Jump returns and firm risk predictability

Chen Wang[a] , Xiong Xiong[a] , Shuhui Wang [b,*], Dehua Shen [c]

[a] College of Management and Economics, Tianjin University, Tianjin, 300072, P.R. China
[b] Surrey Business School, University of Surrey, Guildford, GU2 7XH, UK
[c] School of Finance, Nankai University, Tianjin, 300350, P.R. China

Data Availability Statement:

The data that support the findings of this study are publicly available from the sources noted in the text.

Funding Statement:

We gratefully acknowledge support from the National Natural Science Foundation of China (72141304, 72071141); Key R&D Project of the Ministry of Science and Technology (2022YFC3303304); and China Scholarship Council.

Conflict of Interest Statement:

There is no conflict of interest.

* Corresponding author: Shuhui Wang, shuhui.wang@surrey.ac.uk.
☆ E-mail addresses: wc304@tju.edu.cn (C.Wang), xxpeter@tju.edu.cn (X.Xiong), shuhui.wang@surrey.ac.uk (S.Wang), dhs@nankai.edu.cn (D.Shen).

Jump returns and firm risk predictability

Abstract:

This study explores how firm risk predicts stock jump returns. We find that higher firm risk, which reflects uncertainty before news releasing, is associated with more pronounced negative jump returns and greater absolute jump returns. Firm's information environment plays a crucial role, with greater information asymmetry amplifying the predictive power of firm risk. Additionally, the predictability of firm risk on jump returns intensifies after the financial crisis. These findings validate the predictability of firm risk on jump returns stems from its capture of firm-specific uncertainty. Finally, jump returns influence future firm performance, with firm risk enhancing this effect.

JEL classifications: G12*, *G14, G32

Key Words: firm risk, jump returns, uncertainty, information asymmetry

1. Introduction and motivation

This study examines the relationship between firm risk and stock jump returns. Stock price changes reflect rational responses to news about discount rates and cashflows (Baker et al., 2022). And stock price jumps result from information releases that resolve uncertainty (Maheu & McCurdy, 2004). Megaritis et al. (2021) have demonstrated that macroeconomic uncertainty can be used to predict future stock price jumps. We focus on the firm level, where firm risk represents its risk profile that investors fail to recognize, and encompasses negative information that has not yet been identified (Bouslah et al., 2013). Our research has important implications about the relationship between uncertainty embedded in the firm risk and stock jump returns. Our results indicate that higher firm risk has a significant predictive power in terms of lower negative jump returns and more dramatic absolute jump returns.

Stock price jumps refer to rapid discontinuous price movements, which, whether positive (indicating sudden price increases) or negative (indicating sudden price decreases), have often been identified as the market reactions to external information shocks such as unexpected macroeconomic news and corporate announcement (Jiang & Yao, 2013; Jiang & Zhu, 2017). Jumps do not come to markets regularly but Kapadia and Zekhnini (2019) discover that a stock's annual return is primarily derived from jump returns within that year. Previous studies have shown that asset price jumps are closely associated with the arrivals of new information, whether at the macroeconomic (Evans, 2011; Jiang et al., 2010; Lahaye et al., 2011; Lee, 2012; Rangel, 2011) or firm-specific level (Aït-Sahalia et al., 2024; Baker et al., 2022; Jeon et al., 2022; Lee & Mykland, 2008). What mechanisms underpin the capacity of new information to induce such jumps in asset prices? Maheu and McCurdy (2004) propose that price discontinuities are likely a consequence of uncertainty resolution associated with new information releases. Bansal and Shaliastovich (2011) develop a model in which large moves in asset prices obtain from the actions of the representative agent to acquire more information about the unobserved state of the economy for a cost, which is related to the level of uncertainty in the economy. Uncertainty shocks play a significant role in explaining the sharp drops in output (Alfaro et al., 2024) and it is suggested that the current state of uncertainty can predict future stock price jumps.

The relationship between uncertainty and future stock price jumps can provide insights into how the current state of uncertainty serves as an indicator for the potential stock price jumps before new information arrives. The extant literature has demonstrated a significant relationship between macroeconomic uncertainty and future stock price jumps (Jurado et al., 2015; Megaritis et al., 2021). Firm-specific information can also result in stock price jumps. the variation in corporate strategies (Habib & Hasan, 2017) and different financial risk lead to different price discontinuous drops (Andreou et al., 2021). Jiang and Yao (2013) demonstrate that the predictive power of firm characteristics for cross-sectional stock returns is associated with investors' response to unexpected information shocks. The link between firm characteristics and jump returns proves that the updated new information removes investors' biases towards firm characteristics. Jeon et al. (2022) demonstrate that the probability of jumps at the firm level is significantly correlated with news count, news tone, and uncertainty words. Moreover, due to the limited attention, investors tend to focus more on macroeconomic information rather than firm-specific news (Liu et al., 2022; Peng & Xiong, 2006), we believe that the effect of firm-level uncertainty will be stronger.

Firm risk captures the adverse outcomes that investors fail to perceive, to a certain extent representing investors' uncertainty about the firm. Firm risk reflects a range of firm characteristics.

Attributes such as CSR performance (Albuquerque et al., 2019; Bouslah et al., 2013), CEO power (Adams et al., 2005), board diversity (Bernile et al., 2018), managerial incentives (Coles et al., 2006; Kadan & Swinkels, 2008; Kini & Williams, 2012), firm location (Tuzel & Zhang, 2017) and even the CEO's early life experiences (Bernile et al., 2017) are all reflected in the firm risk profile. Therefore, firm risk is a comprehensive measure of a firm's condition, especially the negative aspects of the firm's performance, and is shaped by various firm policies and characteristics that affect corporate risk-taking decisions. Measures of firm risk can reflect the overall risk status and uncertainties that are either not yet recognized by the market or intentionally concealed by the company. Specifically, the uncertainty embedded in the firm risk can lead to negative price jumps and increase the volatility of stock price jumps. As calculated in Jiang and Zhu (2017), negative jump returns denote substantial decreases in stock prices, which are usually in response to adverse news or occurrences that fall short of market anticipations. Negative jump returns signify investors' pessimistic reaction to the new information, suggesting a downward revision in the firm's valuation. Absolute jump returns are calculated without considering the direction of the price change, reflecting the magnitude of a stock's price movement. This measure highlights the intensity of investors' reactions to news or events and indicates how much a firm's value might fluctuate in response to new information. Therefore, it is essential to investigate the relationship between firm risk and jump returns, especially negative and absolute jump returns.

Leuz et al. (2003) demonstrate that insiders have incentives to conceal firm performance for protecting their private control benefits. Therefore, the external investors' uncertainty about the firm may stem from managerial opportunism aimed at concealing bad news, which can lead to negative stock price jumps when the unfavorable information is eventually disclosed (Andreou et al., 2021).

For example, Enron's stock price collapsed due to financial fraud and accounting scandals concealed by its managers. This suggests that information asymmetry within a firm's environment impacts investors' uncertainty about the company, leading to sharp stock price fluctuations. A firm with greater information asymmetry between insiders and external investors implies a poorer information environment, which exacerbates investors' uncertainty about the firm's information (Cho et al., 2013). We believe that with a greater information asymmetry, firm risk is able to capture more investors' uncertainty about the firm and has a stronger predictability for jump returns.

Using a large sample of US firms for the period of July 1962 to June 2023, we examine the predictive power of firm risk on jump returns and how the firm's information asymmetry influences this relationship. We employ distance to default (DTD), total risk ($TR1$), and idiosyncratic risk ($IR1$) to assess firm risk. The DTD is used to serve as an indicator of default risk while $TR1$ and $IR1$ are used to measure one-year daily stock return volatility. To assess different types of jump returns, we utilize the negative jump returns (JR^{-}) to quantify downward stock price jumps and absolute jump returns (JR^{abs}) for the overall volatility of jump returns. Our empirical analyses reveal that higher firm risk leads to a stronger presence of negative jumps in stock prices over the following year, as well as a greater overall magnitude of stock price jumps. A one standard deviation increases in DTD will result in a 0.5268% increase in JR^{-} and a 3.0029% decrease in JR^{abs}. In terms of total risk and idiosyncratic risk, a one standard deviation increases in $TR1$ leads to a 1.1843% decrease in JR^{-} and a 7.1808% increase in JR^{abs} while a one standard deviation increases in $IR1$ leads to a 1.4052% decrease in JR^{-} and a 7.8788% increase in JR^{abs}.

Furthermore, we investigate the role of the firm's information asymmetry, the results indicate that greater information asymmetry between insiders and external investors enhances the effect of firm risk on jump returns. These empirical results strongly support the significant impact of both firm risk and the information asymmetry on jump returns. We also find that the relationship between firm risk and jump returns strengthens after the 2009 financial crisis, consistent with previous research that financial frictions exacerbate the impact of uncertainty (Alfaro et al., 2024). Additionally, our findings indicate that jump returns impact firm performance, with more pronounced negative jump returns and absolute jump returns leading to a decline in future firm performance. Moreover, firm risk amplifies this effect of jump returns on firm performance.

Our study makes several contributions to the prior literature. First, we contribute to the stock price jumps literature by examining how firm risk predicts the jump returns. Previous studies predominantly focus on the relationship between external information flows and stock price jumps (Jeon et al., 2022; Jiang & Zhu, 2017; Lee, 2012; Maheu & McCurdy, 2004). Exploration into the nature of stock price jumps has revealed that stock price jumps occur due to common knowledge shocks and the resolution of uncertainty for investors (Amatyakul, 2010; Maheu & McCurdy, 2004; Megaritis et al., 2021; Miao et al., 2013). Macroeconomic uncertainty has been shown to predict future stock price jumps (Megaritis et al., 2021). And at the firm level, investors' biases towards firm characteristics have also been proven to result in jump returns (Jiang & Yao, 2013). Our analysis delves into the intrinsic risk characteristics of firms, representing firm-level operational and financial uncertainty, thereby providing a new perspective for predicting stock price jumps.

Second, we categorize jump returns with a specific focus on negative jump returns and absolute jump returns. Previous research rarely categorizes absolute, positive, and negative jumps separately. We concentrate on the jump performance associated with firm risk, specifically focusing on negative jump returns and the volatility of these returns. We introduce a refined empirical framework that captures the complexity of jump dynamics. Using the approach of Jiang and Yao (2013) to identify jumps in a sequence of daily returns over a period and to compute the cumulative return of stock price jumps, we are more concerned with the risk embedded in the jump, and therefore focus on the negative jump returns as well as the absolute cumulative values of the jump returns. This categorization allows us to study the varying impacts of firm-specific risks on different types of jump returns, thereby shedding light on how different risk factors may trigger distinct jump behaviors.

Thirdly, we investigate the predictability of jump returns on future firm performance and the role of firm risk in this relationship. The findings reveal that stronger negative jump returns and absolute jump returns predict weaker future firm performance and firm risk amplifies this effect. The combined effect of firm risk and jump returns on future firm performance provides insight into how different types of jump returns affect firms and how firm risk plays an impact on this relationship in the long run and provides a more comprehensive understanding for risk management and decision making.

The study proceeds as follows. Section 2 provides a brief literature review and hypothesis. Section 3 outlines the variable measurement and sample selection and describes the empirical design. Section 4 reports empirical evidence. Finally, Section 5 concludes this study.

2. Literature and hypothesis

Previous studies have demonstrated the significance of jumps in pricing returns (Bates, 2000; Eraker et al., 2003) and research often associates the causes of jumps with the latent news process (Lee, 2012; Maheu & McCurdy, 2004). The relationship between jumps and news releasing is also supported by empirical evidence, for example, Evans (2011) documents that US macroeconomic news announcements lead to large increases in jumps and the informational surprise accounts for a significant proportion of stock price jumps. Miao et al. (2013) also find a strong correlation between macro news and stock price jumps. Johnson et al. (2022) delve into the historical shifts in the news that cause jump activity and find a transition from major wars to monetary policy announcements as key drivers over the decades. In further investigating the causes of stock price jumps triggered by news, Megaritis et al. (2021) suggest that economic uncertainty prior to the release of new information plays a significant role. Increasing economic uncertainty exposure induces disagreement, amplifying mispricing in the stock market (Cai et al., 2023), and predicts a subsequent rise in stock price jumps caused by the common knowledge shock after news releases.

Current research on predicting stock price jumps with economic uncertainty primarily focuses on macroeconomic uncertainty (Megaritis et al., 2021). However, firm-specific information, such as earnings releases and analyst recommendations, can also serve as firm-specific jump predictors (Lee, 2012). Various risk indicators of a firm represent the firm's current operational status and risk condition, which investors may not yet have captured. Therefore, the principal question that we seek to address is whether higher firm-specific risks have predictive power for jump returns, especially negative jump returns and absolute jump returns.

2.1 Firm risk and negative jump returns

The negative jump returns represent a sudden and sharp decline in stock prices. A smaller negative jump returns indicates a more intense negative jump. Such jumps are caused by negative information shocks, while firm risk reflects the uncertainty and instability of negative information flow, thereby can predict future negative stock price jumps. For instance, Andreou et al. (2021) demonstrate that a higher risk encountered by firms can lead to intensified future stock price crash, which are characterized by lower negative jump returns. Dutt and Humphery-Jenner (2013) also find that high volatility stocks have lower operating returns which might explain the relationship between the low volatility and higher stock returns. And the lower operating return further leads to lower stock returns and price crash. Alfaro et al. (2024) argue that uncertainty shocks play a significant role in explaining the sharp drops in output, which is manifested in stock prices as negative jump returns.

Corporate governance mechanisms and firm's operating environment also have impacts on price crash risk (Habib et al. (2018). Core et al. (2006) provide evidence that the weak governance of firms will lead to lower operating performance, and they find that firms with weak shareholder rights exhibit significant operating underperformance. The high level of outcome uncertainty and associated project failure risk will also result in price crash, as Habib and Hasan (2017) document that firms following innovative business strategies are more susceptible to future crash risk. Pástor and Veronesi (2012) analyze that the price crash should be large if uncertainty is large, and they find that the jump risk premium associated with policy decisions is positive on average. Additionally, the firm risk on the financial side also conveys negative information about the firm. Li et al. (2019) demonstrate that firms with low default risk tend to exhibit more mature operating and controlling mechanisms, as well as an enhanced capacity to generate earnings, further diminishing the stock's negative jump returns. Investors have a strong negative attitude toward bankruptcy-prone firms (Arbel et al., 1977) and there exists a strong positive relationship between short-term changes in financial distress risk and future stock price crashes (Andreou et al., 2021).

In summary, the existing literature suggests a positive relationship between firm-specific risks and stock price crashes. High firm risk and uncertainty lead to significant stock price drops.

Conversely, firms with lower default risk and more mature operational controls tend to mitigate the negative jump returns.

