	0.091	0.163	0.250
ROA	1,094,638	0.048	0.099	0.027	0.053	0.084
DACC	1,094,638	0.300	1.621	0.023	0.069	0.182
Sigma	1,094,638	0.037	0.021	0.023	0.031	0.045
Returns	1,094,638	-0.090	0.139	-0.097	-0.048	-0.026
Other variables						
% of sales to customers	835,177	0.186	0.157	0.100	0.140	0.220
Analyst following	701,142	12.605	11.317	5.000	9.000	17.000
Dispersion of analyst forecasts	654,359	0.155	5.925	0.003	0.008	0.024
Probability of informed trade	662,238	0.171	0.107	0.083	0.167	0.248
Bid–ask spread	1,051,071	0.017	0.033	0.001	0.004	0.020
Idiosyncratic volatility	980,912	0.010	0.005	0.007	0.009	0.013
Sales growth	412,951	0.114	2.469	-0.005	0.060	0.149
Environmental incidents	1,094,638	0.066	0.248	0.000	0.000	0.000
Product recalls	1,094,638	0.085	0.635	0.000	0.000	0.000
Earnings surprises	410,718	-0.010	1.040	0.000	0.000	0.001
Lawsuit cases	1,094,638	0.125	0.331	0.000	0.000	0.000
M&A deals	1,094,638	0.035	0.183	0.000	0.000	0.000
Firm-year variables						
Firm efficiency (T0+1)	18,810	0.330	0.182	0.224	0.273	0.371
Firm efficiency (T0+2)	17,052	0.328	0.180	0.223	0.272	0.368
No. of customer (T0+1)	16,329	2.539	2.515	1.000	2.000	3.000
No. of customer (T0+2)	13,404	2.546	2.537	1.000	2.000	3.000
Product quality (T0+1)	5,748	0.124	0.329	0.000	0.000	0.000
Product quality (T0+2)	5,230	0.134	0.341	0.000	0.000	0.000
12-month CARs	2,968	0.103	0.593	-0.207	0.056	0.340
24-month CARs	2,968	0.150	0.822	-0.281	0.102	0.489

TABLE 2: The Contagion Effect of Stock Price Crashes along the Supply Chain

This table reports results of logit regressions examining the contagion effect of stock price crashes from customer firms to supplier firms. The dependent variable is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in the parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Logit regressions *DepVar = Supplier crash in T0 week*			Marginal effects
	(1)	(2)	(3)	(4)
Customer crash in T0 week	1.5853***	1.5825***	1.5859***	0.0066***
	(4.10)	(4.09)	(4.10)	(3.94)
Customer crash in -1 week	0.5592***	0.5561***	0.5737***	0.0024***
	(2.89)	(2.87)	(2.95)	(2.93)
Customer crash in -2 week	0.6224***	0.6195***	0.6404***	0.0027***
	(3.28)	(3.26)	(3.33)	(3.31)
Customer crash in -3 week	-0.0770	-0.0802	-0.0573	-0.0002
	(-0.29)	(-0.30)	(-0.21)	(-0.21)
Customer crash in -4 week	0.0338	0.0309	0.0524	0.0002
	(0.13)	(0.12)	(0.21)	(0.21)
Supplier firm size		0.0571***	0.0580***	0.0002***
		(4.02)	(4.08)	(4.04)
Supplier market/book		0.0001	0.0001	0.0000
		(0.33)	(0.33)	(0.33)
Supplier leverage		-0.2327	-0.2353	-0.0010
		(-1.59)	(-1.61)	(-1.61)
Supplier ROA		0.3572***	0.3637***	0.0015***
		(2.63)	(2.67)	(2.64)
Supplier DACC		0.0100	0.0102	0.0000
		(0.65)	(0.66)	(0.66)
Supplier sigma		3.6805	3.7130	0.0154
		(1.61)	(1.62)	(1.62)
Supplier returns		0.4657**	0.4695**	0.0019**
		(2.19)	(2.21)	(2.21)
Supplier crash in -1 week			-2.4224***	-0.0100***
			(-3.44)	(-3.41)
Supplier crash in -2 week			-1.7261***	-0.0072***
			(-3.48)	(-3.50)
Supplier crash in -3 week			-1.7043***	-0.0071***
			(-2.77)	(-2.74)
Supplier crash in -4 week			-1.9978***	-0.0083***
			(-2.67)	(-2.64)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	1,094,325	1,094,325	1,094,325	1,094,325
Pseudo R-squared	0.011	0.013	0.015	

TABLE 3: The Importance of Customers to Suppliers

This table shows the impact of market competition on the contagion effect of stock price crashes. The sample is partitioned based on the *% of sales to customers* (proxy for the importance of customers to suppliers). The dependent variable is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in the parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	% of sales to customers		% of sales to customers	
	> 10%	<= 10%	> 25%	<= 25%
	(1)	(2)	(3)	(4)
Customer crash in T0 week	1.5346***	1.7231***	1.2540***	1.6431***
	(4.79)	(2.84)	(3.60)	(3.87)
Customer crash in -1 week	0.5560**	-0.0354	0.8651**	0.3210
	(2.20)	(-0.06)	(2.22)	(1.03)
Customer crash in -2 week	0.6631***	-0.4150	0.8767*	0.3889
	(2.62)	(-0.59)	(1.90)	(1.32)
Customer crash in -3 week	-0.3909	-0.0194	0.0000	-0.0872
	(-1.06)	(-0.03)	(0.00)	(-0.26)
Customer crash in -4 week	0.0619	0.4982	-0.9369	0.3247
	(0.20)	(1.12)	(-0.94)	(1.09)
Firm control variables	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	635,475	196,387	160,288	670,039
Pseudo R-squared	0.015	0.022	0.021	0.016

TABLE 4: Customer Operational Risks and Stock Price Crash Transmission

This table shows the influence of customer firm operational risks on the contagion effect of stock price crashes. Firm operational risks are measured using customers' annual sales growth, environmental incidents (ENV) and their severity (SEV), and the number of product recalls announced in the most recent five weeks, including week T0. The dependent variable in all panels is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Demand shocks

	Value of annual sales growth		Percentile of annual sales growth	
	Negative	Others	Bottom 10%	Others
	(1)	(2)	(3)	(4)
Customer crash in T0 week	3.7374***	1.2929***	2.7694***	1.5568***
	(9.74)	(5.74)	(3.29)	(4.12)
Customer crash in -1 week	0.7072	0.5352**	1.3072**	0.5090**
	(1.61)	(2.42)	(2.51)	(2.38)
Customer crash in -2 week	1.0570***	0.5416***	1.8114***	0.4837**
	(2.71)	(2.60)	(4.22)	(2.27)
Customer crash in -3 week	0.8269**	-0.4025	0.5554	-0.1077
	(2.27)	(-1.03)	(0.78)	(-0.37)
Customer crash in -4 week	0.6346	-0.1320	1.1370**	-0.1009
	(1.40)	(-0.43)	(2.36)	(-0.34)
Firm control variables	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	103,864	985,781	37,134	1,052,556
Pseudo R-squared	0.054	0.014	0.045	0.015

