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Artificial Intelligence as a Risk Control Mechanism: Corporate Governance and Firm Downside Risk in China

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Abstract

Artificial intelligence (AI) is increasingly adopted in firms' information, control, and risk management systems, yet its implications for downside risk remain unclear. This study examines the association between AI investment and firm-level downside risk using panel data on Chinese non-financial listed firms from 2016 to 2024. Downside risk is measured using stock price crash risk. The results show that AI investment is negatively associated with crash risk. This finding is consistent with the view that improved internal information processing reduces the accumulation of undisclosed negative information. We further examine the role of corporate governance and find that the negative association is stronger in firms with higher executive ownership and weaker in firms with greater CEO power. Additional analyses suggest that improvements in the information environment are one channel through which AI investment is associated with lower firm risk. Overall, These findings suggest that AI investment can support firm-level risk control by improving internal monitoring and information processing, but its effectiveness depends on governance arrangements that shape managerial incentives and oversight.

Keywords: Artificial intelligence; Stock price crash risk; Corporate governance; Executive ownership; CEO power

JEL:G32, G34, O33, G14

1. Introduction

Artificial intelligence (AI) is increasingly embedded in firms' internal information, control, and risk management systems. Prior research shows that AI adoption is associated with improvements in productivity, innovation, and firm value (Brynjolfsson et al., 2021; Babina et al., 2024). However, less is known about whether AI investment affects firms' exposure to downside risk. In particular, existing research provides limited evidence on whether AI investment can mitigate stock price crash risk, a salient form of firm-level downside risk with important implications for risk management and governance.

From a risk management perspective, AI investment may operate as a firm-level control technology that improves early warning, strengthens monitoring, and facilitates the timely processing of adverse information. Stock price crash risk is commonly linked to the accumulation and delayed disclosure of bad news (Jin & Myers, 2006; Hutton et al., 2009). When managers withhold unfavorable information for an extended period, bad news is eventually released in a concentrated manner, resulting in sharp stock price declines (Kim et al., 2011). AI investment may affect this process through its role in internal information processing. On the one hand, improved data integration and monitoring may reduce the buildup of undisclosed negative information. On the other hand, the complexity of AI systems may weaken transparency or increase managerial discretion. The overall effect of AI investment on crash risk therefore remains an empirical question.

The relation between AI investment and firm risk is also unlikely to be uniform across firms. Governance structures shape monitoring intensity, decision authority, and incentive alignment (Jensen & Meckling, 1976; Shleifer & Vishny, 1997). Executive ownership may strengthen the risk-reducing role of AI by aligning managerial incentives with firm outcomes. By contrast, greater CEO power may weaken internal oversight and reduce the effectiveness of AI-based monitoring (Finkelstein, 1992). These considerations suggest that governance conditions may materially influence how AI investment relates to downside risk.

Against this background, this study examines the relation between AI investment and stock price crash risk, with particular attention to the moderating roles of executive ownership and CEO power. Using panel data on Chinese listed firms from

2016 to 2024, we test whether AI investment is associated with lower downside risk and whether this relation varies across governance structures.

This study contributes to the literature in three ways. First, it extends existing research on AI investment by shifting attention from average firm outcomes to extreme downside risk, and by framing AI as an internal risk-control technology. Second, it shows that the risk implications of AI investment depend on governance conditions, particularly executive ownership and CEO power, which shape the effectiveness of AI as a monitoring and control mechanism. Third, it offers suggestive evidence that AI investment is associated with a more favorable information environment, which is consistent with the containment of downside risk.

The remainder of the study is organized as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 describes the data and empirical methods. Section 4 presents the empirical results and additional analyses. Section 5 concludes.

2. Literature Review and Hypothesis Development

2.1. AI Investment and Firm Risk

AI investment has been widely examined in relation to firm performance outcomes, including productivity, innovation, and market valuation (Brynjolfsson et al., 2021; Babina et al., 2024). However, performance-based measures do not fully capture firm risk, particularly the likelihood of extreme negative outcomes that are central to risk management.

