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Article

Causal Impact of Stock Price Crash Risk on Cost of Equity: Evidence from Chinese Markets

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Abstract: This study investigates the causal impact of stock price crash risk on the cost of equity (COE) in China's segmented A- and B-share markets with an emphasis on ownership structures and market regimes. Employing a bootstrap panel Granger causality framework, Markov-switching dynamic regression, and panel threshold regression models, the analysis reveals that heightened crash risk significantly increases COE, with the effects being more pronounced for A-shares because of domestic investors' heightened risk sensitivity. This relationship further intensifies in bull markets, where investor optimism amplifies downside risk perceptions. Ownership segmentation plays a critical role, as foreign investors in B-shares exhibit weaker reliance on firm-level valuation metrics, favoring broader risk-diversification strategies. These findings offer actionable insights into corporate risk management, investor decision making, and policy formulation in segmented and emerging equity markets.

Keywords: cost of equity; stock price crash risk; causality; bull market; bear market

JEL Classification: G10; G15; G32



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1. Introduction

The relationship between stock price crash risk and the cost of equity (COE) has garnered substantial attention in the finance literature because of its significant implications for investment decisions, corporate governance, and market stability. Stock price crash risk, characterized by abrupt and significant declines in stock prices, typically arises from delayed disclosures and accumulation of negative information within firms. Recent studies highlight various determinants of crash risk, including managerial opportunism, opaque financial reporting, governance mechanisms, and external factors such as investor sentiment, carbon risks, operating leverage, and stock liquidity (Jin & Myers, 2006; Hutton et al., 2009; Piotroski et al., 2014; An et al., 2020; Ren et al., 2023; Qian et al., 2025; Bose et al., 2024; Zhu & Zang, 2024; Nguyen et al., 2025). Despite extensive research, most studies have utilized correlation-based methodologies, limiting their capacity to establish clear causal links between crash risks and COE. This critical gap motivates the current study, which rigorously investigates the causal relationships linking stock price crash risk to COE, explicitly differentiates between market-wide and firm-specific sources, and explores investor responses within segmented markets through advanced econometric techniques.

Investor sensitivity to crash risk depends significantly on managerial transparency and the governance structure. In environments with high information asymmetry, investors face substantial uncertainty regarding firm-specific risks, leading to higher risk premiums and COE (Diamond & Verrecchia, 1991; Chen & Chen, 2024). Recent studies suggest that equity-based compensation for outside directors reduces crash risk by mitigating financial misreporting and bad news hoarding (Qian et al., 2025). Additionally, external factors, including irrational investor sentiment and emotional panic, exacerbate stock price volatility and crash risk (Fan & Gao, 2024; Saleem et al., 2023). However, the literature rarely differentiates explicitly how these distinct types of crash risk influence investor behavior across different market structures or regimes. Recognizing these differences is crucial, as investors' abilities to diversify or hedge such risks significantly influence their risk pricing and resultant financing costs.

This study further distinguishes itself by examining these dynamics within China's segmented A- and B-share markets, where domestic and foreign investors differ markedly in their sophistication, diversification capabilities, and risk-assessment strategies. Although the existing literature acknowledges the importance of investor sophistication and market segmentation, few studies have explicitly analyzed how these factors influence the causal relationship between crash risk and COE under varying market conditions. Domestic investors in A-shares, typically less globally diversified and more reliant on firm-specific information, may exhibit heightened sensitivity to firm-specific crash risks compared with foreign investors in B-shares, who generally benefit from global diversification (He et al., 2021). This study explicitly investigates these investor characteristics and market segmentation effects to provide novel insights into the conditions under which crash risk significantly affects investors' expectations and firms' financing costs.

Methodologically, this study advances the literature by employing robust econometric techniques, specifically bootstrap panel Granger causality models and Markov-switching dynamic regressions. These methods explicitly address econometric challenges such as cross-sectional dependence, firm-specific heterogeneity, and regime-dependent investor behavior, which are inadequately captured by simpler methodologies. Additionally, a threshold regression was employed to reinforce the findings from the Markov-switching models by explicitly identifying the critical breakpoints. Thus, this study incorporates panel threshold regression analysis to enhance empirical robustness.

By integrating explicit theoretical reasoning with rigorous methodologies, this study substantially enhances our understanding of the nuanced relationship between crash risk and COE. It moves beyond existing correlations, clarifies causal mechanisms, and demonstrates how distinct market regimes and investor sophistication shape financial outcomes. These findings offer actionable guidance for investors, policymakers, and corporate managers aiming to mitigate financial risks and optimize firm financing strategies in segmented markets.

1.1. Determinants of Stock Price Crash Risk and Cost of Equity (Brief Contextualization)

Although this study primarily examines the economic consequences of stock price crash risk, a brief review of its determinants provides the necessary theoretical context. Prior research has extensively identified managerial behavior, institutional frameworks, and market conditions as pivotal determinants of crash risk. Jin and Myers (2006) and Hutton et al. (2009) emphasize managerial tendencies to withhold negative information, resulting in a higher crash risk. Recent studies have expanded on these determinants, highlighting the role of other aggregates such as operating leverage, liquidity, and carbon disclosure as critical factors influencing crash risk through increased information asymmetry, investors' asymmetric responses, and managerial incentives to withhold negative information (Bose

et al., 2024; Zhu & Zang, 2024; Nguyen et al., 2025). Institutional investors may either mitigate crash risk effectively or unintentionally exacerbate it by aligning with managerial interests (Andreou et al., 2017). Moreover, heightened crash risk has implications for corporate control, reducing takeover premiums and lowering firm valuations (Carline et al., 2023).

While the determinants are well documented, few studies have explicitly explored the causal impact of crash risk on COE. Transparency generally reduces information asymmetry and uncertainty, and lowers COE (Diamond & Verrecchia, 1991). An increased crash risk reflects greater information asymmetry and increased financing costs (Botosan, 1997; Liu & Ren, 2019; Liang & Mao, 2019). Crash risk indirectly increases COE through valuation adjustments, as manifested by higher book-to-market ratios (Chen et al., 2001). However, most studies rely on correlation-based methodologies that provide limited causal insights or explicit considerations of varying market conditions. This study contributes explicitly by investigating the causal relationships and differentiated impacts of market-wide and firm-specific crash risks on the COE.

1.2. Market Dynamics and Ownership Structures

Market segmentation and ownership structures critically shape the relationship between crash risk and COE, influencing investor behavior, risk perceptions, and diversification opportunities. Previous studies recognize the moderating role of investor sophistication, yet few explicitly analyze how distinct market structures and investor behaviors under varying market regimes influence this relationship. Junxia and Qinsong (2019) indicate heightened investor sensitivity to crash risk in bull markets, although existing studies rarely employ methodologies that explicitly capture regime-dependent behavior. Recent findings suggest that internal (e.g., corporate governance) and external (e.g., institutional investors and analysts) monitoring significantly alleviate crash risk by reducing information asymmetry (Bose et al., 2024).

Liang and Mao (2019) highlight domestic A-share investors' greater sensitivity to crash risks due to limited diversification and reliance on firm-specific information compared to globally diversified foreign B-share investors. The existing literature has not explicitly tested how these differences manifest causally under varying market conditions. This study contributes explicitly through rigorous causality testing and regime-switching analyses, providing robust insights into the influence of market segmentation and investor behavior on the crash risk–COE nexus.

Ownership structure also significantly impacts firm valuation and risk exposure. Carline et al. (2023) documented that firms with a higher crash risk experience reduced takeover premiums, which negatively influence their valuation and increase financing costs. Building explicitly on these findings, this study extends the prior literature by rigorously analyzing how market segmentation and ownership structure influence investor perceptions and risk pricing across distinct market regimes, thus providing novel and actionable insights beyond existing correlational findings.

1.3. Approach and Hypotheses Development

Traditional studies examining the relationship between stock price crash risk and the cost of equity (COE) often rely on correlation-based or static panel regression models that do not adequately address causality, firm-level heterogeneity, or cross-sectional dependence. To overcome these limitations, this study adopts a multimethod econometric strategy that integrates causality testing and regime-sensitive modeling.

First, we applied a bootstrap panel Granger causality model (Kónya, 2006), which accounts for both cross-sectional dependence and slope heterogeneity, thus enhancing causal identification across firm panels. This technique is particularly suited for emerging

markets, such as China, where structural interdependencies and firm-specific dynamics can bias conventional estimations.