Panel B: Environmental (ENV) incidents

	Incidents		Incidents and severity	
	ENV=1	Others	ENV=1 & SEV>=2	Others
	(1)	(2)	(3)	(4)
Customer crash in T0 week	3.5477***	1.2331***	3.9137***	1.2178***
	(6.08)	(6.64)	(6.42)	(6.59)
Customer crash in -1 week	0.2522	0.5888***	0.6104	0.5757***
	(0.34)	(2.96)	(0.82)	(2.90)
Customer crash in -2 week	1.0420**	0.6104***	1.5171***	0.5905***
	(2.07)	(3.13)	(3.23)	(3.02)
Customer crash in -3 week	0.3763	-0.0910	0.9412	-0.1272
	(0.36)	(-0.37)	(0.88)	(-0.52)
Customer crash in -4 week	-0.3075	0.0903	0.3445	0.0492
	(-0.33)	(0.34)	(0.42)	(0.19)
Firm control variables	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	68,425	1,022,454	49,222	1,041,042
Pseudo R-squared	0.054	0.015	0.070	0.014

Panel C: Product recalls

	Number of product recalls				
	>= 1	>= 2	>= 3	>= 4	Others
	(1)	(2)	(3)	(4)	(5)
Customer crash in T0 week	1.0240	2.0168***	2.3130***	3.1082***	1.5838***
	(1.07)	(5.88)	(6.69)	(3.52)	(4.05)
Customer crash in -1 week	1.1609	2.0269***	2.3317***	3.1224***	0.5498***
	(1.25)	(6.31)	(6.93)	(3.47)	(2.77)
Customer crash in -2 week	0.0000	0.0000	0.0000	0.0000	0.6433***
	(0.00)	(0.00)	(0.00)	(0.00)	(3.34)
Customer crash in -3 week	0.0000	0.0000	0.0000	0.0000	-0.0544
	(0.00)	(0.00)	(0.00)	(0.00)	(-0.20)
Customer crash in -4 week	0.0000	0.0000	0.0000	0.0000	0.0554
	(0.00)	(0.00)	(0.00)	(0.00)	(0.22)
Firm control variables	Yes	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	24,003	17,383	13,482	10,882	1,080,720
Pseudo R-squared	0.044	0.051	0.050	0.063	0.015

TABLE 5: Customer Financial Risks and Stock Price Crash Transmission

This table shows the influence of customer firm financial risks on the contagion effect of stock price crashes. Firm financial risks are measured using customers' quarterly earning surprises, the number of lawsuit cases, and the number of M&A deals announced in the most recent five weeks, including week T0. The dependent variable is an indicator variable, *supplier crash in the T0 week.* Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Value of earnings surprises		Percentile of earnings surprises		Number of lawsuit cases		Number of M&A deals	
	< 0	Others	Top 10%	Others	>=1	= 0	>=1	= 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer crash in T0 week	1.4556**	1.6059***	0.7692	1.6758***	1.2252***	1.6314***	1.8339**	1.5630***
	(2.27)	(5.19)	(1.64)	(4.17)	(2.88)	(4.06)	(2.45)	(4.25)
Customer crash in -1 week	0.7641**	0.4467*	0.9374***	0.4631**	-0.5379	0.7142***	0.0000	0.6213***
	(2.36)	(1.73)	(2.62)	(2.07)	(-0.77)	(3.62)	(0.00)	(3.20)
Customer crash in -2 week	0.7127**	0.5696**	1.0376***	0.5156**	0.1141	0.7126***	0.0000	0.6806***
	(2.24)	(2.28)	(3.19)	(2.32)	(0.21)	(3.43)	(0.00)	(3.53)
Customer crash in -3 week	-0.6980	0.1186	-0.4817	0.0015	-0.3366	-0.0090	0.3231	-0.0720
	(-1.22)	(0.38)	(-0.68)	(0.00)	(-0.49)	(-0.03)	(0.36)	(-0.25)
Customer crash in -4 week	-0.4590	0.2075	-1.2061	0.1874	0.1911	0.0204	1.5238***	-0.0727
	(-0.76)	(0.74)	(-1.19)	(0.71)	(0.29)	(0.08)	(3.03)	(-0.26)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111,317	977,961	34,216	1,053,772	131,502	957,254	33,172	1,056,268
Pseudo R-squared	0.035	0.015	0.036	0.015	0.017	0.016	0.050	0.015

TABLE 6: Information Asymmetry and Stock Price Crash Transmission

This table shows the influence of supplier firm information asymmetry on the the contagion effect of stock price crashes. Analyst following, dispersion of analyst forecasts, probability of informed trade (PINs), bid–ask spread, and idiosyncratic volatility are used as information asymmetry proxies to partition the sample into two groups (bottom 50% vs. top 50%) by ranking observations per fiscal year and industry. The dependent variable in all columns is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Analyst following		Dispersion of analyst forecasts		Probability of informed trading		Bid–ask spread		Idiosyncratic volatility	
	Low	High	High	Low	High	Low	High	Low	Large	Small
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Customer crash in T0 week	1.2994***	1.8335***	1.3380***	2.0385***	1.0520***	0.9273***	1.1360***	1.8680***	1.3863***	1.7727***
	(4.08)	(3.99)	(4.87)	(4.24)	(3.24)	(3.14)	(4.87)	(3.84)	(3.28)	(4.57)
Customer crash in -1 week	0.7921***	0.2534	0.3336	0.2489	-0.2560	0.3052	0.9098***	0.0011	0.8051***	0.2420
	(3.22)	(0.81)	(0.99)	(0.73)	(-0.45)	(0.59)	(3.44)	(0.00)	(3.19)	(0.75)
Customer crash in -2 week	0.9348***	0.1609	0.8343**	0.4700	1.0578***	-0.2542	0.9160***	0.3425	0.8024***	0.4249
	(3.78)	(0.56)	(2.50)	(1.41)	(3.04)	(-0.52)	(3.35)	(1.15)	(2.93)	(1.64)
Customer crash in -3 week	0.1498	-0.3511	0.0673	-0.2284	0.0320	-0.5530	-0.0948	-0.0964	-0.1668	0.0550
	(0.48)	(-0.86)	(0.14)	(-0.51)	(0.05)	(-0.97)	(-0.23)	(-0.29)	(-0.44)	(0.17)
Customer crash in -4 week	0.0519	0.0532	0.4656	0.1084	-1.3710	0.2942	-0.1001	0.0063	0.2353	-0.1960
	(0.16)	(0.15)	(1.28)	(0.29)	(-1.36)	(0.73)	(-0.27)	(0.02)	(0.73)	(-0.46)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	628,391	464,921	322,081	322,206	323,813	332,406	525,427	524,074	599,520	486,230
Pseudo R-squared	0.018	0.017	0.017	0.019	0.017	0.021	0.019	0.017	0.015	0.019

TABLE 7: Post-crash Firm Operational Efficiency, Number of Customers, and Product Quality

This table shows the impact of customer and supplier crashes on the operational efficiency, number of customers, and product quality of suppliers. The dependent variable in Panel A is *firm operational efficiency* measured using the firm efficiency developed in Demerjian et al. (2012). The dependent variable in Panel B is the *number of customers* per supplier-year measured using data from Compustat Segment. The dependent variable in Panel C is *product quality* measured using data from the KLD database. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the firm level, and *t-values* are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Firm operational efficiency