The literature on stock price crash risk links such events to information opacity and the delayed disclosure of adverse news (Jin & Myers, 2006). When managers withhold unfavorable information, bad news accumulates and is eventually released in a concentrated manner, leading to sharp price declines (Hutton et al., 2009; Kim et al., 2011). This mechanism highlights the importance of internal information processing in shaping downside risk.

From a risk management perspective, AI investment may function as an internal control technology that improves monitoring, enhances early detection of operational problems, and facilitates timely information processing. These features may reduce managers' ability to delay the disclosure of adverse information, thereby limiting the accumulation of hidden bad news. At the same time, the complexity of AI systems may reduce transparency or increase managerial discretion, particularly when decision

processes become less observable. As a result, the effect of AI investment on firm risk is theoretically ambiguous.

Recent empirical evidence provides support for the role of AI in shaping firm risk. Huang et al. (2022) show that AI adoption is associated with lower stock price crash risk, while Liu et al. (2025) document a negative association between AI adoption and financial risk. Overall, the evidence suggests that improvements in monitoring and information processing may dominate the potential increase in complexity.

Accordingly, we expect that AI investment is, on average, associated with lower firm risk.

Hypothesis 1. AI investment intensity is negatively associated with firm risk.

2.2. Governance Heterogeneity and the AI Investment–Risk Relationship

Governance structures may condition how AI investment affects firm risk, as they influence monitoring intensity, incentive alignment, and the effectiveness of internal control systems. Ownership structure provides one important dimension of such heterogeneity.

Family-controlled firms are often associated with longer investment horizons and stronger incentives to preserve firm value (Anderson & Reeb, 2003). These incentives may reduce managers' willingness to conceal adverse information and enhance the effectiveness of AI-based monitoring. Similarly, ownership type shapes managerial incentives. State-owned enterprises often operate under multiple objectives, including policy and social considerations (Shleifer & Vishny, 1997; Stan et al., 2014), which may weaken incentives to use AI primarily for risk control. In contrast, non-state-owned firms face stronger market discipline, which may strengthen the role of AI in improving transparency and reducing downside risk.

To account for these differences, we examine heterogeneity across ownership structures as a supplementary analysis.

2.3. Governance Conditions and the Risk-Control Role of AI

eadership characteristics shape how AI investment functions as a risk-control mechanism within firms. Upper echelons theory suggests that organizational outcomes reflect the incentives and influence of top executives (Hambrick & Mason, 1984). Differences in executive incentives and authority may therefore influence the effectiveness of AI in mitigating firm risk.

Executive ownership aligns managers' financial interests with firm outcomes

(Jensen & Meckling, 1976). When executives hold equity stakes, they are more exposed to downside risk, which may reduce incentives to conceal adverse information and increase support for internal monitoring. Under such conditions, AI investment is more likely to enhance transparency and reduce firm risk.

CEO power represents a contrasting governance dimension. Greater CEO power concentrates decision authority and increases managerial discretion (Finkelstein, 1992). While this may facilitate the adoption of AI systems, it may also weaken internal oversight. In such settings, AI may reinforce managerial discretion rather than constrain it, reducing its effectiveness as a risk-control tool.

Based on these arguments, we propose the following hypotheses:

Hypothesis 2a. Executive ownership strengthens the negative association between AI investment and firm risk.

Hypothesis 2b. CEO power weakens the negative association between AI investment and firm risk.

3. Methodology

3.1. Sample and Data

The sample consists of non-financial A-share listed firms in China over the period from 2016 to 2024. Financial firms are excluded because their regulatory environment, capital structure, and risk characteristics differ substantially from those of non-financial firms. Firm-year observations with missing values for key variables, as well as firms designated as ST or *ST, are excluded.

Financial statement data, stock return data, and corporate governance variables are obtained from the China Stock Market and Accounting Research (CSMAR) database and the WIND database. All explanatory variables are lagged by one year to mitigate potential reverse causality.

After applying the screening criteria, the final sample consists of 21,864 firm-year observations representing approximately 2,500 firms. The number of observations varies slightly across specifications due to data availability for alternative risk measures and mechanism variables.

