Against the Gravity as a Jenga Tower? Asset Growth and Stock Price Crash Risk

Siu Kai Choy[ɫ] Gerald J. Lobo[*] Ying Zheng[§]

This version: May 2021

Abstract

Does growth lead to stock price crashes? In this study, we find that total asset growth positively relates to future crash risk. Consistent with the managerial empire-building incentive, agency problems tend to accentuate the asset growth-crash risk relationship while accounting conservatism attenuates the relationship, suggesting that not all growth is harmful. We also find corroborating evidence from overinvestment estimation and a quasi-natural experiment that reduces managers' empire building incentive. Despite the popularity of studying asset growth and future stock returns in the literature, our focus on higher moments of returns sheds light on the consequences of asset growth for stock prices.

JEL Classification: G12, G30, M41.

Keywords: Crash risk; Asset growth; Bad news hoarding; Empire-building incentive.

[ɫ] King's Business School - King's College London. Email: siu_kai.choy@kcl.ac.uk

[*] Bauer College of Business - University of Houston. Email: gjlobo@uh.edu

[§] School of Business - Sun Yat-Sen University. Email: zhengy26@mail.sysu.edu.cn

The authors thank Sai Harsha Katuri, Minjae Koo, and Xiaohua Fang for useful comments.

1. Introduction

An abrupt fall in market value could wipe out a large portion of investors' wealth. As a result, stock price crash has drawn considerable attention from researchers and regulators. Jin and Myers (2006) propose that managers have incentives to hide bad news for reasons such as career concerns and continued extraction of private benefits, and stock price crashes when the accumulated bad news is eventually released. Prior research documents that incentives to hide bad news related to earnings opacity, corporate tax avoidance, equity compensation, CEO overconfidence, regional religiosity, and other corporate and reporting characteristics are associated with stock price crash risk.[1] We add to this line of research by investigating the relationship between asset growth and stock price crash risk.

Recent studies consistently relate asset growth to lower future stock returns (e.g., Cooper, Gluten, and Schill 2008; Lipson, Mortal, and Schill 2011). Despite the intense interest in understanding the implications of asset growth, no studies have investigated the implications on higher moments of returns and, in particular, crash risk. The corporate finance literature suggests that managers have incentives to empire build and control more resources by stockpiling projects and making investments (Jensen and Meckling 1976; Jensen 1986). Managers can extract more private benefits by controlling more resources through means such as raising capital and making capital investments, or delaying contraction by keeping inefficient operations for too long. In addition to managers' incentive to cover up private bad news, the bad news is accumulated up until

[1] For example, Hutton, Marcus, and Tehranian (2009), Kim, Li, and Zhang (2011a, b), Kothari, Shu, and Wysocki (2009), Callen and Fang (2015a, b), and Kim, Wang, and Zhang (2016).

a tipping point, when it is released to investors at one time, and results in a stock price crash. Accordingly, we hypothesize that the combined effect of asset growth from empire building and the tendency to conceal bad news leads to a stock price crash.

We investigate whether asset growth predicts future crash risk using a large sample of U.S. firms between 1988 and 2017. Following prior literature (e.g., Chen, Hong, and Stein 2001), we measure stock price crash risk using three measures: (1) an indicator for whether one or more of the firm's weekly returns is at least 3.2 standard deviations below the mean; (2) the negative of the coefficient of skewness of weekly returns; and (3) the natural logarithm of the ratio of down-market to up-market weekly return volatility. Following Cooper et al. (2008), we measure total asset growth as the year-over-year percentage change in total assets.

A simple univariate sorting of asset growth reveals that next year's probability of a sizable price drop increases monotonically from 13.6% for the lowest asset growth quintile to 20.0% for the highest asset growth quintile. We observe a similar monotonic pattern for the two asymmetric return distribution measures. We confirm this result in a multivariate analysis that controls for other determinants of crash risk identified in the literature, with the predictive power lasting up to three years. In terms of economic significance, an interquartile increase in this year's asset growth indicates a 0.55% increase in the probability of a stock price crash next year.[2,3]

---

[2] The corresponding estimates for the skewness and return volatility ratio measures are 0.021 and 0.010, respectively.

[3] The economic significance of this increase in future stock price crash risk probability is comparable to that of other determinants of crash risk identified in the literature.

The results for asset growth are consistent with our hypothesis that managers' incentives to empire build and to hide bad news contribute to stock price crash risk. We also find that asset growth predicts poor future firm performance, in terms of profit margins and return on assets, which further supports our hypothesis and is consistent with the explanation relating investment and empire building (Titman, Wei, and Xie 2004).[4]

Growth is an important contributor to firm value and successful companies are usually able to sustain high growth for many years. However, the results so far seem to suggest that growths in different balance sheet items lead to higher crash risk. Our results beg the question: does growth universally lead to higher crash risk? We explore the heterogeneity across firms along the following dimensions: the tendency for overinvestment that arises from agency conflicts between managers and shareholders, the suppression of bad news related to accounting reporting practice, and the estimation of overinvestment.

To the extent that the asset growth-crash risk relationship arises from agency conflicts between managers and shareholders, we expect a stronger relationship among firms with more severe empire-building incentives. Using a firm's free cash flow and CEO tenure as proxies for empire-building incentives (Jensen 1986; Berger, Ofek, and Yermack 1997), we find a stronger asset growth-future crash risk relationship for firms whose managers have stronger empire-building incentives. We also examine the cross-sectional implications of bad news hoarding for crash risk. Although managers have a tendency to hide bad news, the amount of hidden bad news

[4] A poorer profit margin may also indicate that managers are reluctant to discontinue inefficient operating activities in a timely manner.

is mitigated for firms with conditionally conservative accounting practices. We expect less bad news hoarding for firms with higher conditional conservatism and, therefore, a weaker relationship between asset growth and crash risk. We find that conditional conservatism significantly attenuates the positive asset growth-crash risk relationship. Next, we examine whether firms with above-normal growth (i.e., firms that overinvest in growth beyond the normal level supported by growth opportunities)[5] exhibit higher crash risk. We find that firms with overinvestment in either capital expenditure or total investment have significantly higher crash risk.

Furthermore, we document that for the firms in the top asset growth quintile, those with the lowest empire-building incentive or the highest accounting conservatism generally have crash risk below the overall sample average. These results indicate that agency issues, accounting conservatism, and the level of overinvestment have moderating effects on the asset growth-crash risk relationship.

Our study contributes to the literature in two important ways. First, it contributes to the literature on the asset growth anomaly. This literature documents that asset growth predicts lower future stock return but disagrees on the underlying mechanism. Under the mispricing perspective, investors underreact to the earnings implications of growth (Rau and Vermaelen 1998; Richardson and Sloan 2003; Hirshleifer, Hou, Teoh, and Zhang 2004; Titman et al. 2004). Under the rational investment perspective, investment is fundamentally linked to discount rate and hence to expected returns (Hou, Xue, and Zhang 2015; Fama and French 2015). Adding to the debate, Cooper, Gulen,

[5] We use the approach in Chen, Hope, and Wang (2011) and Biddle, Hilary, and Verdi (2009) to estimate the amount of overinvestment.

and Ion (2017) argue that asset growth does not necessarily arise from investment and cast doubt on the rational investment explanation. We offer a fresh perspective by investigating how asset growth relates to the likelihood of price crash and left-skewed return distributions. Our evidence suggests that agency problems, together with bad news hoarding, explain the positive asset growth-crash risk relationship. Although our findings on the higher moments of the return distribution cannot resolve the rational investment/mispricing debate, our study investigates the impact of asset growth from a completely different angle and responds to the call to enrich understanding of anomalies by going beyond future average returns (van Binsbergen and Opp 2019).[7]

Second, our study contributes to the stock price crash risk literature. Following Chen et al. (2001), several studies have investigated factors contributing to crash risk. Specifically, Jin and Myers (2006) model that managers have an incentive to extract private benefits and hide bad news from investors. The bad news accumulates to a threshold and leads to a price crash when it eventually becomes public. Later research finds evidence consistent with Jin and Myers (2006) by investigating earnings opacity, CEO equity incentive, tax avoidance, accounting conservatism, religiosity, and dividend payment (Hutton, Marcus, and Tehranian 2009; Kim, Li, and Zhang 2011a, b; Callen and Fang 2015a; Kim, Luo, and Xie 2020). Other explanations relate crash risk to investor disagreement (Chen et al. 2001), stock liquidity (Chang, Chen, and Zolotoy 2017), material weakness in internal control (Lobo, Wang, Yu, and Zhao 2020), CEO overconfidence

[7] In the presence of bad news hoarding by managers, price crash may occur with rational or irrational pricing. Rational pricing only means that current prices correctly incorporate all publicly available information, i.e. prices correct on average. Investors can still be surprised by the sudden release of stockpiled bad news. See Greenwood, Shleifer, and You (2019) for a discussion on market efficiency and price crash.

(Kim, Wang, and Zhang 2016), and contagion along the supply chain from customers to suppliers (Qiu, Xu, and Zeng 2019). We add to this literature by showing that asset growth is a determinant of crash risk. In addition, we document that growths in different balance sheet items, not just total asset growth, also relate to crash risk. Moreover, our measure is simple and easy to calculate from publicly available data, thus facilitating crash prediction by interested investors.

The rest of the paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and presents summary statistics. Section 4 discusses the main findings, investigates agency problems, and examines the impact of accounting conservatism. Section 5 relates overinvestment to crash risk. Section 6 examines the impact of the repeal of the Inevitable Disclosure Doctrine. Section 7 discusses the results of robustness checks, and Section 8 concludes.

2. Literature review and hypotheses development

A large literature in corporate finance studies agency conflicts between managers and shareholders. The seminal paper by Jensen and Meckling (1976) argues that managers have an incentive to empire build through controlling more resources and enjoy private benefits. Although rent extraction damages the firm and eventually damages managers' welfare, the damage to managers' welfare is more than offset by the private benefits because the managers do not fully own the firm. Moreover, CEO compensation is generally higher for larger firms, giving CEOs incentive to engage in empire building (Murphy 1985; Baker, Jensen, and Murphy 1988; Jensen and Murphy 1990; Rose and Shepard 1997). Jin and Myers (2006) extend this framework to risk sharing between managers and shareholders. They show that in the presence of information opacity, managers' welfare is related to the amount of private benefits obtained from the firm's cash flows, and therefore they share part of the cash flow risk with the shareholders. Managers withhold information on negative shocks to expected cash flow to maintain their private benefits. It is only when the negative shocks are accumulated above a threshold that the managers cannot absorb that they release the bad news to shareholders at one time. The sudden release of stockpiled bad news leads to a much lower valuation by shareholders and price crash.

The literature provides evidence supporting Jin and Myers' (2006) agency perspective on crash risk. For example, Hutton et al. (2009) find that earnings opacity is positively related to future crash risk in the sense that bad news can be more stockpiled before release. Kim et al. (2011a) report that crash risk is related to top managers' equity incentives and, consistent with the view that tax avoidance facilitates rent extraction and bad news hoarding, Kim et al. (2011b) show that crash risk is positively related to corporate tax avoidance. Callen and Fang (2015a) relate county-level religiosity to crash risk, suggesting that a more religious environment presents a social norm that forces managers to act for shareholders' welfare.

The empire-building behavior suggested by Jensen and Meckling (1976) can manifest in several ways. Managers can invest in projects with negative net present value (NPV). For example, Richardson and Sloan (2003) show that firms with large amounts of external financing often end up in empire-building projects. Alternatively, managers can keep currently unprofitable investments for too long and delay downsizing or cost-cutting. In the end, managers benefit from higher compensation if they can increase firm size (Murphy 1985; Jensen and Murphy 1990) or make more investments (Balachandran and Mohanram 2010). Moreover, historical cost accounting helps managers to cover up bad news related to existing projects, further aggravating the agency problems (Bleck and Liu 2007). To the extent that empire building results in more resources being controlled by managers, it will eventually result in enlarged balance sheets and higher asset growth. Given managerial tendency to conceal bad news and the agency implications of asset growth, we formulate the following hypothesis (stated in the alternative form):

H1: *Asset growth is positively related to future stock price crash risk.*

While agency conflicts between managers and shareholders underlie the crash risk explanation, some firms are subject to greater conflicts than others. For example, Jensen (1986) proposes that free cash flow can aggravate the agency problem because managers have discretion to invest or distribute free cash to shareholders. Similarly, Kim et al. (2020) suggest that dividend payment can reduce crash risk because dividend payments are sticky and hence can limit free cash available to managers. In addition, while CEOs are generally influential in investment decisions, their incentive and ability to empire build may vary. Prior evidence suggests that a CEO's power to influence decisions increases with tenure in the position (Hill and Phan 1991; Chen, Lu, and Sougiannis 2012). Therefore, a longer-tenured CEO has more incentive to empire build and enjoy more compensation when the firm size increases. In contrast, a CEO who is going to step down shortly has less incentive to empire build because most of the benefits will accrue to the successor. For example, Dechow and Sloan (1991) document lower R&D expenditures for CEOs in their final years and Chen et al. (2012) find a higher likelihood of SG&A expense reduction related to demand shock in the years immediately preceding CEO turnover. We, therefore, expect the hypothesized asset growth-crash risk relationship to be stronger for firms with more agency problems and hypothesize the following (stated in the alternative form):

H2: *The positive asset growth-future stock price crash risk relationship is stronger for firms with more severe agency problems.*

While managers have a tendency to conceal bad news (Kothari et al. 2009), a strand of literature documents that the asymmetric accounting treatment of bad news versus good news offsets this tendency. In particular, under conditional conservatism (Basu 1997), firms have higher verification requirements for good news than for bad news. That is, firms with more conservative accounting practices will recognize bad news faster than good news. Because bad news is released to investors in a timelier manner, it reduces the amount of stockpiled bad news. Moreover, conservative firms discontinue bad projects faster, further reducing accumulated bad news (Francis and Martin 2010; Bushman, Piotroski, and Smith 2011). With less stockpiled bad news, more conservative firms should experience lower crash risk (Kim et al. 2016). Therefore, we expect that conditional conservatism mitigates the adverse effect of empire building on crash risk and hypothesize the following (stated in the alternative form):

H3: *The positive asset growth-future stock price crash risk relationship is weaker for firms with higher conditional conservatism.*

3. Data and variable description

Following the literature, we measure crash risk using three measures of the relative likelihood of more extreme negative returns to positive returns (Chen et al. 2001). Specifically, for each firm and fiscal year, we first estimate the following regression using weekly stock returns:

$$r_{i,w} = \beta_0 + \beta_1 r_{MKT,w-1} + \beta_2 r_{IND,w-1} + \beta_3 r_{MKT,w} + \beta_4 r_{IND,w} + \beta_5 r_{MKT,w+1} + \beta_6 r_{IND,w+1} + \varepsilon_{i,w} \quad (1)$$

where $r_{i,w}$ is the weekly stock return for firm i in week w, $r_{MKT,w}$ is the weekly value-weighted CRSP market return, and $r_{IND,w}$ is the weekly Fama-French value-weighted industry return. In addition to current weekly returns, the model includes lead and lag weekly market and industry returns to capture potential asynchronous stock price movements to common information. Firm-specific return, W_{iw}, for week w is defined as $ln(1 + \varepsilon_{iw})$ and is the building block for the crash risk variables.

