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Asymmetric return dynamics and stock price crash risk: Evidence from a quantile regression analysis of an emerging market

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Abstract

Purpose — Understanding extreme downside risk is particularly important in emerging equity markets, where higher market volatility, lower liquidity, and weaker information environments make stock prices more vulnerable to sudden, severe crashes. This study examines downside risk, stock price crash risk, and lower-tail return dynamics using firm-level stock return data for firms listed in the Pakistan Stock Exchange over the period 2014–2024.

Method — Using panel regression and quantile regression techniques, the study investigates the determinants of crash risk and assesses the predictive role of downside risk for future equity returns.

Findings — The results indicate that downside risk is strongly associated with a higher likelihood of extreme negative return realisations, while its effect on average returns remains limited. Quantile-based estimates further show that the impact of downside risk intensifies substantially in the lower tail of the return distribution, highlighting pronounced return asymmetries. These patterns persist across both financial and non-financial firms, although their magnitude varies with market conditions.

Implications — The results carry important implications for investors, regulators, and risk managers concerned with downside protection and the identification of early warning signals in emerging equity markets.

Originality — This study provides new firm-level evidence from an emerging equity market by jointly examining downside risk, crash risk, and return tail behaviour within a unified empirical framework by using quantile regression.

Keywords — Downside Risk, Crash Risk, Return Asymmetry, Quantile Regression, Emerging Markets

Introduction

The stability of emerging equity markets has become a major focus of global financial research, especially as these markets face significant economic and political changes worldwide (Arkol & Azimli, 2024; Bekaert et al., 2023). In asset pricing and risk management, the conventional dependence on mean-variance frameworks has often been inadequate when confronted with *black swan* events, unexpected, non-linear declines in asset valuations that contradict standard distribution assumptions. This event, known as stock price crash risk, is one of the biggest threats to the wealth of investors and the integrity of the market (Ring, 2023). The theoretical motivation for investigating crash risk is deeply rooted in the bad news hoarding hypothesis (Askarzadeh et

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al., 2024). However, there is a physical limit to information suppression. In markets with a lot of information asymmetry and weak institutional oversight, managers often have different reasons to keep bad news from the public. When the accumulated weight of undisclosed negative news reaches a tipping point, it enters the market simultaneously, triggering a catastrophic, rapid price correction (Cheng et al., 2025). Researchers, investors, and regulators are paying increasing attention to these extreme events. Particularly, after a series of financial crises that revealed the limitations of traditional risk measures based on variance and mean returns (Ang et al., 2006; Harvey et al., 2010). Within this broader context, stock price crash risk has emerged as a critical concern in asset pricing and financial stability research (Dierkes et al., 2021; Kelly & Jiang, 2013; Stoja et al., 2025). Empirical studies document that crash risk is closely linked to asymmetric return distributions and negative skewness, implying that investors face disproportionate downside exposure even when average returns appear stable (Boehme et al., 2020; Goetzmann et al., 2022; Habib et al., 2018; Kelly & Jiang, 2013). As a result, understanding the determinants and consequences of crash risk has become central to modern equity market analysis.

While the literature on downside and crash risk has expanded rapidly, much of the empirical evidence is concentrated in developed markets, where information disclosure standards, liquidity conditions, and investor protection mechanisms are relatively strong (Camilleri et al., 2020; Feldman & Kumar, 1995; Stereńczak, 2024). These structural features make emerging markets particularly vulnerable to abrupt price collapses, thereby increasing the relevance of downside and tail risks for both investors and regulators (Bae et al., 2006; Fernandes et al., 2024; Zhou et al., 2023). Despite these stylised facts, systematic evidence on the interaction between downside risk, crash risk and tail behaviour in emerging equity markets remains relatively limited. The current literature's predominant focus is on average effects. Traditional linear regression frameworks implicitly assume that risk factors exert uniform influences across the return distribution. However, growing evidence indicates that the pricing and transmission of risk are highly asymmetric, with substantially stronger effects in the lower tail of the distribution (Adrian et al., 2023; Sneller, 2025). Quantile-based approaches provide a more suitable framework for capturing these nonlinear dynamics, particularly when the primary interest lies in extreme downside outcomes rather than central tendencies. Quantile regression provides a granular view of the tail that standard OLS-based panel models typically overlook (Hoque et al., 2024).

