Intangible Asset Fragility and Stock Price Crash Risk

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Abstract

We evaluate the effect of intangible intensity, the extent of intangible assets held by firms, on stock prices. We find a significantly higher stock price crash risk for listed US firms with greater intangible intensity from 1983 to 2017. Intangible asset impairments and valuation uncertainty are identified as two underlying channels through which stock price crash risk is affected. In addition, the positive effect of intangible intensity on crash risk is stronger in firms with higher information opacity and shareholder litigation risk, but attenuated in firms with better credit ratings. Overall, our findings demonstrate the fragility of intangible assets and provide implications for financial regulation and portfolio management.

JEL Classification: G10, G11, G14

Keywords: intangible intensity, impairment loss, crash risk

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1 Introduction

In recent decades, the effect of intangible assets on economic growth and stock returns has attracted wide attention from academia.[1] Intangible assets have considerably enhanced the creativity and value creation of business organizations (van de Vrande et al., 2009; Dahlander and Gann, 2010; Huggins, 2010). Such innovations have also led to increased firm productivity (Zahra et al., 2006) and economic growth (Corrado et al., 2009; Robertson et al., 2012; Grimaldi et al., 2017). Nakamura (2010) showed that intangible investment expenditures have increased from 4% of the US GDP in 1977 to approximately 10% in 2006. Along with the rise in the shares of intangible assets in the economy, the aggregate amount of intangible assets held by listed US firms has grown from nearly zero in 1983 to over US$60 billion in 2017. Moreover, the average share in total assets increases from 1.5% to 30% over the same period. However, stock prices experience large impacts following the growth of intangible assets, specifically the indefinite-life ones, owing to subsequent impairment losses.[2] Therefore, understanding the consequences of intangible asset fragility on financial stability provides implications for both investors and regulation agencies.

This study aims to investigate the impact of intangible assets on stock returns, specifically, how the extent of intangible assets held by firms can affect stock price crash risk. We follow Clausen and Hirth (2016) and construct a proxy for intangible intensity, which is defined

[1] See Grimaldi et al. (2017) for a thorough literature review.

[2] For example, Kraft Heinz, which is a listed US firm, wrote down as much as US$15.4 billion intangibles for Kraft and Oscar Mayer brands and faced a US$12.6 billion loss during the forth quarter of 2018. This impairment is unexpected and surprising to the market, with a subsequent share price decline of roughly 27% on the day after the announcement. Another US listed firm, Sears Holdings, recorded a US$3.3 billion intangible asset impairment loss in 2013. Since then, most intangible assets have been impaired. Eventually, investors who faced losses accounted for 89% of their investment in 2018.

as the relative ranking of earnings before interest, taxes, depreciation and amortization (EBITDA) over the net property, plant, and equipment (PPE) in the entire sample. This approach circumvents the problem of sparse coverage and the measurement errors of intangible assets in financial statements, and addresses the bias in Long and Malitz (1985) and Gatchev et al. (2009). Such bias treats R&D expenditure as a measure of intangibility, which fails to account for the value established by firms throughout life, such as brand name, customer base, and other firm characteristics. Additionally, we identify subsequent intangible asset impairments as well as valuation uncertainty as the underlying channels through which stock price crash risk is affected.

To perform the empirical analyses, we first construct a panel dataset containing stock price crash risk measures, intangible intensity, and several firm characteristics for a sample of listed US firms from 1983 to 2017. In particular, we obtain detailed asset impairment information from Calcbench, which is an original dataset derived from the footnotes of 10-K fillings, including detailed disclosures on intangible asset impairment losses for US listed firms.

We begin our analysis by validating our intangible intensity measure. Specifically, we examine how intangible intensity measure is correlated with traditional measures of intangible asset scales. We find strong positive relationship between our intangible intensity measure and the proportion of intangible assets, goodwill and R&D in total assets. Next, we run a panel regression in which the dependent variables, the stock price crash risk measures, are regressed on intangible intensity along with other firm characteristics.The results show that intangible intensity has a significant and positive effect on stock price crash risk. This finding suggests that firms with greater intangible intensity are subject to significantly higher crash risk.

Furthermore, we explore the channel through which the crash risk is affected by intangible intensity. Firstly, we examine whether firms with higher intangible intensity are associated with increased likelihood of intangible asset impairments. According to the US Generally Accepted Accounting Principles and the International Financial Reporting Standards, indefinite-life intangible assets must go through annual impairment tests to reflect the fair value of intangible assets. Firms will write off intangible assets if test result shows sufficient grounds for asset impairments.

Given that firms with a considerable extent of intangible assets are susceptible to asset impairments, whether these asset impairment events reduce firm performance should also be investigated. as impairment losses will affect concurrent net income. Thus, we construct various firm performance measures to test this hypothesis. Specifically, we examine the effect of intangible asset impairments on the likelihood of earnings losses and significant decline in earning growth rate.

Consistent with our expectations, we find that firms with greater intangible intensity are associated with significantly higher likelihood of intangible asset impairments and deterioration of firm performance following impairment events of intangible assets. More importantly, we find that both the intangible intensity and firm performance measures are significantly positive when included in the regression, suggesting that intangible intensity affects crash risk through the increased likelihood of impairment and deterioration of firm performance.

Secondly, we examine whether valuation uncertainty plays a role as mediating factor between intangible intensity and stock price crash risk. The idea is that stock market investors tend to respond strongly to earning surprises when they have uncertain priors for the firm. Greater intangible intensity hinders precise estimate of firm value as firms with higher intangible intensity are prone to experience asset impairments, creating uncertainty for the estimation of profitability growth. Using the similar methodology, we use a two-step approach to test the hypothesis that intangible intensity affect stock price crash risk through increased valuation uncertainty. In the first step, we regress two valuation certainty measures as proposed in Pástor et al. (2008) and Cremers et al. (2016). In the second step, we include valuation certainty measures in the regression as one of explanatory variables. The results suggests that firms with greater intangible intensity are associated with larger valuation uncertainty, and the effect of intangible intensity remain statistically significant when valuation uncertainty measures are added to the regression. Therefore, we show that valuation uncertainty is a mediating factor between intangible intensity and stock price crash risk.

Finally, we examine how firm heterogeneity affects the relationship between intangible intensity and stock price crash risk. In other words, we want to see how this relationship varies with firm characteristics. Specifically, we construct interaction terms between the intangible intensity with proxies for credit ratings, shareholder litigation risk, and information opacity. We find that the positive effect of intangible intensity on crash risk is stronger in firms with higher information opacity and shareholder litigation risk, but attenuated in those with better credit ratings. Finally, we conduct a series of robustness checks, including alternative variable definitions, model specifications, and tests that address potential endogeneity issues. Overall, our results remain intact with all these variations.

We contribute to three strands of literature. First, our study complements previous research examining how R&D or patents affect stock price crash risk. Jia (2018) studied the impact of corporate innovation strategy on crash risk using patents as a proxy for corporate innovation. They showed that exploration-oriented firms are associated with greater stock price crash risk compared to exploitative-oriented firms. Ben-Nasr et al. (2019) used patents, patent citations and R&D as proxies for innovation and demonstrated opposite results that innovation has a negative effect the stock price crash risk. While these studies focus on definite-life intangible assets such as patents, our study provides new evidence on the impact of intangible assets on stock prices and financial stability. In particular, we document the effect of the effect of intangible intensity on stock price crash risk, and identify impairment of indefinite-life intangible assets and increased valuation uncertainty as the underlying channels. Second, our study is closely related to studies on information disclosure of intangible assets. For instance, existing literature has questioned the reliability of the information content of disclosed intangible assets (Lonergan, 2009) and shown information asymmetry due to unreliable estimates of goodwill (Hayn and Hughes, 2006; Johansson et al., 2016; Huikku et al., 2016). We apply a straightforward method of quantifying the extent of intangible assets, which relies purely on publicly available financial data. This approach addresses the measurement errors widely recognized in the literature. Finally, our work also contributes to studies on the determinants of stock price crash risk. Existing literature has mainly examined this issue from the perspectives of accounting transparency (Kim et al., 2014), accounting conservatism, (Kim and Zhang, 2016) and bad news hoarding (Jin and Myers, 2006; Hutton et al., 2009). Other studies have proposed alternative perspectives such as tax avoidance (Kim et al., 2011a,b), auditor–client relationships (Callen and Fang, 2017), and religiosity (Callen and Fang, 2015; Li and Cai, 2016). We revisit this topic by exploring the consequences of rising intangible intensity on stock price crash risk.

2 Hypothesis Development

The academics have been examining the role of intangible assets on firm performance for decades. Intangible assets provide substantial future economic benefits through increased revenue or decreased cost (Zambon and Marzo, 2008; Kim, 2007). Shih (2013) found that firm valuation is positively associated with intangible assets, as firms are likely to distribute cash dividends in the future. Foray (2004) and Alcaniz et al. (2011) concluded that successful businesses commonly driven by intangible, knowledge and resources. Ehie and Olibe (2010) and Gupta et al. (2017) found that R&D, as a proxy for intangible intensity, has a positive effect on the firm value of international and US firms. Studies have also documented negative effect of intangible assets on information disclosure and firm performance. Lonergan (2009) showed sizeable measurement errors for intangible assets due to low disclosure requirements. Similarly, evidence suggests that managers misrepresent intangible assets to pursue personal incentive compensation (Hayn and Hughes, 2006; Johansson et al., 2016; Huikku et al., 2016). The economic consequences of intangible asset impairment include exacerbated financial shocks to the economies and firm values (Li et al., 2010a,b; Detzen and Zlch, 2012). Moreover, the negative effect of intangible asset impairment is stronger in firms with large-scale intangible assets and inadequate information disclosure prior to the impairment announcements (Li et al., 2010a).

Given these findings in the existing literature, we propose our first main hypothesis:

Hypothesis H1: Firms with higher intangible intensity are associated with greater stock price crash risk.

