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Stock price crashes and systematic risk

Suvra Roy [*], Ben R. Marshall, Hung T. Nguyen, Nuttawat Visaltanachoti

Massey Business School, Massey University, New Zealand

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A B S T R A C T

We show that firm systematic risk increases following stock price crashes. This occurs in both low- and high-beta companies and is robust to alternate proxies of systematic risk. Crashed firms face difficulty raising capital or obtaining loans, exacerbating default risk. Our results indicate that the increased systematic risk is due to increased default risk. There is no evidence to support information asymmetry as a channel for higher beta following crashes. We show that the increase in systematic risk results in higher costs for equity financing.

Introduction

Firm systematic risk is an important component of the Capital Asset Pricing Model (CAPM). Firms with higher betas (i.e., more systematic risk) are viewed as riskier than those with lower betas. Asset pricing research typically uses multi-factor models (e.g., Fama and French, 2015). However, Graham (2022) finds that practitioners continue to rely on the CAPM when estimating the cost of equity. Given beta's importance, researchers have focused on improving its estimation (Levi and Welch, 2017; Welch, 2022) and exploring what drives variation in betas across firms, including capital structure (Hamada, 1972), size, and dividends (Ben-Zion and Shalit, 1975).

We contribute to the literature by examining whether firm stock price crashes affect systematic risk. Measuring the determinants of firm systematic risk, which affects the cost of equity, is important for investors managing portfolios and undertaking hedging decisions (Fama and French, 1993; Patton and Verardo, 2012).[1] Thus, studying whether a firm's market risk rises after a stock price crash has implications for practitioners and capital market regulators.

Releasing previously concealed or distorted firm-specific information triggers stock price crashes (Jin and Myers, 2006). As a result, investors may i) discount firm-specific information from crashed firms and assign more weight to the market-level information due to a trust issue,[2] or ii) develop broader negative sentiment, leading to market-wide stock price declines. Investors tend to group assets and allocate their investment to category-level stocks rather than individual stocks (Barberis and Shleifer, 2003). As a result, investors can discount firm-specific information and prefer market-level information on a group of stocks. This suggests that firm-specific stock price

* Corresponding author.
E-mail addresses: s.roy2@massey.ac.nz (S. Roy), b.marshall@massey.ac.nz (B.R. Marshall), h.nguyen3@massey.ac.nz (H.T. Nguyen), n.visaltanachoti@massey.ac.nz (N. Visaltanachoti).

[1] For instance, prior literature demonstrate buy-sell strategies that show the abnormal performance of beta-sorted portfolios (Black, Jensen, and Scholes, 1972; Cederburg and O'Doherty, 2016; Friend and Blume, 1970).

[2] For instance, if investors observe stock price crashes, which damage investor wealth (Callen and Fang, 2017) and confidence in companies and capital markets (Lins, Servaes, and Tamayo, 2017), they may not trust what managers of crashed firms or other firms report.

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crashes can lead to higher systematic risk.

However, systematic risk may not increase following a stock price crash. A crash typically stems from managers' bad news hoarding (Jin and Myers, 2006; Hutton et al., 2009), implicating this adverse event as an idiosyncratic event. Idiosyncratic firm-level news has no or minimal implications for the systematic risk variation (Engelberg et al., 2018), so it cannot trigger a spillover or contagion effect. Investors can consider firm-specific stock price crashes as distinct events and acknowledge both fundamental risk and the uncertainty of expected cash flows, specifically for these crashed firms. So, investors give more attention to firm-level information than market-specific information,[3] resulting in falls in stock beta. Given the conflicting arguments and evidence from prior literature, the effect of adverse events, such as firm price crashes, on firm beta is an empirical question.

We begin with a baseline specification with firm- and year-fixed effects. Using a large sample of U.S. firms covered by both the Center for Research in Security Prices (CRSP) and the Compustat databases between 1950 and 2021. Our results imply that firm beta increases due to firm-specific crashes. For further robustness checks, we implement a difference-in-differences (DiD hereafter) identification approach. The firm-level crash event creates multiple treatment effects over time. We form two groups. First, a treatment group, which includes stocks with a price crash in the previous year but not in the present or following year. Second, a control group, which includes stocks that do not experience a crash during the time at all. We utilize propensity score matching and two multivariate reweighting procedures, namely i) inverse probability weighting; and ii) entropy balancing, to improve the covariate stability between the control and the treatment pairs having very similar firm characteristics. We use propensity score matching, entropy weighting, and inverse probability weighting techniques to run DiD analyses. These test results support our conjecture that firms experience higher beta following crashes.

We follow Dessaint et al. (2019) and Kim, Lee, and Zhu (2022) and use the redemption pressure (*MFHS* hereafter) from mutual fund flow established on expected trades as an instrumental variable to firm price crashes. The redemption pressure from mutual funds causes downward pressure on the value of affected shares but as noted by Bennett et al. (2020) and Edmans et al. (2012), it has little connection with company fundamentals. This endogeneity check confirms that firm systematic risk increases following stock price crashes. This occurs in both low- and high-beta firms and is robust to alternative beta proxies.

We explore default risk as a channel linking stock price crashes to higher systematic risk. Firm crashes harm investor wealth, potentially spreading negative sentiment market-wide (Callen and Fang, 2017; Lins et al., 2017).[4] Negative investor sentiment can cause a firm's stock price to fall in the wider capital markets.[5] As a consequence, firms may face difficulty raising capital or obtaining loans, exacerbating the default risk (An et al., 2015; Myers, 1977). Crashes also reduce equity value, increasing leverage (Christie, 1982), which is tied to default risk (Cathcart, Dufour, Rossi, and Varotto, 2020). Given default risk's links to aggregate factors like industry leverage, economic recession, low asset-market liquidity, and regulatory developments, it is likely positively related to systematic risk (Lang and Stulz, 1992; Denis and Denis, 1995). There is a strong positive relationship between forecasted stock returns and the default risk, as documented by Chava and Purnanandam (2010). Thus, we predict that default risk can explain the firm-level systematic risk.

We also consider information asymmetry as a cross-sectional channel through which a firm's systematic risk can increase after a crash. Crashed firms are considered to be opaque (Hutton et al., 2009) and information asymmetry is a part of the systematic risk (Easley and O'hara, 2004). Information asymmetry influences risk-taking incentives (Hughes, Liu, and Liu, 2007).[6] Brockman, Liebenberg, and Schutte (2010) find more information asymmetry during uncertain periods like recession and suggest that this results in higher stock return co-movement. Therefore, information asymmetry might explain higher systematic risk post-crash.

We find that default risk drives the increase in beta after crashes. Firms facing crashes experience higher default risk, strengthening the link between crashes and beta. However, we do not observe any evidence that information asymmetry channels this effect. Furthermore, we observe an increase in the cost of equity due to crashed firms' higher beta. It explains the important implications of systematic risk increase because it makes equity financing more expensive for crashed firms.

Our paper is related to several empirical studies that investigate the aftermath of stock price crashes. Stock prices instigate management's decision in resource allocation and corporate news affects company governance and valuation in the market-directed economics (Beyer, Cohen, Lys, and Walther, 2010; Goldman, 2004), hence, the effects of firm price crashes should matter to a broad range of stakeholders, for instance, investors, management, suppliers, and regulators. Previous literature documents that after the crash, auditors' fees surge (Hackenbrack, Jenkins, and Pevzner, 2014), and companies encounter hardship in increasing and remodelling capital for investment (An, Li, and Yu, 2015), or an increase in market information efficiency (Kim et al., 2022). Roy, Marshall, Nguyen, and Visaltanachoti (2023) find that managers take several steps like transparency and investment efficiency improvement, agency concern alleviation, and building up investor trust after crashes. This paper further investigates how informational consequences of stock price crashes influence investors to act further on market-specific information than firm-specific information, leading to a rise in firm beta.

Our findings also hold broader significance for capital market regulators and financial stability frameworks. An increase in systematic risk following firm-specific crashes implies that adverse shocks can contribute to amplified return co-movement across firms,

[3] For instance, stock price crashes can attract increased investor attention by increasing the earnings response coefficient (Kim, Lee, and Zhu, 2022).

[4] A related case of this is the crumble of Lehman Brothers in 2008 and this firm-specific event caused a systemic financial crisis (Rodini, 2023).

[5] Existing literature show that investor sentiment can affect asset valuation (Brown and Cliff, 2005; Lemmon and Portniaguina, 2006).

[6] Previous studies also observe the positive relationship between information asymmetry and risk premiums (Bhattacharya, Daouk, and Welker, 2003; Bhattacharya and Daouk, 2002; Jain, 2005).

even when the original event is idiosyncratic. This may affect asset pricing accuracy, increase risk premia, and complicate monetary transmission channels through equity markets. Regulators concerned with market fragility, liquidity risk, and systemic vulnerabilities may use firm-level beta dynamics as an early signal of risk concentration or contagion pathways. While Kim et al. (2022) examine how firm-specific stock price crashes affect market information efficiency, their study focuses on informational frictions and the flow of firm-specific news post-crash. In contrast, our paper explores a novel dimension of crash consequences, namely, how stock price crashes structurally affect a firm's systematic risk and cost of equity. This suggests that the implications of crashes extend beyond informational distortion into the domain of capital market pricing and valuation. The recent study by Chen, Zhao, Liu, Xu, and Liu (2022) examines a novel determinant of stock price crash risk rather than its consequences. They find that crash risk is significantly lower for firms led by CEOs who work in the regions where they were born.