A significant gap exists in the current literature regarding the predictive role of downside risk in the context of the emerging economy. Although volatility and systematic risk have been thoroughly examined, the factors influencing firm-level crash risk and the extent to which investors receive sufficient compensation for assuming this risk remain underexplored. The current study also investigates downside risk and crash risk by differentiating financial and non-financial firms. Financial institutions, which have strict capital requirements and are closely monitored by regulators, may have different crash risk profiles from non-financial firms, which are more sensitive to operational leverage and supply chain shocks (Bagh et al., 2025). This study contributes to the literature in several ways. First, this study contributes to the global discourse on the downside risk premium. In efficient markets, investors should theoretically demand higher returns for stocks that exhibit significant downside beta. The current study extends the downside risk and crash risk literature by providing new evidence from an emerging market setting. Second, by jointly examining financial and non-financial firms, the insights offer a more comprehensive view of crash risk across sectors within the same market. Third, the use of quantile regression allows us to move beyond mean-based inference and directly assess how downside risk influences the lower tail of the return distribution. The findings of the study highlight the importance of tail-oriented risk measures for understanding equity market behaviour in emerging economies.

Early asset pricing theories implicitly assumed that investors are primarily concerned with the variance of returns, treating positive and negative deviations symmetrically. However, subsequent research challenged this assumption by demonstrating that investors exhibit asymmetric preferences, placing greater weight on downside outcomes (Arnott & McQuarrie, 2025; Gao et al., 2025). This recognition led to the development of downside risk measures that focus on returns falling below a specified threshold or target (Markowski, 2024). Empirical evidence further shows that negative return realisations carry disproportionate economic and psychological costs, making downside risk a more relevant measure of risk than total volatility (Stoja et al., 2025; Zourai, 2022). Risk type significantly influences financial performance (Suseno & Bamahriz, 2017). This phenomenon is particularly pronounced in emerging markets, where return distributions often exhibit stronger negative skewness and kurtosis than in developed markets, suggesting a higher propensity for extreme negative returns (Barunik & Nevrla, 2018; Calomiris & Mamaysky, 2019). This asymmetry of returns, where large upward movements are not as equally matched by large drawdowns, highlights the importance of considering downside co-moments in asset pricing models, especially during periods of market stress (Markowski, 2024; Xu, 2018). These features imply that average returns fail to fully reflect investors' exposure to extreme losses. While this literature establishes the importance of downside risk, most empirical analyses focus on developed markets. In emerging markets, where liquidity constraints and delayed information dissemination are more prevalent, downside risk is likely to play a more pronounced role in shaping return behaviour. Moreover, existing studies often rely on mean-based estimation techniques, which may obscure the impact of downside risk on extreme return realisations. Therefore, the first hypothesis of the study is

H_1: Firm-level downside risk is positively associated with the likelihood of extreme negative stock returns.

The concept of stock price crash risk is closely tied to theories of information hoarding and asymmetric disclosure. Jin and Myers (2006) argue that managers have incentives to withhold adverse information, leading to the accumulation of undisclosed bad news that is eventually released in a concentrated manner, resulting in stock price crashes. This framework has been widely adopted and empirically validated in subsequent studies, which show that firms with higher opacity and weaker monitoring are more prone to crash events (Andreou et al., 2023; Liu et al., 2024). Salles (2021) reported firm-level risk is not diversifiable in emerging markets. Crash risk has been operationalised using distribution-based measures such as negative conditional skewness and down-to-up volatility, both of which capture the asymmetry of firm-specific returns (Benkraiem et al., 2022; Fiordelisi et al., 2023). Empirical findings suggest that crash risk is not merely a reflection of volatility but represents a distinct risk dimension linked to downside tail behaviour. However, most of this evidence is drawn from developed markets with relatively strong disclosure regimes and institutional frameworks.