	T0+1 year			T0+2 year		
	(1)	(2)	(3)	(4)	(5)	(6)
Customer crash in T0 year	0.0073**		0.0077**	0.0098***		0.0102***
	(2.18)		(2.29)	(2.72)		(2.83)
Supplier crash in T0 year		-0.0125***	-0.0128***		-0.0116***	-0.0120***
		(-3.66)	(-3.73)		(-3.01)	(-3.11)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,305	12,305	12,305	11,159	11,159	11,159
Adjusted R-squared	0.376	0.377	0.377	0.374	0.374	0.375

Panel B: Number of customers

	T0+1 year			T0+2 year		
	(1)	(2)	(3)	(4)	(5)	(6)
Customer crash in T0 year	0.3115***		0.3109***	0.2928***		0.2917***
	(9.99)		(10.00)	(8.14)		(8.19)
Supplier crash in T0 year		0.0330	0.0217		0.0439*	0.0310
		(1.63)	(1.11)		(1.85)	(1.39)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,308	10,308	10,308	8,257	8,257	8,257
Pseudo R-squared	0.047	0.036	0.047	0.049	0.040	0.049

Panel C: Product quality

	T0+1 year			T0+2 year		
	(1)	(2)	(3)	(4)	(5)	(6)
Customer crash in T0 year	0.0007		0.0015	0.0268**		0.0273**
	(0.06)		(0.13)	(2.23)		(2.26)
Supplier crash in T0 year		-0.0354***	-0.0355***		-0.0190	-0.0197
		(-3.00)	(-3.00)		(-1.43)	(-1.49)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,443	3,443	3,443	3,186	3,186	3,186
Adjusted R-squared	0.238	0.240	0.240	0.247	0.246	0.247

TABLE 8: Post-crash Stock Price Recovery

This table reports the post-crash cumulative abnormal returns (CARs) of supplier stocks in relation to the changes in firm effeiciency, the number of customers, and product quality. When the dependent variable is *12-month CARs*, the changes in firm effeiciency, number of customers, and product quality reflect the differences between year T0+1 and year T0. When the dependent variable is *24-month CARs*, differences between year T0+2 and year T0 are represented. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the firm level, and *t-values* are reported in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	12-month CARs			24-month CARs		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in firm efficiency	0.4346***			0.8835***		
	(3.81)			(5.62)		
Change in no. of customers		0.0263			0.0250	
		(1.41)			(1.64)	
Change in product quality			0.0029			-0.0544
			(0.04)			(-0.49)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,530	2,201	738	2,300	1,793	610
Adjusted R-squared	0.092	0.081	0.146	0.142	0.142	0.196

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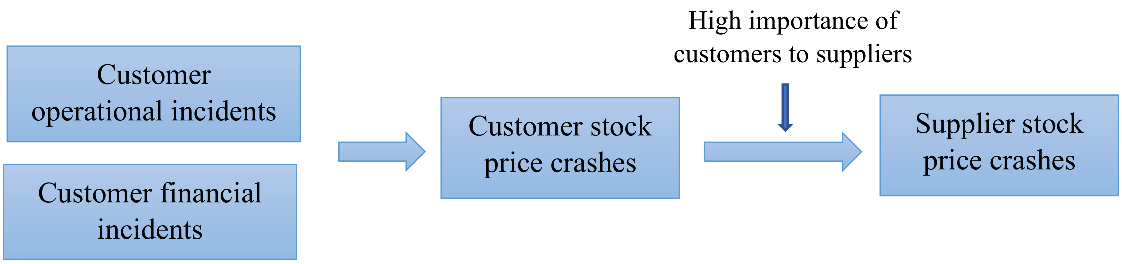
Appendix A. Illustration Figure and Variable Definations

FIGURE A1. Illustration Figure



TABEL A1. Variable Definitions

Variables	Definitions	Data Sources
Crash (Jump)	An indicator variable that equals 1 if a firm's weekly firm-specific return exceeds 3.2 standard deviations below (above) its mean value over fiscal year *t*, and equals 0 otherwise.	CRSP
Firm size	Natural logarithm of the market value of equity.	CRSP
Market/book	Ratio of the market value of equity to the book value of equity.	Compustat
Leverage	Total long-term debt divided by total assets.	Compustat
ROA	Return on assets measured as income before extraordinary items over total assets.	Compustat
DACC	The absolute value of discretionary accruals measured according to Kothari, Leone, and Wasley (2005).	Compustat
Sigma	Standard deviation of firm-specific weekly returns over a fiscal year.	CRSP
Returns	The average of firm-specific weekly returns over a fiscal year time 100.	CRSP
% of sales to customer	Total sales made to the customer divided by the supplier's total annual sales.	Compustat segment
Analyst following	The number of unique analysts providing current-fiscal-year earnings per share forecasts.	IBES
Dispersion of analyst forecasts	The inter-analyst standard deviation of analyst earnings per share forecasts for current fiscal year scaled by current-fiscal-year-end stock price.	IBES
Probability of informed trading (PIN)	An estimate of the probability that a particular trade order originates from a privately informed investor, measured based on the EKOP market microstructure model developed by Easley et al. (1996).	http://terpconnect.umd.edu/~stephenb/pinsdatanew.html
Bid-ask spread	The average of daily bid-ask spreads scaled by prices, calculated from CRSP closing stock quotes and prices over the calendar year.	CRSP
Idiosyncratic volatility	The standard deviation of the residuals from a regression of daily excess stock returns on the daily excess market factor.	CRSP
Annual sales growth	The percentage of changes in total sales.	Compustat
Environmental incidents	The number of environmental-related incidents classified by the RepRisk database.	RepRisk
Product recalls	The number of product recalls following Ball et al. (2018), with the data sourced from the the U.S. Consumer Product Safety Commission (CPSC), the U.S. Food and Drug Administration (FDA), and the Factiva news service.	Factiva, CPSC, FDA
Earnings surprises	The difference between actual EPS and median consensus EPS forecast at the beginning of the EPS announcement quarter, scaled by the end of last quarter stock price.	IBES
Lawsuits	The number of lawsuit cases filed that involve the customer firm as a defendant from the Audit Analytics databases.	Audit Analytics
M&A deals	The number of mergers and acquisitions (M&A) deals announced by the customer firm from Refinitiv SDC Platinum database.	Refinitiv SDC
Firm efficiency	Firm operational efficiency measured using data envelopment analysis of relative efficiency within specific industries following Demerjian et al. (2012).	Demerjian
Number of customers	The annual number of major customers of the supplier reported in Compustat Company Segment files.	Compustat segment
Product quality	The product quality score from the MSCI KLD database following Lam et al. (2022).	MSCI KLD
CARs	Cumulative abnormal stock returns (cumulated using monthly abnormal returns) of the suppliers over the 12 or 24 months after the stock crash week. Monthly abnormal returns are calculated using a market-adjusted model and CRSP value-weighted stock market index.	CRSP
Google SVI	Google search volume index (SVI) for supplier and customer ticker symbols obtained from Google Trend.	Google Trends