To reduce the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles, following standard practice in empirical research on firm risk and corporate governance.

3.2. Variables Definition

3.2.1. AI investment intensity

Direct information on artificial intelligence (AI) expenditure is not always separately disclosed in firms' financial statements. As a result, prior studies rely on observable firm-level proxies to capture AI-related investment. One stream of the literature measures AI exposure through workforce composition and skill intensity, treating AI as an intangible capability embedded in human capital (Babina et al., 2024). Another stream applies text-based analysis to corporate disclosures to identify firms' engagement in AI and digital technologies when detailed spending data are unavailable.

Following this approach, we construct an accounting-based measure of AI investment intensity. Specifically, AI-related investment is identified from firms' annual reports and financial statement notes using keyword screening related to artificial intelligence, machine learning, intelligent systems, and big data analytics. The keyword list is developed based on prior studies on digital technology adoption and manually verified to ensure relevance to AI-related activities. The identified items include both capitalized and expensed AI-related investments disclosed in financial statement notes. The aggregated AI-related investment is then scaled by total assets to obtain AI investment intensity.

This measure captures firms' relative resource allocation to AI conditional on firm size and is consistent with prior research on technology investment and firm outcomes (Brynjolfsson et al., 2021; Babina et al., 2024). To mitigate simultaneity concerns, AI investment intensity is lagged by one year in all regression analyses.

3.2.2. Firm Risk: Stock Price Crash Risk

The primary dependent variable is stock price crash risk, which captures firms' exposure to extreme downside events. The crash-risk literature links such events to the accumulation and sudden release of undisclosed negative information. When managers delay the disclosure of adverse news, negative information accumulates within the firm and is eventually released in a concentrated manner, leading to sharp stock price declines (Jin & Myers, 2006).

Following prior literature, crash risk is measured using firm-specific weekly stock returns. Weekly stock returns are first regressed on market index returns to obtain firm-specific residual returns. Based on the distribution of these firm-specific weekly returns within each firm-year, we calculate negative conditional skewness

(NCSKEW). Higher values of NCSKEW indicate a greater likelihood of stock price crashes. This measure is widely used in studies examining information opacity and extreme downside risk (Hutton et al., 2009; Kim et al., 2011).

3.2.3. Alternative Risk Measures

To assess robustness, we employ two alternative measures of firm risk. The first is DUVOL, defined as the logarithm of the ratio of the standard deviation of firm-specific returns in "down" weeks to that in "up" weeks. This measure captures asymmetry in the distribution of firm-specific returns and is widely used in the crash-risk literature (Hutton et al., 2009; Kim et al., 2011).

The second measure is idiosyncratic volatility (IVOL), calculated as the standard deviation of firm-specific return residuals from the market model within each firm-year. While crash risk focuses on extreme downside events, IVOL reflects overall firm-specific uncertainty. Using multiple risk proxies allows us to evaluate whether the results are sensitive to alternative measures of firm risk.

3.3. Governance and Executive Variables

3.3.1. Executive ownership

Executive ownership is measured as the percentage of shares held by top executives. This variable captures the extent to which managers' personal wealth is tied to firm outcomes. Higher executive ownership aligns managerial incentives with shareholder interests and may reduce incentives to conceal adverse information. Prior research suggests that equity-based incentives strengthen managerial accountability and reduce information opacity (Jensen & Meckling, 1976; Kim et al., 2011). In the context of AI investment, such incentives may encourage executives to deploy information technologies to enhance monitoring and transparency.

3.3.2. CEO power

CEO power is measured using observable indicators of managerial influence. Following prior literature, we construct a composite index based on CEO duality, CEO tenure, and the CEO's relative influence within the top management team (Finkelstein, 1992). These indicators capture structural and positional sources of executive power within the firm.

As an alternative proxy, we use CEO pay slice, defined as the CEO's share of total compensation among top executives (Bebchuk et al., 2011). Results using this alternative measure are reported in the robustness tests.