Emerging markets differ markedly in this respect. Weaker investor protection, heterogeneous disclosure practices, and episodic liquidity shortages may intensify the buildup and release of negative information, thereby amplifying crash risk. Yet, comparative evidence on crash risk dynamics across financial and non-financial firms within emerging markets remains scarce, which leads to the formation of the hypothesis of the study:

H_2: Higher downside risk is associated with greater stock price crash risk at the firm level.

A central question in asset pricing is whether investors are compensated for bearing downside risk. While traditional models focus on the pricing of systematic volatility, recent studies suggest that downside risk may contain predictive information for future returns, particularly during adverse market conditions (Ang et al., 2006). These findings imply that downside risk may influence expected returns through channels that are not captured by standard risk factors.

However, empirical evidence on downside risk predictability remains mixed. Globalisation alters the risk structure, potentially influencing tail risk and crash probability in financial markets (Said et al., 2027). Some studies find that downside risk commands a risk premium, while others report weak or insignificant effects on average returns (Barunik & Nevrla, 2018; Dai & Harris, 2023). One explanation for these inconsistencies is the reliance on mean-based regression frameworks, which may hide heterogeneous effects across the return distribution.

In emerging markets, downside events are more frequent and severe. So, the predictive role of downside risk may be concentrated in the lower tail rather than the conditional mean. Yet, this possibility has received limited empirical attention, particularly in studies using firm-level data, and this leads to the formulation of the next hypothesis:

H_3: Downside risk has limited explanatory power for average stock returns but significantly predicts lower-tail return outcomes.

Recent advances in financial econometrics emphasise the importance of examining risk-return relationships across the entire return distribution. Quantile regression techniques, introduced by Koenker and Bassett (1978), allow for the capture of heterogeneous effects that vary across different market states. Applications in finance demonstrate that risk factors often exert stronger influences during periods of market stress, particularly in the lower tail of the return distribution (Arnott & McQuarrie, 2025). Tail-focused measures such as value at risk and expected shortfall provide additional insights into extreme downside exposure that cannot be inferred from variance-based metrics alone. While these measures are widely used in risk management, their integration into firm-level return analysis in emerging markets remains relatively underdeveloped. Given the structural characteristics of emerging equity markets, it is reasonable to expect that downside risk exerts a disproportionately stronger effect on extreme negative returns than on central or upper quantiles.

H_4: The impact of downside risk on stock returns is significantly stronger in the lower tail of the return distribution than at the mean.

Financial firms differ from non-financial firms in terms of leverage, regulatory oversight, and sensitivity to market-wide shocks, which may influence their exposure to downside and crash risk. Prior studies suggest that financial firms are particularly vulnerable to tail events due to balance-sheet interconnectedness and maturity mismatches (Aufiero et al., 2025; Ellul et al., 2022; Stoja et al., 2025). However, empirical evidence comparing crash risk dynamics across financial and non-financial firms within the same emerging market remains limited. Understanding whether downside and crash risk behave differently across sectors is crucial for both portfolio allocation and regulatory supervision, especially in markets where financial institutions play a central role in economic stability.

H_5: The magnitude of downside and crash risk effects differs between financial and non-financial firms.

Methods

The study employs a well-balanced panel constructed from monthly stock price data of firms listed on the KSE-100 Index over the period 2014–2024. o. The initial universe includes all companies that were constituents of the index during the sample period. To ensure consistency and reliability of return calculations, firms with insufficient trading history, prolonged trading suspensions, or missing price observations were excluded. After applying these filters, the final sample consists of 85 non-financial firms with continuous return data. Stock prices are used to compute firm-level excess returns, downside risk measures, and crash indicators. Each firm contributes 132 monthly observations, resulting in a balanced panel suitable for panel and quantile regression analysis. The sample covers a broad cross-section of industries, with financial firms (banking and insurance) representing approximately 20% of firm-month observations while non-financial firms comprise the remaining 80%, providing sufficient cross-sectional variation to examine heterogeneity in downside-risk effects across firm types. Stock returns are computed using monthly closing prices, and excess returns are calculated by subtracting the contemporaneous risk-free rate. Market excess returns are measured using the value-weighted market index minus the risk-free rate. This construction follows standard asset-pricing practice (Ang et al., 2006; Fama & French, 2015). Downside risk is measured as the firm-level standard deviation of negative excess returns, capturing exposure to adverse return realisations while excluding upside volatility. Formally, downside risk is computed as:

$$DR_i = \sqrt{\frac{1}{N_i - 1}\sum_{t:R_{it}<0}(R_{it} - \bar{R}_{it})^2} \quad (1)$$

where R_{it} denotes the firm i's excess return in month t, and the summation is taken only over periods in which returns are negative. To capture extreme negative return events, a crash indicator is constructed following the tail-event literature (Chen et al., 2001; Kelly & Jiang, 2013). A firm-month observation is classified as a crash if the excess return falls into the bottom 5% of the empirical return distribution. This binary indicator enables the analysis to distinguish between normal negative returns and extreme downside realisations, both of which are central to crash-risk studies. To examine the relationship between downside risk and crash probability, panel logit models are estimated. First, a fixed-effects logit model is employed to control for unobserved firm-specific heterogeneity. However, due to the time-invariant construction of downside risk, this variable is omitted in the fixed-effects specification, reflecting a well-known identification limitation of nonlinear fixed-effects estimators (Wooldridge, 2002). Accordingly, the main crash-risk tests rely on a random-effects logit model, which allows the inclusion of firm-specific characteristics such as downside risk:

$$P(Crash_{it} = 1) = \Lambda(\alpha + \beta_1 DR_i + \beta_2 MKT_t + u_i) \tag{2}$$

This approach is consistent with prior crash-risk studies that incorporate time-invariant firm attributes (Hutton et al., 2009; Kim et al., 2011). To assess whether downside risk is priced in average returns, a fixed-effects panel regression is estimated. The model is as follows:

$$R_{it} = \alpha_i + \beta_1 DR_i + \beta_2 MKT_t + \varepsilon_{it} \tag{3}$$

Given the firm-specific nature of downside risk, the variable is collinear with firm fixed effects and therefore omitted from the estimation. This outcome is informative, indicating that downside risk does not explain within-firm variation in mean returns. This interpretation is consistent with findings in Fama and French (2015), who argue that not all forms of risk command an average return premium.

To capture distributional asymmetries and tail dependence, represented by H_1, H_3, and H_4, a quantile regression is employed in accordance with (Koenker & Bassett, 1978). The baseline quantile regression specification is as follows:

$$Q_\tau(R_{it} \mid X_{it}) = \alpha_\tau + \beta_\tau^{DR} DR_i + \beta_\tau^{MKT} MKT_t \tag{4}$$

Models are estimated at the 10th, 25th, and 50th percentiles. This approach is widely used in tail-risk and asset-pricing research to uncover asymmetric risk–return relationships (Bollerslev et al., 2009; Giglio et al., 2016).

To test whether downside-risk effects differ across firm types (H_5), firms are classified as financial or non-financial based on industry affiliation. Financial firms include banking and insurance companies, consistent with prior studies on systemic and tail risk (Brunnermeier & Oehmke, 2013). Heterogeneity is examined using an interaction-based quantile regression:

$$Q_{0.10}(R_{it}) = \alpha + \beta_1 DR_i + \beta_2 Financial_i + \beta_3 (DR_i \times Financial_i) + \beta_4 MKT_t \tag{5}$$

This specification allows the magnitude of downside-risk effects to differ between financial and non-financial firms while maintaining a unified estimation framework. Standard errors are clustered at the firm level to account for within-firm dependence over time. The consistency of results across fixed-effects, random-effects, and quantile-based estimators mitigates concerns regarding model misspecification or outlier-driven inference.

