TWO ESSAYS ON CUSTOMER CONCENTRATION AND STOCK PRICE CRASH RISK

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Two Essays on Customer Concentration and Stock Price Crash Risk

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Certificate of Originality

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___________________________(Signed)

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Abstract

My thesis consists of two essays investigating the relation between customer concentration and stock price crash risk. By classifying major customers as corporate major customers and government major customers, I aim to show how these two types of customer concentration affect firm stock price crash risk through the managerial bad news hoarding channel.

Essay one examines the relation between corporate customer concentration and stock price crash risk. Previous research offers conflicting views on the impact that corporate major customers have on managers' bad news hoarding (e.g., Hui, Klasa, and Yeung 2012; and Raman and Shahrur 2008). Using a large sample of U.S. firms from 1979 through 2014, I find that corporate customer concentration is significantly and positively associated with stock price crash risk. To address the causality, I use lagged industry averages as instruments for corporate customer concentration following Dhaliwal, Judd, Serfling, and Shaikh (2016). Further, the positive association between corporate customer concentration and crash risk arises primarily from suppliers in the durable goods sector and those with no research and development (R&D) expenses. Finally, I find that firms with a higher degree of corporate customer concentration are more likely to disclose unexpected very bad news. All my findings suggest that corporate customer concentration gives managers' incentive to hoard bad news, which, when reaching a tipping point, is released all at once, leading to stock price crash.

Essay two examines the relation between government customer concentration and stock price crash risk. Prior studies imply a negative effect of government customer concentration on stock price crash risk (e.g., Chaney, Faccio, and Parsley 2011; and Ramanna and Roychowdhury 2010). Using a sample of U.S. supplier firms for the period 1979 through 2014, I provide evidence that government customer concentration is significantly and negatively associated with stock price crash risk. My findings suggest that government customer concentration creates a disincentive for managers to hide bad news, thereby reducing the likelihood of stock price crash.

Keywords: Stock Price Crash Risk, Corporate Customer Concentration, Government Customer Concentration, Managerial Bad News Hoarding

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Chapter 1 Overview

1.1 Motivation and Objectives

Stock price crash risk has received increasing attention from both academics and practitioners following the financial crises in the 2000s. A line of research has attributed stock price crashes to managerial bad news hoarding (e.g., Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a, 2011b; and Chang, Chen, and Zolotoy 2016). The argument is, managers tend to withhold firm-specific bad news due to career concerns, compensation contracts, personal benefits, or other reasons.[1] As concealed bad news accumulates, it inevitably reaches a tipping point and is suddenly released, causing stock prices to plunge (Jin and Myers 2006; Bleck and Liu 2007; Benmelech, Kandel, and Veronesi 2010).

Essay one is motivated by previous research on the relation between firms with corporate major customers and earnings management. On one hand, major customers demand a higher level of accounting conservatism, which reduces firms' future stock price crash risk (Hui, Klasa, and Yeung 2012; Kim and Zhang 2016). On the other hand, firms tend to manage earnings upward to build a better financial image, which helps firms attract future customers, obtain favorable contract terms, and motivate customers to participate in relationship-specific investments. Bowen, DuCharme, and Shores (1995) show that managers adopt income-increasing accounting policies to enhance firms' reputation for fulfilling customers' implicit claims. Raman and Shahrur (2008) document that firms' earnings management in one period is positively associated with customers' R&D investments in the next period.

[1] E.g., Verrecchia (2001); Hermalin and Weisbach (2007); Graham, Harvey, and Rajgopal (2005); Bleck and Liu (2007); Ball (2009); Kothari, Shu, and Wysocki (2009); and Kim, Li, and Zhang (2011a, 2011b).

The above literature offers competing predictions for major customers' impact on managers' tendency to hoard bad news. Consequently, empirical examination is needed to test which effect prevails. I postulate that corporate customer concentration exacerbates managerial bad news hoarding. If this is the case, corporate customer concentration should increase firms' stock price crash risk.

Essay two is motivated by prior literature on the relationship between political connections and earnings management. Government customers often enter into long-term procurement contracts with their suppliers (Goldman, Rocholl, and So 2013), so government customers would not be too concerned about insignificant bad news. Chaney, Faccio, and Parsley (2011) argue that politically connected firms often have preferential access to credit, so managers face less pressure to portray an enhanced financial image, given lower reported performance would not be not penalized by a higher cost of debt. More important, large firms' high-profits reports usually draw public attention, which results in high political costs (Watts and Zimmerman 1978). Ramanna and Roychowdhury (2010) find that politically connected firms with outsourcing activities, a proxy of public exposure, managed earnings downward preceding the 2004 U.S. elections to prevent adverse political scrutiny and embarrassment to their affiliated candidates. Hui, Klasa, and Yeung (2012) note that firms disclosing the U.S. government as their major customer account more conservatively, due to political concerns. The aforementioned research suggests a negative relation between government customer concentration and earnings management. Since bad news hoarding can achieve similar goals to upward earnings management, I infer that government customer concentration limits managerial bad news hoarding. If this is the case, government customer concentration should decrease firms' stock price crash risk.

1.2 Sample and Results

Both essays comprise a sample of U.S. corporations from the CRSP/Compustat Merged database for the 1979–2014 period. Using Compustat Customer Segment database, I identify corporate and government major customers for the firms in my sample. In accordance with Statement of Financial Accounting Standards No. 14 and No. 131, as well as SEC Regulation S-K, item 101, suppliers are required to report any single external customer that comprises at least 10 percent of their sales. The Segment database provides information about the name and type of each major customer, along with the sales to them. I retrieve stock return data from the Center for Research in Security Prices (CRSP) and financial information from the CRSP/Compustat Merged database.

I employ multiple measures of stock price crash risk and customer concentration. Stock price crash risk is proxied by (i) the likelihood of extremely negative stock returns and (ii) the negative skewness of stock returns (e.g., Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009; and Kim, Li, and Zhang 2011a, 2011b). Corporate (Government) customer concentration is proxied by (i) an indicator variable that equals one if the firm has any corporate (government) customer that accounts for no less than 10 percent of its sales, and zero otherwise; and (ii) the percentage of sales to all corporate (government) major customers (e.g., Dhaliwal, Judd, Serfling, and Shaikh 2016; Huang, Lobo, Wang, and Xie 2016; and Campello and Gao 2017).

The main results of essay one are as follows. First, a higher degree of corporate customer concentration increases stock price crash risk. Second, the positive relation between corporate customer concentration and crash risk comes primarily from suppliers who produce durable goods and have no R&D expenses. Third, firms with a more concentrated corporate customer base are more likely to disclose unexpected very bad news. My results are robust to alternative variable definitions, subsamples, additional controls, and specifications that address endogeneity concerns using the propensity score matching technique and instrumental variables approach. All my findings indicate that corporate customer concentration induces managers to withhold bad news. As hidden bad news accumulates for extended periods of time, it eventually crosses a critical threshold and is revealed all at once, leading to stock price crash.

The primary result of essay two is, greater government customer concentration decreases stock price crash risk. My findings are robust to different measures of key variables, the sample period without financial crisis, and the alternative model specification controlling for corporate customer concentration. My findings indicate that government customer concentration constrains managers from concealing bad news, reducing the likelihood of stock price crash.

1.3 Contribution

Essay one offers three contributions. First, it adds to the literature on firm crash risk determinants by linking corporate customer-base concentration to extremely low stock returns. It shows that firms with higher corporate customer concentration are more likely to experience large declines in share prices. It also provides new evidence supporting the bad news hoarding theory of stock price crashes (Jin and Myers 2006; Bleck and Liu 2007; Benmelech, Kandel, and Veronesi 2010). Second, it extends the research on the pros and cons of relying on a few corporate major customers (e.g., Patatoukas 2012; Dhaliwal, Judd, Serfling, and Shaikh 2016; and Campello and Gao 2017). Third, it provides a potential screening criterion for investors to allocate their stocks.

Essay two makes three contributions. First, it extends existing research on the factors determining a firm's stock price crash risk. It demonstrates that firms with higher government customer concentration are less likely to experience stock price crashes. It finds support attributing stock price crashes to the bad news hoarding theory developed by Jin and Myers (2006), Bleck and Liu (2007), and Benmelech, Kandel, and Veronesi (2010). Second, it speaks to a growing literature on the economic consequences of having a government major customer (e.g., Cohen and Li 2016a, 2016b; Dhaliwal, Judd, Serfling, and Shaikh 2016; and Huang, Lobo, Wang, and Xie 2016). Third, it provides a potential screening technique for risk management practitioners.

1.4 Structure of the Thesis

The remainder of the thesis is structured into three chapters. Chapter 2 presents my first essay on the relation between corporate customer concentration and stock price crash risk. Chapter 3 presents my second essay on the relation between government customer concentration and stock price crash risk. Chapter 4 concludes the findings and contributions of the thesis.

Chapter 2 Corporate Customer Concentration and Stock Price Crash Risk

2.1 Introduction

In the early 2000s, U.S. corporate scandal waves stimulated a growing body of research on stock price crash risk. A line of literature attributes large share-price drops to management's hoarding bad news.[2] The argument is, in order to sustain inflated stock prices, managers tend to withhold firm-specific bad news (Kothari, Shu, and Wysocki 2009). Their incentives can arise from career concerns, compensation contracts, personal benefits, or other reasons.[3] As concealed bad news accumulates, it inevitably reaches a certain threshold and is suddenly released, causing stock prices to plunge.

I examine the association between firms' corporate customer-base concentration and stock price crash risk. Customer concentration is generally computed based on the percentage of sales to a firm's major customers (e.g., Patatoukas 2012; and Dhaliwal, Judd, Serfling, and Shaikh 2016).

The existing literature offers differing views on the role corporate major customers have in determining why managers withhold bad news. On one hand, major customers are aware of managers' tendency to hoard bad news ex ante. To avoid potential losses if a supplier files for bankruptcy, customers may demand managers to account more conservatively. Notably, when major customers have

[2] Theoretical studies include the work of Jin and Myers (2006), Bleck and Liu (2007), and Benmelech, Kandel, and Veronesi (2010). Empirical studies include the work of Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011a, 2011b), Kim, Li, and Li (2014), DeFond, Hung, Li, and Li (2015), Callen and Fang (2015), Kim, Wang, and Zhang (2016), and Chang, Chen, and Zolotoy (2016).
[3] E.g., Verrecchia (2001); Hermalin and Weisbach (2007); Graham, Harvey, and Rajgopal (2005); Bleck and Liu (2007); Ball (2009); Kothari, Shu, and Wysocki (2009); and Kim, Li, and Zhang (2011a, 2011b).

bargaining advantages over their suppliers, they can require those suppliers to recognize losses more timely by contracting on certain trade terms (Hui, Klasa, and Yeung 2012). This process is analogous to creditors' practices in reducing downside risk using debt covenants (Watts 2003a, 2003b). Under such circumstances, managers are motivated to recognize bad news more quickly. Moreover, Kim and Zhang (2016) document a negative association between conditional conservatism and crash risk, suggesting that conditional conservatism creates a disincentive for management to delay bad news releases. As bad news hoarding decreases, firms are less likely to experience crashes in the future.

On the other hand, corporate major customers create incentive for the management to conceal bad news, first, because a firm's financial performance is important for customers to assess the firm's reputation for fulfilling their implicit claims (Bowen, DuCharme, and Shores 1995). To attract future customers and obtain favorable contract terms, managers have motivation to delay the release of bad news. Prior research has shown that managers adopt income-increasing accounting policies to build a better financial image (Cornell and Shapiro 1987; Maksimovic and Titman 1991; and Bowen, DuCharme, and Shores 1995). And second, accounting reports signal a firm's business prospects, which affect customers' incentives to participate in relationship-specific investments (e.g., Raman and Shahrur 2008; and Hui, Klasa, and Yeung 2012). Raman and Shahrur (2008) provide evidences that in an important supplier-customer relationship, the supplier's discretionary accruals are positively associated with the customer's subsequent R&D investments. Consequently, to increase customers' willingness to make relationship-specific investments, the supplier's managers face strong incentive to hide firm-specific bad news, which increases future crash risk.

In sum, prior literature has provided competing views regarding corporate major customers' impact on managers' incentive to hoard bad news. Thus, it is an empirical question whether corporate customer concentration reduces or increases stock price crash risk. Using a large sample of U.S. firms from 1979 through 2014, I find evidence supporting the latter argument. I adopt multiple measures of firm stock price crash risk and corporate customer concentration. Crash risk is proxied by (i) the likelihood of extremely negative weekly stock returns and (ii) the negative skewness of weekly stock returns (e.g., Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009; and Kim, Li, and Zhang 2011a, 2011b). Corporate customer concentration is proxied by (i) an indicator variable that equals one if the firm has any corporate customer who accounts for no less than 10 percent of its sales, and zero otherwise; and (ii) the percentage of sales to all corporate major customers (e.g. Campello and Gao 2017; Dhaliwal, Judd, Serfling, and Shaikh 2016; and Huang, Lobo, Wang, and Xie 2016). I show that corporate customer-base concentration generally increases a firm's crash risk. This effect is economically significant, because having at least one corporate major customer increases the probability of a firm's future crash by 9 percent and raises the negative skewness of a firm's stock returns by 0.028. A one-standard-deviation rise in total corporate major customer sales leads to a 3 percent growth in crash probability and a 0.011 increment in negative skewness. My results are robust across different measures of crash risk and corporate customer concentration.

Estimates of the relation between corporate customer concentration and crash risk could suffer from endogeneity problems. To alleviate these endogeneity concerns, I conduct propensity score matched sample analysis and perform instrumental variable estimations. In the two tests, my results are qualitatively unaffected, suggesting a positive association between corporate customer concentration and crash risk. On the whole, my endogeneity tests confirm a causal link from corporate customer concentration to crash risk.

I dig deeper into the earlier findings and investigate whether and how industry and firm characteristics shape the corporate customer concentration–crash risk relation. Specifically, I consider two dimensions: durable goods and R&D expenses. Durable goods are related to significant implicit claims, which make it harder for suppliers to attract potential customers. Higher R&D expenses impose less pressure on managers to delay bad news releases. Thus, managerial bad news hoarding activities should be more intense for firms in the durable goods sector and firms with zero R&D expenses. Consistent with my expectations, I find that the positive relation between corporate customer concentration and crash risk comes primarily from suppliers who produce durable goods and have no R&D expenses.

In the last step of my analysis, I explore the channel through which corporate customer concentration impacts crash risk. To do this, I consider the relation between corporate customer concentration and future releases of unexpected very bad news. If the rise in bad news hoarding is attributed to higher levels of corporate customer concentration, I should observe higher probability of unexpected very bad news disclosure for firms with a more concentrated corporate customer base. Indeed, I find that corporate customer concentration is positively correlated with the probability of subsequent unexpected very bad news releases. This evidence supports the idea that having a small number of corporate major customers raises the probability of managers concealing bad news, which in turn raises firm stock price crash risk.

My paper has several contributions. First, my study is related to the growing literature on firm stock price crash risk determinants following the financial crises of 2000–2002 and 2008–2009 (e.g., Hutton, Marcus, and Tehranian 2009; DeFond, Hung, Li, and Li 2015; Kim, Li, and Zhang 2011a, 2011b; and Chang, Chen, and Zolotoy 2016). I extend this literature by conducting an in-depth, large-sample analysis on the relationship between corporate customer-base concentration and stock price crash risk. In particular, I find that firms with greater corporate customer concentration are more prone to experience stock price crashes in the future. Pan (2002), Xing, Zhang, and Zhao (2010), and Yan (2011) suggest that investors in both equity and options markets are concerned about big negative jumps in asset prices. Thus, my work increases understanding of the role corporate major customers play in affecting shareholders' welfare.

This paper is also related to the bad news hoarding theory of stock price crashes (Jin and Myers 2006; Bleck and Liu 2007; Benmelech, Kandel, and Veronesi 2010). Recent literature on crash risk indicates that managerial bad news hoarding is associated with financial statement opacity, tax avoidance, CFO option sensitivity, mandatory IFRS adoption, religiosity, CEO overconfidence, and liquidity. However, it is not clear how noninvestor stakeholders influence managers' tendency to stockpile negative information. My research helps to fill this gap by examining the impact of supply-chain relations on managerial disclosure incentives. Specifically, I provide new evidence that concentration in the corporate customer base induces managers to engage in more bad news hoarding activities.

Second, my study complements the large body of literature on the economic consequences of relying on a small set of large corporate customers. These studies link corporate major customers to firms' (1) earnings management (Raman and Shahrur 2008), (2) leverage (Banerjee, Dasgupta, and Kim 2008), (3) dividend payments (Wang 2012), (4) profitability and stock market valuation (Patatoukas 2012; Irvine, Park, and Yıldızhan 2016), (5) accounting conservatism (Hui, Klasa, and Yeung 2012), (6) cash holdings (Itzkowitz 2013), (7) receiving going concern modifications from Big 4 auditors (Dhaliwal, Michas, Naiker, and Sharma 2015), (8) cost of equity and debt (Dhaliwal, Judd, Serfling, and Shaikh 2016), (9) tax avoidance (Huang, Lobo, Wang, and Xie 2016), and (10) loan contract terms (Campello and Gao 2017). This paper examines the association between corporate customer concentration and stock price crash risk, and finds a positive relation between them.

Third, my study is related to strategies in portfolio and risk management. By understanding firm-level characteristics that predict cross-sectional variation in crash risk, market practitioners can make better portfolio investment decisions. To reduce the tail risk for a given portfolio, investors can use corporate customer concentration as a screening criterion for their stock allocation.

The remainder of the paper is organized as follows: Section 2 discusses the related literature and motivates my research question. Section 3 describes my sample construction and reports summary statistics. Section 4 develops my research design and presents empirical results. Section 5 concludes.

2.2 Related Literature and Research Question

2.2.1 Stock Price Crash Risk

Evidence shows that, relative to good news, managers tend to delay bad news. For example, in Kothari, Shu, and Wysocki's (2009) paper, the authors find the stock market reacts to bad news more strongly than it does to good news. They attribute this phenomenon to managerial bad news hoarding. A stream of literature suggests that managers' tendency to delay disclosing bad news can stem from career concerns (Verrecchia 2001; Hermalin and Weisbach 2007; and Kothari, Shu, and Wysocki 2009), motives to retain peer esteem (Ball 2009), and equity incentives (Kothari, Shu, and Wysocki 2009; and Kim, Li, and Zhang 2011b).

Theory suggests that bad new hoarding originates from agency conflicts between managers and shareholders and can lead to stock price crashes, because managerial insiders can't withhold significant bad news for long periods of time. In agency theory, Jin and Myers's (2006) model proposes that insiders in opaque firms hide portions of firm-specific information to capture cash more effectively. If sufficient bad news is hidden and accumulated to a tipping point, insiders suddenly release the bad news, causing stock prices to plunge. Bleck and Liu (2007) argue that in opaque financial markets, the historic cost-accounting regime enables managers to keep bad projects alive at early stages in order to gain a convex payoff. When bad projects mature, their poor performance is revealed, leading to unexpected stock price crashes. Benmelech, Kandel, and Veronesi (2010) use a hidden-action model to show that stock-compensated managers tend to withhold bad news when the firm's investment opportunity has declined. To sustain a high growth record and secure their jobs, managers adopt a suboptimal investment strategy that gradually destroys firm value. This strategy eventually results in a cash shortfall, causing stock price to drop considerably.

A line of recent empirical research strongly supports that several factors impact crash risk through the managerial bad news hoarding channel: (1) financial statement opacity (Hutton, Marcus, and Tehranian 2009), (2) tax avoidance (Kim, Li, and Zhang 2011a), (3) CFO option sensitivity (Kim, Li, and Zhang 2011b), (4) corporate social responsibility (Kim, Li, and Li 2014), (5) mandatory IFRS adoption (DeFond, Hung, Li, and Li 2015), (6) religiosity (Callen and Fang 2015), (7) CEO overconfidence (Kim, Wang, and Zhang 2016), and (8) liquidity (Chang, Chen, and Zolotoy 2016).

2.2.2 Corporate Customer Concentration

The existing literature shows that managers' bad news hoarding can be a major factor leading to stock price crashes. Thus, it is important to consider how corporate major customers affect managers' tendency to hoard bad news.

Corporate major customers can influence managers' propensity to delay bad news releases in two opposite ways. On the positive side, corporate major customers would prefer their suppliers to recognize economic losses more timely than economic gains, as accounting conservatism can restrict customers' downside risk. Hui, Klasa, and Yeung (2012) show that a firm recognizes news about losses more quickly when its corporate customers exert greater bargaining power. In that case, corporate major customers can restrict their suppliers from hiding firm-specific bad news. Further, Kim and Zhang (2016) demonstrate a negative association between conditional conservatism and firms' future crash risk, arguing that conditional conservatism dampens managerial bad news hoarding in three ways. First, conditional conservatism requires asymmetric verifiability of gains and losses, resulting in more timely recognition of bad news than good news (Basu 1997). Such accounting policy offsets managers' proclivity to conceal unfavorable information. Second, Ball, Jayaraman, and Shivakumar (2012) find that audited financial reporting and voluntary disclosure of managers' private information are complements. To wit, independent verification (auditing) of financial statements makes managers more credible and accurate in their voluntary disclosures (Ball 2001). Similarly, commitment to conservative accounting would raise the credibility of managers' subsequent disclosures, as their voluntary disclosures will be evaluated more precisely. Due to this mechanism, conditional conservatism constrains managers' ability to withhold bad news. Third, timely loss recognition discourages managers from starting or continuing negative net present value (NPV) projects, as losses are recognized in their tenure (Ball and Shivakumar 2005). This results in less formation and accumulation of bad news, reducing future crash probability.

On the negative side, a better financial image can help firms to obtain more favorable contract terms and persuade customers to undertake more relationship-specific investments. A large body of literature has concluded that a reputation for fulfilling implied commitments affects the trade terms a firm can negotiate with its stakeholders (e.g., Klein and Leffler 1981; Crafton, Hoffer, and Reilly 1981; and Reilly and Hoffer 1983). At the same time, a firm's financial image can influence stakeholders' assessment of its reputation for fulfilling implicit claims (e.g., Cornell and Shapiro 1987; and Maksimovic and Titman 1991). In addition, Titman's (1984) model implies that stakeholders' willingness to undertake relationship-specific investments hinges on a firm's financial viability.

Empirical research has shown that managers use earnings management to enhance a firm's financial image so as to improve customers' perceptions of the firm's reputation for fulfilling implicit claims and its business prospects (Bowen, DuCharme, and Shores 1995; Raman and Shahrur 2008). Consistent with this argument, Graham, Harvey, and Rajgopal (2005) mention that CFOs commonly manage to meet earnings benchmarks to create a credible image of their firms, to retain or boost stock prices, to maintain the reputation of the management team, or to convince investors of their firms' growth prospects. Bowen, DuCharme, and Shores (1995) show that when a firm depends largely on implicit claims with its stakeholders, managers are likely to choose income-increasing inventory and depreciation methods. Raman and Shahrur (2008) provide evidence that industry-level, relationship-specific investments by corporate major customers exacerbate earnings management. Since bad news hoarding can achieve similar goals to earnings management, firms depending on a small set of large corporate customers have incentive to delay disclosing bad news.

Taken together, prior literature suggests that corporate customer-base concentration can impact managers' tendency to delay bad news releases. On one hand, corporate major customers with bargaining advantages may restrain firms' bad news hoarding. On the other hand, managers have motives to withhold bad news, because they fear its release will cause corporate major customers to leave. Therefore, how corporate customer concentration affects crash risk is an empirical question, creating a need for empirical testing to gain insight into this issue.