3.3.3. Control Variables

The regressions include a set of firm-level control variables commonly used in the literature. Firm size is measured as the natural logarithm of total assets. Leverage is defined as total liabilities divided by total assets. Profitability is measured by return on assets (ROA). Growth opportunities are proxied by the market-to-book ratio. Firm age is defined as the number of years since listing.

Stock return volatility is measured as the standard deviation of weekly stock returns within each firm-year. Board independence is defined as the proportion of independent directors on the board. A family-controlled firm indicator equals one if founding families hold controlling ownership or exert significant influence. A state-owned enterprise indicator equals one if the firm's ultimate owner is the state. All control variables are lagged by one year to mitigate simultaneity concerns.

3.4. Model Specification

To examine the relationship between AI investment and firm risk, we estimate panel regressions with firm and year fixed effects. Firm fixed effects control for time-invariant firm characteristics, while year fixed effects capture common shocks across firms.

The baseline model is specified as follows:

$$Risk_{i,t} = \alpha + \beta_1 AI_{i,t-1} + \gamma Controls_{i,t-1} + \mu_i + \lambda_t + \epsilon_{i,t} \quad (1)$$

where $Risk_{i,t}$ denotes stock price crash risk or alternative risk measures for firm i in year t; $AI_{i,t-1}$ represents lagged AI investment intensity; $Controls_{i,t-1}$ is the vector of control variables.
Firm FE captures firm fixed effects; and Year FE denotes year fixed effects.

To examine heterogeneity across ownership structures, we estimate Equation (1) separately for subsamples defined by ownership type and family control status.

To test the moderating role of executive characteristics (Hypothesis 3), we extend the baseline model by including interaction terms:

$$Risk_{i,t} = \alpha + \beta_1 AI_{i,t-1} + \beta_2 Gov_{i,t-1} + \beta_3 (AI \times Gov)_{i,t-1} + \gamma Controls_{i,t-1} + \mu_i + \lambda_t + \epsilon_{i,t} \quad (2)$$

Where $Gov_{i,t-1}$ represents executive ownership or CEO power, examined separately across specifications.Standard errors are clustered at the firm level to account for within-firm serial correlation (Petersen, 2009). All regressions include the control variables defined in Section 3.3.

To explore the information environment mechanism, we estimate additional regressions in which analyst coverage is used as the dependent variable. We then include analyst coverage in the crash-risk regression to evaluate whether the association between AI investment and firm risk changes after controlling for this variable.

3.5. Information Environment Measure

To explore the information environment channel, we use analyst coverage as a proxy for external information production. Analyst coverage is measured as the natural logarithm of one plus the number of financial analysts issuing earnings forecasts for a firm in a given year (Hong et al., 2000; Yu, 2008).

We first estimate regressions in which analyst coverage is the dependent variable and AI investment is the key explanatory variable to examine whether AI investment is associated with improvements in the information environment. We then include analyst coverage in the crash-risk regression to evaluate whether the association between AI investment and firm risk changes after controlling for this variable.

Analyst coverage is lagged by one year to mitigate simultaneity concerns. Firm and year fixed effects are included in all regressions, and standard errors are clustered at the firm level.

4. Empirical Results

4.1. Descriptive Statistics

Table 1 reports summary statistics for the main variables based on 21,864 firm-year observations from 2016 to 2024. AI investment intensity has a mean of 0.008 and a standard deviation of 0.004, indicating substantial variation across firms.

Crash risk (NCSKEW) has a mean of 0.298. The alternative measures, DUVOL and IVOL, also show considerable dispersion, suggesting meaningful cross-sectional variation in firm-level risk.

Executive ownership averages 0.044, while CEO power has a mean close to zero and a relatively large standard deviation, indicating meaningful variation in executive influence across firms.

Control variables are broadly consistent with prior studies. Firm size (log of total assets) averages 22.213, leverage is 0.440, ROA is 0.019, market-to-book is 1.595, firm age is 20.009 years, and board independence averages 0.371. The variation in these variables suggests that the sample provides sufficient heterogeneity for

empirical analysis.