Results and Discussions

Downside risk is computed as the firm-level standard deviation of negative excess returns. The panel is strongly balanced with 132 monthly observations per firm. The empirical analysis is conducted on a well-balanced panel of firm-level monthly data comprising 11,352 observations from January 2014 to December 2024. The sample spans twelve industries, with financial firms accounting for approximately 20% of firm-month observations. This structure provides sufficient variation to examine downside risk, crash risk, and return distribution asymmetries. Table 1 reports descriptive statistics for the main variables used in the analysis.

Firms exhibit substantial heterogeneity in downside risk exposure. The upper bound (0.255) reflects firms with severe exposure to adverse return realisations. The findings confirm that downside risk is well-defined and economically meaningful.

Table 1. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Excess stock return	11,352	-.0026	.1158	-2.03	1.013
Market excess return	11,352	.0021	.0586	-.269	.147
Downside risk	11,352	0.068	0.027	0.00	0.255
Crash indicator	11,352	-	-	0	1

Table 2 reports quantile regression estimates at the 10th percentile of the return distribution. The coefficient on downside risk is negative, large in magnitude, and highly statistically significant, indicating that firms with greater downside exposure experience substantially more severe losses during extreme negative return realisations. Standard errors are heteroskedasticity-robust. This result provides strong support for *hypothesis 1*, confirming that downside risk is a key determinant of extreme adverse equity outcomes.

Table 2. Quantile Regression Estimates at the 10th Percentile of the Excess Return Distribution

Variable	Coefficient	Std. Error	t-stat	*p*-value
Downside risk	−0.786	0.064	−12.24	0.000
Market excess return	0.864	0.028	30.65	0.000
Constant	−0.059	0.005	−12.43	0.000

Table 3 presents panel logit estimates examining the relationship between downside risk and crash probability. In fixed-effects specifications, downside risk is omitted because it is time-invariant. Random effects are specified at the firm level, allowing the inclusion of firm-specific characteristics that are time-invariant over the sample period. The coefficient on downside risk is positive, indicating that firms with greater exposure to adverse return fluctuations are more likely of experience crashes. However, the estimate is not statistically significant at conventional levels, indicating that the influence of downside risk is not uniform across states of the return distribution. Consistent with the fixed-effects logit estimates, the coefficient on market excess returns is large, negative, and highly statistically significant ($z = -17.68$, $p < 0.01$). This finding implies that deteriorating market conditions substantially increase the likelihood of firm-level crash events. The result underscores the dominant role of systematic market stress in triggering extreme downside outcomes, even after controlling for firm-specific risk characteristics. The estimated variance of the random effects ($\sigma_u = 0.587$) is statistically significant, and the intra-class correlation coefficient ($\rho \approx 0.095$) indicates that approximately 9.5% of the unexplained variation in crash risk is attributable to persistent firm-level heterogeneity. This confirms the relevance of accounting for unobserved firm-specific effects in crash-risk modelling. The market excess returns exert a strong and highly significant effect, highlighting the central role of systematic market downturns in driving extreme negative return realisations. The significance of the random-effects variance further confirms the presence of persistent firm-level heterogeneity in crash risk.

Table 3. Downside Risk and Crash Probability

logit estimates	Variable	Coefficient	Std. Error	z-stat	p-value
Panel A: Fixed-Effects Logit	Downside risk	Omitted			
Market excess return	Market excess return	−17.740***			
Panel B: Random-Effects Logit	Downside risk	12.226	8.174	1.50	0.135
Crash indicator	Market excess return	−17.683	1.406	−12.58	0.000

Notes: entries in *** are significant at 1% significance level.