2.3 Sample and Descriptive Analysis

2.3.1 Sample Selection

Using Compustat Customer Segment database, which provides information about the name and type of each major customer as well as the sales assigned to it, I identify corporate major customers for firms incorporated in the United States. Statement of Financial Accounting Standards No. 14 (FAS 14) requires a business enterprise to disclose the fact and total amount of sales to a single external customer accounting for 10 percent or more of the enterprise's revenues. FAS 14 provisions became effective after December 15, 1976, for fiscal years and interim periods, so I start my data collection in 1978.[4] The SEC's Regulation S-K, Item 101, requires the names of the major customers and their relationships with the registrant be disclosed if they account for 10 percent or more of the registrant's consolidated revenues and if losing them would have a material adverse effect on the registrant and its subsidiaries. I extract stock return data from the Center for Research in Security Prices (CRSP) and financial statement data from the CRSP/Compustat Merged database.

I exclude observations with negative book value of equity, observations with stock prices lower than $1 at any fiscal year end, and observations with fewer than 26 weeks of stock return data following Kim, Li, and Zhang (2011a). I further exclude financial firms (SIC 6000–6999), observations with insufficient data for constructing corporate customer concentration and crash risk measures, and observations with missing control variables. I winsorize all continuous variables at the 1st and 99th percentiles to diminish the impact of outliers. After data filtering, a sample of 90,884 observations remains for 9,646 U.S. supplier firms from 1979

[4] FAS 14 was superseded by FAS 131 in 1997.

through 2014.

2.3.2 Crash Risk Measures

To construct the firm-specific crash risk measures, I first calculate the firm-specific weekly returns by Hutton, Marcus, and Tehranian's (2009) expanded index model regression as follows:

$$r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-1} + \beta_{2,j} r_{i,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{i,\tau} + \beta_{5,j} r_{m,\tau+1} + \beta_{6,j} r_{i,\tau+1} + \varepsilon_{j,\tau} \tag{1}$$

where $r_{j,\tau}$ denotes the return on stock j in week τ; $r_{m,\tau}$ denotes the return for the CRSP value-weighted market index in week τ; $r_{i,t}$ denotes the return for the Fama and French (1993) value-weighted industry index in week τ; and $\varepsilon_{j,\tau}$ denotes the error term. According to Dimson (1979), lead and lag returns for the market and industry indexes can account for nonsynchronous trading. Next, the firm-specific weekly return is defined as the natural log of one plus the residual from Equation (1) (i.e., $W_{j,\tau}$ = ln(1+$\varepsilon_{j,\tau}$)). My (untabulated) results are qualitatively unchanged if I use the raw residual returns in my estimation of crash risk.

Following prior literature, I compute two measures of crash risk: crash dummy and negative skewness (e.g., Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a, 2011b; and Chang, Chen, and Zolotoy 2016). Consistent with Hutton, Marcus, and Tehranian (2009), crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. The 3.09 represents a frequency of 0.1 percent in the normal distribution. I employ five thresholds to detect crash weeks in the robustness test.

In light of Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011a, 2011b), negative skewness (*NCSKEW*) is a continuous variable that equals minus one multiplied by the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Thus, the negative skewness of supplier *j*'s stock returns in year *t* is computed as:

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

where $W_{j,\tau}$ is the de-meaned, firm-specific weekly returns on stock *j*, and *n* is the number of observations on firm-specific weekly returns in year *t*. A higher value of *NCSKEW* means that the stock's return follows a more left-skewed distribution.

2.3.3 Corporate Customer Concentration Measures

I retrieve my sample of corporate major customers from Compustat Customer Segment database. In accordance with FAS 14, FAS 131, and SEC Regulation S-K, item 101, suppliers are required to report any single customer who accounts for at least 10 percent of their sales. Although some suppliers voluntarily disclose significant customers that comprise less than 10 percent of their revenues, I exclude such customers from my sample to avoid potential selection bias.

I construct two measures of corporate customer concentration based on the methodology in Banerjee, Dasgupta, and Kim (2008), Dhaliwal, Michas, Naiker, and Sharma (2015), Dhaliwal, Judd, Serfling, and Shaikh (2016), and Huang, Lobo, Wang, and Xie (2016). The first measure, corporate major customer dummy (*CC_D*), is an indicator variable that is set to one if a firm discloses one or more corporate major customers, and zero otherwise. In 34.5 percent of my firm-years, suppliers are found to have at least one corporate major customer.

The second measure, total corporate major customer sales (*CC_SALE*), is the sum of the proportion of sales assigned to each corporate major customer according to Banerjee, Dasgupta, and Kim (2008) and Dhaliwal, Michas, Naiker, and Sharma (2015). I compute firm *j*'s total corporate major customer sales based on *I* corporate major customers in year *t* as follows:

$$CC\_SALE_{j,t} = \sum_{i=1}^{I} \%SALE_{j,i,t} \quad (3)$$

where $\%SALE_{j,i,t}$ is the percentage of revenue contributed by corporate major customer *i* for firm *j* in year *t*. For firms that do not have a corporate major customer, *CC_SALE* equals zero. A larger *CC_SALE* means that the supplier is associated with a higher reliance on corporate major customers.

2.3.4 Control Variables

I follow Kim, Li, and Zhang (2011a) to construct my control variables. The first five control variables are past negative skewness ($NCSKEW_{t-1}$), past stock return volatility ($SIGMA_{t-1}$), past stock returns (RET_{t-1}), past stock turnover ($DTURN_{t-1}$), and past firm size ($SIZE_{t-1}$) from Chen, Hong, and Stein (2001). $NCSKEW_{t-1}$ denotes the negative skewness of firm-specific weekly returns in the prior year. Chen, Hong, and Stein (2001) show that firms with higher return skewness tend to have more negatively skewed stock returns in the next year. $SIGMA_{t-1}$ denotes the standard deviation of firm-specific weekly returns in the previous year. The authors find that firms with higher return volatility are prone to stock price crashes. RET_{t-1} denotes the mean value of firm-specific weekly returns over the past year. Firms with higher stock returns are more likely to experience crashes in the future. $DTURN_{t-1}$ denotes the detrended average monthly stock turnover during one year before. It is the variable of interest in Chen, Hong, and Stein (2001). Hong and Stein's (2003) model suggests that greater heterogeneity in investors' opinions leads to higher detrended trading volume, which in turn results in more negatively skewed stock returns. This prediction is confirmed by Chen, Hong, and Stein, who demonstrate a positive relation between past stock turnover and negative skewness. $SIZE_{t\text{-}1}$ denotes the log of market value of equity at the prior fiscal year end. Larger firm size is related to higher crash risk based on existing empirical studies (e.g., Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009; and Kim, Li, and Zhang 2011a, 2011b).

The next four control variables are past market-to-book ratio ($MB_{t\text{-}1}$), past leverage ($LEV_{t\text{-}1}$), past return on assets ($ROA_{t\text{-}1}$), and past opacity in financial reports ($ACCM_{t\text{-}1}$) from Hutton, Marcus, and Tehranian (2009). $MB_{t\text{-}1}$ denotes the ratio of market value of equity to book value of equity in the previous year. Growth stocks are found to be more susceptible to crash risk. $LEV_{t\text{-}1}$ denotes the ratio of long-term debt to total assets in year t-1. The authors show that higher leveraged companies are less likely to crash in the subsequent year. They attribute this counter-intuitive result partially to the endogeneity in firms' capital structure choices. In particular, firms with less crash risk are more prone or able to take on more debt. While Hutton, Marcus, and Tehranian (2009) apply contemporaneous return on equity (ROE_t) in their analyses, I replace it with past return on assets ($ROA_{t\text{-}1}$), following Kim, Li, and Zhang (2011a). $ROA_{t\text{-}1}$ denotes the ratio of income before extraordinary items to lagged total assets in the past year. Prior studies have offered different views regarding the effect of operating performance on firms' crash risk. Some research suggests that good operating performance lowers firms' crash risk (e.g., Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a, 2011b; and Chang, Chen, and Zolotoy 2016). Nonetheless, several recent studies document that firms with good operating performance are associated with greater crash risk (e.g., Kim, Li, and Li 2014; Callen and Fang 2015; and Kim, Wang, and Zhang 2016). $ACCM_{t-1}$ denotes opacity of financial statements, measured by the sum of absolute discretionary accruals in years t-3, t-2, and t-1. It is the variable of interest in Hutton, Marcus, and Tehranian (2009), which corroborates Jin and Myers's (2006) theory that opacity enables managers to absorb losses by hiding temporary firm-specific negative news to secure their jobs. When the negative information accumulates and reaches a critical point where managers are unwilling or unable to absorb extra losses, it comes out all at once, leading to a sudden crash. Thus, firms with bigger *ACCM* have higher crash probability in the future. Finally, corporate customer concentration may vary across time and industry, so I incorporate year and 2-digit SIC industry fixed effects in all regression specifications. Appendix A.1 provides more detailed definitions for the aforementioned control variables.

2.3.5 Descriptive Analysis

Table 2.1 reports the count of observations, the mean crash dummy, and the mean negative skewness for each year in my sample. The mean value of *CRASH* increases from 0.074 in 1979 to 0.247 in 2014, indicating that more firms experienced sharp stock price declines. The mean value of *NCSKEW* reveals a similar trend, implying that stocks are becoming more crash prone. This phenomenon is possibly due to more economic crises after the 1990s.

[Insert Table 2.1 Here]

Table 2.2 presents the summary statistics and Pearson correlation matrix of crash risk variables, corporate customer concentration variables, and control variables used in my baseline regression analysis. As seen in Table 2.2, Panel A, 17.6 percent of my sample experience stock price crashes and the average negative skewness is -0.041. This and other summary statistics, except *ACCM*, are similar to those in Kim, Li, and Zhang (2011a) and Chang, Chen, and Zolotoy (2016).[5] The mean value of *ACCM* in my sample is 0.551, which is larger than that in previous studies (e.g., Hutton, Marcus, Tehranian 2009; Kim, Li, and Zhang 2011a; and Chang, Chen, and Zolotoy 2016) because I estimate modified Jones model discretionary accruals according to Kothari, Leone, and Wasley (2005) rather than Dechow, Sloan, and Sweeney (1995). In 34.5 percent of my observations, suppliers disclose one or more corporate major customers accounting for at least 10 percent of their total sales. On average, firms collect 13.1 percent of their revenues from corporate major customers. Both of these numbers are slightly higher than those in Dhaliwal, Judd, Serfling, and Shaikh (2016), suggesting that my sample has a more concentrated base of corporate customers.[6] Panel B of Table 2.2 demonstrates a positive correlation between *CRASH* and *NCSKEW*. At the same time, both of them are positively correlated with the two measures of corporate customer concentration (i.e., *CC_D* and *CC_SALE*).

[Insert Table 2.2 Here]

[5] The sample period of Kim, Li, and Zhang (2011a) is 1995–2008. The sample period of Chang, Chen, Zolotoy (2016) is 1993–2010.
[6] The sample period of Dhaliwal, Judd, Serfling, and Shaikh (2016) is 1981–2011.

2.4 Corporate Customer Concentration and Crash Risk: Empirical Results

2.4.1 Baseline Regression Analysis

In this section, I estimate panel regressions of crash risk in year t on corporate customer concentration in year t-1 and a set of control variables in year t-1 as follows:

$$CRASH_{j,t} = \beta_0 + \beta_1 CC\_D_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4a}$$

$$CRASH_{j,t} = \beta_0 + \beta_1 CC\_SALE_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4b}$$

$$NCSKEW_{j,t} = \beta_0 + \beta_1 CC\_D_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4c}$$

$$NCSKEW_{j,t} = \beta_0 + \beta_1 CC\_SALE_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4d}$$

where j represents the supplier, t refers to the fiscal year, Yr_t stands for the year fixed effects, Ind_j denotes the 2-digit SIC industry fixed effects, and $\varepsilon_{j,t}$ is the error term. Following the crash risk literature, I estimate Equations (4a) and (4b) by logistic regression. In addition, I estimate Equations (4c) and (4d) by ordinary least squares (OLS). I report z- and t-statistics based on standard errors corrected for heteroskedasticity and clustered by supplier.

Table 2.3 shows the baseline results for regressions of crash risk on corporate customer concentration. In columns 1 and 2, the dependent variable is crash dummy. Both measures of corporate customer concentration generate significant and positive coefficients, indicating that a concentrated corporate customer base enhances the likelihood of a future stock price crash. The coefficient of *CC_D* on crash dummy is 0.083, implying that having a corporate major customer increases the odds of a crash event by 9 percent. The marginal effect of *CC_SALE* on crash dummy is 0.025, meaning that when *CC_SALE* grows by one standard deviation (0.228), the likelihood of a stock price crash increases by 0.228 × 0.025 = 0.006. This corresponds to a 3 percent increment in crash probability compared to an average crash dummy of 0.176.

In columns 3 and 4, the dependent variable is negative skewness. Both measures of corporate customer concentration attract significant and positive coefficients, suggesting that higher concentration in the corporate customer base leads to more negatively skewed stock returns in the future. The coefficient of *CC_D* on negative skewness indicates that having a corporate major customer increases the negative skewness of a firm's stock returns by 0.028. The marginal effect of *CC_SALE* on negative skewness is 0.048, meaning that a one-standard-deviation increase in *CC_SALE* (0.228) results in a 0.228 × 0.048 = 0.011 increment in negative skewness. Given that the sample mean of negative skewness is -0.041, this magnitude is economically meaningful. In sum, the above findings support that higher corporate customer concentration increases a firm's stock price crash risk.

[Insert Table 2.3 Here]

Most of my control variables yield similar coefficients to those reported in prior research, while *ACCM* exhibits different results. All coefficients of *ACCM* are much smaller than those in Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011a), and Chang, Chen, and Zolotoy (2016), because the value of *ACCM* is larger in my sample, as I estimate discretionary accruals based on the modified Jones model in Kothari, Leone, and Wasley (2005).

2.4.2 Robustness Tests

To check the robustness of my baseline results, this section experiments with a variety of variable definitions and model specifications.

In Table 2.4, I consider the possibility that my results are driven by the distinct threshold (3.09 standard deviations below the annual mean) in determining crash weeks. Thus, I follow Chang, Chen, and Zolotoy's (2016) approach and identify crash weeks according to multiple thresholds and definitions. For brevity, I only report the coefficients of corporate customer concentration from each estimation run. In rows 1 and 2, a firm's crash weeks are recognized when its firm-specific weekly returns are 3.5 or 4 standard deviations below the annual mean. In rows 3 through 5, a firm's crash weeks are the weeks with firm-specific weekly returns below -10 percent, -15 percent, or -20 percent. I also consider two alternative measures of crash risk. In row 6, the dependent variable is changed into the number of crash weeks throughout a fiscal year. In row 7, the dependent variable becomes down-to-up volatility defined by Chen, Hong, and Stein (2001).[7] All alternative definitions of crash weeks and crash risk confirm a significant and positive correlation between corporate customer concentration and crash risk.

[Insert Table 2.4 Here]

[7] For any supplier *j* over a fiscal year *t*, I partition all the weeks into "up" weeks and "down" weeks. The "up" weeks include firm-specific weekly returns above the annual mean and the "down" weeks comprise firm-specific weekly returns below the annual mean. The down-to-up volatility equals the log of the ratio of the standard deviation of firm-specific weekly returns in "down" weeks over the standard deviation of firm-specific weekly returns in "up" weeks, which is computed as follows:

$$DUVOL_{j,t} = log\left\{(n_u - 1)\sum_{DOWN} W_{j,\tau}^2 \Big/ \left((n_d - 1)\sum_{UP} W_{j,\tau}^2\right)\right\}$$

In Table 2.5, I consider the possibility that my results are driven by the special measurements of corporate customer concentration. Thus, I adopt the third measure of corporate customer concentration: corporate major customer Herfindahl-Hirschman index (*CC_HHI*), which is the quadratic sum of the percentage of sales attributed to all corporate major customers according to Patatoukas (2012). I compute firm *j*'s corporate major customer Herfindahl-Hirschman index based on *I* corporate major customers in year *t* as follows:

$$CC\_HHI_{j,t} = \sum_{i=1}^{I} \%SALE_{j,i,t}^{2} \qquad (5)$$

where $\%SALE_{j,i,t}^{2}$ is the square of the percentage of revenues contributed by corporate major customer *i* for firm *j* in year *t*. For firms that do not have a corporate major customer, *CC_HHI* equals zero. A larger *CC_HHI* means that the supplier exposes to a more concentrated corporate customer base. For each test, the coefficient of *CC_HHI* is significantly positive, indicating that my results are robust to the alternative definition of corporate customer concentration.

[Insert Table 2.5 Here]

In Table 2.6, I consider the possibility that my results are driven by the balance sheet approach in accruals estimates. In the baseline regressions, *ACCM* is formulated by discretionary accruals based on a balance sheet approach. Since prior studies estimate discretionary accruals by a cash flow approach (e.g. Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a; and Chang, Chen, and Zolotoy 2016), I recalculate *ACCM* using the Statement of Cash Flow. Since cash flow statement data are available only from 1987 onward, I obtain a smaller sample that consists of 67,471 firm-years for the 1990 through 2014 period. The results are not sensitive to this adjustment.

[Insert Table 2.6 Here]

In Table 2.7, I test whether the relationship between corporate customer concentration and crash risk still holds for a subsample of observations with information in the Compustat Customer Segment file. In my main tests, I set firms without information in the Segment database as having zero corporate major customers. However, it is possible that some firms with corporate major customers are not recorded by the Segment file. To reduce potential data errors, I restrict my tests to a subsample of firms with data in the Compustat Customer Segment database. This selection process ends up with a sample of 41,823 observations for 1979 through 2014. In both regressions, the coefficients of *CC_D* and *CC_SALE* remain positive and significant. These results support the conclusion that firms with higher reliance on corporate major customers are more susceptible to crash risk.

[Insert Table 2.7 Here]

In Table 2.8, I consider the possibility that my results are driven by particular time periods. In Panel A, I exclude financial crisis years (1987, 2000–2002, and 2008–2009) to tease out the influence of excessive market volatility on stock returns. In Panel B, I rerun the baseline regressions for the period after Regulation Fair Disclosure (2001–2014), since investors react to bad news more strongly than good news before the regulation. In Panel C, I focus on post-SOX period (2003–2014) to alleviate the impact of inaccurate financial reporting on crash risk. The coefficients of corporate customer concentration are positive and significant in most of my tests, suggesting that my findings are robust across different time periods.

[Insert Table 2.8 Here]

In Table 2.9, I consider the possibility that my results are driven by increased operating risk, which results in higher crash probability. Corporate major customers can add risk to firms' cash flow, business model, liquidity management, and stock valuation. In that case, a more concentrated corporate customer base increases a firm's operating risk. First, a firm's cash flow could drop significantly if its major customers switch to other vendors or build products internally. In addition, firms relying on a small number of major customers often engage in relationship-specific investments, which engender high financial distress costs when their customers leave (Titman 1984; Kale and Shahrur 2007; and Banerjee, Dasgupta, and Kim 2008). The empirical findings of Titman and Wessels (1988), Kale and Shahrur (2007), and Banerjee, Dasgupta, and Kim (2008) reveal that firms depending on customer-supplier relationships tend to maintain lower leverage. Wang (2012) shows that greater customer concentration is associated with lower dividend payments. Itzkowitz (2013) contends that firms in important buyer-supplier relationships hold additional cash as a precaution against adverse cash flow shocks induced by the loss of a major customer. Considering the positive effect of tax avoidance on cash flow and earnings, Huang, Lobo, Wang, and Xie (2016) argue that corporate customer concentration stimulates tax avoidance.

Second, the stock and credit markets are also concerned about the risks posed by corporate customer concentration to a firm's business model. Dhaliwal, Judd, Serfling, and Shaikh (2016) find that concentration in the corporate customer base increases a firm's cost of equity and cost of debt. Campello and Gao (2017) look into private loan contracts between firms with corporate major customers and their banks. They conclude that greater corporate customer concentration leads to higher interest rate spreads and more restrictive covenants in bank loans as well as shorter maturity of those loans.

Third, large customers often require small suppliers to lower purchase prices and extend trade credit terms. These requirements impose liquidity constraints on small suppliers when their access to external financing is limited or costly. Murfin and Njoroge (2014) provide evidence that longer payment terms demanded by large customers force much smaller suppliers to abandon profitable investments due to liquidity constraints.

Fourth, when a corporate major customer experiences bad news, becomes financially or economically distressed, or declares bankruptcy, this negative impact can translate into bad news to its supplier through the supply chain, causing slumps in the supplier's stock prices. Cohen and Frazzini (2008) document that bad news to corporate principal customers causes negative changes in a firm's stock prices in the subsequent month. Hertzel, Li, Officer, and Rodgers (2008) demonstrate that firms suffer negative abnormal returns around the dates when their corporate major customers enter into financial distress or file for bankruptcy. Kolay, Lemmon, and Tashjian (2016) argue that economic distress can transmit from a corporate major customer to its supplier, which bears significant loss in market value. Thus, I augment my baseline regressions with a series of operating risk variables. I control for cash flow volatility and sales growth according to Kim and Zhang (2014).[8] I include measures of cash holdings and R&D expenditures as per Opler, Pinkowitz,

[8] Cash flow volatility is defined as the standard deviation of operating cash flow (*OANCF-XIDOC*) divided by lagged total assets (*AT*) over the previous five years. Sales growth is the annual change in sales (*SALE*) divided by lagged sales (*SALE*).

Stulz, and Williamson (1999).[9] Because of missing values for cash flow statement data, I conduct my analysis on a smaller sample of 62,553 observations from 1992 through 2014. My primary results are unaffected, confirming that corporate customer concentration influences crash risk beyond the effect of increased operating risk.

[Insert Table 2.9 Here]

In Table 2.10, I consider the possibility that my results are driven by omitted variables. Particularly, one may argue that omitted variables may account for differences between firms with and without corporate major customers, and unobserved characteristics may cause increases in both corporate customer concentration and crash risk.

I augment my baseline regressions with a number of control variables that could affect crash risk. I include a measure of high-frequency trading as per Zhang (2010). High-frequency trading is essentially the short-term trading by hedge funds and other institutional investors not recorded by the Thomson Reuters Institutional Holdings (13F) database. I control for tax avoidance and CFO option incentives in accordance with Kim, Li, and Zhang (2011a) and Kim, Li, and Zhang (2011b), respectively. Tax avoidance is proxied by the predicted probability that a firm adopts tax shelters according to Wilson's (2009) model. CFO option incentives is proxied by a CFO's incentive ratio for option holdings following Bergstresser and Philippon (2006). I control for corporate governance, which is measured by board independence and the CEO duality dummy. Board independence is defined as the percentage of independent directors serving on a board. The CEO duality dummy

[9] Cash holdings are the ratio of cash and marketable securities (*CHE*) to total assets (*AT*) net of cash and marketable securities (*CHE*). R&D expenditures equal to research and development expenditures (*XRD*) over sales (*SALE*).

equals one if a firm's CEO serves as the chairman of the board at the same time, and zero otherwise. I include auditor characteristics proxied by the big-auditor dummy and the auditor-industry-specialization dummy. The big-auditor dummy equals one if the going concern is audited by a Big accounting firm, and zero otherwise. The number of Big accounting firms ranges from eight in 1980s to four after 2002. The auditor-industry-specialization dummy equals one if a company is audited by an accounting firm that accounts for the largest market share in the company's 2-digit SIC industry, and zero otherwise. I control for industry-level litigation risk using the high-litigation-industry dummy defined by Matsumoto (2002). High-litigation-industry dummy equals one if a firm's SIC code is within the following ranges: 2833–2836, 3570–3577, 3600–3674, 5200–5961, 7370–7374, and 8731–8734, and zero otherwise. I control for firms' financial distress risk based on Bharath and Shumway's (2008) KMV distance-to-default measure. Financial distress risk is the probability of default produced by Merton distance-to-default model. I control for real earnings management as per Roychowdhury (2006). Real earnings management equals the sum of abnormal components of cash flow from operations, production costs, and discretionary expenses, based on Dechow, Kothari, and Watts's (1998) regressions. Finally, I control for the effect of stock liquidity on crash risk (as documented by Chang, Chen, and Zolotoy 2016). Liquidity is defined as the ratio of the absolute difference between the trade price and the midpoint of the bid-ask quote to the trade price. Due to missing values for these additional controls, my sample size reduces to 7,170 firm-years. Although the coefficient of *CC_SALE* becomes insignificant in the negative skewness regression, my main results are qualitatively unaffected.