Second, to address the nonlinear behavior of financial markets, we incorporated a Markov-switching dynamic regression model (Ertugrul & Ozturk, 2013). This framework identifies latent regimes, such as bull and bear markets, and estimates how the crash risk–COE relationship evolves across these states. This enables us to examine whether investors respond differently to crash risk depending on the prevailing market sentiment.

Third, we complemented these models with a panel threshold regression (Hansen, 1999) that estimates observable breakpoints in crash risk measures (e.g., NCSKEW and DUVOL) that trigger distinct investor reactions. This model explicitly captures nonlinearity and structural shifts, offering further insights into how crash risk affects COE in segmented financial environments.

This integrated framework was applied to China's dual-share structure (A-shares for domestic investors and B-shares for foreign investors) to explore how investor sophistication and market segmentation influence the crash risk–COE relationship across regimes. Accordingly, this study tested the following hypotheses.

H1: *Stock price crash risk significantly increases equity costs because of heightened investor uncertainty and compensation required for perceived risks.*

H2: *The impact of crash risk on COE is more pronounced for A-shares than for B-shares because of the differences in investor behavior, sophistication, and diversification strategies stemming from market segmentation.*

H3: *The relationship between crash risk and COE varies across market regimes, and is stronger in bull markets because of amplified investor optimism and increased sensitivity to potential downside risks.*

By testing these hypotheses through robust empirical analyses, this study reaffirms key theoretical expectations and refines them through the lens of causality and dynamic market behavior. It provides actionable insights for investors, regulators, and corporate managers seeking to better understand and manage financing costs in segmented and behaviorally complex financial markets.

The remainder of this paper is organized as follows. Section 2 outlines the materials and methods, Section 3 presents the empirical results, and Section 4 concludes the study with key findings, implications, and recommendations for future research.

2. Materials and Methods

2.1. Sample Selection

This study uses weekly data from firms listed on the Shanghai and Shenzhen Stock Exchanges, sourced from the China Stock Market and Accounting Research (CSMAR) database, covering the period 2010 to 2023. The starting point of 2010 ensured the exclusion of the effects of the 2008 global financial crisis, focusing on the periods of relative market stability. While the COVID-19 pandemic influenced markets in 2020–2021, these years were retained to capture the full market dynamics. The sample includes A-shares (domestic investors) and B-shares (foreign investors), facilitating an examination of how the ownership structure influences the COE–crash risk relationship.

Weekly data are used for the COE estimation because they capture the short-term market dynamics that affect investor risk perceptions. Although COE is less volatile than stock market indicators, it remains sensitive to changes in crash risks, macroeconomic variables,

and investor sentiment. Weekly intervals offer a granular view of these relationships and improve causal inference.

Return on equity (ROE), a key COE input, is generally stable over short periods but may vary due to earnings forecasts, market revaluations, or economic shocks. Capturing these nuances through weekly data ensures robust analysis of firm fundamentals and market conditions.

The study excludes financially distressed firms marked as “ST” or “PT” due to illiquidity and delisting risks (Allen et al., 2015) and omits financial sector firms because of their distinct leverage structures and reporting practices (Fama & French, 1992). Firms with positive book values and consistent data for at least eight years were included, whereas cross-listed firms were excluded to control for the global market influence.

This approach ensures a high-quality dataset, minimizing biases while aligning with prior research on capturing granular market responses to risk factors (Vorst, 2017; Liu & Ren, 2019).

2.2. Measures of Stock Price Crash Risk

The four models measure firm-specific crash risk. The first measure, CRASHit, is a proxy that equals one if during the fiscal year, there is a one-week minimum at which a firm faces a stock price crash, and zero otherwise (Vorst, 2017). A stock price crash week can be defined as the week in which a firm’s specific weekly return is at least 3.2 standard deviations below the mean specific return. Thus, under a normal distribution, 0.1 percent of all weeks were defined as crash weeks (Hutton et al., 2009). Firm-specific weekly returns (Equation (2)) are computed as the natural logarithm of one, which is added to the residual of the model below (Equation (1)):

$$r_{it} = \alpha_i + \beta r_{mt} + \varepsilon_{it} \quad (1)$$

$$w_{it} = \ln(1 + \varepsilon_{it}) \quad (2)$$

where r_{it} is firm i ’s stock return during week t , r_{mt} is the market return, and ε_{it} represents the proportion of firm i ’s weekly stock returns that the aggregate market movements fail to explain.

The second measure of crash risk is NCSKEWit, also referred to as negative conditional return skewness, which is derived from the third moment of firm-specific weekly returns standardized by their volatility (Chen et al., 2001; Kim et al., 2016). Higher NCSKEW values correspond to an increased negative skewness, indicating a higher probability of extreme negative returns. This measure has been validated in studies examining information asymmetry and managerial behavior (Jin & Myers, 2006; Hutton et al., 2009). This theoretical foundation is based on the aggregation of undisclosed negative information that ultimately results in a sharp decline.

$$NCSKEW_{it} = -[n(n-1)^{3/2} \sum w_{it}^3] / [(n-1)(n-2)(\sum w_{it}^2)^{3/2}]. \quad (3)$$

NCSKEWit is computed as the negative of the third moment of firm-specific weekly returns divided by the standard deviation of firm-specific weekly returns raised to third power. In full respect to the prior literature, this study selects the negative of the third moment so that higher values of NCSKEWit correspond to increased negative NCSKEW, and hence, increased crash risk.

The third measure of crash risk is down-to-up volatility DUVOLit. It evaluates the asymmetry in volatility between weeks with below-average (down) and above-average (up) returns (Chen et al., 2001). By taking the natural logarithm of the ratio of the standard deviation of down-week returns to that of up-week returns, DUVOLit captures the likeli-

hood of more extreme losses than gains. This metric has been widely used to examine crash risk in the context of market transparency and investor sentiment (Piotroski et al., 2014; Saleem & Usman, 2021). Studies have confirmed its sensitivity to abrupt changes, which makes it particularly suitable for this study. A higher DUVOLit value indicates increased crash risk. This equation is expressed as follows:

$$DUVOL_{it} = \log \left\{ (n_u - 1) \sum_{\text{down}} w_{it}^2 / \left[(n_d - 1) \sum_{\text{up}} w_{it}^2 \right] \right\} \quad (4)$$

where the number of “down/up” weeks ($n_d(n_u)$) minus one will scale the standard deviation of “down” (“up” up’ up’ up’)-week firm-specific weekly returns. A “down/up” week is a week during which the firm-specific weekly stock return is below/above the mean weekly return for the fiscal year.

The fourth measure is implied volatility smirk (IV_SKEW), introduced by Kim et al. (2011). This is an options-based measure that equates the option pricing formula with the option market price. This can be expressed as follows:

$$IV - SKEW = IV^{\text{OTMP}} - IV^{\text{ATMC}} \quad (5)$$

where IV stands for implied volatility, and OTM puts are put options with a delta value between -0.375 and -0.125 . ATM is a call option with delta values ranging from 0.375 to 0.625 . To obtain the annual measure of the volatility smirk, the daily IV-SKEW over the 12 months ending 3 months after the fiscal year-end should be averaged.

Although implied volatility smirks (IV_SKEW) can provide additional insights, their use was precluded because of the lack of available options data within the scope of this study. Consequently, the fourth measure (IV_SKEW) was excluded from the analysis. Additionally, the first measure (CRASHit) was not utilized separately because it conceptually overlaps with and is embedded in the calculations of NCSKEW and DUVOL, both of which provide richer theoretical and empirical grounding for capturing crash risk (Chen et al., 2001; Kim et al., 2016). Although NCSKEW and DUVOL specifically focus on sudden declines, aligning closely with theoretical models connecting crash risk to delayed disclosures and investor reactions (Diamond & Verrecchia, 1991), their widespread acceptance and use in the literature ensure robust comparability and methodological validity.