The preceding arguments form the basis for our first hypothesis, stated in the alternative form:

H1. Higher firm risk leads to lower negative jump returns.

2.2 Firm risk and absolute jump returns

The absolute jump returns of a stock denote the intensity of jumps and the instability of the stock price, with higher absolute jump returns representing more volatile price movements. Stock volatility and jump is significantly affected by the rising degree of unpredictability in the macroeconomy (Megaritis et al., 2021). Engle et al. (2013) introduce a new model which links short- and long-run sources of volatility to economic variables that significantly contribute to stock market volatility. And Wachter (2013) proposes a model based on the time-varying probability of consumption disaster and finds that the time-variation in the probability drives high stock volatility.

At the firm level, empirical studies also demonstrate a close relationship between firm risk and stock price volatility or absolute jumps (Giesecke et al., 2011). Zhang et al. (2009) propose a novel measure to capture the stochastic volatility and jumps and find such volatility and jump risk measures account for a high proportion of the variation in credit default swap (CDS) premium, which represents a component of firm risk. Chen and Kou (2009) also show that stock price jump has a varying connection with firm risk regarding firm default possibility, optimal capital structure, and implied volatility of equity options. Dutt and Humphery-Jenner (2013) confirm that higher stock volatility represents poorer operating performance and find firms with low stock volatility outperform firms with high stock volatility. The firm's risk measures reflect its operating performance, indicating that higher firm risk can predict greater stock volatility or absolute jump returns.

Ai and Kiku (2016) demonstrate that the idiosyncratic volatility carries significant information about firms’ investment and growth. Thus, the factors captured by firm risk are expected to cause more pronounced fluctuations in stock price jumps, which lead to higher absolute jump returns. In light of the preceding discussion, the following hypothesis is put forth:

H2. Higher firm risk leads to higher absolute jump returns.

2.3 Information asymmetry, firm risk, and jump returns

Stock price jumps occur because the release of new information eliminates uncertainty about the firm’s condition. Therefore, we hypothesize that firm risk, which, to some extent, measures the firm's current condition, can predict jump returns. Investors' uncertainty about the stock may stem from a poor information environment within the firm. Andreou et al. (2021) demonstrate that the relationship between the firm’s financial distress risk and its stock price crashes is driven by managers hiding bad news. Given the association between jump returns and the release of new information, the information asymmetry between insiders and external investors can impact the stock price jump phenomenon.

Information asymmetry is determined by information transparency and earnings quality (Cho et al., 2013). A more transparent information environment of a firm can reduce its potential risk (Li et al., 2019). Hutton et al. (2009) and Li and Stewart (2006) find that opaque stocks are more likely to crash. Meanwhile, Bhattacharya et al. (2003) find that higher earnings opacity is associated with an increased cost of equity and reduced stock trading. Agarwal and Hauswald (2010) use physical distance between loan applicant and bank as a measure for the facilitation of collecting information in the credit market and find that the credit is more readily accessible to nearby firms. This finding indicates that the accessibility of firm information is also an important component in assessing firm risk. Furthermore, Sato (2014) finds that the opacity of financial markets has a significant impact on investor behavior, asset prices, and welfare, and the results show that the opaque assets trade at a premium over transparent ones despite identical payoffs. Thus, a poorer information environment with greater information asymmetry between investors and the firm heightens investors' uncertainty about the firm's condition. This can lead to greater information shocks when new information is released. Thus, we can hypothesize that the information asymmetry between investors and the firm can amplify the predictive power of firm risk on jump returns:

H3. The predicted relationships between firm risk and jump returns in H1 and H2 are strengthened when the firm's information asymmetry is greater.

3. Sample selection, variable measurement, and empirical design

3.1. Sample selection

The sample in our main analysis includes all firms (SHRCD = 10 or 11) traded on the NYSE, Amex, and Nasdaq (EXCHED = 1, 2, or 3) in the CRSP stock database that have valid market capitalization and with stock price of no less than \$5 at the end of June 1962 to June 2023[1]. The \$5 price restriction helps to mitigate market microstructure issues in measuring returns according to Jiang and Yao (2013). And we exclude financial firms (Standard Industrial Classification codes between 6000 and 6999 in CRSP). The information on firm characteristics is obtained from COMPUSTAT.

3.2. Variable measurement

[1] Due to data availability, the sample starts from 1962 after merging with various data sources, and this also corresponds to the timespan used in most empirical asset pricing studies (Boons, M., 2016).

3.2.1. Measurement of jump returns

Jumps in stock prices can be effectively captured by employing the Poisson process. Press (1967) argues that the logged stock price changes do not adhere to a stable distribution, but rather a Poisson mixture of normal distributions, which decomposes stock prices into two components: continuous changes and discontinuous jump. Following the methodology of Jiang and Oomen (2008), we can identify the jump days during a long period. Please refer to appendix B for details on how to identify jump days. In our empirical analysis, we apply the jump test each quarter to daily return observations for stocks in our sample and identify jumps in daily returns[2]. Following Jiang and Yao (2013), the main reason to perform jump tests each quarter is to take into account time-varying volatility of stock returns. The jumps are identified at the 1% critical level and we require at least 44 daily return observations during each quarter to ensure the robustness of the jump test.[3] After identifying the jump days for each quarter, we compute the cumulative return of the negative jump returns as the JR^{-} for year t, as well as the cumulative return of the absolute value of the jump returns as the JR^{abs} for year t, using the identified jumps from July of year t to June of year $t+1$. Let r_k^j be the kth jump (measured in log return), $k=1,\dots,K_1$ and r_k^{nj} be the kth negative jump (measured in log return), $k=1,\dots,K_2$, identified during the period. The negative jump returns for the year is computed as $JR^{-}=\exp\left(\sum_{k=1}^{K_1} r_k^{nj}\right)-1$ and the absolute jump returns for the year is computed as $JR^{abs}=\exp\left(\sum_{k=1}^{K_2}\left|r_k^j\right|\right)-1$.

[2] Based on Jiang and Yao (2013), we focus on daily data in our study for the following reasons: first, intraday data are only available for a relatively short period of time. Second, intraday stock returns are known to be subject to severe market microstructure effect. Third, since the focus of our empirical analysis is jump returns predictability over an annual horizon, daily frequency is appropriate for identifying large changes in stock prices driven by economically important information shocks.

[3] In Appendix B, we present cross-sectional summary statistics of identified jumps of individual stock prices in the periods consistent with Jiang and Yao (2013). The jumps we calculated exhibit similar cross-sectional summary statistics.

Panel A of Table 1 reports the statistics of cross-sectional distributions of jump frequency and jump size from July 1962 to June 2023. For each stock, jump frequency is calculated as the ratio of the total number of jumps to the total number of years the stock is in our sample. Jump size is the average of all realized jumps, including both positive and negative ones and expressed in log returns. Across stocks, the mean and median jump frequencies are 1.4432 and 1.2647 per year. The mean and median of the absolute jump sizes are 14.25% and 11.90%, respectively. We also provide cross-sectional statistics for positive and negative jumps separately. The positive (negative) jump per year is the ratio of the total number of positive (negative) jumps to the total number of years the stock is in our sample. The positive (negative) jump size is the time-series average of all realized positive (negative) jumps for each stock in our sample. The average size of positive jumps is 13.24% and the average size of negative jumps is -15.59%. Compared with number of positive jumps and negative jumps per year, we find that positive jumps are much more frequent than negative ones.

3.2.2. Measurement of the risk variables

Firm risk is a multi-dimensional measure, with default risk and stock return volatility being our primary concerns. Default risk refers to the risk of a firm's failing to service its debt obligations, which can be extracted from the equity data (Vassalou & Xing, 2004), it not only affects the firm performance but also has a strong impact on the firm's stock returns (Bao et al., 2023; Chava & Purnanandam, 2010; Li et al., 2019). Default risk is closely connected to financial markets (Longstaff et al., 2011) and is highly regarded in capital markets research. It has been argued that default risk is a systematic risk and related to size effect and BM effect (Fama & French, 1992; Vassalou & Xing, 2004). If it is indeed systematic, then it should have a positive correlation with subsequent realized returns (Dichev, 1998). But the existing evidence on the relation of default risk to stock returns is mostly contradictory (Arbel et al., 1977; Campbell et al., 2008; Chava & Purnanandam, 2010; Dichev, 1998). Therefore, the relationship between default risk and jump returns merits attention.

Previous studies often measure default risk by extracting information from the bond market, utilizing default spreads—defined as the yield or return difference between long-term BAA corporate bonds and long-term AAA or U.S. Treasury bonds (Fama & French, 1989). However, Vassalou and Xing (2004) take a different approach by using equity data to calculate DTD, a score derived from observed stock prices and book leverage through a structural model of default risk, which has demonstrated strong empirical performance. The DTD measures how many standard deviation the log of the ratio of a firm's asset value to its debt needs to deviate from its mean for a default to occur (Vassalou & Xing, 2004). A larger DTD indicates that the asset-to-debt ratio is further from the default threshold, implying a lower risk of default for the company. Please refer to appendix C for details of calculating DTD. We consider the DTD calculated at the end of June in year t as the DTD for that year.

Beyond the default risk, we use the $TR1$ and $IR1$ to measure stock return volatility that captures the effects of uncertainty in corporate policy and market environment of the firm. The $TR1$ and $IR1$ capture the volatility and uncertainty of its stock performance, which encompasses a broad spectrum of firm behaviors. The characteristics captured by $TR1$ and $IR1$, such as governance and investment, directly impact the performance of stock returns. For example, portfolios formed to capture the importance of internal governance generates significant abnormal returns (Cremers & Nair, 2005), high risk investment projects will increase the volatility of firm’s cash flows, in turn making firm stock returns more volatile (Cassell et al., 2012), and policy changes should increase volatilities and correlations among stocks (Pástor & Veronesi, 2012).

$TR1$ is the variance of daily firm stock returns in year t, which is calculated as the standard deviation of the daily stock returns from July of year $t-1$ to June of year t, and we drop firm-year observations with less than 200 daily CRSP returns in a given 12-month window for accuracy. However, firm stock returns can also be driven by market fluctuations, the volatility of daily firm stock returns may not entirely reflect firm-specific risks (Cassell et al., 2012; Çolak & Korkeamäki, 2021), therefore, we measure the $IR1$ as a volatility measure constructed after controlling for market fluctuations. To calculate the $IR1$ in year t, we use the daily stock returns and daily market portfolio returns (CSRP value-weighted index) three years prior to the beginning of July of year $t-1$ to estimate the market model. With the estimated parameters, we construct expected daily stock returns from July of year $t-1$ to June of year t by subtracting the expected daily returns from the realized returns, and we obtain the daily residual returns. $IR1$ of year t is estimated as the standard deviation of daily residual returns from July of year $t-1$ to June of year t. For accuracy in measuring idiosyncratic risk, we also drop firm-year observations with less than 200 daily residual returns when calculating $IR1$ in the given window. Following Cassell et al. (2012), we take the natural logarithm of all the measures to mitigate the concern that skewness in the distribution of these measures may affect our inferences.

The statistical summary of DTD, $TR1$, and, $IR1$ are shown in Panel B of Table 1. DTD has a mean of 8.1154 and a standard deviation of 5.2684, indicating significant variability, with values ranging from -1.4582 to 37.3568. The distribution of DTD is similar to that calculated by Batten et al. (2021). The measures of stock returns variance, $TR1$ and $IR1$, exhibit means of -2.9792 and -3.1680 with standard deviations of 0.9399 and 0.9691, respectively. The distributions of $TR1$ and

$IR1$ are similar to that calculated by Cassell et al. (2012).

<Please Insert Table 1 Here>

3.3. Empirical methodology

We estimate the following regression to examine the relation between firm risk and jump returns of its stocks:

$$JR_{i,t+1} = \beta_0 + \beta_1 Firm\ Risk_{i,t} + \sum_{j=2}^{n} \beta_j\ Control\ Variables_{i,t} + \gamma_{id} + \delta_t + \varepsilon_{i,t} \qquad (1)$$

where $JR_{i,t+1}$ is the jump returns of stock i in year $t+1$ including negative jump returns and absolute jump returns calculated from July of year t to June of year $t+1$. γ_{id} and δ_t represent industry and year fixed effects respectively.

$Firm\ Risk_{i,t}$ denotes the DTD, $TR1$, and $IR1$ of firm i in year t calculated from July of year $t-1$ to June of year t. Following Jiang and Yao (2013), we include several firm specific control variables that have significant effect on the jump returns of stocks, including size ($SIZE$), the book-to-market ratio (BM), momentum (MOM), the Amihud (2002) illiquidity measure ($ILLIQ$), and the change in shares outstanding (NS).

$SIZE$ is the natural log of market capitalization at the end of June of year t. BM is the natural log of the book-to-market ratio. MOM is the 11-month buy-and-hold return from July of year $t-1$ to May of year t. $ILLIQ$ is the ratio of the absolute daily stock return to the daily dollar trading volume, averaged over a given period from July of year $t-1$ to June of year t. Since trading volume is defined differently for Nasdaq and NYSE/Amex stocks, the trading volumes of Nasdaq stocks are adjusted by a factor of 0.7 (Boehmer, 2005). NS is the change in the natural log of split-adjusted shares outstanding from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$. Detailed description of all the variables is provided in Appendix A.

We further investigate the impact of firm-specific information asymmetry on the effect of firm risk and apply the model (2) to examine this relationship

$$JR_{i,t+1} = \beta_0 + \beta_1 Firm\ Risk_{i,t} + \beta_2 Information_{i,t} + \beta_3 Information_{i,t} * Firm\ Risk_{i,t} + \sum_{j=4}^{n} \beta_j\ Control\ Variables_{i,t} + \gamma_{id} + \delta_t + \varepsilon_{i,t} \quad (2)$$

We used two proxies for information asymmetry between investors and insiders. The first proxy is $Intangible$, calculated as the ratio of recognized intangible assets including goodwill to total assets, adjusted by subtracting the industry median ratio, where we use four-digit SIC codes to identify industries. According to Barth and Kasznik (1999) and Barth et al. (2002), firms with substantial intangible assets, most of which are not recognized in firms'financial statements, have greater information asymmetry and more inherent uncertainty about firm value than do other firms. The second information asymmetry measure reflects the firm's earnings quality. Following the methodologies of Dechow and Dichev (2002) and Aboody et al. (2005), we construct total current accruals based on cash flows from operations (TCA), which defines accrual quality as the extent to which accruals map into cash flow realizations. The total current accruals ($Accruals_{i,t}$), and cash flow from operations ($CFO_{i,t}$) for firm i and year t are calculated as:

$$TA_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STDEBT_{i,t} - DEPN_{i,t} \quad (3)$$

$$Accruals_{i,t} = \Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STDEBT_{i,t} \quad (4)$$

$$CFO_{i,t} = NIBE_{i,t} - TA_{i,t} \quad (5)$$

where $\Delta CA_{i,t}$ is firm i's change in current assets in year t, $\Delta CL_{i,t}$ is firm i's change in current liabilities in year t, $\Delta CASH_{i,t}$ is firm i's change in cash in year t, $\Delta STDEBT_{i,t}$ is firm i's change in short-term debt in year t. $DEPN_{i,t}$ is firm i's depreciation and amortization expense in year t, and $NIBE_{i,t}$ is firm i's net income before extraordinary items in year t.