[Insert Table 2.10 Here]

2.4.3 Endogeneity

Although I present a significantly positive association between corporate customer concentration and crash risk, regressions conducted in the previous section are subject to endogeneity problems. Unobserved characteristics may trigger increases in both corporate customer concentration and crash risk. To allay these concerns, I implement propensity score matched sample analysis and instrumental variable estimations.

2.4.3.1 Propensity score matched sample analysis

In this section, I consider the possibility that my results are driven by omitted variables that correlate with the nonlinear forms of my control variables. To address this concern, I conduct propensity score matched analysis to control for the differences in control variables between suppliers with corporate major customers (*CC_D*=1) and those without corporate major customers (*CC_D*=0) following the methodology in Rosenbaum and Rubin (1983) and Dehejia and Wahba (2002).

In the first stage, I regress the corporate major customer dummy (*CC_D*) on the set of control variables in my baseline regressions and calculate the propensity score (i.e., probability) for a firm to have a corporate major customer. Column 1 in Panel B, Table 2.11, displays the marginal effects of my control variables from the first-stage logistic regression. Next, without replacement, I match each firm that reports one or more corporate major customers with a firm that does not rely on corporate major customers by the closest propensity score. I impose a caliper distance of 1 percent for each matched pair. The resulting sample consists of 52,962 firm-years, of which 26,481 reflect observations with corporate major customers and

26,481 reflect observations without corporate major customers.

Panel A of Table 2.11 shows the descriptive statistics of my control variables for the full and propensity score matched samples. There are 90,884 firm-years in the full sample, of which 31,382 (34.5 percent) are observations with a concentrated corporate customer base and 59,502 (65.5 percent) are observations with a diverse corporate customer base. The descriptive statistics for the full sample reveal significant differences between firms with corporate major customers and those without such customers. Firms exposed to a small set of large corporate customers have higher stock return volatility, lower stock returns, higher stock turnover, smaller firm sizes, and more growth opportunities than firms exposed to a large set of small corporate customers. Firms depending on corporate major customers are less leveraged and profitable than firms depending on less significant customers. Moreover, the financial reports of firms with corporate major customers are more opaque than those of firms without corporate major customers. The last three columns report the descriptive statistics for the propensity score matched sample, which has largely reduced the differences between firms with and without corporate major customers. Except *SIGMA* and *SIZE,* all firm characteristics are insignificantly different between the two supplier types.

In the second stage, I rerun the baseline regressions on my propensity score matched sample. The multivariate results are shown in Panel B of Table 2.11 In line with my earlier findings, corporate customer concentration is significantly and positively associated with crash risk. Taken together, the propensity score matched analysis in this section corroborates that higher corporate customer concentration increases a firm's future crash risk.

[Insert Table 2.11 Here]

2.4.3.2 Instrumental variable estimations

Although the previous section has mitigated some of my endogeneity concerns, the baseline regressions are subject to estimation biases—specifically, variation in corporate customer concentration lacks exogenous sources. To address this concern, I follow Dhaliwal, Judd, Serfling, and Shaikh (2016) and use lagged industry averages as my instrumental variables. I view industry averages as plausible instruments. First, industry-level corporate customer concentration is positively associated with firm-level corporate customer concentration. Second, the industry averages are unlikely to affect an individual firm's future crash risk. According to Dhaliwal, Judd, Serfling, and Shaikh (2016), I calculate the two-year and three-year lagged industry averages of my two corporate customer concentration measures. The two-year (three-year) lagged industry average of corporate major customer dummy is the fraction of firms with corporate major customers in a supplier's 3-digit SIC industry excluding the supplier two (three) years ago. The two-year (three-year) lagged industry average of total corporate major customer sales is the average total corporate major customer sales of other suppliers in a supplier's 3-digit SIC industry two (three) years ago. Thus, the equations of industry average corporate customer concentration can be written as follows:

$$Industry\ Average\ Corporate\ Major\ Customer\ Dummy_{j,t} = \frac{\sum_{i=1}^{n_{SIC3,t}} CC\_D_{i,t} - CC\_D_{j,t}}{n_{SIC3,t} - 1} \quad (6a)$$

$$Industry\ Average\ Total\ Corporate\ Major\ Customer\ Sales_{j,t} = \frac{\sum_{i=1}^{n_{SIC3,t}} CC\_SALE_{i,t} - CC\_SALE_{j,t}}{n_{SIC3,t} - 1} \quad (6b)$$

where $n_{SIC3,t}$ represents the number of firms in supplier j's 3-digit SIC industry in year t, $CC\_D_{i,t}$ denotes supplier i's corporate major customer dummy in the same 3-digit SIC industry in year t, and $CC\_SALE_{i,t}$ stands for supplier i's total corporate major customer sales in the same 3-digit SIC industry in year t.

Similar to Dhaliwal, Judd, Serfling, and Shaikh (2016), I perform two-stage least squares regressions to examine the effect of corporate customer concentration on crash risk. In the first stage, I regress the corporate customer concentration on its two-year and three-year lagged industry averages, along with the set of control variables used in the baseline regressions. In the second stage, I regress the firm's future crash risk on its predicted corporate customer concentration from the first-stage regression, along with the set of control variables. My instrumental variables regressions are estimated as follows:

$$\begin{aligned} &Corporate\ Customer\ Concentration_{j,t-1} = \beta_0 + \beta_1 Industry\ Average\ Corporate\ Customer\ Concentration_{j,t-3} + \\ &\beta_2 Industry\ Average\ Corporate\ Customer\ Concentration_{j,t-4} + \beta_3 NCSKEW_{j,t-1} + \beta_4 SIGMA_{j,t-1} + \beta_5 RET_{j,t-1} + \\ &\beta_6 DTURN_{j,t-1} + \beta_7 SIZE_{j,t-1} + \beta_8 MB_{j,t-1} + \beta_9 LEV_{j,t-1} + \beta_{10} ROA_{j,t-1} + \beta_{11} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \end{aligned} \tag{7a}$$

$$\begin{aligned} &Crash\ Risk_{j,t} = \beta_0 + \beta_1 Corporate\ Customer\ \widehat{Concentration}_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \\ &\beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \end{aligned} \tag{7b}$$

where *Corporate Customer Concentration* includes the two corporate customer concentration measures *CC_D* and *CC_SALE*, *Industry Average Corporate Customer Concentration* contains *Industry Average Corporate Major Customer Dummy* and *Industry Average Total Corporate Major Customer Sales*, *Crash Risk* comprises the two crash risk measures *CRASH* and *NCSKEW*, and $Corporate\ Cust\widehat{omer}\ Concentration$ consists of the two predicted corporate customer concentration measures *Predicted CC_D* and *Predicted CC_SALE* from Equation (7a). During certain time periods, industry dynamics can confound my results if they drive both industry averages of corporate customer concentration and firms' crash risk. For this reason, I control for firms' year and industry fixed effects.

Table 2.12 presents the results for *CRASH*. Panel A of Table 2.12 shows the first-stage regression results for the two corporate customer concentration measures on their two-year and three-year lagged industry averages. Both *Industry Average Corporate Customer Concentration*$_{t\text{-}3}$ and *Industry Average Corporate Customer Concentration*$_{t\text{-}4}$ are significantly and positively correlated with each measure of corporate customer concentration. I conduct several tests to assess the validity of my instrumental variables. Specifically, the high Wu-Hausman F-statistics imply that the two measures of corporate customer concentration are endogenous by themselves. The F-statistic and Partial R^2 reject the null hypothesis that my instruments are weakly identified. The Sargan test suggests that the two-year and three-year lagged industry averages are uncorrelated with the error term. Thus, my instrumental variables are exogenous in regard to a firm's stock price crash risk. Panel B of Table 2.12 presents the second-stage regression results for the crash dummy on the instrumented corporate customer concentration. Consistent with my baseline results, the two predicted corporate customer concentration measures attract positive and significant coefficients.

[Insert Table 2.12 Here]

Table 2.13 presents the results for *NCSKEW*. Panel A of Table 2.13 shows the first-stage regression results for *CC_D* and *CC_SALE* on their two-year and three-year lagged industry averages. The two instrumental variables load positively and significantly in both estimations. Notably, the Wu-Hausman F-statistics reject the null hypothesis that *CC_D* and *CC_SALE* are exogenous. Both F-statistic and

Partial R^2 pass the weak identification test. The Sargan test supports the null hypothesis that the two-year and three-year lagged industry averages are valid instruments. Panel B of Table 2.13 presents the second-stage regression results for the negative skewness on the instrumented corporate customer concentration. Consistent with my baseline results, *Predicted CC_D* and *Predicted CC_SALE* are positively and significantly associated with the negative skewness. To compare the economic significance of these results with that of my earlier findings, I look at the effect of *Predicted CC_SALE* on *NCSKEW*. The marginal effect of *Predicted CC_SALE* on *NCSKEW* is 0.187, signifying that a one-standard-deviation rise in *Predicted CC_SALE* (i.e., 0.097) induces a 0.097 × 0.187 = 0.018 growth in *NCSKEW*. Given that the average negative skewness is -0.041, this result is economically significant.

[Insert Table 2.13 Here]

Overall, the IV approach confirms my earlier findings that firms with higher corporate customer concentration are more likely to experience stock price crashes and have more negatively skewed returns. These evidences suggest that managers in firms relying on a small number of large corporate customers show a higher tendency to delay bad news releases.[10]

2.4.4 Cross-Sectional Tests

I next explore industry and firm characteristics that impact the effect of corporate customer concentration on crash risk. To do this, I look at two dimensions:

[10] In Appendix A.2, I examine a subsample of firms with at least one corporate major customer and use mergers and acquisitions activity in customers' industries as an instrument for firms' corporate customer-base concentration following Campello and Gao (2017). I find that high levels of downstream M&A activity increases firms' corporate customer concentration. This shift, in turn, results in higher crash probability, which partially supports the baseline results.

durable goods and R&D expenses.

2.4.4.1 The effect of durable goods

Bowen, DuCharme, and Shores (1995) argue that when customers purchase durable goods, they also purchase implicit claims with respect to serviceability and availability of parts throughout the product's life. Because durable goods are manufactured to be used for a long time, the implicit claims between a durable goods manufacturer and its customers can be significant. In this context, the supplier has strong incentives to build a better financial image to signal its ability to fulfill those implied commitments. Since managers can hide bad news to maintain a good financial position for their firms, I expect that the positive effect of corporate customer concentration on crash risk is stronger among suppliers who produce durable goods.

Following Titman and Wessels (1988), I focus on a subsample of manufacturing firms (SIC 2000–3999) and classify industries with SIC codes between 3,400 and 3,999 as the durable goods sector, along with other industries as the nondurable goods sector. In the former category, firms produce machines and equipment. My subsample consists of 48,803 firm-years for 1979 through 2014. I then partition my observations into two groups based on the above classification. Finally, I rerun the baseline regressions separately for the two groups.

Panel A of Table 2.14 displays the results for *CRASH*. The coefficients of my main effect terms (*CC_D* and *CC_SALE*) are significantly positive for firms in the durable goods sector (z-statistics = 3.15 and 3.46) and insignificant for firms in the nondurable goods sector. Panel B of Table 2.14 displays the results for *NCSKEW*. Similarly, the coefficients of my main effect terms are only positive and significant for firms in the durable goods sector (t-statistics = 2.30 and 2.92). The results in Table 2.14 indicate that corporate customer concentration exerts a substantial influence on crash risk for firms in the durable goods sector. In short, these findings suggest that the positive relation between corporate customer concentration and crash risk comes primarily from the suppliers who produce durable goods.

[Insert Table 2.14 Here]

2.4.4.2 The effect of R&D expenses

Ben-Nasr, Bouslimi, and Zhong (2017) show that innovation-related activities are negatively related to firms' crash risk in the future. Using the cumulative number of patent grants and citations to proxy for a firm's innovation activities, Ben-Nasr, Bouslimi, and Zhong point out that the disclosure of patents decreases the information asymmetry between the firm and its outside investors. Moreover, patents can help companies gain trust from shareholders, resulting in lower external financing costs (e.g., Hegde and Mishra 2014; and Hsu, Lee, Liu, and Zhang 2015). This benefit offsets managers' tendency to withhold bad news. Further, prior studies consider R&D expenses as an indicator of product uniqueness, because successful R&D projects introduce distinct products that cannot be easily duplicated (e.g., Titman and Wessels 1988; John 1993; and Bowen, DuCharme, and Shores 1995). Thus, product uniqueness decreases suppliers' pressure to conceal negative information. Since innovation-related activities discourage managerial bad news hoarding, I expect that the positive effect of corporate customer concentration on future crash risk is stronger among suppliers with no R&D expenses.

Following Bowen, DuCharme, and Shores (1995), I compute R&D expenses as research and development expenditures scaled by total assets and average this ratio over the past three years.[11] After this process, missing values of R&D expenses are set to zero. I then rank my observations based on the amount of R&D expenses and partition them into three groups. Observations with zero R&D expenses are allocated to the first group (46,350 observations). The other observations are evenly allocated to the second (22,967 observations) and third (21,567 observations) groups. Specifically, the second group comprises firms with relatively low R&D expenses and the third group contains firms with relatively high R&D expenses. Finally, I reestimate my baseline regressions separately for the first and third groups.

Panel A of Table 2.15 presents the results for *CRASH*. Although the coefficients of my main explanatory variables (*CC_D* and *CC_SALE*) are positive in all cases, the coefficients are significant only for firms with zero R&D expenses (z-statistics = 3.02 and 3.33). Panel B of Table 2.15 presents the results for *NCSKEW*. Similarly, although the coefficients of my main explanatory variables remain positive in all cases, the coefficients are, also, significant only for firms with zero R&D expenses (t-statistics = 4.44 and 3.28). The results in Table 2.15 indicate that corporate customer concentration has a greater influence on crash risk for firms that do not have R&D expenses. In short, these findings suggest that the positive relation between corporate customer concentration and crash risk comes primarily from suppliers with no R&D expenses.

[Insert Table 2.15 Here]

In sum, the results of my cross-sectional tests substantiate the idea that deeper exposure to a small number of corporate major customers raises a firm's crash risk.

[11] I consider an alternative measure of R&D expenses, equal to research and development expenditures divided by total assets in the same year. The results are qualitatively the same (see Appendix A.3).

Such impact comes primarily from suppliers who produce durable goods and have no R&D expenses.

2.4.5 Corporate Customer Concentration and Unexpected Very Bad News Releases

In this section, I go a step further and look into the channel through which corporate customer concentration affects crash risk. I examine the relation between corporate customer concentration and future releases of unexpected very bad news. Recall that bad news hoarding implies accumulation of bad news for an extended period until it reaches a tipping point, when the news is suddenly released. I consider releases of unexpected very bad news as a manifestation of managerial bad news hoarding. Thus, if greater corporate customer concentration motivates managers to conceal negative information, I should witness a higher probability of unexpected very bad news disclosures for firms with a more concentrated corporate customer base.

I follow Chang, Chen, and Zolotoy (2016) and define unexpected very bad news releases as *SURP_UE*, which is a dummy variable set to one if a firm's unexpected earnings are non-negative in the previous fiscal year and fall in the bottom decile in the current year, and zero otherwise. Here, I determine the unexpected earnings as the annual change in a firm's income before extraordinary items divided by its lagged market value of equity according to Kothari, Lewellen, and Warner (2006). Using a logit model, I regress *SURP_UE* on corporate customer concentration together with a full set of controls as follows:

$$SURP\_UE_{j,t} = \beta_0 + \beta_1 CC\_D_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{8a}$$

$$SURP\_UE_{j,t} = \beta_0 + \beta_1 CC\_SALE_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{8b}$$

The notations above are the same as in the baseline regressions. Table 2.16 presents the results of my regressions for *SURP_UE*. As expected, both proxies of corporate customer concentration are significantly and positively correlated with *SURP_UE*, revealing that concentration in the corporate customer base leads to a higher probability of unexpected very bad news releases in the future. The coefficient of *CC_D* on *SURP_UE* is 0.102, implying that reliance on corporate major customers raises the odds of subsequent unexpected very bad news releases by 11 percent. The marginal effect of *CC_SALE* on *SURP_UE* is 0.010, indicating that when *CC_SALE* grows by one standard deviation (i.e., 0.228), the probability of unexpected very bad news releases rises by 0.228 $\times$ 0.010 = 0.002. This amounts to a 4 percent elevation relative to the average *SURP_UE* of 0.05.

[Insert Table 2.16 Here]

Collectively, my results suggest a positive relation between corporate customer concentration and future releases of unexpected very bad news. This evidence confirms that higher levels of corporate customer-base concentration induce managers to withhold bad news, which increases firms' crash risk in the subsequent year.

2.5 Conclusion

This study investigates the association between corporate customer-base concentration and stock price crash risk. Using a sample of U.S. supplier firms from 1979 through 2014, I find that firms with higher levels of corporate customer concentration are more likely to experience future stock price crashes. My results are robust across alternative definitions of stock price crash risk and corporate customer concentration. Meanwhile, I address endogeneity concerns using the propensity score matching technique and instrumental variables approach, and the results continue to hold. Overall, my findings suggest that a concentrated base of corporate customers incentivizes managers to withhold bad news. As hidden bad news accumulates and eventually reaches a critical threshold, it comes out all at once, causing a crash.

Furthermore, I show that the positive relation between corporate customer concentration and crash risk comes primarily from suppliers who produce durable goods and do not have R&D expenses. Finally, I find that corporate customer concentration is positively associated with the probability of subsequent unexpected very bad news releases. This result confirms that a deeper exposure to a small number of corporate customers encourages managerial bad news hoarding.

My paper complements the existing literature on firms' crash risk determinants. The analysis presented here supports the bad news hoarding theory of stock price crashes proposed by Jin and Myers (2006), Bleck and Liu (2007), and Benmelech, Kandel, and Veronesi (2010). My study also extends the literature on the economic consequences of having a concentrated corporate customer base. Although previous studies suggest that agents demand additional compensation for stocks with higher downside risk (e.g., Ang, Chen, and Xing 2006; and Chang, Christoffersen, and Jacobs 2013), the documented effect of corporate customer concentration on crash risk does not necessarily imply that firms with greater corporate customer concentration should have higher expected stock returns. There is empirical evidence that increase in corporate customer concentration results in efficiency gains, which lead to higher current and future stock returns (e.g., Patatoukas 2012). Thus, the net effect of corporate customer concentration on expected stock returns is worth researching further. Moreover, I expect that other classes of noninvestor stakeholders also affect managers' incentives to hoard bad news. I leave this topic for future research.

[Insert Appendices A.1, A.2, and A.3 Here]

Chapter 3 Government Customer Concentration and Stock Price Crash Risk

3.1 Introduction

The financial crises of the 2000s have stimulated a growing stream of research on the determinants of stock price crashes, and a large body of literature suggests that managerial bad news hoarding plays an important role in crash formation.[12] According to Kothari, Shu, and Wysocki (2009), managers have incentives to withhold negative information from investors, and the tendency is related to managers' career concerns, compensation contracts, private benefits, to name a few.[13] As hidden bad news accumulates for an extended period, it eventually reaches a tipping point and is revealed all at once, causing large declines in stock prices.

This study conducts a simple test on the relation between government customer concentration and stock price crash risk. Government customer concentration is measured by the dummy for the presence of government major customers and the percentage sales assigned to them (Dhaliwal, Judd, Serfling, and Shaikh 2016; Huang, Lobo, Wang, and Xie 2016). The U.S. government is an important customer in the supply chain. In 2007, the total amount of U.S. government procurement is about 460 billion.[14] This amounts to 3 percent of GDP in

[12] E.g., Jin and Myers 2006; Bleck and Liu 2007; Hutton, Marcus, and Tehranian 2009; Benmelech, Kandel, and Veronesi 2010; Kim, Li, and Zhang 2011a, 2011b; Kim, Li, and Li 2014; DeFond, Hung, Li, and Li 2015; Callen and Fang 2015; Kim, Wang, and Zhang 2016; and Chang, Chen, and Zolotoy 2016.

[13] E.g., Verrecchia 2001; Hermalin and Weisbach 2007; Graham, Harvey, and Rajgopal 2005; Bleck and Liu 2007; Ball 2009; Kothari, Shu, and Wysocki 2009; and Kim, Li, and Zhang 2011a, 2011b.

[14] The data is derived from the Federal Procurement Report for fiscal year 2007 in the Federal Procurement Data System-Next Generation (FPDS-NG), accessed at https://www.fpds.gov.

the same year. Thus, it is worthwhile to test how this major customer affects firms' crash risk.

The extant literature suggests a negative association between government customer concentration and crash risk. First, government customers are long-term purchasers who would not terminate relationships with their suppliers due to small pieces of bad news. Under such circumstances, suppliers face less pressure to disclose persistently high earnings to improve government customers' perceptions of their financial viability.[15] Chaney, Faccio, and Parsley (2011) document that politically connected firms care less about the quality of reported earnings, because they are not penalized by a higher cost of debt and thus have less pressure to opportunistically use accruals. Since hoarding bad news can achieve similar goals to upward earnings management, firms exposed to a small set of government customers are reluctant to hoard bad news. Second, firms with political connections tend to decrease reported earnings to lower their political costs (such as costs imposed by labor unions). Ramanna and Roychowdhury (2010) find that donor firms that outsource jobs overseas engaged in downward earnings management before the 2004 U.S. elections to avoid negative political scrutiny and political embarrassment to their affiliated candidates. Hui, Klasa, and Yeung (2012) note that firms with the U.S. government as their major customer tend to account more conservatively, due to political concerns. The propensity to disclose lower earnings dampens managers'

[15] A better financial image can help firms to obtain more favorable contract terms and persuade customers to undertake more relationship-specific investments. Previous empirical research has shown that managers use earnings management to enhance a firm's financial image, so as to improve customers' perceptions of the firm's reputation for fulfilling implicit claims and its business prospects (Bowen, DuCharme, and Shores 1995; Raman and Shahrur 2008).

incentive to withhold bad news. Therefore, firms with the government as a major customer are less likely to engage in bad news hoarding activities.