Table 4. Fixed-Effects Regressions of Average Excess Returns

Variable	Coefficient	Std. Error	*t*-stat	*p*-value
Downside risk	Omitted			
Market excess return	0.947	0.048	19.73	0.000

Table 4 reports fixed-effects regression results for average excess returns. The findings indicate that market excess returns remain the dominant determinant of average return dynamics. The coefficient on downside risk is omitted due to collinearity, reflecting that downside risk is treated as a firm-specific, time-invariant characteristic. This result implies that downside risk does not help explain within-firm variation in average returns over time, consistent with the hypothesis that downside risk is not systematically priced in the conditional mean of returns. In contrast, the coefficient on market excess returns is positive, large, and statistically significant ($\beta = 0.947$, $t = 19.73$, $p < 0.05$). The within R^2 of 0.23 indicates that approximately 23% of the within-firm variation in excess returns is explained by market movements. The result directly supports that Downside risk is not priced in average returns, as it does not explain within-firm return variation once firm fixed effects are accounted for. Further, systematic market risk dominates the conditional mean; the economic relevance of downside risk therefore lies outside the mean.

Table 5. Quantile Regression across the Return Distribution

Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$
Downside risk	−0.786***	−0.142***	−0.001
Market excess return	0.864***	0.876***	0.896***
Pseudo R^2	0.140	0.131	0.133
Observations	11,103	11,103	11,103

Entries in *** are significant at 1% significance level.

Table 5 shows the test results of H_3 and H_4. It indicates that downside risk significantly predicts returns in the lower tail of the distribution, with strong effects at the 10th percentile and weaker but still significant effects at the 25th percentile. These results strongly support hypothesis 3, which posits that downside risk is not priced in terms of average returns but is highly relevant during adverse return states. Return asymmetry and distributional effects (H_4) test results of quantile regression estimates reveal a clear monotonic decline in the magnitude of downside-risk coefficients from the lower tail toward the centre of the return distribution. This attenuation indicates that downside risk primarily amplifies losses during extreme adverse states. The coefficient on downside risk at the median is economically negligible and statistically insignificant ($\beta = -0.0014$, $t = -0.04$, $p = 0.967$). This result indicates that downside risk has no discernible effect on median returns, implying that firms with higher downside exposure do not systematically earn higher or lower typical returns. In contrast, market excess returns remain positive and highly statistically significant ($\beta = 0.896$, $t = 61.90$, $p < 0.01$), confirming that systematic market movements dominate return dynamics around the median, consistent with standard asset pricing models. These findings indicate that downside risk is not priced in typical return outcomes, but instead materialises primarily during adverse states, highlighting pronounced return asymmetries.

Table 6. Quantile Regression Estimates at $\tau = 0.10$ with an Interaction Term

Variable	Coefficient	Std. Error	t-stat	p-value
Downside risk (non-financial firms)	−0.518	0.063	−8.20	0.000
Financial firm dummy	0.090	0.015	6.00	0.000
Downside risk × Financial	−1.110	0.228	−4.87	0.000
Market excess return	0.856	0.026	32.33	0.000

Table 6 reports quantile regression estimates incorporating an interaction between downside risk and a financial-firm indicator. The interaction term is negative and highly statistically significant, indicating that the adverse impact of downside risk on lower-tail returns is significantly stronger for financial firms than for non-financial firms. This finding provides strong support for Hypothesis 5 and suggests that financial institutions are particularly vulnerable to downside shocks during extreme market downturns. Consistent with prior specifications, market excess returns remain positive and highly statistically significant ($\beta = 0.856$, $t = 32.33$, $p < 0.01$), confirming the dominant role of systematic market conditions in shaping firm-level returns even in the lower tail.

The pseudo-R^2 of 0.146 suggests that the model explains a meaningful portion of the variation in lower-tail returns, which is notable given the inherent volatility of extreme returns. The statistically significant negative interaction term provides strong evidence of heterogeneity, indicating that downside risk has a significantly larger adverse impact on lower-tail returns for financial firms than for non-financial firms.

Table 7. Robustness Check

Variables	Baseline Q10	Financial Control	Bootstrap Q10
Downside risk	-0.779***	-0.694***	-0.779***
Market return	0.886***	0.862***	0.886***

Entries in *** are significant at 1% significance level.