Since we propose hypothesis that intangible intensity positively associated with stock price crash risk, it is intrigued to further seek underlying channels through which stock price crash risk is affected. Our first channel is related to asset impairment. According to accounting standards, intangible assets can be classified into definite-life and indefinite-life assets, which comply with different fair value measurements. On the one hand, definite-life intangible assets are measured by cost less accumulated amortization based on a predetermined amortization over time. Therefore, definite-life intangible assets are generally subject to lower information asymmetry due to smooth deduction of expected economic benefits. On the other hand, indefinite-life intangible assets must undergo annual impairment tests before they are written off. The impairment of intangible assets creates price pressure for the stock as the firm profitability deteriorates, leading to stock price crash risk when the earning surprises is revealed to the public.

Our second channel is related to valuation uncertainty, which is the uncertainties associated with firm value. The valuation uncertainty comes from low disclosure requirement as well as measurement errors of intangible assets. For instance, managers might be opportunistic in misrepresenting intangible assets to boost short-term firm performance. Moreover, the impairment decisions of intangible assets are under managerial discretion to some extent, bringing difficulties in firm valuation for investors. Therefore, firms with higher intangible intensity are expected to associate with greater uncertainties due to information asymmetry between investors and managers. Such valuation uncertainty is detrimental to investors, as they will respond strongly to announcement of surprising deteriorated earnings with remarkable price declines.

Hence, we propose our second main hypothesis:

Hypothesis H2a: Firms with higher intangible intensity are associated with greater likelihood of intangible asset impairments and firm performance deterioration, which contributes to increased stock price crash risk.

Hypothesis H2b: Firms with higher intangible intensity are associated with greater valuation uncertainty, which contributes to increased stock price crash risk.

In addition, one of the most popular explanations for crash risk in the existing literature is the hoarding of bad news (Jin and Myers, 2006; Hutton et al., 2009). Bad news hoarding theory contends that when managers intentionally conceal negative information, the accumulation of bad news exaggerates valuation uncertainty, causing the stock price to crash once the bad news is finally disclosed. Kim and Zhang (2016) examined the relationship between accounting conservatism and future stock price crash risk and concluded that a low degree of conservatism is associated with greater stock price crash risk. Zhu (2016) demonstrated similar results by using accruals as a proxy for accounting conservatism. Apart from bad news hoarding theory, other studies have also examined the effect of financial regulation on information flows and stock price crash risk. Kim et al. (2017) showed that the disclosure of internal control weaknesses under the Sarbanes–Oxley Act significantly reduces stock price crash risk. Previous literatures suggests several factors that considerably relate to information disclosure, such as credit rating, shareholder litigation risks and information opacity. First, firms with higher credit ratings are recognized as having better fundamentals and less information asymmetry (He et al., 2011; He, 2015). He et al. (2011) demonstrated that information asymmetry and analysts' forecast earnings dispersion diminish significantly after firms' bond ratings are upgraded. He (2015) showed that managers tend to ensure better disclosure transparency for higher credit ratings. Second, previous studies have shown that firms experiencing remarkable shareholder litigation risk tend to have a lower quality of information disclosure which exasperate information asymmetry. Using Rule 10b-5 of the Securities Exchange Act of 1934 (Trueman, 1997) and universal demand laws (Bourveau et al., 2017) as exogenous shocks that reduce shareholder litigation risk, these studies have found that managers tend to disclose greater amounts and accurate information which eventually reduce information asymmetry. Third, Hutton et al. (2009) and Wang and Du (2012) demonstrated that firms with high opacity reveal lower degree of firm-specific information and face greater crash risk. In addition, Kim and Zhang (2014) found similar results by using the steepness of option-implied volatility skew as a proxy for crash risk. Thus, we propose our third hypothesis as follows:

Hypothesis H3a: The effect of intangible intensity on stock price crash risk is stronger for firms with lower credit rating.

Hypothesis H3b: The effect of intangible intensity on stock price crash risk is stronger for firms with higher shareholder litigation.

Hypothesis H3c: The effect of intangible intensity on stock price crash risk is stronger for firms with greater information opacity.

3 Data and Methodology

3.1 Sample

Our initial sample starts with all the listed firms incorporated in the United States from 1983 to 2017. We obtain stock prices, number of outstanding shares, SIC codes, and weekly stock returns from the Center for Research in Security Prices (CRSP). In addition, we obtain firm-level annual accounting data from Compustat and detailed information on the impairment of intangible assets from Calcbench. Calcbench is an original dataset derived from the footnotes of 10-k fillings prepared by firms. The intangible assets and goodwill section of this dataset contains the type and amount of impaired intangible assets. Following the convention, we exclude firms operating in financial (SIC 6000–6999) and utility (SIC 4000–4999) industries. Thus, our final sample consists of 91,383 firm-year observations from 1983–2017.

3.2 Measures of Stock Price Crash Risk

We calculate firm-specific weekly returns by estimating the following expanded market model regression for each firm in a fiscal year:

$$\mathrm{r}_{i,t} = \alpha_j + \beta_{1,i} r_{m,t-1} + \beta_{2,i} r_{m,t} + \beta_{3,i} r_{m,t+1} + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the return of stock i in week t, and $r_{m,t}$ is the return of the CRSP value-weighted market index in week t. We follow Jin and Myers (2006) and exclude firms whose shares trade is less than 26 weeks over a fiscal year. The firm-specific weekly return $R_{j,t}$ is defined as the natural log of one plus the residual from Eq.(1):

$$R_{i,t} = \ln(1 + \varepsilon_{i,t}). \tag{2}$$

We construct three measures of firm-specific crash risk. Following Kim et al. (2011a,b), the first measure, *NCSKEW*, is calculated by taking the negative value of the third central moment of the firm-specific weekly return scaled by the sample variance of the firm-specific weekly return raised to 3/2.

$$\text{NCSKEW}_{j,t} = \left[n(n-1)^{\frac{2}{3}} \sum R_{j,t}^3\right] / \left[(n-1)(n-2)(\sum R_{j,t}^2)^{\frac{3}{2}}\right], \tag{3}$$

where n is the number of observations in a fiscal year. A large *NCSKEW* indicates that the stock returns have a negatively-skewed distribution, which implies higher crash risk.

Our second crash risk measure *DUVOL* is the down-to-up volatility. It is calculated as the log of the ratio of the standard deviation of firm-weekly returns on down weeks to that on up weeks. The standard deviations of firm-specific weekly returns on down weeks are calculated for each firm and fiscal year if the firm-specific weekly returns on the weeks are lower than the mean of the respective annual firm-specific returns, and vice versa.

$$\text{DUVOL}_{i,t} = \log\left\{\left[\sum_{DOWN} R_{i,t}^2/(n_d - 1)\right] / \left[\sum_{UP} R_{i,t}^2/(n_u - 1)\right]\right\}. \tag{4}$$

The last measure of crash risk *COUNT* is defined as the number of crashes minus jumps over a fiscal year in which a crash (jump) event occurs when a firm-specific weekly return is 3.09 standard deviations below (above) its mean over a fiscal year.

3.3 Measure of Intangible Intensity

Intangible intensity measures the extent of intangible assets possessed by firms. We follow Clausen and Hirth (2016) to construct our main explanatory variable, the intangible intensity of firms, by following three steps. First, we derive the return on tangible assets *(ROTA)* as follows:

$$ROTA_{it} = \frac{EBITDA_{i,t-1}}{NETPPE_{i,t-1}} \tag{5}$$

The *ROTA* is calculated at the beginning of the year to alleviate endogeneity concerns.

However, *ROTA* is not an appropriate indicator to measure the intensity of intangible assets because it may be influenced by business cycles or industry-wide characteristics. Following Clausen and Hirth (2016), we eliminate the noises by adjusting *ROTA* for industry and business cycle variations. Specifically, in the second step, we subtract from *ROTA* the industry-year median, and then scaled by the industry-year standard deviation to get the adjusted *ROTA*.

$$ADJROTA_{i,t} = \frac{ROTA_{i,t} - Median(ROTA_{ind,t})}{\sigma(ROTA_{ind,t})} \tag{6}$$

Finally, we calculate our main explanatory variable, *ROTARANK*, as the relative ranking of adjusted *ROTA* in the entire sample. As a result, *ROTARANK* ranges from 0 to 1, in which a high value indicates a greater intangible intensity. We also construct an alternative measure, *INTANTA* for robustness checks. *INTANTA* is defined as intangible assets scaled by total assets and represents the proportion of intangible assets held by firms.

3.4 Summary Statistics

Figure 1 reports the total amount and proportion of the intangible assets of listed firms in the United States from 1983 to 2017. The figure shows that the total amount of intangible assets held by listed US firms was nearly zero in 1983 but increases tremendously to over US$60 billion in 2017. Meanwhile, the percentage of intangible assets in total assets has increased from less than 5% to nearly 30% in recent years. Such enormous growth highlights the importance of intangible assets in firm operations in recent decades.

Panel A of Table 1 reports the descriptive statistics of the variables. The means of *NCSKEW*, *DUVOL*, and *COUNT*, are -0.112, -0.071 and -0.129, respectively. The proxies for intangible intensity, *ROTARANK* and *INTANTA*, have means of 0.517 and 0.285, respectively. In addition, the firms have an average size of US$2.28 billion, firm age of 15.034 years, profitability *ROA* of -5.6%, leverage (*LEV*) of 0.498, and market-to-book ratio (*MTB*) of 14.611. On average, 33.3% of the firms' outstanding shares are held by institutional investors.

Panel B of Table 1 presents the Spearman correlation matrix for the main variables. We find a strong and significant positive correlation among the stock price crash risk measures. In addition, the intangible intensity measures, *ROTARANK* and *INTANTA*, are significantly positively correlated with stock price crash risk. The correlation coefficient between *ROTARANK* and the crash risk measures ranges from 0.09 to 0.12. The alternative intangible intensity measure, *INTANTA*, also has a positive correlation with the crash risk measures. Overall, the correlation matrix shows that intangible intensity is positively correlated with stock price crash risk.