Contractions periods	An indicator variable that equals 1 for July 1990 to March 1991, March 2001 to November 2001, and December 2007 to June 2009, as defined by the NBER business cycle.	NBER
Bear (bull) markets	An indicator variable that equals 1 for the periods during which the S&P 500 index decreases (increases) 20% or more without a 20% rally (correction).	NBER
Customer negative sales growth (1/0)	An indicator variable that equals 1 if the customer's annual sales growth is negative.	Compustat
Customer environmental incidents (1/0)	An indicator variable that equals 1 if the customer incurred environmental-related incidents.	RepRisk
Customer >= 1 product recalls (1/0)	An indicator variable that equals 1 if the customer recalled 1 or more products.	Factiva, CPSC, FDA
Customer negative earnings surprises (1/0)	An indicator variable that equals 1 if the customer had negative earnings surprises.	IBES
Customer >= 1 Lawsuits (1/0)	An indicator variable that equals 1 if the customer had 1 or more lawsuit cases.	Audit Analytics
Customer >= 1 M&A deals (1/0)	An indicator variable that equals 1 if the customer announced 1 or more M&A deals.	Refinitiv SDC
Customer XRET	Customer portfolio weekly stock returns weighted on the sales of a supplier to its major customer in a given year in excess of the CRSP value-weighted market returns.	CRSP, Compustat segment file
Supplier XRET	Supplier weekly stock returns in excess of the CRSP value-weighted market returns.	CRSP, Compustat segment file
> = 1 crashed customers	An indicator variable that equals 1 if at least one of the major customers of the firm experienced stock price crash in the corresponding week, and 0 otherwise.	CRSP, Compustat segment file
No. of crashed customers	The total number of customers that experienced stock price crashes in the corresponding week.	CRSP, Compustat segment file

Appendix B. Further Analyses and Robustness Checks

TABLE B1. Stock Price Crashes Estimated with Cutoffs at 0.1%

This table reports the results of logit regressions examining the contagion effect of stock price crashes estimated with the 0.1% cutoffs. The dependent variable is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Logit regressions *DepVar = Supplier* crash *in T0 week*			Marginal effects
	(1)	(2)	(3)	(4)
Customer crash in T0 week	1.3133***	1.3175***	1.3174***	0.0020***
	(4.48)	(4.47)	(4.47)	(4.31)
Customer crash in -1 week	0.8217**	0.8249**	0.8272**	0.0013**
	(2.35)	(2.35)	(2.36)	(2.32)
Customer crash in -2 week	0.6675*	0.6764*	0.6714*	0.0010*
	(1.85)	(1.86)	(1.86)	(1.86)
Customer crash in -3 week	0.3498	0.3556	0.3633	0.0006
	(0.78)	(0.80)	(0.82)	(0.82)
Customer crash in -4 week	-1.3020	-1.3006	-1.2987	-0.0020
	(-1.30)	(-1.29)	(-1.29)	(-1.29)
Supplier firm size		0.0633**	0.0635**	0.0001**
		(2.53)	(2.53)	(2.45)
Supplier market/book		0.0001	0.0001	0.0000
		(0.23)	(0.23)	(0.23)
Supplier leverage		0.3503	0.3501	0.0005
		(1.63)	(1.63)	(1.63)
Supplier ROA		-0.3735***	-0.3743***	-0.0006***
		(-5.49)	(-5.51)	(-5.36)
Supplier DACC		-0.0289	-0.0289	-0.0000
		(-1.08)	(-1.08)	(-1.08)
Supplier sigma		24.3678***	24.3998***	0.0379***
		(5.74)	(5.74)	(5.53)
Supplier returns		1.7718***	1.7734***	0.0028***
		(4.62)	(4.62)	(4.50)
Supplier crash in -1 week			-0.3701	-0.0006
			(-0.50)	(-0.50)
Supplier crash in -2 week			0.4942	0.0008
			(0.91)	(0.91)
Supplier crash in -3 week			0.0000	0.0000
			(0.00)	(0.00)
Supplier crash in -4 week			-0.0606	-0.0001
			(-0.10)	(-0.10)
Constant	-7.4809***	-8.8123***	-8.8148***	
	(-7.25)	(-8.30)	(-8.30)	
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	1,088,229	1,088,229	1,086,547	1,086,547
Pseudo R-squared	0.030	0.036	0.036	

TABLE B2. Subperiod Analyses of Costomer-Supplier Stock Crash Contagion

This table reports the results of logit regressions examining the contagion effect of stock price crashes over different periods. The dependent variable is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Logit regressions *DepVar = Supplier crash in T0 week*	
	1989-2014	2015-2019
	(1)	(2)
Customer crash in T0 week	1.5579***	1.6544***
	(3.34)	(5.03)
Customer crash in -1 week	0.5075**	0.7202**
	(2.08)	(2.22)
Customer crash in -2 week	0.6879***	0.5289
	(3.08)	(1.40)
Customer crash in -3 week	-0.0515	-0.0630
	(-0.15)	(-0.15)
Customer crash in -4 week	-0.1437	0.4140
	(-0.45)	(1.03)
Supplier firm size	0.0700***	0.0279
	(4.48)	(0.78)
Supplier market/book	0.0002	-0.0053
	(1.01)	(-1.26)
Supplier leverage	-0.3079*	0.1651
	(-1.87)	(0.52)
Supplier ROA	0.3960**	0.2060
	(2.49)	(0.76)
Supplier DACC	0.0139	-0.0208
	(0.87)	(-0.50)
Supplier sigma	6.5665**	-0.4985
	(2.33)	(-0.13)
Supplier returns	0.8056***	-0.3325**
	(2.89)	(-2.07)
Supplier crash in -1 week	-2.7752***	-1.9742**
	(-2.78)	(-1.99)
Supplier crash in -2 week	-1.3855***	0.0000
	(-2.81)	(0.00)
Supplier crash in -3 week	-1.6548**	-1.9343*
	(-2.21)	(-1.91)
Supplier crash in -4 week	-1.6548**	0.0000
	(-2.21)	(0.00)
Constant	-6.5711***	-4.2379***
	(-10.78)	(-7.85)
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Observations	907,232	182,739
Pseudo R-squared	0.015	0.016

TABLE B3: Investor Attention and Delayed Crash Contagion

This table reports the impact of investor attention on the delayed supplier-customer crash contagion using three investor attention proxies: Google search volume index (SVI), earnings announcements of the suppliers, and financial market condition. In Panel A, the sample is partitioned based on whether the Google SVI of a supplier firm (or customer firm) in the most recent month (*t-1*) is greater than its median Google SVI over the past three months (from *t-3* to *t-1*). In Panel B, the sample is partitioned based on whether the associated supplier reports an earnings announcement in the recent four (-3 to 0) or two (-1 to 0) weeks. In Panel C, the sample is partitioned based on the business cycle (expansions vs. contractions) or the status of financial markets (bull vs. bear). The dependent variable used in all panels is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Google search volume