To estimate total current accruals based on cash flows from operations (TCA) for firm i in year t, we perform the following cross-sectional regression for each of Fama and French (1997) 48 industry groups containing at least 20 firms in each year:

$$\frac{Accruals_{i,t}}{Aveasset_{i,t}} = \theta_{0,i} + \theta_{1,i}\frac{CFO_{i,t-1}}{Aveasset_{i,t}} + \theta_{2,i}\frac{CFO_{i,t}}{Aveasset_{i,t}} + \theta_{3,i}\frac{CFO_{i,t+1}}{Aveasset_{i,t}} + v_{i,t} \qquad (6)$$

where $Aveasset_{i,t}$ is firm i's average total assets over years t and $t-1$. And the $TCA_{i,t}$ is the absolute value of the firm i's residual $|\hat{v}_{i,t}|$ from equation (6). Larger TCA is interpreted as lower earnings quality and greater information asymmetry.

We further investigate the impact of stock's jump returns and firm risk on firm performance, examining this relationship from two perspectives: return on assets (ROA) and net income on assets (NI).

$$\begin{aligned} Firm\ Performance_{i,t+1} &= \beta_0 + \beta_1 JR_{i,t} + \beta_2 Firm\ Risk_{i,t-1} + \beta_3 JR_{i,t} * Firm\ Risk_{i,t-1} \\ &+ \sum_{j=4}^{n} \beta_j\ Control\ Variables_{i,t} + \gamma_{id} + \delta_t + \varepsilon_{i,t} \end{aligned} \qquad (7)$$

We measure the firm performance from two dimensions. ROA is ratio of the earnings before interests and taxes to total assets (Faccio et al., 2016). NI is the net income divided by lagged total assets (Cohen et al., 2020).

We control for year and industry-level fixed effects in all regressions[4]. All continuous variables are winsorized at their respective 1st and 99th percentiles to reduce the influence of outliers except for variables that take logarithms in calculations. And standard errors are adjusted for heteroskedasticity and clustered at firm level (Petersen, 2009).

4. Empirical results

4.1 Firm risk and the jump returns: equal-weighted quintile portfolios

[4] In our robustness checks, we also control for year and firm fixed effects, which does not alter our results.

We begin by analyzing the jump returns associated with firms having different risk levels. First, we compute standard sorted portfolios. At the end of June of each year in our sample period, stocks are sorted into equal-weighted quintile portfolios based on each of the firm risk variables. The portfolios are held from July of year t to June of year $t+1$, and are rebalanced annually. The grouping variables increase monotonically from quintile 1 to quintile 5. Therefore, for DTD, firm risk decreases from Q1 to Q5, while for $TR1$ and $IR1$, firm risk increases from Q1 to Q5.

Table 2 reports the averages of jump returns of individual stocks within each quintile portfolio sorted on each of the three firm risk variables. The JR^{-} of an individual stock is compounded negative jumps over the 12-month holding period (from July of year t to June of year $t+1$) and this reports in Panel A. The JR^{abs} of an individual stock is compounded absolute jumps over the 12-month holding period (from July of year t to June of year $t+1$) and this presents in Panel B. Panel A shows that the negative jump returns of stocks with higher firm risk are lower than those with lower firm risk, while Panel B indicates that the absolute jump returns are higher for stocks with higher firm risk. For the entire sample period, the top-bottom spread of negative and absolute jump returns are all significant for all the three firm risk variables in both Panel A and B. Taken as a whole, Table 2 indicates that firms with higher risk tend to have lower negative jump returns and higher absolute jump returns and gives a preliminary support to our hypotheses 1 and 2.

<Please Insert Table 2 Here>

4.2. Firm risk and the jump returns: panel regressions

The main challenge of using portfolio sorts is the difficulty of controlling for confounding effects. Therefore, we further examine the relationship between firm risk and jump returns using a regression analysis. Table 3 presents the regression results of $DTD, TR1$, and $IR1$ on JR^{-} and

JR^{abs}. In column (1) of Panel A, the coefficient of DTD on JR^{-} is positive and statistically significant at the 1% level, suggesting a one standard deviation increases in DTD is associated with a 0.5268% increase in JR^{-}. In column (1) of Panel B, the coefficient of DTD on JR^{abs} is negative and statistically significant at the 1% level, and in terms of economic significance, a one standard deviation increases in DTD is associated with a 3.0029% decrease in JR^{abs}. It is indicated that if a firm has a lower probability of default, then its stock exhibits weaker negative jump and overall jumps intensity.

In terms of total risk and idiosyncratic risk, in columns (2) and (3) of Panel A, $TR1$ and $IR1$ both have negative coefficients on JR^{-} which are statistically significant at the 1% level. In terms of economic significance, a one standard deviation increases in $TR1$ leads to a 1.1843% decrease in JR^{-} while a one standard deviation increases in $IR1$ leads to a 1.4052%decrease in JR^{-}. In columns (2) and (3) of Panel B, $TR1$ and $IR1$ both have positive coefficients on JR^{abs} and the coefficients are statistically significant at the 1% level. A one standard deviation increases in $TR1$ leads to a 7.1808% increase in absolute jump returns while a one standard deviation increases in $IR1$ leads to a 7.8788% increase in absolute jump returns. The results suggest that higher total risk and idiosyncratic risk predict more dramatic negative jump returns and overall jumps intensity. Lower DTD, higher total risk, and higher idiosyncratic risk indicate greater firm risk, corresponding to greater intensity of negative jump returns and absolute jump returns. The results in Table 3 are highly consistent with H1 and H2 that higher firm risk predicts lower negative jump returns and greater absolute jump returns.

<Please Insert Table 3 Here>

4.3 Firm risk and the jump returns: the impact of information asymmetry

In this section, we examine the role of corporate information asymmetry in the relationship between firm risk and stock price jumps. Stock price jumps, as manifestations of information shocks, may arise from delays in the incorporation of information into stock prices (Jiang & Zhu, 2017). In other words, the uncertainty about the firm faced by investors is resolved upon future information releases, leading to stock price jumps (Megaritis et al., 2021). Firm risk captures uncertainty not yet priced into the stock price; hence, we anticipate a stronger predictive power for jump returns when investors do not receive timely updates about the firm. $Intangible$ and TCA both serve as proxies for the information environment at firm level. A higher $Intangible$ indicates that the firms have substantial intangible assets that are not recognized in firms'financial statements, resulting in greater uncertainty about firm value. And a larger TCA indicates lower earnings quality. This means a lower degree of alignment between accruals and cash flow realizations and represents greater information asymmetry.

We examine the impact of $Intangible$ and TCA on the existing relationship between firm risk and stock price jumps. We present this result in Table 4 and Table 5. The results in the Panel A of Table 4 show the effect for JR^{-}. The coefficient of DTD is positive and statistically significant at 1% level. Furthermore, the coefficient of the interaction term between $Intangible$ and DTD is also positive which aligns with the positive coefficient of DTD and it is statistically significant at 1% level. This suggests that an upward change in DTD corresponding to one standard deviation translates into an additional effect on JR^{-} of 0.1018% for a change from the 25th percentile to the 75th percentile in $Intangible$. In terms of the total risk and idiosyncratic risk, the coefficients of $TR1$ and $IR1$ are both negative and statistically significant at 1% level. And the coefficients of the interaction terms in columns (2) and (3) are negative and are both statistically significant at 1% level.

When $Intangible$ changes from the 25th percentile to the 75th percentile, an increase of one standard deviation in $TR1$ and $IR1$ will additionally decrease JR^{-} by 0.0790% and 0.0840%, respectively.

Additionally, the results in the Panel B of Table 4 show the effect on JR^{abs}. The coefficient of DTD is negative and statistically significant at 1% level, and the coefficient of the interaction term between $Intangible$ and DTD has the same sign and is statistically significant at 1% level. The economic significance of the coefficient is that when $Intangible$ changes from the 25th percentile to the 75th percentile, an increase of one standard deviation in DTD will additionally decreases JR^{abs} by 0.2860%. The columns (2) and (3) of Panel B show the effect of total risk and idiosyncratic risk. $TR1$ and $IR1$ both have positive coefficients that are statistically significant at 1% level. The coefficients of the interaction term between $Intangible$ and $TR1$ and the interaction term between $Intangible$ and of $IR1$ are both positive and statistically significant at 1% level. A one standard deviation increases in $TR1$ and $IR1$ result in an additionally 0.2300% and 0.2345% increase of JR^{abs}, respectively, for a change from the 25th percentile to the 75th percentile in $Intangible$.The result demonstrates a stronger relationship between firm risk and jump returns for firms with higher intangible assets. These results are highly consistent with our H3 that the predicted relationships between firm risk and jump returns are strengthened when the firm's information asymmetry is greater.

<Please Insert Table 4 Here>

In Table 5, we employ TCA as a measure of information asymmetry between investors and insiders, with a larger TCA indicating lower earnings quality and greater information asymmetry. Consistent with our previous findings, the results in Panel A of Table 5 show that the regression coefficient of DTD on JR^{-} is positive and statistically significant at the 1% level, while the coefficients of $TR1$ and $IR1$ on JR^{-} are negative and both statistically significant at the 1% level. Furthermore, the coefficient of the interaction term between DTD and TCA is statistically positive significant at the 5% level and the coefficients of the interaction term between $TR1$ and TCA, as well as $IR1$ and TCA, is statistically negative significant at the 1% level. In terms of economic significance, this indicates that when TCA changes from the 25th percentile to the 75th percentile, an increase of one standard deviation in DTD will additionally increase JR^{-} by 0.0358%, and an increase of one standard deviation in $TR1$ and $TR3$ will additionally reduce JR^{-} by 0.0690% and 0.0630%, respectively.

Panel B of Table 5 presents the regression results of firm risk on JR^{abs}. Consistent with our previous findings, the coefficient of DTD is negative and the coefficients of $TR1$ and $IR1$ are positive after including TCA and the interaction terms between firm risk and TCA, which are all statistically significant at the 1% level. The coefficient of the interaction term between DTD and TCA is statistically negative significant at the 1% level and the coefficient of the interaction term between $TR1$ and TCA, as well as $IR1$ and TCA, is statistically positive significant at the 1% level. In terms of the economic significance, when TCA changes from the 25th percentile to the 75th percentile, an increase of one standard deviation in DTD will additionally reduce JR^{abs} by 0.3630% and an increase of one standard deviation in $TR1$ and $IR1$ will additionally increase JR^{abs} by 0.4786% and 0.4287%, respectively. The results suggest that for stocks with higher information asymmetry resulting from lower earnings quality, the impact of firm risk on stock price jump returns is more pronounced. The results in Table 5 are again consistent with H3 that the predicted relationships between firm risk and jump returns are strengthened when the firm's information asymmetry is greater.

<Please Insert Table 5 Here>

4.4 Further analysis: the impact of financial crisis

To examine the pure impact of firm risk and uncertainty on firm's jump returns, we have identified and incorporated exogenous events that have a significant effect on firm's risk and uncertainty. The financial crisis of 2007-2009 promotes the financial industry and researchers to recognize the significance of firm risk and uncertainty, and invites scholars to reexamine the role of them (Nelson & Katzenstein, 2014). After the financial crisis, stricter regulations on financial activities, tighter credit conditions, and lower liquidity have intensified frictions in financial markets (Duval et al., 2020). Under greater market frictions, or for companies that are more financially constrained, the impact of uncertainty is amplified (Alfaro et al., 2024). Consequently, in this section we seek to ascertain whether the role of firm risk to capture firm-specific uncertainty and the relationship between firm risk and jump returns has been strengthened in the post-2009 financial crisis era. We include a dummy variable, $post2009$, in the regression, along with the interaction term between $post2009$ and firm risk. The variable $post2009$ equals one for samples corresponding to the years after 2009.

Table 6 presents the regression analysis results that examine the change of impact of firm risk on jump returns after the financial crisis. Consistent with the results in Table 3, the DTD exhibits a positive correlation with JR^- and a negative correlation with JR^{abs} which are statistically significant at 1% level. And the coefficients of interaction terms $DTD * \text{post2009}$ have the same signs with those of DTD and are both statistically significant at 1% level, demonstrating that the impact of DTD having experienced a certain increase in the aftermath of the financial crisis. In economic terms, an increase of one standard deviation in DTD will increase JR^{-} 0.5268%and decrease JR^{abs} by 2.5800%, in the periods after 2009, an increase of one standard deviation of DTD increases JR^{-} by additional 0.3161% and decreases JR^{abs} by additional 2.4761%.

Similarly, the role of $TR1$ and $IR1$ is strengthened after 2009. Based on the regression coefficients, there is a negative correlation between $TR1$ ($IR1$) and JR^{-} and a positive correlation between $TR1$ ($IR1$) and JR^{abs}. A one standard deviation increases in $TR1$ ($IR1$) will result in a 0.8271% (1.0563%) decrease in JR^{-}, and a 4.3987% (5.2719%) increase in JR^{abs}. And the coefficient for the interaction terms between $TR1$ ($IR1$) and $post2009$ have the same sign with that of $TR1$ ($IR1$) which are statistically significant, suggesting that the effect of $TR1$ ($IR1$) is intensified after 2009.

These results indicate that due to the intensified financial frictions following the 2009 financial crisis, the impact of uncertainty has been amplified. This strengthens the relationship between firm risk and jump returns in the post-2009 financial crisis era.

<Please Insert Table 6 Here>

4.5 Further analysis: jump returns, firm risk, and firm performance

In the preceding research, we demonstrate that firm risk has the significant predictable impact on jump returns. In this section, we examine the relationship between jump returns and firm performance, as well as the impact of firm risk on this relationship. Jump returns may reflect the stock's sensitivity to unexpected firm or market events, which in turn may negatively affect the firm's performance. Therefore, examining the combined effect of firm risk and jump returns on future firm performance can help to understand how different types of risk affect firms in the long run and provide investors, managers, and policy makers with a more comprehensive understanding for risk management and decision making. Table 7 and Table 8 present regression analyses examining the influence of jump returns and firm risk on two key indicators of firm performance: return on assets (ROA) and net income on assets (NI). ROA and NI are both important indicators of a firm's operational performance, reflecting the efficiency of asset utilization and profitability, thus they serve as reliable proxies for the overall performance of the firm.