4 Empirical Results

4.1 Validation of Intangible Intensity Measure

To ensure that intangible intensity reflect the extent of intangible assets, we validate our proxy for intangible intensity by examining how intangible intensity captures intangible asset scale. The panel regression is specified as follows:

$$Y_{i,t+1} = \beta ROTARANK_{i,t} + \gamma X_{i,t} + \delta_j + \theta_t + \epsilon_{i,t}, \tag{7}$$

where $Y_{i,t+1}$ is the intangible assets scale for firm i in year $t + 1$. Specifically, *INTAN*, *GOODWILL*, and *R&D* are defined as intangible assets, goodwill, and R&D over total assets, respectively. Our main explanatory variable, *ROTARANK*, is defined as the relative ranking of EBITDA-to-net PPE ratio in the entire sample. The intangible intensity measure ranges from 0 to 1, and higher value implies greater extent of intangible intensity.

We also include several firm characteristics as control variables. *SIZE* is the natural logarithm of market capitalization, *AGE* is the number of years since a firm's initial public offerings, *ROA* is the income before extraordinary items over total assets, *LEV* is total liabilities over total assets, and *MTB* is the market-to-book ratio. We add *DTURN*, which is the change in the average monthly turnover from year t to $t - 1$ to account for stock liquidity. In addition, we control for *RET*, which is the average idiosyncratic return in year t, and the volatility of the firm-specific return measured by *SIGMA*. Moreover, we include the firms' earnings management *ABACC*, which is the absolute value of abnormal current accruals, and *INSTHOLD*, the percentage of institutional holdings. Following convention in the literature, we include both industry and year fixed effects in all the specifications.

Table 2 presents the results for the validation of the intangible intensity measure. The results in all specifications demonstrate that our main explanatory variable, *ROTARANK*, is positively correlated with all the intangible asset scale measures. For instance, in Column (1), the estimated coefficient of *ROTARANK* is 0.1147, which is significant at the 1% level, with a t-statistic over 10. This finding suggests that higher intangible intensity is associated with a greater proportion of intangible assets in a firm's total assets. The results in Columns (2) and (3) are quantitatively similar. Therefore, our constructed proxy for the extent of intangible assets, *ROTARANK*, reflects the firms' intangible intensity.

4.2 Intangible Intensity and Stock Price Crash Risk

Figure 2 reports the value-weighted average of intangible intensity and stock price crash risk *NCSKEW* from 1983 to 2017. The time-series average of these two variables indicates a positive correlation between them, especially during the later part of the sample period. The time-series pattern shows that intangible intensity moves closely with stock price crash risk.

We conduct an univariate analysis to examine the effect of intangible intensity on stock price crash risk without additional controls. Specifically, the sample is divided into tercile groups based on *ROTARANK* and *INTANTA*. The univariate test aims to demonstrate how stock price crash risk is affected by intangible intensity without additional factors. Table 3 presents the means of the stock price crash risk measures for each tercile group based on the intangible intensity measures. The result of univariate test shows that stock price crash risk increases with intangible intensity. The mean of *NCSKEW* increases from -0.0561 in the lowest group G1, to -0.0391 in the highest group G3, with a t-statistic of -2.87 for the mean difference test. Similarly, we find that the other two stock price crash risk measures follow the same pattern. Moreover, we yield quantitatively similar results when the rough measure of the intangible intensity *INTANTA* is used to sort the sample into tercile groups.

Next, we examine the relationship between intangible intensity and stock price crash risk controlling for other firm characteristics. The panel regression model is formulated as follows:

$$Y_{i,t+1} = \beta ROTARANK_{i,t} + \gamma X_{i,t} + \delta_j + \theta_t + \epsilon_{i,t}, \tag{8}$$

where $Y_{i,t+1}$ is stock price crash risk measures (i.e., *NCSKEW*, *DUVOL*, and *COUNT*) for firm i in year $t+1$. We include the other firm characteristics, lagged *NCSKEW* as well as industry and year fixed effects in the regression.

Table 4 presents the effect of intangible intensity on stock price crash risk. Column (1) shows that intangible intensity *ROTARANK* has a positive and significant effect on the *NCSKEW*. The estimated coefficient of *ROTARANK* is 0.0955, which is significant at the 1% level with a t-statistic of 6.59. This result suggests that firms with greater intangible intensity are associated with higher stock price crash risk. We find qualitatively similar results in Columns (2) and (3), as the estimated coefficients of *ROTARANK* are positive and highly significant. For instance, Column (2) shows that the main explanatory variable, *ROTARANK*, has an estimated coefficient of 0.0430 (t-statistic=3.74), which is significant at the 1% level, suggesting that higher intangible intensity can lead to a greater extent of stock price crash risk.

In summary, the result of our baseline regressions provides supportive evidence for our first hypothesis H1, suggesting that intangible intensity has a significant and positive impact on stock price crash risk, and the effect is robust to alternative crash risk measures.

5 How Does Intangible Intensity Affect Crash Risk?

5.1 Asset Impairments

In this section, we explore the possible channel through which stock price crash risk is affected by intangible intensity. In particular, we investigate how intangible intensity is associated with subsequent intangible asset impairments and firm performance deterioration, which in turn can lead to stock price crashes. We obtain detailed information on intangible asset impairments from Calcbench. Calcbench covers the period from 2007 to 2017, thus our sample size is reduced to approximately 24,000 observations. Firstly, we estimate the following linear probability model to examine the effect of intangible intensity on the likelihood of intangible asset impairments.

$$Y_{i,t+1} = \beta ROTARANK_{i,t} + \gamma X_{i,t} + \delta_j + \theta_t + \epsilon_{i,t}, \tag{9}$$

where $Y_{i,t+1}$ denotes the intangible asset impairments measure, *ITIMPAIR*, which is a dummy variable that equals one if a fir's m intangible assets are impaired in a fiscal year and zero otherwise.

Column (1) of Table 5 presents the effect of intangible intensity on the future likelihood of intangible asset impairments. We find that the estimated coefficient of intangible intensity *ROTARANK* is 0.0244, with a t-statistic of 2.46. It suggests that intangible intensity has a positive and significant effect on intangible asset impairments. Firms with higher intangible intensity are subject to a higher likelihood of intangible asset impairments.

Next, we proceed to examine how intangible asset impairments affect firm performance. The reason for this investigation is that the impairment of intangible assets will affect concurrent net income, thereby reducing firm profitability. In our context, we examine if intangible asset impairment increases the likelihood of firms reporting earnings losses or severe earnings growth rate decline. Essentially, we estimate the following linear probability model:

$$Y_{i,t+1} = \beta ITIMPAIR_{i,t+1} + \gamma X_{i,t} + \delta_i + \theta_t + \epsilon_{i,t}, \tag{10}$$

where $Y_{i,t+1}$ denotes two firm performance measures that represent earnings losses and performance decline. Specifically, the first performance measure, *NILOSS*, is a dummy variable that equals one if a firm has negative earnings in year *t+1* and zero otherwise. The second performance indicator, *NIDOWN*, is a dummy variable that equals one if a firm has an earnings growth rate below -20% in year *t+1* and zero otherwise. We aim to examine if intangible asset impairments will lead to increased probability of reporting earnings losses or severe performance decline.

Columns (2) and (3) of Table 5 present the effect of intangible asset impairments on firm performance. The result shows that intangible asset impairments have a significant and positive effect on the probability of negative reported earnings or performance decline in the subsequent year. Specifically, the estimated coefficient of the intangible asset impairment in Column (2) is 0.0292, which is significant at the 5% level. This finding suggests that firms that experience intangible asset impairments are associated with a 2.92% increase in the probability of negative earnings in the subsequent year. The result in Column (3) shows that the intangible asset impairment, *ITIMPAIR*, has a significantly positive effect on the performance decline indicator *NIDOWN*, which suggests a large reduction in the earnings growth rate following impairments.

Finally, in Columns (4) and (5), we include firm performance measures in the regression models. We find that the estimated coefficient of intangible intensity *ROTARANK* is positive and significant. In addition, *NILOSS* and *NIDOWN* are significantly positive at the 1% level. The result indicates that the positive effect of intangible intensity on stock price crash risk is partially driven by the increased likelihood of earnings losses and performance decline. Therefore, the findings in Table 5 are supportive of our second hypothesis H2a that asset impairments and firm performance deterioration is the channel through which stock price crash risk is affected by intangible intensity.

5.2 Valuation Uncertainty

To test our second hypothesis H2b, we investigate the relationship between intangible intensity and firm valuation uncertainty. Since probability of impairment losses increases with intangible intensity, and the intangible asset impairment decisions are somehow subject to managerial discretion, it suggests that firms with greater intangible intensity are associated with greater uncertainty in firm profitability as the impairment of intangible assets would affect concurrent earnings. If investors are uncertain about firm profitability, they would respond more strongly to earning surprises, leading to stock price crashes after the impairment announcement.

Following Pástor et al. (2008) and Cremers et al. (2016), we construct our valuation uncertainty measures as earnings response coefficients *ERC1* and *ERC2*, which is based on stock market reactions to earnings announcement surprises. Specifically, the first valuation uncertainty measure, *ERC1*, is mean of firm's previous 12 stock price reactions to quarterly earnings shocks. The second valuation uncertainty measure, *ERC2*, is minus the regression slope of firm's last 12 quarterly earnings surprises on abnormal stock returns at the time of earnings announcement. The main idea is that the when investors have flatter priors about future earnings, the earnings response coefficients will be larger.

Table 6 presents the relationship among intangible intensity, firm valuation uncertainty and stock price crash risk. Firstly, we examine the effect of our main explanatory variable, *ROTARANK* on the dependent variable *ERC1* and *ERC2*. The result in Columns (1) and (2) shows that there is a positive and significant relationship between intangible intensity and valuation uncertainty measures. For instance, the coefficients of intangible intensity are 0.7645 (t-statistic=3.90) and 0.1172 (t-statistic=5.87), respectively. The empirical evidence shows that higher intangible intensity are associated with greater valuation uncertainty measured by earning response coefficients.