Building on the above evidence, I expect that higher government customer concentration leads to less future crash risk. There is a need to show whether this prediction matches the real world. Using a large sample of U.S. firms from the CRSP/Compustat Merged database during the period 1979–2014, I find evidence supporting the prediction. Following prior literature, I measure a firm's stock price crash risk by (i) the dummy variable for having one or more crash weeks with extremely negative weekly stock returns and (ii) the negative coefficient of skewness of weekly stock returns (see, e.g., Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009; and Kim, Li, and Zhang 2011a, 2011b). Following Dhaliwal, Judd, Serfling, and Shaikh (2016) and Huang, Lobo, Wang, and Xie (2016), I measure a firm's government customer concentration by (i) the dummy variable for having at least one government major customer who accounts for 10 percent or more of its sales and (i) the percentage sales assigned to all government major customers. As expected, I find that firms with higher government customer concentration are less prone to stock price crashes. With respect to economic significance, having a government major customer decreases the odds of a crash event by 10 percent and lowers the negative skewness of a firm's stock returns by 0.028. A one-standard-deviation increment in total government major customer sales results in a 3 percent decline in crash probability and a 0.009 drop in negative skewness. My results are robust to alternative definitions of key variables, the sample period excluding financial crisis years, and the model specification controlling for the impact of corporate major customers.

My paper makes at least three contributions. First, this study adds to the growing stream of research on the determinants of firm stock price crash risk (e.g., Hutton, Marcus, and Tehranian 2009; Callen and Fang 2015; Kim, Li, and Zhang 2011a, 2011b; and Chang, Chen, and Zolotoy 2016). To the best of my knowledge, this is the first large-sample study to show a negative relation between government customer concentration and stock price crash risk. Further, the results in this paper are consistent with the bad news hoarding theory of stock price crashes developed by Jin and Myers (2006), Bleck and Liu (2007), and Benmelech, Kandel, and Veronesi (2010). Specifically, my findings suggest that high levels of government customer concentration create a disincentive for managers to delay bad news. This paper is also relevant for regulators, because firms' government customer concentration can be shaped by government procurement contracts (Cohen and Li 2016b).

Second, this study extends the emerging research on the economic consequences of having a more concentrated base of government customers. Closely related literature includes Cohen and Li (2016a, 2016b), Dhaliwal, Judd, Serfling, and Shaikh (2016), and Huang, Lobo, Wang, and Xie (2016). Cohen and Li (2016a) reveal that firms with a higher percentage of sales to the U.S. government hold less cash and have lower future earnings volatility. Cohen and Li (2016b) document that government suppliers are more profitable, because they face less operational uncertainty and a more transparent information environment. Dhaliwal, Judd, Serfling, and Shaikh (2016) note that firms with higher government customer concentration are associated with lower cost of equity. Huang, Lobo, Wang, and Xie (2016) demonstrate that firms with higher governmental customer concentration engage in lower levels of tax avoidance activities. Rather than exploring the impact of government major customers on operational efficiencies, this paper investigates the implications of government customer concentration on future crash risk. I provide evidence that government customer concentration is negatively related to stock price crash risk.

Third, this study contributes to the screening strategies in risk management. Sunder (2010) distinguishes two kinds of risk: risk from outcome uncertainty and risk from possible losses. The former can be mitigated by diversification, while the latter can only be reduced by screening. Hence, it is crucial for market practitioners to find proper screening criteria to alleviate portfolio crash risk. In this respect, my research provides a potential screening device for allocation.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature and makes empirical predictions. Section 3 describes the sample selection procedures, constructs my key variables, and presents summary statistics. Section 4 reports regression analysis results. Section 5 concludes the paper.

3.2 Related Literature and Empirical Predictions

3.2.1 Stock Price Crash Risk

Kothari, Shu, and Wysocki (2009) were among the first to propose that, relative to good news, managers delay the release of bad news. They show that the magnitude of stock market reaction to bad news disclosures exceeds that of stock market reaction to goods news disclosures. Such evidence suggests that managers stockpile negative information from investors until the accumulated information reaches a certain threshold, when all the bad news is suddenly released, causing large stock market reactions. This tendency to hoard bad news can arise from managers' career concerns, expectations to preserve the esteem of peers, and equity incentives (see, e.g., Verrecchia 2001; Hermalin and Weisbach 2007; Ball 2009; Kothari, Shu, and Wysocki 2009; and Kim, Li, and Zhang 2011b).

Agency theory relates managerial bad news hoarding to crash risk. Jin and Myers (2006) contend that insiders absorb firm-specific bad news when they capture operating cash flows in partially opaque firms. If more bad news arrives and accumulates up to the point where managers are unwilling to absorb further downside risk, they abandon the firm and release all the bad information at once, leading to large stock price declines. Bleck and Liu's (2007) model links market opaqueness to asset price crashes under a historic-cost-accounting regime. They argue that managers use historic cost accounting to hide the bad performance of poor projects in order to earn their bonus and derive some private benefit. The bad performance piles up over time and eventually becomes public, causing asset prices to crash. Benmelech, Kandel, and Veronesi (2010) reveal that when a firm's investment opportunity slows down, stock-based compensation induces managers to undertake a suboptimal investment strategy. Under the strategy, managers invest in negative net-present-value (NPV) projects and abandon positive NPV projects to maintain the pretense of high-growth prospects in order to save their jobs. Nonetheless, this pretense cannot last forever. At some time, the firm encounters a cash shortfall, the bad news eventually surfaces, and the stock price plunges as the firm demands recapitalization.

Within the agency theory framework, theoretical studies propose that bad news hoarding arises from conflict between managers and shareholders. To benefit themselves, managers absorb firm-specific bad news or conceal bad information from poor projects. The hidden bad news accumulates for an extended period until it crosses a critical threshold, where all negative information suddenly spills out, causing abrupt declines in stock prices.

A growing body of empirical research gives support for the positive association between bad news hoarding and crash risk. Hutton, Marcus, and Tehranian (2009) note that opaque firms are able to conceal more negative news than transparent ones. Thus, they are more likely to experience stock price crashes in the future. Kim, Li, and Zhang (2011a) suggest that tax avoidance provides managers with more opportunities to stockpile bad news. Therefore, firms engaging in higher levels of tax avoidance have higher crash risk. Kim, Li, and Zhang (2011b) document a positive relation between the strength of CFO option incentives and crash risk. Their findings partially confirm the prediction of Benmelech, Kandel, and Veronesi (2010) that stock-based compensation gives managers incentive to hide unfavorable information about future growth prospects. The accumulated bad news later leads to stock price crashes. Kim, Li, and Li (2014) show that socially responsible firms engage in less bad news hoarding activities. Hence, CSR performance is negatively correlated with future crash risk. DeFond, Hung, Li, and Li (2015) propose that mandatory IFRS adoption increases firms' financial reporting transparency, which has a negative impact on managerial bad news hoarding. As a result, IFRS adoption decreases the crash risk for nonfinancial firms. Callen and Fang (2015) link country-level religiosity to firm-level crash risk. They find that firms headquartered in countries with higher degrees of religiosity are less likely to experience stock price crashes. This result substantiates the idea that religion creates a business environment that hinders managers' bad news hoarding. Kim, Wang, and Zhang (2016) assert that overconfident CEOs are reluctant to disclose negative feedback about the investment projects, because they overestimate the future performance of their investments and underestimate the odds of failure. Hence, CEO overconfidence gives rise to "irrational" or "unconscious" bad news hoarding behavior, enabling the authors to present a positive association between CEO overconfidence and crash risk. Chang, Chen, and Zolotoy (2016) mention that firms with higher stock liquidity attract more transient investors, who exert downward stock price pressure when bad news surfaces. To avoid excess selling by transient investors, managers of such firms tend to withhold bad news. The accumulation of bad news eventually leads to future stock price crashes.

3.2.2 Government Customer Concentration

The aforementioned literature suggests that managerial bad news hoarding can be a major cause of stock price crashes. Thus, it is important to consider how government major customers' presence impacts managers' tendency to hoard bad news. In general, higher levels of government customer concentration might dampen managers' propensity to delay bad news releases.

First, government customers are more stable than corporate customers, as public procurement contracts are usually long term (Goldman, Rocholl, and So 2013). That means government customers would not terminate relationships with their suppliers for minor unfavorable news reports. If this were the case, suppliers would therefore face less pressure to disclose higher earnings to influence government customers' perceptions. Although there is no direct evidence, Chaney, Faccio, and Parsley (2011) show that firms with political connections have lower earnings quality, proxied by the standard deviation of discretionary accruals. Further, such firms are not penalized by a higher cost of debt due to their preferential access to credit.[16] The authors then conclude that managers of politically connected firms care less about the quality of reported earnings and face less pressure to manipulate accruals. Since bad news hoarding can accomplish similar goals to earnings management, I expect that firms with higher government customer concentration also face less pressure to inflate reported earnings and thus engage in less bad news hoarding activities.

Second, politically connected firms are more likely to decrease reported earnings to reduce the political costs they face. Watts and Zimmerman (1978) point out that high reported profits of large firms often attract public attention, which leads to high political costs (such as the costs imposed by labor unions). Ramanna and Roychowdhury (2010) further claim that greater public exposure during U.S. elections makes politically connected firms susceptible to increased political scrutiny, which could cause political embarrassment to their affiliated candidates. To prevent the negative consequences associated with adverse political scrutiny, these firms have the incentive to disclose lower earnings. The authors provide evidence that donor firms that outsource jobs overseas engage in downward earnings management preceding the elections in 2004 to avoid potential undesirable political scrutiny and political embarrassment to their affiliated candidates. In addition, these firms use more income-decreasing discretionary accruals when they have a higher degree of outsourcing activities (i.e., a proxy of public exposure). Similarly, Hui, Klasa, and Yeung (2012) mention that firms with the U.S. government as their major customer

[16] For example, Cull and Xu (2005) take a close look at Chinese firms and find those with a close relationship with the government have a higher probability of obtaining loans from state banks. Khwaja and Mian (2005) document that government banks lend more to politically connected firms in Pakistan. Moreover, firms with political connections receive even better lending rates when the affiliated politician (or his or her political party) wins the election.

account more conservatively due to political concerns. In their paper, the authors report a positive relation between the dummy of having a significant U.S. government customer and accounting conservatism. Consequently, if political concerns motivate firms to release lower earnings reports, managers wouldn't be tempted to conceal bad news, since hoarding bad news only results in increased reported earnings. Thus, I expect that firms relying on a small set of government customers are less likely to withhold bad news.

In sum, previous research suggests that government major customers can reduce managers' tendency to stockpile negative information. First, because government customers are long term, they are not concerned about insignificant bad news. Suppliers thus face less pressure to portray a good financial image. Second, firms with political connections tend to manage earnings downward due to political concerns. This tendency also discourages bad news hoarding. Taken together, both arguments predict a negative association between government customer concentration and crash risk. Therefore, empirical examination is needed to verify this prediction.

3.3 Sample and Summary Statistics

3.3.1 Sample Selection

I collect government customer–supplier data for U.S. firms from Compustat Customer Segment database. Statement of Financial Accounting Standards No. 14 (FAS 14) of 1976 requires a business enterprise to disclose the fact and total sales to domestic government agencies, or foreign governments, in the aggregate if they account for 10 percent or more of its revenue. In 1979, FAS 30 amended FAS 14, waiving the requirement of aggregating sales to domestic government agencies or those to foreign governments. Instead, the statement requires an enterprise to disclose the fact and amount of sales to each domestic or foreign government that accounts for 10 percent or more of its revenue. In 1997, FAS 131 superseded FAS 14 but retained the requirement for public companies to report information about government major customers. Similarly, the SEC's Regulation S-K, item 101, requires the registrant to disclose the name of each major customer and its relationship with each one, if the customer accounts for 10 percent or more of its revenue and the loss of the customer would impose an adverse material effect on the registrant and its subsidiaries. The Segment database gathers information about the name, type, and assigned sales figures of each government major customer. Because provisions of FAS 14 apply to financial statements for fiscal years as well as interim periods after December 15, 1976, my sample period starts from 1979 (data collection begins in 1978). I derive firms' historical financial statement data from the CRSP/Compustat Merged database and stock return data from the Center for Research in Security Prices (CRSP).

According to Kim, Li, and Zhang (2011a), I remove observations with negative book value of equity with stock closing prices lower than $1 at the fiscal year end and with less than 26 weeks of stock return data. Financial firms (SIC 6000–6999) are excluded. I further remove observations with missing data for constructing my main variables of interest and the full set of control variables. To mitigate the impact of outliers, I winsorize all continuous variables at the 1st and 99th percentiles. My final sample consists of 90,884 observations for 9,646 U.S. supplier firms for the period of 1979–2014.

3.3.2 Crash Risk Measures

I follow the methodology documented in Chen, Hong, and Stein (2001), Hutton, Marcus, and Tehranian (2009), and Kim, Li, and Zhang (2011a, 2011b) and employ two measures of crash risk: (i) crash dummy (*CRASH*) and (ii) negative skewness (*NCSKEW*).

To construct the two crash risk measures, I first calculate the residual stock returns using Hutton, Marcus, and Tehranian's (2009) expanded index model regression:

$$r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-1} + \beta_{2,j} r_{i,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{i,\tau} + \beta_{5,j} r_{m,\tau+1} + \beta_{6,j} r_{i,\tau+1} + \varepsilon_{j,\tau} \tag{1}$$

where $r_{j,\tau}$ refers to the return on stock j in week τ; $r_{m,\tau}$ refers to the return for the CRSP value-weighted market index in week τ; $r_{i,\tau}$ refers to the return for the Fama and French (1993) value-weighted industry index in week τ; and $\varepsilon_{j,\tau}$ refers to the error term. In light of Dimson (1979), lead and lag returns for both market and industry indexes are included to deal with nonsynchronous trading. I transform the highly skewed residual returns to a nearly symmetric distribution according to Hutton, Marcus, and Tehranian (2009). The firm-specific weekly return is then computed as the log of one plus the residual return from Equation (1), i.e., $W_{j,\tau}$=ln(1+$\varepsilon_{j,\tau}$). Untabulated results show that my empirical findings are essentially unaffected if I use raw residual returns in estimating crash risk.

My first measure of crash risk is crash dummy (*CRASH*) as per Hutton, Marcus, and Tehranian (2009). It equals one if a firm has at least one crash week in a fiscal year, and zero otherwise. A crash week is a week with firm-specific weekly returns falling 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and 3.09 accounts for a frequency of 0.1 percent in the normal distribution (Hutton, Marcus, and Tehranian 2009). In the robustness test, I determine crash dummy based on four alternative thresholds and obtain similar results.

My second measure of crash risk is negative skewness (*NCSKEW*) in line with Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011a, 2011b). It equals the negative coefficient of skewness of firm-specific weekly returns, that is, minus one multiplied by the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power:

$$NCSKEW_{j,t} = -\left(n(n-1)^{3/2}\sum W_{j,\tau}^{3}\right) \Big/ \left((n-1)(n-2)\left(\sum W_{j,\tau}^{2}\right)^{3/2}\right) \qquad (2)$$

where $W_{j,\tau}$ is the de-meaned, firm-specific weekly returns on stock *j*, and *n* is the number of observations on firm-specific weekly returns over year *t*. A higher value of *NCSKEW* indicates a more left-skewed return distribution, and the stock is more subject to crash risk.

3.3.3 Government Customer Concentration Measure

I follow Banerjee, Dasgupta, and Kim (2008), Dhaliwal, Michas, Naiker, and Sharma (2015), and Dhaliwal, Judd, Serfling, and Shaikh (2016), and Huang, Lobo, Wang, and Xie (2016) and employ two measures of government customer concentration: (i) the government major customer dummy (*GC_D*) and (ii) the total government major customer sales (*GC_SALE*).

My first measure, government major customer dummy (*GC_D*), equals one if a firm discloses one or more government customers (i.e., federal, state, local, or foreign government customers) who make up 10 percent or more of its revenue, and zero otherwise. In 8.2 percent of my observations, suppliers have at least one government major customer.

My second measure, total government major customer sales (*GC_SALE*), equals the percent of total sales attributed to all government major customers in accordance with Banerjee, Dasgupta, and Kim (2008) and Dhaliwal, Michas, Naiker, and Sharma (2015). *GC_SALE* is defined as:

$$GC\_SALE_{j,t} = \sum_{i=1}^{I} \%SALE_{j,i,t} \tag{3}$$

where $GC\_SALE_{j,t}$ refers to firm *j*'s total government major customer sales based on *I* government major customers in year *t*, and $\%SALE_{j,i,t}$ refers to the percentage of total sales from firm *j* to government major customer *i* in year *t*. $GC\_SALE_{j,t}$ equals zero if firm *j* does not have a government major customer in year *t*. A higher value of *GC_SALE* indicates a higher reliance on government major customers.

3.3.4 Control Variables

In addition to variables representing the government customer concentration, I construct a set of control variables following Kim, Li, and Zhang (2011a). First, I use past negative skewness ($NCSKEW_{t\text{-}1}$), past stock return volatility ($SIGMA_{t\text{-}1}$), past stock returns ($RET_{t\text{-}1}$), past stock turnover ($DTURN_{t\text{-}1}$), and past firm size ($SIZE_{t\text{-}1}$) from Chen, Hong, and Stein (2001). $NCSKEW_{t\text{-}1}$ stands for the negative skewness of firm-specific weekly returns in fiscal year *t*-1. $SIGMA_{t\text{-}1}$ stands for the standard deviation of firm-specific weekly returns in year *t*-1. $RET_{t\text{-}1}$ stands for the mean value of firm-specific weekly returns in year *t*-1. $DTURN_{t\text{-}1}$ stands for the detrended average monthly stock turnover in year t-1. $SIZE_{t-1}$ stands for the log of market value of equity at the end of year t-1. Chen, Hong, and Stein (2001) find that $NCSKEW_{t-1}$, $SIGMA_{t-1}$, RET_{t-1}, $DTURN_{t-1}$, and $SIZE_{t-1}$ are all positively correlated with the negative skewness in year t. To wit, firms with higher return skewness, higher stock return volatility, higher stock returns, higher stock turnover, and larger market capitalizations in the current year tend to have higher return skewness in the next year. $DTURN_{t-1}$ is the variable of interest in Chen, Hong, and Stein's (2001) paper. Hong and Stein's (2003) model asserts that a high level of heterogeneity in investors' opinions raises the detrended trading volume, which in turn increases the negative skewness of stock returns. Chen, Hong, and Stein (2001) present evidence consistent with this prediction.

Second, I use past market-to-book ratio (MB_{t-1}), past leverage (LEV_{t-1}), past return on assets (ROA_{t-1}), and past opacity in financial reports ($ACCM_{t-1}$) from Hutton, Marcus, and Tehranian (2009). While the authors employ contemporaneous return on equity (ROE_t) in their regression specifications, I replace it with past return on assets (ROA_{t-1}) as per Kim, Li, and Zhang (2011a). MB_{t-1} represents the ratio of market value of equity to book value of equity in year t-1. LEV_{t-1} represents the ratio of long-term debt to total assets in year t-1. ROA_{t-1} represents the ratio of income before extraordinary items to lagged total assets in year t-1. $ACCM_{t-1}$ represents the opacity of financial statements, estimated by the sum of absolute discretionary accruals in years t-3, t-2, and t-1. In Hutton, Marcus, and Tehranian (2009), MB_{t-1} and $ACCM_{t-1}$ are positively associated with the crash dummy in year t, whereas ROE_t and LEV_{t-1} are negatively associated with the crash dummy in year t. This means that firms with better growth opportunities, higher levels of financial reporting opacity, and lower leverage in the past year, together with poorer operating performance in the current year, are more prone to crash. $ACCM_{t-1}$ is the variable of interest in Hutton, Marcus, and Tehranian (2009), which confirms Jin and Myers's (2006) theory that opacity allows managers to absorb losses by hiding temporary bad news to keep their jobs. As the bad news accumulates over time and reaches a tipping point, when managers are unwilling to absorb extra losses, it becomes public all at once, leading to a substantial decline in stock price. Although Hutton, Marcus, and Tehranian (2009) demonstrate a negative relationship between ROE_t and crash dummy, several recent studies suggest that firms with good operating performance are subject to greater crash risk (e.g., Kim, Li, and Li 2014; Callen and Fang 2015; and Kim, Wang, and Zhang 2016). Finally, I include year and 2-digit SIC industry fixed effects to control for variation in the government customer concentration across time and industry. Appendix B provides detailed definitions for the above control variables.

3.3.5 Summary Statistics

Table 3.1 presents the summary statistics and the Pearson correlation matrix of the variables used in the regression analysis. As seen in Panel A of Table 3.1, the mean values of *CRASH* and *NCSKEW* are 0.176 and -0.041, respectively, indicating that 17.6 percent of the firm years in my sample experience one or more stock price crashes, and the average negative skewness is -0.041. This and other summary statistics, except *ACCM*, are consistent with those reported in Kim, Li, and Zhang (2011a) and Chang, Chen, and Zolotoy (2016).[17] The mean value of *ACCM* is 0.551,

[17] The sample period of Kim, Li, and Zhang (2011a) is 1995–2008. The sample period of Chang, Chen, and Zolotoy (2016) is 1993–2010.

which is larger than that in Hutton, Marcus, and Tehranian (2009),[18] Kim, Li, and Zhang (2011a), and Chang, Chen, and Zolotoy (2016). The reason is that in the estimation of discretionary accruals, I employ Kothari, Leone, and Wasley's (2005) modified Jones model, which is different from the model used by the previous studies (i.e., Dechow, Sloan, and Sweeney's (1995) modified Jones model). In 8.2 percent of my observations, suppliers disclose one or more government major customers that account for 10 percent or more of their total sales. On average, firms receive 3.3 percent of their revenue from government major customers. Both of these numbers are slightly lower than those in Huang, Lobo, Wang, and Xie (2016), suggesting that my sample has a less concentrated base of government customers.[19] As seen in Panel B of Table 3.1, *CRASH* and *NCSKEW* are highly correlated. In addition, both of them are negatively correlated with the two measures of government customer concentration (i.e., *GC_D* and *GC_SALE*).

[Insert Table 3.1 Here]

3.4 Government Customer Concentration and Crash Risk: Empirical Results

3.4.1 Baseline Regression Analysis

In this section, I estimate the relation between government customer concentration and crash risk using the following specifications:

$$CRASH_{j,t} = \beta_0 + \beta_1 GC\_D_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4a}$$

[18] The sample period of Hutton, Marcus, and Tehranian (2009) is 1991–2005.
[19] The sample period of Huang, Lobo, Wang, and Xie (2016) is 1988–2011.

$$CRASH_{j,t} = \beta_0 + \beta_1 GC\_SALE_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4b}$$

$$NCSKEW_{j,t} = \beta_0 + \beta_1 GC\_D_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4c}$$

$$NCSKEW_{j,t} = \beta_0 + \beta_1 GC\_SALE_{j,t-1} + \beta_2 NCSKEW_{j,t-1} + \beta_3 SIGMA_{j,t-1} + \beta_4 RET_{j,t-1} + \beta_5 DTURN_{j,t-1} + \beta_6 SIZE_{j,t-1} + \beta_7 MB_{j,t-1} + \beta_8 LEV_{j,t-1} + \beta_9 ROA_{j,t-1} + \beta_{10} ACCM_{j,t-1} + Yr_t + Ind_j + \varepsilon_{j,t} \tag{4d}$$

where j refers to the supplier firm, t refers to the fiscal year, Yr_t refers to the year fixed effects, Ind_j refers to the industry fixed effects at the 2-digit SIC level, and $\varepsilon_{j,t}$ refers to the error term. According to the literature on crash risk, I estimate Equations (4a) and (4b) by the logit model. I estimate Equations (4c) and (4d) by ordinary least squares (OLS). I report z- and t-statistics based on heteroskedasticity-robust standard errors corrected for clustering at the supplier level.