The results in Panel A of Table 7 underscore a positive correlation between JR^{-} and ROA and the coefficient is statistically significant at 1% level with different firm risk indicators, suggesting that the diminishing intensity of negative jump returns is indicative of a potential uptrend in the firm's future value. Firms with weaker negative jump returns are perceived as more valuable in the market. The interaction term, $JR^{-} * DTD$, elucidates that DTD exerts a significant influence on the beneficial effects of weaker negative jump returns on market valuation. This implies that a higher default risk intensifies the positive impact of JR^{-} on firm valuation. Similarly, a higher $TR1$ and $IR1$ within the firm substantially enhances the influence of JR^{-}. In Panel B of Table 7, the coefficients of JR^{abs} on ROA also provide a similar conclusion: a higher JR^{abs} reduces the firm's ROA, which is amplified for firms with higher firm risk. And all coefficients are statistically significant at the 1% level. Our empirical results indicate that firm risk is not only closely related to jump returns, but higher firm risk also amplifies the impact of jump returns on firm performance.

<Please Insert Table 7 Here>

The results in Panel A of Table 8 reveal a positive correlation between JR^{-} and NI, and the coefficient is statistically significant at 1% level with different firm risk indicators. Consistent with the results in Table 7, the positive coefficients of JR^{-} also demonstrate that weaker negative jump returns indicate a higher future net income per assets. And the interaction terms between JR^{-} and different risk measures suggest that this effect is amplified under higher firm risk. The coefficients of JR^{abs} on NI in Panel B of Table 8 also provide a similar conclusion that a higher JR^{abs} reduces the firm's NI, and this negative relation is amplified for firms with higher firm risk. All coefficients are statistically significant at the 1% level. From the perspective of net income, our results further confirm that firm risk not only strongly predicts jump returns but also amplifies their impact on future firm performance.

<Please Insert Table 8 Here>

4.6 Robustness check

We perform various robustness checks of the empirical results. First, we construct new measures of jump returns and jump risk. Following Jiang and Yao (2013), we construct the cumulative jump returns, JR, without considering the sign. Let r_k^j be the kth jump (measured in log return), $k = 1, \ldots, K$ identified from July of year t to June of year $t+1$, the JR for the year is computed as $JR = \exp\left(\sum_{k=1}^{K} r_k^j\right) - 1$. Following Barndorff-Nielsen and Shephard (2004), we further calculate the total jump risk ($JRISK$) of stock returns, which is the difference between RV and BPV. Please refer to appendix B for details of calculating RV and BPV. $JRISK$ captures the variance of jump returns. The regression results in Table 9 show that higher firm risk is associated with significantly higher JR and $JRISK$ and these are highly consistent with our previous findings.

<Please Insert Table 9 Here>

Second, we use $TR3$ and $IR3$ to capture total and idiosyncratic risk instead of the previously used $TR1$ and $IR1$. These two variables measure the daily stock return volatility from July of year $t-3$ to June of year t, thereby assessing firm risk over a longer historical period. The results in Table 10 show that, consistent with $TR1$ and $IR1$, higher $TR3$ and $IR3$ are associated with lower

JR^{-} and higher JR^{abs}, with coefficients being significant at the 1% level. Again, these results are highly consistent with our previous findings.

<Please Insert Table 10 Here>

Furthermore, to ensure that our results are not influenced by firm-specific characteristics, we examine the main regression results after controlling for firm and year fixed effects. The results in Table 11 indicate that controlling for firm and year fixed effects does not alter our conclusions: higher firm risk is associated with lower negative jump returns and higher absolute jump returns. The coefficients for DTD and $IR1$ remain statistically significant at the 1% level, while the coefficients for $TR1$ are statistically significant at the 5% level.

<Please Insert Table 11 Here>

Finally, in addition to ROA and NI, the gross sales are also an important indicator of firm performance, measuring the scale of operations and sales capability. We construct the measure of $Sales$, defined as sales divided by lagged total assets (Cohen et al., 2020). Using $Sales$ as a proxy for firm performance, we obtain results consistent with previous findings: weaker negative jump returns and absolute jump returns both enhance future firm performance. And this effect is further amplified by firm risk.

<Please Insert Table 12 Here>

5. Conclusion

We examine the relationship between firm risk and jump returns using US firms' data from July 1962 to June 2023. Firm risk is measured by distance to default (DTD), total risk ($TR1$), and idiosyncratic risk ($IR1$), while jump returns is assessed through cumulative negative jump returns (JR^{-}) and absolute jump returns (JR^{abs}). Our findings reveal that higher firm risk is associated with lower negative jump returns and greater absolute jump returns and this effect is even more pronounced in poorer information environments. These results are highly consistent with our hypotheses and highlight the significant predictability of firm risk on jump returns. After the 2007-2009 financial crisis, financial frictions amplify the impact of uncertainty, thereby strengthening the relationship between firm risk and jump returns. We also investigate the impact of jump returns on firm performance, as well as the role of firm risk in influencing this relationship. Stronger negative jump returns, and absolute jump returns both contribute to weaker firm performance, with this effect being further amplified under conditions of higher firm risk.

Stock price jumps are the result of information shocks brought about by new information releases. Prior to the release of information, uncertainty regarding the stock leads to investor disagreement, which in turn causes trading that drives continuous price changes. The release of new information eliminates this uncertainty and investor disagreement, resulting in stock price jumps. Therefore, the uncertainty of stock can predict future jumps following information releases, which has already been confirmed at the macro level (Megaritis et al., 2021). Our results confirm the previous findings at the firm level that stock price jumps occur due to the resolution of uncertainty when new information is released, creating common knowledge shocks that lead to stock price jumps. This research highlights the significant role of firm risk and information asymmetry in predicting stock price jumps and sheds light on the relationship between uncertainty about the firm with its jump returns.

Reference

Aboody, D., Hughes, J., & Liu, J. (2005). Earnings Quality, Insider Trading, and Cost of Capital. *Journal of Accounting Research*, *43*(5), 651-673. https://doi.org/10.1111/j.1475-679X.2005.00185.x

Adams, R. B., Almeida, H., & Ferreira, D. (2005). Powerful CEOs and Their Impact on Corporate Performance. *Review of Financial Studies*, *18*(4), 1403-1432. https://doi.org/10.1093/rfs/hhi030

Agarwal, S., & Hauswald, R. (2010). Distance and Private Information in Lending. *Review of Financial Studies*, *23*(7), 2757-2788. https://doi.org/10.1093/rfs/hhq001

Ai, H., & Kiku, D. (2016). Volatility Risks and Growth Options. *Management Science*, *62*(3), 741-763. https://doi.org/10.1287/mnsc.2014.2129

Aït-Sahalia, Y., Li, C. X., & Li, C. (2024). *Working Paper*. https://doi.org/10.3386/w32746

Albuquerque, R., Koskinen, Y., & Zhang, C. (2019). Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence. *Management Science*, *65*(10), 4451-4469. https://doi.org/10.1287/mnsc.2018.3043

Alfaro, I., Bloom, N., & Lin, X. (2024). The Finance Uncertainty Multiplier. *Journal of Political Economy*, *132*(2), 577-615. https://doi.org/10.1086/726230

Amatyakul, P. (2010). The relationship between trading volume and jump processes in financial markets. *Duke. Journal of Economics*, *XXII*, 1–28.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31-56. https://doi.org/10.1016/s1386-4181(01)00024-6

Andreou, C. K., Andreou, P. C., & Lambertides, N. (2021). Financial distress risk and stock price crashes. *Journal of Corporate Finance*, *67*, 101870. https://doi.org/10.1016/j.jcorpfin.2020.101870

Arbel, A., Kolodny, R., & Lakonishok, J. (1977). The Relationship Between Risk of Default and Return on Equity: An Empirical Investigation. *The Journal of Financial and Quantitative Analysis*, *12*(4), 615-625. https://doi.org/10.2307/2330339

Baker, S. R., Bloom, N., Davis, S. J., & Sammon, M. (2022). What Triggers Stock Market Jumps? *Working Paper*. https://doi.org/https://ssrn.com/abstract=3821973

Bansal, R., & Shaliastovich, I. (2011). Learning and Asset-price Jumps. *Review of Financial Studies*, *24*(8), 2738-2780. https://doi.org/10.1093/rfs/hhr023

Bao, J., Hou, K., & Zhang, S. (2023). Systematic default and return predictability in the stock and bond markets. *Journal of Financial Economics*, *149*(3), 349-377. https://doi.org/10.1016/j.jfineco.2023.05.006

Barndorff-Nielsen, O. E., & Shephard, N. (2004). Power and Bipower Variation with Stochastic Volatility and Jumps. *Journal of Financial Econometrics*, *2*(1), 1-37. https://doi.org/https://doi.org/10.1093/jjfinec/nbh001

Barth, M. E., & Kasznik, R. (1999). Share repurchases and intangible assets. *Journal of Accounting and Economics*, *28*(2), 211-241. https://doi.org/10.1016/s0165-4101(99)00020-8

Barth, M. E., Kasznik, R., & McNichols, M. F. (2002). Analyst Coverage and Intangible Assets. *Journal of Accounting Research*, *39*(1), 1-34. https://doi.org/10.1111/1475-679x.00001

Bates, D. S. (2000). Post-'87 crash fears in s&p 500 futures options. *Journal of Econometrics*, *94*, 181–238. https://doi.org/https://doi.org/10.1016/S0304-4076(99)00021-4

Batten, J. A., Khaw, K. L.-H., & Young, M. R. (2021). Convertible debt and asset substitution of multinational corporations. *Journal of Corporate Finance*, *67*, 101843. https://doi.org/10.1016/j.jcorpfin.2020.101843

Bernile, G., Bhagwat, V., & Rau, P. R. (2017). What Doesn't Kill You Will Only Make You More Risk-Loving: Early-Life Disasters and CEO Behavior. *The Journal of Finance*, *72*(1), 167-206. https://doi.org/10.1111/jofi.12432

Bernile, G., Bhagwat, V., & Yonker, S. (2018). Board diversity, firm risk, and corporate policies. *Journal of Financial Economics*, *127*(3), 588-612. https://doi.org/10.1016/j.jfineco.2017.12.009

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, *81*(3), 637-654. https://doi.org/https://doi.org/10.1086/260062

Boehmer, E. (2005). Dimensions of execution quality: Recent evidence for US equity markets. *Journal of Financial Economics*, *78*(3), 553-582. https://doi.org/10.1016/j.jfineco.2004.11.002

Bouslah, K., Kryzanowski, L., & M'Zali, B. (2013). The impact of the dimensions of social performance on firm risk. *Journal of Banking & Finance*, *37*(4), 1258-1273. https://doi.org/10.1016/j.jbankfin.2012.12.004

Cai, C. X., Fu, X., & Kerestecioglu, S. (2023). Economic uncertainty: Mispricing and ambiguity premium. *European Financial Management*, *29*(5), 1702-1751. https://doi.org/https://doi.org/10.1111/eufm.12403

Campbell, J. Y., Hilscher, J., & Szilagyi, J. A. N. (2008). In Search of Distress Risk. *The Journal of Finance*, *63*(6), 2899-2939. https://doi.org/10.1111/j.1540-6261.2008.01416.x

Cassell, C. A., Huang, S. X., Manuel Sanchez, J., & Stuart, M. D. (2012). Seeking safety: The relation between CEO inside debt holdings and the riskiness of firm investment and financial policies. *Journal of Financial Economics*, *103*(3), 588-610. https://doi.org/10.1016/j.jfineco.2011.10.008

Chava, S., & Purnanandam, A. (2010). Is Default Risk Negatively Related to Stock Returns? *Review of Financial Studies*, *23*(6), 2523-2559. https://doi.org/10.1093/rfs/hhp107

Chen, N., & Kou, S. G. (2009). Credit Spreads, Optimal Capital Structure, and Implied Volatility with Endogenous Default and Jump Risk. *Mathematical Finance*, *19*(3), 343-378. https://doi.org/10.1111/j.1467-9965.2009.00375.x

Cho, S. Y., Lee, C., & Pfeiffer, R. J. (2013). Corporate social responsibility performance and information asymmetry. *Journal of Accounting and Public Policy*, *32*(1), 71-83. https://doi.org/10.1016/j.jaccpubpol.2012.10.005

Cohen, L., Malloy, C., & Nguyen, Q. (2020). Lazy Prices. *The Journal of Finance*, *75*(3), 1371-1415. https://doi.org/10.1111/jofi.12885

Çolak, G., & Korkeamäki, T. (2021). CEO mobility and corporate policy risk. *Journal of Corporate Finance*, *69*, 102037. https://doi.org/10.1016/j.jcorpfin.2021.102037

Coles, J. L., Daniel, N. D., & Naveen, L. (2006). Managerial incentives and risk-taking. *Journal of Financial Economics*, *79*(2), 431-468. https://doi.org/10.1016/j.jfineco.2004.09.004

Core, J. E., Guay, W. R., & Rusticus, T. O. (2006). Does Weak Governance Cause Weak Stock Returns? An Examination of Firm Operating Performance and Investors' Expectations. *The Journal*

of Finance, *61*(2), 655-687. https://doi.org/10.1111/j.1540-6261.2006.00851.x
Cremers, K. J. M., & Nair, V. B. (2005). Governance Mechanisms and Equity Prices. *The Journal of Finance*, *60*(6), 2859-2894. https://doi.org/10.1111/j.1540-6261.2005.00819.x
Dechow, P. M., & Dichev, I. D. (2002). The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. *The Accounting Review*, *77*(s-1), 35-59. https://doi.org/10.2308/accr.2002.77.s-1.35
Dichev, I. D. (1998). Is the Risk of Bankruptcy a Systematic Risk? *The Journal of Finance*, *53*(3), 1131-1147. https://doi.org/10.1111/0022-1082.00046
Dutt, T., & Humphery-Jenner, M. (2013). Stock return volatility, operating performance and stock returns: International evidence on drivers of the 'low volatility' anomaly. *Journal of Banking & Finance*, *37*(3), 999-1017. https://doi.org/10.1016/j.jbankfin.2012.11.001
Duval, R., Hong, G. H., Timmer, Y., & Strahan, P. (2020). Financial Frictions and the Great Productivity Slowdown. *The Review of Financial Studies*, *33*(2), 475-503. https://doi.org/10.1093/rfs/hhz063
Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock Market Volatility and Macroeconomic Fundamentals. *Review of Economics and Statistics*, *95*(3), 776-797. https://doi.org/10.1162/REST_a_00300
Eraker, B., Johannes, M., & Polson, N. (2003). The Impact of Jumps in Volatility and Returns. *The Journal of Finance*, *58*(3), 1269-1300. https://doi.org/https://doi.org/10.1111/1540-6261.00566
Evans, K. P. (2011). Intraday jumps and US macroeconomic news announcements. *Journal of Banking & Finance*, *35*(10), 2511-2527. https://doi.org/10.1016/j.jbankfin.2011.02.018
Faccio, M., Marchica, M.-T., & Mura, R. (2016). CEO gender, corporate risk-taking, and the efficiency of capital allocation. *Journal of Corporate Finance*, *39*, 193-209. https://doi.org/10.1016/j.jcorpfin.2016.02.008
Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427-465. https://doi.org/https://doi.org/10.7208/9780226426983-017
Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, *43*(2), 153-193. https://doi.org/10.1016/s0304-405x(96)00896-3
Giesecke, K., Longstaff, F. A., Schaefer, S., & Strebulaev, I. (2011). Corporate bond default risk: A 150-year perspective. *Journal of Financial Economics*, *102*(2), 233-250. https://doi.org/10.1016/j.jfineco.2011.01.011
Habib, A., & Hasan, M. M. (2017). Business strategy, overvalued equities, and stock price crash risk. *Research in International Business and Finance*, *39*, 389-405. https://doi.org/10.1016/j.ribaf.2016.09.011
Habib, A., Hasan, M. M., & Jiang, H. (2018). Stock price crash risk: review of the empirical literature. *Accounting & Finance*, *58*(S1), 211-251. https://doi.org/10.1111/acfi.12278
Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, *94*(1), 67-86. https://doi.org/https://doi.org/10.1016/j.jfineco.2008.10.003
Jeon, Y., McCurdy, T. H., & Zhao, X. (2022). News as sources of jumps in stock returns: Evidence from 21 million news articles for 9000 companies. *Journal of Financial Economics*, *145*(2), 1-17. https://doi.org/10.1016/j.jfineco.2021.08.002