Next, we examine the effect of intangible intensity on stock price crash risk while controlling for valuation uncertainty. The result in Columns (3) and (4) shows that consistent with our expectations, both valuation uncertainty measures have a positive effect on stock price crash risk, and the effect is significant at 5% and 10%, respectively. Our main explanatory variable, *ROTARANK*, remains to have positive and highly significant effect on stock price crash risk. The empirical findings are consistent with the notion that stock market reaction to earning surprises due to impairment losses will be greater for firms with larger valuation uncertainty, leading to increased stock price crash risk. Overall, the findings in Table 6 identify valuation uncertainty as another underlying channel through which stock price crash risk is affected by intangible intensity. Therefore, we show supporting evidence for the second hypothesis H2b that intangible intensity affects stock price crash risk through increased valuation uncertainty.

6 Firm Heterogeneity

6.1 Credit Rating

In this section, we examine the effect of firm heterogeneity on the relationship between intangible intensity and stock price crash risk. In particular, we examine how the effect of intangible intensity varies with firm characteristics. First of all, we interact the main explanatory variable, *ROTARANK*, with credit ratings *RATING*, to test the hypothesis H3a. *RATING* is an ordinal variable ranging from 0 to 7, in which a higher value stands for better credit rating for firm i in year t.[3]

Table 7 presents the moderating effect of credit rating on stock price crash risk. The result in Column (1) shows that the positive effect of intangible intensity *ROTARANK* on stock price crash risk is reduced when firms' credit ratings are higher, as the interaction term *ROTARANK**RATING* is significant at the 1% level (t-statistic=-3.08), with a negative coefficient of -0.0291. We find similar results when alternative crash risk measures are used

[3] We group S&P credit ratings into seven categories. Specifically, *RATING*=1 if Rating <= CCC+, *RATING*=2 if CCC+ <Rating <= B+, *RATING*=3 if B+ < Rating <=BB+, *RATING*=4 if BB+ < Rating <= BBB+, *RATING*=5 if BBB+ < Rating <= A+, *RATING*=6 if A+ < Rating <= AA+, and *RATING*=7 if Rating> AA+.

as dependent variables. This result indicates that the downside price pressure driven by high intangible intensity is attenuated in firms with better credit ratings of their corporate bonds. Credit ratings reflect corporate solvency and information transparency. Thus, the result also suggests that firms with better fundamentals and disclosure quality suffer less from the negative impact of intangible intensity on stock returns.

The results in Table 7 lends support to our hypothesis H3a as we show that the positive effect of intangible intensity on stock price crash risk is attenuated in firms with higher credit ratings. In other words, firms with better fundamentals and solvency are less prone to crash risk with similar levels of intangible intensity.

6.2 Shareholder Litigation Risk

Second, we examine how the quality of information disclosure affects crash risk. We identify firms operating in industries that are characterized by large shareholder litigation risk to test our hypothesis H3b. Specifically, we interact our main explanatory variable *ROTARANK* with *LITIG*, which is a dummy variables that equals one for all the firms in the biotechnology (SIC 2833–2836 and 8731–8734), computer (SIC 3570–3577 and 7370–7374), electronics (SIC 3600–3674), and retail (SIC 5200–5961) industries and zero otherwise.

Table 8 presents the moderating effect of shareholder litigation risk on stock price crash risk. The results in Columns (1)–(3) show that the positive effect of intangible intensity on stock price crash risk is stronger in firms with higher shareholder litigation risk. Specifically, the variable of interest, *ROTARANK*LITIG*, is positive and significant at the 5% level, suggesting that shareholder litigation risk exaggerates the effect of intangible intensity on crash risks. The result remains quantitatively the same when alternative crash risk measures are applied. The finding supports our second hypothesis H3b. One possible explanation for these results is that firms with higher shareholder litigation risk are associated with lower reporting quality and tend to misrepresent intangible assets in their financial statements. Thus, when the concealed negative information is revealed to the public, stock price crash follows.

6.3 Information Opacity

Finally, we examine how the effect of intangible intensity on stock price crash risks varies with information opacity. Our hypothesis H3c contends that the effect of intangible intensity on stock price crash risk is stronger for firms with greater information opacity. To test this hypothesis, we construct an information opacity measure, *OPAQUE*, which is calculated as the sum of the abnormal current accrual, estimated from Dechow et al. (1995), over the past 3 years. The information opacity measure is constructed from the earnings management variable, suggesting that firms' information opacity increases with the extent of earnings management behaviors.

Table 9 presents the moderating effect of information opacity on stock price crash risk. We find that the variable of interest, *ROTARANK*OPAQUE*, is positive and significant across all specifications, suggesting that the positive relationship between intangible intensity and stock price crash risk is greater in firms with a higher degree of information opacity. The findings are supportive of our hypothesis H3c. The reason is that high extent of information opacity impede evaluation of the true value of firm assets, especially intangible assets. These firms also tend to withhold bad news on intangible assets until its final release, creating severe downside price pressure.

7 Robustness Checks

7.1 Endogeneity

Our primary findings might be subject to potential endogeneity problems for two reasons. First, the regression might suffer from omitted variable bias when unobservable firm characteristics are correlated with both intangible intensity and firm outcomes. Second, the measurement errors in the intangible intensity measures may also contribute to the endogeneity issue. Thus, we apply two methods to address the endogeneity concerns.

7.1.1 Dynamic Panel Regression

Our first approach estimates a dynamic panel regression formulated as follows:

$$Y_{i,t+1} = \alpha Y_{i,t} + \beta ROTARANK_{i,t} + \gamma X_{i,t} + \delta_i + \theta_t + \epsilon_{i,t}, \tag{11}$$

where the dependent variable, $Y_{i,t+1}$ denotes the stock price crash measures for firm i in year $t+1$. $Y_{i,t}$ is the lagged dependent variable. Given the highly persistent nature of stock price crash risk, we focus primarily on the results from a system GMM estimator that addresses the weak instrument problems of difference GMM by jointly estimating a regression of Eq.(11) in differences and in levels, using lagged levels as instruments for the regression in differences and lagged differences as instruments for the regression in levels (Arellano and Bond, 1991; Arellano and Bover, 1995). Specifically, we use lagged dependent variable as an explanatory variable, and maximum of 3 lags as their instruments. In addition, we treat *ROTARANK* as an endogenous variable, and use 1 lag as its instrument. We also perform AR (2) test to examine the autocorrelation of the error term from system GMM. In addition, the result of Sargan test is reported to show whether all instruments are valid.

Table 10 presents the results of the dynamic panel regression. We find that our main explanatory variable, *ROTARANK*, is positive with a coefficient of 0.3399 and significant at the 1% level (t-statistic=4.58). The lagged dependent variable is also significant and positive, suggesting that stock price crash risk is highly persistent. The result in Column (1) shows that the intangible intensity has a positive and significant effect on stock price crash risk when endogeneity is addressed using system GMM estimation method. Moreover, the AR (2) test statistics indicate that we can not reject the null hypothesis of no autocorrelation for the error term. We also find support for the validity of our instruments, as the result of Sargan statistic fails to reject the null hypothesis that all instruments are valid. Columns (2)–(3) report quantitatively similar results for *DUVOL* and *COUNT*. For instance, the intangible intensity, *ROTARANK*, in Column (2) and (3) has a positive coefficient, both of which are significant at the 1% level. These results suggest that our main finding remains quantitatively the same when the system GMM estimator is applied.

Overall, the result of the dynamic panel regressions show that our primary findings are robust when the endogeneity concern is addressed. By estimating dynamic panel regressions with a system GMM estimator, we find positive and significant effect of intangible intensity on stock price crash risk.

7.1.2 Change-in-Variable Regression

Our second approach to address endogeneity concern is using change-in-variable regression. We aware of the possible endogeneity due to omitted variable biases in the panel data regression model. Chung et al. (2008) argued that change-in-variable regression is more effective in reducing spurious relationship between variables compared to level-variables regression. Besides, change-in-variable regression is a better way of examining longer-term relationship between intangible intensity and stock price crash risk. Therefore, we run change-in-variable regression by conducting a first-difference regression on all the variables in Table 4. The change-in-variable regression is formulated as follows:

$$Y_{i,t+1} = \beta DROTARANK_{i,t} + \gamma DX_{i,t} + \delta_i + \theta_t + \epsilon_{i,t}, \tag{12}$$

where $Y_{i,t+1}$ is the changes in stock price crash risk measures (i.e., *NCSKEW*, *DUVOL*, and *COUNT*). The main explanatory variable and the other firm characteristics are also in first-difference form. Following the literature, we control for lagged *DNCSKEW* in the regression as well as industry and year fixed effects.

Table 11 presents the results of the change-in-variable regressions. The result in Column (1) documents that the change in the intangible intensity *DROTARANK* is positively correlated with the change in *NCSKEW*. Moreover, the coefficient is statistically significant at the 5% level. This result suggests that when other firm characteristics are controlled, the change in intangible intensity is positively associated with the change in stock price crash risk. Similarly, the relationship between the change in *ROTARANK* and the measures of stock price crash risk is positive and highly significant, as shown in Columns (2) and (3). For instance, the change in intangible intensity *DROTARANK* has a coefficient of 0.0583 (t-statistic=2.40), and the change in stock price crash risk measured by *DUVOL* and *COUNT* has a coefficient of and 0.0415 (t-statistic=2.11).

Overall, we find that our results are robust to alternative intangible intensity measures and model specifications. Moreover, our main findings remain quantitatively similar after the endogeneity issues are addressed by dynamic regression and change-in-variable regression.

7.2 Alternative Intangible Intensity Measure

We construct our main explanatory variable, *ROTARANK*, following Clausen and Hirth (2016). This approach circumvents missing data and measurement error problems in intangible assets by using the relative ranking of EBITDA over net PPE in the entire sample. Nevertheless, we construct a direct measure of intangible intensity, *INTANTA*, which is the proportion of intangible assets in total assets for robustness purpose. This raw measure reflects the relative size of the intangible assets of a particular firm. We estimate the same regressions in which the explanatory variable, *ROTARANK*, is replaced by *INTANTA* across all specifications. The dependent variables are stock price crash risk.