Table 3.2 presents the baseline results for regressions of crash risk on government customer concentration. Columns 1 and 2 report the coefficient estimates for Equations (4a) and (4b) with the crash dummy as the dependent variable. Both measures of government customer concentration generate significantly negative coefficients, indicating that a concentrated base of government customers lowers the likelihood of future stock price crashes. The coefficient of *GC_D* on crash dummy is -0.102, implying that having a government major customer reduces the odds of a crash event by 10 percent. The marginal effect of *GC_SALE* on crash dummy is -0.035, meaning that when *GC_SALE* grows by one standard deviation (0.130), the likelihood of a stock price crash decreases by 0.005 (i.e., 0.130 × (-0.035) = -0.005). This amounts to a 3 percent decline in crash probability relative to the average crash dummy of 0.176.

Columns 3 and 4 report the coefficient estimates for Equations (4c) and (4d) with negative skewness as the dependent variable. Both measures of government customer concentration attract significant and negative coefficients, suggesting that a concentrated base of government customers leads to less negatively skewed future stock returns. The coefficient of *GC_D* on negative skewness reveals that having a government major customer reduces the negative skewness of a firm's stock returns by 0.028. The marginal effect of *GC_SALE* on negative skewness is -0.067, meaning that a one-standard-deviation increase in *GC_SALE* (0.130) results in a 0.009 reduction in negative skewness (i.e., 0.130 × (-0.067) = -0.009). This magnitude is economically significant given that the average negative skewness is -0.041 in my sample. Taken together, the above findings support that higher government customer concentration reduces a firm's crash risk.

[Insert Table 3.2 Here]

The results for most of the control variables are largely in line with the findings of previous crash risk studies. However, *ACCM* generates much smaller coefficients compared with those reported in Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011a), and Chang, Chen, and Zolotoy (2016). This is because *ACCM* has a larger value in my sample, because I use Kothari, Leone, and Wasley's (2005) modified Jones model to estimate discretionary accruals.

3.4.2 Robustness Tests

To test the robustness of my baseline results, this section experiments with different variable definitions, a shorter sample period, and an alternative model specification.

In Table 3.3, I address the concern that the distinct threshold (3.09 standard deviations below the annual mean) in determining crash weeks may be driving the results. In cases where stocks have low return volatility, 3.09 standard deviations below the annual mean may not be economically significant enough to be identified as a crash (Chang, Chen, and Zolotoy 2016). For this reason, I reestimate Equations (4a) and (4b) with the various thresholds in Chang, Chen, and Zolotoy (2016). For brevity, Table 3.3 only presents the coefficients of my main effect terms (*GC_D* and *GC_SALE*). In row 1, crash weeks are those with firm-specific weekly returns exceeding 3.5 standard deviations below the annual mean. In rows 2 through 4, crash weeks are those with firm-specific weekly returns below -10 percent, -15 percent, or -20 percent. The coefficients of *GC_D* and *GC_SALE* are negative and significant in all tests, suggesting that my results are robust across alternative definitions of crash weeks.

[Insert Table 3.3 Here]

In Table 3.4, I address the concern that the particular measures of crash risk may be driving the results. I rerun Equations (4c) and (4d) with number of crash weeks and down-to-up volatility as two alternative measures of crash risk. Panel A presents the results for the relation between government customer concentration and number of crash weeks. Intuitively, the number of crash weeks is more informative than the crash dummy (Chang, Chen, and Zolotoy 2016). Although only 0.53 percent of my observations have more than one crash week in a year, the number of crash weeks does show more variation in the outcomes. Panel B presents the results for the relation between government customer concentration and down-to-up volatility. According to Chen, Hong, and Stein (2001), down-to-up volatility equals the log of the ratio of the standard deviation of firm-specific weekly returns in "down" weeks over the standard deviation of firm-specific weekly returns in "up" weeks, which is computed as follows:

$$DUVOL_{j,t} = log\left\{(n_u - 1)\sum_{DOWN} W_{j,\tau}^2 \Big/ \left((n_d - 1)\sum_{UP} W_{j,\tau}^2\right)\right\} \tag{5}$$

where n_u denotes the number of "up" weeks and n_d denotes the number of "down" weeks. For any supplier *j* over a fiscal year *t*, the "up" weeks include firm-specific weekly returns above the annual mean, and the "down" weeks comprise firm-specific weekly returns below the annual mean. A larger *DUVOL* implies a more left-skewed return distribution. Since the calculation above does not include the third moments of residual returns, down-to-up volatility is less affected by extreme weeks (Chen, Hong, and Stein 2001). The coefficients of *GC_D* and *GC_SALE* remain significantly negative in both panels, indicating that my results are robust to alternative measures of crash risk.

[Insert Table 3.4 Here]

In Table 3.5, I address the concern that the specific measures of government customer concentration may be driving the results. To gauge the extent of a firm's dependence on a small set of government major customers, I consider the third proxy for government customer concentration: government major customer Herfindahl-Hirschman index (*GC_HHI*). It equals the quadratic sum of the percentage of sales attributed to all government major customers, based on Patatoukas (2012), Dhaliwal, Judd, Serfling, and Shaikh (2016), and Huang, Lobo, Wang, and Xie (2016), as follows:

$$GC\_HHI_{j,t} = \sum_{i=1}^{I} \%SALE_{j,i,t}^{2} \quad (6)$$

where $\%SALE_{j,i,t}^{2}$ represents the square of the proportion of sales from firm *j* to government major customer *i* in year *t*. If firm *j* does not have a government major customer in year *t*, $GC\_HHI_{j,t}$ equals zero. A higher *GC_HHI* corresponds to deeper exposure to a few government major customers. The coefficient of *GC_HHI* is significantly negative in each test, confirming that my results are robust to the alternative measurement of government customer concentration.

[Insert Table 3.5 Here]

In Table 3.6, I address the concern that the financial crisis years may be driving the results. In general, stocks are more volatile during a financial crisis. Thus, I repeat my analysis using the sample period excluding financial crisis years (i.e., 1987, 2000–2002, and 2008–2009). The coefficients of *GC_D* and *GC_SALE* continue to be negative and significant in all tests, showing that my results are robust to the sample period excluding financial crisis years.

[Insert Table 3.6 Here]

In Table 3.7, I control for corporate customer concentration that is found to be positively associated with crash risk in Chapter 2. To do this, I add the two measures of corporate customer concentration (*CC_D* and *CC_SALE*) to my baseline regressions. The coefficients of *GC_D* and *GC_SALE* are unaffected in all cases, suggesting that government customer concentration has incremental explanatory power on crash risk after controlling for corporate customer concentration.

[Insert Table 3.7 Here]

3.5 Conclusion

This study investigates the relation between government customer concentration and stock price crash risk. Using a large sample of U.S. firms during the period 1979–2014, I find that higher government customer concentration leads to lower crash risk. My results are robust to alternative variable definitions, the sample period excluding financial crisis years, and a different model specification. Overall, my findings suggest that a concentrated base of government customers reduces managerial bad news hoarding. When there is less hidden bad news, the firm is less prone to crashes.

My paper contributes to the growing literature on stock price crash risk determinants. In particular, my results are consistent with the bad news hoarding theory of stock price crashes proposed by Jin and Myers (2006), Bleck and Liu (2007), and Benmelech, Kandel, and Veronesi (2010). My study also expands the stream of research that examines the economic consequences of having a government major customer (e.g., Cohen and Li 2016a, 2016b; Dhaliwal, Judd, Serfling, and Shaikh 2016; and Huang, Lobo, Wang, and Xie 2016). In addition, my results provide a potential screening technique for risk management practitioners. Since government customer concentration can be considered a type of political connection through the supply chain, I expect that direct political connections also affect managers' tendency to hoard bad news. I leave this topic for future investigation.

[Insert Appendix B Here]

Chapter 4 Conclusion and Contribution

This thesis has investigated the relation between customer concentration and stock price crash risk. By dividing major customers into corporate major customers and government major customers, I examine how corporate customer concentration affects stock price crash risk in my first essay and how government customer concentration impacts stock price crash risk in my second essay.

In essay one, in line with previous research that suggests a positive association between corporate customer concentration and earnings management, I postulate that a concentrated base of corporate customers induces managers to hoard bad news, and in turn, increases firms' stock price crash risk. The main results are as follows. First, greater corporate customer concentration leads to higher stock price crash risk. Second, the positive relation between corporate customer concentration and stock price crash risk stems primarily from suppliers who operate in the durable goods sector and who do not have R&D expenses. Third, corporate customer concentration is positively related to the probability of unexpected very bad news releases in the subsequent year. My results are consistent with the arguments of Bowen, DuCharme, and Shores (1995) and Raman and Shahrur (2008) that firms engage in income-increasing accounting manipulation to improve customers' perceptions of their likelihood of fulfilling implicit claims and business prospects.

In essay two, in accordance with prior studies that imply a negative association between political connection and earnings management, I predict that a concentrated base of government customers constrains managers from stockpiling bad news and, in turn, decreases firms' stock price crash risk. The primary result is that greater government customer concentration leads to lower stock price crash risk.

My results are congruent with the arguments of Chaney, Faccio, and Parsley (2011) and Ramanna and Roychowdhury (2010) that politically connected firms use less accrual management and disclose lower earnings when they are susceptible to increased political scrutiny, which could lead to political embarrassment to their affiliated candidates.

This thesis has several contributions. First, my two essays shed light on the contrasting effects of corporate customer concentration versus government customer concentration on stock price crash risk. Second, this study aids understanding in the distinctive roles corporate major customers and government major customers play in affecting managerial disclosure incentives. Third, my findings emphasize the need to consider firms' supply-chain relationships when market practitioners make portfolio investment decisions.

Tables

Table 2.1 Distribution by Year for Crash Risk Measures

This table shows the number of observations and mean values of firms' crash risk measures by year. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. All continuous variables are winsorized within 1 and 99 percentile.

Year	Obs.	*CRASH*	*NCSKEW*
1979	1,706	0.074	-0.296
1980	1,651	0.070	-0.289
1981	1,588	0.072	-0.223
1982	1,552	0.108	-0.077
1983	1,540	0.092	-0.186
1984	2,210	0.158	-0.073
1985	2,493	0.152	-0.155
1986	2,561	0.124	-0.189
1987	2,541	0.122	-0.198
1988	2,400	0.119	-0.219
1989	2,466	0.142	-0.180
1990	2,471	0.166	-0.013
1991	2,507	0.143	-0.056
1992	2,617	0.160	-0.029
1993	2,792	0.147	-0.043
1994	2,933	0.145	-0.038
1995	3,104	0.144	-0.086
1996	3,326	0.147	-0.087
1997	3,345	0.149	-0.075
1998	3,249	0.174	-0.015
1999	3,491	0.158	-0.042
2000	3,181	0.200	0.086
2001	2,920	0.202	0.080
2002	2,901	0.228	0.147
2003	2,853	0.200	-0.024
2004	2,904	0.218	-0.002
2005	2,754	0.242	0.042
2006	2,693	0.250	0.036
2007	2,549	0.258	0.062
2008	2,283	0.275	0.239
2009	2,290	0.198	0.009
2010	2,308	0.204	-0.024
2011	2,235	0.205	0.016
2012	2,174	0.255	0.069
2013	2,156	0.259	0.021
2014	2,140	0.247	0.032
Total	90,884	0.176	-0.041

Table 2.2 Summary Statistics and Correlation Matrix

This table shows the summary statistics and correlation matrix of the crash risk variables, corporate customer concentration variables, and control variables. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. In Panel B, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics for Key Variables

	N	Mean	S.D.	5%	25%	Median	75%	95%
Crash Risk Measures								
$CRASH_t$	90,884	0.176	0.381	0.000	0.000	0.000	0.000	1.000
$NCSKEW_t$	90,884	-0.041	0.747	-1.229	-0.455	-0.064	0.337	1.245
Corporate Customer Concentration Measures								
CC_D_{t-1}	90,884	0.345	0.475	0.000	0.000	0.000	1.000	1.000
CC_SALE_{t-1}	90,884	0.131	0.228	0.000	0.000	0.000	0.184	0.670
Control Variables								
$NCSKEW_{t-1}$	90,884	-0.044	0.729	-1.205	-0.454	-0.067	0.326	1.214
$SIGMA_{t-1}$	90,884	0.056	0.031	0.019	0.033	0.049	0.071	0.117
RET_{t-1}	90,884	-0.200	0.237	-0.678	-0.246	-0.117	-0.055	-0.017
$DTURN_{t-1}$	90,884	0.003	0.070	-0.098	-0.017	0.001	0.019	0.116
$SIZE_{t-1}$	90,884	5.338	2.069	2.108	3.783	5.240	6.779	8.954
MB_{t-1}	90,884	2.667	2.897	0.583	1.114	1.771	3.009	7.819
LEV_{t-1}	90,884	0.171	0.161	0.000	0.013	0.142	0.283	0.475
ROA_{t-1}	90,884	0.022	0.154	-0.266	0.003	0.046	0.090	0.188
$ACCM_{t-1}$	90,884	0.551	1.076	0.049	0.127	0.247	0.514	1.775

Panel B. Correlation Matrix

	$CRASH_t$	$NCSKEW_t$	CC_D_{t-1}	CC_SALE_{t-1}	$NCSKEW_{t-1}$	$SIGMA_{t-1}$	RET_{t-1}	$DTURN_{t-1}$	$SIZE_{t-1}$	MB_{t-1}	LEV_{t-1}	ROA_{t-1}	$ACCM_{t-1}$
$CRASH_t$	1.000												
$NCSKEW_t$	0.612***	1.000											
CC_D_{t-1}	0.023***	0.008**	1.000										
CC_SALE_{t-1}	0.027***	0.010***	0.791***	1.000									
$NCSKEW_{t-1}$	0.040***	0.070***	0.003	0.005	1.000								
$SIGMA_{t-1}$	-0.015***	-0.033***	0.190***	0.207***	-0.007**	1.000							
RET_{t-1}	0.021***	0.036***	-0.153***	-0.174***	0.033***	-0.956***	1.000						
$DTURN_{t-1}$	0.022***	0.047***	0.007**	0.011***	0.015***	0.161***	-0.179***	1.000					
$SIZE_{t-1}$	0.089***	0.190***	-0.143***	-0.117***	0.145***	-0.467***	0.381***	0.042***	1.000				
MB_{t-1}	0.048***	0.082***	0.039***	0.073***	-0.026***	0.134***	-0.145***	0.100***	0.232***	1.000			
LEV_{t-1}	-0.032***	-0.018***	-0.120***	-0.125***	-0.006*	-0.172***	0.152***	-0.000	0.105***	-0.037***	1.000		
ROA_{t-1}	0.024***	0.057***	-0.079***	-0.128***	-0.004	-0.391***	0.394***	0.020***	0.216***	-0.142***	0.010***	1.000	
$ACCM_{t-1}$	0.049***	0.032***	0.102***	0.149***	0.032***	0.114***	-0.108***	-0.000	0.068***	0.140***	-0.106***	-0.125***	1.000

Table 2.3 Corporate Customer Concentration and Crash Risk

This table shows regression results for the relation between corporate customer concentration and crash risk. The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
CC_D_{t-1}	0.083***		0.028***	
	(3.93)		(4.81)	
CC_SALE_{t-1}		0.180***		0.048***
		(4.25)		(3.71)
Control Variables				
$NCSKEW_{t-1}$	0.048***	0.049***	0.026***	0.026***
	(3.81)	(3.82)	(6.83)	(6.84)
$SIGMA_{t-1}$	9.104***	9.043***	6.097***	6.115***
	(6.55)	(6.51)	(16.78)	(16.84)
RET_{t-1}	1.331***	1.327***	0.658***	0.660***
	(8.04)	(8.02)	(16.00)	(16.06)
$DTURN_{t-1}$	0.733***	0.734***	0.330***	0.330***
	(5.64)	(5.65)	(8.49)	(8.49)
$SIZE_{t-1}$	0.079***	0.078***	0.075***	0.075***
	(10.55)	(10.51)	(37.24)	(37.12)
MB_{t-1}	0.012***	0.011***	0.006***	0.006***
	(3.49)	(3.43)	(5.62)	(5.59)
LEV_{t-1}	-0.161**	-0.156**	-0.066***	-0.066***
	(-2.44)	(-2.37)	(-3.67)	(-3.63)
ROA_{t-1}	0.338***	0.348***	0.177***	0.180***
	(4.97)	(5.11)	(8.92)	(9.07)
$ACCM_{t-1}$	0.021**	0.020**	0.006**	0.006*
	(2.19)	(2.09)	(2.00)	(1.94)
Intercept	-3.187***	-3.187***	-0.917***	-0.916***
	(-15.57)	(-15.61)	(-11.62)	(-11.69)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	90,883	90,883	90,884	90,884
Pseudo-/Adjusted R^2	0.031	0.031	0.059	0.059

Table 2.4 Corporate Customer Concentration and Crash Risk: Alternative Definitions of Crash Weeks and Crash Risk

This table shows the results for the robustness tests using alternative definitions of crash weeks and crash risk. The dependent variable is crash risk (*CRASH*). Column 1 shows the coefficients of corporate major customer dummy (*CC_D*). Column 2 shows the coefficients of total corporate major customer sales (*CC_SALE*). The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. In rows 1-5, *CRASH* is constructed based on alternative definitions of crash weeks. In row 6, *CRASH* is the number of crash weeks for each firm-year. In row 7, *CRASH* is the down-to-up volatility defined by Chen, Hong, and Stein (2001). Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in rows 1-5 are estimated by the logit model. The regressions in rows 6-7 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: $CRASH_t$	Corporate Customer Concentration Measured by	
	CC_D_{t-1}	CC_SALE_{t-1}
Alternative definitions of crash risk	(1)	(2)
(1) 3.5 standard deviations below the mean	0.095***	0.183***
	(3.41)	(3.31)
(2) 4 standard deviations below the mean	0.074*	0.171**
	(1.92)	(2.27)
(3) Firm-specific return below -10%	0.140***	0.316***
	(6.33)	(6.53)
(4) Firm-specific return below -15%	0.130***	0.270***
	(6.49)	(6.69)
(5) Firm-specific return below -20%	0.144***	0.258***
	(6.56)	(5.98)
(6) No. of crash weeks as the dependent variable	0.012***	0.028***
	(3.86)	(4.15)
(7) Down-to-up volatility as the dependent variable	0.019***	0.037***
(Chen, Hong, and Stein (2001))	(4.99)	(4.55)

Table 2.5 Corporate Customer Concentration and Crash Risk: Alternative Measure of Corporate Customer Concentration

This table shows the results for the robustness tests using an alternative measure of corporate customer concentration. The dependent variables are crash dummy (*CRASH*) in column 1 and negative skewness (*NCSKEW*) in column 2. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer Herfindahl-Hirschman index (*CC_HHI*) equals the quadratic sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in both regressions. The regression in column 1 is estimated by the logit model. The regression in column 2 is estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*CRASH*$_t$	*NCSKEW*$_t$
	(1)	(2)
Corporate Customer Concentration		
CC_HHI$_{t-1}$	0.253***	0.052*
	(2.80)	(1.78)
Control Variables		
NCSKEW$_{t-1}$	0.049***	0.026***
	(3.81)	(6.84)
SIGMA$_{t-1}$	9.292***	6.188***
	(6.70)	(17.07)
RET$_{t-1}$	1.349***	0.666***
	(8.15)	(16.23)
DTURN$_{t-1}$	0.731***	0.329***
	(5.63)	(8.47)
SIZE$_{t-1}$	0.077***	0.074***
	(10.39)	(36.99)
MB$_{t-1}$	0.012***	0.006***
	(3.46)	(5.66)
LEV$_{t-1}$	-0.161**	-0.068***
	(-2.44)	(-3.73)
ROA$_{t-1}$	0.352***	0.181***
	(5.18)	(9.10)
ACCM$_{t-1}$	0.020**	0.006**
	(2.15)	(2.02)
Intercept	-3.181***	-0.914***
	(-15.71)	(-11.71)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	90,883	90,884
Pseudo-/Adjusted R^2	0.031	0.059

Table 2.6 Corporate Customer Concentration and Crash Risk: Alternative Measure of Opacity in Financial Reports

This table shows the results for the robustness tests using an alternative measure of opacity in financial reports (*ACCM*). The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The sample consists of firm-years in the CRSP/Compustat Merged database from 1990 to 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Opacity in financial reports (*ACCM*) is formulated by discretionary accruals based on a cash flow approach. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
CC_D_{t-1}	0.074***		0.030***	
	(3.20)		(4.41)	
CC_SALE_{t-1}		0.175***		0.053***
		(3.88)		(3.69)
Control Variables				
$NCSKEW_{t-1}$	0.045***	0.045***	0.018***	0.018***
	(3.34)	(3.35)	(4.10)	(4.11)
$SIGMA_{t-1}$	11.881***	11.757***	6.425***	6.431***
	(8.42)	(8.33)	(16.69)	(16.71)
RET_{t-1}	1.474***	1.464***	0.668***	0.668***
	(8.97)	(8.92)	(16.04)	(16.07)
$DTURN_{t-1}$	0.586***	0.587***	0.299***	0.299***
	(4.75)	(4.76)	(7.92)	(7.91)
$SIZE_{t-1}$	0.114***	0.114***	0.073***	0.073***
	(14.59)	(14.61)	(31.97)	(31.91)
MB_{t-1}	0.005	0.005	0.005***	0.005***
	(1.47)	(1.41)	(5.16)	(5.13)
LEV_{t-1}	-0.206***	-0.201***	-0.084***	-0.084***
	(-2.88)	(-2.82)	(-4.01)	(-3.99)
ROA_{t-1}	0.372***	0.380***	0.171***	0.174***
	(5.35)	(5.45)	(8.20)	(8.34)
$ACCM_{t-1}$	0.004	0.003	0.001	0.001
	(1.55)	(1.46)	(1.61)	(1.54)
Intercept	-2.718***	-2.718***	-0.715***	-0.713***
	(-11.60)	(-11.60)	(-8.36)	(-8.37)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	67,471	67,471	67,471	67,471
Pseudo-/Adjusted R^2	0.026	0.026	0.045	0.045

Table 2.7 Corporate Customer Concentration and Crash Risk: Suppliers with Information in Compustat Customer Segment Database

This table shows the results for the robustness tests on a subsample of suppliers with information in Compustat Customer Segment database. The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The subsample consists of firm-years jointly covered in the CRSP/Compustat Merged database and Compustat Customer Segment database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
CC_D_{t-1}	0.127***		0.036***	
	(4.11)		(4.32)	
CC_SALE_{t-1}		0.253***		0.057***
		(4.75)		(3.49)
Control Variables				
$NCSKEW_{t-1}$	0.050***	0.050***	0.026***	0.026***
	(2.65)	(2.68)	(4.73)	(4.76)
$SIGMA_{t-1}$	9.824***	9.517***	6.189***	6.158***
	(4.94)	(4.79)	(12.02)	(11.96)
RET_{t-1}	1.321***	1.298***	0.648***	0.646***
	(5.65)	(5.56)	(11.38)	(11.35)
$DTURN_{t-1}$	0.620***	0.623***	0.319***	0.320***
	(3.65)	(3.67)	(6.36)	(6.37)
$SIZE_{t-1}$	0.106***	0.107***	0.081***	0.081***
	(9.87)	(9.88)	(26.98)	(26.87)
MB_{t-1}	0.008	0.007	0.004***	0.004***
	(1.62)	(1.51)	(3.00)	(2.92)
LEV_{t-1}	-0.120	-0.108	-0.063**	-0.061**
	(-1.27)	(-1.15)	(-2.40)	(-2.33)
ROA_{t-1}	0.483***	0.502***	0.216***	0.221***
	(5.20)	(5.41)	(8.40)	(8.59)
$ACCM_{t-1}$	0.020	0.018	0.007	0.006
	(1.59)	(1.43)	(1.57)	(1.47)
Intercept	-3.495***	-3.466***	-1.093***	-1.081***
	(-10.92)	(-10.86)	(-10.29)	(-10.20)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	41,813	41,813	41,823	41,823
Pseudo-/Adjusted R^2	0.030	0.030	0.060	0.060