We then define the crash risk variables as follows. *CRASH* is an indicator variable that equals one if the firm has at least one week in which W_{iw} is at least 3.2 standard deviations below the mean firm-specific return over the fiscal year, and zero otherwise. The choice of 3.2 standard deviations implies a probability of approximately 0.1 percent in a normal distribution. Therefore, *CRASH* measures the occurrence of extreme negative price movements. The other two measures are based on the intuition that when stock price crash occurs, the probability of observing a large negative return is greater than that of a large positive return of a similar magnitude. *NCSKEW*, the negative coefficient of skewness for each firm and fiscal year, is the negative of the third moment of the distribution of W_{iw} divided by its standard deviation raised to the third power. *DUVOL* measures the asymmetric volatility of negative versus positive returns. For each firm and fiscal year, we compute the ratio of the variance of the negative W_{iw} values to the variance of the positive W_{iw} values. *DUVOL* is the natural logarithm of this ratio. In summary, higher values of *CRASH*, *NCSKEW*, and *DUVOL* indicate a higher likelihood of stock price crash.

Our main explanatory variable, asset growth or *ASSETG*, is defined as the annual percentage change in total assets.

We control for the following determinants of crash risk identified in prior research. *DTURNOVER* is the yearly change in share turnover. *RET* and *SIGMA* are the mean and standard deviation, respectively, of the firm-specific weekly returns for the fiscal year. *SIZE* is the natural logarithm of the market value of common equity. *MB* is the market-to-book ratio. *LEV* is the leverage ratio, computed as long-term debt divided by total assets. *ROA* is return on assets. *OPAQUE* is earnings opacity, defined as the three-year moving sum of the absolute value of discretionary accruals, following Hutton et al. (2009).

Appendix A contains detailed definitions of all the variables used in the models. The descriptions of the variables for agency problems and conditional conservatism are included in their respective sections.

Sample selection and summary statistics

Our sample includes all firms in the CRSP and Compustat universe with sufficient information to calculate the three crash risk variables, *ASSETG*, and the control variables. The sample period begins in fiscal 1990 because cash flow information required to calculate *OPAQUE* is available only from 1988. The first year of predicted crash risk is therefore 1991. We require sample firms to have a stock price of at least $1, non-negative book value of common equity, and at least 26 weekly firm-specific returns in a fiscal year to compute next year's crash risk. The selection criteria result in 65,788 firm-year observations.

Table 1 presents summary statistics for the crash risk, asset growth, and control variables. Panel A reports the mean, median, standard deviation, and lower and upper quartiles for the overall sample. Average *CRASH* is 0.170, meaning that, on average, there is a 17% chance for a firm to have at least one firm-specific weekly return 3.2 standard deviations below its mean in a given year. *NCSKEW* has a mean of -0.115 and a median of -0.134, meaning that an average firm is more likely to experience positive return skewness. In terms of downside versus upside volatility, *DUVOL* has a mean of -0.069 and a median of -0.080, implying that upside price movements exhibit more volatility than downside movements. Chen et al. (2001) also report a negative average *DUVOL* for all firms and for each size quartile. Average annual asset growth (*ASSETG*) is 12.2%, with a median of 5.7%. The summary statistics for the control variables are consistent with those reported in the literature (e.g., Hutton et al. 2009; Kim et al. 2011a, b).

Panel B reports correlations among the crash risk, asset growth, and control variables. As expected, $CRASH_{t+1}$, $NCSKEW_{t+1}$, and $DUVOL_{t+1}$, are highly correlated with one another, with pair-wise correlations ranging from 0.561 to 0.961. $ASSETG_t$ is positively correlated with the three crash risk variables, with correlations ranging from 0.043 to 0.080, providing preliminary evidence of a positive relationship. $ASSETG_t$ is also moderately correlated with the control variables, with correlations of 0.247 with *ROA*, 0.161 with *DTURNOVER*, 0.124 with *MB*, 0.108 with *SIZE*, and 0.087 with *OPAQUE*.

4. Empirical Results

4.1 Relationship between asset growth and future crash risk

Univariate sorting analysis

We first conduct a univariate analysis by sorting firms into quintiles based on $ASSETG_t$ each fiscal year and calculating the average of next year's crash risk for each quintile. The sorting procedure results in a time-series of crash risk for each quintile of asset growth. Table 2 reports the time-series mean of crash risk for each quintile and the average difference in crash risk between the lowest and highest quintiles. We observe a monotonically increasing pattern of crash risk going from the lowest to the highest quintile of *ASSETG*: $CRASH_{t+1}$ increases from 0.136 to 0.200, $NCSKEW_{t+1}$ from -0.257 to -0.008, and $DUVOL_{t+1}$ from -0.136 to -0.022. The differences in crash risk between the lowest and highest quintiles are statistically significant for all three crash risk measures. The sorting analysis in Table 2 indicates that asset growth is positively related to future crash risk, consistent with the correlation results.

Multivariate results

We estimate the following regressions to investigate the relationship between asset growth and future crash risk:

$$RISK_{t+1} = \alpha_0 + \alpha_1 ASSETG_t + \alpha_2' Control_t + \varepsilon_{1t+1} \tag{4}$$

where *RISK* is *CRASH* or *NCSKEW* or *DUVOL.* We estimate a logistic model when *CRASH* is the dependent variable, because *CRASH* is an indicator variable. We estimate linear panel regressions when *NCSKEW* or *DUVOL* is the dependent variable, because *NCSKEW* and *DUVOL* are continuous variables. In all models, we include control variables as described in the last section, as well as year and industry fixed effects, and estimate standard errors using two-way clustering by firm and year. We winsorize all the continuous variables at the 1st and 99th percentiles to mitigate the potential undue effects of extreme values.

Table 3 reports the main results of the study. In all specifications, the coefficients of *ASSETG* are significantly positive, indicating that higher *ASSETG* predicts higher crash risk next year. In Column 1, the coefficient of *ASSETG* is 0.213 in terms of log odds and is significant at 1% in the logistic regression predicting $CRASH_{t+1}$. In Columns 2 and 3, *ASSETG* is also significant in predicting $NCSKEW_{t+1}$ and $DUVOL_{t+1}$, with coefficients of 0.098 and 0.045, respectively. We measure the economic significance of *ASSETG* by calculating the predicted change in next year's crash risk when *ASSETG* increases from the lower quartile to the upper quartile.[8] Table 3 shows that an interquartile increase in *ASSETG* results in an increase of 0.55% in next year's *CRASH*, and an increase of 0.021 and 0.010 in next year's *NCSKEW* and *DUVOL*, respectively. We discuss

[8] To calculate the impact of *ASSETG* on *CRASH*, we assume that all variables except *ASSETG* take the average values and we calculate log odds at the lower and upper quartiles of *ASSETG*, respectively. Then the log odds are transformed to probability of a crash using the formula p = odds/(1+odds) and the difference of probabilities across quartiles of *ASSETG* is reported. The impacts of *ASSETG* on *NCKSEW* and *DUVOL* are calculated by multiplying the corresponding coefficients by the interquartile range of *ASSETG*.

the economic significance of *ASSETG* relative to other known determinants after discussing the results of the control variables.

The signs and magnitudes of the control variable coefficients are qualitatively similar to those reported in other papers (e.g., Hutton et al. 2009; Kim et al. 2011a, b; Chang et al. 2017). For example, *DTURNOVER*, lagged *NCSKEW*, *SIGMA*, *RET*, and *OPAQUE* are all significantly positively related to next year's crash risk. *SIZE*, *MB*, and *ROA* are also positively related to the probability of a crash. Campbell, Hilscher, and Szilagyi (2008) indicate that high leverage firms have higher bankruptcy risk, which suggests that they would therefore have higher crash risk. In contrast to this prediction and consistent with the crash risk literature, we find a negative relationship between leverage and future crash risk. Hutton et al. (2009) attribute the negative relationship to the endogeneity of capital structure when more crash-prone firms choose less debt. Zhu (2016) argues that investors underprice highly leveraged firms, thus making crash less likely.

To appreciate the relative importance of *ASSETG*, we calculate the economic significance of the control variables in a similar manner to *ASSETG* and report the results in Table 3. Collectively, across the three crash risk measures, *SIZE*, *SIGMA*, and *RET* have the biggest impacts on future crash risk. For example, going from the 25^{th} to the 75^{th} percentile of size increases the probability of *CRASH* by 2.18%. The other control variables have impacts that are smaller than *SIZE*, *SIGMA*, and *RET*. For example, an interquartile increase in *MB*, *DTURNOVER*, *OPAQUE*, and *ROA* predicts an increase in next year's *CRASH* of 0.17%, 0.37%, 0.40%, and 0.59%, respectively. Recall that the corresponding impact of *ASSETG* on *CRASH* is 0.55%, which is larger in economic significance that most of the other known determinants. Comparisons of the relative impact of *ASSETG* with those of other determinants are similar for *NCSKEW* and *DUVOL*. In other words, *ASSETG* is at least as important a determinant of future crash risk as other determinants.

Crash risk prediction in future years

In Table 4, we investigate whether the predictive power of *ASSETG* for future crash risk extends beyond one year by replacing the dependent variables in Equation (4) by their corresponding values up to five years ahead. We do not report the control variable coefficients for brevity. The predictive power generally declines by approximately 50 percent for two-year-ahead predictions. For instance, the coefficient of *ASSETG* in the regression predicting $CRASH_{t+2}$ is 0.139 compared with the corresponding coefficient of 0.213 in Table 3 for $CRASH_{t+1}$. Although the coefficients are smaller, *ASSETG* is still significant in predicting crash risk for up to three years ahead. The predictive power is no longer significant in year *t+4*. In summary, there is a long-lasting effect of asset growth on the probability of future price crash.

Is asset growth related to future firm performance?

Given the long-horizon predictive power of asset growth for future crash risk, we next investigate whether asset growth is related to (weaker) future firm performance. We do so by estimating the following regression:

$$FP_{t+1} = \delta_0 + \delta_1 ASSETG_t + \delta_2 \Delta FP_t + \delta_3 FP_t + \delta_4 SIZE_t + \delta_5 MB_t + \varepsilon_{2t+1} \quad (5)$$

where FP_t represents firm performance in fiscal year *t* and ΔFP_t is the difference between year *t* and year *t-1* performance. We measure firm performance using either profit margin (*PM*) or return on assets (*ROA*). If high asset growth results from agency problems related to managers' empire building, we expect weaker future firm performance and hence a negative δ_1. This expectation is supported by the results in Panel A of Table 5, which show a significantly negative relationship between *ASSETG* and future firm performance, after controlling for market-to-book ratio, size, current performance, and change in performance.

Does crash concentrate around earnings release?

Given that higher asset growth is related to poorer future firm performance, a logical question is whether the poorer future earnings trigger a crash around their release date. Prior research provides evidence that return predictability concentrates around future earnings announcements. For example, Bernard and Thomas (1989) find that a disproportionate fraction of post-earnings announcement drift is realized around the next earnings release. La Porta, Lakonishok, Shleifer, and Vishny (1997) find that investors seem to be disappointed by actual earnings of growth stocks, leading to underperformance in stock returns for these stocks around future earnings release. From a q-theory prospective, Wu, Zhang, and Zhang (2010) argue that realized stock returns should relate to realized investment around information events.

If a crash is triggered by poor announced earnings, we should observe a concentration of price crashes around future earnings announcements. We investigate this possibility by re-calculating firm-specific weekly returns after excluding the three-day windows around earnings announcements during the fiscal year. We then re-estimate Equation (4) with each of the recomputed crash risk variables and report the results in Panel B of Table 5.[9] The coefficients of *ASSETG* are in general 10-20% smaller in magnitude than those in Table 3. For example, the coefficient of *ASSETG* relating to next year's *CRASH* is 0.191 in Table 5 compared to 0.213 in Table 3. Nevertheless, *ASSETG* is still significant in predicting future crash risk and the predictive power does not drop significantly after excluding earnings announcement returns. This result indicates that although some crashes occur around earnings release, the majority of sudden price declines happen outside the three-day earnings announcement window.

4.2. An agency problem explanation

The vast literature on stock price crash attributes crash risk to misalignments of managers' and investors' incentives (e.g., Jin and Myers 2006; Hutton et al. 2009; Kim et al. 2011a, b; Chang et al. 2017). If the relationship between asset growth and future crash risk arises from managers stockpiling negative NPV projects to satisfy empire-building needs, we should observe a stronger asset growth-crash risk relationship for firms with more severe agency problems.