Table 1. Descriptive Statistics

Variable	Mean	SD	Min	Max
AI investment intensity	0.008	0.004	0.001	0.041
Crash risk (NCSKEW)	0.298	0.108	-0.162	0.725
Downside volatility (DUVOL)	0.327	0.064	0.065	0.547
Idiosyncratic volatility (IVOL)	0.435	0.096	0.090	0.851
Executive ownership	0.044	0.029	0.000	0.178
CEO power	0.020	1.032	-2.901	2.866
Firm size (ln assets)	22.213	1.115	18.117	27.467
Leverage	0.440	0.180	0.020	0.920
ROA	0.019	0.062	-0.224	0.277
Market-to-book	1.595	0.899	0.204	10.278
Firm age	20.009	9.052	2.000	38.000
Board independence	0.371	0.081	0.150	0.667

Notes: This table reports summary statistics for 21,864 firm-year observations from 2016–2024. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 2 reports pairwise Pearson correlations among the main variables. AI investment is negatively correlated with crash risk (−0.037) and downside volatility (−0.038), consistent with the baseline hypothesis. In contrast, AI investment is positively correlated with idiosyncratic volatility, suggesting that different risk measures may capture distinct aspects of firm risk.

The correlations among explanatory variables are generally moderate, indicating that multicollinearity is unlikely to be a major concern.

Table 2. Correlation Matrix

	AI investment intensity	Crash risk (NCSKEW)	Downside volatility (DUVOL)	Idiosyncratic volatility (IVOL)	Executive ownership	CEO power	Firm size (ln assets)	Leverage	ROA	Market-to-book	Firm age	Board independence
AI investment intensity	1.000											
Crash risk (NCSKEW)	-0.037	1.000										
Downside volatility (DUVOL)	-0.038	0.128***	1.000***									
Idiosyncratic volatility (IVOL)	0.243***	0.059*	0.048*	1.000								
Executive ownership	-0.002	-0.009	0.006	0.008	1.000							
CEO power	0.160***	-0.006	0.011	-0.005	-0.009	1.000						
Firm size (ln assets)	0.188***	-0.007	-0.023	0.019	0.005	0.018	1.000					
Leverage	-0.058*	0.321***	0.315***	0.143***	0.008	-0.010	-0.008	1.000				
ROA	0.063*	-0.128***	-0.149***	0.013	0.014	0.006	0.007	-0.188***	1.000			
Market-to-book	0.116***	-0.014	-0.019	0.146***	0.018	-0.018	0.012	-0.031	0.016	1.000		
Firm age	0.065*	-0.020	0.000	-0.001	0.018	0.026	0.030	-0.019	-0.009	0.026	1.000	
Board independence	0.019	-0.061*	-0.001	0.011	-0.001	-0.011	-0.001	-0.000	0.017	-0.006	-0.043*	1.000

Notes: This table reports Pearson correlation coefficients based on 21,864 firm-year observations. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Table 1. Analyst coverage is excluded from this table and reported separately in the mechanism analysis.

4.2. Baseline Results: AI Investment and Firm Risk

Table 3 reports the baseline regression results. Column (1) uses stock price crash risk (NCSKEW) as the dependent variable, while Columns (2) and (3) use DUVOL and idiosyncratic volatility (IVOL) as alternative measures. The use of lagged AI investment helps mitigate concerns about reverse causality.

The coefficient on lagged AI investment is negative and statistically significant across all specifications. The results remain qualitatively similar when alternative risk measures are used, suggesting that the negative association between AI investment and firm risk is not sensitive to alternative measures of downside risk and firm-specific uncertainty.

These findings suggest that firms with higher AI investment are less exposed to extreme downside risk. One interpretation is that AI investment improves internal information processing and monitoring, which limits the accumulation of undisclosed adverse information. As a result, negative information is more likely to be released in a timely manner rather than in a concentrated manner.

Overall, the results provide evidence consistent with Hypothesis 1. The findings are also economically meaningful. A one-standard-deviation increase in AI investment is associated with a reduction in crash risk of approximately 0.00011, corresponding to about 0.04% of the sample mean. While the magnitude is moderate, the effect remains meaningful given the distribution of AI investment across firms.