Table 12 reports the corresponding results for the alternative intangible intensity measure. Column (1) demonstrates that the alternative intangible intensity measure, intangible asset scale, *INTANTA*, has a positive effect on stock price crash risk, with an estimated coefficient of 0.0418 (t-statistic=1.84), which is significant at the 10% level. This result suggests that firms with a greater intangible assets scale have a higher stock price crash risk. In addition, we also estimate the effects of the intangible assets scale on alternative crash risk measures. Consistent with the results in Column (1), Columns (2)–(3) show that the explanatory variable, *INTANTA*, is positive and statistically significant. Therefore, we contend that our primary findings are not sensitive to the alternative intangible intensity measure.

Overall, we find consistent results that firms with greater intangible intensity are associated with higher stock price crash risk by using an alternative measure of intangible intensity.

7.3 Alternative Specifications

Finally, we conduct additional robustness checks using alternative specifications. Specifically, we include the firm and industry-year fixed effect in Column (1) to account for industry-wide, time-varying characteristics. Moreover, in Columns (2)–(4), we control for additional firm characteristics such as the alternative intangible intensity measure, *INTANTA*, firm tangibility, *TANG* (PPE plus total current assets and inventories over total assets), and sustainable growth rate, *PEG* (forward PE to the 1-year growth ratio), respectively. These additional controls help alleviate the concern for the omitted variable bias in our previous regressions.

Table 13 presents the effect of intangible intensity on stock price crash risk with alternative model specifications. Column (1) shows that the significant and positive effect of intangible intensity *ROTARANK* on the stock price crash risk remains quantitatively similar when we control for firm and industry-year fixed effect. This result indicates that our findings remain quantitatively intact when industry-specific, time-varying characteristics are controlled in the regression.

In Columns (2)–(4), we control for additional firm characteristics that predominantly affect stock price crash risk. In particular, in Column (2), we include the alternative intangible intensity measure, *INTANTA*, which is defined as intangible assets over total assets. We find that *ROTARANK* and *INTANTA* are positive and significant at the 1% and 5% level, respectively. The result demonstrates that the effect of intangible intensity, *ROTARANK*, on stock price crash risk is robust when an alternative measure is further included. By controlling for *TANG*, Column (3) documents a positive and significant relationship between intangible intensity *ROTARANK* and stock price crash risk, with a t-statistic of 6.55, while *TANG* itself is insignificant. Finally, Column (4) presents the result when *PEG* is added to the regression. We find that *ROTARANK* remains positive and significant at the 1% level. This finding suggests that the positive effect of intangible intensity on stock price crash risk remains qualitatively similar when we consider the firms' sustainable growth rate.

In summary, our main findings are robust to alternative specifications that account for firm and industry-year fixed effects as well as to additional firm characteristics.

8 Conclusion

The importance of intangible assets in firm valuation has been recognized by financial economists and practitioners over the past decade. Intangible assets are characterized by the difficulty of initial measurement and the subsequent reevaluation of fair value. Intangible assets can be classified into two categories, namely, definite-life intangible assets, such as patent or copyright, and indefinite-life assets, such as trademark or perpetual franchise. Definite-life intangible assets are amortized according to a predetermined scheme, while indefinite-life intangible assets are subject to annual impairment tests. Thus, most of the valuation uncertainty comes from indefinite-life intangible assets. This study aims to shed light on the relationship between intangible intensity, the extent of intangible assets held by a firm, and stock price crash risk. In addition, we explore the channel through which the crash risk is affected by establishing the link between intangible intensity and subsequent impairment losses as well as valuation uncertainty.

We first validate our proxy for intangible intensity by showing its high correlation with the proportion of intangible assets, goodwill and R&D in the total assets. The primary results demonstrate that intangible intensity has a significantly positive effect on stock price crash risk. These findings suggest that firms with greater intangible intensity are associated with higher crash risk. Moreover, we demonstrate that firms with higher intangible intensity are associated with a increased likelihood of subsequent intangible asset impairments, which exacerbate firm profitability. In addition, firms with greater intangible intensity are associated with larger valuation uncertainty, which contributes to higher crash risk. Therefore, we show that the fragility of intangible assets is the driving force for the downside risk of stock prices. In addition, we find that the positive effect of intangible intensity is stronger in firms with higher information opacity and shareholder litigation risk, but alleviated with better credit ratings. As robustness checks, we address endogeneity issues using dynamic panel regression and change-in-variable regression. We also construct a direct measure of intangible intensity as the proportion of intangible assets in total assets to replace the intangible intensity measure. In addition, we check robustness by estimating alternative models. Our findings remain qualitatively the same.

The findings of our study provide useful implications for regulation agencies and investors. Our empirical findings highlight the role of financial regulators, such as the Financial Accounting Standards Board, in further enhancing the fair value measurement and information disclosure procedures of intangible assets. The improvement in relevant policies can protect financial markets from stock price crash risk caused by the fragility of intangible assets. Meanwhile, our findings also calls on portfolio managers and retail investors to be wary of excessive downside risks brought by firms with high intangible intensity.

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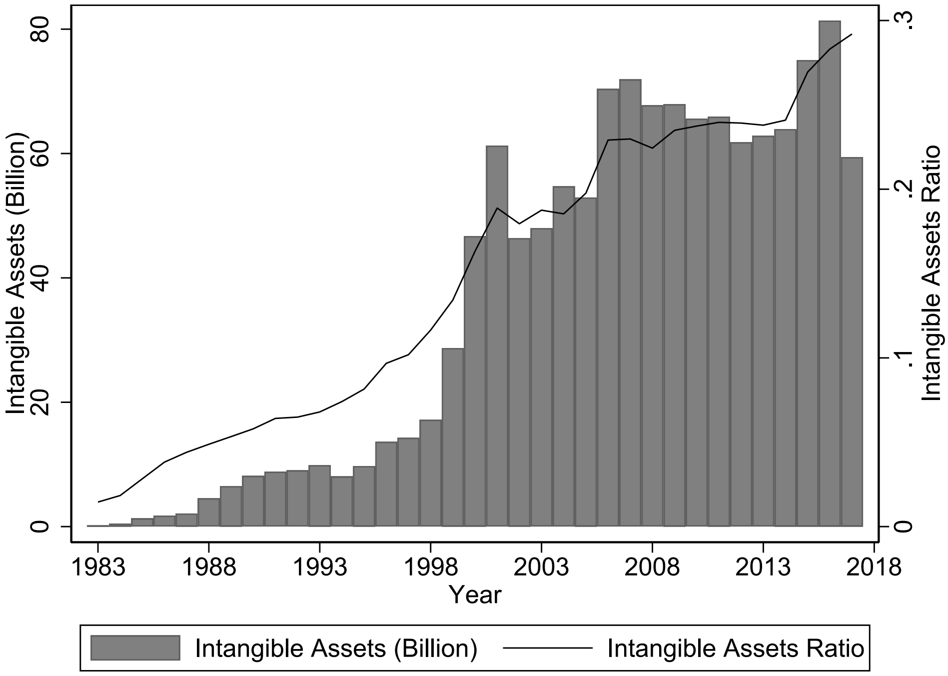

Figure 1: Intangible Assets of US Listed Firms

This figure reports the total intangible assets and the proportion of intangible assets in total assets from 1983 to 2017.

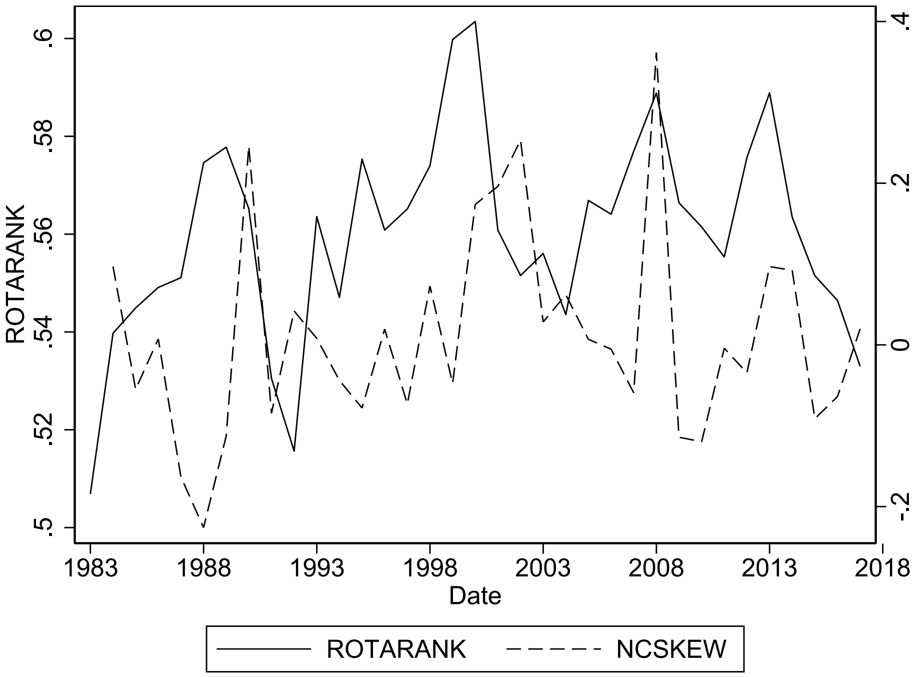

Figure 2: Intangible Intensity and Stock Price Crash Risk

This figure reports the time-series value-weighted average of intangible intensity and the stock price crash risk measure, *NCSKEW*.

Table 1: Descriptive Statistics

This table presents descriptive statistics and Spearman correlation matrix for a sample of listed US firms from 1983 to 2017. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. *ROTARANK* is the relative ranking of EBITDA over net PPE in the entire sample. *INTANTA* is calculated as intangible assets over total assets. *SIZE* is the firm's market capitalization (in billion). *AGE* is number of years since a firm's establishment. *ROA* is the contemporaneous income before extraordinary items scaled by total assets. *LEV* is the book value of all liabilities scaled by total assets. *MTB* is calculated as market capitalization over the book value of equity. *DTURN* is the change in turnover rate, where turnover rate is calculated as average ratio of monthly turnover over monthly trading volume over a fiscal year. *RET* is the average firm-specific weekly return over the fiscal year. *SIGMA* is the standard deviation of the firm-specific weekly return over the fiscal year. *ABACC* is absolute value of abnormal current accruals, estimated from Dechow et al. (1995). *INSTHOLD* is the percentage of institutional holdings.