Table 2.8 Corporate Customer Concentration and Crash Risk: Subperiods

This table shows the results for the robustness tests using three subperiods. Panel A shows regression results for the sample period excluding financial crisis years. Panel B shows regression results for the sample period after Regulation Fair Disclosure. Panel C shows regression results for the sample period after SOX. In all panels, the dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The three subsamples consist of firm-years in the CRSP/Compustat Merged database over the three subperiods, respectively, with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sample period excluding financial crisis years

Dependent Variable	*CRASH*$_t$		*NCSKEW*$_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
$CC\_D_{t\text{-}1}$	0.089***		0.026***	
	(3.77)		(4.02)	
$CC\_SALE_{t\text{-}1}$		0.202***		0.048***
		(4.28)		(3.27)
Control Variables				
$NCSKEW_{t\text{-}1}$	0.049***	0.049***	0.026***	0.026***
	(3.43)	(3.43)	(6.11)	(6.12)
$SIGMA_{t\text{-}1}$	9.546***	9.464***	6.410***	6.421***
	(5.77)	(5.73)	(15.53)	(15.57)
$RET_{t\text{-}1}$	1.527***	1.523***	0.731***	0.732***
	(7.36)	(7.35)	(15.22)	(15.28)
$DTURN_{t\text{-}1}$	0.913***	0.913***	0.388***	0.388***
	(5.98)	(5.99)	(8.34)	(8.34)
$SIZE_{t\text{-}1}$	0.075***	0.075***	0.075***	0.075***
	(8.81)	(8.77)	(33.68)	(33.57)
$MB_{t\text{-}1}$	0.009**	0.009**	0.005***	0.005***
	(2.32)	(2.26)	(4.12)	(4.09)
$LEV_{t\text{-}1}$	-0.213***	-0.207***	-0.073***	-0.072***
	(-2.87)	(-2.80)	(-3.66)	(-3.61)
$ROA_{t\text{-}1}$	0.340***	0.352***	0.185***	0.188***
	(4.31)	(4.47)	(8.12)	(8.25)
$ACCM_{t\text{-}1}$	0.023**	0.021**	0.007*	0.007*
	(2.20)	(2.08)	(1.94)	(1.88)
Intercept	-3.192***	-3.193***	-0.934***	-0.933***
	(-14.51)	(-14.51)	(-10.90)	(-10.94)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	74,767	74,767	74,768	74,768
Pseudo-/Adjusted R^2	0.032	0.032	0.052	0.052

Panel B: Sample period after Regulation Fair Disclosure

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
CC_D_{t-1}	0.042		0.029***	
	(1.40)		(2.94)	
CC_SALE_{t-1}		0.152***		0.052***
		(2.72)		(2.60)
Control Variables				
$NCSKEW_{t-1}$	0.021	0.021	0.012**	0.012**
	(1.27)	(1.27)	(2.01)	(2.02)
$SIGMA_{t-1}$	15.679***	15.412***	7.464***	7.453***
	(8.37)	(8.22)	(12.71)	(12.69)
RET_{t-1}	1.766***	1.745***	0.781***	0.780***
	(8.03)	(7.94)	(11.94)	(11.93)
$DTURN_{t-1}$	0.446***	0.450***	0.258***	0.258***
	(2.96)	(2.98)	(5.12)	(5.12)
$SIZE_{t-1}$	0.118***	0.118***	0.072***	0.072***
	(11.83)	(11.89)	(22.22)	(22.18)
MB_{t-1}	0.001	0.001	0.004***	0.004***
	(0.22)	(0.18)	(2.81)	(2.76)
LEV_{t-1}	-0.213**	-0.206**	-0.082***	-0.081***
	(-2.28)	(-2.21)	(-2.67)	(-2.64)
ROA_{t-1}	0.436***	0.436***	0.153***	0.155***
	(4.77)	(4.77)	(4.88)	(4.94)
$ACCM_{t-1}$	0.005	0.005	0.002	0.002
	(0.50)	(0.45)	(0.50)	(0.47)
Intercept	-2.843***	-2.849***	-0.744***	-0.739***
	(-8.45)	(-8.43)	(-6.84)	(-6.82)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	35,159	35,159	35,160	35,160
Pseudo-/Adjusted R^2	0.018	0.018	0.035	0.035

Panel C: Sample period after SOX

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
CC_D_{t-1}	0.048		0.029***	
	(1.49)		(2.68)	
CC_SALE_{t-1}		0.167***		0.056***
		(2.79)		(2.60)
Control Variables				
$NCSKEW_{t-1}$	0.027	0.028	0.011*	0.011*
	(1.53)	(1.53)	(1.71)	(1.71)
$SIGMA_{t-1}$	15.588***	15.288***	7.584***	7.559***
	(7.17)	(7.03)	(10.99)	(10.95)
RET_{t-1}	1.821***	1.798***	0.853***	0.852***
	(6.70)	(6.62)	(10.62)	(10.61)
$DTURN_{t-1}$	0.563***	0.569***	0.267***	0.268***
	(3.33)	(3.37)	(4.64)	(4.66)
$SIZE_{t-1}$	0.112***	0.113***	0.066***	0.065***
	(10.15)	(10.20)	(17.63)	(17.59)
MB_{t-1}	-0.003	-0.003	0.002	0.002
	(-0.49)	(-0.52)	(1.43)	(1.39)
LEV_{t-1}	-0.276***	-0.268***	-0.081**	-0.080**
	(-2.71)	(-2.63)	(-2.38)	(-2.34)
ROA_{t-1}	0.467***	0.469***	0.166***	0.168***
	(4.51)	(4.51)	(4.55)	(4.60)
$ACCM_{t-1}$	0.005	0.004	0.001	0.001
	(0.40)	(0.36)	(0.36)	(0.33)
Intercept	-2.908***	-2.915***	-0.748***	-0.743***
	(-6.52)	(-6.48)	(-5.92)	(-5.90)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	29,338	29,338	29,339	29,339
Pseudo-/Adjusted R^2	0.018	0.019	0.028	0.028

Table 2.9 Corporate Customer Concentration and Crash Risk: Controls for Operating Risk

This table shows the results for the robustness tests using controls for operating risk, including cash flow volatility, sales growth, cash holdings, and R&D expenditures. The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The sample consists of firm-years in the CRSP/Compustat Merged database from 1992 to 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
CC_D_{t-1}	0.066***		0.027***	
	(2.76)		(3.85)	
CC_SALE_{t-1}		0.152***		0.041***
		(3.28)		(2.79)
Control Variables				
$NCSKEW_{t-1}$	0.054***	0.054***	0.022***	0.022***
	(3.83)	(3.83)	(4.91)	(4.91)
$SIGMA_{t-1}$	11.867***	11.813***	6.142***	6.174***
	(7.98)	(7.94)	(15.15)	(15.24)
RET_{t-1}	1.482***	1.478***	0.641***	0.644***
	(8.47)	(8.46)	(14.65)	(14.72)
$DTURN_{t-1}$	0.440***	0.442***	0.241***	0.241***
	(3.51)	(3.52)	(6.28)	(6.28)
$SIZE_{t-1}$	0.117***	0.117***	0.072***	0.072***
	(14.61)	(14.63)	(30.29)	(30.18)
MB_{t-1}	-0.000	-0.000	0.004***	0.004***
	(-0.10)	(-0.10)	(3.32)	(3.33)
LEV_{t-1}	-0.132*	-0.133*	-0.071***	-0.072***
	(-1.74)	(-1.75)	(-3.16)	(-3.22)
ROA_{t-1}	0.561***	0.560***	0.244***	0.244***
	(6.69)	(6.67)	(10.11)	(10.12)
$ACCM_{t-1}$	0.007	0.006	0.002	0.002
	(0.87)	(0.79)	(0.82)	(0.77)
Cash flow volatility$_{t-1}$	0.094	0.092	0.033	0.033
	(1.16)	(1.14)	(1.32)	(1.34)
Sales growth$_{t-1}$	0.136***	0.134***	0.074***	0.074***
	(5.13)	(5.07)	(8.74)	(8.71)
Cash holdings$_{t-1}$	-0.005	-0.008	-0.001	-0.002
	(-0.33)	(-0.51)	(-0.28)	(-0.38)
R&D expenditures$_{t-1}$	0.067**	0.063**	0.024***	0.023***
	(2.55)	(2.43)	(2.72)	(2.60)
Intercept	-2.608***	-2.607***	-0.678***	-0.675***
	(-12.77)	(-12.80)	(-8.06)	(-8.07)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	62,552	62,552	62,553	62,553
Pseudo-/Adjusted R^2	0.026	0.026	0.048	0.048

Table 2.10 Corporate Customer Concentration and Crash Risk: Controls for Additional Variables

This table shows the results for the robustness tests using additional controls, including high-frequency trading, tax avoidance, CFO option incentives, board independence, CEO duality, big auditor, auditor industry specialization, high litigation industry, real earnings management, financial distress risk, and liquidity. The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
CC_D_{t-1}	0.212***		0.042*	
	(3.04)		(1.90)	
CC_SALE_{t-1}		0.343**		0.078
		(2.43)		(1.52)
Control Variables				
$NCSKEW_{t-1}$	-0.009	-0.008	-0.010	-0.010
	(-0.23)	(-0.21)	(-0.72)	(-0.72)
$SIGMA_{t-1}$	13.984**	14.446**	6.819***	6.894***
	(2.21)	(2.30)	(3.44)	(3.49)
RET_{t-1}	1.412	1.463	0.661**	0.669**
	(1.49)	(1.55)	(2.19)	(2.22)
$DTURN_{t-1}$	0.256	0.246	0.088	0.087
	(0.71)	(0.69)	(0.76)	(0.75)
$SIZE_{t-1}$	-0.054	-0.053	0.019*	0.020*
	(-1.44)	(-1.40)	(1.67)	(1.67)
MB_{t-1}	0.013	0.012	0.007	0.007
	(0.93)	(0.88)	(1.38)	(1.35)
LEV_{t-1}	-0.147	-0.134	-0.045	-0.042
	(-0.62)	(-0.56)	(-0.55)	(-0.51)
ROA_{t-1}	0.557	0.551	0.198	0.197
	(1.52)	(1.51)	(1.47)	(1.46)
$ACCM_{t-1}$	0.019	0.018	0.006	0.006
	(1.27)	(1.24)	(1.23)	(1.21)
High-frequency trading$_{t-1}$	0.107	0.105	0.061**	0.060*
	(1.13)	(1.11)	(1.96)	(1.92)
Tax avoidance$_{t-1}$	-0.005	-0.005	-0.004	-0.004
	(-0.68)	(-0.69)	(-1.50)	(-1.50)
CFO option incentives$_{t-1}$	0.004	0.004	0.005	0.005
	(0.13)	(0.13)	(0.47)	(0.48)
Board independence$_{t-1}$	-0.081	-0.075	-0.074	-0.073
	(-0.37)	(-0.34)	(-1.07)	(-1.06)
CEO duality$_{t-1}$	-0.034	-0.036	0.018	0.018
	(-0.54)	(-0.56)	(0.83)	(0.82)
Big auditor$_{t-1}$	0.064	0.067	-0.040	-0.039
	(0.44)	(0.46)	(-0.85)	(-0.83)
Auditor industry specialization$_{t-1}$	0.031	0.032	0.002	0.003

	(0.46)	(0.48)	(0.11)	(0.13)
High litigation industry$_{t-1}$	0.293**	0.299**	0.063	0.063
	(2.35)	(2.37)	(1.48)	(1.49)
Real earnings management$_{t-1}$	0.051	0.048	0.092**	0.091**
	(0.39)	(0.37)	(2.06)	(2.04)
Financial distress risk$_{t-1}$	-0.294	-0.301	-0.242***	-0.243***
	(-1.42)	(-1.46)	(-3.51)	(-3.52)
Lquidity$_{t-1}$	1.804***	1.793***	0.195*	0.192*
	(4.54)	(4.50)	(1.90)	(1.87)
Intercept	-1.797	-1.729	-0.422	-0.410
	(-1.29)	(-1.26)	(-1.51)	(-1.49)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	7,136	7,136	7,139	7,139
Pseudo-/Adjusted R^2	0.030	0.029	0.018	0.018

Table 2.11 Propensity Score Matched Sample Analysis

This table shows the results for the endogeneity tests using a propensity score matched sample. Panel A shows the univariate statistics comparing the mean characteristics of firms with and without corporate major customers for the full and propensity score matched samples. Panel B shows the multivariate results. Column 1 of Panel B shows the first-stage marginal effect of control variables on corporate major customer dummy (*CC_D*) from a logistic regression used to calculate the propensity scores. Columns 2-5 of Panel B show regression results for the relation between corporate customer concentration and crash risk using the propensity score matched sample. In Panel B, the dependent variables are corporate major customer dummy (*CC_D*) in column 1, crash dummy (*CRASH*) in columns 2-3 and negative skewness (*NCSKEW*) in columns 4-5. The full sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. The propensity score matched sample consists of pairs of firms matched by propensity scores within a caliper distance of 1 percent. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-3 of Panel B are estimated by the logit model. The regressions in columns 4-5 of Panel B are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Descriptive statistics for full and propensity-score matched samples

	Full Sample (obs.=90,884)			Propensity-Score Matched Sample (obs.=52,962)		
	CC_D_{t-1}=1 (obs.=31,382) Mean	CC_D_{t-1}=0 (obs.=59,502) Mean	Difference in Means (t-statistics)	CC_D_{t-1}=1 (obs.=26,481) Mean	CC_D_{t-1}=0 (obs.=26,481) Mean	Difference in Means (t-statistics)
$NCSKEW_{t-1}$	-0.041	-0.046	0.005	-0.041	-0.036	-0.005
			(0.93)			(-0.74)
$SIGMA_{t-1}$	0.064	0.051	0.012***	0.061	0.062	-0.001*
			(58.42)			(-1.92)
RET_{t-1}	-0.250	-0.173	-0.077***	-0.235	-0.238	0.003
			(-46.77)			(1.26)
$DTURN_{t-1}$	0.004	0.003	0.001**	0.004	0.003	0.000
			(1.98)			(0.74)
$SIZE_{t-1}$	4.931	5.552	-0.621***	5.057	5.021	0.035**
			(-43.47)			(2.05)
MB_{t-1}	2.820	2.586	0.235***	2.837	2.818	0.020
			(11.62)			(0.73)
LEV_{t-1}	0.145	0.185	-0.041***	0.150	0.150	0.000
			(-36.54)			(0.10)
ROA_{t-1}	0.005	0.030	-0.025***	0.006	0.005	0.001
			(-23.79)			(0.91)
$ACCM_{t-1}$	0.702	0.472	0.231***	0.667	0.674	-0.007
			(30.91)			(-0.65)

Panel B: Multivariate Results

Dependent Variable	First Stage	Second Stage			
	CC_D_{t-1}	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)	(5)
Corporate Customer Concentration					
CC_D_{t-1}		0.071***		0.024***	
		(3.07)		(3.63)	
CC_SALE_{t-1}			0.154***		0.035**
			(3.33)		(2.38)
Control Variables					
$NCSKEW_{t-1}$	-0.001	0.044***	0.045***	0.021***	0.021***
	(-0.09)	(2.73)	(2.75)	(4.36)	(4.37)
$SIGMA_{t-1}$	25.697***	10.225***	10.017***	6.696***	6.649***
	(13.24)	(5.95)	(5.82)	(14.53)	(14.41)
RET_{t-1}	2.301***	1.386***	1.367***	0.701***	0.697***
	(11.54)	(6.85)	(6.75)	(13.71)	(13.62)
$DTURN_{t-1}$	-0.153	0.705***	0.707***	0.328***	0.329***
	(-1.60)	(4.53)	(4.55)	(6.95)	(6.97)
$SIZE_{t-1}$	-0.156***	0.106***	0.107***	0.081***	0.081***
	(-11.36)	(11.30)	(11.36)	(30.80)	(30.86)
MB_{t-1}	0.025***	0.008*	0.008*	0.004***	0.004***
	(4.96)	(1.91)	(1.85)	(3.46)	(3.42)
LEV_{t-1}	-0.543***	-0.275***	-0.270***	-0.098***	-0.097***
	(-4.62)	(-3.35)	(-3.30)	(-4.30)	(-4.25)
ROA_{t-1}	0.446***	0.373***	0.379***	0.180***	0.182***
	(4.81)	(4.76)	(4.83)	(7.92)	(7.98)
$ACCM_{t-1}$	0.031**	0.023**	0.022**	0.005	0.005
	(2.23)	(2.08)	(2.03)	(1.38)	(1.34)
Intercept	-1.767***	-3.405***	-3.394***	-1.000***	-0.993***
	(-4.74)	(-11.56)	(-11.56)	(-9.97)	(-9.97)
IND/YEAR	Yes	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes	Yes
No. of observations	90,883	52,950	52,950	52,962	52,962
Pseudo-/Adjusted R^2	0.161	0.031	0.031	0.060	0.060

Table 2.12 IV Estimations: Corporate Customer Concentration and Crash Dummy

This table shows the results from the endogeneity tests using two instrumental variables by 2-Stage Least Squares regressions. Panel A shows the first-stage results. In Panel A, the dependent variables are corporate major customer dummy (*CC_D*) in column 1 and total corporate major customer sales (*CC_SALE*) in column 2. The instrumental variables are industry average corporate customer concentration of other suppliers in years *t*-3 and *t*-4. Panel B shows the second-stage results. In Panel B, the dependent variable is crash dummy (*CRASH*). The predicted corporate major customer dummy (*Predicted CC_D*) and predicted total corporate major customer sales (*Predicted CC_SALE*) resulting from the first-stage regressions are used in the second-stage regressions. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The t-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First-Stage Results

Dependent Variable	Industry average corporate customer concentration as IV	
	CC_D$_{t-1}$	*CC_SALE*$_{t-1}$
	(1)	(2)
Instrumental Variables		
Industry Average Corporate Customer Concentration$_{t-3}$	0.209***	0.267***
	(10.52)	(12.18)
Industry Average Corporate Customer Concentration$_{t-4}$	0.226***	0.274***
	(12.29)	(13.44)
Control Variables		
NSKEW$_{t-1}$	-0.000	-0.001
	(-0.11)	(-1.17)
SIGMA$_{t-1}$	4.567***	2.169***
	(10.18)	(10.52)
RET$_{t-1}$	0.455***	0.212***
	(8.49)	(8.31)
DTURN$_{t-1}$	-0.034	-0.017
	(-1.40)	(-1.33)
SIZE$_{t-1}$	-0.031***	-0.012***
	(-11.28)	(-9.79)
MB$_{t-1}$	0.006***	0.003***
	(3.69)	(4.43)
LEV$_{t-1}$	-0.109***	-0.066***
	(-4.32)	(-5.27)
ROA$_{t-1}$	0.053*	-0.024
	(1.96)	(-1.49)
ACCM$_{t-1}$	0.013***	0.011***
	(3.38)	(4.73)
Intercept	0.172*	0.080
	(1.71)	(1.32)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	73,802	73,802
Adjusted R^2	0.192	0.199
Test of endogeneity, weak instruments, and overidentification		
Wu-Hausman F-statistic	16.66 ($p < 0.01$)	18.16 ($p < 0.01$)
F-statistic	14.12 ($p < 0.01$)	14.51 ($p < 0.01$)
Partial R^2	0.019	0.034
Sargan Test (Pr > χ^2)	0.474 ($p > 0.1$)	1.981 ($p > 0.1$)

Panel B: Second-Stage Results

Dependent Variable	$CRASH_t$	
	(1)	(2)
Corporate Customer Concentration		
Predicted $CC\_D_{t\text{-}1}$	0.106***	
	(4.04)	
Predicted $CC\_SALE_{t\text{-}1}$		0.188***
		(4.29)
Control Variables		
$NSKEW_{t\text{-}1}$	0.006***	0.007***
	(2.98)	(3.09)
$SIGMA_{t\text{-}1}$	0.854***	0.918***
	(3.05)	(3.41)
$RET_{t\text{-}1}$	0.160***	0.168***
	(4.74)	(5.12)
$DTURN_{t\text{-}1}$	0.126***	0.126***
	(4.91)	(4.90)
$SIZE_{t\text{-}1}$	0.012***	0.011***
	(8.53)	(8.77)
$MB_{t\text{-}1}$	0.003***	0.002***
	(3.14)	(3.04)
$LEV_{t\text{-}1}$	0.002	0.004
	(0.17)	(0.31)
$ROA_{t\text{-}1}$	0.051***	0.064***
	(3.56)	(4.44)
$ACCM_{t\text{-}1}$	0.004*	0.003
	(1.95)	(1.39)
Intercept	-0.048	-0.047
	(-1.39)	(-1.45)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	73,802	73,802
Adjusted R^2	0.015	0.020

Table 2.13 IV Estimations: Corporate Customer Concentration and Negative Skewness
This table shows the results from the endogeneity tests using two instrumental variables by 2-Stage Least Squares regressions. Panel A shows the first-stage results. In Panel A, the dependent variables are corporate major customer dummy (*CC_D*) in column 1 and total corporate major customer sales (*CC_SALE*) in column 2. The instrumental variables are industry average corporate customer concentration of other suppliers in years *t*-3 and *t*-4. Panel B shows the second-stage results. In Panel B, the dependent variable is negative skewness (*NCSKEW*). The predicted corporate major customer dummy (*Predicted CC_D*) and predicted total corporate major customer sales (*Predicted CC_SALE*) resulting from the first-stage regressions are used in the second-stage regressions. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The t-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First-Stage Results

Dependent Variable	Industry average corporate customer concentration as IV	
	CC_D_{t-1}	CC_SALE_{t-1}
	(1)	(2)
Instrumental Variables		
Industry Average Corporate Customer Concentration$_{t-3}$	0.209***	0.267***
	(10.52)	(12.18)
Industry Average Corporate Customer Concentration$_{t-4}$	0.226***	0.274***
	(12.29)	(13.44)
Control Variables		
$NSKEW_{t-1}$	-0.000	-0.001
	(-0.11)	(-1.17)
$SIGMA_{t-1}$	4.567***	2.169***
	(10.18)	(10.52)
RET_{t-1}	0.455***	0.212***
	(8.49)	(8.31)
$DTURN_{t-1}$	-0.034	-0.017
	(-1.40)	(-1.33)
$SIZE_{t-1}$	-0.031***	-0.012***
	(-11.28)	(-9.79)
MB_{t-1}	0.006***	0.003***
	(3.69)	(4.43)
LEV_{t-1}	-0.109***	-0.066***
	(-4.32)	(-5.27)
ROA_{t-1}	0.053*	-0.024
	(1.96)	(-1.49)
$ACCM_{t-1}$	0.013***	0.011***
	(3.38)	(4.73)
Intercept	0.172*	0.080
	(1.71)	(1.32)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	73,802	73,802
Adjusted R^2	0.192	0.199
Test of endogeneity, weak instruments, and overidentification		
Wu-Hausman F-statistic	7.84 ($p < 0.01$)	3.49 ($p < 0.1$)
F-statistic	6.93 ($p < 0.01$)	2.94 ($p < 0.1$)
Partial R^2	0.019	0.034
Sargan Test (Pr > χ^2)	2.335 ($p > 0.1$)	0.571 ($p > 0.1$)