Jiang, G. J., & Oomen, R. C. A. (2008). Testing for jumps when asset prices are observed with noise– a "swap variance" approach. *Journal of Econometrics*, *144*(2), 352-370. https://doi.org/https://doi.org/10.1016/j.jeconom.2008.04.009

Jiang, G. J., & Yao, T. (2013). Stock Price Jumps and Cross-Sectional Return Predictability. *Journal of Financial and Quantitative Analysis*, *48*(5), 1519-1544. https://doi.org/https://doi.org/10.1017/S0022109013000513

Jiang, G. J., & Zhu, K. X. (2017). Information Shocks and Short-Term Market Underreaction. *Journal of Financial Economics*, *124*(1), 43-64. https://doi.org/https://doi.org/10.1016/j.jfineco.2016.06.006

Jiang, G. J., Lo, I., & Verdelhan, A. (2010). Information Shocks, Liquidity Shocks, Jumps, and Price Discovery: Evidence from the U.S. Treasury Market. *Journal of Financial and Quantitative Analysis*, *46*(02), 527-551. https://doi.org/10.1017/s0022109010000785

Johnson, J. A., Medeiros, M. C., & Paye, B. S. (2022). Jumps in stock prices: New insights from old data. *Journal of Financial Markets*, *60*, 100708. https://doi.org/https://doi.org/10.1016/j.finmar.2022.100708

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, *105*(3), 1177-1216. https://doi.org/10.1257/aer.20131193

Kadan, O., & Swinkels, J. M. (2008). Stocks or Options? Moral Hazard, Firm Viability, and the Design of Compensation Contracts. *Review of Financial Studies*, *21*(1), 451-482. https://doi.org/10.1093/rfs/hhm077

Kapadia, N., & Zekhnini, M. (2019). Do idiosyncratic jumps matter? *Journal of Financial Economics*, *131*(3), 666-692. https://doi.org/10.1016/j.jfineco.2018.08.014

Kini, O., & Williams, R. (2012). Tournament incentives, firm risk, and corporate policies. *Journal of Financial Economics*, *103*(2), 350-376. https://doi.org/10.1016/j.jfineco.2011.09.005

Lahaye, J., Laurent, S., & Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, *26*(6), 893-921. https://doi.org/10.1002/jae.1149

Lee, S. S. (2012). Jumps and Information Flow in Financial Markets. *Review of Financial Studies*, *25*(2), 439-479. https://doi.org/10.1093/rfs/hhr084

Lee, S. S., & Mykland, P. A. (2008). Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. *Review of Financial Studies*, *21*(6), 2535-2563. https://doi.org/10.1093/rfs/hhm056

Leuz, C., Nanda, D., & Wysocki, P. D. (2003). Earnings management and investor protection: an international comparison. *Journal of Financial Economics*, *69*(3), 505-527. https://doi.org/10.1016/s0304-405x(03)00121-1

Li, J., & Stewart, C. M. (2006). R2 around the world: New theory and new tests. *Journal of Financial Economics*, *79*(2), 257-292. https://doi.org/https://doi.org/10.1016/j.jfineco.2004.11.003

Li, K., Niskanen, J., & Niskanen, M. (2019). Capital structure and firm performance in European SMEs. *Managerial Finance*, *45*(5), 582-601. https://doi.org/10.1108/mf-01-2017-0018

Liu, H., Peng, L., & Tang, Y. (2022). Retail Attention, Institutional Attention. *Journal of Financial and Quantitative Analysis*, *58*(3), 1005-1038. https://doi.org/10.1017/s0022109022000734

Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2011). How Sovereign Is Sovereign Credit Risk? *American Economic Journal: Macroeconomics*, *3*(2), 75-103. https://doi.org/10.1257/mac.3.2.75

Maheu, J. M., & McCurdy, T. H. (2004). News Arrival, Jump Dynamics, and Volatility Components for Individual Stock Returns. *The Journal of Finance*, *59*(2), 755-793. https://doi.org/https://doi.org/10.1111/j.1540-6261.2004.00648.x

Megaritis, A., Vlastakis, N., & Triantafyllou, A. (2021). Stock market volatility and jumps in times of uncertainty. *Journal of International Money and Finance*, *113*, 102355. https://doi.org/10.1016/j.jimonfin.2021.102355

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance*, *29*(2). https://doi.org/10.2307/2978814

Miao, H., Ramchander, S., & Zumwalt, J. K. (2013). S&P 500 Index-Futures Price Jumps and Macroeconomic News. *Journal of Futures Markets*, *34*(10), 980-1001. https://doi.org/10.1002/fut.21627

Nelson, S. C., & Katzenstein, P. J. (2014). Uncertainty, Risk, and the Financial Crisis of 2008. *International Organization*, *68*(2), 361-392. https://doi.org/10.1017/s0020818313000416

Pástor, L. u., & Veronesi, P. (2012). Uncertainty about Government Policy and Stock Prices. *The Journal of Finance*, *67*(4), 1219-1264. https://doi.org/10.1111/j.1540-6261.2012.01746.x

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563-602. https://doi.org/10.1016/j.jfineco.2005.05.003

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies*, *22*(1), 435-480. https://doi.org/10.1093/rfs/hhn053

Press, S. J. (1967). A Compound Events Model for Security Prices. *The Journal of Business*, *40*(3), 317-335. https://doi.org/https://www.jstor.org/stable/2351754

Rangel, J. G. (2011). Macroeconomic news, announcements, and stock market jump intensity dynamics. *Journal of Banking & Finance*, *35*(5), 1263-1276. https://doi.org/10.1016/j.jbankfin.2010.10.009

Sato, Y. (2014). Opacity in Financial Markets. *Review of Financial Studies*, *27*(12), 3502-3546. https://doi.org/10.1093/rfs/hhu047

Tuzel, S., & Zhang, M. B. (2017). Local Risk, Local Factors, and Asset Prices. *The Journal of Finance*, *72*(1), 325-370. https://doi.org/10.1111/jofi.12465

Vassalou, M., & Xing, Y. (2004). Default Risk in Equity Returns. *The Journal of Finance*, *59*(2), 831-868. https://doi.org/10.1111/j.1540-6261.2004.00650.x

Wachter, J. A. (2013). Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility? *The Journal of Finance*, *68*(3), 987-1035. https://doi.org/10.1111/jofi.12018

Zhang, B. Y., Zhou, H., & Zhu, H. (2009). Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms. *Review of Financial Studies*, *22*(12), 5099-5131. https://doi.org/10.1093/rfs/hhp004

Table 1 Summary statistics

Panel A. Summary Statistics of Stock Price Jumps

	Percentile						
	5th	**25th**	**Mean**	**Median**	**75th**	**95th**	**Std Dev**
No. of jumps per year	0.0000	0.6667	1.4432	1.2647	1.9565	3.5000	1.3240
No. of positive jumps per year	0.0000	0.4000	0.9422	0.8333	1.2941	2.3333	0.8610
No. of negative jumps per year	0.0000	0.0000	0.5009	0.3636	0.6923	1.5000	0.6698
Absolute jump size	0.0481	0.0848	0.1425	0.1190	0.1715	0.3132	0.0938
Positive jump size	0.0476	0.0798	0.1324	0.1103	0.1550	0.2936	0.0907
Negative jump size	-0.3666	-0.1944	-0.1559	-0.1256	-0.0803	-0.0359	0.1228

Panel B Summary statistics of firm risk

	Obs.	mean	sd	p10	p25	p50	p75	p90	min	max
DTD	47839	8.1154	5.2684	2.5542	4.4304	7.0971	10.6455	14.9501	-1.4582	37.3568
$TR1$	47839	-2.9792	0.9399	-4.1465	-3.6305	-3.0215	-2.3807	-1.7802	-7.6906	2.9905
$TR3$	47839	-2.9043	0.8791	-4.0085	-3.5031	-2.9419	-2.3445	-1.7852	-6.2443	2.5780
$IR1$	47839	-3.1680	0.9691	-4.3756	-3.8433	-3.2112	-2.5604	-1.9226	-7.6333	2.9889
$IR3$	47839	-3.1040	0.9229	-4.2462	-3.7479	-3.1511	-2.5294	-1.9243	-6.2387	2.5791

Panel C Summary statistics of firm characteristics

	Obs.	mean	sd	p10	p25	p50	p75	p90	min	max
$SIZE$	47839	20.1506	2.1067	17.4388	18.5721	20.1118	21.5981	22.9417	11.5838	28.3425
BM	47839	-0.5651	0.8602	-1.6187	-1.0266	-0.4731	0.0098	0.3918	-11.3080	3.0633
MOM	47839	0.1846	0.4889	-0.2831	-0.0938	0.1090	0.3526	0.6882	-0.8613	5.9595
$ILLIQ$	47839	0.6215	2.5018	0.0002	0.0015	0.0185	0.2142	1.2191	0.0000	56.4525
NS	47839	0.0282	0.1338	-0.0297	-0.0009	0.0041	0.0208	0.1042	-2.9044	4.6052
$Intangibles$	47839	0.1428	0.4380	-0.0282	0.0000	0.0023	0.0920	0.4286	-0.7149	4.9132
TCA	47839	0.0683	0.1826	0.0037	0.0103	0.0262	0.0588	0.1254	0.0000	2.9581
ROA	44347	0.0744	0.1293	-0.0064	0.0481	0.0863	0.1291	0.1770	-1.5756	0.3799
NI	45861	0.0355	0.1247	-0.0459	0.0187	0.0500	0.0847	0.1266	-2.0815	0.4916
$Sales$	45864	1.2490	0.8650	0.3623	0.6312	1.0993	1.6203	2.2444	0.0000	6.6315

This table reports the summary statistics of the main variables. The stock sample in our main analysis includes all common stocks (SHRCD = 10 or 11) traded on the NYSE, Amex, and Nasdaq (EXCHED = 1, 2, or 3) in the CRSP stock database. The information on firm characteristics is obtained from Compustat. The sample period in our research is from July 1962 to June 2023. All continuous variables are winsorized at the 1st and 99th percentiles except for variables that take logarithms in calculations. Detailed variable definitions are in the Appendix A.

Table 2 Jump returns across stock quintiles

Panel A JR^{-}

	DTD	$TR1$	$IR1$
Q1	-0.0544***	-0.0297***	-0.0277***
	(-11.2265)	(-13.3729)	(-12.4500)
Q2	-0.0501***	-0.0412***	-0.0400***
	(-13.7466)	(-13.8563)	(-13.7470)
Q3	-0.0475***	-0.0512***	-0.0484***
	(-13.6093)	(-14.8930)	(-14.5343)
Q4	-0.0447***	-0.0602***	-0.0581***
	(-14.4319)	(-13.8046)	(-14.0071)
Q5	-0.0436***	-0.0690***	-0.0660***
	(-14.5835)	(-10.7240)	(-10.8294)
Q5 – Q1	0.0108***	-0.0393***	-0.0383***
	(3.5864)	(-7.6494)	(-7.8411)

Panel B JR^{abs}

	DTD	$TR1$	$IR1$
Q1	0.3626***	0.0963***	0.0866***
	(9.1141)	(19.5036)	(18.2808)
Q2	0.2181***	0.1386***	0.1306***
	(19.5507)	(20.5316)	(20.3818)
Q3	0.1802***	0.1854***	0.1738***
	(18.1728)	(21.2737)	(21.9034)
Q4	0.1565***	0.2438***	0.2315***
	(18.0002)	(18.9958)	(20.8277)
Q5	0.1412***	0.4651***	0.4368***
	(19.6836)	(8.7894)	(9.0606)
Q5 – Q1	-0.2215***	0.3688***	0.3502***
	(-5.9304)	(7.1586)	(7.4554)

This Table reports time-series averages of negative jump returns (JR^{-}) and absolute jump returns (JR^{abs}) for each quintile portfolio sorted on each of the three firm risk variables: DTD, $TR1$, and $IR1$. The grouping variables increase monotonically from quintile 1 to quintile 5. Therefore, for DTD, firm risk decreases from Q1 to Q5, while for $TR1$ and $IR1$, firm risk increases from Q1 to Q5. The spreads of the negative jump returns and the absolute jump returns between top and bottom quintiles, as well as their time-series t-statistics (in parentheses), are also reported.