Several corporate events could affect return covariance. Examples include the impact of earnings announcement news (Patton and Verardo, 2012; Savor and Wilson, 2016), investigation around adding stocks to indexes (Barberis et al., 2005; Greenwood, 2008), repurchasing and offering shares (Denis and Kadlec, 1994), or increasing the number of shares by splitting (Green and Hwang, 2009) on firm beta. Kelly and Jiang (2014) find that firm-specific price crashes have a strong ability to predict aggregate market returns. By linking betas to firm-level adverse events, we shed light on beta dynamics around information shocks. In the following Section 2, we describe the data and main variable construction. Section 3 provides the research design and the core findings. Section 4 reports the results of robustness checks. In Section 5, we discuss the mechanism of increased systematic risk after crashes and supplementary analyses. Section 6 concludes the paper.

Hypothesis development

Stock price crashes may result in investors losing trust in firm management and firm-specific information (Roy et al., 2023). If this occurs, investors may rely less on firm-specific information and more on market-level data. This shift in focus can amplify the firm's exposure to market risk, thereby increasing its beta. This suggests that systematic risk may rise following stock price crashes, as investors tend to prefer market-wide signals over firm-specific ones. Therefore, our first hypothesis is:

H1: Stock price crashes lead to an increase in firm systematic risk.

When a firm's stock crashes, it may experience heightened financial distress, making it harder to raise capital or secure loans (An et al., 2015; Myers, 1977). Increased financial leverage following equity loss further raises default risk (Cathcart, Dufour, Rossi, and Varotto, 2020), which is correlated with broader market risks. This could result in a feedback loop where the firm's default risk spills over into its exposure to systematic risk. Thus, we hypothesize:

H2: The increase in firm systematic risk following stock price crashes is driven by heightened default risk.

Information asymmetry might be another channel that can affect systematic risk. Firms that experience stock price crashes are often perceived as less transparent (Hutton et al., 2009), leading to greater uncertainty among investors. However, it remains unclear whether this lack of transparency directly contributes to increased systematic risk. Previous studies have provided mixed evidence on this point, and we hypothesize that information asymmetry may have a significant role in amplifying systematic risk after a crash. Therefore, we propose:

H3: Information asymmetry contributes to increased systematic risk following stock price crashes.

Framework and diagrammatic representation

To clarify the underlying mechanisms supporting the above hypotheses, we present a conceptual framework that outlines two primary channels through which stock price crashes may affect systematic risk: (1) financial distress and default risk, and (2) information asymmetry. These channels are illustrated in the diagram below, which offers a visual representation of the proposed relationships.[7]

Fig. 1 illustrates the relation between stock price crash and firm systematic risk. It shows the two primary moderating channels through which stock price crashes may lead to an increase in firm-level systematic risk. The first moderating channel operates through default risk. A stock price crash can significantly reduce a firm's equity value, leading to increased financial leverage and heightened financial distress (An et al., 2015; Myers, 1977). This distress elevates the probability of default, which in turn increases the firm's exposure to market-wide risks (Cathcart, Dufour, Rossi, and Varotto, 2020; Denis and Denis, 1995), thereby raising its systematic risk. The second moderating channel centers on information asymmetry. A decline in transparency following a crash (Hutton et al., 2009) can heighten information asymmetry, prompting investors to demand higher risk premiums due to greater uncertainty (Bhattacharya et al., 2003; Bhattacharya and Daouk, 2002; Jain, 2005). This also contributes to an increase in the firm's beta, or systematic risk. Together, these two moderating channels—default risk and information asymmetry may help explain how stock price crashes can systematically increase a firm's sensitivity to market-wide fluctuations.

Data and variable construction

This segment discusses the data and the composition of the main measures. We also report the summary statistics for our sample

[7] We are grateful to an anonymous reviewer for suggesting the idea to further improvement of the paper.

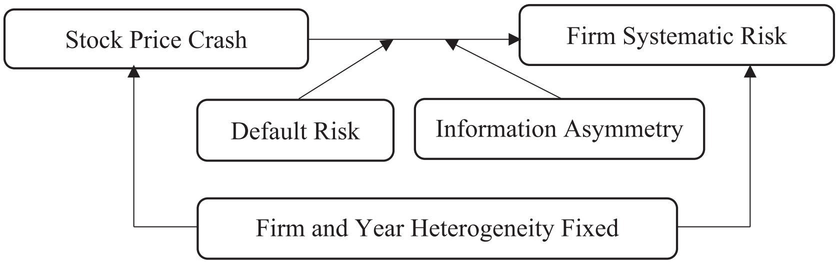

Fig. 1. Diagrammatic representation of the two channels.

and compare them with the other experiments utilized in the previous research studies.

Data source

Our sample consists of a comprehensive list of U.S. firms covered by both the Center for Research in Security Prices (CRSP) and the Compustat databases between 1950 and 2021.[8] We obtain daily stock returns and value-weighted market returns data from CRSP and annual financial data from Compustat. Further, we obtain daily industry return and risk-free return data from Kenneth French's website.[9] We obtain beta estimation based on a market model from the WRDS' Beta Suite database. Following Bollerslev et al. (2022), we exclude "penny stocks" whose values are below five dollars from the analyses to lessen concerns.[10] We also collect analysts' forecasted mean one-year-ahead annual earnings per stock and forecasted mean two-year-ahead annual earnings per stock from I/B/E/S on the Thomson Reuters Datastream database.[11]

Main variable construction

We capture systematic risk by employing beta (*BM*) measure based on the market model from the WRDS database. The formula for *BM* calculation based on the market model is given as:

$$BM_{i,y} = \frac{cov[r_{i,d}, r_{m,d}]}{var[r_{m,d}]} \tag{1}$$

where $BM_{i,y}$ is the systematic risk of the firm *i* in year *y*. $r_{i,d}$ is a firm's daily excess return in year *y*; $r_{m,d}$ is a daily market's excess return in year *y*. We require each year *y* to have a valid $r_{i,d}$ for at least 126 daily observations when estimating the market model to minimize measurement errors (Fama and MacBeth, 1973).

We consider two more beta measures to proxy for systematic risk. We follow Welch (2022) and calculate the winsorized daily stock return, $r_{i,d}^{sw}$, by restricting the daily stock return, $r_{i,d}$, to be between −200 % and 400 % of the daily market return, $r_{m,d}$ as in equation 2 below:

$$r_{i,d}^{sw} \in (1 + [-\Delta_s + \Delta_s])r_{m,d} \tag{2}$$

where $\Delta_s = 3$; $r_{i,d}^{sw}$ is a firm's slope winsorized excess return on the day *d*. We estimate the slope winsorized annual beta, $BSW_{i,y}$, by following the model below:

$$BSW_{i,y} = \frac{cov[r_{i,d}^{sw}, r_{m,d}]}{var[r_{m,d}]} \tag{3}$$

Welch (2022) mentions the applications of historical return decay with age and proposes a weighted least-squares specification to address the issue of historical return decay with the increasing number of years. Following Welch (2022), we winsorize the slope and employ age decay to calculate the other systematic risk measure, $BSWA_{i,y}$. In the first step, we execute model (2) to obtain slope winsorized excess return. In the second step, we estimate the beta by running the proposed market specification, in which the weight of individual observation declines with age. The decay parameter is set to $p = 2/252$ per day, which reflects a semi-lifespan of nearly 90 trading days.

Next, we estimate the crash indicator variable as follows. Following the stock price crash literature (e.g., Kim et al., 2011a, 2011b),

[8] The sample begins in 1950 as this is when the Compustat database begins. The sample ends in 2021, which is the latest data available at the time of writing this paper.

[9] We collect Fama and French value-weighted industry index data from https://mba.tuck.dartmouth.edu. We are grateful to Kenneth French for generously handing out the data.

[10] Our findings are not affected if we include the penny stocks in the sample.

[11] I/B/E/S data starts from 1981 (Mohanram and Gode, 2013), hence, we include the data available for our sample.

we consider a crash event to occur when a company's weekly return (after removing the impact of overall weekly market returns), called $R_{i,w}$, falls below a certain limit. We measure crash as an indicator variable that is equal to one if within its year, a firm experiences one or more firm-specific weekly $R_{i,w}$ falling 3.09 or more standard deviations below the mean ($R_{i,w}$) return for its year and equal to zero otherwise.[12] Following Hutton, Marcus, and Tehranian, (2009) and Kim, Li, and Zhang (2011a,b), we first estimate the firm-idiosyncratic excess return, $R_{i,w}$, as follows:

$$r_{i,w} = \alpha + \beta_1 r_{j,w-1} + \beta_2 r_{m,w-1} + \beta_3 r_{j,w} + \beta_4 r_{m,w} + \beta_5 r_{j,w+1} + \beta_6 r_{m,w+1} + \varepsilon_{i.w} \tag{4}$$

where $r_{i,w}$ is a firm's return for an individual firm i on the week w; $r_{j,t}$ and $r_{m,t}$ are the value-weighted industry (Fama and French) and market returns. We incorporate lead and lag periods to control for the effect of non-synchronous trading. We extract the residual returns from Equation (4) and employ the natural logarithm method, i.e., $R_{i,w} = log(1 + \varepsilon_{i,w})$.