To test this conjecture, we draw on the literature on agency conflicts to identify proxies for managers' empire building incentive due to agency problems. The first proxy is free cash flow (*FCF*). *FCF* arising from the mismatch between available cash flows and growth prospects is a commonly used variable to measure agency problems (Jensen 1986; Richardson 2006; Chen et al. 2012). More *FCF* allows managers to invest more in operations or negative NPV projects to pursue

[9] In the re-construction of *CRASH*, we compare the firm-specific weekly returns with the mean and standard deviation of the original version so that an original non-crash week will not become a crash week, vice versa, under the reduced sample excluding earnings announcements.

their self-interest in empire building.[10] The second proxy is number of years of CEO tenure. The probability of a manager accumulating power and building coalitions within the firm increases with tenure. A more powerful manager has more influence over spending decisions, which facilitates empire building (Hill and Phan 1991; Berger, Ofek, and Yermack 1997; Chen et al. 2012). The third proxy is whether the CEO will leave office in the near future. When the CEO expects to leave soon, the CEO has less incentive to empire build because he/she will not be at the firm for a sufficiently long period to derive the accumulated benefits. For example, Dechow and Sloan (1991) document less R&D spending for CEOs in the final year. Furthermore, because the CEOs will be leaving shortly, they are more willing to cut spending if necessary (Chen et al. 2012).

We use data from Compustat to construct the free cash flow variable (*FCF*) and from Capital IQ to construct the CEO tenure (*CEO_Tenure*) and CEO horizon (*CEO_Horizon*) variables. We measure *FCF* as cash flow from operations minus dividends to preferred and common shares. *CEO_Tenure* is the number of years a CEO has been in office. *CEO_Horizon* is a dummy variable that equals one in the year before and the year of CEO departure, and zero otherwise. The data for *FCF* starts from 1988 when cash flow information first became available and the data in Capital IQ starts in 1992.[11]

---

[10] We obtain qualitatively similar results if we use an aggregate measure of cash balance and leverage (Biddle et al. 2009) where a higher leverage can restrain managers from overinvestment due to debt-overhang (Myers 1977).

[11] Although the Capital IQ coverage is sparse in the first few years, it covers more firms than the commonly used Execucomp database which covers firms that are or have once been in the S&P 1500.

We expect more agency problems when *FCF* and *CEO_Tenure* are larger and *CEO_Horizon* equals zero. To investigate whether agency issues influence the asset growth-stock price crash risk relationship, we augment Equation (4) as follows:

$$RISK_{t+1} = \eta_0 + \eta_1 ASSETG_t + \eta_2 Agency_t + \eta_3 Agency_t \times ASSETG_t + \eta_4' Control_t + \varepsilon_{3t+1} \quad (6)$$

where *RISK* is *CRASH* or *NCSKEW* or *DUVOL*, and *Agency* is *FCF* or *CEO_Tenure* or *CEO_Horizon*. If one of the mechanisms driving the asset growth-crash risk relationship involves agency problems of managers, we should observe significant coefficients for the interaction term *Agency*ASSETG*; positive for the interactions of *FCF* and *CEO_Tenure* with asset growth, and negative for the interaction of *CEO_Horizon* with asset growth.

Table 6 reports the estimated coefficients for Equation (6). Columns (1) – (3) show that free cash flows positively interact with asset growth to predict future crash risk and the coefficients of the interactions are statistically significant. Columns (4) – (6) show that CEO tenure also significantly interacts with asset growth in predicting future crash risk. Columns (7) – (9) show that the asset growth effect on future crash risk is mitigated when a CEO is leaving; the interaction term *CEO_Horizon*ASSETG* has significantly negative coefficients in predicting future *CRASH*, *NCSKEW* and *DUVOL*. Overall, our tests provide strong evidence that agency problems are one of the mechanisms driving the asset growth-crash risk relationship.

4.3. Does accounting conservatism mitigate the asset growth-crash risk relationship?

Prior literature suggests that some firms have a tendency for conditionally conservative financial reporting, i.e., requiring a higher degree of verification for recognizing economic good news as gains than for recognizing economic bad news as losses (Basu 1997).[12] The practice of conditional accounting conservatism should mitigate the extent to which bad news is stockpiled and should therefore reduce stock price crash risk (Kim et al. 2016). Moreover, conservative accounting practices will promptly identify unprofitable projects and force managers to discontinue them, thus indirectly reducing overinvestment. If bad news hoarding by managers is one of the mechanisms driving our documented asset growth-crash risk relationship, the relationship should be weaker for firms with more conservative accounting.

We employ the following three measures of conditional conservatism to test this prediction:[13] *C_SKEW*, the negative of the ratio of earnings skewness to cash flow skewness over the past 20 fiscal quarters; *C_ACCR*, the negative of non-operating assets scaled by total assets over the past five fiscal years; and *C_SCORE*, the augmented asymmetric timeliness coefficient developed by Khan and Watts (2009).

---

[12] Conditional conservatism is in contrast to the news independent unconditional conservatism which records lower book values at the inception of assets and liabilities such as immediate expensing of R&D expenditures rather than capitalizing and amortizing them. Beaver and Ryan (2005) suggest that unconditional conservatism creates unrecorded goodwill as accounting slack that pre-empts the application of conditional conservatism unless news is sufficiently bad to use up the slack. Although the choice of unconditional conservatism is partly the result of mangers' choice, it is less directly related to bad news hoarding because of its "ex-ante" nature. Indeed, we find insignificant results when regressing crash risk on proxies of unconditional conservatism such as unrecorded goodwill (Penman and Zhang 2002).

[13] Detailed variable definitions are in Appendix A.

Firms with conditionally conservative accounting practices are likely to recognize bad news faster than good news, resulting in sudden large negative earnings relative to cash flows from assets being written down, accumulation of non-operating accruals, and earnings reflecting bad news in returns in a timelier manner (see Basu 1997; Givoly and Hayn 2000; Khan and Watts 2009). Therefore, more conditionally conservative accounting should result in higher values of *C_SKEW*, *C_ACCR*, and *C_SCORE*. To facilitate interpretation across measures, we transform them into decile rankings. Because each variable may reflect a subset of the dimensions of conditional conservatism, we also use a composite conservatism measure, *C_AVG*, calculated as the average of the above three decile variables.

We include *C_SKEW*, *C_ACCR*, *C_SCORE*, and *C_AVG*, and their interaction terms with *ASSETG* in Equation (4) and report the results in Table 7. Six out of nine specifications in Panel A show significant negative coefficients for the interaction term between conditional conservatism and asset growth, implying that the effect of asset growth on future crash risk is mitigated when firms require higher verification for good news than for bad news. Panel B shows that the interaction of *ASSETG* with the composite conservative measure, *C_AVG*, also has a significantly negative coefficient.[14] In summary, these results indicate that the practice of early recognition of

[14] The impacts of conditional conservatism in mitigating crash risk from asset growth are as follows: at the average *ASSETG*, a unit increase of *ASSETG* going across the quartiles for *C_AVG* (i.e., from deciles "2.5" to "7.5") will result in a drop of log odds of 0.46 for *CRASH*, and a drop of 0.11 and 0.055 for *NCSKEW* and *DUVOL*, respectively. The impacts are economically significant given that the coefficients for *ASSETG* for log odds for *CRASH*, *NCSKEW*, and *DUVOL* are 0.213, 0.098, and 0.045, respectively.

bad news does reduce the stockpiling of bad news and the probability of price crash when firms are expanding.

4.4. A short discussion

To further address the question of whether all growth is bad, we illustrate below that, even among firms with high asset growth, low agency conflicts and high conservative accounting can reduce the overall crash risk. Specifically, we first select firms in the highest asset growth quintile, sort them independently by free cash flows (i.e., by their empire-building incentive) or conservatism score *C_SCORE* (i.e., by their accounting conservatism), and calculate the average crash risk in the next year for each group.

Table 8 reports the sorting results for firms in the highest asset growth quintile. In Panel A, which includes firms in the lowest *FCF* quintile, the average $CRASH_{t+1}$ is 0.174, which is close to the overall average in Table 1, and the average $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ are below their respective overall averages. In Panel B, which includes firms with the highest *C_SCORE* quintile, the crash risk measures are below their respective overall averages. These results indicate that growth is not universally bad. Growth is bad when empire-building incentives are not constrained or when accounting practices are aggressive.

5. Testing the effects of overinvestment

The results so far establish a positive relationship between asset growth and future crash risk. However, growth should only be justified if corporate investments are supported by growth opportunities. In this section, we examine whether abnormal investments, i.e., investments in excess of normal investments that are consistent with growth prospects, are related to crash risk.

We use the following model to estimate normal investment (Chen et al. 2011; Biddle et al. 2009):

$$INVEST_t = \theta_0 + \theta_1 NEG_{t-1} + \theta_2 REVGRW_{t-1} + \theta_3 NEG_{t-1} \times REVGRW_{t-1} + \varepsilon_{4t} \qquad (7)$$

where $INVEST$ is either capital expenditure or total investment that includes annual capital expenditure, R&D and acquisition costs, *REVGRW* is the year-to-year sales growth percentage, and *NEG* is a dummy variable that equals one for negative sales growth, and zero otherwise. We estimate Equation (7) cross-sectionally for each of the Fama-French 48 industries with at least 10 observations in a year. The residual, ε, is the abnormal investment; a positive (negative) value indicates overinvestment (underinvestment). Table 9 presents the estimation results using abnormal investment in place of *ASSETG* in Equation (4). It shows that both abnormal capital expenditure (*Ab_CAPEX*) and abnormal total investment (*Ab_TOTINV*) are significantly positively related to next year's crash risk, with the coefficients comparable to the corresponding estimates in Table 3. We obtain qualitatively similar results when the market-to-book ratio is used to measure growth opportunities.

6. Sensitivity checks

We conduct a battery of sensitivity checks to make sure that our results are robust. We summarize the results here and include the detailed results in Online Appendix B. These sensitivity checks include (1) controlling for two-week leads and lags of market and industry returns when estimating firm-specific weekly returns; (2) re-estimating the models separately for the financial crisis period (2007-2009) and the non-crisis period (all other years); (3) using a longer sample period (from the 1970's when *OPAQUE* is omitted from the regression); (4) including firm fixed effects; (5) using the full sample of *C_SCORE*, that is, without restricting it to the common sample of *C_ACCR* and *C_SKEW*; (6) controlling for stock liquidity (Chang et al. 2017); (7) defining *CEO_Horizon* as the current and preceding year of a CEO change to mitigate the reverse causality concern that a CEO changes after a realized crash; (8) using alternative definitions of asset growth following Lipson et al. (2011); (9) using a broader definition of assets, including on- and off-balance sheet physical and intangible assets (Peters and Taylor 2017); (10) controlling for the precautionary motives of cash holding (Opler, Pinkowitz, Stulz, and Williamson 1999; Bates, Kahle, and Stulz 2009) when we explain crash risk by asset growth;[15] (11) controlling for short interest ratio (Callen and Fang 2015b); (12) controlling for institutional ownerships and their classifications (Callen and Fang 2013; An and Zhang 2013); and (13) controlling for the 10-K file size (Ertugrul, Lei, Qiu, and Wan 2017). In all of the above sensitivity checks, asset growth remains significantly positively related to future crash risk.

8. Conclusion

Although many studies relate asset growth to future stock returns in the recent market efficiency literature, the implications of asset growth for future stock price crash risk have not been

[15] It is possible that managers foresee a future crash and therefore stockpile assets, especially cash, as a precautionary motive.

investigated. We document that asset growth positively relates to future price crash for up to three years.

We provide evidence consistent with the overinvestment from managerial empire building and the bad news hoarding explanations. In particular, high asset growth is related to poor future firm performance in terms of profit margin and return on assets, suggesting overinvestment or operating inefficiency. We also find that firms with more agency problems have incrementally higher crash risk related to asset growth and firms with more conditionally conservative accounting practices have incrementally lower crash risk.

While asset growth of certain firms may be bad, it appears that investors are unaware of the implications for future price movements until adverse market adjustments take place, like a Jenga tower collapse.

References

Aboody, D., and B. Lev. 2000. Information asymmetry, R&D, and insider gains. *The Journal of Finance* 55 (6): 2747-2766.

An, H., and T. Zhang. 2013. Stock price synchronicity, crash risk, and institutional investors. *The Journal of Corporate Finance* 21 (June): 1-15.

Baker, G. P., M. C. Jensen, and K. J. Murphy, 1988. Compensation and incentives: Practice vs. Theory. *The Journal of Finance* 43 (3): 593-616.

Ball, R., S. Jayaraman, and L. Shivakumar. 2012. Audited financial reporting and voluntary disclosure as complements: A test of the confirmation hypothesis. *Journal of Accounting and Economics* 53 (1–2): 136–166.

Balachandran, S., and P. Mohanram. 2010. Are CEOs compensated for value destroying growth in earnings? *Review of Accounting Studies* 15 (3): 545-577.

Basu, S. 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics* 24 (1): 3–37.

Bates, T. W., K. M. Kahle, and R. M. Stulz. 2009. Why do US firms hold so much more cash than they used to? *Journal of Finance* 64 (5): 1985-2021.

Beaver, W. H., and S. G. Ryan. 2005. Conditional and unconditional conservatism: Concepts and modeling. *Review of Accounting Studies* 10 (2-3): 269-309.

Berger, P. G., E. Ofek, and D. L. Yermack. 1997. Managerial entrenchment and capital structure decisions. *The Journal of Finance* 52 (4): 1411-38.

Bernard, V. L., and J. K. Thomas. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting Research* 27: 1-36.

Biddle, G. C., G. Hilary, and R. S. Verdi. 2009. How does financial reporting quality relate to investment efficiency? *Journal of Accounting and Economics* 48 (2-3): 112-131.

Bleck, A., and X. Liu. 2007. Market transparency and the accounting regime. *Journal of Accounting Research* 45 (2): 229-256.