Table 3 Regressions: firm risk and jump returns

Panel A JR^{-}			
	(1)	(2)	(3)
DTD	0.0010***		
	(9.3383)		
$TR1$		-0.0126***	
		(-14.9529)	
$IR1$			-0.0145***
			(-17.0354)
$SIZE$	0.0044***	0.0025***	0.0013***
	(12.4276)	(6.8004)	(3.4371)
BM	0.0049***	0.0025***	0.0025***
	(5.8302)	(3.1636)	(3.0739)
MOM	-0.0060***	-0.0023*	-0.0017
	(-4.6881)	(-1.7780)	(-1.3297)
$ILLIQ$	0.0012***	0.0016***	0.0017***
	(4.9991)	(6.5202)	(6.7878)
NS	-0.0240***	-0.0176***	-0.0158***
	(-4.8718)	(-3.5938)	(-3.2448)
const	-0.1445***	-0.1381***	-0.1231***
	(-20.5587)	(-20.2509)	(-17.9503)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.0950	0.0995	0.1019
Panel B JR^{abs}			
	(1)	(2)	(3)
DTD	-0.0057***		
	(-15.4298)		
$TR1$		0.0764***	
		(18.9981)	
$IR1$			0.0813***
			(20.5085)
$SIZE$	-0.0390***	-0.0271***	-0.0218***
	(-20.7233)	(-16.5373)	(-12.9628)
BM	-0.0164***	-0.0029	-0.0030
	(-5.1488)	(-0.9833)	(-1.0210)
MOM	-0.0046	-0.0266***	-0.0286***
	(-1.0442)	(-5.7730)	(-6.2265)
$ILLIQ$	-0.0020	-0.0047***	-0.0048***
	(-1.5802)	(-3.5756)	(-3.7122)
NS	0.1446***	0.1043***	0.0987***
	(4.7990)	(3.4892)	(3.3070)
const	1.0115***	0.9683***	0.8917***
	(25.9322)	(27.1191)	(25.6366)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes

Observations	47839	47839	47839
Adjusted R-squared	0.1240	0.1385	0.1418

This table reports the results of panel regressions of firm risk on jump returns: negative jump returns (Panel A) and absolute jump returns (Panel B). The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measure used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas higher $TR1$ and $IR1$ indicate greater firm risk. The detailed description of all the jump returns measures, firm risk measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4 The effect of information asymmetry, proxied by intangible assets

Panel A JR^{-}			
	(1)	(2)	(3)
$Intangible$	-0.0147***	-0.0285***	-0.0328***
	(-5.3629)	(-5.3079)	(-5.8758)
DTD	0.0008***		
	(7.2694)		
$DTD * Intangible$	0.0021***		
	(8.3445)		
$TR1$		-0.0114***	
		(-13.3742)	
$TR1 * Intangible$		-0.0091***	
		(-5.8348)	
$IR1$			-0.0131***
			(-15.1150)
$IR1 * Intangible$			-0.0094***
			(-6.4892)
$SIZE$	0.0042***	0.0025***	0.0014***
	(11.8344)	(6.6963)	(3.4687)
BM	0.0048***	0.0027***	0.0026***
	(5.7569)	(3.3401)	(3.2890)
MOM	-0.0061***	-0.0025*	-0.0020
	(-4.7622)	(-1.9601)	(-1.5907)
$ILLIQ$	0.0011***	0.0015***	0.0016***
	(4.6590)	(6.1557)	(6.3329)
NS	-0.0236***	-0.0168***	-0.0149***
	(-4.7627)	(-3.4216)	(-3.0449)
const	-0.1383***	-0.1334***	-0.1183***
	(-19.8956)	(-19.5673)	(-17.2625)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.0971	0.1009	0.1037
Panel B JR^{abs}			
	(1)	(2)	(3)
$Intangible$	0.0380***	0.0840***	0.0927***
	(3.0905)	(3.3572)	(3.3989)
DTD	-0.0051***		
	(-13.3999)		
$DTD * Intangible$	-0.0059***		
	(-5.4711)		
$TR1$		0.0727***	
		(17.8948)	
$TR1 * Intangible$		0.0266***	
		(3.7353)	
$IR1$			0.0772***
			(19.0617)
$IR1 * Intangible$			0.0263***
			(3.7307)
$SIZE$	-0.0381***	-0.0271***	-0.0219***
	(-20.2847)	(-16.4289)	(-12.9769)
BM	-0.0159***	-0.0034	-0.0036
	(-5.0121)	(-1.1337)	(-1.2081)
MOM	-0.0044	-0.0259***	-0.0277***
	(-1.0014)	(-5.6683)	(-6.0746)

$ILLIQ$	-0.0017	-0.0044***	-0.0045***
	(-1.3586)	(-3.3431)	(-3.4368)
NS	0.1438***	0.1020***	0.0959***
	(4.7532)	(3.3871)	(3.1913)
const	0.9901***	0.9554***	0.8796***
	(25.5531)	(26.7752)	(25.3062)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.1254	0.1394	0.1429

This table reports the results of panel regressions of firm risk and information asymmetry on negative jump returns (Panel A) and absolute jump returns (Panel B). The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measures used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas a higher $TR1$ and $IR1$ indicates greater firm risk. Information asymmetry is proxied by intangible assets ($Intangible$), where a higher $Intangible$ indicates greater information asymmetry. The detailed description of all the jump returns measures, firm risk measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 The effect of information asymmetry, proxied by total current accruals

Panel A JR^{-}

	(1)	(2)	(3)
TCA	-0.0267***	-0.0489***	-0.0480***
	(-3.9179)	(-4.7668)	(-4.5736)
DTD	0.0009***		
	(8.2202)		
$DTD * TCA$	0.0014**		
	(2.2461)		
$TR1$		-0.0114***	
		(-13.2614)	
$TR1 * TCA$		-0.0151***	
		(-4.1864)	
$IR1$			-0.0133***
			(-15.1650)
$IR1 * TCA$			-0.0133***
			(-4.1183)
$SIZE$	0.0043***	0.0024***	0.0012***
	(12.1257)	(6.4756)	(3.2132)
BM	0.0046***	0.0023***	0.0023***
	(5.5475)	(2.9062)	(2.8312)
MOM	-0.0059***	-0.0021	-0.0015
	(-4.6378)	(-1.6355)	(-1.2009)
$ILLIQ$	0.0012***	0.0016***	0.0017***
	(4.9672)	(6.3721)	(6.6003)
NS	-0.0231***	-0.0157***	-0.0140***
	(-4.7289)	(-3.2584)	(-2.9168)
const	-0.1404***	-0.1313***	-0.1166***
	(-20.0070)	(-19.2241)	(-16.9042)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.0958	0.1009	0.1033

Panel B JR^{abs}

	(1)	(2)	(3)
TCA	0.1632***	0.2840***	0.2765***
	(4.1750)	(4.7634)	(4.5785)
DTD	-0.0047***		
	(-11.2855)		
$DTD * TCA$	-0.0142***		
	(-4.2094)		
$TR1$		0.0682***	
		(17.5612)	
$TR1 * TCA$		0.1050***	
		(4.9589)	
$IR1$			0.0729***
			(18.9184)
$IR1 * TCA$			0.0912***
			(4.8117)
$SIZE$	-0.0383***	-0.0264***	-0.0214***
	(-20.8899)	(-16.3933)	(-12.8392)
BM	-0.0154***	-0.0022	-0.0024
	(-4.8813)	(-0.7479)	(-0.8073)
MOM	-0.0045	-0.0275***	-0.0294***
	(-1.0306)	(-5.9611)	(-6.3917)

$ILLIQ$	-0.0018	-0.0044***	-0.0044***
	(-1.4969)	(-3.3866)	(-3.4787)
NS	0.1399***	0.0932***	0.0880***
	(4.6921)	(3.1661)	(2.9934)
const	0.9875***	0.9299***	0.8552***
	(26.2017)	(26.8737)	(25.1254)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.1261	0.1422	0.1453

This table reports the results of panel regressions of firm risk and information asymmetry on negative jump returns (Panel A) and absolute jump returns (Panel B). The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measures used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas a higher $TR1$ and $IR1$ indicates greater firm risk. Information asymmetry is proxied by total current accruals (TCA), where a higher TCA indicates lower earning quality and greater information asymmetry. The detailed description of all the jump returns measures, firm risk measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 The impact of financial crisis

Panel A JR^{-}			
	(1)	(2)	(3)
$post2009$	-0.0334***	-0.0517***	-0.0630***
	(-14.1358)	(-11.8515)	(-13.8647)
DTD	0.0010***		
	(9.9988)		
$DTD * post2009$	0.0006***		
	(3.0659)		
$TR1$		-0.0088***	
		(-12.6872)	
$TR1 * post2009$		-0.0086***	
		(-6.6808)	
$IR1$			-0.0109***
			(-14.8332)
$IR1 * post2009$			-0.0111***
			(-9.1174)
$SIZE$	0.0024***	0.0011***	-0.0003
	(7.3871)	(3.3022)	(-0.7533)
BM	0.0078***	0.0055***	0.0050***
	(9.8860)	(7.2268)	(6.6764)
MOM	-0.0044***	-0.0014	-0.0005
	(-3.8745)	(-1.2892)	(-0.4647)
$ILLIQ$	0.0007***	0.0010***	0.0011***
	(3.1115)	(4.2003)	(4.4951)
NS	-0.0237***	-0.0170***	-0.0131***
	(-4.8800)	(-3.5744)	(-2.7797)
const	-0.0940***	-0.0872***	-0.0693***
	(-14.7248)	(-13.6513)	(-11.0566)
Year fixed effects	No	No	No
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.0635	0.0695	0.0763

Panel C JR^{abs}			
	(1)	(2)	(3)
$post2009$	0.1492***	0.2832***	0.3070***
	(12.7198)	(11.4253)	(11.8087)
DTD	-0.0049***		
	(-13.0590)		
$DTD * post2009$	-0.0047***		
	(-5.6631)		
$TR1$		0.0468***	
		(17.3785)	
$TR1 * post2009$		0.0629***	
		(8.7921)	
$IR1$			0.0544***
			(18.8919)
$IR1 * post2009$			0.0634***
			(9.1778)
$SIZE$	-0.0325***	-0.0238***	-0.0186***
	(-20.0781)	(-17.6618)	(-14.0076)
BM	-0.0246***	-0.0120***	-0.0103***
	(-8.3504)	(-4.3952)	(-3.7997)
MOM	-0.0140***	-0.0302***	-0.0344***
	(-3.4174)	(-7.4881)	(-8.4711)

$ILLIQ$	-0.0003	-0.0017	-0.0020*
	(-0.2397)	(-1.3997)	(-1.6806)
NS	0.1463***	0.1035***	0.0915***
	(4.9017)	(3.5834)	(3.1841)
const	0.8357***	0.7760***	0.7059***
	(26.3651)	(27.5403)	(26.0695)
Year fixed effects	No	No	No
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.1046	0.1246	0.1324

This table reports the results of panel regressions of firm risk on negative jump returns (Panel A) and absolute jump returns (Panel B). The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measures used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas a higher $TR1$ and $IR1$ indicates greater firm risk. The detailed description of all the jump risk measures, firm risk measures, and control variables are shown in the Appendix A. The variable $post2009$ is a binary variable, where $post2009$ equals 1 indicates that the observation corresponds to the period after fiscal year of 2009, and $post2009$ equals 0 indicates that the observation corresponds to the period before fiscal year of 2009 and earlier. The detailed description of all the jump returns measures, firm risk measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Jump returns, firm risk, and ROA

Panel A JR^{-}			
	(1)	(2)	(3)
JR^{-}	0.1888***	0.4218***	0.4240***
	(9.0273)	(9.5288)	(9.3910)
DTD	0.0041***		
	(19.2953)		
$JR^{-} * DTD$	-0.0063***		
	(-3.0655)		
$TR1$		-0.0331***	
		(-18.7150)	
$JR^{-} * TR1$		0.1174***	
		(7.8262)	
$IR1$			-0.0333***
			(-18.9070)
$JR^{-} * IR1$			0.1126***
			(7.8142)
$SIZE$	0.0165***	0.0117***	0.0097***
	(15.5960)	(12.7512)	(10.7129)
BM	-0.0002	-0.0087***	-0.0084***
	(-0.0860)	(-4.0967)	(-3.9597)
MOM	0.0213***	0.0348***	0.0354***
	(10.6174)	(17.0696)	(17.2507)
$ILLIQ$	0.0005	0.0018***	0.0018***
	(1.2539)	(4.2859)	(4.2088)
NS	-0.1668***	-0.1468***	-0.1458***
	(-13.1449)	(-12.4549)	(-12.4065)
const	-0.2843***	-0.2633***	-0.2303***
	(-13.5625)	(-13.6939)	(-12.3499)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	44347	44347	44347
Adjusted R-squared	0.2700	0.2880	0.2893

Panel B JR^{abs}			
	(1)	(2)	(3)
JR^{abs}	-0.0659***	-0.1035***	-0.1037***
	(-9.5043)	(-7.7276)	(-7.7310)
DTD	0.0040***		
	(17.5263)		
$JR^{abs} * DTD$	0.0017**		
	(2.0799)		
$TR1$		-0.0318***	
		(-16.9404)	
$JR^{abs} * TR1$		-0.0297***	
		(-5.4315)	
$IR1$			-0.0322***
			(-17.4385)
$JR^{abs} * IR1$			-0.0288***
			(-5.5199)
$SIZE$	0.0149***	0.0111***	0.0092***
	(14.8826)	(12.3976)	(10.3986)
BM	-0.0005	-0.0086***	-0.0084***
	(-0.2002)	(-4.0972)	(-3.9871)
MOM	0.0201***	0.0328***	0.0333***

	(10.1983)	(16.5638)	(16.7763)
$ILLIQ$	0.0006	0.0021***	0.0021***
	(1.4898)	(4.8104)	(4.7827)
NS	-0.1619***	-0.1433***	-0.1423***
	(-13.0498)	(-12.2343)	(-12.1870)
const	-0.2495***	-0.2479***	-0.2169***
	(-12.4566)	(-12.9486)	(-11.6731)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	44347	44347	44347
Adjusted R-squared	0.2784	0.2944	0.2958

This table reports the results of panel regressions of jump returns and firm risk on firm performance measures, ROA. The jump returns measure used in Panel A is JR^{-}, representing negative jump returns. And the jump returns measure used in Panel B is JR^{abs}, representing absolute jump returns. A higher JR^{-} indicates a lower intensity of negative jump returns, whereas a higher JR^{abs} indicates more intense absolute jump returns. The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measures used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas a higher $TR1$ and $IR1$ indicates greater firm risk. The detailed description of all the jump returns measures, firm risk measures, firm performance measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8 Jump returns, firm risk, and NI

Panel A JR^-

	(1)	(2)	(3)
JR^-	0.2241***	0.4493***	0.4464***
	(10.6120)	(10.0032)	(9.7888)
DTD	0.0044***		
	(22.1460)		
$JR^- * DTD$	-0.0089***		
	(-4.0413)		
$TR1$		-0.0325***	
		(-19.6897)	
$JR^- * TR1$		0.1204***	
		(7.8426)	
$IR1$			-0.0331***
			(-19.8982)
$JR^- * IR1$			0.1136***
			(7.7312)
$SIZE$	0.0137***	0.0094***	0.0074***
	(13.7126)	(10.8599)	(8.7111)
BM	0.0031	-0.0058***	-0.0055**
	(1.3596)	(-2.6921)	(-2.5696)
MOM	0.0232***	0.0373***	0.0379***
	(10.5457)	(16.5757)	(16.7968)
$ILLIQ$	0.0006	0.0018***	0.0018***
	(1.0998)	(3.6081)	(3.5662)
NS	-0.1470***	-0.1289***	-0.1277***
	(-10.6333)	(-9.8293)	(-9.7702)
const	-0.2675***	-0.2527***	-0.2200***
	(-13.4838)	(-13.8010)	(-12.4650)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	45861	45861	45861
Adjusted R-squared	0.2331	0.2472	0.2488