Panel A. Summary Statistics

	Mean	S.D.	Q5	Q25	Median	Q75	Q95	N
NCSKEW	-0.112	0.777	-1.387	-0.531	-0.103	0.301	1.110	97,815
DUVOL	-0.071	0.495	-0.891	-0.391	-0.069	0.252	0.684	97,815
COUNT	-0.129	0.661	-1.000	-1.000	0.000	0.000	1.000	97,815
ROTARANK	0.517	0.281	0.061	0.280	0.530	0.756	0.948	97,815
INTANTA	0.285	0.341	0.000	0.025	0.156	0.414	1.051	97,815
SIZE	2.280	7.283	0.007	0.052	0.241	1.092	10.478	97,815
AGE	15.034	14.745	1.000	4.000	10.000	21.000	45.000	97,815
ROA	-0.056	0.285	-0.611	-0.053	0.030	0.073	0.155	97,815
LEV	0.498	0.267	0.117	0.297	0.484	0.654	0.945	97,815
MTB	14.611	61.268	0.024	1.044	2.275	5.621	51.586	97,815
DTURN	0.007	0.087	-0.116	-0.021	0.001	0.028	0.148	97,815
RET	-0.004	0.005	-0.012	-0.004	-0.002	-0.001	-0.000	97,815
SIGMA	0.073	0.043	0.026	0.042	0.063	0.092	0.157	97,815
ABACC	0.107	0.135	0.005	0.026	0.062	0.132	0.365	97,815
INSTHOLD	0.333	0.337	0.000	0.000	0.232	0.626	0.937	97,815

Panel B. Spearman Correlation Matrix

	NCSKEW	DUVOL	COUNT	ROTARANK	INTANTA	SIZE	MTB	LEV	ROA
NCSKEW	1.00								
DUVOL	0.88***	1.00							
COUNT	0.77***	0.61***	1.00						
ROTARANK	0.12***	0.09***	0.10***	1.00					
INTANTA	0.07***	0.07***	0.05***	0.07***	1.00				
SIZE	0.04***	0.03***	0.04***	0.12***	0.08***	1.00			
MTB	-0.06***	-0.07***	-0.04***	-0.01*	-0.08***	0.25***	1.00		
LEV	-0.02***	-0.00	-0.02***	-0.06***	0.06***	0.05***	0.00	1.00	
ROA	0.06***	0.03***	0.08***	0.51***	-0.20***	0.12***	-0.02***	-0.14***	1.00

Table 2: Validation of Intangible Intensity Measure

This table presents the association between intangible intensity and measures of intangible asset scales for a sample of listed US firms from 1983 to 2017. The dependent variables in Columns (1)–(3) are *INTAN*, *GOODWILL* and *R&D* in year $t + 1$, respectively. *INTAN* is the percentage of intangible assets in total assets. *GOODWILL* is the percentage of goodwill in total assets. *R&D* is percentage of R&D in total assets.. The main explanatory variable *ROTARANK* is the relative ranking of EBITDA over net PPE in the entire sample. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include lagged *NCSKEW*, industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) INTAN	(2) GOOGWILL	(3) R&D
ROTARANK	0.1147***	0.0742***	0.0206***
	(11.13)	(10.47)	(3.50)
SIZE	0.0074***	0.0053***	0.0029***
	(5.61)	(4.68)	(5.83)
AGE	-0.0005***	-0.0003***	-0.0003***
	(-4.54)	(-3.78)	(-4.21)
ROA	-0.0489***	-0.0247***	-0.2803***
	(-8.50)	(-5.89)	(-15.09)
LEV	0.0574***	0.0379***	-0.0488***
	(10.39)	(9.11)	(-8.48)
MTB	-0.0001***	-0.0001***	-0.0000***
	(-5.03)	(-5.55)	(-2.76)
DTURN	-0.0145**	-0.0124**	0.0225*
	(-2.07)	(-2.05)	(1.83)
RET	-5.6865***	-4.1886***	4.4290***
	(-4.93)	(-4.45)	(6.80)
SIGMA	-0.6961***	-0.5633***	0.4651***
	(-4.85)	(-4.60)	(7.29)
ABACC	-0.0767***	-0.0588***	-0.0375***
	(-6.36)	(-7.72)	(-3.20)
INSTHOLD	0.0033	0.0095**	-0.0031
	(0.53)	(2.08)	(-0.88)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	91,383	91,383	91,383
Number of Firms	9,964	9,964	9,964
Adjusted R^2	0.26	0.21	0.29

Table 3: Univariate Test

This table reports mean stock crash risk measures for each tercile group based on intangible intensity measures. The sample consists of firm-year observations for listed US firms from 1983 to 2017. The firms are divided into tercile groups based on *ROTARANK* and *INTANTA*. G1 is the lowest group and G3 is the highest group. G1-G3 denotes the mean difference between G1 and G3. The *t*-statistics are reported in brackets.

ROTARANK	(1) NCSKEW	(2) DUVOL	(3) COUNT
G1	-0.0561	-0.1405	-0.1168
	(0.0044)	(0.0023)	(0.0032)
G2	-0.0371	-0.0221	-0.0798
	(0.0042)	(0.0027)	(0.0031)
G3	-0.0391	-0.1316	-0.0674
	(0.0040)	(0.0022)	(0.0030)
G1-G3	-0.0171***	-0.0089***	-0.0494***
	[-2.87]	[-2.77]	[-11.27]
INTANTA	(1) NCSKEW	(2) DUVOL	(3) COUNT
G1	-0.0731	-0.1021	-0.1087
	(0.0041)	(0.0025)	(0.0031)
G2	-0.0442	-0.0947	-0.0834
	(0.0042)	(0.0024)	(0.0031)
G3	-0.0146	-0.0862	-0.0713
	(0.0042)	(0.0024)	(0.0031)
G1-G3	-0.0586***	-0.0159***	-0.0374***
	[-9.89]	[-4.58]	[-8.53]

Table 4: Intangible Intensity and Stock Price Crash Risk

This table presents the effect of intangible intensity on stock price crash risk for a sample of listed US firms from 1983 to 2017. The dependent variables in Columns (1)–(3) are *NCSKEW*, *DUVOL* and *COUNT* in year $t+1$, respectively. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. The main explanatory variable, *ROTARANK*, is the relative ranking of EBITDA over net PPE in the entire sample. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include lagged *NCSKEW*, industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) NCSKEW	(2) DUVOL	(3) COUNT
ROTARANK	0.0955***	0.0430***	0.0633***
	(6.59)	(3.74)	(7.11)
SIZE	0.0508***	0.0277***	0.0370***
	(7.63)	(5.78)	(8.89)
AGE	-0.0023***	-0.0016***	-0.0012***
	(-7.48)	(-8.57)	(-5.46)
ROA	0.1009***	0.0541***	0.0902***
	(5.77)	(4.27)	(6.93)
LEV	-0.0498***	-0.0222*	-0.0329***
	(-3.16)	(-2.04)	(-2.83)
MTB	-0.0005***	-0.0003***	-0.0004***
	(-6.51)	(-4.84)	(-8.89)
DTURN	0.2246***	0.1153***	0.1702***
	(4.36)	(3.68)	(5.65)
RET	-2.1854	-4.7528	2.8222
	(-0.46)	(-1.48)	(1.09)
SIGMA	0.3709	0.1113	0.1139
	(0.65)	(0.30)	(0.33)
ABACC	0.0604***	0.0278**	0.0514**
	(2.92)	(2.05)	(2.61)
INSTHOLD	0.1340***	0.0880***	0.0903***
	(5.52)	(5.37)	(5.65)
NCSKEW	0.0490***	0.0324***	0.0259***
	(9.58)	(8.78)	(7.35)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	91,443	91,443	91,483
Number of Firms	9,975	9,975	9,976
Adjusted R^2	0.05	0.05	0.04

Table 5: Intangible Intensity and Asset Impairments

This table presents the effect of intangible intensity on stock price crash risk through asset impairment and performance deterioration for a sample of listed US firms from 2007 to 2017. The dependent variables in Column (1) is *ITIMPAIR*, a dummy variable that equals one if a firm has impairment of intangible assets in year $t+1$ and zero otherwise. The dependent variables in Columns (2) and (3) are *NILOSS* and *NIDOWN*, respectively. *NILOSS* is a dummy variable that equals one if a firm has negative earnings and zero otherwise. *NIDOWN* is a dummy variable that equals one if a firm has earnings growth rate below -20% and zero otherwise. The dependent variable in Columns (5) and (6) is a stock price crash risk measure, *NCSKEW*. The main explanatory variable *ROTARANK* is the relative ranking of EBITDA over net PPE in the entire sample. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) IMPAIR	(2) NILOSS	(3) NIDOWN	(4) NCSKEW	(5) NCSKEW
ROTARANK	0.0244**			0.1274***	0.0722**
	(2.46)			(4.73)	(2.71)
ITIMPAIR		0.0292**	0.0752***		
		(2.28)	(5.07)		
NILOSS				0.1742***	
				(8.06)	
NIDOWN					0.0694***
					(5.87)
SIZE	0.0179***	-0.0144***	-0.0225***	0.0568***	0.0552***
	(4.53)	(-3.62)	(-3.88)	(6.22)	(5.81)
AGE	0.0005*	-0.0011***	0.0007**	-0.0014**	-0.0017**
	(2.14)	(-4.74)	(2.59)	(-2.40)	(-2.75)
ROA	-0.0309**	-0.3214***	0.0302	0.1268***	0.0599**
	(-3.00)	(-7.06)	(1.15)	(4.93)	(2.27)
LEV	0.0519***	-0.0747**	0.0486*	-0.0982***	-0.1069***
	(3.22)	(-2.87)	(1.89)	(-5.39)	(-6.24)
MTB	-0.0002	0.0003**	-0.0002	0.0004*	0.0005*
	(-1.69)	(2.53)	(-1.31)	(1.91)	(2.08)
DTURN	-0.0493*	-0.0638	0.0524	0.1598	0.1466
	(-1.84)	(-1.60)	(0.80)	(1.77)	(1.55)
RET	1.7751	45.0446***	18.2350***	-3.4839	2.4734
	(1.10)	(7.27)	(3.92)	(-0.38)	(0.30)
SIGMA	0.4626*	6.2393***	2.2757***	-0.1461	0.7544
	(1.86)	(8.36)	(3.50)	(-0.14)	(0.77)
ABACC	-0.0261	-0.1046***	0.2195***	0.0433	0.0057
	(-1.70)	(-3.57)	(9.84)	(1.35)	(0.17)
INSTHOLD	-0.0117	-0.0834***	0.0339**	0.0507*	0.0382
	(-1.17)	(-3.78)	(2.33)	(2.09)	(1.53)
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	27,265	27,362	27,362	24,134	24,134
Number of Firms	4,414	4,430	4,430	3,962	3,962
Adjusted R^2	0.09	0.23	0.06	0.05	0.05