Bushman, R. M., J. D. Piotroski, and A. J. Smith. 2011. Capital allocation and timely accounting recognition of economic losses. *Journal of Business Finance and Accounting* 38 (1-2): 1-33.

Callen, J. L., and X. Fang. 2013. Institutional investor stability and crash risk: Monitoring versus short-termism? *Journal of Banking and Finance* 37 (8): 3047-3063.

Callen, J. L., and X. Fang. 2015a. Religion and stock price crash risk. *Journal of Financial and Quantitative Analysis* 50 (1-2): 169–195.

Callen, J. L., and X. Fang. 2015b. Short interest and stock price crash risk. *Journal of Banking and Finance* 60 (November): 181-194.

Chang, X., Y. Chen, and L. Zolotoy. 2017. Stock liquidity and stock price crash risk. *Journal of Financial and Quantitative Analysis* 52 (4): 1605-1637.

Chen J., H. Hong, and J. C. Stein. 2001. Forecasting crashes, Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics* 61 (3): 345-381.

Chen, F., O. K. Hope, Q. Li, and X. Wang. 2011. Financial reporting quality and investment efficiency of private firms in emerging markets. *The Accounting Review* 86 (4): 1255-1288.

Chen, C. X., H. Lu, and T. Sougiannis. 2012. The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. *Contemporary Accounting Research* 29 (1): 252-282.

Cooper, M. J., H. Gulen, and M. Ion. 2017. The use of asset growth in empirical asset pricing models. Working paper.

Cooper, M., H. Gulen, and M. Schill. 2008. Asset growth and the cross-section of stock returns. *The Journal of Finance* 63 (4):1609-1652.

Dechow, P. M., and R. G. Sloan. 1991. Executive incentives and the horizon problem: An empirical investigation. *Journal of Accounting and Economics* 14 (1): 51–89.

Demerjian, P., B. Lev, and S. McVay. 2012. Quantifying managerial ability: A new measure and validity tests. *Management Science* 58 (7): 1229-1248.

Ertugrul, M., J. Lei, J. Qiu, and C. Wan. 2017. Annual report readability, tone ambiguity, and the cost of borrowing. *Journal of Financial and Quantitative Analysis* 52 (2): 811-836.

Fama, E. F., and K. R. French. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116 (1): 1-22.

Francis, J. R., and X. Martin. 2010. Acquisition profitability and timely loss recognition. *Journal of Accounting and Economics* 49 (1–2): 161–178.

Givoly, D., and C. Hayn. 2000. The changing time-series properties of earnings, cash flows and accruals: Has financial reporting become more conservative? *Journal of Accounting and Economics* 29 (3): 287-320.

Greenwood, R., A. Shleifer, and Y. You. 2019. Bubbles for Fama. *Journal of Financial Economics* 131 (1): 20-43.

Hill, C. W. L., and P. Phan. 1991. CEO tenure as a determinant of CEO pay. *Academy of Management Journal* 34 (3): 707–17.

Hirshleifer, D., K. Hou, S. H. Teoh, and Y. Zhang. 2004. Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38 (December): 297-331.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting anomalies: an investment approach. *Review of Financial Studies* 28 (3): 650-705.

Hutton A. P, Marcus A. J, and H. Tehranian. 2009. Opaque financial reports, R^2, and crash risk. *Journal of Financial Economics* 94 (1): 67-86.

Jensen, M. C. 1986. Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review* 76 (2): 323-329.

Jensen, M. C., and W. H. Meckling. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3 (4): 305-360.

Jensen, M. C., and K. J. Murphy. 1990. Performance pay and top-management incentives. *Journal of Political Economy* 98 (2): 225–64.

Jin, L., and S. C. Myers. 2006. R^2 around the World: New theory and new tests. *Journal of Financial Economics* 79 (2): 257-292.

Khan, M., and R. L. Watts. 2009. Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics* 48 (2-3): 132-150.

Kim, J. B., Y. Li, and L. Zhang. 2011a. CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics* 101 (3): 713-730.

Kim, J. B., Y. Li, and L. Zhang. 2011b. Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics* 100 (3): 639-662.

Kim, J. B., L. Luo, and H. Xie. 2020. Do dividends mitigate bad news hoarding, overinvestment, and stock price crash risk? Working paper.

Kim, J. B., Z. Wang, and L. Zhang. 2016. CEO overconfidence and stock price crash risk. *Contemporary Accounting Research* 33 (4): 1720-1749.

Kim, J. B., and L. Zhang. 2016. Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary Accounting Research* 33 (1): 412-441.

Kothari, S. P., S. Shu, and P. D. Wysocki. 2009. Do managers withhold bad news? *Journal of Accounting Research* 47 (1): 241-276.

La Porta, R., J. Lakonishok, A. Shleifer, and R. Vishny. 1997. Good news for value stocks: Further evidence on market efficiency. *The Journal of Finance* 52 (2): 859-874.

LaFond, R., and R. L. Watts. 2008. The information role of conservatism. *The Accounting Review* 83 (2): 447–478.

Lipson, M. L., S. Mortal, and M. J. Schill. 2011. On the scope and drivers of the asset growth effect. *Journal of Financial and Quantitative Analysis* 46 (6): 1651-1682.

Lobo, G., C. Wang, X. Yu, and Y. Zhao. 2020. Material weakness in internal controls and stock price crash risk. *Journal of Accounting, Auditing and Finance* 35 (1): 106-138.

Murphy, K. J. 1985. Corporate performance and managerial remuneration: An empirical analysis. *Journal of Accounting and Economics* 7 (1-3): 11–42.

Myers, S. C. 1977. Determinants of corporate borrowing. *Journal of Financial Economics* 5 (2): 147-175.

Na, K. 2020. CEOs' outside opportunities and relative performance evaluation: Evidence from a natural experiment. *Journal of Financial Economics* 137 (3): 679-700.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52 (1): 3-46.

Qiu, B., F. Xu, and C. Zeng. 2019. Contagious stock price crashes. Working paper.

Penman, S. H., and X. J. Zhang. 2002. Accounting conservatism, the quality of earnings, and stock returns. *The Accounting Review* 77 (2): 237-264.

Peters, R. H., and L. A. Taylor. 2017. Intangible capital and the investment-q relation. *Journal of Financial Economics* 123 (2): 251-272.

Rau, P. R., and T. Vermaelen. 1998. Glamour, value and the post-acquisition performance of acquiring firms. *Journal of Financial Economics* 49 (2): 223-253.

Richardson, S. A., and R. G. Sloan. 2003. External financing and future stock returns. Rodney L. White Center for Financial Research Working Paper, (03-03).

Richardson, S. 2006. Over-investment of free cash flow. *Review of Accounting Studies* 11 (2-3): 159–89.

Rose, N. L., and A. Shepard. 1997. Firm diversification and CEO compensation: Managerial ability or executive entrenchment? *RAND Journal of Economics* 28 (3): 489–514.

Titman, S., K. J. Wei, and F. Xie. 2004. Capital investments and stock returns. *Journal of Financial and Quantitative Analysis* 39 (4): 677-700.

van Binsbergen, J.H., and C.C. Opp. 2019. Real anomalies. *The Journal of Finance* 74 (4): 1659-1706.

Watts, R. L. 2003. Conservatism in accounting part I: Explanations and implications. *Accounting Horizons* 17 (3): 207–221.

Wu, J., L. Zhang, and X. F. Zhang. 2010. The q-theory approach to understanding the accrual anomaly. *Journal of Accounting Research* 48 (1): 177-223.

Zhu, W. 2016. Accruals and price crashes. *Review of Accounting Studies* 21 (2): 349-399.

Appendix A. Variable definitions

Variable	Definitions
Crash risk variables	
CRASH	The following regression is run for each firm and fiscal year: $r_{i,w} = \beta_0 + \beta_1 r_{MKT,w-1} + \beta_2 r_{IND,w-1} + \beta_3 r_{MKT,w} + \beta_4 r_{IND,w} + \beta_5 r_{MKT,w+1} + \beta_6 r_{IND,w+1} + \varepsilon_{i,w}$, where $r_{i,w}$ is the weekly stock return for firm *i* in week *t*, $r_{MKT,w}$ is the weekly value-weighted CRSP market return , and $r_{IND,t}$ is the weekly Fama-French value-weighted industry return. Firm-specific return W_{it} for week *w* is defined as $\ln(1 + \varepsilon_{iw})$. *CRASH* is a dummy variable equal to one, zero otherwise, if the firm has at least one week for which W_{it} is below 3.2 standard deviation of the mean of firm-specific return for the fiscal year.
NCSKEW	Negative coefficient of skewness, defined as the negative of the third moments of firm-specific returns W_{iw} divided by the standard deviation of W_{iw} raised to the third power for each firm and fiscal year.
DUVOL	Asymmetric volatility of negative versus positive returns. For each firm and fiscal year, the sample is divided into halves with positive and negative firm-specific weekly returns W_{iw}. Volatilities for the positive and negative return weeks are calculated respectively. *DUVOL* is the log of the ratio of the negative week volatility to positive week volatility.
Asset growth variable	
ASSETG	Asset growth: Year-on-year percentage change in total assets: $\frac{AT_t - AT_{t-1}}{AT_{t-1}}$.
Control variables	
DTURNOVER	Yearly change in turnover: Average monthly stock turnover for the current fiscal year over the previous fiscal year. Monthly stock turnover is defined as the total volume divided by the number of shares outstanding. Volume and shares outstanding data are from CRSP.

SIGMA	Standard deviation of firm-specific weekly return for the fiscal year.
RET	Mean of firm-specific weekly return for the fiscal year.
SIZE	Natural logarithm of market value of common equity: log $[PRCC\_F_t * CSHI_t]$.
MB	Market-to-book ratio: $\frac{PRCC\_F_t * CSHPRI_t}{CEQ_t}$.
LEV	Leverage ratio as total long-term debt divided by total assets: $DLTT_t/AT_t$.
ROA	Income before extraordinary item divided by total assets: IB_t/TA_t.
OPAQUE	Opacity measure by Hutton et al. (2009): the three-year moving sum of absolute value of discretionary accruals, where discretionary accruals are defined as the residuals from a cross-section regression of total accruals per lagged total assets on 1/lagged total assets, change in sales over receivables/lagged total assets, and PP&E/lagged total assets. The cross-section regression is run across firms within a Fama-French industry for each fiscal year.
PM	Profit margin as income before extraordinary items divided by sales: $IB_t/SALE_t$.

Agency variables

FCF	Free cash flow: cash flow from operating activities minus common and preferred dividends scaled by total assets: $\frac{OANCF_t - DVC_t - DVP_t}{AT_t}$.
CEO_Tenure	Years of CEO in office.
CEO_Horizon	Dummy variable equals one for the year of a CEO change or the year immediately preceding a change.

Conservatism variables

*C_ACCR**	Conservatism measured by negative non-operating accruals, calculated as (-1) × the average of non-operating accruals scaled by total assets over a five-year window (with a minimum of two years) for fiscal year (*t*-4, *t*). Non-operating accruals are defined as *NI+DP-OANCF+RECCH+INVCH-ΔXPP+APALCH+TXACH* scaled by *AT*.

*C_SKEW** Conservatism measured by relative skewness of earnings versus cash flows, calculated as (−1) × skewness of earnings scaled by skewness of cash flows over a 20-quarter window (with a minimum of five quarters) for fiscal years (*t*-4, *t*). Earnings and cash flows are from Compustat items *IBQ* and *OANCFY*, respectively.

*C_SCORE** Conditional conservatism. Firm-specific asymmetric timeliness score developed by Khan and Watts (2009). A five-year rolling panel regression is run: $\frac{X_{it}}{P_{i(t-1)}} = a_1 + a_2 D_{it} + a_{3it} Ret_{it} + a_{4it} D_{it} Ret_{it} + \varepsilon_{it}$ where X_{it} is earnings per share, $P_{i(t-1)}$ is the price at the beginning of the year, Ret_{it} is the annual compounded return ending in the fiscal year end for firm *i*, and D_{it} is a dummy variable equal to one when Ret_{it} is negative, otherwise zero.The coefficients a_{3it} and a_{4i} are linear functions of market value of equity, market-to-book ratio and leverage ratio (total debt/total assets). The regression results in firm-specific coefficients $\hat{a}_{3it}$ and $\hat{a}_{4it}$ for each fiscal year. Timelines of good news is measured by $\hat{a}_{3it}$. *C_SCORE* is measured by $\hat{a}_{4it}$.

C_AVG Average of the conditional conservatism ranks. For each fiscal year, firms are sorted into deciles according to *C_ACCR*, *C_SKEW*, and *C_SCORE*, respectively. *C_AVG* is the average across the ranked variables.

* We use decile ranking in the regression with high ranking meaning more conservative.

Overinvestments

Ab_CAPEX The regression residual of regressing capital expenditure scaled by lagged total assets ($CAPEX_t$) on lagged percentage sales growth ($REVGRW_{t-1}$), an indicator variable of negative lagged sales growth (NEG_{t-1}), and the interaction between the two. The regression is estimated cross-sectionally for each Fama-French 48 industries with at least 10 observations.

Ab_TOTINV The regression residual of regressing total investment scaled by lagged total assets ($TOTINV_t$) on lagged percentage sales growth ($REVGRW_{t-1}$), an indicator variable of negative lagged sales growth (NEG_{t-1}), and the interaction between the two. The regression is estimated cross-sectionally for each Fama-French 48 industries with at least 10 observations. Total investment is the sum of capital expenditure, R&D and acquisitions.