Panel B JR^{abs}

	(1)	(2)	(3)
JR^{abs}	-0.0785***	-0.1233***	-0.1237***
	(-8.0970)	(-9.0926)	(-9.0797)
DTD	0.0042***		
	(16.9733)		
$JR^{abs} * DTD$	0.0031***		
	(2.5984)		
$TR1$		-0.0298***	
		(-17.0166)	
$JR^{abs} * TR1$		-0.0371***	
		(-6.9633)	
$IR1$			-0.0306***
			(-17.4152)
$JR^{abs} * IR1$			-0.0359***
			(-7.0801)
$SIZE$	0.0121***	0.0089***	0.0069***
	(13.0344)	(10.5503)	(8.4202)
BM	0.0029	-0.0057***	-0.0055***
	(1.2903)	(-2.6767)	(-2.5801)
MOM	0.0216***	0.0350***	0.0356***

	(10.0421)	(16.1811)	(16.4492)
$ILLIQ$	0.0007	0.0021***	0.0021***
	(1.3931)	(4.2526)	(4.2662)
NS	-0.1416***	-0.1240***	-0.1227***
	(-10.6037)	(-9.9094)	(-9.8499)
const	-0.2308***	-0.2344***	-0.2040***
	(-12.4992)	(-13.1433)	(-11.8376)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	45861	45861	45861
Adjusted R-squared	0.2439	0.2590	0.2610

This table reports the results of panel regressions of jump returns and firm risk on firm performance measures, NI. The jump returns measure used in Panel A is JR^{-}, representing negative jump returns. And the jump returns measure used in Panel B is JR^{abs}, representing absolute jump returns. A higher JR^{-} indicates a lower intensity of negative jump returns, whereas a higher JR^{abs} indicates more intense absolute jump returns. The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measures used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas a higher $TR1$ and $IR1$ indicates greater firm risk. The detailed description of all the jump returns measures, firm risk measures, firm performance measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9 Robustness check: Firm risk, jump returns, and jump risk

Panel A JR

	(1)	(2)	(3)
DTD	-0.0017***		
	(-8.6655)		
$TR1$		0.0196***	
		(10.9622)	
$IR1$			0.0188***
			(10.7425)
$SIZE$	-0.0178***	-0.0150***	-0.0141***
	(-23.5668)	(-20.4967)	(-18.5993)
BM	0.0007	0.0044***	0.0042***
	(0.4492)	(2.7931)	(2.6660)
MOM	-0.0146***	-0.0205***	-0.0206***
	(-5.9943)	(-8.2925)	(-8.3089)
$ILLIQ$	0.0013**	0.0006	0.0006
	(2.1588)	(0.9965)	(1.0723)
NS	0.0193*	0.0095	0.0096
	(1.7745)	(0.8819)	(0.8867)
const	0.4236***	0.4144***	0.3990***
	(27.4315)	(28.2066)	(27.3899)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	47839	47839	47839
Adjusted R-squared	0.0790	0.0817	0.0815

Panel B $JRISK$

	(1)	(2)	(3)
DTD	-0.0013***		
	(-22.5143)		
$TR1$		0.0178***	
		(30.9618)	
$IR1$			0.0179***
			(31.5636)
$SIZE$	-0.0059***	-0.0031***	-0.0021***
	(-22.3098)	(-13.5559)	(-9.0929)
BM	-0.0059***	-0.0028***	-0.0030***
	(-10.8215)	(-5.7880)	(-6.0481)
MOM	-0.0006	-0.0057***	-0.0059***
	(-0.8075)	(-7.3869)	(-7.7189)
$ILLIQ$	0.0020***	0.0013***	0.0013***
	(6.9537)	(5.0192)	(5.0167)
NS	0.0297***	0.0202***	0.0196***
	(7.5314)	(5.3240)	(5.1952)
const	0.1482***	0.1378***	0.1222***
	(27.0196)	(28.2637)	(25.6634)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	47837	47837	47837
Adjusted R-squared	0.1777	0.2137	0.2157

This table reports the results of panel regressions of firm risk on jump returns (Panel A) and jump risk (Panel B). The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measure used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas higher $TR1$ and $IR1$ indicate greater firm risk. The detailed description of all the firm risk measures and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10 Robustness check: $TR3$ and $IR3$

	JR^{-}		JR^{abs}	
$TR3$	-0.0129***		0.0819***	
	(-14.0286)		(17.8175)	
$IR3$		-0.0152***		0.0870***
		(-16.3573)		(19.3655)
$SIZE$	0.0023***	0.0009**	-0.0250***	-0.0189***
	(6.1476)	(2.2562)	(-15.5721)	(-11.0828)
BM	0.0023***	0.0020**	-0.0008	-0.0001
	(2.8238)	(2.4753)	(-0.2777)	(-0.0402)
MOM	-0.0021*	-0.0012	-0.0283***	-0.0317***
	(-1.6564)	(-0.9625)	(-6.0259)	(-6.7192)
$ILLIQ$	0.0015***	0.0016***	-0.0041***	-0.0042***
	(6.1032)	(6.3289)	(-3.1814)	(-3.2446)
NS	-0.0151***	-0.0122**	0.0854***	0.0764**
	(-3.0756)	(-2.4905)	(2.8364)	(2.5354)
const	-0.1341***	-0.1160***	0.9379***	0.8473***
	(-19.6165)	(-16.7205)	(26.9897)	(24.9274)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	47839	47839	47839	47839
Adjusted R-squared	0.0986	0.1012	0.1377	0.1409

This table reports the results of panel regressions of firm risk on jump returns: negative jump returns and absolute jump returns. The firm risk measure are total risk and idiosyncratic risk, denoted as $TR3$ and $IR3$, respectively. A higher $TR3$ and $IR3$ indicate greater firm risk. The detailed description of all the jump returns measures, firm risk measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11 Robustness check: firm and year fixed effect

Panel A JR^{-}

	(1)	(2)	(3)
DTD	0.0006***		
	(4.1714)		
$TR1$		-0.0027**	
		(-2.5558)	
$IR1$			-0.0039***
			(-3.6449)
$SIZE$	-0.0127***	-0.0123***	-0.0128***
	(-9.6515)	(-9.4936)	(-9.7883)
BM	0.0027**	0.0024*	0.0024*
	(2.1018)	(1.8871)	(1.8702)
MOM	-0.0041***	-0.0030**	-0.0027**
	(-2.9587)	(-2.1432)	(-1.9678)
$ILLIQ$	-0.0003	-0.0002	-0.0002
	(-0.8537)	(-0.6592)	(-0.5259)
NS	0.0044	0.0044	0.0047
	(0.8563)	(0.8530)	(0.9101)
const	0.2041***	0.1918***	0.1975***
	(7.8128)	(7.5243)	(7.7318)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	46937	46937	46937
Adjusted R-squared	0.1850	0.1848	0.1850

Panel B JR^{abs}

	(1)	(2)	(3)
DTD	-0.0018***		
	(-3.8579)		
$TR1$		0.0104**	
		(2.3382)	
$IR1$			0.0125***
			(2.8461)
$SIZE$	-0.0479***	-0.0487***	-0.0475***
	(-7.1782)	(-7.3958)	(-7.0765)
BM	0.0037	0.0046	0.0046
	(0.8121)	(1.0265)	(1.0281)
MOM	-0.0034	-0.0072	-0.0077*
	(-0.7389)	(-1.5714)	(-1.6782)
$ILLIQ$	0.0016	0.0013	0.0012
	(0.9430)	(0.7771)	(0.7296)
NS	-0.0375	-0.0378	-0.0384
	(-1.2525)	(-1.2621)	(-1.2815)
const	1.1705***	1.2048***	1.1898***
	(8.8082)	(9.3226)	(9.1101)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Observations	46937	46937	46937
Adjusted R-squared	0.2702	0.2701	0.2702

This table reports the results of panel regressions of firm risk on jump returns: negative jump returns (Panel A) and absolute jump returns (Panel B). The firm risk measure used in Equation (1) is DTD

(distance to default), while the firm risk measure used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas higher $TR1$ and $IR1$ indicate greater firm risk. The detailed description of all the jump returns measures, firm risk measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include firm and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12 Robustness check: jump returns, firm risk, and sales

Panel A JR^{-}			
	(1)	(2)	(3)
JR^{-}	0.3164***	0.4695***	0.4792***
	(4.7114)	(4.1565)	(4.1834)
DTD	0.0144***		
	(8.1269)		
$JR^{-} * DTD$	-0.0217***		
	(-2.6670)		
$TR1$		-0.0705***	
		(-6.1663)	
$JR^{-} * TR1$		0.1267***	
		(2.9544)	
$IR1$			-0.0656***
			(-5.9596)
$JR^{-} * IR1$			0.1245***
			(3.0654)
$SIZE$	-0.0785***	-0.0824***	-0.0850***
	(-14.0333)	(-13.8605)	(-13.6475)
BM	-0.0673***	-0.0914***	-0.0904***
	(-6.3153)	(-8.3581)	(-8.2780)
MOM	0.1106***	0.1450***	0.1450***
	(12.2163)	(16.9297)	(16.8260)
$ILLIQ$	0.0002	0.0023	0.0021
	(0.0841)	(0.8684)	(0.7731)
NS	-0.2504***	-0.2347***	-0.2363***
	(-8.0563)	(-7.6959)	(-7.7693)
const	2.6710***	2.6335***	2.6886***
	(24.4394)	(24.0488)	(24.0172)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	45864	45864	45864
Adjusted R-squared	0.4265	0.4236	0.4233

Panel B JR^{abs}			
	(1)	(2)	(3)
JR^{abs}	-0.0877***	-0.1285***	-0.1294***
	(-5.0668)	(-4.3480)	(-4.3610)
DTD	0.0145***		
	(8.1832)		
$JR^{abs} * DTD$	0.0053**		
	(1.9848)		
$TR1$		-0.0677***	
		(-5.8813)	
$JR^{abs} * TR1$		-0.0405***	
		(-2.9535)	
$IR1$			-0.0632***
			(-5.7449)
$JR^{abs} * IR1$			-0.0390***
			(-3.0119)
$SIZE$	-0.0800***	-0.0828***	-0.0854***
	(-14.1921)	(-13.8531)	(-13.6501)
BM	-0.0675***	-0.0913***	-0.0904***
	(-6.3406)	(-8.3587)	(-8.2844)
MOM	0.1090***	0.1427***	0.1427***

	(12.1316)	(16.7804)	(16.6773)
$ILLIQ$	0.0004	0.0027	0.0025
	(0.1651)	(1.0116)	(0.9278)
NS	-0.2453***	-0.2297***	-0.2312***
	(-7.9812)	(-7.6289)	(-7.7016)
const	2.7030***	2.6494***	2.7026***
	(24.4395)	(23.9612)	(23.9235)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Observations	45864	45864	45864
Adjusted R-squared	0.4266	0.4238	0.4235

This table reports the results of panel regressions of jump returns and firm risk on firm performance measures, $Sales$. The jump returns measure used in Panel A is JR^{-}, representing negative jump returns. And the jump returns measure used in Panel B is JR^{abs}, representing absolute jump returns. A higher JR^{-} indicates a lower intensity of negative jump returns, whereas a higher JR^{abs} indicates more intense absolute jump returns. The firm risk measure used in Equation (1) is DTD (distance to default), while the firm risk measures used in Equations (2) and (3) are total risk and idiosyncratic risk, denoted as $TR1$ and $IR1$, respectively. A higher DTD indicates lower firm risk, whereas a higher $TR1$ and $IR1$ indicates greater firm risk. The detailed description of all the jump returns measures, firm risk measures, firm performance measures, and control variables are shown in the Appendix A. The sample is from July 1962 to June 2023. All regressions include industry and year fixed effects. Standard errors are clustered by firm. The numbers in parentheses are t-statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix A. Variable definitions

This table reports the definition of variables calculated in year t.

Variables	Definitions and Calculations
Jump Returns	
JR^{-}	JR^{-} for year t is the cumulative negative jump returns from July of year t to June of year $t+1$ after identifying the jump days for each quarter. Let r_k^{nj} be the kth negative jump (measured in log return), $k=1,\dots,K_2$, identified during the period, the negative jump returns for the year is computed as $JR^{-}=\exp\left(\sum_{k=1}^{K_1} r_k^{nj}\right)-1$.
JR^{abs}	JR^{abs} for year t is the cumulative absolute jump returns from July of year t to June of year $t+1$ after identifying the jump days for each quarter. Let r_k^{j} be the kth jump (measured in log return), $k=1,\dots,K_2$, identified during the period, the absolute jump returns for the year is computed as $JR^{abs}=\exp\left(\sum_{k=1}^{K_2}\left\|r_k^{j}\right\|\right)-1$.
JR	JR for year t is the cumulative jump returns from July of year t to June of year $t+1$ after identifying the jump days for each quarter. Let r_k^{j} be the kth jump (measured in log return), $k=1,\dots,K$ identified from July of year t to June of year $t+1$, the JR for the year is computed as $JR=\exp\left(\sum_{k=1}^{K} r_k^{j}\right)-1$.
$JRISK$	$JRISK$ is the total jump risk, which is the difference between RV and BPV. Please refer to appendix B for details of calculating RV and BPV.
Firm Risk	
DTD	DTD measures how many standard deviations the log of the ratio of a firm's asset value to its debt needs to deviate from its mean for a default to occur. Please refer to appendix C for details of calculating DTD, to calculate DTD, we use the Compustat annual files to get the firm's "Debt in One Year" and "Long-Term Debt" series for all frims, thus we use the "Debt in One Year" plus half the "Long-Term Debt" to get the book value of debt. We use annual data for the book value of debt. To avoid problems related to reporting delays, we do not use the book value of debt of the new fiscal year, until 4 months have elapsed from the end of the previous fiscal year. We get the daily market values for firms from the CRSP daily files. The book value of equity information is extracted from Compustat.
$TR1$	$TR1$ is the variance of daily firm stock returns during one-year period, which is calculated as the standard deviation of the daily stock returns from July of year $t-1$ to June of year t, and we drop firm-year observations with less than 200 daily CRSP returns in a given 12-month window for accuracy.
$TR3$	$TR3$ is the variance of daily firm stock returns during three-year period, which is calculated as the standard deviation of the daily stock returns from July of year $t-3$ to June of year t, and we drop firm-year observations with less than 600 daily CRSP returns in a given 36-month window for accuracy.
$IR1$	$IR1$ as a volatility measure during one-year period constructed after controlling for market fluctuations. To calculate the $IR1$ in year t, we use the daily stock returns and daily market portfolio returns (CSRP value-weighted index) three years prior to the beginning of July of each year to estimate the market model. With the estimated parameters, we construct expected daily stock returns from July of year $t-1$ to June of year t by subtracting the expected daily returns