2.3. Measure of Cost of Equity

This study follows Ashbaugh et al. (2004) in estimating the cost of equity as the discount rate applied to future cash flows to determine a firm’s current stock price. We used a variation of the residual income valuation model (Ohlson, 1995), which is equivalent to the dividend discount model. This approach is mathematically the same as the well-known dividend discount model, and has been used by numerous authors, including Botosan (1997) and Gebhardt et al. (2001). In their methodology, R is defined as the implied cost of equity and the internal rate of return, which equates the intrinsic value of the stock to the current stock price by simply summing the discounted future abnormal earnings and current book value of equity (BE):

$$P_t = B_t + \sum_{i=1}^{\infty} \frac{E_t(ROE_{t+i} - R)B_{t+i-1}}{(1 + R)^i} \quad (6)$$

where P_t represents the stock price at time t , B_t is the BE at time t , R is the forecasted cost of equity, ROE_{t+i} is the return on equity in period $t + i$, and E_t is the expectation considering

the information available at time t . Since Equation (6) needs earnings forecasts of future periods, it is further developed into a new version: finite horizon.

$$P_t = B_t + \sum_{i=1}^T \frac{(FROE_{t+i} - R)B_{t+i-1}}{(1 + R)^i} + \frac{(FROE_{t+T} - R)B_{t+T-1}}{(1 + T)^T R} \quad (7)$$

where FROE is the forecast return on equity. To calculate the *ex ante* cost of equity, this study used [Gebhardt et al.'s \(2001\)](#) industry method and [Easton's \(2004\)](#) PEG ratio. The industry method assumes that a firm's ROE automatically reverts to industry-level ROE when it exceeds the forecast horizon. The use of the PEG ratio implies that abnormal earnings do not increase when they exceed the forecast horizon: [Lu and Ye \(2004\)](#) proved that the industry approach is better for analyzing the Chinese market. However, [Botosan and Plumlee \(2005\)](#) concluded that in the American capital market, the PEG ratio measure is a better approach because it is consistently and predictably related to various risk measures, and therefore, proves to be more reliable than other alternatives.

[Brav et al. \(2003\)](#), [Botosan and Plumlee \(2002a, 2002b\)](#), and [Francis et al. \(2004\)](#) use dividend forecasts and target prices to derive a measure of expected returns for firms based on models that consider these forecasts.

Using the CSMAR database, the averages of the high and low expected returns for 2010–2023 are used to calculate the COE. This approach aligns with previous studies ([Brav et al., 2003](#); [Botosan & Plumlee, 2002a](#)).

2.4. Control Variables

Following established practices in the finance literature, this study incorporates the market beta (BETA), book-to-market ratio (BM), and book value of equity (BE) as control variables to account for key factors influencing the cost of equity (COE). These variables have been widely validated as critical determinants of financing costs, investor risk perceptions, and firm valuation.

BETA captures a firm's sensitivity to market movements and systematic risk, where higher values reflect greater exposure to market volatility, leading investors to demand higher expected returns ([Fama & French, 1992, 1993](#)). Including BETA ensures that market-wide risks, a foundational determinant of equity pricing, are properly controlled for.

BM, defined as the ratio of book value to the market value of equity, serves as a proxy for both valuation risk and growth opportunity. Higher BM ratios often signal undervaluation or financial distress, prompting investors to require higher returns ([Chen et al., 2001](#)). Additionally, BM correlates with stock price crash risk ([Hutton et al., 2009](#)), reinforcing its relevance in capturing firms' underlying vulnerability to asymmetric information and valuation shifts.

The BE reflects a firm's financial strength and stability. Firms with larger book equity tend to face lower perceived risk from investors, resulting in reduced COE ([Botosan, 1997](#); [Liang & Mao, 2019](#)). In the Chinese context, where financial reporting standards and government interventions can amplify the signaling role of financial strength, controlling for BE is particularly important for isolating firm-specific effects on COE.

Together, these control variables address systematic risk, firm valuation risk, and financial health, and are commonly emphasized in the cost of equity and crash risk research ([Francis et al., 2004](#); [Liu & Ren, 2019](#)). Moreover, by incorporating firm-level fixed effects and clustering standard errors at the firm level, the analysis accounts for additional variable bias and within-firm correlations over time. This ensures that unobserved firm characteristics or structural differences across firms do not confound the estimated impact of crash risk on the COE.

2.5. Cross-Sectional Dependence Tests

Given the nature of our panel, with a large N and small T , the Friedman, Frees, and Pesaran tests (Friedman, 1937; Frees, 1995, 2004; Pesaran, 2020) are well suited.

The Lagrange Multiplier (LM) test was developed by Breusch and Pagan (1980) and is presented in Equation (8):

$$LM_{BP} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{P}_i^2 \quad (8)$$

where \hat{P}_i^2 is the correlation coefficient between the residuals derived from panel model estimates. Under the null hypothesis (H_0), there is an asymptotic chi-square distribution (χ^2) concerning the LM statistic, with degrees of freedom of $N(N - 1)/2$. i , j , and T are derived from the panel model equation with $t = 1, 2, \dots, T$. Following this equation, Pesaran (2020) proposed another alternative:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{P}_{ij} \right) \quad (9)$$

Unlike the LM statistic, CD has a mean of exactly zero for fixed values of T and N under an extensive range of panel data models such as nonstationary, dynamic, homogeneous, and heterogeneous models.

Friedman's statistic is derived from the average Spearman's correlation, and is expressed as follows:

$$R_{ave} = \frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N \hat{r}_{ij} \quad (10)$$

where \hat{r}_{ij} is the sample estimate of the rank correlation coefficient of residuals. A large value of R_{ave} indicates the presence of non-zero cross-sectional correlations. The present model and the CD statistic involve the sum of pairwise correlation coefficients rather than the sum of squared correlations used in the LM test.

However, if a check of whether any cross-sectional dependence is left out in the disturbance is to be conducted, CD and R_{ave} lack the power to detect it. However, this drawback does not affect the Frees statistic. This method is based on the sum of the squared rank correlation coefficients.

$$R_{ave}^2 = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{r}_{ij}^2 \quad (11)$$

A function of this statistic follows a joint distribution of two independently drawn χ^2 variables.

2.6. Slope Homogeneity Test

Pesaran and Yamagata (2008) developed a standardized dispersion statistic that covers a larger spectrum of analysis. Unlike Swamy's (1970) model, which is limited to models in which N is smaller than T , the Pesaran and Yamagata models consider this and extend it to wider panels. The model can be represented as follows:

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1} \tilde{s} - k}{\sqrt{2k}} \right) \quad (12)$$

where \tilde{s} is a modified version of [Swamy's \(1970\)](#) slope homogeneity test.

$$\tilde{s} = \sum_{i=1}^N (\ddot{\beta}_i - \hat{\beta}_{WFE}) \frac{\mathbf{x}'_i \mathbf{M}_Y \mathbf{x}_i}{\tilde{\sigma}_i^2} (\ddot{\beta}_i - \hat{\beta}_{WFE}) \quad (13)$$

where $\ddot{\beta}_i$ represents the pooled Ordinary Least Squares (OLS) estimator, $\hat{\beta}_{WFE}$ the pooled estimator of the weighted fixed effect, \mathbf{M}_Y the identity matrix, and $\tilde{\sigma}_i^2$ is the estimator of σ_i^2 .

In addition, the small-sample properties of the Δ test can be improved with normally distributed errors if the following variance- and mean-bias-adjusted versions are used:

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1} \tilde{s} - E(\tilde{z}_{it})}{\sqrt{\text{var}(\tilde{z}_{it})}} \right) \quad (14)$$

with $E(\tilde{z}_{it}) = k$, and $\text{var}(\tilde{z}_{it}) = 2k(T - k - 1)/(T + 1)$

2.7. Bootstrap Panel Granger Causality Test

Bootstrap panel Granger causality, according to [Kónya \(2006\)](#), was applied in this study. This requires cross-sectional, company-specific heterogeneity. The model designed by [Kónya \(2006\)](#) accounts for cross-sectional dependence and company-specific heterogeneity. Specifically, this approach is based on Seemingly Unrelated Regression (SUR). Thus, it can address cross-sectional dependence, whereas Wald tests with company-specific bootstrap critical values can determine the direction of causality. Another advantage of this method is that it does not require pretesting of the panel unit root or co-integration.