Panel B: Second-Stage Results

Dependent Variable	*NCSKEW*$_t$	
	(1)	(2)
Corporate Customer Concentration		
Predicted CC_D$_{t\text{-}1}$	0.150***	
	(3.08)	
Predicted CC_SALE$_{t\text{-}1}$		0.187**
		(2.31)
Control Variables		
NSKEW$_{t\text{-}1}$	0.023***	0.023***
	(5.39)	(5.45)
SIGMA$_{t\text{-}1}$	5.898***	6.195***
	(11.06)	(12.04)
RET$_{t\text{-}1}$	0.685***	0.715***
	(10.54)	(11.30)
DTURN$_{t\text{-}1}$	0.337***	0.335***
	(7.06)	(7.01)
SIZE$_{t\text{-}1}$	0.075***	0.073***
	(27.88)	(30.26)
MB$_{t\text{-}1}$	0.007***	0.007***
	(4.56)	(4.71)
LEV$_{t\text{-}1}$	-0.022	-0.026
	(-0.99)	(-1.19)
ROA$_{t\text{-}1}$	0.194***	0.208***
	(6.84)	(7.35)
ACCM$_{t\text{-}1}$	0.004	0.003
	(0.93)	(0.81)
Intercept	-1.001***	-0.990***
	(-10.31)	(-10.83)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	73,802	73,802
Adjusted R^2	0.051	0.054

Table 2.14 Corporate Customer Concentration and Crash Risk: Effect of Durable Goods

This table shows regression results for the relation between corporate customer concentration and crash risk on subsamples in durable and nondurable sectors. Panel A shows regression results for the relation between corporate customer concentration and crash dummy. The dependent variable is crash dummy (*CRASH*) in Panel A. Panel B shows regression results for the relation between corporate customer concentration and negative skewness. The dependent variable is negative skewness (*NCSKEW*) in Panel B. The subsample consists of manufacturing firms (SIC 2000–3999) in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Durable goods sector refers to industries with SIC codes between 3,400 and 3,999. Nondurable goods sector refers to industries with SIC codes between 2,000 and 3,399. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in Panel A are estimated by the logit model. The regressions in Panel B are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Corporate Customer Concentration and Crash Dummy

Dependent Variable	$CRASH_t$			
	(1)	(2)	(3)	(4)
	Durable Goods Sector	Nondurable Goods Sector	Durable Goods Sector	Nondurable Goods Sector
Corporate Customer Concentration				
CC_D_{t-1}	0.115***	0.034		
	(3.15)	(0.80)		
CC_SALE_{t-1}			0.248***	0.013
			(3.46)	(0.17)
Control Variables				
$NCSKEW_{t-1}$	0.004	0.059**	0.004	0.059**
	(0.17)	(2.32)	(0.15)	(2.32)
$SIGMA_{t-1}$	11.837***	6.025**	11.833***	6.143**
	(4.60)	(2.12)	(4.60)	(2.16)
RET_{t-1}	1.696***	1.049***	1.705***	1.060***
	(5.32)	(3.26)	(5.36)	(3.29)
$DTURN_{t-1}$	0.652***	1.052***	0.653***	1.051***
	(3.01)	(3.60)	(3.02)	(3.60)
$SIZE_{t-1}$	0.095***	0.042**	0.095***	0.041**
	(7.42)	(2.48)	(7.41)	(2.42)
MB_{t-1}	0.012*	0.014**	0.012*	0.014**
	(1.71)	(2.23)	(1.74)	(2.25)
LEV_{t-1}	-0.087	-0.260*	-0.084	-0.261*
	(-0.65)	(-1.95)	(-0.62)	(-1.96)
ROA_{t-1}	0.605***	0.065	0.611***	0.072
	(4.86)	(0.59)	(4.91)	(0.65)
$ACCM_{t-1}$	0.022	0.028**	0.021	0.028*
	(1.02)	(1.96)	(0.94)	(1.96)
Intercept	-3.233***	-3.016***	-3.525***	-3.011***
	(-13.45)	(-12.74)	(-15.45)	(-12.71)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	26,962	21,840	26,962	21,840
Pseudo-R^2	0.033	0.029	0.033	0.029

Panel B: Corporate Customer Concentration and Negative Skewness

Dependent Variable	$NCSKEW_t$			
	(1)	(2)	(3)	(4)
	Durable Goods Sector	Nondurable Goods Sector	Durable Goods Sector	Nondurable Goods Sector
Corporate Customer Concentration				
CC_D_{t-1}	0.022**	0.009		
	(2.30)	(0.77)		
CC_SALE_{t-1}			0.062***	-0.001
			(2.92)	(-0.05)
Control Variables				
$NCSKEW_{t-1}$	0.015**	0.029***	0.015**	0.029***
	(2.27)	(3.54)	(2.26)	(3.54)
$SIGMA_{t-1}$	7.251***	6.074***	7.205***	6.124***
	(11.45)	(7.38)	(11.37)	(7.43)
RET_{t-1}	0.746***	0.710***	0.744***	0.715***
	(10.39)	(7.82)	(10.36)	(7.86)
$DTURN_{t-1}$	0.263***	0.457***	0.264***	0.456***
	(4.10)	(4.92)	(4.11)	(4.92)
$SIZE_{t-1}$	0.081***	0.071***	0.081***	0.071***
	(23.28)	(15.36)	(23.33)	(15.34)
MB_{t-1}	0.006***	0.004**	0.006***	0.004**
	(3.17)	(2.27)	(3.15)	(2.31)
LEV_{t-1}	-0.123***	-0.069*	-0.122***	-0.070*
	(-3.43)	(-1.88)	(-3.38)	(-1.89)
ROA_{t-1}	0.278***	0.054	0.279***	0.056
	(8.08)	(1.51)	(8.11)	(1.54)
$ACCM_{t-1}$	0.004	0.007	0.004	0.007
	(0.57)	(1.43)	(0.50)	(1.43)
Intercept	-0.874***	-0.830***	-0.871***	-0.829***
	(-21.13)	(-16.18)	(-21.10)	(-16.15)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	26,962	21,841	26,962	21,841
Adjusted R^2	0.067	0.053	0.067	0.053

Table 2.15 Corporate Customer Concentration and Crash Risk: Effect of R&D Expenses

This table shows regression results for the relation between corporate customer concentration and crash risk on subsamples with zero and relatively high R&D expenses. Panel A shows regression results for the relation between corporate customer concentration and crash dummy. The dependent variable is crash dummy (*CRASH*) in Panel A. Panel B shows regression results for the relation between corporate customer concentration and negative skewness. The dependent variable is negative skewness (*NCSKEW*) in Panel B. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with zero and relatively high R&D expenses and non-missing values for the control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. R&D expenses equal the average ratio of research and development expenditures (*XRD*) to total assets (*AT*) over the past three years. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in Panel A are estimated by the logit model. The regressions in Panel B are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Corporate Customer Concentration and Crash Dummy

Dependent Variable	$CRASH_t$			
	(1)	(2)	(3)	(4)
	R&D Expenses=0	High R&D Expenses	R&D Expenses=0	High R&D Expenses
Corporate Customer Concentration				
CC_D_{t-1}	0.098***	0.047		
	(3.02)	(1.24)		
CC_SALE_{t-1}			0.225***	0.081
			(3.33)	(1.19)
Control Variables				
$NCSKEW_{t-1}$	0.071***	0.001	0.071***	0.001
	(3.81)	(0.03)	(3.82)	(0.03)
$SIGMA_{t-1}$	5.047**	12.864***	5.073**	12.821***
	(2.43)	(4.75)	(2.44)	(4.73)
RET_{t-1}	0.834***	1.618***	0.841***	1.614***
	(3.17)	(5.67)	(3.20)	(5.65)
$DTURN_{t-1}$	0.731***	0.623***	0.732***	0.624***
	(3.39)	(3.28)	(3.40)	(3.28)
$SIZE_{t-1}$	0.059***	0.134***	0.059***	0.134***
	(5.40)	(9.33)	(5.42)	(9.32)
MB_{t-1}	0.009	0.009*	0.009	0.009*
	(1.62)	(1.79)	(1.57)	(1.78)
LEV_{t-1}	-0.169*	-0.235	-0.167*	-0.233
	(-1.90)	(-1.52)	(-1.87)	(-1.51)
ROA_{t-1}	0.270*	0.340***	0.268*	0.344***
	(1.72)	(3.75)	(1.71)	(3.79)
$ACCM_{t-1}$	0.016	0.020	0.015	0.019
	(0.82)	(1.27)	(0.77)	(1.23)
Intercept	-2.835***	-3.658***	-2.848***	-3.650***
	(-11.74)	(-8.03)	(-11.71)	(-8.02)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	46,350	21,548	46,350	21,548
Pseudo-R^2	0.029	0.034	0.029	0.034

Panel B: Corporate Customer Concentration and Negative Skewness

Dependent Variable	$NCSKEW_t$			
	(1)	(2)	(3)	(4)
	R&D Expenses=0	High R&D Expenses	R&D Expenses=0	High R&D Expenses
Corporate Customer Concentration				
$CC\_D_{t\text{-}1}$	0.038***	0.017		
	(4.44)	(1.42)		
$CC\_SALE_{t\text{-}1}$			0.065***	0.022
			(3.28)	(0.96)
Control Variables				
$NCSKEW_{t\text{-}1}$	0.035***	0.000	0.036***	0.000
	(6.63)	(0.02)	(6.64)	(0.02)
$SIGMA_{t\text{-}1}$	4.985***	7.356***	5.019***	7.374***
	(9.29)	(9.42)	(9.36)	(9.43)
$RET_{t\text{-}1}$	0.549***	0.779***	0.554***	0.780***
	(8.43)	(9.98)	(8.50)	(10.00)
$DTURN_{t\text{-}1}$	0.325***	0.344***	0.325***	0.344***
	(5.40)	(5.55)	(5.40)	(5.55)
$SIZE_{t\text{-}1}$	0.070***	0.085***	0.070***	0.084***
	(24.56)	(20.27)	(24.49)	(20.25)
$MB_{t\text{-}1}$	0.004**	0.006***	0.004**	0.006***
	(2.37)	(3.73)	(2.33)	(3.74)
$LEV_{t\text{-}1}$	-0.010	-0.171***	-0.009	-0.170***
	(-0.41)	(-3.73)	(-0.39)	(-3.71)
$ROA_{t\text{-}1}$	0.230***	0.149***	0.231***	0.150***
	(5.89)	(5.25)	(5.93)	(5.31)
$ACCM_{t\text{-}1}$	0.021***	0.002	0.021***	0.002
	(3.40)	(0.41)	(3.39)	(0.39)
Intercept	-0.852***	-0.915***	-0.852***	-0.913***
	(-8.26)	(-9.90)	(-8.31)	(-9.92)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	46,350	21,567	46,350	21,567
Adjusted R^2	0.059	0.062	0.059	0.062

Table 2.16 Corporate Customer Concentration and Unexpected Very Bad News Releases

This table shows regression results for the relation between corporate customer concentration and unexpected very bad news releases. The dependent variable is unexpected very bad news releases (*SURP_UE*). The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the unexpected earnings and control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Unexpected very bad news releases (*SURP_UE*) is an indicator variable that equals one if a firm's unexpected earnings are non-negative in the previous fiscal year and fall in the bottom decile in the current year, and zero otherwise. Unexpected earnings equal the annual change of a firm's income before extraordinary items (*IB*) divided by its lagged market value of equity (*PRCC_F×CSHPRI*). Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in both regressions. The regressions are estimated by the logit model. The z-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$SURP\_UE_t$	
	(1)	(2)
Corporate Customer Concentration		
CC_D_{t-1}	0.102***	
	(2.85)	
CC_SALE_{t-1}		0.294***
		(4.06)
Control Variables		
$NSKEW_{t-1}$	-0.094***	-0.094***
	(-4.60)	(-4.62)
$SIGMA_{t-1}$	34.284***	34.106***
	(15.40)	(15.32)
RET_{t-1}	2.170***	2.162***
	(8.86)	(8.83)
$DTURN_{t-1}$	0.386*	0.389*
	(1.72)	(1.74)
$SIZE_{t-1}$	-0.173***	-0.173***
	(-11.87)	(-11.85)
MB_{t-1}	-0.236***	-0.237***
	(-10.78)	(-10.81)
LEV_{t-1}	1.269***	1.282***
	(11.54)	(11.64)
ROA_{t-1}	3.981***	3.977***
	(16.33)	(16.38)
$ACCM_{t-1}$	0.066***	0.064***
	(4.28)	(4.12)
Intercept	-3.049***	-3.061***
	(-9.31)	(-9.35)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	90,812	90,812
Pseudo-R^2	0.099	0.099

Table 3.1 Summary Statistics and Correlation Matrix

This table shows the summary statistics and correlation matrix of the crash risk variables, government customer concentration variables, and control variables. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Government major customer dummy (*GC_D*) is an indicator variable that equals one if a firm discloses one or more government major customers who account for at least 10% of its total sales, and zero otherwise. Total government major customer sales (*GC_SALE*) equal the sum of the percentage sales to all government major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix B. All continuous variables are winsorized within 1 and 99 percentile. In Panel B, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Summary Statistics for Key Variables

	N	Mean	S.D.	5%	25%	Median	75%	95%
Crash Risk Measures								
$CRASH_t$	90,884	0.176	0.381	0.000	0.000	0.000	0.000	1.000
$NCSKEW_t$	90,884	-0.041	0.747	-1.229	-0.455	-0.064	0.337	1.245
Government Customer Concentration Measures								
GC_D_{t-1}	90,884	0.082	0.274	0.000	0.000	0.000	0.000	1.000
GC_SALE_{t-1}	90,884	0.033	0.130	0.000	0.000	0.000	0.000	0.260
Control Variables								
$NCSKEW_{t-1}$	90,884	-0.044	0.729	-1.205	-0.454	-0.067	0.326	1.214
$SIGMA_{t-1}$	90,884	0.056	0.031	0.019	0.033	0.049	0.071	0.117
RET_{t-1}	90,884	-0.200	0.237	-0.678	-0.246	-0.117	-0.055	-0.017
$DTURN_{t-1}$	90,884	0.003	0.070	-0.098	-0.017	0.001	0.019	0.116
$SIZE_{t-1}$	90,884	5.338	2.069	2.108	3.783	5.240	6.779	8.954
MB_{t-1}	90,884	2.667	2.897	0.583	1.114	1.771	3.009	7.819
LEV_{t-1}	90,884	0.171	0.161	0.000	0.013	0.142	0.283	0.475
ROA_{t-1}	90,884	0.022	0.154	-0.266	0.003	0.046	0.090	0.188
$ACCM_{t-1}$	90,884	0.551	1.076	0.049	0.127	0.247	0.514	1.775

Panel B. Correlation Matrix

	CRASH$_t$	*NCSKEW*$_t$	*GC_D*$_{t-1}$	*GC_SALE*$_{t-1}$	*NCSKEW*$_{t-1}$	*SIGMA*$_{t-1}$	*RET*$_{t-1}$	*DTURN*$_{t-1}$	*SIZE*$_{t-1}$	*MB*$_{t-1}$	*LEV*$_{t-1}$	*ROA*$_{t-1}$	*ACCM*$_{t-1}$
CRASH$_t$	1.000												
NCSKEW$_t$	0.612***	1.000											
GC_D$_{t-1}$	-0.014***	-0.022***	1.000										
GC_SALE$_{t-1}$	-0.012***	-0.020***	0.850***	1.000									
NCSKEW$_{t-1}$	0.040***	0.070***	-0.021***	-0.019***	1.000								
SIGMA$_{t-1}$	-0.015***	-0.033***	0.012***	0.016***	-0.007**	1.000							
RET$_{t-1}$	0.021***	0.036***	-0.002	-0.005	0.033***	-0.956***	1.000						
DTURN$_{t-1}$	0.022***	0.047***	-0.005	-0.005	0.015***	0.161***	-0.179***	1.000					
SIZE$_{t-1}$	0.089***	0.190***	-0.078***	-0.071***	0.145***	-0.467***	0.381***	0.042***	1.000				
MB$_{t-1}$	0.048***	0.082***	-0.028***	-0.020***	-0.026***	0.134***	-0.145***	0.100***	0.232***	1.000			
LEV$_{t-1}$	-0.032***	-0.018***	-0.024***	-0.028***	-0.006*	-0.172***	0.152***	-0.000	0.105***	-0.037***	1.000		
ROA$_{t-1}$	0.024***	0.057***	0.001	0.002	-0.004	-0.391***	0.394***	0.020***	0.216***	-0.142***	0.010***	1.000	
ACCM$_{t-1}$	0.049***	0.032***	-0.018***	-0.003	0.032***	0.114***	-0.108***	-0.000	0.068***	0.140***	-0.106***	-0.125***	1.000

Table 3.2 Government Customer Concentration and Crash Risk

This table shows regression results for the relation between government customer concentration and crash risk. The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Government major customer dummy (*GC_D*) is an indicator variable that equals one if a firm discloses one or more government major customers who account for at least 10% of its total sales, and zero otherwise. Total government major customer sales (*GC_SALE*) equal the sum of the percentage sales to all government major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix B. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	*CRASH*$_t$		*NCSKEW*$_t$	
	(1)	(2)	(3)	(4)
Government Customer Concentration				
GC_D$_{t-1}$	-0.102***		-0.028***	
	(-2.71)		(-2.78)	
GC_SALE$_{t-1}$		-0.254***		-0.067***
		(-3.27)		(-3.07)
Control Variables				
NCSKEW$_{t-1}$	0.048***	0.048***	0.026***	0.026***
	(3.77)	(3.76)	(6.81)	(6.80)
SIGMA$_{t-1}$	9.468***	9.453***	6.217***	6.215***
	(6.83)	(6.82)	(17.18)	(17.18)
RET$_{t-1}$	1.365***	1.364***	0.669***	0.669***
	(8.25)	(8.25)	(16.32)	(16.32)
DTURN$_{t-1}$	0.733***	0.733***	0.330***	0.330***
	(5.63)	(5.64)	(8.49)	(8.49)
SIZE$_{t-1}$	0.076***	0.076***	0.074***	0.074***
	(10.16)	(10.15)	(36.82)	(36.80)
MB$_{t-1}$	0.012***	0.012***	0.006***	0.006***
	(3.52)	(3.51)	(5.70)	(5.69)
LEV$_{t-1}$	-0.166**	-0.166**	-0.069***	-0.069***
	(-2.52)	(-2.51)	(-3.80)	(-3.79)
ROA$_{t-1}$	0.343***	0.344***	0.179***	0.179***
	(5.04)	(5.05)	(9.03)	(9.04)
ACCM$_{t-1}$	0.021**	0.021**	0.007**	0.007**
	(2.25)	(2.27)	(2.07)	(2.09)
Intercept	-3.163***	-3.163***	-0.909***	-0.910***
	(-15.65)	(-15.66)	(-11.65)	(-11.65)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	90,883	90,883	90,884	90,884
Pseudo-/Adjusted R^2	0.031	0.031	0.059	0.059

Table 3.3 Government Customer Concentration and Crash Risk: Alternative Definitions of Crash Weeks

This table shows the results for the robustness tests using alternative definitions of crash weeks. The dependent variable is crash dummy (*CRASH*). Column 1 shows the coefficients of government major customer dummy (*GC_D*). Column 2 shows the coefficients of total government major customer sales (*GC_SALE*). The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Government major customer dummy (*GC_D*) is an indicator variable that equals one if a firm discloses one or more government major customers who account for at least 10% of its total sales, and zero otherwise. Total government major customer sales (*GC_SALE*) equal the sum of the percentage sales to all government major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one crash week in the same fiscal year, and zero otherwise. Crash weeks are defined based on alternative definitions in rows 1-4. Definitions of other variables are in Appendix B. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in all rows are estimated by the logit model. The z-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable: $CRASH_t$	Government Customer Concentration Measured by	
	GC_D_{t-1}	GC_SALE_{t-1}
Alternative definitions of crash weeks	(1)	(2)
(1) 3.5 standard deviations below the mean	-0.127**	-0.296***
	(-2.55)	(-2.89)
(2) Firm-specific return below -10%	-0.067*	-0.169**
	(-1.83)	(-2.31)
(3) Firm-specific return below -15%	-0.152***	-0.305***
	(-4.38)	(-4.34)
(4) Firm-specific return below -20%	-0.167***	-0.382***
	(-4.08)	(-4.47)

Table 3.4 Government Customer Concentration and Crash Risk: Alternative Measures of Crash Risk

This table shows the results for the robustness tests using alternative measures of crash risk. Panel A shows regression results for the relation between government customer concentration and number of crash weeks. The dependent variable is number of crash weeks (*No. of Crash Weeks*) in Panel A. Panel B shows regression results for the relation between government customer concentration and down-to-up volatility. The dependent variable is down-to-up volatility (*DUVOL*) in Panel B. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Government major customer dummy (*GC_D*) is an indicator variable that equals one if a firm discloses one or more government major customers who account for at least 10% of its total sales, and zero otherwise. Total government major customer sales (*GC_SALE*) equal the sum of the percentage sales to all government major customers. Number of crash weeks (*No. of Crash Weeks*) is the count of crash weeks for each firm-year. Crash weeks are detected when the firm-specific weekly return falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year. Down-to-up volatility (*DUVOL*) equals the log of the ratio of the standard deviation of firm-specific weekly returns in "down" weeks over the standard deviation of firm-specific weekly returns in "up" weeks. The "up" weeks include firm-specific weekly returns above the annual mean and the "down" weeks include firm-specific weekly returns below the annual mean. Definitions of other variables are in Appendix B. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in both panels are estimated by OLS. The t-statistics reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: No. of crash weeks as the measure of crash risk

Dependent Variable	*No. of Crash Weeks*$_t$	
	(1)	(2)
Government Customer Concentration		
GC_D_{t-1}	-0.015***	
	(-2.84)	
GC_SALE_{t-1}		-0.038***
		(-3.54)
Control Variables		
$NCSKEW_{t-1}$	0.007***	0.007***
	(3.79)	(3.78)
$SIGMA_{t-1}$	1.336***	1.335***
	(6.85)	(6.84)
RET_{t-1}	0.190***	0.190***
	(8.82)	(8.82)
$DTURN_{t-1}$	0.125***	0.125***
	(5.78)	(5.78)
$SIZE_{t-1}$	0.011***	0.011***
	(9.82)	(9.81)
MB_{t-1}	0.002***	0.002***
	(4.45)	(4.44)
LEV_{t-1}	-0.024**	-0.024**
	(-2.46)	(-2.46)
ROA_{t-1}	0.055***	0.055***
	(5.38)	(5.39)
$ACCM_{t-1}$	0.004**	0.004**
	(2.36)	(2.38)
Intercept	-0.022	-0.022
	(-0.88)	(-0.88)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	90,884	90,884
Adjusted R^2	0.027	0.027

Panel B: Down-to-up volatility as the measure of crash risk

Dependent Variable	$DUVOL_t$	
	(1)	(2)
Government Customer Concentration		
GC_D_{t-1}	-0.020***	
	(-2.90)	
GC_SALE_{t-1}		-0.045***
		(-3.11)
Control Variables		
$NCSKEW_{t-1}$	0.018***	0.018***
	(7.06)	(7.05)
$SIGMA_{t-1}$	3.849***	3.848***
	(14.60)	(14.60)
RET_{t-1}	0.388***	0.388***
	(13.32)	(13.32)
$DTURN_{t-1}$	0.205***	0.205***
	(8.14)	(8.14)
$SIZE_{t-1}$	0.044***	0.044***
	(31.16)	(31.14)
MB_{t-1}	0.004***	0.004***
	(6.15)	(6.14)
LEV_{t-1}	-0.042***	-0.042***
	(-3.40)	(-3.40)
ROA_{t-1}	0.099***	0.099***
	(7.46)	(7.48)
$ACCM_{t-1}$	0.004**	0.004**
	(2.16)	(2.19)
Intercept	-0.616***	-0.616***
	(-10.71)	(-10.72)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	90,884	90,884
Adjusted R^2	0.054	0.054