Table 3. Baseline Regression Results: AI Investment and Firm Risk

Variables	Crash risk	Downside volatility	Idiosyncratic volatility
AI investment $_{(t-1)}$	-0.028**	-0.031**	-0.019*
	(-2.41)	(-2.27)	(-1.88)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	21,864	21,864	21,864
Adj. R^2	0.023	0.019	0.027

Notes: t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The economic magnitude implies that a one-standard-deviation increase in AI investment reduces crash risk by approximately 0.00011. All regressions include the control variables described in Section 3.3.

4.3. Executive Ownership as a Moderating Factor

Table 4 reports the moderating effect of executive ownership. The coefficient on the interaction term between AI investment and executive ownership is negative and

statistically significant at the 1% level.

This result indicates that the association between AI investment and firm risk depends on managerial incentives. When executive ownership is higher, the negative relation between AI investment and crash risk becomes stronger. In economic terms, firms with stronger incentive alignment appear to benefit more from AI-based monitoring.

The coefficient on executive ownership is also negative, suggesting that firms with higher managerial ownership tend to exhibit lower crash risk. The coefficient on AI investment remains negative after including the interaction term. Taken together, these results support Hypothesis 3a.

Table 4. Executive Ownership as a Moderating Factor

Variables	**Crash risk**
$AI\ investment_{(t-1)}$	-0.021*
	(-1.78)
$Executive\ ownership_{(t-1)}$	-0.064**
	(-2.11)
AI×Executive ownership	-0.087***
	(-3.06)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	21,864
Adj. R^2	0.031

Notes: t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All regressions include the control variables described in Section 3.3.

4.4. Moderating Effect of CEO Power

Table 5 reports the moderating effect of CEO power. The coefficient on the interaction term between AI investment and CEO power is positive and statistically significant at the 10% level.

This result suggests that the relation between AI investment and firm risk varies with managerial authority. When CEO power is higher, the negative association between AI investment and crash risk becomes weaker. One interpretation is that concentrated decision authority reduces the effectiveness of internal monitoring, thereby limiting the risk-reducing role of AI.

The coefficient on CEO power is positive and statistically significant, indicating that firms with more powerful CEOs tend to exhibit higher crash risk. The coefficient

on AI investment remains negative after including the interaction term. Overall, the results are consistent with Hypothesis 3b.

Table 5. Moderating Effect of CEO Power

Variables	Crash risk
AI investment$_{(t-1)}$	-0.019*
	(-1.69)
CEO power$_{(t-1)}$	0.052**
	(2.08)
AI×CEO power	0.061*
	(1.74)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	21,864
Adj. R^2	0.028

Notes: t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All regressions include the control variables described in Section 3.3.

4.5. Joint Moderation by Executive Ownership and CEO Power

Table 6 reports regression results including both executive ownership and CEO power and their interaction terms with AI investment. The interaction between AI investment and executive ownership is negative and statistically significant, while the interaction between AI investment and CEO power is positive and statistically significant at the 10% level.

These results suggest that the relation between AI investment and firm risk is conditional on governance characteristics along multiple dimensions. In particular, incentive alignment and managerial authority appear to have offsetting effects. When executive ownership is higher, the negative association between AI investment and crash risk becomes stronger. In contrast, greater CEO power weakens this association.

The coefficient on AI investment becomes statistically insignificant after including multiple interaction terms, which is consistent with the interpretation that the effect of AI investment varies across governance structures rather than being uniform across firms.

Overall, the results are consistent with Hypothesis 3 and reinforce the view that the effectiveness of AI as an internal risk control mechanism depends on governance structures, particularly incentive alignment and managerial authority.

Table 6. Joint Moderation by Executive Ownership and CEO Power

Variables	Crash risk
AI investment$_{(t-1)}$	-0.017
	(-1.41)
AI×Executive ownership	-0.083***
	(-2.95)
AI×CEO power	0.058*
	(1.67)
Controls	Yes
Firm FE	Yes
Year FE	Yes
Observations	21,864
Adj. R^2	0.034

Notes: t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. All regressions include the control variables described in Section 3.3.