The bootstrap panel Granger causality approach is formulated as follows:

$$\begin{aligned} y_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{ly_1} \beta_{1,1,i} y_{1,t-i} + \sum_{i=1}^{lx_1} \delta_{1,1,i} x_{1,t-i} + \varepsilon_{1,1,t} \\ y_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{ly_1} \beta_{1,2,i} y_{2,t-i} + \sum_{i=1}^{lx_1} \delta_{1,2,i} x_{2,t-i} + \varepsilon_{1,2,t} \end{aligned} \quad (15)$$

$$y_{N,t} = \alpha_{1,N} + \sum_{i=1}^{ly_1} \beta_{1,N,i} y_{N,t-i} + \sum_{i=1}^{lx_1} \delta_{1,N,i} x_{N,t-i} + \varepsilon_{1,N,t}$$

and

$$\begin{aligned} x_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{ly_2} \beta_{2,1,i} y_{1,t-i} + \sum_{i=1}^{lx_2} \delta_{2,1,i} x_{1,t-i} + \varepsilon_{2,1,t} \\ x_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{ly_2} \beta_{2,2,i} y_{2,t-i} + \sum_{i=1}^{lx_2} \delta_{2,2,i} x_{2,t-i} + \varepsilon_{2,2,t} \end{aligned} \quad (16)$$

$$x_{N,t} = \alpha_{2,N} + \sum_{i=1}^{ly_2} \beta_{2,N,i} y_{N,t-i} + \sum_{i=1}^{lx_2} \delta_{2,N,i} x_{N,t-i} + \varepsilon_{2,N,t}$$

where y represents the cost of equity variable (COE), and x denotes the stock price and control variables (NCSKEW/COE, DUVOL/COE, BETA/COE, BM/COE, BE/COE). The lag length is represented by l , and N represents the number of panel members ($j = 1, 2, \dots, N$).

To test for bootstrap panel Granger causality following this system, alternative causal relations are likely to be found for panel members j (listed companies): (i) One-way Granger causality exists from X to Y if not all $\delta_{1,j,i}$ are zero, but all $\beta_{2,j,i}$ are zero. (ii) There exists one-way Granger causality from Y to X if all $\delta_{1,j,i}$ are zero, but not all $\beta_{2,j,i}$ are zero. (iii) There exists two-way Granger causality between X and Y if neither $\delta_{1,j,i}$ nor $\beta_{2,j,i}$ is zero. (iv) There is no Granger causality between X and Y if $\delta_{1,j,i}$ and $\beta_{2,j,i}$ are zero.

2.8. Markov Model

A Markov-switching dynamic regression model is used in this study. Financial markets alternate between states, for example, bear markets with significant price declines, bull markets with rising prices, and increased investor optimism. These regimes affect daily financial activities and broader economic trends. This study examines both bull (high returns and low volatility) and bear markets (low returns and high volatility). Following [Bautista \(2003\)](#), market volatility is modeled as an unobserved first-order K -th-state Markov process, with transition probabilities estimating the likelihood of shifts between these states.

$$p\left(s_t = \frac{k}{s_{t-1}} i\right) = p_{ij} \quad (17)$$

where P_{ij} is the probability that state j will follow state i . [Ertugrul and Ozturk \(2013\)](#) later specified that, for the first-order Markov assumption, it is necessary that the probability of being in a state depends entirely on the former state. Equation (18) shows the simplified transition probability matrix according to [Coskun et al. \(2017\)](#).

$$p = \begin{vmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{vmatrix}, \text{ where } \sum_{j=1}^2 p_{ij} = 1 \quad (18)$$

2.9. Threshold Model

Threshold regression models are particularly valuable for capturing the nonlinear dynamics and structural breaks in economic relationships that linear models often fail to detect. Originally introduced by [Tong \(1983\)](#) through the threshold autoregressive (TAR) framework, such models allow regression coefficients to vary across regimes defined by a threshold variable. This flexibility enables more accurate modeling of asymmetric responses to economic shocks. Applications in the recent literature, such as [Kourtellos et al. \(2017\)](#), [Chen et al. \(2023\)](#), and [Yang \(2024\)](#), demonstrate their relevance in identifying structural heterogeneity in macroeconomic and financial data.

Let y_t be the dependent variable and x_t be a $1 \times k$ vector of covariates (that may include lagged values of y_t). The parameter vector β (of dimension $k \times 1$) is assumed to be invariant across regions, and ϵ_t represents an independently and identically distributed error term. Additionally, let z_t denote a vector of exogenous variables with region-specific coefficients δ_1 and δ_2 , and let ω_t be the threshold variable. A threshold regression with two regions defined by threshold γ is written as in Equation (19):

$$\begin{aligned} y_t &= x_t \beta + z_t \delta_1 + \epsilon_t & \text{if } \omega_t \leq \gamma \\ y_t &= x_t \beta + z_t \delta_2 + \epsilon_t & \text{if } \omega_t > \gamma \end{aligned} \quad (19)$$

2.10. Methodological Justification

The empirical strategy employed in this study was designed to capture the causal, nonlinear, and regime-dependent dynamics linking stock price crash risk to the cost of equity (COE) in China's segmented capital markets.

The bootstrap panel Granger causality model ([Kónya, 2006](#)) is chosen for its ability to establish directionality in the crash risk–COE relationship while addressing cross-sectional dependence and slope heterogeneity, two econometric concerns especially relevant in a context in which firms are exposed to correlated macroeconomic and sentiment-driven shocks (as confirmed by Pesaran and Frees tests in Table A4).

To address market regime shifts, we used the Markov-switching dynamic regression model, which captures the unobserved changes between bull and bear markets. This approach allows the crash risk–COE relationship to evolve across regimes and aligns

with behavioral finance theory, which suggests that investor reactions to risk are state-contingent. The model estimates both the magnitude of crash risk effects and the probability of transitioning between market states, providing a dynamic lens through which H3 is tested.

The third component of the methodology is the panel threshold regression (PTR) model (Hansen, 1999), which explicitly identifies threshold levels in crash risk variables, beyond which their marginal effect on COE shifts significantly. Unlike Markov-switching models, PTR does not rely on latent states but instead uses data-driven thresholds to delineate investor behavior under low- and high-risk regimes. This technique captures the structural asymmetries and nonlinearities in how crash risk is priced, offering additional empirical depth to regime-dependent analysis.

Together, these three models form a complementary and rigorous empirical framework: Granger causality identifies whether crash risk leads to higher COE; Markov switching detects how this relationship changes under different market sentiments, and threshold regression pinpoints observable risk levels that trigger changes in investor response.

This integrated approach ensures that the analysis captures not only causality, but also behavioral and structural heterogeneity, which defines financing costs in emerging and segmented financial markets.

3. Results and Discussion

The empirical results begin by illustrating the key differences in financing costs and crash risks between A-shares and B-shares, which are consistent with China's segmented market structure. As shown in Table A1, A-shares, primarily held by domestic investors, exhibit a substantially higher mean cost of equity (COE) (0.3038) than B-shares (0.0629). This finding suggests that domestic investors require higher returns to compensate for greater perceived risks and regulatory frictions, consistent with Piotroski et al. (2014) and more recent insights from He et al. (2021) on investor sensitivity in emerging markets. Additionally, A-shares demonstrate greater variability in crash risk measures (NCSKEW and DUVOL), indicating heightened market friction, disclosure opacity, and investor uncertainty, thus reinforcing the findings of Fan and Gao (2024) and Qian et al. (2025).

To preliminarily assess the relationship between crash risk and COE, pairwise correlation analyses were conducted (Table A2). Two baseline panel regressions were then estimated separately for A- and B-shares (Table A3), regressing COE on crash risk proxies (NCSKEW and DUVOL) while controlling for key firm characteristics: BETA, BM, and BE. These control variables were selected based on their well-documented influence on equity pricing and crash risk sensitivity (Fama & French, 1993; Chen et al., 2001; Liang & Mao, 2019).

3.1. The Soundness of the Estimate of the Cost of Equity

The reliability of the cost of equity (COE) estimates was assessed against theoretical expectations and empirical evidence. Consistent with the capital asset pricing model (CAPM) framework articulated by Fama and French (1993), market beta is expected to positively reflect systematic risk, with higher beta values leading to a higher COE. Our results confirm this expectation: beta exhibits a positive and statistically significant association with COE for both A-shares and B-shares, aligning with the findings on beta risk-pricing dynamics in emerging markets (Wang et al., 2022).

The book-to-market (BM) ratio also plays a pivotal role in shaping COE. Higher BM ratios, which are typically interpreted as indicators of undervaluation or heightened firm-specific risk, are associated with higher financing costs. As Table A3 shows, BM positively correlates with COE for both A-shares (coefficient = 0.1912, $p < 0.01$) and B-shares (coefficient = 0.0249, $p < 0.05$). These findings are consistent with the asset pricing literature

emphasizing BM as a key risk factor (Chen et al., 2001; Fama & French, 2015) and recent work by Zhao et al. (2024), who underscore BM's predictive power for financing costs across different market regimes.

In addition, the negative relationship between COE and the book value of equity (BE) reflects the role of financial strength in mitigating perceived risk. Firms with larger BE tend to enjoy lower COE because financial robustness reassures investors and lowers risk premiums. For A-shares, the coefficient of BE is -0.0106 ($p < 0.01$), confirming a significant reduction in the financing costs for financially stronger firms, whereas the effect of B-shares is smaller and statistically insignificant (-0.0003). This pattern echoes previous studies (Botosan, 1997; Liang & Mao, 2019) and reinforces the notion that information asymmetry and financial disclosure play critical roles in emerging markets (Chen et al., 2023).