	Based on Supplier Google SVI		Based on Customer Google SVI	
	(t-1) month < = median over (t-3) to (t-1)	(t-1) month > median over (t-3) to (t-1)	(t-1) month < = median over (t-3) to (t-1)	(t-1) month > median over (t-3) to (t-1)
	(1)	(2)	(3)	(4)
Customer crash in T0 week	0.8979***	1.0255**	0.9423***	0.9611**
	(3.24)	(2.30)	(3.71)	(2.56)
Customer crash in -1 week	0.2959	0.0014	0.6471**	0.2714
	(0.86)	(0.00)	(2.30)	(0.47)
Customer crash in -2 week	0.6979**	-0.6473	0.6821**	0.3137
	(2.37)	(-0.65)	(2.57)	(0.66)
Customer crash in -3 week	-0.6410	-0.6890	-0.5722	-0.1940
	(-1.11)	(-0.69)	(-0.98)	(-0.37)
Customer crash in -4 week	-0.6348	-0.6522	-1.6578*	-0.1846
	(-1.11)	(-0.65)	(-1.65)	(-0.25)
Constant	-6.9843***	-4.7723***	-5.0995***	-4.4594***
	(-5.39)	(-3.72)	(-4.93)	(-6.67)
Firm control variables	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	259,687	108,974	284,874	124,054
Pseudo R-squared	0.014	0.020	0.013	0.013

Panel B: Supplier earnings announcements

	Report date in -3 to 0 weeks		Report date in -1 to 0 weeks	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Customer crash in T0 week	1.5539***	1.4894***	1.9631***	0.8233***
	(4.13)	(3.57)	(3.64)	(3.87)
Customer crash in -1 week	0.2402	0.4387*	0.2150	0.2406
	(0.69)	(1.93)	(0.66)	(1.04)
Customer crash in -2 week	0.8071**	0.2193	0.6378**	0.1945
	(2.41)	(0.93)	(2.01)	(0.83)
Customer crash in -3 week	-1.1150	-0.0705	-0.9776*	0.1620
	(-1.58)	(-0.24)	(-1.69)	(0.50)
Customer crash in -4 week	-0.1079	-0.0590	-0.3243	0.3342
	(-0.26)	(-0.20)	(-0.79)	(1.17)
Constant	-6.0842***	-5.6874***	-6.2927***	-5.4749***
	(-8.10)	(-10.56)	(-8.40)	(-8.96)
Firm control variables	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	763,287	326,991	926,815	163,561
Pseudo R-squared	0.013	0.039	0.015	0.051

Panel C: Business cycles and bear/bull markets

	Business cycle		Bear vs. Bull markets	
	Expansion	Contraction	Bull	Bear
	(1)	(2)	(3)	(4)
Customer crash in T0 week	1.6711***	0.8093*	0.8521***	1.2660***
	-4.03	-1.78	(3.93)	(3.11)
Customer crash in -1 week	0.5680***	0.5498	0.4447	0.2774
	-2.65	-1.16	(1.40)	(0.47)
Customer crash in -2 week	0.6458***	0.5573	0.5915**	0.5445
	-3.07	-1.18	(2.22)	(1.00)
Customer crash in -3 week	-0.2436	0.5705	-0.3971	0.7597
	(-0.88)	-0.91	(-0.99)	(1.26)
Customer crash in -4 week	0.1642	-1.0659	0.0738	-0.7254
	-0.63	(-1.05)	(0.22)	(-0.72)
Constant	-5.1792***	-5.4393***	-6.7299***	-4.8846***
	(-12.64)	(-6.97)	(-6.36)	(-5.71)
Firm control variables	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	931,149	158,959	669,471	155,984
Pseudo R-squared	0.016	0.021	0.015	0.024

TABLE B4: Controlling for Customer Operational and Financial Incidents

This table reports the contagion effect of stock price crashes after controlling for customers' operational and financial incidents. All operational and financial incident proxies are indicator variables measured in the five-week windows preceding the end of each calendar week. The dependent variable is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer crash in T0 week	1.5859***	1.5911***	1.5859***	1.5878***	1.5591***	1.5858***	1.5854***	1.5663***
	(4.10)	(4.09)	(4.09)	(4.10)	(4.05)	(4.10)	(4.10)	(4.02)
Customer crash in -1 week	0.5737***	0.5676***	0.5738***	0.5759***	0.5443***	0.5759***	0.5733***	0.5467***
	(2.95)	(2.92)	(2.95)	(2.96)	(2.79)	(2.96)	(2.95)	(2.80)
Customer crash in -2 week	0.6404***	0.6342***	0.6404***	0.6412***	0.6088***	0.6408***	0.6403***	0.6084***
	(3.33)	(3.30)	(3.33)	(3.33)	(3.15)	(3.33)	(3.33)	(3.15)
Customer crash in -3 week	-0.0573	-0.0648	-0.0575	-0.0566	-0.0895	-0.0565	-0.0577	-0.0910
	(-0.21)	(-0.24)	(-0.21)	(-0.21)	(-0.33)	(-0.21)	(-0.21)	(-0.34)
Customer crash in -4 week	0.0524	0.0442	0.0522	0.0531	0.0179	0.0546	0.0519	0.0176
	(0.21)	(0.18)	(0.21)	(0.21)	(0.07)	(0.22)	(0.21)	(0.07)
Customer negative sales growth (1/0)		0.0876						0.0592
		(0.97)						(0.67)
Customer environmental incidents (1/0)			0.0062					0.0017
			(0.06)					(0.02)
Customer >=1 product recalls (1/0)				0.1543				0.1692
				(1.49)				(1.63)
Customer negative earnings surprises (1/0)					0.1463***			0.1358**
					(2.61)			(2.57)
Customer >=1 Lawsuits (1/0)						-0.0537		-0.0584
						(-1.05)		(-1.14)
Customer >=1 M&A deals (1/0)							0.0472	0.0481
							(0.51)	(0.52)
Constant	-5.7511***	-5.7515***	-5.7513***	-5.7620***	-5.7720***	-5.7488***	-5.7497***	-5.7786***
	(-14.27)	(-14.27)	(-14.27)	(-14.28)	(-14.31)	(-14.27)	(-14.28)	(-14.32)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,094,325	1,094,325	1,094,325	1,094,325	1,094,325	1,094,325	1,094,325	1,094,325
Pseudo R-squared	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015

TABLE B5: Controlling for the Interations of Customer Operational and Financial Incidents with Customer T0 Crash