Table 6: Intangible Intensity and Valuation Uncertainty

This table presents the effect of intangible intensity on stock price crash risk through valuation uncertainty for a sample of listed US firms from 2007 to 2017. Following the methodology in Pástor et al. (2008) and Cremers et al. (2016), the dependent variables in Column (1) is *ERC1*, which is calculated as average the quarterly RC_{it} for firm i over the last 3 years, where RC_{it} is defined as

$$RC_{it} = \frac{AR_{it}}{(EPS_{it} - E[EPS_{it}])/BE_{it}}$$

We compute *ERC1* only if there are at least six valid observations of RC_{it}. The dependent variable in Column (2) is *ERC2*. *ERC2* is obtained by estimating the following regression for firm i over the last 5 years:

$$(EPS_{it} - E[EPS_{it}])/BE_{it} = \gamma_{i1} AR_{it} + \varepsilon_{it}$$

and $ERC_2(i) = -\hat{\gamma}_{i1}$ We estimate the regressions in without the intercept, and require at least 10 observations to estimate the regression. The dependent variable in Columns (3) and (4) is a stock price crash risk measure, *NCSKEW*. The main explanatory variable *ROTARANK* is the relative ranking of EBITDA over net PPE in the entire sample. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) ERC1	(2) ERC2	(3) NCSKEW	(4) NCSKEW
ROTARANK	0.7645***	0.1172***	0.1238***	0.1216***
	(3.90)	(5.87)	(6.54)	(6.55)
ERC1			0.0017**	
			(2.65)	
ERC2				0.0158*
				(2.01)
SIZE	0.1784***	0.0033	0.0398***	0.0385***
	(5.54)	(1.01)	(6.29)	(6.11)
AGE	-0.0001	-0.0035***	-0.0016***	-0.0014***
	(-0.05)	(-6.15)	(-5.54)	(-4.88)
ROA	0.7224***	-0.1049***	0.1716***	0.1574***
	(3.17)	(-4.54)	(4.47)	(4.11)
LEV	-3.2792***	-0.1084***	-0.0693***	-0.0749***
	(-11.89)	(-5.72)	(-3.86)	(-4.18)
MTB	-0.0045***	-0.0001	-0.0004***	-0.0004***
	(-4.51)	(-1.09)	(-3.74)	(-3.49)
DTURN	0.0077	-0.0473*	0.2036***	0.1878**
	(0.02)	(-1.76)	(3.14)	(2.74)
RET	-1.5e+02***	21.5299***	-4.6464	-7.9871
	(-3.75)	(6.43)	(-0.64)	(-1.09)
SIGMA	-20.5409***	2.8725***	0.7462	0.4996
	(-4.79)	(6.81)	(1.09)	(0.72)
ABACC	-0.4660*	-0.0586**	0.0816**	0.0784**
	(-1.74)	(-2.33)	(2.06)	(2.15)
INSTHOLD	1.4122***	0.0089	0.0527***	0.0519***
	(8.45)	(0.58)	(2.97)	(2.87)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	59,673	55,379	54,873	51,089
Number of Firms	7,334	6,427	6,659	5,841
Adjusted R^2	0.09	0.13	0.04	0.04

Table 7: Credit Rating

This table presents the moderating effect of credit ratings on stock price crash risk for a sample of listed US firms from 1983 to 2017. The dependent variables in Columns (1)–(3) are *NCSKEW*, *DUVOL* and *COUNT* in year $t+1$, respectively. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. The main explanatory variable *ROTARANK* is the relative ranking of EBITDA over net PPE in the entire sample. Credit rating, *RATING*, is an ordinal variable ranging from 0–7, in which higher value stands for better credit ratings. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include lagged *NCSKEW*, industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) NCSKEW	(2) DUVOL	(3) COUNT
ROTARANK	0.1171***	0.0528***	0.0820***
	(7.39)	(4.06)	(8.52)
ROTARANK*RATING	-0.0291***	-0.0132**	-0.0249***
	(-3.08)	(-2.09)	(-3.95)
RATING	0.0157**	0.0073	0.0157***
	(2.11)	(1.61)	(2.95)
SIZE	0.0511***	0.0277***	0.0367***
	(6.74)	(5.16)	(7.83)
AGE	-0.0023***	-0.0016***	-0.0012***
	(-6.15)	(-7.13)	(-4.61)
ROA	0.0918***	0.0500***	0.0827***
	(5.29)	(4.05)	(6.26)
LEV	-0.0493***	-0.0222*	-0.0353***
	(-2.94)	(-1.91)	(-2.94)
MTB	-0.0005***	-0.0003***	-0.0004***
	(-6.07)	(-4.43)	(-7.86)
DTURN	0.2212***	0.1137***	0.1669***
	(4.30)	(3.64)	(5.58)
RET	-2.4481	-4.8543	2.8019
	(-0.54)	(-1.56)	(1.16)
SIGMA	0.3500	0.1043	0.1242
	(0.65)	(0.29)	(0.38)
ABACC	0.0572**	0.0264*	0.0496**
	(2.63)	(1.87)	(2.50)
INSTHOLD	0.1335***	0.0877***	0.0896***
	(5.56)	(5.42)	(5.74)
NCSKEW	0.0491***	0.0324***	0.0258***
	(9.67)	(8.89)	(7.42)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	91,443	91,443	91,483
Number of Firms	9,975	9,975	9,976
Adjusted R^2	0.05	0.05	0.04

Table 8: Shareholder Litigation Risk

This table presents the moderating effect of shareholder litigation risk on stock price crash risk for a sample of listed US firms from 1983 to 2017. The dependent variables in Columns (1)–(3) are *NCSKEW*, *DUVOL* and *COUNT* in year $t+1$, respectively. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. The main explanatory variable, *ROTARANK*, is the relative ranking of EBITDA over net PPE in the entire sample. Shareholder litigation risk, *LITIG*, is a dummy variables that equals one for all firms in the biotechnology (SIC 2833–2836 and 8731–8734), computer (SIC 3570–3577 and 7370–7374), electronics (SIC 3600–3674), and retail (SIC 5200–5961) industries and zero otherwise. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include lagged *NCSKEW*, industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) NCSKEW	(2) DUVOL	(3) COUNT
ROTARANK	0.0783***	0.0246*	0.0566***
	(4.92)	(1.87)	(5.65)
ROTARANK*LITIG	0.0566**	0.0604***	0.0218
	(2.17)	(3.16)	(1.12)
LITIG	-0.0283	-0.0373**	0.0012
	(-1.37)	(-2.64)	(0.08)
SIZE	0.0508***	0.0277***	0.0369***
	(7.62)	(5.78)	(8.89)
AGE	-0.0023***	-0.0016***	-0.0012***
	(-7.53)	(-8.69)	(-5.38)
ROA	0.0943***	0.0467***	0.0884***
	(5.37)	(3.68)	(6.79)
LEV	-0.0506***	-0.0236**	-0.0322***
	(-3.21)	(-2.20)	(-2.76)
MTB	-0.0005***	-0.0003***	-0.0004***
	(-6.49)	(-4.83)	(-8.89)
DTURN	0.2236***	0.1140***	0.1701***
	(4.34)	(3.64)	(5.67)
RET	-2.3394	-4.8716	2.6849
	(-0.49)	(-1.52)	(1.03)
SIGMA	0.3530	0.1006	0.0926
	(0.62)	(0.27)	(0.26)
ABACC	0.0592***	0.0262*	0.0512**
	(2.88)	(1.96)	(2.59)
INSTHOLD	0.1336***	0.0876***	0.0899***
	(5.55)	(5.39)	(5.68)
NCSKEW	0.0490***	0.0324***	0.0259***
	(9.54)	(8.73)	(7.35)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	91,443	91,443	91,483
Number of Firms	9,975	9,975	9,976
Adjusted R^2	0.05	0.05	0.04

Table 9: Information Opacity

This table presents the moderating effect of information opacity on stock price crash risk for a sample of listed US firms from 1983 to 2017. The dependent variables in Columns (1)–(3) are *NCSKEW*, *DUVOL* and *COUNT* in year $t+1$, respectively. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. The main explanatory variable, *ROTARANK*, is the relative ranking of EBITDA over net PPE in the entire sample. Information opacity, *OPAQUE*, is calculated as the sum of abnormal current accrual, estimated from Dechow et al. (1995) over the past 3 years. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include lagged *NCSKEW*, industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) NCSKEW	(2) DUVOL	(3) COUNT
ROTARANK	0.0795***	0.0325**	0.0553***
	(4.83)	(2.27)	(5.44)
ROTARANK*OPAQUE	0.0548**	0.0362**	0.0273*
	(2.68)	(2.23)	(1.90)
OPAQUE	-0.0095	-0.0074	-0.0065*
	(-0.77)	(-0.89)	(-1.76)
SIZE	0.0510***	0.0277***	0.0371***
	(7.62)	(5.79)	(8.89)
AGE	-0.0023***	-0.0016***	-0.0012***
	(-7.43)	(-8.54)	(-5.44)
ROA	0.0947***	0.0499***	0.0868***
	(5.60)	(3.97)	(6.85)
LEV	-0.0501***	-0.0225**	-0.0331***
	(-3.20)	(-2.07)	(-2.85)
MTB	-0.0005***	-0.0003***	-0.0004***
	(-6.52)	(-4.86)	(-8.90)
DTURN	0.2252***	0.1156***	0.1704***
	(4.36)	(3.69)	(5.66)
RET	-2.5762	-5.0046	2.6373
	(-0.54)	(-1.56)	(1.03)
SIGMA	0.3129	0.0745	0.0873
	(0.55)	(0.20)	(0.25)
ABACC	0.0382	0.0150	0.0433*
	(1.57)	(1.01)	(1.91)
INSTHOLD	0.1348***	0.0884***	0.0906***
	(5.58)	(5.42)	(5.69)
NCSKEW	0.0491***	0.0324***	0.0259***
	(9.62)	(8.80)	(7.37)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	91,443	91,443	91,483
Number of Firms	9,975	9,975	9,976
Adjusted R^2	0.05	0.05	0.04