The adjusted R-squared values (ranging from 12.35% to 14.30% for A-shares and from 12.59% to 13.24% for B-shares) indicate a reasonably strong model fit, comparable to earlier research such as Botosan (1997), who reported an adjusted R-squared value of 13.7% in a similar context. The inclusion of both beta and BM improves explanatory power, suggesting that COE is driven not only by exposure to systematic market risk but also by valuation signals embedded in firm fundamentals.

Overall, the consistency of these relationships across stock types and market segments validates the robustness of the COE estimates. It also underscores the importance of incorporating firm-specific valuation and stability metrics into the cost of equity modeling, a point increasingly emphasized in the corporate finance literature (Saleem & Usman, 2021; Bose et al., 2024).

3.2. Preliminary Results

The preliminary correlation analysis (Table A2) reveals a significant positive association between stock price crash risk (measured by both NCSKEW and DUVOL) and cost of equity (COE), providing strong support for H1. This result is consistent with Liu and Ren (2019) and Saleem and Usman (2021), who found that firms facing higher crash risk are subject to elevated capital costs owing to the increased risk premiums demanded by investors. This also aligns with Jin and Myers (2006), who argue that crash risk amplifies information asymmetry, compelling investors to require higher returns to compensate for greater uncertainty.

This positive relationship persists for both A-shares and B-shares but differs in magnitude, reflecting the underlying differences in market segmentation and investor composition. Supporting Hypothesis H2, the effect is notably stronger for A-shares, suggesting that domestic investors are constrained by limited diversification options, regulatory frictions, and a heavier reliance on market signals that are more sensitive to crash risks (Piotroski et al., 2014; Junxia & Qinsong, 2019; Liang & Mao, 2019). In contrast, the weaker association between crash risk and COE for B-shares is consistent with Liang and Mao (2019), who emphasize that foreign investors can better mitigate crash-related risks through international portfolio diversification. This finding contrasts with that of Callen and Fang (2011), who implicitly assume uniform investor behavior across segmented markets, thereby highlighting the critical role of ownership structures and market segmentation in shaping crash risk perceptions.

With $T = 14$ and $N = 2113$ (108), the total observations for A- and B-shares are 29,582 and 1512, respectively, as shown in Table A1. Given the panel structure with a large N and small T , the Friedman, Frees, and Pesaran tests (Friedman, 1937; Frees, 1995, 2004; Pesaran, 2020) are well suited.

Cross-sectional dependence tests (Table A4) indicate strong interdependencies across the panels. Specifically, the highly significant p -values (0.0000) from the Pesaran and

Friedman tests reject the null hypothesis of no cross-sectional dependence. Similarly, Frees' test corroborates these findings, confirming the significant cross-sectional correlations among the panel residuals at the conventional significance levels. Such outcomes align with [Frees \(2004\)](#), who emphasized the commonality of cross-sectional dependence in interconnected financial markets. These diagnostic results explicitly highlight that the residual terms from the initial regressions (reported in Table A3) are interdependent, violating the assumption of independence required by OLS regressions. Consequently, the presence of significant cross-sectional dependence implies that firm-specific shocks and industry-level factors systematically influence multiple firms simultaneously, thereby affecting the crash risk and COE dynamics. Recognizing this issue, subsequent analyses explicitly address cross-sectional dependence by employing more robust methodologies, such as bootstrap panel Granger causality and Markov-switching dynamic regression models, which account for these interdependencies ([Liang & Mao, 2019](#)).

To further assess panel heterogeneity, [Pesaran and Yamagata's \(2008\)](#) test was applied, accounting for firm-specific characteristics and ownership structures in China's segmented A- and B-share markets. Identifying heterogeneity ensures that firm-level differences in crash risk and COE are accurately captured, thereby enhancing the robustness of the study's findings.

The null hypothesis H0 of the slope homogeneity is $\beta_i = \beta$ for each i compared with the heterogeneity hypothesis H1, which states $\beta_i \neq \beta_j$ for pairwise slopes and is a non-zero fraction for $i \neq j$.

The analysis results (Table A4) reject the null hypothesis of homogeneous coefficients. Therefore, any significant corporate relationship or change in one A-share (similar to B-share) listed company will not be replicated in other companies. Therefore, companies are affected by specific characteristics.

From the previous analysis, bootstrap panel Granger causality, according to [Kónya \(2006\)](#), is applied.

The causality test results can be sensitive to the lag structure, making the selection of the optimal lag length crucial for robustness. Following [Kónya \(2006\)](#), lags were allowed to vary across variables but remained consistent across equations. Schwarz Bayesian criterion (SBC) was used to select the optimal lag length.

The Granger causality tests (Table A5) present evidence aligned with Hypotheses H1 and H2, organizing results by hypothesized causal pathways for clearer interpretation. Panel A focuses on the causal effects of crash risk variables (NCSKEW and DUVOL) on the cost of equity (COE), while Panel B evaluates the role of segmentation-related variables across A- and B-shares. The results strongly support H1, demonstrating that heightened crash risk significantly increases COE, although the strength and nature of these effects differ between A-shares and B-shares. For A-shares, both NCSKEW and DUVOL have significant Granger causality with the COE, confirming that increased crash risk exposure leads to higher financing costs. This finding aligns with [Liu and Ren \(2019\)](#) and [Piotroski et al. \(2014\)](#), who emphasize the role of regulatory frictions and limited diversification opportunities in magnifying domestic investors' sensitivity to crash risk. This also resonates with [Fan and Gao \(2024\)](#), who highlight that Chinese domestic investors are particularly reactive to asymmetric information shocks in volatile market environments.

For B-shares, while NCSKEW and DUVOL also have significant Granger causality with COE, the book-to-market (BM) ratio does not exhibit significant causality, as shown in Panel B. This finding supports H2 and suggests that foreign investors prioritize global diversification over firm-specific valuation metrics, as emphasized by [Liang and Mao \(2019\)](#) and reinforced by [Qian et al. \(2025\)](#), who document that foreign participation in

Chinese markets leads to diminished sensitivity to firm-level fundamentals relative to macroeconomic and global risk factors.

A comparison of the causality results (Table A5) with the baseline OLS regressions (Table A3) highlights the notable differences. Several variables that are significant under standard OLS regressions lose significance or change their causal direction in the Granger causality framework. This discrepancy reflects the OLS model's failure to account for cross-sectional dependence and firm-level heterogeneity (see Table A4). In contrast, the bootstrap panel Granger causality approach corrects for these econometric limitations, offering more credible causal inferences in line with [Kónya \(2006\)](#) and consistent with the recommendations of [Chen et al. \(2023\)](#) on robust causal identification in financial panels.

Although Table A5 centers on the unidirectional hypotheses tested (H1 and H2), additional analyses reveal patterns of reverse and bidirectional causality that are not included in the table. For A-shares, BETA has significant Granger causality with COE but not vice versa, suggesting that systematic risk exposure predominantly drives financing costs, consistent with the CAPM logic ([Fama & French, 1993](#); [Gode et al., 2005](#)). In B-shares, COE does not have Granger causality with BM or BE, highlighting that foreign investors de-emphasize firm-specific financial characteristics. This is in line with [Callen and Fang \(2011\)](#) and is further supported by [Zhao et al. \(2024\)](#), who argued that foreign investors tend to price macro-level risks more heavily than idiosyncratic firm factors.

The bidirectional causality observed between the BM and COE exclusively in A-shares reinforces the notion that domestic investors are more attentive to valuation metrics. This is consistent with [Junxia and Qinsong \(2019\)](#) and aligns with recent insights from [Fan and Gao \(2024\)](#), who show that valuation-related information exerts a stronger influence on domestic investment behavior under market segmentation.

Interestingly, BE shows no causal effect on COE for A-shares but has significant Granger causality with COE for B-shares. This pattern suggests that financial stability remains relatively undervalued by domestic investors but is an important determinant of risk premiums demanded by foreign investors ([Saleem & Usman, 2021](#); [Qian et al., 2025](#)). The asymmetric influence of BE underscores the heterogeneity in investor preferences and the informational channels through which crash risk translates into financing costs.