We then define $CRASH_{i,y}$ as an indicator variable, which is one if there is any week w in the year y that the $R_{i,w}$ is less than the Mean ($R_{i,w}$) − 3.09 SD($R_{i,w}$), otherwise zero. We utilize the subsequently extended model regression and produce firm-level returns $R_{i,w}$ weekly.

Appendix A1 describes the definition of the remaining dependent variables, control variables, and the other variables.

Summary statistics

Table 1 states the summary statistics of the key measures used in our empirical study. The continuous measures in our sample are winsorized at 1 % and 99 %. The mean of *CRASH* is 0.215. We observe that our main measure for identifying crashed firms is usually similar to the literature.[13] We show that firms encounter massively positive incidents more than awfully adverse incidents.[14]

A typical firm has mean (0.8980) and median (0.8409) values of systematic risk or beta (*BM*) in our sample. The other beta measures based on slope winsorization and age decay are comparable to our main beta proxy. An average firm has an expected default frequency (*EDF*) of 2 %, while the median is zero. The mean (median) of *EFFSPREAD* is −3.948 (−3.941). The average firm has a cost of equity of 6.15 % and 7.29 %, which we measure through *RPEG* and *RGM* respectively. We present summary statistics of the remaining measures in Table 1.

Stock price crashes and beta

Research design

To examine the effect of firm price crashes on systematic risk, we utilize the following multivariate baseline specification:

$$Beta_{i,y+1} = \beta CRASH_{i,y} + \sum_{k=1}^{K} \gamma_k Controls_{i,k,y} + \mu_i + \tau_y + e_{i,y+1} \tag{4}$$

where, $Beta_{i,y+1}$ denotes our main dependent variable, justified by crashed-firm proxies, in the following year $y + 1$. $Beta_{i,y+1}$ indicates systematic risk, is proxied by *BM*, *BSW*, *BSWA*. $CRASH_{i,y}$ is a dummy variable for identifying crashed firms in the current year y. We add suitable control variables, $Controls_{i,y}$, which can explain $Beta_{i,y+1}$ and lessen omitted variable problems. We follow Kim et al. (2022) and employ firm-fixed effects and year-fixed effects, μ_i and τ_y, to Equation (4) to control for unidentifiable firm and time-specific changes. We include firm characteristics in the baseline specification (Gomes, Kogan, and Zhang, 2003; Hong and Sarkar, 2007; Livdan, Sapriza, and Zhang, 2009). We make an inference based on the firm-clustered standard errors (Petersen, 2009).

Baseline results

We begin by estimating the baseline specification in Equation (4) for systematic risk increasing following stock price crashes. Table 2 covers the main findings. Columns (1) through (3) present estimates for the main proxy and alternative proxies for systematic risk, respectively, in our sample. These estimates provide strong evidence of increased firm beta after stock price crashes. For instance, the coefficient that we observe from *CRASH* for systematic risk, *BM*, is 0.0278 (t-statistic = 9.34). These results are robust to alternative beta proxies, which are reported in columns (2) to (3). We observe that the findings in Table 2 are consistent and statistically significant at a 1 % level.

We observe not only statistically but also economically significant outcomes in Table 2. The extent of the coefficient on *CRASH* shows that a standard deviation shift in *CRASH* increases *BM* by 1.14 (i.e., (0.0278 × 0.4108) × 100) percent, which amounts to 1.40 % (i.e., 1.14/ 0.812) of the sample median of *BM*. In economic terms, such an increase is non-trivial. Even modest changes in beta can affect the firm's cost of equity and valuation, particularly in asset pricing and capital budgeting contexts. This reinforces the practical relevance of our findings that stock price crashes not only have short-term price effects but may also structurally alter a firm's sensitivity to market-wide shocks.

[12] We thank an anonymous referee for the suggestions regarding defining crash risk.

[13] For instance, the average crash is 0.161 for a sample of 1995–2008 (Kim, Li, and Zhang, 2011a). The average crash in another paper is 0.225 for a sample of 1994–2014 (Kim, Wang, Zhang, 2019).

[14] These findings are comparable to the results of Hutton, Marcus, and Tehranian (2009) and Chen, Kim, and Yao (2017).

Table 1
Summary statistics.

Variables	Nobs	Mean	Std	Pctl.25th	Median	Pctl.75th
CRASH	115,695	0.2150	0.4108	0.0000	0.0000	0.0000
BM	111,277	0.8658	0.5891	0.4230	0.8121	1.2303
BSW	115,695	0.8414	0.4892	0.4807	0.8129	1.1611
BSWA	115,695	0.8409	0.4970	0.4741	0.8111	1.1660
EDF	115,695	0.0318	0.1597	0.0000	0.0000	0.0000
ZSCORE	115,695	0.1609	0.3674	0.0000	0.0000	0.0000
EFFSPREAD	115,695	−3.9483	0.6417	−4.3376	−3.9406	−3.5227
AMIHUD	115,695	0.4042	0.9935	0.0041	0.0433	0.2875
PIN	20,739	0.1170	0.0611	0.0701	0.1114	0.1549
RPEG	48,069	0.0615	0.0681	0.0289	0.0466	0.0730
RGM	49,373	0.0729	0.1019	0.0315	0.0502	0.0818
MFHS	66,569	−0.0705	0.0964	−0.0940	−0.0351	−0.0075
SIZE	115,695	5.8541	2.0598	4.3291	5.7205	7.2426
BTM	115,695	0.6620	0.5666	0.2904	0.5263	0.8742
LEV	115,695	0.2255	0.1975	0.0532	0.1929	0.3468
VOL	115,695	0.7440	1.5250	0.1528	0.3068	0.6364
LIQ	115,695	2.8275	2.5715	1.4159	2.1195	3.2049
AGE	115,695	17.5157	13.7269	7.0000	14.0000	25.0000

Table 1 reports summary statistics of the variables utilized in this paper. Appendix A1 provides variable descriptions. Our sample period is from 1950 to 2021. We winsorize all continuous variables at the 1st and 99th percentiles to address potential outliers within the pooled data. Our sample covers 115,695 firm-year observations along with 20,776 unique companies.

Table 2
Firm Beta after Stock Price Crashes.

Dependent variable:	*BM*	*BSW*	*BSWA*
CRASH	0.0278***	0.0245***	0.0232***
	(9.34)	(10.17)	(9.21)
SIZE	0.0361***	0.0369***	0.0331***
	(6.32)	(8.02)	(7.18)
BTM	−0.0985***	−0.0781***	−0.0738***
	(−17.58)	(−17.56)	(−16.36)
LEV	0.0041	−0.0049	0.0049
	(0.20)	(−0.29)	(0.29)
VOL	0.0102***	0.0092***	0.0087***
	(5.39)	(6.26)	(5.84)
LIQ	−0.0004	−0.0002	−0.0011
	(−0.28)	(−0.17)	(−0.87)
AGE	0.011**	0.0067*	0.0048
	(2.53)	(1.82)	(1.28)
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of observations	111,277	115,695	115,695
Adj. R-Squared	50.37 %	49.99 %	47.74 %

This table reports the results from specifications using systematic risk or beta (*BM, BSW,* and *BSWA*) as the dependent variables, and *CRASH* as the main independent variable. *CRASH* is a dummy variable that indicates ‘1′ if within its year, a company faces one or more firm-specific crashes and ‘0′ otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

To put this into perspective, assume a firm with an initial beta of 0.812 and a market risk premium (*mr*) of 6 %. According to the CAPM, the firm’s cost of equity would be 6.87 % (i.e., $rf + \text{beta} \times mr = 2\,\% + 0.812 \times 6\,\%$). A 1.14 % increase in beta raises it to approximately 0.8213, increasing the cost of equity to 6.93 % (i.e., $rf + \text{beta} \times mr = 2\,\% + 0.8213 \times 6\,\%$). This 6-basis-point increase in cost of capital may appear modest, but when applied to large investment projects or firm valuation models, it can materially affect investment decisions, discount rates, and firm value. Therefore, the observed effect of stock price crashes on beta has important financial implications for both firm managers and investors, beyond statistical relevance.

These results support our conjecture that stock price crashes cause firm beta to increase. Nevertheless, these findings are subject to endogeneity concerns like omitted variables and reverse causality issues. We require an approach to address these issues so that we can establish a causal effect of stock price crashes on systematic risk.

Robustness tests

Difference-in-differences analyses

In this segment, we implement a difference-in-differences (DiD hereafter) identification strategy. The firm-level crash event creates multiple treatment effects over time. We form two groups: i) a treatment group, which does not exhibit a crash in the present and the following year but exhibits a crash in the previous year, and a control group, which does not experience a crash during the aforementioned time at all. We utilize propensity score matching (PSM hereafter) and two multivariate reweighting procedures, i) inverse probability weighting and ii) entropy balancing, to improve the covariate stability between the control and the treatment pairs having very similar fund characteristics. We apply the propensity score matching and the multivariate weighting techniques to do the DiD analysis.[15] Stock price crash is endogenous, and that before the crash event, the characteristics of the soon-to-crash firms are different from the non-crash firms. In Table 3, we apply the PSM, Entropy, and IPW matching techniques in the difference-in-difference regression. This allows us to perform a statistical control of the confounders.