Table 1. Summary Statistics

This table reports the descriptive summary statistics and correlations for the following variables. *CRASH* is a dummy variable when firm-specific return is below 3.2 standard deviation of the mean for at least one week for the fiscal year, otherwise zero. *NCSKEW* is the negative coefficient of skewness for firm-specific return. *DUVOL* is the log of down-market volatility to up-market volatility. Firm-specific returns are the regression residuals of weekly returns on market and industry returns with one-week lead and lagged values. *ASSETG* is the annual change in total asset scaled by last year total asset. *DTURNOVER* is the year-to-year change in share turnover. *LAGNCSKEW* is last year value of *NCSKEW*. *SIGMA* is the standard deviation of firm-specific return for the fiscal year. *RET* is the average firm-specific return for the fiscal year. *SIZE* is the market capitalization. *MB* is the market-to-book ratio. *LEV* is leverage ratio as long-term debts divided by total assets. *ROA* is return on assets. *OPAQUE* is earnings opacity by Hutton et al. (2009). All changes in balance sheet items are scaled by last year total assets. Appendix A provides detailed variable definitions.

Panel A: Descriptive summary statistics

Variable	N	Mean	Std	25%	Median	75%
CRASH	65,788	0.170	0.375	0.000	0.000	0.000
NCSKEW	65,788	-0.115	0.794	-0.555	-0.134	0.293
DUVOL	65,788	-0.069	0.361	-0.311	-0.080	0.159
ASSETG	65,788	0.122	0.336	-0.035	0.057	0.182
DTURNOVER	65,788	0.000	0.088	-0.025	-0.001	0.023
LAGNCSKEW	65,788	-0.101	0.766	-0.536	-0.126	0.291
SIGMA	65,788	0.059	0.033	0.035	0.052	0.075
RET	65,788	-0.228	0.276	-0.278	-0.131	-0.062
SIZE	65,788	5.622	2.251	3.946	5.534	7.150
MB	65,788	2.742	2.903	1.143	1.883	3.190
LEV	65,788	0.161	0.168	0.004	0.120	0.265
ROA	65,788	0.001	0.164	-0.013	0.038	0.078
OPAQUE	65,788	0.212	0.162	0.100	0.164	0.271

Panel B. Correlation matrix for crash risks, *ASSETG*, and control variables.

		A	B	C	D	E	F	G	H	I	J
CRASH	A	1.000									
NCSKEW	B	0.615	1.000								
		0.000									
DUVOL	C	0.561	0.961	1.000							
		0.000	0.000								
ASSETG	D	0.043	0.080	0.079	1.000						
		0.000	0.000	0.000							
DTURNOVER	E	0.030	0.048	0.049	0.161	1.000					
		0.000	0.000	0.000	0.000						
LAGNCSKEW	F	0.038	0.053	0.053	0.006	0.011	1.000				
		0.000	0.000	0.000	0.125	0.005					
SIGMA	G	-0.053	-0.108	-0.119	-0.038	0.091	-0.077	1.000			
		0.000	0.000	0.000	0.000	0.000	0.000				
RET	H	0.053	0.105	0.114	0.064	-0.097	0.107	-0.955	1.000		
		0.000	0.000	0.000	0.000	0.000	0.000	0.000			
SIZE	I	0.080	0.181	0.187	0.108	0.056	0.147	-0.571	0.479	1.000	
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
MB	J	0.037	0.066	0.064	0.124	0.089	-0.011	-0.034	0.013	0.270	1.00
		0.000	0.000	0.000	0.000	0.000	0.006	0.000	0.001	0.000	
LEV	K	-0.013	-0.001	0.001	0.045	0.027	0.006	-0.082	0.068	0.120	0.01
		0.001	0.836	0.748	0.000	0.000	0.159	0.000	0.000	0.000	0.00
ROA	L	0.052	0.112	0.119	0.247	0.097	0.044	-0.468	0.468	0.318	-0.01
		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00
OPAQUE	M	-0.018	-0.054	-0.059	0.087	-0.005	-0.052	0.429	-0.388	-0.327	0.09
		0.000	0.000	0.000	0.000	0.186	0.000	0.000	0.000	0.000	0.00

Table 2. Univariate sorting analysis

For each year, firms are grouped into quintiles according *ASSETG*. The means of next year *CRASH*, *NCSKEW*, and *DUVOL* are calculated within each quintile for each year, and the high and low group differences are also calculated. This results in a time-series of crash risk for each quintile and the high-minus-low group, and the time-series averages are reported.

Quintile	1 (Low *ASSETG*)	2	3	4	5 (High *ASSETG*)	5-1	5-1 *t*-value
CRASH(t+1)	0.136	0.162	0.168	0.182	0.200	0.064	13.951
NCSKEW(t+1)	-0.257	-0.154	-0.106	-0.047	-0.008	0.249	25.418
DUVOL(t+1)	-0.136	-0.087	-0.064	-0.038	-0.022	0.114	25.723

Table 3. Asset growth and crash risk

This table reports the regression results for Equation (4), with Column 1 reporting coefficients in log odds from a logit regression. *CRASH* is a dummy variable when firm-specific return is below 3.2 standard deviation of the mean for at least one week for the fiscal year, otherwise zero. *NCSKEW* is the negative coefficient of skewness for firm-specific return. *DUVOL* is the log of down-market volatility to up-market volatility. Firm-specific returns are the regression residuals of weekly returns on market and industry returns with one-week lead and lagged values. *ASSETG* is the annual change in total asset scaled by last year total asset. *DTURNOVER, LAGNCSKEW, SIGMA, RET, SIZE, MB, LEV, ROA,* and *OPAQUE* are control variables. Appendix A provides detailed variable definitions. In all specifications, year- and industry-level fixed effects are included and standard errors, in parenthesis, are two-way clustered at firm and year levels. Significance levels for 1%, 5%, and 10% are represented by ***, **, and * respectively.

	(1)	(2)	(3)	From 25th to 75th percentile of a dependent variable, the impact on		
	CRASH	*NCSKEW*	*DUVOL*	*CRASH*	*NCSKEW*	*DUVOL*
ASSETG	0.213***	0.098***	0.045***	0.0055	0.021	0.010
	(0.034)	(0.010)	(0.005)			
DTURNOVER	0.648***	0.233***	0.110***	0.0037	0.011	0.057
	(0.129)	(0.038)	(0.018)			
LAGNCSKEW	0.073***	0.022***	0.010***	0.0072	0.018	0.056
	(0.015)	(0.004)	(0.002)			
SIGMA	5.777***	3.090***	1.088***	0.0272	0.124	0.191
	(2.090)	(0.569)	(0.281)			
RET	0.856***	0.352***	0.135***	0.0230	0.076	0.236
	(0.215)	(0.054)	(0.028)			
SIZE	0.057***	0.060***	0.026***	0.0218	0.192	0.128
	(0.012)	(0.005)	(0.002)			
MB	0.007*	0.004***	0.002***	0.0017	0.008	0.020
	(0.004)	(0.001)	(0.001)			
LEV	-0.004	-0.054**	-0.027**	-0.0001	-0.014	-0.001
	(0.083)	(0.024)	(0.011)			
ROA	0.531***	0.238***	0.115***	0.0059	0.022	0.087
	(0.107)	(0.026)	(0.012)			
OPAQUE	0.196**	0.033	0.019**	0.0040	0.006	0.032
	(0.077)	(0.021)	(0.009)			
Constant	-2.368***	-0.622***	-0.269***			
	(0.228)	(0.044)	(0.021)			
Year/Industry	Yes	Yes	Yes			
Adjusted R^2	0.026	0.051	0.055			
N	65,788	65,788	65,788			

Table 4. Predicting years ahead crash risks

This table reports the regression results for Equation (4) with crash risks replaced by their years ahead counterparts, and Panel A reporting coefficients in log odds from a logit regression. *CRASH* is a dummy variable when firm-specific return is below 3.2 standard deviation of the mean for at least one week for the fiscal year, otherwise zero. *NCSKEW* is the negative coefficient of skewness for firm-specific return. *DUVOL* is the log of down-market volatility to up-market volatility. Firm-specific returns are the regression residuals of weekly returns on market and industry returns with one-week lead and lagged values. *ASSETG* is the annual change in total asset scaled by last year total asset. Coefficients for control variables are not reported for brevity. Appendix A provides detailed variable definitions. In all specifications, year- and industry-level fixed effects are included and standard errors, in parenthesis, are two-way clustered at firm and year levels. Significance levels for 1%, 5%, and 10% are represented by ***, **, and * respectively.

Panel A: *CRASH* as the dependent variable

	(1) *CRASH(t+2)*	(2) *CRASH(t+3)*	(3) *CRASH(t+4)*	(4) *CRASH(t+5)*
ASSETG	0.139***	0.120***	-0.025	0.007
	(0.037)	(0.039)	(0.049)	(0.047)
Control	Yes	Yes	Yes	Yes
Year/Industry	Yes	Yes	Yes	Yes
R^2	0.023	0.021	0.020	0.019
N	56,085	49,037	43,253	38,213

Panel B: *NCSKEW* as the dependent variable

	(1) *NCSKEW(t+2)*	(2) *NCSKEW(t+3)*	(3) *NCSKEW(t+4)*	(4) *NCSKEW(t+5)*
ASSETG	0.046***	0.036***	-0.006	0.005
	(0.013)	(0.014)	(0.010)	(0.015)
Control	Yes	Yes	Yes	Yes
Year/Industry	Yes	Yes	Yes	Yes
R^2	0.039	0.031	0.029	0.026
N	56,094	49,033	43,250	38,210

Panel C: *DUVOL* as the dependent variable

	(1) *DUVOL(t+2)*	(2) *DUVOL(t+3)*	(3) *DUVOL(t+4)*	(4) *DUVOL(t+5)*
ASSETG	0.021***	0.011*	-0.003	0.001
	(0.006)	(0.006)	(0.005)	(0.007)
Control	Yes	Yes	Yes	Yes
Year/Industry	Yes	Yes	Yes	Yes
R^2	0.043	0.035	0.032	0.029
N	56,092	49,032	43,249	38,209

Table 5. Prediction of asset growth on future operating performance. Concentration of negative returns

Panel A reports results when next year's operating performance (profit margin and return on assets) is regressed on *ASSETG* and other variables. Panel B reports results for Equation (4) when the three-day window around earnings announcement dates are excluded in crash risk calculations. Appendix A provides detailed variable definitions. Standard errors are reported in parenthesis. Significance levels for 1%, 5%, and 10% are represented by ***, **, and * respectively

Panel A: Future operating performance

	(1) *FuturePM*	(2) *FutureROA*
ASSETG	-0.061***	-0.026***
	(0.015)	(0.004)
Δ*PM*	-0.108***	
	(0.037)	
PM	0.769***	
	(0.044)	
Δ*ROA*		-0.134***
		(0.017)
ROA		0.618***
		(0.028)
MB	0.009	0.012***
	(0.008)	(0.002)
SIZE	0.015***	0.009***
	(0.002)	(0.001)
Constant	-0.098***	-0.062***
	(0.015)	(0.006)
Industry	Yes	Yes
Adjusted R^2	0.528	0.413
N	64,917	65,057

Panel B: Crash risks excluding three-day earnings announcement window.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.191***	0.081***	0.037***
	(0.038)	(0.010)	(0.005)
DTURNOVER	0.643***	0.215***	0.103***
	(0.138)	(0.043)	(0.020)
LAGNCSKEW	0.071***	0.018***	0.008***
	(0.017)	(0.004)	(0.002)
SIGMA	4.991**	3.179***	1.096***
	(2.051)	(0.536)	(0.269)
RET	0.770***	0.384***	0.148***
	(0.210)	(0.046)	(0.024)
SIZE	0.064***	0.057***	0.025***
	(0.013)	(0.005)	(0.002)
MB	0.010**	0.004***	0.002***
	(0.004)	(0.001)	(0.001)
LEV	-0.074	-0.055**	-0.025**
	(0.088)	(0.023)	(0.010)
ROA	0.339***	0.243***	0.118***
	(0.116)	(0.029)	(0.014)
OPAQUE	0.293***	0.013	0.005
	(0.089)	(0.026)	(0.012)
Constant	-2.574***	-0.597***	-0.258***
	(0.158)	(0.037)	(0.018)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Adjusted R^2	0.020	0.045	0.048
N	63,589	63,589	63,589

Table 6. Agency explanations

This table reports the regression results for Equation (6) with Columns 1, 4, and 7 reporting coefficients in log odds for the logit regression. *CRASH* is a dummy variable when firm-specific return is below 3.2 standard deviation of the mean for at least one week for the fiscal year, otherwise zero. *NCSKEW* is the negative coefficient of skewness for firm-specific return. *DUVOL* is the log of down-market volatility to up-market volatility. Firm-specific returns are the regression residuals of weekly returns on market and industry returns with one-week lead and lagged values. *ASSETG* is the annual change in total asset scaled by last year total asset. *Agency* represents either *FCF*, *CEO_Tenure*, or *CEO_Horizon*. *FCF* is free cash flow for the year. *CEO_Tenure* is the number of year the CEO in office. *CEO_horizon* equals one when for the year and the immediate year preceding a CEO change, otherwise zero. Columns 1 to 3 report results with *FCF* as the agency variable. Columns 4 to 6 report results when *CEO_Tenure* as the agency variable. Columns 7 to 9 report results with *CEO_Horizon* as the agency variable. *DTURNOVER, LAGNCSKEW, SIGMA, RET, SIZE, MB, LEV, ROA,* and *OPAQUE* are control variables. Appendix A provides detailed variable definitions. In all specifications, year- and industry-level fixed effects are included and standard errors, in parenthesis, are two-way clustered at firm and year levels. Significance levels for 1%, 5%, and 10% are represented by ***, **, and * respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	CRASH	*NCSKEW*	*DUVOL*	*CRASH*	*NCSKEW*	*DUVOL*	*CRASH*	*NCSKEW*	*DUVOL*
	FCF as Agency Variable			*CEO_Tenure* as Agency Variable			*CEO_Horizon* as Agency Variable		
Agency	-0.001	0.063	0.032*	-0.015	-0.009	-0.003	0.127***	0.036***	0.014**
	(0.197)	(0.041)	(0.017)	(0.022)	(0.006)	(0.003)	(0.035)	(0.014)	(0.006)
Agency ASSETG*	0.472***	0.254***	0.114***	0.105**	0.041**	0.015*	-0.302**	-0.081**	-0.034**
	(0.175)	(0.055)	(0.024)	(0.051)	(0.019)	(0.009)	(0.134)	(0.035)	(0.015)
ASSETG	0.203***	0.100***	0.046***	0.011	0.022	0.018	0.254***	0.110***	0.051***
	(0.035)	(0.010)	(0.004)	(0.103)	(0.042)	(0.017)	(0.052)	(0.021)	(0.009)
DTURNOVER	0.659***	0.233***	0.110***	0.451***	0.228***	0.110***	0.449***	0.227***	0.109***
	(0.131)	(0.038)	(0.018)	(0.120)	(0.056)	(0.027)	(0.120)	(0.056)	(0.027)
LAGNCSKEW	0.071***	0.021***	0.010***	0.052***	0.014**	0.006*	0.050**	0.014*	0.006*