This table shows the contagion effect of stock price crashes after controlling for the internations of customers' operational and financial incidents with custmer T0 crash. All operational and financial incident proxies are indicator variables measured in the five-week windows preceding the end of each calendar week. The dependent variable is an indicator, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Customer crash in T0 week	1.2964***	1.2349***	1.5847***	1.6071***	1.6283***	1.5642***	1.0915***
	(5.71)	(6.61)	(4.05)	(5.20)	(4.04)	(4.25)	(4.77)
Customer negative YoY sales growth	0.0369						0.0069
	(0.52)						(0.10)
Customer crash in T0 week X Customer negative YoY sales growth	2.5611***						2.0368***
	(5.20)						(6.72)
Customer environmental incidents		-0.0735					-0.0748
		(-0.98)					(-0.99)
Customer crash in T0 week X Customer environmental incidents		2.2332***					1.7309***
		(2.95)					(3.12)
Customer No. of product recalls >= 3			0.1743				0.1994
			(1.28)				(1.46)
Customer crash in T0 week X Customer No. of product recalls >= 3			0.2870				0.7538*
			(0.53)				(1.71)
Customer negative earnings surprises				0.1529***			0.1551***
				(2.80)			(2.90)
Customer crash in T0 week X Customer negative earnings surprises				-0.1777			-0.2327
				(-0.42)			(-0.47)
Customer No. of Lawsuits >= 1					-0.0475		-0.0528
					(-0.91)		(-1.02)
Customer crash in T0 week X Customer No. of Lawsuits >= 1					-0.3542		0.0110
					(-0.88)		(0.03)
Customer No. of Mergers >= 1						0.0364	0.0344
						(0.38)	(0.36)
Customer crash in T0 week X Customer No. of Mergers >= 1						0.3693	0.5964
						(0.74)	(1.01)
Constant	-5.7499***	-5.7531***	-5.7644***	-5.7734***	-5.7502***	-5.7490***	-5.7788***
	(-14.26)	(-14.25)	(-14.27)	(-14.32)	(-14.27)	(-14.28)	(-14.31)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged customer crashs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,094,325	1,094,325	1,094,325	1,094,325	1,094,325	1,094,325	1,094,325
Pseudo R-squared	0.016	0.016	0.015	0.015	0.015	0.015	0.017

TABLE B6: Stock Price Crashes Estimated with Market and Industry Returns

This table reports results of logit regressions showing the contagion of stock price crashes from customer firms to supplier firms. Stock price crashes are estimated by using the expanded index model suggested in Hutton et al. (2009) using both market and industry returns. The dependent variable is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Logit regressions *DepVar = Supplier crash in T0 week*			Marginal effects
	(1)	(2)	(3)	(4)
Customer crash in T0 week	0.6781***	0.6796***	0.6843***	0.0028***
	(3.98)	(3.99)	(4.02)	(3.99)
Customer crash in -1 week	0.6783***	0.6798***	0.6870***	0.0028***
	(3.99)	(4.00)	(4.05)	(3.99)
Customer crash in -2 week	0.2983	0.3004	0.3127	0.0013
	(1.40)	(1.41)	(1.47)	(1.47)
Customer crash in -3 week	-0.3209	-0.3193	-0.3073	-0.0012
	(-1.14)	(-1.14)	(-1.09)	(-1.09)
Customer crash in -4 week	0.2058	0.2077	0.2159	0.0009
	(0.94)	(0.95)	(0.99)	(0.99)
Supplier firm size		0.0631***	0.0640***	0.0003***
		(4.45)	(4.52)	(4.50)
Supplier market/book		-0.0007	-0.0007	-0.0000
		(-0.75)	(-0.76)	(-0.75)
Supplier leverage		-0.1150	-0.1160	-0.0005
		(-0.75)	(-0.75)	(-0.76)
Supplier ROA		0.4347***	0.4420***	0.0018***
		(3.12)	(3.16)	(3.12)
Supplier DACC		0.0082	0.0083	0.0000
		(0.49)	(0.50)	(0.50)
Supplier sigma		7.9340***	8.0383***	0.0327***
		(2.89)	(2.92)	(2.91)
Supplier returns		0.8541***	0.8645***	0.0035***
		(3.09)	(3.11)	(3.09)
Supplier crash in -1 week			-1.6977***	-0.0069***
			(-3.40)	(-3.36)
Supplier crash in -2 week			-2.3856***	-0.0097***
			(-3.37)	(-3.33)
Supplier crash in -3 week			-1.9774***	-0.0080***
			(-3.40)	(-3.35)
Supplier crash in -4 week			-1.4670***	-0.0060***
			(-2.75)	(-2.72)
Constant	-5.6231***	-6.0814***	-6.0758***	
	(-14.70)	(-14.89)	(-14.87)	
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	1,093,533	1,093,533	1,093,525	1,093,525
Pseudo R-squared	0.011	0.013	0.015	

TABLE B7: Regression Coefficient Estimates from 1,000 Bootstrapped Pseudo Supplier-Customer Samples

This table reports summary statistics of the regression coefficient estimates generated using 1,000 bootstrapped pseudo supplier-customer samples. For each supplier-customer-year link in our sample, the *Supplier* is replaced with a pseudo supplier that is randomly selected from a pool of firms in the same industry (defined using Fama-French 48 industries) and the same fiscal year. This procedure is repeated 1,000 times to generate 1,000 bootstrapped samples. The specification of model 4 in Table 2 is used for logit regressions with the bootstrapped samples. The mean, standard deviation, *t*-values, and extreme values of the 1,000 sets of regression coefficients are presented in Panel A of this table. The same procedure is employed to replace the *Customer* with a pseudo customer, and the results are shown in Panel B of this table. In all logit regressions, the dependent variable is an indicator variable, *supplier crash in the T0 week*. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. For comparison, columns 1 and 2 show the coefficients and *t*-values of *customer crash in T0, -1, -2, -3,* or *-4 week* in the baseline regression using the main sample.

	Main sample		Bootstrapped pseudo samples (1000 times)											
	Coeffs	*t*-values	Mean	S.D.	*t*-values	Min	P5	P10	P25	P50	P75	P90	P95	Max
*Panel A: Replace the **Supplier** with another firm randomly selected from the same industry*														
Customer crash in T0 week	1.5859***	(4.10)	1.1157***	0.145	(7.69)	0.639	0.867	0.930	1.022	1.119	1.215	1.296	1.351	1.570
Customer crash in -1 week	0.5737***	(2.95)	0.3929*	0.226	(1.74)	-0.264	-0.020	0.077	0.247	0.414	0.552	0.673	0.740	0.975
Customer crash in -2 week	0.6404***	(3.33)	0.2574	0.239	(1.08)	-0.712	-0.169	-0.040	0.101	0.285	0.436	0.546	0.606	0.868
Customer crash in -3 week	-0.0573	(-0.21)	0.0518	0.269	(0.19)	-1.301	-0.444	-0.285	-0.106	0.083	0.241	0.373	0.448	0.655
Customer crash in -4 week	0.0524	(0.21)	-0.1656	0.301	(-0.55)	-1.559	-0.714	-0.576	-0.348	-0.154	0.047	0.189	0.283	0.587
*Panel B: Replace the **Customer** with another firm randomly selected from the same industry*														
Customer crash in T0 week	1.5859***	(4.10)	1.0419***	0.142	(7.34)	0.542	0.803	0.853	0.953	1.047	1.145	1.213	1.259	1.444
Customer crash in the -1 week	0.5737***	(2.95)	0.3192	0.216	(1.48)	-0.581	-0.075	0.033	0.185	0.337	0.469	0.586	0.640	0.834
Customer crash in the -2 week	0.6404***	(3.33)	0.2091	0.232	(0.90)	-0.702	-0.220	-0.121	0.058	0.238	0.372	0.486	0.553	0.777
Customer crash in the -3 week	-0.0573	(-0.21)	0.0365	0.253	(0.14)	-1.140	-0.386	-0.297	-0.119	0.059	0.209	0.346	0.408	0.668
Customer crash in the -4 week	0.0524	(0.21)	-0.0923	0.282	(-0.33)	-1.657	-0.591	-0.466	-0.276	-0.070	0.113	0.245	0.324	0.665