The more appropriate name for "entropy weighting" is "entropy balancing" (EB hereafter). The EB is used to ensure that the covariates' distributions are accurately balanced. This allows us to identify control samples that are almost identical to the treatment sample. The primary goal of EB is to reduce bias in observational studies by making samples more comparable and is used to establish causal effects (Hainmueller, 2012). EB measures and assigns weights to each observation so that the treatment and control samples match on key firm characteristics like size, leverage, age, etc. EB is popular in many extant literatures (i.e. Bonsall and Miller, 2017; Joshi, 2020; Shroff, Verdi, and Yost, 2017).

Entropy balancing directly imposes moment conditions on the covariate distributions, ensuring exact matching on means and variances of observed covariates (Hainmueller, 2012). Using entropy balancing in this study is suitable for the following three reasons.

First, our setting involves several covariates that are correlated with both treatment and outcome. Unlike the propensity score matching (PSM) or the inverse probability of treatment weighting (IPTW) models, which require a correct specification, the entropy balancing can balance these covariates and avoid model dependence.

Second, the entropy balancing is flexible and transparent because it ensures exact balance on selected moments (mean and variance), which can be specified directly based on the empirical relevance. This reduces reliance on the iterative model mining and avoids problems of poor overlap or extrapolation between the propensity of the treated and control group.

Third, the entropy balancing is superior in improving covariate balance. To validate its effectiveness, we report pre- and post-weighting covariate balance metrics in Appendix A5, showing substantial improvement in balance across all observed dimensions. Appendix A5 presents covariate balance statistics before and after entropy balancing. As shown, standardized mean differences are reduced to zero or near-zero for all observed covariates, confirming exact mean balance and supporting the robustness of the entropy balancing procedure in aligning treated and control groups. These strengths justify entropy balancing as an appropriate and methodologically sound choice in our DiD estimation framework. By construction, the number of observations for entropy balancing and inverse probability weighting should be closer to that of the baseline model (e.g., Hainmueller, 2012). If you look at the observations of entropy balancing and inverse probability weighting (Table 3, Columns 4–9), they are similar and closer to the observations of our baseline model (Table 2). In contrast, propensity score matching (PSM) often results in fewer observations due to restrictions and matching quality (Table 3, Columns 1 to 4). We explain the advantages of entropy balancing in the previous comments and also refer to the seminal work of Hainmueller (2012), which highlights that entropy balancing reweights control observations, ensuring matched treatment and control samples have similar post-weighting properties. Therefore, entropy balancing retains more observations compared to propensity score matching (e.g., Hainmueller, 2012; Cumming et al., 2020).[16]

We also employ the firm fixed effects to account for time-invariant firm-level heterogeneity between more and less crash-prone firms. We agree that the identification strategy via matching can be imperfect as we do not have an exogenous event to separate the treatment and control groups. We use matching techniques to show that our results are robust to the potential confounders' bias.[17]

We provide the results of the difference-in-differences analyses in Table 3. *Treatment* implies whether firms fall in the treatment group and is equal to 1, or else '0′. *After* takes the value '1′ if the year is following the event of a crash, '0′ if not. The estimate on *Treatment*After* for *BM*, 0.0407 (t-statistic = 5.98) in PSM DiD analysis. In entropy weighting, we observe the statistically significant and positive estimate of 0.0369 for *Treatment*After*, implying that crashed firms experience higher beta compared to the control group. In Table 3, the coefficients for all beta measures are positive and statistically significant at a 1 % level, advocating that firms experience higher beta following crashes. The results from the DiD analyses are in line with the findings from our baseline specification.

In addition to being statistically significant, the estimated effects from the DiD analysis also demonstrate meaningful economic significance. In the propensity score matched (PSM) sample, the coefficient on the interaction term Treatment × After for beta (BM) is 0.0407, suggesting that firms experiencing a crash see their beta increase by approximately 1.67 % for a one-standard-deviation

[15] First, we run pre-match regression on the treatment and control pairs. In the pre-match specification, firms do not have similar characteristics and are not comparable. That is why we find statistically significant coefficients for some control variables in pre-match regression. Due to matching process, we select firms that have similar propensity scores. As a result, we do not find any significant results for post-match regression and that confirms that the characteristics of the treatment pair are same as the characteristics of the control pair. These results along with propensity score distribution are reported in Appendix A4.

[16] We thank an anonymous referee for the suggestions regarding entropy balancing and inverse probability weighting.

[17] We thank an anonymous referee for the suggestions regarding difference-in-difference analysis.

Table 3
Difference-in-differences Analysis of the Effect of Stock Price Crashes on Beta.

	Propensity Score Matching			Entropy Weighting			Inverse Probability Weighting		
Dependent variable:	*BM*	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
*Treatment*After*	0.0407***	0.0374***	0.0341***	0.0369***	0.0276***	0.0244***	0.0327***	0.0278***	0.0251***
	(5.98)	(7.80)	(6.83)	(4.28)	(4.88)	(4.14)	(4.51)	(4.78)	(4.11)
Treatment	−0.0138***	−0.0142***	−0.0105***	−0.0112***	−0.0121***	−0.0094***	−0.0129***	−0.0115***	−0.0089***
	(−3.16)	(−4.00)	(−2.89)	(−2.75)	(−4.35)	(−3.27)	(−3.68)	(−4.03)	(−3.01)
After	0.0194***	0.0127***	0.0098***	0.0096**	0.0108***	0.017***	0.0112***	0.0065**	0.0122***
	(4.54)	(3.71)	(2.75)	(2.20)	(3.57)	(5.37)	(3.04)	(2.21)	(3.94)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	39,284	39,284	39,284	108,374	108,374	108,374	108,374	108,374	108,374
Adj. R-Squared	51.10 %	52.68 %	50.91 %	53.06 %	53.82 %	52.05 %	53.53 %	54.70 %	52.88 %

Table 3 presents a difference-in-differences analysis of the effect of stock price crashes on firm beta. We examine whether changes in firm beta are different in the post-crashes compared to the pre-crash periods. Systematic risks or betas (*BM, BSW,* and *BSWA*) act as the dependent variables, and *Treatment*After* as the main independent variable. *Treatment* implies whether firms fall in the treatment group and is equal to 1, otherwise ‘0′ and *After* indicates ‘1′ if the year is after the crash event, ‘0′ otherwise. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We use three methods to run DiD analyses, namely propensity score matching (PSM), entropy balancing (EB), and inverse probability weighting (IPW). Following PSM specification, we report pre-match and post-match regression results along with propensity score distribution in Appendix A4. We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

change in the crash proxy (i.e., 0.0407 × 0.4108 × 100). Relative to the sample median of BM (0.812), this translates to an approximate 2.06 % (i.e., 1.67 %/0.812) increase in systematic risk exposure. Similarly, under entropy balancing, the Treatment × After coefficient is 0.0369, corresponding to a 1.52 % (i.e., 0.0369 × 0.4108 × 100) increase in beta or 1.87 % (1.52 %/0.812) of the median beta level. Therefore, these DiD estimates reinforce that the effect of stock price crashes on systematic risk is not only statistically robust but also economically material.

Mutual fund flow expected sale as an exogenic shock

Motivated by Dessaint et al. (2019) and Kim et al. (2022), we present additional evidence to reinforce the validity of our main findings by utilizing *MFHS* established on expected trades as an exogenic shock to the crashes of share prices. We employ mutual fund flow hypothetical sales, an exogenous variable, as an instrumental variable (IV). We compute *MFHS* from a mutual fund's formerly revealed portfolio instead of real trades. Hence, it tracks the fall of a fund's holdings, and investors' fund outflows are immediately accountable for that decrease. Bennett et al. (2020) and Edmans et al. (2012) mention that *MFHS* (mutual fund redemptions) apply downward pressure on the prices of affected stocks with minimal connection to firm fundamentals. Since investor opinions on firm fundamentals are more likely to impact immediate trading of the firm's stock rather than mutual fund shares, these fund outflows are exogenous to the specific firm held by the fund. Edmans et al. (2012) argue that mutual fund flow hypothetical sales can demonstrate the causal effect of stock price changes on a firm by meeting the exclusion restriction (see Roberts and Whited, 2013), affecting firms solely through stock price movements. Using mutual fund flow hypothetical sales (MFHS) as our IV, we address the endogeneity issue. Our approach is consistent with Kim et al. (2022) which also employed MFHS as their instrumental variable.

In Table 4, we observe from the first-stage specification that *MFHS* is positively correlated with crash events, proving that this force notably raises the occurrence of firms' crash events. We show that the coefficient on *MFHS* for stock price crashes is 0.2442 (*t*-statistic = 7.27). We use all the control variables corresponding to our previous specifications. We find the F-statistics obtained from our first-stage specification passing the Stock and Yogo (2005) identification checks at the 1 % level. The second-stage regressions (columns 2 to 4) in Table 4, provide consistent and statistically significant results to our panel regression results in section 3.

The Table 4 results are also economically significant, for instance, *Fitted_Crash* coefficient is 1.0571 for BM, indicating that a one-standard-deviation increase in the instrumented crash variable leads to an estimated 0.4346 (i.e., 1.0571 × 0.4108) increase in firm beta (BM). When compared to the sample median beta of 0.812, this corresponds to approximately 53.5 % (i.e., (0.4346/0.812) × 100) of the median value. The IV approach isolates the exogenous component of stock price crashes, which may capture more pronounced shifts in investor perception and market risk sensitivity. Thus, we conclude that firm systematic risk increases following stock price crashes.