	(0.016)	(0.004)	(0.002)	(0.020)	(0.007)	(0.003)	(0.020)	(0.007)	(0.003)
SIGMA	5.721***	3.057***	1.081***	13.488***	4.759***	2.081***	13.356***	4.733***	2.070***
	(2.067)	(0.561)	(0.280)	(2.285)	(0.779)	(0.361)	(2.286)	(0.768)	(0.357)
RET	0.849***	0.349***	0.135***	1.625***	0.555***	0.252***	1.615***	0.552***	0.251***
	(0.212)	(0.054)	(0.028)	(0.249)	(0.075)	(0.035)	(0.250)	(0.074)	(0.034)
SIZE	0.058***	0.060***	0.026***	0.074***	0.055***	0.025***	0.073***	0.056***	0.025***
	(0.012)	(0.005)	(0.002)	(0.013)	(0.007)	(0.003)	(0.013)	(0.007)	(0.003)
MB	0.006	0.004**	0.002**	0.005	0.003	0.001	0.005	0.003	0.001
	(0.004)	(0.001)	(0.001)	(0.006)	(0.002)	(0.001)	(0.006)	(0.002)	(0.001)
LEV	-0.001	-0.053**	-0.026**	-0.051	-0.050*	-0.023*	-0.050	-0.050*	-0.023*
	(0.080)	(0.024)	(0.011)	(0.114)	(0.029)	(0.013)	(0.115)	(0.029)	(0.013)
ROA	0.497***	0.203***	0.098***	0.561***	0.234***	0.119***	0.597***	0.240***	0.121***
	(0.129)	(0.031)	(0.014)	(0.158)	(0.042)	(0.019)	(0.150)	(0.042)	(0.018)
OPAQUE	0.206***	0.039*	0.022**	0.071	0.045	0.033**	0.064	0.044	0.033**
	(0.078)	(0.021)	(0.009)	(0.084)	(0.036)	(0.016)	(0.085)	(0.036)	(0.016)
Constant	-2.385***	-0.632***	-0.273***	-2.362***	-0.536***	-0.249***	-2.406***	-0.562***	-0.258***
	(0.232)	(0.042)	(0.020)	(0.275)	(0.088)	(0.040)	(0.252)	(0.082)	(0.038)
Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.026	0.051	0.055	0.024	0.041	0.046	0.024	0.042	0.046
N	65,294	65,294	65,294	31,654	31,665	31,665	31,654	31,665	31,665

Table 7. Accounting conservatism

This table reports the regression results for Equation (4) adding interaction terms of *ASSSETG* with accounting conservatism. The columns for *CRASH* report coefficients in log odds from a logit regression. *CRASH* is a dummy variable when firm-specific return is below 3.2 standard deviation of the mean for at least one week for the fiscal year, otherwise zero. *NCSKEW* is the negative coefficient of skewness for firm-specific return. *DUVOL* is the log of down-market volatility to up-market volatility. Firm-specific returns are the regression residuals of weekly returns on market and industry returns with one-week lead and lagged values. *ASSETG* is the annual change in total asset scaled by last year total asset. In Panel A, *Conservatism* represents either *C_SKEW*, *C_ACCR*, or *C_SCORE*. *C_SKEW* is the negative of ratio of earnings skewness to cash flow skewness. *C_ACCR* is non-operating accruals for the fiscal year. *C_SCORE* is the asymmetric timeliness coefficient from Khan and Watts (2009) model. All the conservatism variables are decile ranks within the year. Columns 1 to 3 report results with *C_SKEW* as the conservatism variable. Columns 4 to 6 report results when *C_ACCR* as the conservatism variable. Columns 7 to 9 report results with *C_SCORE* as the conservatism variable. In Panel B, *C_AVG* is the average decile ranks for *C_SKEW*, *C_ACCR*, and *C_SCORE*. *DTURNOVER, LAGNCSKEW, SIGMA, RET, SIZE, MB, LEV, ROA,* and *OPAQUE* are control variables. Appendix A provides detailed variable definitions. In all specifications, year- and industry-level fixed effects are included and standard errors, in parenthesis, are two-way clustered at firm and year levels. Significance levels for 1%, 5%, and 10% are represented by ***, **, and * respectively.

Panel A: Accounting conservatism

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*	(4) *CRASH*	(5) *NCSKEW*	(6) *DUVOL*	(7) *CRASH*	(8) *NCSKEW*	(9) *DUVOL*
	C_SKEW as *Conservatism*			*C_ACCR* as *Conservatism*			*C_SCORE* as *Conservatism*		
Conservatism	0.007	0.002	0.001	-0.001	-0.001	0.000	-0.037^{**}	-0.017^{***}	-0.006^{**}
	(0.008)	(0.003)	(0.001)	(0.011)	(0.002)	(0.001)	(0.019)	(0.005)	(0.002)
*ASSETG**	-0.038^{**}	-0.012^{**}	-0.006^{**}	-0.026^{*}	-0.001	-0.001	-0.044^{**}	-0.008	-0.006^{**}
Conservatism	(0.016)	(0.005)	(0.002)	(0.013)	(0.004)	(0.002)	(0.018)	(0.007)	(0.003)
ASSETG	0.483^{***}	0.185^{***}	0.088^{***}	0.394^{***}	0.120^{***}	0.058^{***}	0.464^{***}	0.147^{***}	0.078^{***}
	(0.111)	(0.034)	(0.015)	(0.082)	(0.030)	(0.015)	(0.120)	(0.037)	(0.016)
DTURNOVER	0.542^{**}	0.208^{***}	0.103^{***}	0.535^{**}	0.206^{***}	0.102^{***}	0.490^{*}	0.189^{**}	0.092^{***}

	(0.258)	(0.069)	(0.033)	(0.258)	(0.069)	(0.033)	(0.260)	(0.074)	(0.035)
LAGNCSKEW	0.070***	0.016**	0.008***	0.070***	0.016**	0.008***	0.062**	0.014*	0.007**
	(0.024)	(0.007)	(0.003)	(0.024)	(0.007)	(0.003)	(0.025)	(0.007)	(0.003)
SIGMA	-0.326	1.836**	0.478	-0.410	1.811**	0.476	1.240	2.205***	0.626*
	(2.987)	(0.726)	(0.332)	(2.966)	(0.729)	(0.336)	(3.354)	(0.785)	(0.366)
RET	0.303	0.226***	0.077**	0.294	0.224***	0.076**	0.520	0.273***	0.095***
	(0.286)	(0.067)	(0.031)	(0.283)	(0.068)	(0.032)	(0.342)	(0.075)	(0.036)
SIZE	0.057***	0.063***	0.027***	0.057***	0.063***	0.027***	0.019	0.047***	0.021***
	(0.017)	(0.006)	(0.003)	(0.017)	(0.006)	(0.003)	(0.021)	(0.008)	(0.004)
MB	0.011	0.004*	0.002*	0.011	0.004*	0.002*	0.013	0.004*	0.002*
	(0.008)	(0.002)	(0.001)	(0.008)	(0.002)	(0.001)	(0.009)	(0.002)	(0.001)
LEV	-0.097	-0.043	-0.015	-0.095	-0.044	-0.015	0.012	0.031	0.015
	(0.136)	(0.032)	(0.014)	(0.135)	(0.031)	(0.014)	(0.155)	(0.038)	(0.016)
ROA	0.429**	0.227***	0.107***	0.441**	0.230***	0.107***	0.500***	0.273***	0.133***
	(0.167)	(0.039)	(0.018)	(0.178)	(0.041)	(0.019)	(0.186)	(0.045)	(0.021)
OPAQUE	0.155	0.020	0.016	0.153	0.019	0.016	0.184*	0.040	0.025*
	(0.100)	(0.027)	(0.012)	(0.101)	(0.027)	(0.012)	(0.108)	(0.031)	(0.013)
Constant	-1.832***	-0.556***	-0.230***	-1.772***	-0.540***	-0.226***	-1.381***	-0.375***	-0.167***
	(0.327)	(0.085)	(0.038)	(0.347)	(0.089)	(0.042)	(0.418)	(0.099)	(0.047)
Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.029	0.059	0.063	0.029	0.059	0.063	0.029	0.055	0.059
N	28,609	28,609	28,609	28,609	28,609	28,609	27,093	27,093	27,093

Panel B: Average of conservatism measures

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
C_AVG	-0.006	-0.005	-0.001
	(0.017)	(0.005)	(0.002)
*ASSETG*C_AVG*	-0.086***	-0.017*	-0.010***
	(0.021)	(0.009)	(0.004)
ASSETG	0.718***	0.203***	0.105***
	(0.135)	(0.052)	(0.022)
DTURNOVER	0.508*	0.195***	0.095***
	(0.261)	(0.074)	(0.035)
LAGNCSKEW	0.062**	0.014*	0.007**
	(0.025)	(0.007)	(0.003)
SIGMA	1.552	2.281***	0.669*
	(3.281)	(0.775)	(0.361)
RET	0.571*	0.289***	0.102***
	(0.330)	(0.073)	(0.035)
SIZE	0.050***	0.060***	0.026***
	(0.017)	(0.006)	(0.003)
MB	0.014	0.005**	0.002**
	(0.008)	(0.002)	(0.001)
LEV	-0.105	-0.019	-0.004
	(0.141)	(0.033)	(0.014)
ROA	0.500***	0.274***	0.132***
	(0.190)	(0.045)	(0.021)
OPAQUE	0.183*	0.040	0.025*
	(0.109)	(0.031)	(0.013)
Constant	-1.740***	-0.518***	-0.227***
	(0.390)	(0.097)	(0.046)
Year/Industry	Yes	Yes	Yes
R^2	0.029	0.055	0.059
N	27,092	27,092	27,092

Table 8. Crash risks among high asset growth firms

This table presents the sorting results for firms in the top asset growth quintile. For each year, we independently sort firms by asset growths, free cash flow (*FCF*), and *C_SCORE* into quintiles. We select the top asset growth quintile and report the average crash risk for sub-quintiles of *FCF* in Panel A and *C_SCORE* in Panel B. *C_SCORE* is the asymmetric timeliness coefficient from Khan and Watts (2009) model. A higher *C_SCORE* means more accounting conservatism.

Panel A. Sorting by free cash flow (*FCF*)

Quintile	1 (Low *FCF*)	2	3	4	5 (High *FCF*)
CRASH(t+1)	0.174	0.195	0.203	0.202	0.213
NCSKEW(t+1)	-0.146	-0.034	0.027	0.029	0.053
DUVOL(t+1)	-0.091	-0.035	-0.004	-0.005	0.008

Panel B. Sorting by accounting conservatism (*C_SCORE*)

Quintile	1 (High *C_SCORE*)	2	3	4	5 (Low *C_SCORE*)
CRASH(t+1)	0.163	0.190	0.207	0.220	0.205
NCSKEW(t+1)	-0.175	-0.046	0.022	0.061	0.080
DUVOL(t+1)	-0.101	-0.042	-0.009	0.007	0.024

Table 9. The effects of overinvestments

This table reports the regression results for Equation (4) when *ASSETG* is replaced by either abnormal capital expenditure (*Ab_CAPEX*) or abnormal total investment (*Ab_TOTINV*). *CRASH* is a dummy variable when firm-specific return is below 3.2 standard deviation of the mean for at least one week for the fiscal year, otherwise zero. *NCSKEW* is the negative coefficient of skewness for firm-specific return. *DUVOL* is the log of down-market volatility to up-market volatility. Firm-specific returns are the regression residuals of weekly returns on market and industry returns with one-week lead and lagged values. *Ab_CAPEX* and *Ab_TOTINV* are regression residuals of capital expenditure and total investment, respectively, on sales growth and the interaction with a negative sales growth dummy. *DTURNOVER, LAGNCSKEW, SIGMA, RET, SIZE, MB, LEV, ROA,* and *OPAQUE* are control variables. Appendix A provides detailed variable definitions. In all specifications, year- and industry-level fixed effects are included and standard errors, in parenthesis, are two-way clustered at firm and year levels. Significance levels for 1%, 5%, and 10% are represented by ***, **, and * respectively.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*	(4) *CRASH*	(5) *NCSKEW*	(6) *DUVOL*
Ab_CAPEX	0.160***	0.058***	0.026***			
	(0.040)	(0.011)	(0.005)			
Ab_TOTINV				0.277***	0.139***	0.062***
				(0.093)	(0.026)	(0.012)
DTURNOVER	0.744***	0.270***	0.126***	0.730***	0.260***	0.122***
	(0.138)	(0.040)	(0.019)	(0.138)	(0.041)	(0.019)
LAGNCSKEW	0.067***	0.020***	0.009***	0.069***	0.021***	0.010***
	(0.015)	(0.004)	(0.002)	(0.015)	(0.004)	(0.002)
SIGMA	6.148***	3.281***	1.183***	6.381***	3.327***	1.206***
	(2.198)	(0.581)	(0.284)	(2.203)	(0.581)	(0.285)
RET	0.899***	0.371***	0.145***	0.913***	0.372***	0.146***
	(0.231)	(0.057)	(0.029)	(0.235)	(0.057)	(0.029)
SIZE	0.062***	0.062***	0.027***	0.061***	0.062***	0.027***
	(0.012)	(0.005)	(0.002)	(0.012)	(0.005)	(0.002)
MB	0.006	0.004**	0.002**	0.007	0.004**	0.002**
	(0.004)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)
LEV	0.075	-0.028	-0.014	0.023	-0.047*	-0.023**
	(0.083)	(0.025)	(0.011)	(0.083)	(0.025)	(0.011)
ROA	0.639***	0.295***	0.141***	0.679***	0.311***	0.148***
	(0.107)	(0.023)	(0.011)	(0.105)	(0.023)	(0.011)
OPAQUE	0.248***	0.063***	0.033***	0.270***	0.068***	0.035***
	(0.075)	(0.020)	(0.009)	(0.076)	(0.021)	(0.009)
Constant	-2.457***	-0.666***	-0.290***	-2.451***	-0.661***	-0.287***
	(0.253)	(0.038)	(0.018)	(0.253)	(0.038)	(0.018)
Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.026	0.051	0.055	0.025	0.051	0.051
N	64,740	64,734	64,732	64,785	64,779	64,777

Online Appendix B. Sensitivity Checks and Further Tests

In this appendix, we detail the procedures and report results for sensitivity checks. These include alternative definitions of asset growths, measuring crash risks using an augmented industry and market adjusted model, different sample periods, controlling for more known determinants of crash risks, and addressing reverse causality concerns.