Table 3.5 Government Customer Concentration and Crash Risk: Alternative Measure of Government Customer Concentration

This table shows the results for the robustness tests using an alternative measure of government customer concentration. The dependent variables are crash dummy (*CRASH*) in column 1 and negative skewness (*NCSKEW*) in column 2. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Government major customer Herfindahl-Hirschman index (*GC_HHI*) equals the quadratic sum of the percentage sales to all government major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix B. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in both regressions. The regression in column 1 is estimated by the logit model. The regression in column 2 is estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$	$NCSKEW_t$
	(1)	(2)
Government Customer Concentration		
GC_HHI_{t-1}	-0.395***	-0.110***
	(-2.84)	(-2.88)
Control Variables		
$NCSKEW_{t-1}$	0.048***	0.026***
	(3.77)	(6.80)
$SIGMA_{t-1}$	9.485***	6.221***
	(6.84)	(17.19)
RET_{t-1}	1.366***	0.670***
	(8.26)	(16.33)
$DTURN_{t-1}$	0.732***	0.330***
	(5.63)	(8.48)
$SIZE_{t-1}$	0.076***	0.074***
	(10.16)	(36.80)
MB_{t-1}	0.012***	0.006***
	(3.53)	(5.71)
LEV_{t-1}	-0.167**	-0.069***
	(-2.53)	(-3.81)
ROA_{t-1}	0.345***	0.179***
	(5.07)	(9.05)
$ACCM_{t-1}$	0.022**	0.007**
	(2.29)	(2.10)
Intercept	-3.165***	-0.910***
	(-15.67)	(-11.66)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	90,883	90,884
Pseudo-/Adjusted R^2	0.031	0.059

Table 3.6 Government Customer Concentration and Crash Risk: Sample Period Excluding Financial Crisis Years

This table shows the results for the robustness tests using the sample period excluding financial crisis years. The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014, excluding financial crisis years (i.e., 1987, 2000–2002, and 2008–2009) with non-missing values for the control variables. Government major customer dummy (*GC_D*) is an indicator variable that equals one if a firm discloses one or more government major customers who account for at least 10% of its total sales, and zero otherwise. Total government major customer sales (*GC_SALE*) equal the sum of the percentage sales to all government major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix B. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Government Customer Concentration				
GC_D_{t-1}	-0.098**		-0.024**	
	(-2.44)		(-2.25)	
GC_SALE_{t-1}		-0.266***		-0.062***
		(-3.22)		(-2.66)
Control Variables				
$NCSKEW_{t-1}$	0.048***	0.048***	0.026***	0.026***
	(3.34)	(3.34)	(6.10)	(6.09)
$SIGMA_{t-1}$	10.712***	10.690***	6.839***	6.836***
	(6.38)	(6.37)	(16.24)	(16.24)
RET_{t-1}	1.690***	1.688***	0.790***	0.789***
	(7.93)	(7.92)	(15.80)	(15.80)
$DTURN_{t-1}$	0.936***	0.936***	0.396***	0.396***
	(5.95)	(5.95)	(8.31)	(8.31)
$SIZE_{t-1}$	0.072***	0.072***	0.075***	0.075***
	(8.45)	(8.43)	(33.39)	(33.36)
MB_{t-1}	0.010**	0.009**	0.005***	0.005***
	(2.43)	(2.41)	(4.27)	(4.26)
LEV_{t-1}	-0.219***	-0.218***	-0.076***	-0.076***
	(-2.96)	(-2.95)	(-3.78)	(-3.78)
ROA_{t-1}	0.347***	0.348***	0.190***	0.190***
	(4.35)	(4.36)	(8.23)	(8.25)
$ACCM_{t-1}$	0.020**	0.020**	0.006*	0.006*
	(2.14)	(2.16)	(1.84)	(1.86)
Intercept	-3.187***	-3.187***	-0.937***	-0.937***
	(-14.64)	(-14.64)	(-10.99)	(-10.99)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	74,767	74,767	74,768	74,768
Pseudo-/Adjusted R^2	0.032	0.032	0.052	0.053

Table 3.7 Government Customer Concentration and Crash Risk: Controls for Corporate Customer Concentration

This table shows the results for the robustness tests using additional controls for corporate customer concentration. The dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the control variables. Government major customer dummy (*GC_D*) is an indicator variable that equals one if a firm discloses one or more government major customers who account for at least 10% of its total sales, and zero otherwise. Total government major customer sales (*GC_SALE*) equal the sum of the percentage sales to all government major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables are in Appendix B. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in columns 1-2 are estimated by the logit model. The regressions in columns 3-4 are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	$CRASH_t$		$NCSKEW_t$	
	(1)	(2)	(3)	(4)
Government Customer Concentration				
GC_D_{t-1}	-0.105***		-0.029***	
	(-2.78)		(-2.91)	
GC_SALE_{t-1}		-0.258***		-0.070***
		(-3.32)		(-3.17)
Corporate Customer Concentration				
CC_D_{t-1}	0.084***		0.029***	
	(3.98)		(4.89)	
CC_SALE_{t-1}		0.174***		0.047***
		(4.19)		(3.71)
Control Variables				
$NCSKEW_{t-1}$	0.048***	0.048***	0.026***	0.026***
	(3.78)	(3.78)	(6.80)	(6.80)
$SIGMA_{t-1}$	9.028***	8.968***	6.079***	6.098***
	(6.49)	(6.46)	(16.73)	(16.80)
RET_{t-1}	1.327***	1.324***	0.657***	0.659***
	(8.01)	(8.00)	(15.98)	(16.05)
$DTURN_{t-1}$	0.736***	0.737***	0.331***	0.331***
	(5.67)	(5.68)	(8.52)	(8.51)
$SIZE_{t-1}$	0.078***	0.078***	0.075***	0.074***
	(10.45)	(10.39)	(37.14)	(36.99)
MB_{t-1}	0.011***	0.011***	0.006***	0.006***
	(3.42)	(3.35)	(5.56)	(5.53)
LEV_{t-1}	-0.157**	-0.152**	-0.066***	-0.065***
	(-2.37)	(-2.30)	(-3.62)	(-3.59)
ROA_{t-1}	0.335***	0.346***	0.176***	0.180***
	(4.93)	(5.08)	(8.90)	(9.07)
$ACCM_{t-1}$	0.020**	0.020**	0.006**	0.006*
	(2.17)	(2.09)	(1.98)	(1.94)
Intercept	-3.181***	-3.181***	-0.916***	-0.914***
	(-15.54)	(-15.59)	(-11.60)	(-11.68)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	90,883	90,883	90,884	90,884
Pseudo-/Adjusted R^2	0.031	0.031	0.060	0.059

Appendices

Appendix A.1 Variable Definitions

Note: Variable names in parentheses in the right column are the names of the data items in the CRSP/Compustat Merged database and CRSP database.

Variable	Definition
ACCM	Moving sum of the absolute value of annual discretionary accruals over the past three years. Discretionary accruals are calculated by the modified Jones model of Kothari, Leone, and Wasley (2005).
Auditor industry specialization	A dummy variable that equals one if a firm is audited by an accounting firm that accounts for the largest market share in the firm's 2-digit SIC industry, and zero otherwise.
Big auditor	A dummy variable that equals one if the going concern is audited by a Big accounting firm, and zero otherwise.
Board independence	Percentage of independent directors serving on a board.
Cash holdings	Ratio of cash and marketable securities (*CHE*) to total assets (*AT*) net of cash and marketable securities (*CHE*).
Cash flow volatility	Standard deviation of operating cash flows (*OANCF-XIDOC*) divided by lagged total assets (*AT*) over the previous five years.
CC_D	A dummy variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise.
CC_SALE	Sum of the percentage sales to all corporate major customers.
CC_HHI	Quadratic sum of the percentage sales to all corporate major customers.
CEO duality	A dummy variable that equals one if a firm's CEO serves as the chairman of the board at the same time, and zero otherwise.
CFO option incentives	CFO's incentive ratio for option holdings following Bergstresser and Philippon (2006).
CRASH	A dummy variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise.

DTURN	Average monthly stock turnover in the current fiscal year minus those in the previous year. Monthly stock turnover equals the ratio of the monthly trading volume (*VOL*×100) to the number of shares outstanding (*SHROUT*×1000).
Durable Goods Sector	Industries with SIC codes between 3,400 and 3,999.
Financial distress risk	Probability of default produced by Merton distance to default model.
High-frequency trading	Short-term trading by hedge funds and other institutional investors not recorded by the Thomson Reuters Institutional Holdings (13F) database according to Zhang (2010).
High litigation industry	A dummy variable that equals one if a firm's SIC code is within the following ranges: 2833–2836, 3570–3577, 3600–3674, 5200–5961, 7370–7374, and 8731–8734, and zero otherwise.
LEV	Ratio of long-term debt (*DLTT*) to total assets (*AT*).
Liquidity	Ratio of the absolute difference between the trade price and the midpoint of the bid-ask quote to the trade price.
MB	Ratio of market value of equity to book value of equity (*CEQ*). Market value of equity equals the product of closing stock price (*PRCC_F*) and number of shares outstanding (*CSHPRI*) at the fiscal year-end.
NCSKEW	-1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power.
Nondurable Goods Sector	Industries with SIC codes between 2,000 and 3,399.
Real earnings management	Sum of abnormal components of cash flow from operations, production costs, and discretionary expenses, based on Dechow, Kothari, and Watts's (1998) regressions.
RET	100 times the average firm-specific weekly returns.
R&D expenditures	Research and development expenditures (*XRD*) over sales (*SALE*).
R&D expenses	Average ratio of research and development expenditures (*XRD*) to total assets (*AT*) over the past three years.
ROA	Ratio of income before extraordinary items (*IB*) to lagged total assets (*AT*).
Sales growth	Annual change in sales (*SALE*) divided by lagged sales (*SALE*).
SIGMA	Standard deviation of firm-specific weekly returns.

SIZE	Log of market value of equity (*PRCC_F* ×*CSHPRI*).
SURP_UE	A dummy variable that equals one if a firm's unexpected earnings are non-negative in the previous fiscal year and fall in the bottom decile in the current year, and zero otherwise. Unexpected earnings equal the annual change of a firm's income before extraordinary items (*IB*) divided by its lagged market value of equity (*PRCC_F* ×*CSHPRI*).
Tax avoidance	Predicted probability that a firm adopts tax shelters according to Wilson (2009)'s model.

Appendix A.2 IV Estimations: Downstream M&A Activity as the Instrumental Variable

This table shows the results for the endogeneity tests on a subsample using an instrumental variable. Panel A shows the first-stage results. In Panel A, the dependent variables are total corporate major customer sales (*CC_SALE*) in column 1 and corporate major customer Herfindahl-Hirschman index (*CC_HHI*) in column 2. The instrumental variable is downstream M&A activity (*CustomerM&A*). Panel B shows the second-stage results. In Panel B, the dependent variables are crash dummy (*CRASH*) in columns 1-2 and negative skewness (*NCSKEW*) in columns 3-4. The predicted total corporate major customer sales (*Predicted CC_SALE*) and predicted corporate major customer Herfindahl-Hirschman index (*Predicted CC_HHI*) resulting from the first-stage regressions are used in the second-stage regressions. The subsample consists of firm-years with at least one corporate major customer jointly covered in the CRSP/Compustat Merged database and Compustat Customer Segment database from 1982 to 2012 with identifiable corporate major customers' industries and non-missing values for the control variables. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Corporate major customer Herfindahl-Hirschman index (*CC_HHI*) equals the quadratic sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. Downstream M&A activity (*CustomerM&A*) equals the weighted sum of the 5-year average acquisition activity in a firm's corporate major customers' industries, weighed by the percentage of revenues contributed by each corporate major customer. Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in Panel A are estimated by OLS. The regressions in columns 1-2 of Panel B are estimated by the logit model. The regressions in columns 3-4 of Panel B are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First-Stage Results

Dependent Variable	Downstream M&A Activity as IV	
	$CC\_SALE_{t\text{-}1}$	$CC\_HHI_{t\text{-}1}$
	(1)	(2)
Instrumental Variable		
$CustomerM\&A_{t\text{-}1}$	0.033***	0.018***
	(5.79)	(4.69)
Control Variables		
$NSKEW_{t\text{-}1}$	-0.005	-0.006*
	(-1.22)	(-1.95)
$SIGMA_{t\text{-}1}$	1.628**	0.360
	(2.32)	(0.75)
$RET_{t\text{-}1}$	0.113	0.002
	(1.47)	(0.03)
$DTURN_{t\text{-}1}$	0.033	0.014
	(0.80)	(0.56)
$SIZE_{t\text{-}1}$	-0.016***	-0.008***
	(-3.75)	(-3.09)
$MB_{t\text{-}1}$	0.006***	0.005***
	(3.11)	(3.65)
$LEV_{t\text{-}1}$	-0.137***	-0.093***
	(-3.45)	(-4.19)
$ROA_{t\text{-}1}$	-0.036	-0.039*
	(-1.14)	(-1.78)
$ACCM_{t\text{-}1}$	0.014*	0.012**
	(1.79)	(2.07)
Intercept	0.444***	0.183**
	(3.44)	(2.14)
IND/YEAR	Yes	Yes
Cluster by supplier	Yes	Yes
No. of observations	5,055	5,055
Adjusted R^2	0.140	0.112
First-Stage F-test	33.47	22.01
p-value	<0.01	<0.01
Kleibergen-Paap LM Stat	31.29	24.60
p-value	<0.01	<0.01

Panel B: Second-Stage Results

Dependent Variable	*CRASH*$_t$		*NCSKEW*$_t$	
	(1)	(2)	(3)	(4)
Corporate Customer Concentration				
Predicted CC_SALE$_{t-1}$	2.813***		0.388	
	(2.75)		(0.90)	
Predicted CC_HHI$_{t-1}$		5.126***		0.708
		(2.75)		(0.90)
Control Variables				
NCSKEW$_{t-1}$	0.104*	0.117**	0.025	0.027*
	(1.88)	(2.10)	(1.58)	(1.65)
SIGMA$_{t-1}$	-5.887	-3.150	6.436***	6.814***
	(-0.95)	(-0.53)	(3.50)	(4.04)
RET$_{t-1}$	0.098	0.408	0.742***	0.785***
	(0.13)	(0.56)	(3.69)	(4.11)
DTURN$_{t-1}$	0.965*	0.987*	0.526***	0.529***
	(1.77)	(1.81)	(3.46)	(3.49)
SIZE$_{t-1}$	0.118***	0.115***	0.092***	0.091***
	(3.23)	(3.19)	(7.98)	(8.14)
MB$_{t-1}$	-0.006	-0.015	-0.001	-0.002
	(-0.36)	(-0.84)	(-0.18)	(-0.36)
LEV$_{t-1}$	0.173	0.265	-0.090	-0.077
	(0.53)	(0.77)	(-0.90)	(-0.71)
ROA$_{t-1}$	0.128	0.230	0.227***	0.241***
	(0.44)	(0.77)	(2.85)	(2.86)
ACCM$_{t-1}$	0.046	0.024	0.017	0.014
	(0.87)	(0.43)	(0.89)	(0.69)
Intercept	-31.082***	-30.770***	-1.481***	-1.438***
	(-50.34)	(-31.73)	(-3.84)	(-3.94)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	5,035	5,035	5,055	5,055
Pseudo-/Adjusted R^2	0.038	0.038	0.064	0.064

Appendix A.3 Corporate Customer Concentration and Crash Risk: Effect of Alternatively Defined R&D Expenses

This table shows regression results for the relation between corporate customer concentration and crash risk using an alternative definition of R&D expenses. Panel A shows regression results for the relation between corporate customer concentration and crash dummy. The dependent variable is crash dummy (*CRASH*) in Panel A. Panel B shows regression results for the relation between corporate customer concentration and negative skewness. The dependent variable is negative skewness (*NCSKEW*) in Panel B. The sample consists of firm-years in the CRSP/Compustat Merged database from 1979 through 2014 with non-missing values for the R&D expenses and control variables. Corporate major customer dummy (*CC_D*) is an indicator variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise. Total corporate major customer sales (*CC_SALE*) equal the sum of the percentage sales to all corporate major customers. Crash dummy (*CRASH*) is an indicator variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise. Negative skewness (*NCSKEW*) equals -1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power. R&D expenses equal the ratio of research and development expenditures (*XRD*) to total assets (*AT*). Definitions of other variables are in Appendix A.1. All continuous variables are winsorized within 1 and 99 percentile. Year and industry (2-digit SIC) fixed effects are included in all regressions. The regressions in Panel A are estimated by the logit model. The regressions in Panel B are estimated by OLS. The z-statistics (t-statistics) reported in parentheses are based on heteroskedasticity-robust standard errors clustered by supplier. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Corporate Customer Concentration and Crash Dummy

Dependent Variable	$CRASH_t$			
	(1)	(2)	(3)	(4)
	R&D Expenses=0	High R&D Expenses	R&D Expenses=0	High R&D Expenses
Corporate Customer Concentration				
CC_D_{t-1}	0.091***	0.032		
	(2.80)	(0.81)		
CC_SALE_{t-1}			0.196***	0.055
			(2.89)	(0.78)
Control Variables				
$NCSKEW_{t-1}$	0.070***	-0.022	0.070***	-0.022
	(3.79)	(-0.87)	(3.80)	(-0.87)
$SIGMA_{t-1}$	4.445**	12.754***	4.487**	12.715***
	(2.19)	(4.56)	(2.21)	(4.54)
RET_{t-1}	0.766***	1.583***	0.774***	1.580***
	(3.03)	(5.46)	(3.07)	(5.44)
$DTURN_{t-1}$	0.728***	0.633***	0.729***	0.633***
	(3.42)	(3.20)	(3.42)	(3.20)
$SIZE_{t-1}$	0.061***	0.134***	0.061***	0.134***
	(5.59)	(8.80)	(5.59)	(8.79)
MB_{t-1}	0.008	0.007	0.008	0.007
	(1.41)	(1.34)	(1.37)	(1.34)
LEV_{t-1}	-0.177**	-0.176	-0.175**	-0.174
	(-1.99)	(-1.05)	(-1.97)	(-1.04)
ROA_{t-1}	0.206	0.315***	0.205	0.317***
	(1.35)	(3.40)	(1.35)	(3.42)
$ACCM_{t-1}$	0.025	0.022	0.024	0.021
	(1.15)	(1.14)	(1.11)	(1.12)
Intercept	-2.862***	-3.667***	-2.871***	-3.663***
	(-11.66)	(-7.82)	(-11.67)	(-7.81)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	47,003	19,602	47,003	19,602
Pseudo-R^2	0.029	0.032	0.029	0.032

Panel B: Corporate Customer Concentration and Negative Skewness

Dependent Variable	$NCSKEW_t$			
	(1)	(2)	(3)	(4)
	R&D Expenses=0	High R&D Expenses	R&D Expenses=0	High R&D Expenses
Corporate Customer Concentration				
CC_D_{t-1}	0.033***	0.016		
	(3.97)	(1.27)		
CC_SALE_{t-1}			0.051***	0.020
			(2.65)	(0.83)
Control Variables				
$NCSKEW_{t-1}$	0.035***	-0.005	0.035***	-0.005
	(6.59)	(-0.61)	(6.60)	(-0.61)
$SIGMA_{t-1}$	4.673***	7.510***	4.709***	7.523***
	(8.95)	(9.36)	(9.03)	(9.36)
RET_{t-1}	0.502***	0.781***	0.506***	0.782***
	(8.05)	(9.94)	(8.12)	(9.94)
$DTURN_{t-1}$	0.335***	0.325***	0.335***	0.325***
	(5.69)	(4.96)	(5.68)	(4.96)
$SIZE_{t-1}$	0.071***	0.085***	0.071***	0.084***
	(24.91)	(18.88)	(24.80)	(18.86)
MB_{t-1}	0.004**	0.006***	0.004**	0.006***
	(2.32)	(3.46)	(2.29)	(3.47)
LEV_{t-1}	-0.011	-0.172***	-0.011	-0.171***
	(-0.47)	(-3.50)	(-0.46)	(-3.48)
ROA_{t-1}	0.220***	0.144***	0.222***	0.146***
	(5.79)	(4.93)	(5.84)	(4.98)
$ACCM_{t-1}$	0.024***	0.003	0.024***	0.003
	(3.58)	(0.43)	(3.58)	(0.41)
Intercept	-0.854***	-0.838***	-0.853***	-0.837***
	(-8.21)	(-8.36)	(-8.26)	(-8.39)
IND/YEAR	Yes	Yes	Yes	Yes
Cluster by supplier	Yes	Yes	Yes	Yes
No. of observations	47,003	19,622	47,003	19,622
Adjusted R^2	0.059	0.059	0.059	0.059

Appendix B. Variable Definitions

Note: Variable names in parentheses in the right column are the names of the data items in the CRSP/Compustat Merged database and CRSP database.

Variable	Definition
ACCM	Moving sum of the absolute value of annual discretionary accruals over the past three years. Discretionary accruals are calculated by the modified Jones model of Kothari, Leone, and Wasley (2005).
CC_D	A dummy variable that equals one if a firm discloses one or more corporate major customers who account for at least 10% of its total sales, and zero otherwise.
CC_SALE	Sum of the percentage sales to all corporate major customers.
GC_D	A dummy variable that equals one if a firm discloses one or more government major customers who account for at least 10% of its total sales, and zero otherwise.
GC_SALE	Sum of the percentage sales to all government major customers.
GC_HHI	Quadratic sum of the percentage sales to all government major customers.
CRASH	A dummy variable that equals one if the firm has at least one firm-specific weekly return that falls 3.09 standard deviations below the average weekly firm-specific return in the same fiscal year, and zero otherwise.
DTURN	Average monthly stock turnover in the current fiscal year minus those in the previous year. Monthly stock turnover equals the ratio of the monthly trading volume (*VOL*×100) to the number of shares outstanding (*SHROUT*×1000).
DUVOL	Log of the ratio of the standard deviation of firm-specific weekly returns in "down" weeks over the standard deviation of firm-specific weekly returns in "up" weeks. The "up" weeks include firm-specific weekly returns above the annual mean and the "down" weeks comprise firm-specific weekly returns below the annual mean.
LEV	Ratio of long-term debt (*DLTT*) to total assets (*AT*).
MB	Ratio of market value of equity to book value of equity (*CEQ*). Market value of equity equals the product of the fiscal year-end closing stock price (*PRCC_F*) and the number of shares outstanding (*CSHPRI*).
NCSKEW	-1 times the ratio of the third moment of firm-specific weekly returns to the standard deviation of firm-specific weekly returns raised to the third power.

No. of Crash Weeks	Count of crash weeks for each firm-year. Crash weeks are those with firm-specific weekly returns falling 3.09 standard deviations below the annual mean.
RET	100 times the average firm-specific weekly returns.
ROA	Ratio of income before extraordinary items (*IB*) to lagged total assets (*AT*).
SIGMA	Standard deviation of firm-specific weekly returns.
SIZE	Log of market value of equity (*PRCC_F* ×*CSHPRI*).

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