Beta increase after crashes irrespective of their history

In this part, we check whether historically high- and low-beta firms have consistently higher systematic risk following crashes. Companies with higher equity risk can continue to have higher equity risk. So, we investigate both historical high and low beta firms to investigate that firm beta increases after crashes irrespective of their past beta conditions. We create four sub-samples based on the historical beta. For instance, our first and second sub-sample groups are constructed depending on the average beta of lag 3 years, which is higher and lower than the beta 1 value respectively. Similarly, we create two more groups based on an average beta of lag 5

Table 4
2SLS Specification with Mutual Fund Flow Hypothetical Sale.

Dependent variable:	*CRASH*	*BM*	*BSW*	*BSWA*
MFHS	0.2442*** (7.27)			
Fitted_Crash		1.0571*** (7.17)	0.7562*** (6.16)	0.7021*** (5.74)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Weak identification test:				
F-Statistic		54.28	60.15	60.15
Hausman endogeneity test:				
p-value		0.00	0.00	0.00
No. of observations	39,129	35,002	36,478	36,478

Table 4 reports the endogeneity tests that derive from mutual fund flow redemption pressure depending on hypothetical sales (*MFHS*) as an exogenous shock to *CRASH*. Following Kim et al. (2022), we employ *CRASH*, implying a dummy variable that indicates '1′ if within its year, a firm faces one or more firm-specific crashes and '0′ otherwise, as the dependent variable in the first-stage regression. We add the constant control variables used in the baseline specification. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). In the second-stage models, we regress *Fitted_Crash* acquired from the first-stage specification, on firm beta, for instance, *BM*, *BSW*, and *BSWA*. We parenthesize t-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

years. Then, we run a panel regression using equation (4) for each sub-sample.

In Panel A of Table 5, we observe that either high- or low-beta firms, based on lag 3 years, face consistently high beta after stock price crashes. For example, the coefficient on *CRASH* for *BM* on sub-sample whose historical beta is more than 1 (historical beta less than 1) based on lag 3 years, 0.0285 with *t*-statistic = 5.65 (0.0257 with *t*-statistic = 7.14). We observe constantly statistically significant results throughout the entire columns at the 1 % level in both Panel A and B in Table 5. These results also have economic significance. Using the standard deviation of CRASH (0.4108), these coefficients imply a 1.17 % increase in beta for high-beta firms and a 1.06 % increase for low-beta firms, respectively. These results imply that firms' systematic risks increase following crashes irrespective of their high or low historical betas.

Mechanism of beta increase after crashes and additional analyses

Default risk as a channel

We conjecture default risk as a channel that can steer the association between stock price crashes and systematic risk. A stock price crash leads to a significant drop in equity which in turn leads to higher financial leverage (Christie, 1982). Higher financial leverage results in higher stock return co-movement (Do, Nguyen, Nguyen, and Truong, 2023) and higher stock return volatility (Li, 2011).[18] Firms experience challenges to raise capital amid extreme price declines (An et al., 2015), this situation can induce default risk. Default risk could be positively related to systematic risk as Denis and Denis (1995) argued that default risk is related to aggregate factors. The average beta of failing firms increases as their financial situations worsen (Castagna and Matolcsy, 1981; Ro et al., 1992). Therefore, firms encountering stock price crashes face the probability of increased default risk that results in the positive relation between stock price crashes and firm betas.

We report our estimation, 0.0945 (*t*-statistics = 2.02), on *CRASH* × *EDF* for *BM* in Table 6 and find the estimation positively and statistically significant at the 5 % level. In addition to statistical relevance, the interaction effect reported in Table 6 is also economically meaningful. So, a one-standard-deviation increase in both *CRASH* (0.4108) and *EDF* (0.1597) leads to a 0.62 % (i.e., 0.0945 × 0.4108 × 0.1597 × 100) increase in beta (BM), which is approximately 1 % of the sample median beta (0.812). Likewise, we see that the coefficient of interaction terms of *ZSCORE* and *CRASH* are positive and highly statistically significant for our main systematic risk measure (*BM*). Our results indicate if a firm faces a crash event, it can increase its beta through its default risk.

Information asymmetry as a channel

We also study information asymmetry as another channel, which can rationalize the relationship between firm price crashes and firm betas. Prior literature shows that information asymmetry is a part of the systematic risk (Easley and O'hara, 2004; Hughes et al., 2007). Stock price crashes invoke uncertainty, and this situation may lead to less accessible firm-specific information. Thus, we predict that the information asymmetry can explain the firm-level systematic risk. We use information asymmetry proxies like *EFFSPREAD*, *AMIHUD*, and *PIN*. We follow Easley et al. (1996) to use the probability of private information trade (*PIN*).[19]

Table 7 presents the findings of interaction terms between *CRASH* and information asymmetry proxies, such as *EFFSPREAD*, *AMIHUD*, and *PIN*. Here, we do not find any consistent significant results to conclude that information asymmetry can explain the relationship between the crashes and betas. Thus, we rule out information asymmetry as a channel for a stock price crash to cause a beta increase.

Implication of beta increase

We also test whether an increase in firm beta after crashes has any implication on the firm cost of equity. We begin with two proxies for the cost of equity. Motivated by Heckman (1979), we employ the inverse mills ratio to address any concern for sample selection bias in the panel regressions.[20] We find that the cost of equity increases after the crashes. Table 8 provides the coefficient of 0.0033 (*t*-statistics = 1.95) on *CRASH* for *RPEG*. We also observe a positive coefficient, 0.0069, for *RGM* at the 1 % significance level. Our results from Table 8 explain the important implications of systematic risk increase because it makes equity financing more expensive for crashed firms.[21]

Economically, this effect is also significant. Given a sample mean *RPEG* of 0.0615 (or 6.15 %), a coefficient of 0.0033 implies an approximate 5.37 % increase relative to the average cost of equity (i.e., 0.0033 / 0.0615 × 100). This would raise a firm's cost of equity from 6.15 % to approximately 6.48 %, or by 33 basis points, which can materially impact firm valuation and project appraisal. Similarly, given the mean of 0.0729 for *RGM* as a proxy, the coefficient of 0.0069 represents a nearly 9.47 % increase relative to the

[18] Appendix A7 provides results that correlation and relative volatility, the ratio of the standard deviation of a firm returns and the standard deviation of market returns, go up after the crash.

[19] We thank Duarte, Hu, and Young (2020) for making annual data available to calculate *PIN* in their website, https://edwinhu.github.io/pin/. The data is available from 1993 to 2012.

[20] The reason is that I/B/E/S coverage starts from 1981 for this dataset.

[21] We also report results for the cost of equity measures by using alternative crash proxies in Appendix A6 and find similarly statistically significant results.

Table 5
The Effect of Crashes on Betas based on their History.

Panel A: A beta split analysis based on lag 3 years						
	Lag 3 years beta > 1			Lag 3 years beta < 1		
	BM	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*
CRASH	0.0285***	0.0265***	0.0264***	0.0257***	0.0217***	0.0205***
	(5.65)	(6.51)	(6.22)	(7.14)	(7.24)	(6.52)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	37,030	38,293	38,293	55,018	57,046	57,046
Adj. R-Squared	38.55 %	37.50 %	35.82 %	44.07 %	43.71 %	42.08 %
Panel B: A beta split analysis based on lag 5 years						
	Lag 5 years beta > 1			Lag 5 years beta < 1		
	BM	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*
CRASH	0.0261***	0.0234***	0.0228***	0.0302***	0.0261***	0.0252***
	(4.98)	(5.44)	(5.09)	(7.94)	(8.20)	(7.53)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	32,031	33,081	33,081	48,285	49,972	49,972
Adj. R-Squared	39.25 %	38.14 %	36.58 %	45.58 %	45.00 %	43.29 %

Table 5 presents the results from specifications using systematic risk or beta (*BM, BSW,* and *BSWA*) as the dependent variables, and *CRASH* as the main independent variable. However, the purpose of these tests is to check whether historically high- and low-beta firms have consistently higher systematic risk following crashes. Panel A reports the beta split analysis based on lag 3 years and Panel B reports the beta split analysis based on lag 5 years. *CRASH* is a dummy variable that indicates '1′ if within its year, a company faces one or more firm-specific crashes and '0′ otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 6
Default Risk Channel.

Dependent variable:	*BM*	
*CRASH*EDF*	0.0945**	
	(2.02)	
*CRASH*ZSCORE*		0.0341***
		(3.34)
CRASH	0.0249***	0.0213***
	(7.55)	(6.06)
EDF	0.1601***	
	(8.47)	
ZSCORE		0.0042
		(0.45)
Control variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
No. of observations	81,170	81,170
Adj. R-Squared	52.14 %	52.05 %

Table 6 reports the results from specifications utilizing the main firm beta measure (*BM*) as the dependent variable, and *CRASH* interacted with default risk proxies like *EDF* and *ZSCORE* (i.e., *CRASH*EDF* and *CRASH*ZSCORE*) as the main independent variables. *CRASH* is a dummy variable that indicates '1′ if within its year, a company faces one or more firm-specific crashes and '0′ otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

sample mean of 0.0729 (i.e., 0.0069 / 0.0729 × 100). This corresponds to a rise in the cost of equity from 7.29 % to about 7.98 %, or 69 basis points. In economic terms, these increases in cost of equity, driven by greater systematic risk following crashes, can significantly raise the cost of financing for firms.

Table 7
Information Asymmetry Channel.