TABLE B8: Other Robustness Checks

This table presents the results of various robustness analyses. The dependent variable is an indicator variable, *supplier crash in the T0 week*. Panel A includes the lagged weekly excess returns (*XRET*) of the portfolio of customers and the supplier between -1 and -4 weeks. Customer portfolio excess returns are constructed as sales-weighted portfolio returns of customers in excess of the CRSP value-weighted market returns. In Panel B, our variables of interest are replaced with *> = 1 crashed customers in T0, -1, -2, -3,* and *-4 week*, which are indicator variables that equal 1 if at least one of the customers crash in the corresponding week, and 0 otherwise. In Panel C, our variables of interest are replaced with *No. of crashed customers in T0, -1, -2, -3,* and *-4 week*, which are the number of customers that crashes in the corresponding week. All regressions in Panels B and C control for lagged customer returns, lagged supplier returns, lagged supplier crash dummies, and supplier firm controls. In Panel D, year and industry fixed effects are changed to year × industry fixed effects or year and firm fixed effects. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Lagged customer and supplier returns

	(1)	(2)	(3)	(4)
Customer crash in T0 week	1.5859***	1.5852***	1.5852***	1.5846***
	(4.10)	(4.09)	(4.11)	(4.10)
Customer crash in -1 week	0.5737***	0.5586***	0.5771***	0.5601***
	(2.95)	(2.76)	(2.96)	(2.77)
Customer crash in -2 week	0.6404***	0.6382***	0.6327***	0.6410***
	(3.33)	(3.30)	(3.29)	(3.31)
Customer crash in -3 week	-0.0573	-0.0299	-0.0669	-0.0259
	(-0.21)	(-0.10)	(-0.25)	(-0.09)
Customer crash in -4 week	0.0524	-0.0301	0.0374	-0.0249
	(0.21)	(-0.12)	(0.15)	(-0.10)
Customer XRET in -1 week		-0.1607		-0.1819
		(-0.26)		(-0.28)
Customer XRET in -2 week		-0.0425		0.0739
		(-0.07)		(0.13)
Customer XRET in -3 week		0.3219		0.4814
		(0.47)		(0.71)
Customer XRET in -4 week		-0.8693		-0.6507
		(-1.42)		(-1.06)
Supplier XRET in -1 week			0.1476	0.1557
			(0.21)	(0.22)
Supplier XRET in -2 week			-0.5648*	-0.5711*
			(-1.76)	(-1.79)
Supplier XRET in -3 week			-0.6218*	-0.6410*
			(-1.88)	(-1.93)
Supplier XRET in -4 week			-0.9598***	-0.9264***
			(-3.19)	(-3.06)
Constant	-5.7511***	-5.7499***	-5.7534***	-5.7527***
	(-14.27)	(-14.27)	(-14.29)	(-14.28)
Firm control variables	Yes	Yes	Yes	Yes
Lagged supplier crashes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	1,094,325	1,094,325	1,094,325	1,094,325
Pseudo R-squared	0.015	0.015	0.016	0.016

Panel B: Crash dummies =1 if there is at least 1 crash

	(1)	(2)	(3)	(4)
> = 1 crashed customer in T0 week	1.4615***	1.4622***	1.4605***	1.4613***
	(4.75)	(4.75)	(4.76)	(4.76)
> = 1 crashed customer in -1 week	0.5451***	0.5132**	0.5524***	0.5132**
	(2.89)	(2.57)	(2.92)	(2.57)
> = 1 crashed customer in -2 week	0.5776***	0.4939**	0.5697***	0.4962***
	(3.10)	(2.56)	(3.05)	(2.58)
> = 1 crashed customer in -3 week	-0.0234	0.0032	-0.0314	0.0060
	(-0.09)	(0.01)	(-0.12)	(0.02)
> = 1 crashed customer in -4 week	0.0842	-0.0217	0.0678	-0.0196
	(0.33)	(-0.08)	(0.27)	(-0.07)
Constant	-5.5964***	-5.5936***	-5.5966***	-5.5937***
	(-13.93)	(-13.93)	(-13.94)	(-13.93)
Lagged customer XRET	No	Yes	No	Yes
Lagged supplier XRET	No	No	Yes	Yes
Other firm controls, crash dummies	Yes	Yes	Yes	Yes
Year and industry fixed effects	Yes	Yes	Yes	Yes
Observations	720,434	720,434	720,434	720,434
Pseudo R-squared	0.014	0.014	0.014	0.015

Panel C: No. of customer crashes in each week

	(1)	(2)	(3)	(4)
No. of crashed customer in T0 week	1.2273***	1.2262***	1.2256***	1.2247***
	(6.43)	(6.44)	(6.44)	(6.44)
No. of crashed customer in -1 week	0.4869***	0.4603***	0.4916***	0.4590***
	(2.99)	(2.68)	(3.04)	(2.68)
No. of crashed customer in -2 week	0.5526***	0.4855***	0.5451***	0.4860***
	(3.60)	(3.02)	(3.55)	(3.04)
No. of crashed customer in -3 week	-0.0619	-0.0391	-0.0695	-0.0369
	(-0.25)	(-0.15)	(-0.28)	(-0.14)
No. of crashed customer in -4 week	0.0430	-0.0543	0.0274	-0.0531
	(0.19)	(-0.23)	(0.12)	(-0.22)
Constant	-5.5887***	-5.5862***	-5.5893***	-5.5866***
	(-13.92)	(-13.92)	(-13.93)	(-13.92)
Lagged customer XRET	No	Yes	No	Yes
Lagged supplier XRET	No	No	Yes	Yes
Other firm controls, crash dummies	Yes	Yes	Yes	Yes
Year and industry fixed effects	Yes	Yes	Yes	Yes
Observations	720,434	720,434	720,434	720,434
Pseudo R-squared	0.014	0.014	0.015	0.015

Panel D: Fixed effects

	(1)	(2)
Customer crash in T0 week	1.5712***	1.5803***
	(4.39)	(4.03)
Customer crash in -1 week	0.5655***	0.5698***
	(2.91)	(2.92)
Customer crash in -2 week	0.6307***	0.6404***
	(3.30)	(3.29)
Customer crash in -3 week	-0.0663	-0.0583
	(-0.24)	(-0.21)
Customer crash in -4 week	0.0437	0.0482
	(0.17)	(0.19)
Constant	-5.0291***	-7.9680***
	(-5.06)	(-9.51)
Firm control variables	Yes	Yes
Lagged supplier crashes	Yes	Yes
Industry × year fixed effects	Yes	No
Firm and year fixed effects	No	Yes
Observations	1,094,325	1,094,325
Pseudo R-squared	0.032	0.045