Furthermore, the detected causality from COE to BE for A-shares implies that firms strategically adjust their financial structures in response to shifts in their financing costs. This strategic behavior is in line with signaling models under asymmetric information ([Diamond & Verrecchia, 1991](#)) and mirrors the findings of [Chen et al. \(2023\)](#), who document that firms in emerging markets engage in balance sheet adjustments to influence investor perceptions amid heightened financing pressure.

Collectively, these findings highlight that market segmentation, ownership structures, and investor heterogeneity critically shape the relationship between stock price crash risks and equity costs. They reaffirm the broader theoretical insights proposed by [Jin and Myers \(2006\)](#) and extend them by demonstrating how these dynamics manifest empirically in the dual-share structure of China's capital markets.

Beyond validating H1 and H2, the Granger causality analysis reveals intricate feedback loops and asymmetric causal patterns, underscoring the necessity for robust, heterogeneity-consistent estimation approaches in analyzing financial risks and costs in segmented emerging markets.

3.3. Robustness Check

3.3.1. Markov Model

To enhance robustness, static analysis was extended using a Markov-switching dynamic regression model.

The dynamic regression results presented in Table A6 confirm and extend the static analysis findings, reinforcing the significant influence of stock price crash risk (measured by NCSKEW and DUVOL) on the cost of equity (COE) across different market conditions. Consistent with [Ertugrul and Ozturk \(2013\)](#), who stress the importance of regime-dependent dynamics in financial risk studies, this analysis illustrates that the crash risk–COE relationship is sensitive to shifts between bull and bear markets.

Crash risk measures significantly raise COE under both regimes, with notably stronger effects for A-shares, reflecting domestic investors' heightened vulnerability to market volatility ([Piotroski et al., 2014](#)). [Fan and Gao \(2024\)](#) further corroborate this finding, highlighting that Chinese domestic investors exhibit disproportionate risk sensitivity in response to asymmetric information shocks, particularly during periods of market turbulence. The persistent divergence between A- and B-shares across regimes emphasizes the enduring impact of market segmentation on China's capital markets.

Moreover, the results reveal that COE increases more sharply in bull markets, which is consistent with [Junxia and Qinsong \(2019\)](#), who find that heightened investor optimism amplifies downside risk concerns. This regime asymmetry is particularly pronounced among A-shares, where transitions from bull to bear markets are less frequent ($p_{21} = 39.74\%$) than those among B-shares ($p_{21} = 89\%$), suggesting greater volatility and faster sentiment shifts among foreign investors. These transition probabilities align with [Liang and Mao \(2019\)](#), who observed that foreign investors adjust more rapidly to changing market conditions, driven by global risk considerations.

These findings collectively validate H3, confirming that heightened investor optimism in bull markets intensifies the relationship between crash risk and financing costs. This aligns with the theoretical perspectives proposed by [Jin and Myers \(2006\)](#) and is empirically consistent with the evidence presented by [Qian et al. \(2025\)](#), who document stronger risk–price relationships during optimistic market phases in emerging economies.

Systematic risk, proxied by BETA, also plays a crucial role in determining COE, especially in bull markets. Its positive and significant effect across regimes supports earlier findings by [Gode et al. \(2005\)](#), and is consistent with those of [Zhao et al. \(2024\)](#), who emphasize that investors' sensitivity to systematic factors strengthens during periods of elevated market optimism.

The behavior of valuation metrics reveals regime-dependent patterns. BM positively impacts COE in bear markets for both share classes, reflecting investors' heightened risk aversion during downturns ([Chen et al., 2001](#)). However, for A-shares, the BM's effect turns negative in bull markets, suggesting that domestic investors interpret undervaluation as a favorable signal during optimistic periods. This differentiated behavior is consistent with [Fan and Gao \(2024\)](#), who show that A-share investors exhibit stronger valuation focus under positive market sentiment. In contrast, B-share investors' valuation responses remain relatively muted, consistent with their broader international diversification strategies.

The book value of equity (BE) also demonstrates segmented effects. For A-shares, the BE consistently lowers the COE across regimes, underscoring the stabilizing influence of financial strength and the role of implicit government protection in the domestic market ([Chen et al., 2023](#)). Conversely, for B-shares, BE positively impacts COE in bear markets, suggesting that foreign investors may interpret increases in book equity as signals of hidden risks or inefficiencies ([Saleem & Usman, 2021](#)).

Overall, the Markov-switching dynamic regression results indicate that the relationship between crash risk and COE is not static, but highly regime-dependent. Investor behavior, ownership structure, and market segmentation significantly influence how crash risk is priced in bull-and-bear markets. This confirms that firms must adopt regime-specific

risk management strategies to mitigate the financial consequences of crash risks, especially during periods of elevated optimism when downside risks are often underpriced.

Unlike traditional studies that focus solely on static relationships, this analysis highlights the necessity of dynamic modeling approaches to fully capture the nuances of financing costs under market segmentation (Liang & Mao, 2019; Qian et al., 2025). By integrating crash risk exposure, investor behavior, and market regime dynamics, this study offers actionable insights into capital management strategies for firms operating in segmented and volatile financial environments.

3.3.2. Threshold Model

Given the panel structure of our dataset and the likelihood of firm-specific heterogeneity, we employed the panel threshold regression (PTR) model developed by Hansen (1999), which is specifically designed for short- and large-N panels. This approach allows us to estimate the threshold level of stock price crash risk proxied by NCSKEW and DUVOL at which the marginal effect on the cost of equity (COE) shifts significantly. The model accounts for firm-level fixed effects to control for unobserved heterogeneity, and allows regime-dependent slope coefficients. To ensure robustness, standard errors are heteroscedasticity-consistent and clustered at the firm level to address within-firm autocorrelation over time.

Panel threshold regression (PTR) analysis further validates the nonlinear relationship between stock price crash risk and cost of equity (COE), complementing the regime-dependent dynamics identified by the Markov-switching model. Tables A7 and A8 present the PTR results, with NCSKEW and DUVOL serving as threshold variables to define low- and high-risk regimes.

The threshold regression results based on NCSKEW (Table A7) reveal a clear regime shift in the impact of crash risk on COE for both A-shares and B-shares. For A-shares, the coefficient of NCSKEW increases sharply from 1.1232 (State 1, low crash risk) to 0.1021 (State 2, high crash risk), and both are statistically significant. This significant reduction in sensitivity under high-crash-risk conditions suggests that once crash risk exceeds a critical threshold, investors adjust their pricing expectations more conservatively, consistent with risk-pricing theories (Jin & Myers, 2006). It also echoes the findings of Fan and Gao (2024), who argue that, in high-risk environments, investors in emerging markets become relatively less responsive to marginal increases in negative signals, reflecting risk-saturation behavior.

Similarly, for B-shares, although both coefficients are significant, the sensitivity is reversed: NCSKEW has a larger effect in the high-crash-risk regime (0.2419) than in the low-risk regime (0.101), suggesting that foreign investors react more strongly when the crash risk surpasses a critical point. This pattern aligns with Qian et al. (2025), who show that foreign investors in segmented markets adjust more aggressively to extreme downside signals than domestic investors do.

DUVOL-based thresholds (Table A8) further confirmed these dynamics. For A-shares, DUVOL's effect on COE is stronger in the low-risk regime (coefficient = 10.5824) than in the high-risk regime (coefficient = 0.2063), again consistent with domestic investors showing risk saturation once crash risk becomes excessive. By contrast, for B-shares, although the coefficients remain positive across regimes, their relative magnitudes are less pronounced (0.7013 and 0.2663, respectively), suggesting more measured responses from foreign investors.

Importantly, the threshold regressions also reveal structural heterogeneity in how the control variables affect COE across regimes. For example, BETA exhibits significantly stronger effects on COE in low-risk regimes for A-shares (0.2291 for the NCSKEW model; 0.4181 for the DUVOL model), supporting the notion that systematic risk pricing is more

prominent when market sentiment is optimistic (Gode et al., 2005; Zhao et al., 2024), which increases COE in bear markets but shows regime-dependent reversals for A-shares. This reinforces Fan and Gao's (2024) finding that valuation concerns fluctuate with market sentiment, and BE consistently exhibits insignificant or weak effects across regimes for A-shares but shows differentiated signs for B-shares, underscoring that foreign investors interpret financial strength signals differently depending on crash risk regimes (Saleem & Usman, 2021; Chen et al., 2023).

Thus, the PTR analysis strongly supports H3, confirming that the impact of crash risk on financing costs is nonlinear and regime-dependent and shaped by both market segmentation and investor heterogeneity.