Table 10: Dynamic Panel Regression

This table reports system GMM dynamic panel regressions of intangible intensity on stock price crash risk for a sample of listed US firms from 1983 to 2017. The dependent variables in the second stage are *NCSKEW*, *DUVOL*, and *COUNT* in year $t+1$, respectively. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. We use lagged dependent variable as an explanatory variable, and maximum of 3 lags as their instruments. The main explanatory variable, *ROTARANK*, is the relative ranking of EBITDA over net PPE in the entire sample. We treat it as an endogenous variable, and use 1 lag as its instrument. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) NCSKEW	(2) DUVOL	(3) COUNT
L.NCSKEW	0.0355***		
	(7.41)		
L.DUVOL		0.0285***	
		(5.52)	
L.COUNT			0.0192***
			(4.36)
ROTARANK	0.3399***	0.1631***	0.1849***
	(4.58)	(3.41)	(3.11)
SIZE	0.3051***	0.2099***	0.1810***
	(41.28)	(43.07)	(32.41)
AGE	-0.0031	-0.0014	-0.0026
	(-0.57)	(-0.37)	(-0.95)
ROA	0.0277	0.0213	0.0598**
	(0.75)	(0.90)	(1.99)
LEV	0.0826**	0.0623***	0.0458
	(2.22)	(2.65)	(1.57)
MTB	-0.0003**	-0.0002**	-0.0001
	(-2.31)	(-2.15)	(-1.00)
DTURN	-0.0262	-0.0316	-0.0370
	(-0.65)	(-1.23)	(-1.13)
RET	-62.2961***	-29.6404***	-33.6979***
	(-14.33)	(-11.49)	(-12.51)
SIGMA	-8.7170***	-4.5172***	-3.9212***
	(-15.07)	(-13.19)	(-10.80)
ABACC	0.0064	-0.0047	0.0220
	(0.20)	(-0.23)	(0.83)
INSTHOLD	0.2686***	0.1646***	0.1317***
	(6.23)	(6.14)	(3.84)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	91,443	91,443	91,488
AR(2) test statistic	0.39	0.69	0.07
Sargan statistic	144.19	127.98	136.21

Table 11: Change-in-Variable Regression

This table presents the effect of change in intangible intensity on change in stock price crash risk for a sample of listed US firms from 1983 to 2017. The dependent variables in Columns (1)–(3) are changes in *NCSKEW*, *DUVOL* and *COUNT*, respectively. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. The main explanatory variable, *DROTARANK*, is change in relative ranking of EBITDA over net PPE in the entire sample. Other control variables include first difference of *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). The regressions include lagged *DNCSKEW*, industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) NCSKEW	(2) DUVOL	(3) COUNT
DROTARANK	0.0806**	0.0585**	0.0415**
	(2.43)	(2.40)	(2.11)
DSIZE	0.1952**	0.1502**	0.1154**
	(2.66)	(2.59)	(2.72)
DAGE	-0.0004	0.0019	-0.0010
	(-0.09)	(0.50)	(-0.29)
DMTB	-0.0002	-0.0001	-0.0001
	(-1.31)	(-0.73)	(-0.76)
DLEV	-0.0386	-0.0082	-0.0265
	(-0.88)	(-0.23)	(-0.72)
DROA	0.0167	0.0075	0.0393*
	(0.48)	(0.27)	(1.96)
DDTURN	0.2080***	0.0933*	0.1095**
	(2.99)	(1.99)	(2.39)
DRET	-1.5488	4.6481	5.1408*
	(-0.35)	(1.48)	(1.77)
DSIGMA	-1.0211	-0.1712	0.9675**
	(-1.45)	(-0.34)	(2.16)
DINSTHOLD	0.3950***	0.2338***	0.2243***
	(4.77)	(3.98)	(4.16)
DNCSKEW	-0.4703***	-0.2624***	-0.2985***
	(-57.74)	(-45.53)	(-57.00)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	93,705	93,705	93,757
Number of Firms	9,635	9,635	9,642
Adjusted R^2	0.26	0.23	0.15

Table 12: Alternative Intangible Intensity Measure

This table reports the effect of alternative intangible intensity measure on stock price crash risk for a sample of listed US firms. The dependent variables in Columns (1)–(3) are*NCSKEW*, *DUVOL*, and *COUNT* in year $t+1$, respectively. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *DUVOL* is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *COUNT* is the number of crashes minus the number of jumps over the fiscal year and a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. The alternative intangible intensity measure, *INTANTA*, is defined as intangible assets over total assets. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). All regressions include lagged *NCSKEW*, industry and year fixed effects. The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1) NCSKEW	(2) DUVOL	(3) COUNT
INTANTA	0.0418*	0.0317*	0.0341**
	(1.84)	(1.84)	(2.09)
SIZE	0.0517***	0.0279***	0.0376***
	(7.70)	(5.79)	(9.02)
AGE	-0.0023***	-0.0016***	-0.0012***
	(-7.49)	(-8.54)	(-5.49)
ROA	0.1482***	0.0752***	0.1232***
	(8.05)	(5.65)	(9.99)
LEV	-0.0488***	-0.0230**	-0.0324***
	(-3.09)	(-2.13)	(-2.83)
MTB	-0.0005***	-0.0003***	-0.0004***
	(-6.46)	(-4.79)	(-8.84)
DTURN	0.2367***	0.1218***	0.1778***
	(4.56)	(3.90)	(5.77)
RET	-2.7719	-5.0177	2.6018
	(-0.59)	(-1.58)	(1.01)
SIGMA	0.2695	0.0669	0.0672
	(0.47)	(0.18)	(0.19)
ABACC	0.0722***	0.0337**	0.0610***
	(3.22)	(2.38)	(2.97)
INSTHOLD	0.1388***	0.0899***	0.0933***
	(5.64)	(5.46)	(5.76)
NCSKEW	0.0494***	0.0326***	0.0260***
	(9.78)	(8.95)	(7.53)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	91,685	91,685	91,726
Number of Firms	10,001	10,001	10,003
Adjusted R^2	0.05	0.05	0.04

Table 13: Alternative Model Specifications

This table reports the effect of intangible intensity on stock price crash risk for a sample of listed US firms from 1983 to 2017. The dependent variable is *NCSKEW* in year $t+1$. The main explanatory variable, *ROTARANK*, is the relative ranking of EBITDA over net PPE in the entire sample. In Columns (2)–(4) we include *INTANTA* (intangible assets over total assets), *TANG* (PPE plus total current assets and inventories over total assets), and *PEG* (forward PE to 1-year growth ratio), respectively. Other control variables include *SIZE* (natural logarithm of market capitalization), *AGE* (number of years since a firm's initial public offerings), *ROA* (income before extraordinary items over total assets), *LEV* (total liabilities over total assets), *MTB* (market-to-book ratio), *DTURN* (change in average monthly turnover from year t to $t-1$), *RET* (average idiosyncratic return in year t), and *SIGMA* (standard deviation of idiosyncratic return in year t), *ABACC* (absolute value of abnormal current accruals) and *INSTHOLD* (percentage of institutional holdings). We include lagged *NCSKEW* in all specifications. In addition, we control for firm and industry-year fixed effects in Column (1) and industry and year fixed effect in Columns (2)–(4). The robust t-statistics clustered by firm and year are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
ROTARANK	0.0879***	0.0891***	0.0961***	0.0969***
	(4.34)	(6.09)	(6.55)	(6.65)
INTANTA		0.0263**		
		(2.18)		
TANG			0.0077	
			(0.42)	
PEG				-0.0030***
				(-3.82)
SIZE	0.0795***	0.0504***	0.0510***	0.0507***
	(9.81)	(7.55)	(7.63)	(7.64)
AGE	0.0001	-0.0023***	-0.0023***	-0.0023***
	(0.06)	(-7.35)	(-7.48)	(-7.47)
ROA	0.1003***	0.1112***	0.1003***	0.1024***
	(4.43)	(5.85)	(5.55)	(5.86)
LEV	-0.0669***	-0.0522***	-0.0492***	-0.0492***
	(-2.83)	(-3.34)	(-3.19)	(-3.13)
MTB	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	(-4.79)	(-6.45)	(-6.57)	(-6.50)
DTURN	0.2283***	0.2258***	0.2243***	0.2236***
	(4.51)	(4.39)	(4.34)	(4.34)
RET	-7.0742	-2.0145	-2.2512	-2.4093
	(-1.59)	(-0.43)	(-0.48)	(-0.51)
SIGMA	-0.6385	0.3940	0.3636	0.3417
	(-1.24)	(0.69)	(0.64)	(0.60)
ABACC	0.0419*	0.0660***	0.0599***	0.0615***
	(1.84)	(3.03)	(2.81)	(2.97)
INSTHOLD	0.1544***	0.1336***	0.1341***	0.1355***
	(4.34)	(5.53)	(5.53)	(5.62)
NCSKEW	-0.0633***	0.0489***	0.0491***	0.0489***
	(-9.51)	(9.56)	(9.59)	(9.55)
Firm FE	Y	N	N	N
Industry-Year FE	Y	N	N	N
Industry FE	N	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	90,163	91,443	91,443	91,443
Number of Firms	8,698	9,975	9,975	9,975
Adjusted R^2	0.09	0.05	0.05	0.05