Dependent variable:	*BM*		
*CRASH*EFFSPREAD*	1.3195		
	(1.46)		
*CRASH*AMIHUD*		−0.0355***	
		(−3.95)	
*CRASH*PIN*			−0.0617
			(−0.53)
CRASH	−0.0046	0.0276***	0.0477***
	(−0.24)	(7.20)	(3.40)
EFFSPREAD	4.2946***		
	(4.33)		
AMIHUD		−0.0355***	
		(−7.50)	
PIN			−0.7502***
			(−5.28)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of observations	64,887	64,887	14,205
Adj. R-Squared	50.13 %	52.05 %	59.08 %

Table 7 presents the results from specifications utilizing the main firm beta measure (*BM*) as the dependent variable, and *CRASH* interacted with information asymmetry proxies like *EFFSPREAD*, *AMIHUD*, and *PIN* (i.e., *CRASH*EFFSPREAD*, *CRASH*AMIHUD*, and *CRASH*PIN*) as the main independent variables. *CRASH* is a dummy variable that indicates ‘1′ if within its year, a company faces one or more firm-specific crashes and ‘0′ otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Cost of Equity Following Stock Price Crashes.

	RPEG	*RGM*
CRASH	0.0033*	0.0069**
	(1.95)	(2.41)
Control variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Inverse mills ratio	Yes	Yes
No. of observations	19,360	20,705
Adj. R-Squared	6.50 %	7.06 %

Table 8 presents the results from specifications using cost of equity (*RPEG,* and *RGM*) as the dependent variables, and *CRASH* as the main independent variable. *CRASH* is a dummy variable that indicates ‘1′ if within its year, a company faces one or more firm-specific crashes and ‘0′ otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

Additional analyses

We also run some additional tests to confirm the impact of stock price crashes on systematic risks and report the results in Appendices A2 and A3. We employ additional crash measures to verify the robustness of the reported main results. Additionally, we use an instrumental measure approach by exploiting state-specific crash events. Geographically neighboring firms are subjected to parallel circumstances (Gao et al., 2011; John et al., 2011; Thomadsen, 2005). Inspired by Addoum et al. (2020) and following Roy et al. (2023), we calculate the mean of occurrences of all firm price crashes in the matching state disregarding firm *i* to employ a state-specific crash measure. An adverse incident can spread and create undesirable spillover impacts on regional companies (Brunnermeier and Pedersen, 2009; Kaminsky et al., 2003), implying that the probability of price-crash incidents from geographically neighboring firms can be associated with that of an individual firm in the matching state. On the other hand, we do not see any apparent connection between the systematic risk of a firm and the state-specific crashes. Thus, the state-specific crash measure seems to fulfill the requirement of exclusion and relevance robustness checks (Roberts and Whited, 2013). Our findings indicate that state-specific crashes are correlated with a rise in firm-specific crashes. Our results from the fitted crash proxy uphold our main panel specification findings and are constantly robust. Thus, we conclude that crashed firms affect the firm beta.

Conclusion

Systematic risk plays a vital role in the Capital Asset Pricing Model (CAPM). Financial market experts remain attached to the CAPM while estimating the cost of equity. Generally, riskier firms are the firms with higher systematic risk. Judging the critical role of firm beta, academics have leaned on investigating its precise estimate and determinants. In this paper, we examine i) whether stock price crashes affect firm beta ii) why firm beta increases, and iii) whether an increase in crashed firm beta makes equity financing more expensive.

We find that firm beta increases after stock price crashes. This result is robust to other beta measures and is persistent in low- and high-beta firms. The evidence suggests that the beta increase occurs because of increased default risk. Our evidence does not support that information efficiency is an explanation for the beta increase. Finally, we find that the cost of equity increases after the crashes. We adopt difference-in-differences analysis to check the beta change after crashes by comparing the states of before- and after-crash beta. We also utilize the redemption pressure from mutual fund flow as an exogenic shock to perform the core identification test. The robustness checks in this paper verify the robust positive association between stock price crashes and firm beta.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A1

Variable Definition

Variables	Description
BM	*BM* refers to systematic risk. We collect this beta data from Beta Suite by WRDS database. The formula for *BM* calculation based on the market model is given as: $BM_{i,y} = \frac{cov[r_{i,d}, r_{m,d}]}{var[r_{m,d}]}$ (Fama and MacBeth, 1973).
BSW	*BSW* is a proxy for systematic risk. We use the slope winsorization method to firms' excess returns, topped within the constrained factors of market returns, as follows: $r^{sw}_{i,d} \in (1 + [-\Delta_s + \Delta_s]).r_{m,d}, \quad BSW_{i,y} = \frac{cov[r^{sw}_{i,d}, r_{m,d}]}{var[r_{m,d}]}$ where $\Delta_s = 3$; $r^{sw}_{i,d}$ is a firm's slope winsorized excess return on the day *d* (Welch, 2022).
BSWA	*BSWA* refers to a firm's systematic risk. We execute model (2) to obtain slope winsorized excess return and then estimate the beta by running a weighted least squares market model, in which the weight of each observation decays with age. The decay parameter is set to ρ = 2/252 per day, which reflects a half-life of nearly 90 trading days (Welch, 2022).
CRASH	An indicator variable that is equal to one if within its year, a firm experiences one or more firm-specific weekly $R_{i,w}$ falling 3.09 or more standard deviations below the mean ($R_{i,w}$) return for its year and equal to zero otherwise. $R_{i,w} = \log(1 + \varepsilon_{i,w})$ for firm *i* on the week *w*, estimated on weekly return data: $r_{i,w} = \alpha + \beta_1 r_{j,w-1} + \beta_2 r_{m,w-1} + \beta_3 r_{j,w} + \beta_4 r_{m,w} + \beta_5 r_{j,w+1} + \beta_6 r_{m,w+1} + \varepsilon_{i,w}$ where for firm *i* and on the week *w*, $r_{i,w}$ is a firm's raw return; $r_{j,w}$ is the Fama and French value-weighted industry (*j*, to which firm *i* belongs) return; and $r_{m,t}$ is the CRSP value-weighted market return on the week *w* (Hutton, Marcus, and Tehranian, 2009).
EDF	*EDF* refers to the expected default frequency. We follow below the model and use the cumulative standard normal distribution function on *DD*: $EDF_{i,y} = N(-DD_{i,y})$ (Brogaard, Li, and Xia, 2017).
ZSCORE	We follow Altman (1968) and calculate defaults from five accounting ratios. Please refer to their paper or see details of this default risk measure, a type of accounting measure, from (Abinzano, Gonzalez-Urteaga, Muga, and Sanchez, 2020). We use an indicator variable from this score to denote the default risk. *ZSCORE* equals 1 if the score is below 1.8 as it observes a firm's default risk, otherwise 0.
EFFSPREAD	We apply the natural logarithm to the annual average of daily effective spreads, calculated as twice the absolute difference between the trading price and the bid-ask midpoint, divided by the trading price (Anderson, Duru, and Reeb, 2009).
AMIHUD	It refers to the annual mean of the daily ratio of the absolute value of stock return and trading volume and then multiplied by one million (Brogaard, Li, and Xia, 2017).
PIN	The probability of private information trade = αμαμ + 2ε (Easley Kiefer, O'hara and Paperman, 1996).

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(*continued*)

Variables	Description
RGM	It is the implied cost of equity depending on the Ohlson-Juettner model. The calculation is based on the following equation: $RGM = A + \sqrt{A^2 + \frac{EPS_1}{P_0}*(STG - (\gamma - 1))}$, $A = \frac{1}{2}\left((\gamma - 1) + \frac{DPS_1}{P_0}\right) and STG = \frac{EPS_2}{EPS_1} - 1$ where EPS_1 and EPS_2 are forecasted one-year and two-year ahead earnings per share, respectively.
RPEG	It represents the implied cost of equity. We calculate *RPEG* based on the following equation: $RPEG = \sqrt{\frac{EPS_1}{P_0}*STG}$ (Mohanram and Gode, 2013).
SIZE	Log of total assets (AT) (Gomes, Kogan, and Zhang, 2003).
BKMKT	The book-to-market ratio is the ratio of the book value (BKVLPS) to the market value (PRCC_F) of a firm (Gomes, Kogan, and Zhang, 2003).
LEV	Book value of debt (DLC + DLTT) divided by total asset (AT) (Livdan, Sapriza, and Zhang, 2009).
VOL	Refers to earnings volatility. It represents the standard deviation of fractional changes in the earnings stream and is calculated for a five-year period (Hong and Sarkar, 2007).
LIQ	The current ratio of a firm (ACT/LCT) (Beaver and Manegold, 1975).
AGE	Log of the number of years since the stock's first listing on the stock market (McAlister, Srinivasan, and Kim, 2007).

Appendix A2

Alternative Measures of Crashes.