1. An augmented industry and market adjusted model

   In Equation (1), we regress a firm's weekly return on one lead and lag of market and industry returns and calculate crash risks based on the residuals. In this robustness check, we augment Equation (1) by including two weeks lead and lag of market and industry returns and repeat the analysis for our main results in Table 3. Results are reported in Table B1 and are very similar to those in Table 3.

2. Financial crisis

   In Table B2, we partition the sample into 2007-2009 financial crisis period and the non-financial crisis period. With reduced sample of only 6,652 firm-year observations in the crisis period, we still observe a positive relationship between asset growth and future crash risk albeit with lower statistical significance. Within the non-crisis period, the positive relationship between asset growth and future crash risks remains significant as our main results. In other words, our results are not driven by the 2007-2009 financial crisis.

3. Using sample from 1970's

   Our main specification include *OPAQUE* using cash-flow statement data which is only available from 1988. In this check, we omit *OPAQUE* and use the sample from 1970. It is shown in Table B3 that the number of observations almost doubles compared to the main results. Nevertheless, *ASSETG* still have similar predictive power for future crash risks.

4. Firm fixed effects

   To address the omitted variable concern, we run our main regressions (4) - (6) by including firm-fixed effects. As reported in Table B4, results are qualitatively similar to the main results.

5. Full sample of *C_SCORE*

In the accounting conservatism analysis, we accommodate the reduced sample of *C_ACCR* and *C_SKEW* by requiring common sample from *C_SCORE* to facilitate the construction of an aggregate variable. In this robustness check, we conduct the analysis by only using ranked values of *C_SCORE* and check if more conservative firms have lower crash risks related to asset growth in this sample. Table B5 shows that the interaction terms *ASSETG**C_SCORE* are still negative and significant.

6. Controlling for stock liquidity

Chang, Chen, and Zolotoy (2017) finds that more liquid stocks are subject to higher crash risks from the exit behavior of transient institutional investors to bad news release. We augment our main specifications by including stock liquidity, *Liquid*, which is the negative of percentage bid-ask spreads from the closing prices. Closing bid and ask information is available from CRSP starting 1992. Table B6 shows that coefficients for *ASSETG* are still positive and significant. *Liquid* is weaker in Table B6 than in Chang et al. (2017) because we use closing information while Chang et al. (2017) use the more accurate intraday trade-weighted average of relative effective spreads.

7. CEO year change

In the main analysis, we follow Chen, Lu, and Sougiannis (2012) and define *CEO_Horizon* as the year of a CEO change or the year immediately preceding a change. This might cause some reverse causality concern. For example, if a crash occurs in 2005, it can be related to a CEO change in 2006. We believe that this channel is unlikely because we find a negative relationship between *CEO_Horizon* and crash risk. Nevertheless, we align the time line of *CEO_Horizon* to make it predictive. For instance, the crash risk values in 2005 are matched with whether there is a CEO change in 2003 or 2004. Table B7 shows that we still observe a significant mitigating effect from *CEO_Horizon* on crash risks.

8. Alternative definitions of asset growths

Lipson, Mortal, and Schill (2011) examine the return predictability of alternative asset growth variables. Specifically, they examine the percentage growth in assets per split-adjusted share (*AG_FF*), the change in inventories and gross PP&E scaled by lagged assets (*AG_LSZ*), capital expenditure scaled by last year net PP&E (*AG_PS*), percentage growth in capital expenditure (*AG_XING*), percentage growth in capital expenditure over two years (*AG_AGF*), percentage growth in capital expenditure over previous 3 years' average (*AG_TWX*), and percentage growth in split-adjusted shares outstanding (*AG_PW*). In Table B8, they are all positive and significant in predicting future crash risks.

9. A broader definition of assets including off-balance sheet intangible assets

Assets on the balance sheets only contribute to a portion of the total real economic assets (or capitals) of the firm. For example, knowledge is an intangible asset related to the R&D expenditure but is not recorded in the balance sheet. It can be argued that a considerate portion of total real economic capital is in the form of intangibles off the balance sheet. Peters and Taylor (2017) estimate the off-balance sheet knowledge and organizational capital from R&D and SG&A expenditure, respectively, using a perpetual inventory method. They construct the total capital of a firm by expressing total capital (*K_Total*) as the sum of physical capital (*K_Phy*), intangible capital on balance sheets (*K_Int_BS*), intangible knowledge capital off-balance sheets (*K_Int_Know*), and intangible organizational capital off-balance sheets (*K_Int_Org*). We obtain the off-balance sheet intangible variables from WRDS and calculate the on-balance sheet quantities from Compustat. We then calculate the corresponding growths as the yearly-change of each component, scale them by beginning year total capital, and replace *ASSETG* by these variables in regressions.

The purpose of this exercise is to investigate whether our asset growth results hold when a more general definition of asset is used. Table B9 reports the results and shows that the asset growth-crash risk relationship still holds from the broader perspective of assets. In particular, besides physical capital growths, intangible capital growth on-balance sheets and off-balance sheet growth in knowledge and organizational capitals are all positive and significantly predict future crash risks.

We acknowledge that even under Peters and Taylor (2017) framework, not all intangible assets, for example internally generated reputation, are captured. It is an open question whether other hard-to-measure intangible assets are still related to future crash risk. Nevertheless, to the extent that knowledge and organizational capitals result from prior expenditures, the rationale of empire building should also apply to these off-balance sheet items and it is indeed the case from the sensitivity check.

10. A reverse causality explanation of asset growth

It is possible that managers with better inside information foresee a crash in the future and therefore stockpile assets, especially cash, as a precautionary measure. When the crash is realized, the managers can then use the cash or sell assets to convert to cash. This can be a reverse causality explanation of our findings: it is the insight of a future crash that leads to the decision of an asset growth. To address this issue, we draw on the literature of cash holding to determine the propensity of holding more cash. Specifically, we employ the cash holding model by Opler, Pinkowitz, Stulz, and Williamson (1999) and Bates, Kahle, and Stulz (2009):

$$Cash = a_0 + a_1 MB + a_2 Size + a_3 Cashflow + a_4 NWC + a_5 Capex + a_6 Lev + a_7 Divdu + a_8 Acq + a_9 Indusig \qquad \text{(B1)}$$

, where *MB* is the market-to-book ratio, *Size* is the natural logarithm of total assets, *Cashflow* is the operating income before depreciation minus total interest and related expenses minus total income taxes, minus dividends, scaled by total assets, *NWC* is the net working capital as working capital minus cash and short-term investments, scaled by total assets, *Capex* is the capital expenditure scaled by total assets, *Lev* is total long-term debt and debt in current liabilities, scaled by total assets, *Divdu* is the dividend payout dummy, *Acq* is acquisitions divided by total assets, and *Indusig* is the industry cash flow risk as the average of past 10 years cash flow to total assets ratio standard deviations within the matched two-digit SIC code.

Many of the determinants in (B1) measure the future need for cash and the ease of raising cash for a firm: precautionary savings needs (*Indusig*), financial distress costs (*Capex* and *R&D*), liquidity demand (*Cashflow*), leverage ratio (*Lev*), and economies of scale (*Size*).

Because our focus is on the growth dimension, we use a change model of (B1) and define a dummy of high cash growth when cash growth is in the top quintile in the year. The idea is that an observed large increase in cash as a decision of the firm may indicate its precautionary need for future crash:

$$Dummy_{\Delta Cash\_quintile} = a_0 + a_1 \Delta MB + a_2 \Delta Size + a_3 \Delta Cashflow + a_4 \Delta NWC + a_5 \Delta Capex + a_6 \Delta Lev + a_7 \Delta Divdu + a_8 \Delta Acq + a_9 \Delta Indusig \qquad \text{(B2)}$$

We then estimate a Heckman selection model based on (B2) and calculate the inverse Mills ratio as a measure of precautionary cash need. The inverse Mills ratio is then included into the main regressions (4)-(6) to control for the possible selection effects of stockpiling cash. The results are reported in Table B10. As shown in Table B10, all of the inverse Mills ratio λ are insignificant and most of them are positive, indicating that the precautionary motive for holding more cash can relate, though insignificantly, to future crash risks. Nevertheless, the coefficients of asset growth are qualitatively unchanged compared with Tables 3 and 4. Note that cash growth is insignificant in both Tables 4 and B10 in explaining *CRASH*.

We only conduct the Heckman selection analysis using cash growth as the outcome of a selection model. The reason is that, to the best of our knowledge, only the cash holding model has a precautionary savings component. While a firm can sell other assets in the case of a liquidity shortfall (e.g. asset fire sale by airline firms), the most obvious and least costly precautionary tactic is to hold more cash, and we are not aware of models of other asset components of the balance sheet that have a precautionary savings component.

11. Controlling for short interest ratio

Callen and Fang (2015) find that a higher short interest ratio can predict future crash risk when informed short-sellers build up short position before bad news is released. We control for short interest ratio calculated as the ratio of short interest and number of shares outstanding. Short interest data are retrieved from Compustat. Table B11 shows that *ASSETG* remains significant.

12. Controlling for institutional ownerships and their stability

An and Zhang (2013) and Callen and Fang (2013) find that institutional ownerships can mitigate or aggravate crash risk depending on the ownership stability. In particular, dedicated long-term investors should be better in monitoring while transient institutional investors may encourage managerial short-termism. We therefore control for the institutional ownerships and their stability. We download the investor classification from Prof. Bushee's website (http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html) and merge with Thomson Reuters 13F database. Table B12 shows that *ASSETG* remains significant.

13. Controlling for 10-K file size

    Ertugrul, Lei, Qiu, and Wan (2017) find that firms with larger 10-K file size (in megabytes) have higher future crash risk because 10-K file size is related to managerial information hoarding. We control for 10-K file size by the natural logarithm of number of words of the 10-K reports downloaded from Prof. McDonalds' website (https://www3.nd.edu/~mcdonald/). Table B13 shows that *ASSETG* remains significant.

Reference

An, H., and T. Zhang. 2013. Stock price synchronicity, crash risk, and institutional investors. *Journal of Corporate Finance* 21 (June): 1-15.

Bates, T. W., K. M. Kahle, and R. M. Stulz. 2009. Why do US firms hold so much more cash than they used to? *Journal of Finance* 64 (5): 1985-2021.

Callen, J. L., and X. Fang. 2013. Institutional investor stability and crash risk: Monitoring versus short-termism? *Journal of Banking and Finance* 37 (8): 3047-3063.

Callen, J. L., and X. Fang. 2015. Short interest and stock price crash risk. *Journal of Banking and Finance* 60 (November): 181-194.

Chang, X., Y. Chen, and L. Zolotoy. 2017. Stock liquidity and stock price crash risk. *Journal of Financial and Quantitative Analysis* 52 (4): 1605-1637.

Chen, C. X., H. Lu, and T. Sougiannis. 2012. The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. *Contemporary Accounting Research* 29 (1): 252-282.

Ertugrul, M., J. Lei, J. Qiu, and C. Wan. 2017. Annual report readability, tone ambiguity, and the cost of borrowing. *Journal of Financial and Quantitative Analysis* 52 (2): 811-836.

Giroud, X., and H. M. Mueller. 2010. Does corporate governance matter in competitive industries? *Journal of Financial Economics* 95 (3): 312-331.

Kale, J. R., E. Reis, and A. Venkateswaran. 2009. Rank-order tournaments and incentive alignment: The effect on firm performance. *Journal of Finance* 64 (3): 1479-1512.

Lipson, M. L., S. Mortal, and M. J. Schill. 2011. On the scope and drivers of the asset growth effect. *Journal of Financial and Quantitative Analysis* 46 (6): 1651-1682.

Na, K. 2020. CEOs' outside opportunities and relative performance evaluation: Evidence from a natural experiment. Journal of Financial Economics 137 (3): 679-700.

Parrino, R. 1997. CEO turnover and outside succession a cross-sectional analysis. *Journal of Financial Economics* 46 (2): 165-197.

Peters, R. H., and L. A. Taylor. 2017. Intangible capital and the investment-q relation. *Journal of Financial Economics* 123 (2): 251-272.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52 (1): 3-46.