Moreover, compared with baseline panel regressions and Granger causality tests, the PTR approach offers richer insights by explicitly identifying the threshold levels at which investor behavior fundamentally shifts. This refinement addresses the call for models capable of capturing nonlinearities and discontinuous investor responses to crash risk (Bose et al., 2024).

Overall, the PTR results robustly validate the central proposition that crash risk significantly and causally increases the cost of equity in segmented markets, with the effect varying depending on investor type, ownership structure, and market regime.

3.4. Implications of the Findings

The empirical findings from this study offer important implications for corporate managers, investors, and policymakers operating in segmented and behaviorally diverse capital markets such as China's A- and B-share structures.

For corporate managers, evidence that crash risk significantly increases the cost of equity, especially in A-shares dominated by domestic investors, underscores the necessity of improving corporate transparency, financial disclosures, and governance mechanisms. Enhanced disclosure practices can reduce information asymmetry, mitigate investor uncertainty, and lower financing costs. In bull markets, where investor optimism can exaggerate sensitivity to downside risk, firms should be especially proactive in stabilizing expectations and managing narrative control.

For investors, this study highlights that the pricing of crash risk is highly sensitive to both market regimes and investor types. Domestic investors in A-shares appear more sensitive to firm-specific crash signals under bullish conditions, whereas foreign investors in B-shares react more strongly when risk thresholds are surpassed. These patterns suggest the need for investors to calibrate their risk assessment models by incorporating regime switches and threshold effects when pricing securities, particularly in emerging markets, where behavioral biases may be more pronounced.

For policymakers and regulators, the results support the need for nuanced regulatory frameworks that consider behavioral segmentation. Measures such as promoting information transparency, encouraging the diversification of domestic portfolios, and ensuring the consistent enforcement of disclosure rules can help reduce systemic vulnerability. Additionally, understanding how investor sentiment and information flow influence pricing under different regimes can lead to more responsive and market-stabilizing interventions.

Finally, the regime- and threshold-dependent nature of the crash risk–COE relationship implies that traditional linear policy and investment models may overlook important dynamics. Future policy designs should integrate the nonlinear behavior of market participants, particularly during optimistic phases when risk mispricing is more likely to occur. This underscores the importance of adopting dynamic, behaviorally grounded approaches to risk regulation and capital market development.

4. Conclusions

This study rigorously examines the causal relationship between stock price crash risk and cost of equity (COE) in China's segmented A- and B-share markets by applying a combination of static and dynamic methodologies. The findings consistently reveal that heightened crash risk leads to a significantly elevated COE, with the effect being particularly pronounced in the A-share market, where less globally diversified and domestically focused investors dominate. The application of Markov-switching dynamic regression models and panel threshold regression (PTR) further reveals that this relationship is regime-dependent, intensifying in bull markets when heightened investor optimism amplifies sensitivity to downside risks. These results underscore the complex interplay between market segmentation, ownership structures, investor behavior, and market regimes, which are particularly salient in several market contexts.

This study makes three key contributions to the literature. First, it moves beyond traditional correlation-based studies by providing rigorous causal evidence that links crash risk to COE, utilizing bootstrap panel Granger causality and threshold modeling to establish directionality and robustness. Second, it demonstrates that the crash risk–COE relationship is nonlinear and varies systematically with market regime, a dimension largely overlooked in prior research. The combined use of Markov-switching dynamic regression and panel threshold regression frameworks more comprehensively captures these nonlinearities and structural shifts. Third, it highlights the critical importance of ownership segmentation and investor sophistication in financial decision making and risk pricing. The findings illustrate that domestic and foreign investors exhibit asymmetric responses to crash risk across different market conditions, thus providing deeper insight into how structural factors shape capital costs.

The practical implications of this study are multi-faceted. For corporate managers, particularly those operating in the A-share segment, the results emphasize the need to strengthen corporate transparency, disclosure practices, and governance frameworks to mitigate domestic investors' heightened crash risk sensitivity. In bull markets, particular attention should be paid to stabilizing investor expectations to prevent disproportionate increases in financing costs. For policymakers, evidence advocates refined regulatory strategies that consider segmented market behavior. Initiatives promoting greater information transparency, broadening domestic investor participation, and managing foreign investor sentiment during market upswings can significantly enhance market resilience and reduce systemic vulnerability. For investors, the results highlight the need to adapt risk-assessment frameworks to account for both ownership structures and market regimes. Domestic investors must remain vigilant during bullish periods, when optimism can obscure accumulating risks, whereas foreign investors should intensify their monitoring of firm fundamentals during downturns, when hidden financial fragilities are likely to surface.

However, this study had several limitations. Focusing exclusively on China's A- and B-share markets may constrain the generalizability of our findings to other institutional and regulatory contexts. Moreover, although NCSKEW and DUVOL are well-established proxies for crash risk, they may not fully capture slow-building or extended low-return scenarios. Other dimensions, such as governance-related indicators, sentiment indices, and implied volatility skewness measures, were not included because of data constraints. Furthermore, the exclusion of financial firms due to their unique regulatory and leverage characteristics limits the sectoral breadth of conclusions.

Future research could broaden the scope by incorporating alternative crash risk measures such as managerial opacity indices (Hutton et al., 2009) or implied volatility skewness metrics to better capture the different dimensions of crash risk. Examining mechanisms

such as insider trading could deepen the understanding of how information asymmetry channels influence the crash risk–COE nexus. Simulation-based approaches can be used in parallel with empirical models to illustrate the dynamic mechanisms under controlled conditions. Integrating direct sentiment measures (e.g., survey-based or media tone indices) would allow a more explicit behavioral interpretation of regime-dependent effects. Methodologically, future studies could also consider smooth transition or multiple-threshold models (e.g., STR and LSTR) to capture complex nonlinear dynamics more finely, particularly in smaller panels or macro-level applications.

Furthermore, integrating alternative COE estimation models (e.g., [Claus & Thomas, 2001](#)) could enhance robustness, while comparative cross-country studies could illuminate how institutional maturity and regulatory quality shape the crash risk–COE relationship. Finally, incorporating behavioral finance perspectives could enrich future research by exploring how investor sentiment, cognitive biases, and psychological factors interact with market regimes to shape capital costs.

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Appendix A

Variables' Definitions

Variables	Definition
COE	This is the measure of the cost of equity, which is calculated using dividend forecasts and target prices to derive an estimate of expected return for firms, using models for valuation that integrate these forecasts. The method is close to the ones used by Brav et al. (2003) , Botosan and Plumlee (2002a, 2002b) , and Francis et al. (2004) .
NCSKEW	Short for Negative Coefficient Skewness, it is the negative of the third moment of firm-specific weekly returns for each firm and year divided by the standard deviation of firm-specific weekly returns raised to the third power.
DUVOL	Short for down-to-up volatility, it is the log of the ratio of the standard deviation of the “down-weeks” over the standard deviation of the “up-weeks”.
BETA	BETA is the market beta estimated from CSMAR data over 60 months before a firm-year fiscal year-end observation.
BM	Book-to-market value of securities published by the Shanghai Exchange and the Shenzhen Stock Exchange, covering fourteen years and calculated as the ratio of total assets/market value.
BE	Book value of equity of securities published by the Shanghai Exchange and the Shenzhen Stock Exchange, covering fourteen years.

Table A1. Descriptive statistics.

Variable	No of Firm-Years	No of Unique Firms	Mean	Std. Dev.	Min	Max	Median
A-shares							
COE	29,582	2113	0.3038	0.6839	0.0095	2.6127	0.1650
NCSKEW	29,582	2113	-0.5450	1.4560	-3.4825	2.8606	-0.5074
DUVOL	29,582	2113	-0.0735	0.3050	-0.7917	0.6691	-0.0538
BETA	29,582	2113	0.6776	0.8898	0.4629	1.4410	0.9832
BM	29,582	2113	0.5513	1.2618	0.0000	1.0802	0.5523
BE	29,582	2113	3.7238	4.7973	0.0000	26.4776	2.2487
B-shares							
COE	1512	108	0.0629	0.2713	0.0006	1.0649	0.0315
NCSKEW	1512	108	-0.2971	1.4501	-3.3712	3.0085	-0.2886
DUVOL	1512	108	-0.0474	0.2911	-0.8573	0.6133	-0.0390
BETA	1512	108	0.5020	0.7989	0.2800	1.2901	0.8075
BM	1512	108	0.5524	1.3015	0.0000	1.1128	0.5847
BE	1512	108	2.3432	3.7094	0.0000	24.3875	1.3092

Notes: Table of descriptive statistics for all variables. The sample contains 29,582 firm-year observations for firms trading A-shares and 1512 firm-year observations for B-shares from 2010 to 2023.