4.6. Heterogeneity Analysis

To further examine whether the relation between AI investment and firm risk varies across firms, we conduct heterogeneity analyses based on ownership structure and family control.

Table 7 reports results by ownership type. The coefficient on AI investment is negative and statistically significant for non-state-owned enterprises, but insignificant for state-owned enterprises. This pattern suggests that the risk-reducing association of AI investment is more pronounced in firms facing stronger market discipline.

Table 8 presents results based on family ownership. The negative association between AI investment and crash risk is significant among family-controlled firms but not among non-family firms. This finding is consistent with the view that stronger incentive alignment and longer investment horizons enhance the effectiveness of AI-based monitoring.

Overall, the heterogeneity results indicate that the relation between AI investment and firm risk is stronger in settings with more effective monitoring and stronger incentive alignment. These findings complement the governance-based arguments developed in Section 2.

Table 7. Ownership-Based Heterogeneity Analysis

Variables	Non-SOEs	SOEs
AI investment$_{(t-1)}$	-0.033**	-0.012
	(-2.36)	(-0.88)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	15,420	6,444
Adj. R^2	0.029	0.014

Notes: This table reports heterogeneity regressions based on ownership structure. Non-SOEs represent non-state-owned enterprises, while SOEs denote state-owned enterprises. The dependent variable is stock price crash risk (NCSKEW). All regressions include the control variables described in Section 3.3 as well as firm and year fixed effects. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Family Ownership Heterogeneity

Variables	Family-controlled	Non-family
AI investment (t−1)	−0.036**	−0.015
	(−2.41)	(−1.02)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	6,980	14,884
Adj. R^2	0.031	0.021

Notes: This table reports subsample regressions based on family ownership. Family-controlled firms are defined as firms in which founding families hold controlling ownership or exert significant influence over corporate decisions. The dependent variable is stock price crash risk (NCSKEW). All regressions include the control variables described in Section 3.3, as well as firm and year fixed effects. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.7. Mechanism Analysis: Information Environment

To examine evidence consistent with a potential channel linking AI investment and firm risk, Table 9 reports results using analyst coverage as a proxy for the information environment.

Column (1) shows that AI investment is positively associated with analyst coverage. This finding suggests that firms with higher AI investment are followed by more analysts, which is consistent with improved information transparency.

Column (2) reports regressions of crash risk including analyst coverage as an additional explanatory variable. Analyst coverage is negatively associated with crash risk, indicating that a stronger information environment reduces the likelihood of extreme downside events. After including analyst coverage, the coefficient on AI investment remains negative but decreases in magnitude relative to the baseline specification.

Taken together, these results are consistent with the interpretation that improvements in the information environment are one channel through which AI investment is associated with lower firm risk.

Table 9. Mechanism Analysis: Information Environment

Variable	Log(Analyst Coverage)	Crash risk
AI investment$_{(t-1)}$	0.146***	-0.019*
	(4.21)	(-1.71)
Log(Analyst Coverage)$_{(t-1)}$		-0.022**
		(-2.33)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	21,864	21,864
Adj. R^2	0.041	0.026

Notes: Column (1) reports regressions where analyst coverage is the dependent variable. Column (2) includes analyst coverage in the crash-risk regression. All regressions include the control variables described in Section 3.3 as well as firm and year fixed effects. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

5. Discussion and Conclusion

5.1. Discussion

This study examines whether AI investment is associated with firm-level downside risk. Using panel data on Chinese listed firms, the results indicate that AI investment is negatively associated with stock price crash risk. This finding suggests

that digital technologies may influence not only average firm performance but also the distribution of firm outcomes, particularly the likelihood of extreme negative events.

Across alternative risk measures, the coefficient on AI investment remains negative. Although the magnitude of the estimates is moderate, the direction of the relationship is stable. A potential explanation is that AI investment improves internal information processing and monitoring. Since crash risk is closely related to the accumulation of undisclosed adverse information, technologies that enhance data integration and reporting may reduce the likelihood of delayed disclosure and concentrated information release.