Table B1. An augmented industry- and market-adjusted model

In this table, we estimate the weekly firm-specific return by regressing weekly returns on two leads and lags of market and industry returns. Please refer to definitions of other variables in Appendix A.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.236***	0.090***	0.042***
	(0.042)	(0.008)	(0.004)
Control/Year/Industry	Yes	Yes	Yes
R^2	0.023	0.045	0.047
N	65,782	65,782	65,782

Table B2. Financial crisis and non-crisis subsample.

In this table, we report the results when the sample in our main analysis is divided according to 2007-2009 financial crisis and non-crisis period. Please refer to definitions of other variables in Appendix A.

Panel A: 2007-2009 financial crisis

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.273*	0.052	0.030**
	(0.148)	(0.034)	(0.014)
Control/Year/Industry	Yes	Yes	Yes
R^2	0.022	0.064	0.070
N	6,652	6,652	6,652

Panel B. Non-crisis period

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.212***	0.100***	0.046***
	(0.035)	(0.010)	(0.005)
Control/Year/Industry	Yes	Yes	Yes
R^2	0.027	0.050	0.054
N	59,136	59,136	59,136

Table B3. Sample from 1970.

This table reports results when sample from 1970 is used after omitting *OPAQUE* which requires cash-flow statement information available from 1988. Please refer to definitions of other variables in Appendix A.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.213***	0.098***	0.045***
	(0.029)	(0.009)	(0.004)
DTURNOVER	0.813***	0.225***	0.104***

	(0.126)	(0.046)	(0.023)
LAGNCSKEW	0.102***	0.037***	0.018***
	(0.015)	(0.006)	(0.003)
SIGMA	-0.674	1.335**	0.171
	(1.978)	(0.661)	(0.348)
RET	0.324*	0.091	-0.001
	(0.191)	(0.057)	(0.030)
SIZE	0.044***	0.061***	0.027***
	(0.014)	(0.004)	(0.002)
MB	0.013***	0.006***	0.003***
	(0.004)	(0.001)	(0.001)
LEV	-0.104	-0.053***	-0.028***
	(0.078)	(0.019)	(0.009)
ROA	0.016	0.035	0.021
	(0.082)	(0.028)	(0.014)
Constant	-2.079***	-0.616***	-0.273***
	(0.181)	(0.047)	(0.024)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
R^2	0.030	0.046	0.050
N	122,268	122,268	122,268

Table B4. Controlling for firm-fixed effects

In this table, we include firm-fixed effects in the estimation. Please refer to definitions of other variables in Appendix A.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.152***	0.070***	0.033***
	(0.041)	(0.012)	(0.006)
Control/Year/Industry	Yes	Yes	Yes
Firm	Yes	Yes	Yes
R^2	0.106	0.093	0.091
N	52,098	65,788	65,788

Table B5. Whole sample for C_SCORE

In this table, we use all observations with available *C_SCORE* information and do not restrict the common sample with *C_ACCR* and *C_SKEW*. *C_SCORE* in this table is the yearly decile value. Please refer to definitions of other variables in Appendix A.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
CSCORE	-0.007	-0.005**	-0.002**
	(0.009)	(0.002)	(0.001)
ASSETG CSCORE*	-0.014*	-0.004*	-0.003**
	(0.008)	(0.002)	(0.001)
ASSETG	0.219***	0.098***	0.046***

	(0.033)	(0.013)	(0.006)
Control/Year/Industry	Yes	Yes	Yes
R^2	0.028	0.049	0.053
N	57,379	57,379	57,379

Table B6. Controlling for stock liquidity

In this table, we include the annual average of percentage bid-ask spreads from closing prices. *Liquid* is negative of the average spread.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.182***	0.089***	0.042***
	(0.034)	(0.011)	(0.005)
Liquid	0.053***	0.008**	0.002
	(0.013)	(0.004)	(0.002)
Control/Year/Industry	Yes	Yes	Yes
R^2	0.028	0.050	0.054
N	62,045	62,045	62,045

Table B7. A predictive definition of *CEO_Horizon*

In this table, we employ a predictive definition of *CEO_Horizon*. For instance, a change in CEO in year 2005 will result in *CEO_Horizon* = 1 for year 2004 and 2005 and is matched to crash risk in 2006.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
	CEO_Horizon as Agency Variable		
Agency	0.006	0.003	-0.000
	(0.052)	(0.011)	(0.005)
*Agency*ASSETG*	-0.331***	-0.100***	-0.037**
	(0.111)	(0.036)	(0.016)
ASSETG	0.243***	0.115***	0.052***
	(0.060)	(0.023)	(0.010)
Control/Year/Industry	Yes	Yes	Yes
R^2	0.024	0.039	0.043
N	30,109	30,109	30,109

Table B8. Alternative definitions of asset growth

In this table, we use different definitions of asset growth in the literature. Lipson et al. (2011) summarize them as the percentage growth in assets per split-adjusted share (*AG_FF*), the change in inventories and gross PP&E scaled by lagged assets (*AG_LSZ*), capital expenditure scaled by last year net PP&E (*AG_PS*), percentage growth in capital expenditure (*AG_XING*), percentage growth in capital expenditure over two years (*AG_AGF*), percentage growth in capital expenditure over previous 3 years' average (*AG_TWX*), and percentage growth in split-adjusted shares outstanding (*AG_PW*). Panel A, B, and C report the results for *CRASH*, *NCSKEW*, and *DUVOL*, respectively.

Panel A. Results for *CRASH*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CRASH	*CRASH*	*CRASH*	*CRASH*	*CRASH*	*CRASH*	*CRASH*
	ASSETG as measured by						
	AG_FF	*AG_LSZ*	*AG_PS*	*AG_XING*	*AG_AGF*	*AG_TWX*	*AG_PW*
ASSETG	0.251***	0.285***	0.178***	0.030**	0.017***	0.048***	0.367***
	(0.051)	(0.085)	(0.044)	(0.012)	(0.005)	(0.011)	(0.073)
Control/Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.026	0.025	0.025	0.025	0.025	0.025	0.025
N	65,748	65,265	65,250	65,021	64,840	58,430	65,844

Panel B. Results for *NCSKEW*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	NCSKEW	*NCSKEW*	*NCSKEW*	*NCSKEW*	*NCSKEW*	*NCSKEW*	*NCSKEW*
	ASSETG as measured by						
	AG_FF	*AG_LSZ*	*AG_PS*	*AG_XING*	*AG_AGF*	*AG_TWX*	*AG_PW*
ASSETG	0.103***	0.175***	0.073***	0.013***	0.009***	0.021***	0.188***
	(0.013)	(0.025)	(0.011)	(0.003)	(0.002)	(0.003)	(0.028)
Control/Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.050	0.050	0.050	0.049	0.049	0.050	0.050
N	65,742	65,259	65,244	65,015	64,834	65,159	65,742

Panel C. Results for *DUVOL*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)

	DUVOL	*DUVOL*	*DUVOL*	*DUVOL*	*DUVOL*	*DUVOL*	*DUVOL*
	ASSETG as measured by						
	AG_FF	*AG_LSZ*	*AG_PS*	*AG_XING*	*AG_AGF*	*AG_TWX*	*AG_PW*
ASSETG	0.046***	0.084***	0.034***	0.006***	0.004***	0.010***	0.090***
	(0.006)	(0.012)	(0.005)	(0.001)	(0.001)	(0.001)	(0.013)
Control/Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.054	0.055	0.054	0.053	0.053	0.054	0.054
N	65,740	65,257	65,242	65,013	64,832	65,157	65,740

Table B9. A broader definition of asset including off-balance sheet intangible knowledge and organizational capital

In this table, we follow Peters and Taylor (2017) and include off-balance sheet intangible knowledge and organizational capital in total assets of a firm. Peters and Taylor (2017) construct the total capital of a firm by expressing total capital (*K_Total*) as the sum of physical capital (*K_Phy*), intangible capital on balance sheets (*K_Int_BS*), intangible knowledge capital off-balance sheets (*K_Int_Know*), and intangible organizational capital off-balance sheets (*K_Int_Org*). We obtain the off-balance sheet intangible variables from WRDS and calculate on-balance sheet quantities from Compustat. We then calculate the corresponding growths as the yearly-change of each component and scale them by last year total capital: growth in total capital (*KG_Total*), growth in physical capital (*KG_Phy*), growth in intangible capital on balance sheets (*KG_Int_BS*), growth in intangible knowledge capital off-balance sheets (*KG_Int_Know*), growth in intangible organizational capital off-balance sheets (*KG_Int_Org*), and growth in off-balance sheet capital (*KG_Int_OffBS*). Please refer to definitions of other variables in Appendix A.

Panel A. Results for *CRASH*.

	(1) *CRASH*	(2) *CRASH*	(3) *CRASH*	(4) *CRASH*	(5) *CRASH*	(6) *CRASH*
	ASSETG measured by					
	KG_Total	*KG_Phy*	*KG_Int_BS*	*KG_Int_Know*	*KG_Int_Org*	*KG_Int_OffBS*
ASSETG	0.239***	0.295***	0.416***	0.607	1.521***	0.600***
	(0.045)	(0.099)	(0.078)	(0.386)	(0.258)	(0.142)
Control/Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.025	0.025	0.025	0.025	0.026	0.026
N	65,663	65,663	65,663	65,663	65,663	58,857

Panel B. Results for *NCSKEW*.

	(1) *NCSKEW*	(2) *NCSKEW*	(3) *NCSKEW*	(4) *NCSKEW*	(5) *NCSKEW*	(6) *NCSKEW*
	ASSETG measured by					
	KG_Total	*KG_Phy*	*KG_Int_BS*	*KG_Int_Know*	*KG_Int_Org*	*KG_Int_OffBS*
ASSETG	0.098***	0.163***	0.147***	0.201**	0.505***	0.301***
	(0.012)	(0.026)	(0.017)	(0.095)	(0.077)	(0.051)
Control/Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.050	0.049	0.050	0.050	0.050	0.050
N	65,657	65,657	65,657	65,657	65,657	65,657

Panel C. Results for *DUVOL*.

	(1) *DUVOL*	(2) *DUVOL*	(3) *DUVOL*	(4) *DUVOL*	(5) *DUVOL*	(6) *DUVOL*
	ASSETG measured by					
	KG_Total	*KG_Phy*	*KG_Int_BS*	*KG_Int_Know*	*KG_Int_Org*	*KG_Int_OffBS*
ASSETG	0.044***	0.078***	0.064***	0.082*	0.213***	0.126***
	(0.005)	(0.011)	(0.009)	(0.045)	(0.035)	(0.021)
Control/Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.054	0.053	0.054	0.054	0.054	0.054
N	65,655	65,655	65,655	65,655	65,655	65,655

Table B10. Controlling for Reverse Causality by including inverse Mills ratio of increased cash holdings

This table reports the results when the inverse Mills ratio (λ) from a selection model is included in the main regression (4). A Heckman selection model is estimated based on the top quintile of cash holding changes (a dummy) regressing on a number of changes in cash holding determinants as detailed in Appendix B, and the inverse Mills ratio is calculated. We report estimates when crash risk is regressed on asset growth and control variables. Coefficients for the control variables and intercepts are not reported for brevity. Please refer to definitions of other variables in Appendix A.

	(1) *CRASH*	(2) *NCSKEW*	(3) *DUVOL*
ASSETG	0.190***	0.101***	0.047***
	(0.043)	(0.013)	(0.006)
λ	0.334	0.106	0.028
	(0.545)	(0.176)	(0.076)
Control/Year/ Industry	Yes	Yes	Yes
R^2	0.025	0.049	0.052
N	48,375	48,371	48,370

Table B11. Controlling for short interest ratio

In this table, we include the short interest ratio (*SIR*) as ratio between short interest and number of shares outstanding at the end of fiscal year.

	(1)	(2)	(3)
	CRASH	NCSKEW	*DUVOL*
ASSETG	0.210^{***}	0.097^{***}	0.045^{***}
	(0.035)	(0.010)	(0.005)
SIR	0.877	0.267^{*}	0.116^{*}
	(0.869)	(0.152)	(0.063)
Control/Year/Industry	Yes	Yes	Yes
R^2	0.026	0.051	0.055
N	65,796	65,790	65,788

Table B12. Controlling for institutional ownerships and their stability

In this table, we include the institutional ownership and their stability. *IOR* is the institutional ownership at the end of a fiscal year, *IOR_TRA* is the ownership by transient institutional investors, and *IOR_DED* is the ownership by dedicated institutional investors. We download the institutional investor classification from Prof. Bushee's website.

	(1)	(2)	(3)	(4)	(5)	(6)
	CRASH	*CRASH*	*NCSKEW*	*NCSKEW*	*DUVOL*	*DUVOL*
ASSETG	0.211^{***}	0.179^{***}	0.097^{***}	0.085^{***}	0.045^{***}	0.040^{***}
	(0.035)	(0.034)	(0.010)	(0.010)	(0.005)	(0.004)
IOR	0.297^{***}		0.128^{***}		0.057^{***}	
	(0.049)		(0.017)		(0.008)	
IOR_TRA		1.112^{***}		0.475^{***}		0.212^{***}
		(0.142)		(0.050)		(0.023)
IOR_DED		-0.736^{***}		-0.143^{*}		-0.067^{*}
		(0.285)		(0.080)		(0.037)
Control/Year/Industry	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.027	0.028	0.053	0.054	0.057	0.058
N	65,796	65,796	65,790	65,790	65,788	65,788

Table B13. Controlling for 10-K file size

In this table, we control for the 10-K file size by the natural logarthim of number of words (*LOGWORDS*), downloaded from Prof. McDonald's website.

	(1)	(2)	(3)
	CRASH	*NCSKEW*	*DUVOL*
ASSETG	0.243^{***}	0.102^{***}	0.046^{***}
	(0.043)	(0.015)	(0.006)
LOGWORDS	0.028	0.007	0.000
	(0.024)	(0.008)	(0.003)
Control/Year/Industry	Yes	Yes	Yes

R^2	0.028	0.052	0.056
N	43,465	43,469	43,468