TABLE B9. The Contagion Effect of Stock Price Jumps

This table reports results of logit regressions showing the contagion of stock price jumps from customer firms to supplier firms. The dependent variable is an indicator variable, *supplier jump in the T0 week*, that equals 1 if a supplier's firm-specific return in the *T0* week exceeds 3.2 standard deviations above its mean value over the fiscal year, and 0 otherwise. Definitions of the variables are in E-Companion Table A1. Standard errors are clustered at the calendar-week level, and *t-values* are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Logit regressions *DepVar = Supplier jump in T0 week*			Marginal effects
	(1)	(2)	(3)	(4)
Customer jump in T0 week	0.9226***	0.9240***	0.9221***	0.0039***
	(4.68)	(4.69)	(4.68)	(4.64)
Customer jump in -1 week	0.4204*	0.4211*	0.4232*	0.0018*
	(1.84)	(1.83)	(1.84)	(1.83)
Customer jump in -2 week	0.1974	0.1983	0.2050	0.0009
	(0.79)	(0.79)	(0.82)	(0.82)
Customer jump in -3 week	-0.1793	-0.1798	-0.1713	-0.0007
	(-0.61)	(-0.61)	(-0.58)	(-0.58)
Customer jump in -4 week	0.1270	0.1264	0.1333	0.0006
	(0.45)	(0.45)	(0.47)	(0.47)
Supplier firm size		-0.1335***	-0.1349***	-0.0006***
		(-8.03)	(-8.09)	(-8.21)
Supplier market/book		-0.0001	-0.0001	-0.0000
		(-0.25)	(-0.25)	(-0.25)
Supplier leverage		0.1283	0.1287	0.0005
		(0.88)	(0.88)	(0.88)
Supplier ROA		-0.1305**	-0.1319**	-0.0006**
		(-2.04)	(-2.07)	(-2.07)
Supplier DACC		0.0052	0.0053	0.0000
		(0.48)	(0.49)	(0.49)
Supplier sigma		-0.8728	-0.8488	-0.0036
		(-0.72)	(-0.70)	(-0.70)
Supplier returns		-0.1213**	-0.1211**	-0.0005**
		(-2.40)	(-2.41)	(-2.42)
Supplier jump in -1 week			-0.4754	-0.0020
			(-1.48)	(-1.48)
Supplier jump in -2 week			-1.3207**	-0.0056**
			(-2.28)	(-2.28)
Supplier jump in -3 week			-1.1612**	-0.0049**
			(-2.10)	(-2.09)
Supplier jump in -4 week			-1.4985**	-0.0063**
			(-2.08)	(-2.09)
Constant	-5.2375***	-4.8315***	-4.8154***	
	(-12.41)	(-11.15)	(-11.11)	
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	1,094,638	1,094,638	1,094,638	1,094,638
Pseudo R-squared	0.004	0.010	0.011	

TABLE B10. Correlation Matrix

This table reports the correlation coefficients of the variables used in the baseline regression and the supplier information asymmetry proxies. All variables are defined in E-Companion Table A1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(13)	(14)	(15)
Supp crash in T0 week	(1)	1.000													
Cust crash in T0 week	(2)	0.008***	1.000												
Supp firm size	(3)	0.010***	0.003	1.000											
Supp market/book	(4)	0.001	0.001	0.053***	1.000										
Supp leverage	(5)	-0.005**	-0.001	0.123***	0.071***	1.000									
Supp ROA	(6)	0.007***	-0.004**	0.288***	-0.021***	-0.002	1.000								
Supp DACC	(7)	0.004**	0.000	-0.005**	0.004*	-0.047***	-0.017***	1.000							
Supp sigma	(8)	-0.008***	0.001	-0.484***	0.002	-0.111***	-0.345***	-0.013***	1.000						
Supp returns	(9)	0.007***	-0.001	0.398***	-0.002	0.101***	0.331***	0.018***	-0.956***	1.000					
Analyst following	(10)	0.006***	0.005**	0.716***	0.025***	0.068***	0.088***	0.029***	-0.267***	0.219***	1.000				
Dispersion of forecasts	(11)	-0.001	0.000	-0.029***	-0.001	-0.015***	-0.010***	-0.003	0.012***	-0.008***	-0.014***	1.000			
PIN	(13)	-0.010***	-0.003	-0.685***	-0.023***	-0.142***	-0.109***	-0.018***	0.269***	-0.210***	-0.565***	0.005**	1.000		
Bid-ask spread	(14)	-0.012***	-0.004*	-0.526***	-0.008***	-0.024***	-0.107***	-0.063***	0.348***	-0.318***	-0.323***	0.017***	0.540***	1.000	
Idiosyncratic volatility	(15)	-0.007***	-0.001	-0.082***	-0.016***	0.020***	-0.146***	0.053***	0.282***	-0.245***	0.009***	0.026***	-0.067***	-0.066***	1.000

Appendix C. Examples of Operational-incident-related Stock Price Crash Contagion and Financial-incident-related Stock Price Crash Contagion

Examples of operational-incident-related stock price crash contagion

Kinder Morgan Inc:

On December 9th, 2014, Sightline Institute shed light on the staggering levels of pollution generated by the energy giant Kinder Morgan Inc, revealing that the company had caused severe pollution in many states, including Louisiana, Houston, South Carolina, and Virginia. For instance, in Louisiana, Kinder Morgan's terminal was found to be spilling coal directly into the Mississippi River and nearby wetlands. The pollution was so severe that satellite photos showed coal-polluted water spreading from the facility in black plumes, significantly affecting neighborhoods and rivers. This environmental concern led to panic among investors, resulting in a stock crash that continued from December 9th to December 18th. Additionally, its supplier, Energy Transfer Partners, also experienced a crash in its stock price.

Marathon Petroleum Corp:

According to a report from the Windsor Star on February 1st, 2016, Marathon Petroleum Corp was poised to obtain a permit from the Michigan Department of Environmental Quality to increase the release of sulfur dioxide and other pollutants from its facility. The proposed plan involved an additional discharge of 22 tons of sulfur dioxide annually, representing a significant 40 percent increase over the refinery's current emission level of 58 tons. Furthermore, Marathon sought to augment emissions of various other harmful substances. Investors reacted negatively to this news. As a result, Marathon Petroleum experienced a stock crash from February 1st to February 19th. Additionally, Marathon's supplier firm, Denbury Inc, also exhibited a crash in its stock price.

Examples of financial-incident-related stock price crash contagion

Cardinal Health Inc

Cardinal Health Inc is a large healthcare services company engaged in providing pharmaceutical and medical products and services in the United States and international markets. On May 3rd, 2018, Cardinal Health reported third-quarter results for fiscal year 2018, revealing that despite a 6% increase in revenue, its adjusted earnings decreased by 9.2% on a year-over-year basis to $1.39 per share. Notably, this figure missed the analyst consensus estimate of $1.51 per share. Subsequently, Cardinal Health Inc experienced a stock crash starting within a week. Additionally, the stock price of its supplier, Pfizer Inc, also declined significantly.

AT&T Inc

The large U.S. wireless carrier, AT&T Inc, reported its third-quarter results on October 24th, 2018. The firm's total operating revenue rose 15.3% to $45.74 billion. The firm's net income rose to $4.7 billion, or 65 cents per share, from $3.0 billion, or 49 cents per share, a year earlier. However, excluding some items, the company earned 90 cents per share, missing analysts' consensus estimate of 94 cents per share, according to Refinitiv data. This news triggered a stock price crash for AT&T. Additionally, its supplier, Westell Tech Inc, also experienced a crash in its stock price.