	BM		*BSW*		*BSWA*	
NCSKEW	0.0179***		0.0182***		0.0172***	
	(18.35)		(22.88)		(20.74)	
DUVOL		0.0264***		0.0286***		0.0271***
		(14.12)		(18.90)		(17.20)
SIZE	0.0337***	0.0348***	0.0344***	0.0352***	0.0307***	0.0315***
	(5.89)	(6.08)	(7.47)	(7.65)	(6.66)	(6.83)
BTM	−0.0955***	−0.0975***	−0.0751***	−0.0768***	−0.071***	−0.0726***
	(−17.03)	(−17.39)	(−16.93)	(−17.30)	(−15.78)	(−16.12)
LEV	0.0117	0.0079	0.0044	0.0004	0.0139	0.01
	(0.57)	(0.38)	(0.27)	(0.02)	(0.83)	(0.60)
VOL	0.0102***	0.0103***	0.0093***	0.0093***	0.0088***	0.0087***
	(5.40)	(5.42)	(6.34)	(6.31)	(5.90)	(5.88)
LIQ	−0.0004	−0.0004	−0.0002	−0.0002	−0.001	−0.0011
	(−0.24)	(−0.27)	(−0.14)	(−0.17)	(−0.84)	(−0.88)
AGE	0.0108**	0.0107**	0.0067*	0.0065*	0.0048	0.0046
	(2.50)	(2.47)	(1.82)	(1.76)	(1.28)	(1.22)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	111,114	111,273	115,524	115,691	115,524	115,691
Adj. R-Squared	50.54 %	50.43 %	50.32 %	50.20 %	48.04 %	47.93 %

Appendix A2 presents the results from specifications using systematic risk or beta (BM, BSW and BSWA) as the dependent variables, and NCSKEW and DUVOL as the main independent variables. NCSKEW and DUVOL, crash proxies, refer to the negative coefficient of skewness and the down-to-up volatility of residual return obtained from expanded model regressions, respectively. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize t-statistics under each coefficient. *, **, and *** imply statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix A3

2SLS Analysis with State-level Crash as an Instrument.

	NCSKEW	*BM*	*BSW*	*BSWA*
State_Ncskew	0.1087***			
	(4.66)			
Fitted_Crash		0.225***	0.1906***	0.1662***
		(3.70)	(3.83)	(3.22)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Weak identification test:				

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(*continued*)

	NCSKEW	*BM*	*BSW*	*BSWA*
F-Statistic		446.20	465.10	465.10
Hausman endogeneity test:				
p-value		0.00	0.00	0.00
No. of observations	115,391	110,975	115,384	115,384

Appendix A3 reports the estimation of the two-stage least square (2SLS) specification. In the first stage of regression, we employ NCSKEW, which implies the negative coefficient of skewness of residual return acquired from the expanded model specifications, as the dependent variable and State_Ncskew, which we calculate through yearly state-level NCSKEW by averaging the crashes of firms, excluding firm i, in a year t, as the main independent variable. In the second-stage models, we regress Fitted_Crash acquired from the first-stage specification, on firm beta, for instance, BM, BSW, and BSWA. We add the constant control variables used in the baseline specification. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize t-statistics under each coefficient. *, **, and *** imply statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix A4

Probit Regressions and Propensity Score Distribution following PSM.

Panel A: Probit regressions with pre-matched and post-matched samples

		Pre-match			Post-match	
SIZE		0.0324***			0.0011	
		(12.29)			(0.29)	
BTM		−0.3681***			−0.0078	
		(−40.93)			(−0.55)	
LEV		−0.7409***			0.0088	
		(−29.7)			(0.24)	
VOL		−0.0317***			0.0037	
		(−10.06)			(0.60)	
LIQ		−0.0307***			0.0014	
		(−15.83)			(0.47)	
AGE		−0.1573***			−0.0033	
		(−25.5)			(−0.36)	
No. of observations		108,374			39,284	
p-value of $\chi 2$		0.0001			0.9806	
Pseudo R2		0.1630			0.0000	
Panel B: Propensity score distribution						
Group	Nobs	Mean	Min.	Median	Max.	Std Dev
Treatment	19,642	0.2304	0.0359	0.2341	0.4136	0.0540
Control	19,642	0.2301	0.0359	0.2339	0.4170	0.0538
Difference	19,642	0.0003	0.0000	0.0002	−0.0034	0.0002

Appendix A4 reports the findings from a probit specification, following which we run regressions on pre-matched and post-matched firms in the treatment and control groups. The dependent variable of the probit specification indicates "1″ if the firm falls in the treatment group and "0" if the firm comes under the control group. We employ the constant control variables used in the baseline specification. We present the statistical distribution of the propensity scores of the firms in both treatment and control groups along with their differences.

Appendix A5

Covariate Balance Summary.

Covariate	**Mean.Treated**	**Mean.Control.Raw**
SIZE	6.034	5.717
BTM	0.575	0.715
LEV	0.223	0.245
VOL	0.687	0.740
LIQ	2.708	2.662
AGE	2.842	2.816

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Covariate	**Mean.Treated**	**Mean.Control.Raw**
Covariate	**Std.Diff.Raw**	**Mean.Control.Weighted**
SIZE	0.165	6.034
BTM	−0.263	0.575
LEV	−0.118	0.223
VOL	−0.036	0.687
LIQ	0.020	2.708
AGE	0.039	2.842
Covariate	**Std.Diff.Weighted**	
SIZE	0	
BTM	0	
LEV	0	
VOL	0	
LIQ	0	
AGE	0	

Appendix A5 presents the covariate balance before and after implementing Entropy balancing (EB) and Inverse Probability Weighting (IPW). The standardized mean differences (SMD) between the treated and control groups were non-negligible prior to weighting, particularly for variables like *BTM* (SMD = −0.263) and *SIZE* (SMD = 0.165). After applying EB and IPW, the SMDs for all covariates were reduced to approximately zero, indicating successful balancing of the covariate distributions between treated and control groups. This confirms the effectiveness of the weighting procedure and supports the assumption of covariate balance necessary for causal inference using EB and IPW.

Appendix A6

Alternative Measures of Crashes to Check its Effect on Cost of Equity.

	RPEG		*RGM*	
NCSKEW	0.0005***		0.0005**	
	(3.14)		(2.21)	
DUVOL		0.0013***		0.0014***
		(3.77)		(2.95)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
No. of observations	25,943	25,961	27,582	27,605
Adj. R-Squared	43.89 %	43.84 %	39.79 %	39.72 %

Appendix A6 presents the results from specifications using cost of equity (RPEG, and RGM) as the dependent variables, and NCSKEW and DUVOL as the main independent variables. NCSKEW and DUVOL, crash proxies, refer to the negative coefficient of skewness and the down-to-up volatility of residual return obtained from expanded model regressions, respectively. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize t-statistics under each coefficient. *, **, and *** imply statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix A7

Decomposed Beta.

	CORR			*RVOL*		
CRASH	0.0061***			0.1690***		
	(5.35)			(4.02)		
NCSKEW		0.0048***			0.0746***	
		(12.62)			(6.34)	
DUVOL			0.0065***			0.0998***
			(9.06)			(4.16)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	115,691	115,522	115,689	115,691	115,525	115,691
Adj. R-Squared	44.75 %	44.83 %	44.78 %	21.20 %	23.04 %	21.20 %

Appendix A7 shows the results from specifications using correlation and relative volatility (CORR, and RVOL) as the dependent variables, and CRASH, NCSKEW, and DUVOL as the main independent variables. CORR refers to the correlation between stock and market returns, whereas RVOL refers to the ratio of the standard deviation of a stock return and the standard deviation of a market return. CRASH denotes '1′ if, within its year, a firm encounters one or more firm-specific crashes, and '0′ otherwise. NCSKEW and DUVOL, crash proxies, refer to the negative coefficient of skewness and the down-to-up volatility of residual return obtained from expanded model regressions, respectively. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize t-statistics under each coefficient. *, **, and *** imply statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Data availability

Data will be made available on request.