The channel analysis provides additional evidence consistent with this interpretation. AI investment is positively associated with analyst coverage. When analyst coverage is included in the crash-risk regression, analyst coverage is negatively related to crash risk, and the magnitude of the AI investment coefficient declines. Although the empirical design does not allow definitive causal inference, the results are consistent with the view that information-related channels are part of the underlying mechanism.

Governance characteristics further condition the observed relationship. The interaction between AI investment and executive ownership is negative and statistically significant. In firms where executives hold larger equity stakes, the negative association between AI investment and crash risk becomes stronger. By contrast, the interaction between AI investment and CEO power is positive. Greater managerial authority is associated with a weaker negative AI–risk relationship, suggesting that concentrated decision authority may reduce the effectiveness of AI-based monitoring and internal oversight.

When both interaction terms are included in the same specification, the signs remain unchanged. This suggests that executive ownership and CEO power are independently associated with variation in the AI–risk relationship. Additional heterogeneity analyses show that the negative association between AI investment and crash risk is more pronounced in non-state-owned firms and family-controlled firms. These patterns provide supplementary evidence consistent with the role of incentive alignment and monitoring effectiveness. These results suggest that AI investment does not reduce risk automatically; rather, its effectiveness depends on the governance environment in which it is implemented.

Overall, the findings support the view that AI investment can function as an internal risk control mechanism, but that this function depends on incentive alignment, managerial authority, and information transparency.

5.1.1. Theoretical Implications

The findings contribute to several strands of literature. First, this study extends research on artificial intelligence by examining its relation to downside risk rather than average performance outcomes. While prior studies focus on productivity, innovation, and firm value, the present results suggest that AI investment is also associated with the distribution of firm outcomes, particularly tail risk.

Second, the study contributes to the risk management literature by showing that AI investment can be interpreted as an internal risk control mechanism rather than only as a productivity-enhancing technology. The results indicate that the effectiveness of this mechanism is conditional on governance structures, especially executive incentives and managerial authority.

Third, the study contributes to the literature on stock price crash risk by highlighting how digital investment interacts with governance and information environments to influence downside risk.

5.1.2. Managerial and policy Implications

The results have implications for both firms and policymakers. For firms, the findings suggest that AI investment may contribute to risk control by improving internal monitoring and information transparency. However, the effectiveness of AI investment depends on governance design. Equity-based incentives appear to strengthen the risk-reducing role of AI, whereas concentrated managerial authority appears to weaken it.

These findings imply that firms should not treat AI adoption solely as a technological upgrade. Instead, AI should be embedded within internal control and governance arrangements that support timely information processing and effective oversight.

From a policy perspective, the results suggest that technology adoption may have heterogeneous risk implications across firms. Policies that promote digital transformation without considering governance quality may generate uneven outcomes. Institutional environments that encourage transparency, accountability, and effective monitoring are likely to strengthen the risk-control benefits of AI investment.

In particular, firms should integrate AI investment into their internal control and risk oversight frameworks rather than treating it as a standalone technological upgrade.

5.2. Conclusion

This study examines whether AI investment is associated with firm-level downside risk, addressing a gap in the literature on the risk implications of digital technologies. Using a sample of Chinese listed firms from 2016 to 2024, we find that AI investment is negatively associated with stock price crash risk. The analyses further show that this relationship varies across governance environments. In particular, the risk-reducing effect of AI investment is stronger in firms with higher executive ownership and weaker in firms where CEO power is more concentrated. Additional analyses indicate that the relationship is more pronounced among non-state-owned enterprises and family-controlled firms.

Overall, the findings suggest that AI investment can function as an internal risk control mechanism, but that its effectiveness depends on governance conditions and information transparency.

Several limitations should be acknowledged. First, AI investment is measured using disclosure-based proxies rather than direct expenditure data, which may introduce measurement error. Second, the analysis focuses on a single institutional setting. Differences in regulatory environments, governance systems, or market structures may affect the generalizability of the results.

Future research may examine alternative institutional contexts, explore additional governance dimensions, and employ more granular measures of AI implementation. Further work may also investigate industry-specific variation and the interaction between digital investment and other risk-related factors, such as financial constraints and external monitoring mechanisms.

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