	from the realized returns, we obtain the daily residual returns. $IR1$ of year t is estimated as the standard deviation of daily residual returns from July of year $t-1$ to June of year t. For accuracy in measuring idiosyncratic risk, we also drop firm-year observations with less than 200 daily residual returns when calculating $IR1$ in the given 12-month window.
$IR3$	$IR3$ as a volatility measure during three-year period constructed after controlling for market fluctuations. To calculate the $IR3$ in year t, we use the daily stock returns and daily market portfolio returns (CSRP value-weighted index) three years prior to the beginning of July of each year to estimate the market model. With the estimated parameters, we construct expected daily stock returns from July of year $t-3$ to June of year t by subtracting the expected daily returns from the realized returns, we obtain the daily residual returns. $IR3$ of year t is estimated as the standard deviation of daily residual returns from July of year $t-3$ to June of year t. For accuracy in measuring idiosyncratic risk, we also drop firm-year observations with less than 600 daily residual returns when calculating $IR3$ in the given 36-month window.
Control Variables	
$SIZE$	The natural log of market capitalization (from CRSP) at the end of June of year t.
BM	The natural log of the book-to-market ratio. Book value of equity is stockholders' equity plus balance-sheet deferred taxes and investment tax credit (TXDITC, from Compustat), if available, minus preferred stock liquidating value (PSTKL), if available, or redemption value (PSTKRV), if available, or carrying value (PSTK). Depending on availability, stockholders' equity is Compustat variable SEQ, or CEQ + PSTK, or AT−LT, in that order. All Compustat items are measured for the fiscal year ending in calendar year $t-1$. For the period prior to 1950, book value of equity is from Ken French's Web site.5 Market value of equity is stock price times shares outstanding at the end of December of year $t-1$, from CRSP. If book value of equity is not positive, BM is treated as missing.
MOM	11-month buy-and-hold return from July of year $t-1$ to May of year t. If less than 11 monthly return observations are available, MOM is treated as missing.
$ILLIQ$	The ratio of the absolute daily stock return to the daily dollar trading volume, averaged over a given period from July of year $t-1$ to June of year t. Since trading volume is defined differently for Nasdaq and NYSE/Amex stocks, the trading volumes of Nasdaq stocks are adjusted by a factor of 0.7 (Boehmer, 2005).
NS	The change in the natural log of split-adjusted shares outstanding (CSHO× AJEX, from Compustat) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in calendar year $t-1$.
Information asymmetry	
$Intangible$	$Intangible$ is the ratio of recognized intangible assets including goodwill (INTAN, from Compustat) to total assets (AT, from Compustat) for the fiscal year ending in calendar year $t-1$, adjusted by subtracting the industry median ratio, where we use four-digit SIC codes to identify industries.
TCA	TCA measures of earnings quality proceed from estimates of total current accruals based on cash flows from operations. The calculate TCA, we use current assets (ACT), current liabilities (LCT), cash

	(CHE), short-term debt (DLC), depreciation and amortization expense (DP), net income before extraordinary items (IB), and total assets (AT) from Compustat.
Firm Performance	
ROA	ROA is the ratio of the earnings before interests and taxes (EBIT, from Compustat) to total assets (AT, from Compustat).
NI	NI is the net income (NI, from Compustat) divided by lagged total assets (AT, from Compustat).
$Sales$	$Sales$ is the sales (SALE, from Compustat) divided by lagged total assets (AT, from Compustat).

Appendix B Approaches to identifying jump days and the summary statistics of stock price jumps

Stock price changes can be characterized as continuous changes in the form of diffusion or discontinuous changes in the form of jumps:

$$dlnS_t = a_t dt + \sqrt{V_t} dW_t + J_t dq_t, \qquad (B-1)$$

where S_t is the stock price at time t, a_t is the instantaneous drift, V_t is the instantaneous variance when there are no jumps, J_t represents jumps in asset prices, W_t is the standard Brownian motion, and q_t is a counting process with finite instantaneous intensity λ_t.

We employ the variance swap jump test proposed by Jiang and Oomen (2008), applying Itô's lemma to Eq.(B-1) and the integrating over time, we have

$$2\int_0^T \left[\frac{dS_t}{S_t} - dlnS_t\right] = V_{(0,T)} + 2\int_0^T (e^{J_t} - 1 - J_t)\, dq_t, \qquad (B-2)$$

where $V_{(0,T)} = \int_0^T V_t\, dt$ is the integrated variance. In the absence of jumps, the difference between the simple return and the log return captures one-half of the instantaneous return variance (or the variance swap). The variance swap can therefore be perfectly replicated using the log contract. However, in the presence of jumps, the replication strategy is imperfect and the replication error can be used for the jump test. The test does not rely on any specific stock return model, since the process in Eq. (1) imposes no functional form restriction on the drift, the diffusion, or the jump components. In addition, simulations show that the variance swap jump test has good power in detecting infrequent but large changes in stock prices. This feature particularly suits the purpose of our study since we focus on significant information shocks.

To be specific, realized variance is defined as $RV_N = \sum_{i=1}^{N} {r_i}^2$, where $r_{t_i} = \ln\left[\frac{S_{t_i}}{S_{t_{i-1}}}\right]$. The variance swap in the discretized version is defined as

$$SWV_N = 2\sum_{i=1}^{N}(R_i - r_i) = 2\sum_{i=1}^{N} R_i - 2\ln\left(\frac{S_T}{S_0}\right) \qquad (B-3)$$

where $R_{t_i} = \frac{S_{t_i}}{S_{t_{i-1}}} - 1$.

Jiang and Oomen (2008) show that

$$\frac{V_{(0,T)} N}{\sqrt{\Omega_{SWV}}}\left(1 - \frac{RV_N}{SWV_N}\right) \xrightarrow{d} N(0,1) \qquad (B-4)$$

Where N is the number of observations sampled between zero and T, $\Omega_{SWV} = \frac{1}{9}\mu_6 X_{(0,T)}$, $X_{(0,T)} = \int_0^T {V_u}^3\, du$, and $\mu_p = 2^{\frac{\mu}{2}}\Gamma\left[\frac{p+1}{2}\right]/\sqrt{\pi}$. The consistent estimators of $V_{(0,T)}$ proposed by Barndorff-Nielsen and Shephard (2006) can be calculated based on the bi-power variation:

$$BPV_N = \frac{1}{{\mu_1}^2}\sum_{i=1}^{N-1} |r_i||r_{i+1}| \qquad (B-5)$$

Besides, the consistent estimator of Ω_{SWV} is

$$\widehat{\Omega}_{SWV} = \frac{1}{9}\mu_6 \frac{N^3 \mu_{\frac{6}{p}}^{-p}}{N-p+1} \sum_{i=0}^{N-p} \prod_{k=1}^{p} |r_{i+k}|^{\frac{6}{p}} \qquad (B-6)$$

with p=6.

Specifically, at the beginning of each month we test whether stock prices experienced jumps over the past three months. If the test rejects the null hypothesis of no jumps in a given three-month window, we proceed to identify those days with stock price jumps following a sequential procedure. Jumps are identified at the 1% critical level.

Let (Baker et al., 2022) be daily returns over the interval $[t_1, t_N]$. The sequential jump identification procedure is then described as follows:

Step 1: If the jump test does not reject the null hypothesis of no jumps, we move to the next three-month window; otherwise we record the jump test statistic JS_0 and proceed to Step 2.

Step 2: Replace each daily return by the median of the sample (denoted r_{median}) and perform the jump test on the series. For each day replaced, we perform the jump test and record the test statistic JS_i for i=1,…,N.

Step 3: Construct the series $JS_0 - JS_i$ for i=1,…,N. Then, the stock price change on day j is identified as jump if $JS_0 - JS_i$ has the highest value of all days.

Step 4: Replace the identified jump observation by r_{median} and start again from Step 1 with a new sample of stock returns.

The above procedure continues until all jumps are identified. To ensure that identified jump returns are not the result of bid-ask bounce or the effect of nontrading, we impose the following restrictions: First, the absolute value of an identified jump must be more than twice the tick size. Second, we exclude those jumps if there is no trading on that day or during any of the previous 3 trading days. A no-trading day is defined as one with zero or missing trading volume in CRSP. We do not impose this restriction for NASDAQ stocks prior to 1982 since daily trading volume is not available for these stocks in CRSP.

We present cross-sectional summary statistics of identified jumps of individual stock prices in the periods consistent with the sample period of Jiang and Yao (2013), and the summary statistics of the jumps we calculate are similar to those reported in Jiang and Yao (2013).

Table B.1 Summary Statistics of Stock Price Jumps

	Percentile						
	5th	**25th**	**Mean**	**Median**	**75th**	**95th**	**Std Dev**
Panel A. Sample Period 07/1927-06/2009							
No. of jumps per year	0.0000	1.0000	1.6955	1.5000	2.2000	4.0000	1.4249
No. of positive jumps per year	0.0000	0.5000	1.1669	1.0000	1.5833	2.7917	0.9658
No. of negative jumps per year	0.0000	0.0000	0.5283	0.4000	0.7143	1.5714	0.6859
Absolute jump size	0.0472	0.0766	0.1200	0.1058	0.1463	0.2396	0.0666

Positive jump size	0.0469	0.0738	0.1112	0.0988	0.1322	0.2167	0.0601
Negative jump size	-0.2997	-0.1683	-0.1324	-0.1092	-0.0712	-0.0355	0.0936
Panel B. Sample Period 07/1927-06/1962							
No. of jumps per year	0.1594	1.1176	1.5444	1.5000	1.9512	2.8684	0.7646
No. of positive jumps per year	0.0000	0.7971	1.1292	1.0769	1.4655	2.0424	0.6028
No. of negative jumps per year	0.0000	0.2181	0.4151	0.3750	0.5625	1.0000	0.3358
Absolute jump size	0.0368	0.0564	0.0789	0.0713	0.0903	0.1433	0.0410
Positive jump size	0.0357	0.0542	0.0744	0.0681	0.0846	0.1284	0.0366
Negative jump size	-0.1705	-0.1038	-0.0886	-0.0785	-0.0574	-0.0332	0.0540
Panel C. Sample Period 07/1962-06/2009							
No. of jumps per year	0.0000	1.0000	1.7062	1.5000	2.2353	4.0000	1.4549
No. of positive jumps per year	0.0000	0.5000	1.1752	1.0000	1.6154	2.8333	0.9864
No. of negative jumps per year	0.0000	0.0000	0.5309	0.4000	0.7308	1.6000	0.6987
Absolute jump size	0.0467	0.0772	0.1207	0.1070	0.1473	0.2402	0.0669
Positive jump size	0.0466	0.0746	0.1119	0.0998	0.1331	0.2173	0.0603
Negative jump size	-0.3012	-0.1703	-0.1334	-0.1108	-0.0707	-0.0347	0.0947

Appendix C. Calculation of *DTD*

In Merton (1974), the equity of a firm is viewed as a call option on the firm's assets. The strike price of the call option is the book value of the firm's liabilities. When the value of the firm's assets is less than the strike price, the value of equity is zero.

We assume that the capital structure of the firm includes both equity and debt. The market value of a firm's underlying assets follows a geometric Brownian motion of the form:

$$dV_A = \mu V_A dt + \sigma_A V_A dW, \qquad (C-1)$$

where V_A is the firm's assets value, with an instantaneous drift μ, and an instantaneous volatility σ_A. A standard Wiener process is W.

We denote by X_t the book value of the debt at time t, that has maturity equal to T. X_t plays the role of the strike price of the call, since the market value of equity can be thought of as a call option on V_A with time to expiration equal to T. The market value of equity, V_E, will then be given by the Black and Scholes (1973) formula for call options:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) \qquad (C-2)$$

where

$$d_1 = \frac{\ln\left(\frac{V_A}{X}\right) + \left(r + \frac{1}{2}{\sigma_A}^2\right)T}{\sigma_A\sqrt{T}}, d_2 = d_1 - \sigma_A\sqrt{T}, \qquad (C-3)$$

r is the risk-free rate, and N is the cumulative density function of the standard normal distribution.

To calculate σ_A we adopt an iterative procedure. We use daily data from the past 12 months to obtain an estimate of the volatility of equity σ_E, which is then used as an initial value for the estimation of σ_A. Using the Black–Scholes formula, and for each trading day of the past 12 months, we compute V_A using V_E as the market value of equity of that day. In this manner, we obtain daily values for V_A. We then compute the standard deviation of those V_A's, which is used as the value of σ_A, for the next iteration. This procedure is repeated until the values of σ_A from two consecutive iterations converge. Our tolerance level for convergence is 10E-4. For most firms, it takes only a few iterations for σ_A to converge. Once the converged value of σ_A is obtained, we use it to back out V_A through Eq. (C-2).

The above process is repeated at the end of every month, resulting in the estimation of monthly values of σ_A. The estimation window is always kept equal to 12 months. The risk-free rate used for each monthly iterative process is the 1-year T-bill rate observed at the end of the month. Once daily values of V_A are estimated, we can compute the drift μ, by calculating the mean of the change in lnV_A.

The default probability is the probability that the firm's assets will be less than the book value of the firm's liabilities. In other words,

$$P_{def,t} = Prob\left(V_{A,t+T} \leq X_t \middle| V_{A,t}\right) = Prob\left(\ln\left(V_{A,t+T}\right) \leq \ln(X_t) \middle| V_{A,t}\right). \qquad (C-4)$$

Since the value of the assets follows the geometric Brownian motion of Eq. (C-1), the value of the assets at any time t is given by:

$$\ln\left(V_{A,t+T}\right) = \ln\left(V_{A,t}\right) + \left(\mu - \frac{{\sigma_A}^2}{2}\right)T + \sigma_A\sqrt{T}\varepsilon_{t+T}, \qquad (C-5)$$

$$\varepsilon_{t+T} = \frac{W(t+T) - W(t)}{\sqrt{T}}, and\ \varepsilon_{t+T} \sim N(0,1). \qquad (C-6)$$

Therefore, we can rewrite the default probability as follows:

$$P_{def,t} = Prob(\ln(V_{A,t}) - \ln(X_t) + \left(\mu - \frac{{\sigma_A}^2}{2}\right)T + \sigma_A\sqrt{T}\varepsilon_{t+T} \le 0)$$

$$P_{def,t} = Prob\left(-\frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{{\sigma_A}^2}{2}\right)T}{\sigma_A\sqrt{T}} \ge \varepsilon_{t+T}\right). \qquad (C-7)$$

We can the define the distance to default (DTD) as follows:

$$DTD_t = \frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left(\mu - \frac{{\sigma_A}^2}{2}\right)T}{\sigma_A\sqrt{T}}. \qquad (C-8)$$