References

Abinzano, I., Gonzalez-Urteaga, A., Muga, L., Sanchez, S., 2020. Performance of default-risk measures: the sample matters. J. Bank. Financ. 120, 105959.
Addoum, J.M., Kumar, A., Le, N., Niessen-Ruenzi, A., 2020. Local bankruptcy and geographic contagion in the bank loan market. Eur. Finan. Rev. 24 (5), 997–1037.
Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Financ. 23 (4), 589–609.
An, Z., Li, D., Yu, J., 2015. Firm crash risk, information environment, and speed of leverage adjustment. Finance 31, 132–151.
Anderson, R.C., Duru, A., Reeb, D.M., 2009. Founders, heirs, and corporate opacity in the United States. J. Financ. Econ. 92 (2), 205–222.
Barberis, N., Shleifer, A., 2003. Style investing. J. Financ. Econ. 68 (2), 161–199.
Barberis, N., Shleifer, A., Wurgler, J., 2005. Comovement. J. Financ. Econ. 75 (2), 283–317.
Beaver, W., Manegold, J., 1975. The association between market-determined and accounting-determined measures of systematic risk: some further evidence. J. Finan. Quantitative Anal. 10 (2), 231.
Bennett, B., Stulz, R., Wang, Z., 2020. Does the stock market make firms more productive? J. Financ. Econ. 136 (2), 281–306.
Ben-Zion, U., Shalit, S.S., 1975. Size, leverage, and dividend record as determinants of equity risk. J. Financ. 30 (4), 1015–1026.
Beyer, A., Cohen, D.A., Lys, T.Z., Walther, B.R., 2010. The financial reporting environment: Review of the recent literature. J. Account. Econ. 50 (2–3), 296–343.
Bhattacharya, U., Daouk, H., 2002. The world price of insider trading. J. Financ. 57 (1), 75–108.
Bhattacharya, U., Daouk, H., Welker, M., 2003. The world price of earnings opacity. Account. Rev. 78 (3), 641–678.
Black, F., Jensen, M.C., Scholes, M., 1972. *The Capital Asset Pricing Model: Some Empirical Tests*.
Bollerslev, T., Patton, A.J., Quaedvlieg, R., 2022. Realized semibetas: disentangling "good" and "bad" downside risks. J. Financ. Econ. 144 (1), 227–246.
Bonsall, S.B., Miller, B.P., 2017. The impact of narrative disclosure readability on bond ratings and the cost of debt. Rev. Acc. Stud. 22 (2), 608–643.
Brockman, P., Liebenberg, I., Schutte, M., 2010. Comovement, information production, and the business cycle. J. Financ. Econ. 97 (1), 107–129.
Brogaard, J., Li, D., Xia, Y., 2017. Stock liquidity and default risk. J. Financ. Econ. 124 (3), 486–502.
Brown, G.W., Cliff, M.T., 2005. Investor sentiment and asset valuation. J. Bus. 78 (2), 405–440.
Brunnermeier, M.K., Pedersen, L.H., 2009. Market liquidity and funding liquidity. Rev. Financ. Stud. 22 (6), 2201–2238.
Callen, J.L., Fang, X., 2017. Crash risk and the auditor-client relationship. Contemp. Account. Res. 34 (3), 1715–1750.
Castagna, A.D., Matolcsy, Z.P., 1981. The market characteristics of failed companies: extensions and further evidence. J. Bus. Financ. Acc. 8 (4), 467–483.
Cederburg, S., O'Doherty, M.S., 2016. Does it pay to bet against beta? on the conditional performance of the beta anomaly: does it pay to bet against beta? J. Financ. 71 (2), 737–774.
Chava, S., Purnanandam, A., 2010. Is default risk negatively related to stock returns? Rev. Financ. Stud. 23 (6), 2523–2559.
Chen, C., Kim, J.-B., Yao, L., 2017. Earnings smoothing: does it exacerbate or constrain stock price crash risk? Finance 42, 36–54.
Chen, J., Zhao, D., Liu, X., Xu, C., Liu, L., 2022. Home sweet home: do local ceos curb stock price crash risk? Financial Res. Lett. 50, 103314.
Cumming, D., Ji, S., Peter, R., Tarsalewska, M., 2020. Market manipulation and innovation. J. Bank. Financ. 120, 105957.
Denis, D.J., Denis, D.K., 1995. Causes of financial distress following leveraged recapitalizations. J. Financ. Econ. 37 (2), 129–157.
Denis, D.J., Kadlec, G.B., 1994. Corporate events, trading activity, and the estimation of systematic risk: evidence from equity offerings and share repurchases. J. Financ. 49 (5), 1787–1811.
Dessaint, O., Foucault, T., Frésard, L., Matray, A., 2019. Noisy stock prices and corporate investment. Rev. Financ. Stud. 32 (7), 2625–2672.
Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. J. Financ. 51 (4), 1405–1436.
Easley, D., O'hara, M., 2004. Information and the cost of capital. J. Financ. 59 (4), 1553–1583.
Edmans, A., Goldstein, I., Jiang, W., 2012. The real effects of financial markets: the impact of prices on takeovers. J. Financ. 67 (3), 933–971.
Engelberg, J., Mclean, R.D., Pontiff, J., 2018. Anomalies and news: anomalies and news. J. Financ. 73 (5), 1971–2001.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81 (3), 607–636.
Friend, I., Blume, M., 1970. Measurement of portfolio performance under uncertainty. Am. Econ. Rev. 60 (4), 561–575.
Gao, W., Ng, L., Wang, Q., 2011. Does corporate headquarters location matter for firm capital structure? Financ. Manag. 40 (1), 113–138.
Goldman, E., 2004. The impact of stock market information production on internal resource allocation. J. Financ. Econ. 71 (1), 143–167.
Gomes, J., Kogan, L., Zhang, L., 2003. Equilibrium cross section of returns. J. Polit. Econ. 111 (4), 693–732.
Graham, J.R., 2022. Presidential address: corporate finance and reality. J. Financ. 77 (4), 1975–2049.
Green, T.C., Hwang, B.-H., 2009. Price-based return comovement. J. Financ. Econ. 93 (1), 37–50.
Greenwood, R., 2008. Excess comovement of stock returns: evidence from cross-sectional variation in nikkei 225 weights. Rev. Financ. Stud. 21 (3), 1153–1186.
Hackenbrack, K.E., Jenkins, N.T., Pevzner, M., 2014. Relevant but delayed Information in Negotiated Audit fees. Audit. J. Pract. Theory 33 (4), 95–117.
Hainmueller, J., 2012. Entropy balancing for causal effects: a multivariate reweighting method to produce balanced samples in observational studies. Polit. Anal. 20.
Hamada, R.S., 1972. The effect of the firm's capital structure on the systematic risk of common stocks. J. Financ. 27 (2), 435–452.
Hong, G., Sarkar, S., 2007. Equity systematic risk (beta) and its determinants. Contemp. Account. Res. 24 (2), 423–466.
Hughes, J.S., Liu, J., Liu, J., 2007. Information asymmetry, diversification, and cost of capital. Account. Rev. 82 (3), 705–729.
Hutton, A.P., Marcus, A.J., Tehranian, H., 2009. Opaque financial reports, R2, and crash risk. J. Financ. Econ. 94 (1), 67–86.
Jain, P.K., 2005. Financial market design and the equity premium: electronic versus floor trading. J. Financ. 60 (6), 2955–2985.
Jin, L., Myers, S., 2006. R2 around the world: New theory and new tests. J. Financ. Econ. 79 (2), 257–292.
John, K., Knyazeva, A., Knyazeva, D., 2011. Does geography matter? firm location and corporate payout policy. J. Financ. Econ. 101 (3), 533–551.

Joshi, P., 2020. Does private country-by-country reporting deter tax avoidance and income shifting? evidence from BEPS Action Item 13. J. Account. Res. 58 (2), 333–381.
Kaminsky, G.L., Reinhart, C.M., Végh, C.A., 2003. The unholy trinity of financial contagion. J. Econ. Perspect. 17 (4), 51–74.
Kelly, B., Jiang, H., 2014. Tail risk and asset prices. Rev. Financ. Stud. 27 (10), 2841–2871.
Kim, J., Lee, E., Zhu, Z. (Judy), 2022. Do Firm-specific stock price crashes lead to a stimulation or distortion of market information efficiency? Contemp. Account. Res. 39 (3), 2175–2211.
Kim, J.-B., Li, Y., Zhang, L., 2011a. Corporate tax avoidance and stock price crash risk: firm-level analysis. J. Financ. Econ. 100 (3), 639–662.
Kim, J.-B., Li, Y., Zhang, L., 2011b. CFOs versus CEOs: Equity incentives and crashes. J. Financ. Econ. 101 (3), 713–730.
Lang, L.H.P., Stulz, R.M., 1992. Contagion and competitive intra-industry effects of bankruptcy announcements. J. Financ. Econ. 32 (1), 45–60.
Lemmon, M., Portniaguina, E., 2006. Consumer confidence and asset prices: some empirical evidence. Rev. Financ. Stud. 19 (4), 1499–1529.
Levi, Y., Welch, I., 2017. Best practice for cost-of-capital estimates. J. Financ. Quant. Anal. 52 (2), 427–463.
Lins, K.V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis: social capital, trust, and firm performance. J. Financ. 72 (4), 1785–1824.
Livdan, D., Sapriza, H., Zhang, L., 2009. Financially constrained stock returns. J. Financ. 64 (4), 1827–1862.
McAlister, L., Srinivasan, R., Kim, M., 2007. Advertising, research and development, and systematic risk of the firm. J. Mark. 71 (1), 35–48.
Mohanram, P., Gode, D., 2013. Removing predictable analyst forecast errors to improve implied cost of equity estimates. Rev. Acc. Stud. 18 (2), 443–478.
Myers, S.C., 1977. Determinants of corporate borrowing. J. Financ. Econ. 5 (2), 147–175.
Patton, A.J., Verardo, M., 2012. Does beta move with news? firm-specific information flows and learning about profitability. Rev. Financ. Stud. 25 (9), 2789–2839.
Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22 (1), 435–480.
Ro, B.T., Zavgren, C.V., Hsieh, S.-J., 1992. The effect of bankruptcy on systematic risk of common stock: an empirical assessment. J. Bus. Financ. Acc. 19 (3), 309–328.
Roberts, M. R., and Whited, T. M. (2013). Endogeneity in Empirical Corporate Finance1. In *Handbook of the Economics of Finance* (Vol. 2, pp. 493–572).
Roy, S., Marshall, B.R., Nguyen, H.T., Visaltanachoti, N., 2023. How does management respond to stock price crashes? Int. J. Manag. Financ., ahead-of-print
Savor, P., Wilson, M., 2016. Earnings announcements and systematic risk: earnings announcements and systematic risk. J. Financ. 71 (1), 83–138.
Stock, J.H., Yogo, M., 2005. Testing for Weak Instruments in Linear IV Regression. In: Andrews, D.W.K., Stock, J.H. (Eds.), *Identification and Inference for Econometric Models*, (1st ed.,. Cambridge University Press, pp. 80–108.
Thomadsen, R., 2005. The effect of ownership structure on prices in geographically differentiated industries. Rand J. Econ. 36 (4), 908–929.
Welch, I., 2022. Simply better market betas. Critical Finance Rev. 11 (1), 37–64.