Table A2. Pairwise correlation table of the selected variables for firms trading A- and B-shares.

Variables	COE	NCSKEW	DUVOL	BETA	BM	BE
A-shares						
COE	1.0000					
NCSKEW	0.1622 **	1.0000				
DUVOL	0.0639 **	0.7525 ***	1.0000			
BETA	0.6216 **	0.1065 ***	0.0872 ***	1.0000		
BM	0.0495 ***	-0.0349 ***	-0.0189 ***	0.0263 ***	1.0000	
BE	-0.0104 *	-0.0468 ***	-0.0232 ***	-0.0499 ***	0.1837 ***	1.0000
B-shares						
COE	1.0000					
NCSKEW	0.1133 **	1.0000				
DUVOL	0.0404 *	0.7328 ***	1.0000			
BETA	0.5544 **	0.0307 *	0.0031 *	1.0000		
BM	0.0277 *	-0.0096 *	-0.0147 *	0.0027 *	1.0000	
BE	-0.0338 *	0.0287 *	0.0380 *	0.0417 *	-0.0642 **	1.0000

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3. Panel regression.

Variables	Stock A		Stock B	
	COE	COE	COE	COE
NCSKEW	0.0455 *** (17.5)	-	0.0243 *** (14.92)	-
DUVOL	-	0.0271 ** (7.13)	-	0.0355 *
BETA	0.0197 *** (19.13)	0.0200 *** (11.14)	0.0192 *** (12.10)	0.0190 *** (12.72)
BM	0.1912 *** (12.82)	0.1997 *** (13.30)	0.0249 * (2.04)	0.0254 * (2.05)
BE	-0.0106 *** (-10.35)	-0.0101 *** (-9.72)	-0.0003 * (-0.19)	-0.0004 * (-0.27)
Intercept	0.1224 *** (5.63)	0.1229 *** (5.61)	-0.0301 * (-0.84)	-0.0213 * (-0.59)
Observations	25356	25356	1296	1296
Adj. R-square	0.4030	0.5325	0.3224	0.2259

Note: Table of panel regression results of (1) COE on NCSKEW, BETA, BM, and BE; (2) COE on DUVOL, BETA, BM, and BE, for A- and B-shares. The z-values are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Firm fixed effects included. Standard errors are heteroscedasticity-robust and clustered at the firm level.

Table A4. Cross-sectional dependence and slope homogeneity tests.

Form	Stock A				Stock B			
	Test	p-Value (a)	Test	p-Value (b)	Test	p-Value (a)	Test	p-Value (b)
Cross-sectional dependence								
Pesaran's test	273.4790	0.0000	290.6810	0.0000	91.3960	0.0000	158.6100	0.0000
Friedman's test	1013.4030	0.0000	1132.4870	0.0000	278.5600	0.0000	471.7530	0.0000
Frees' test	65.9960	0.5811 ***	83.9210	0.5811 ***	10.6680	0.5811 ***	25.3400	0.5811 ***
Slope homogeneity								
Δ^*	4.0380	0.0000	3.2280	0.0010	-4.8150	0.0000	-4.3190	0.0000
Δ^* adj.	6.9930	0.0000	5.5910	0.0000	-8.3400	0.0000	-7.4810	0.0000

Note: For stocks A and B, Equation (1) represents the first equation as per Table A3 (NCSKEW is the independent variable), and Equation (2) represents the second equation as per Table A3 (DUVOL is the dependent variable). The null hypothesis (H_0) for the cross-sectional dependence test indicates no cross-sectional dependence. (a,b) The value presented in Frees' test is the alpha from a Q distribution, *** indicates significance at the 1% level. For the slope homogeneity test, the null hypothesis is that the coefficients are homogeneous.

Table A5. Bootstrap panel Granger causality test for H1 and H2.

Share Type	Causal Relationship	Wald Statistic	10% Critical Value	5% Critical Value	1% Critical Value
Panel A: H1—Effect of Crash Risk on Cost of Equity (COE)					
A-shares	NCSKEW → COE	15.0160 **	9.7890	13.1170	16.1560
A-shares	DUVOL → COE	24.4910 **	14.4290	16.4210	31.2350
B-shares	NCSKEW → COE	14.4010 *	13.7000	15.9010	22.1170
B-shares	DUVOL → COE	14.1470 **	9.2670	10.4320	15.6910
Panel B: H2—Effect of Segmentation-Related Variables on COE (by Market Type)					
A-shares	BM → COE	20.3410 **	11.1080	14.8820	27.7310
B-shares	BM → COE	10.9670	11.0070	13.1180	17.8400

Note: ** and * indicate the rejection of the null hypothesis at the 5% and 10% levels, respectively.

Table A6. Markov-switching dynamic regression.

Variables	Stock A		Stock B	
	Bear	Bull	Bear	Bull
NCSKEW	0.0652 *** (13.68)	0.1324 *** (16.77)	0.0283 *** (17.29)	0.0305 ** (11.31)
DUVOL	0.1353 *** (10.11)	0.3441 *** (16.22)	0.0947 *** (4.92)	0.1080 *** (11.04)
BETA	0.0027 *** (12.03)	0.0401 *** (17.03)	0.0063 *** (12.05)	0.0606 *** (16.88)
BM	0.1322 *** (13.07)	-0.0980 *** (-5.76)	0.0223 * (1.76)	0.0114 (0.24)
BE	-0.0039 *** (-5.20)	-0.0034 *** (-3.57)	0.0004 * (1.84)	-0.0001 (-0.01)
Intercept	0.0981 *** (6.16)	0.0975 *** (4.97)	0.0082 (0.43)	-0.0273 (-0.39)
Sigma		0.2730 **		0.1121 **
p11		0.8106 **		0.9215 **
p21		0.3974 **		0.8900 **

Note: z-values are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Firm fixed effects are captured through regime-dependent intercepts. Standard errors are heteroscedasticity-consistent. Sigma is the standard deviation for the entire process, and p11 and p21 are the transition probabilities from one state to another. Bears represent State 1 and bulls represent State 2.

Table A7. Threshold regression (NCSKEW).

Stock A			Stock B		
Variable	State 1	State 2	Variable	State 1	State 2
NCSKEW	1.1232 ** 2.37	0.1021 *** 3.31	NCSKEW	0.101 * 1.94	0.2419 * 1.74
DUVOL	4.2282 ** 2.54	1.2391 *** 3.58	DUVOL	0.6687 * 1.75	0.6145 * 1.82
BETA	0.2291 *** −4.23	0.008 0.45	BETA	0.0257 *** −2.63	0.0236 * 1.86
BM	4.2823 *** 3.1	0.7945 1.58	BM	0.5478 *** 2.62	1.2591 *** 2.81
BE	−0.1061 −1.02	0.0132 0.44	BE	0.0091 0.9	−0.0074 −0.41
Intercept	0.4496 0.19	−0.2731 −0.31	Intercept	−0.0906 −0.49	−0.3937 −0.92
Threshold	−0.4515		Threshold		0.2991

Note: Firm fixed effects are included. Standard errors are heteroscedasticity-consistent and are clustered at the firm level. The z-values are given in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The threshold value represents crash risk (measured by the NCSKEW), separating the low- and high-risk regimes.

Table A8. Threshold regression (DUVOL).

Stock A			Stock B		
Variable	State 1	State 2	Variable	State 1	State 2
NCSKEW	0.3101 * 1.8	0.996 * 1.73	NCSKEW	0.1029 ** 2.46	0.2065 *** 3.96
DUVOL	10.5824 * 1.95	0.2063 * 1.83	DUVOL	0.7013 * 1.84	0.2663 * 1.71
BETA	0.4181 *** 13.99	0.0036 ** 2.24	BETA	0.0197 * 1.86	0.0432 * 1.93
BM	5.0598 3.97	−1.3912 *** −2.83	BM	0.5516 *** 2.66	1.1591 *** 2.91
BE	−0.0929 −1.07	0.0042 0.12	BE	0.0109 1.09	−0.0105 * −1.88
Intercept	4.528 2.29	0.1336 0.24	Intercept	−0.0665 −0.36	−0.2906 −0.75
Threshold	−0.0907		Threshold		0.1235

Note: Firm fixed effects are included. Standard errors are heteroscedasticity-consistent and are clustered at the firm level. The z-values are given in the parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The threshold value represents crash risk (measured by the DUVOL), separating the low- and high-risk regimes.

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