Table 7 presents the robustness checks of the empirical findings. The quantile regression model was re-estimated by including an industry control variable that distinguishes financial firms from non-financial firms. The results indicate that downside risk continues to exhibit a strong negative and statistically significant impact on stock returns in the lower quantile of the return distribution and confirm that the main results are robust to industry-specific effects. Additionally, bootstrap quantile regression was estimated using 200 replications. The results remain consistent with the baseline estimation as downside risk continues to exhibit a strong negative and statistically significant effect on stock returns in the lower quantile of the distribution (-0.779, $p < 0.01$). These findings confirm that the main results are robust to alternative estimation techniques and sampling variation.

Summary of the Hypotheses Testing:

Hypothesis	Description	Result
H_1	Downside risk → extreme negative returns	Supported
H_2	Downside risk → crash probability	Partial support
H_3	Not priced in mean, priced in tail	Supported
H_4	Stronger tail effect than the mean	Strongly supported
H_5	Financial vs. non-financial heterogeneity	Supported

The empirical results provide strong evidence that downside risk is closely linked to extreme negative return realisations, rather than to average return dynamics. These findings are especially relevant for emerging equity markets, where structural vulnerabilities and information frictions magnify tail risk (Arkol & Azimli, 2024; Bekaert et al., 2023). These results align closely with foundational and recent evidence emphasising downside and tail risk in asset pricing. In particular, Ang et al. (2006) and Ang et al. (2009) demonstrate that downside risk and volatility asymmetries become economically meaningful during market downturns. More recent studies also document that tail risk is a dominant feature of equity markets facing heightened macroeconomic and political uncertainty (Ammann et al., 2023; Stoja et al., 2025). By providing firm-level evidence from the PSX, this study extends the downside-risk literature to an emerging market context where non-normal return behaviour and downside asymmetry are especially pronounced (Barunik & Nevrla, 2018; Zhou et al., 2023). In contrast, the weak and statistically imprecise relationship between downside risk and average crash probability is consistent with the crash-risk literature emphasising the role of systematic market stress rather than firm-specific characteristics. Kelly and Jiang (2013) show that crash risk is fundamentally linked to aggregate tail risk, while recent evidence highlights the dominant role of macro-financial shocks in triggering market-wide crashes (Ring, 2023; Stoja et al., 2025). The absence of downside risk effects in fixed effects mean regressions further suggests that downside risk is not rewarded in average returns. These findings reinforce the limitations of mean-variance frameworks and are consistent with the argument that traditional linear models fail to capture the pricing of rare but severe downside events (Bekaert et al., 2023; Ring, 2023). While some studies document downside-related premia under specific conditions (Lee & Yang, 2022). The present evidence suggests that such compensation does not manifest in average returns once firm-specific heterogeneity is controlled. The decline in the magnitude of downside-risk coefficients from the 10th percentile to the median provides compelling evidence of return asymmetry, consistent with behavioural and long-run risk theories. Investors' heightened sensitivity to losses during adverse states, as formalised by Epstein and Zin (1990), implies that downside risk should exert disproportionate effects in the lower tail of the return distribution. Recent empirical work further supports this view by demonstrating that tail risks cannot be adequately captured by mean-based estimation techniques (Sneller, 2025). The quantile-based approaches provide a more suitable framework for analysing downside and crash risk, particularly in emerging markets where extreme outcomes are more frequent (Hoque et al., 2024). The results are also consistent with Giglio and Xiu (2021) that tail risks are not captured by mean-variance frameworks and require distribution-sensitive methods.

A key contribution of this study lies in documenting heterogeneity across firm types. The interaction-based quantile regressions reveal that downside risk has a significantly stronger adverse impact on lower-tail returns for financial firms compared to non-financial firms, consistent with prior research emphasising the heightened vulnerability of financial institutions due to leverage, balance-sheet interconnectedness, and maturity mismatch (Aufiero et al., 2025; Ellul et al., 2022). In emerging markets, where regulatory buffers and crisis-resolution mechanisms are comparatively weaker, these vulnerabilities are likely to amplify the transmission of downside shocks (Bagh et al., 2025). At the same time, our results contrast with those of Bali et al. (2017), that financial firms may benefit from implicit guarantees that dampen downside exposure in developed markets. The divergence likely reflects institutional differences between advanced and emerging economies, where regulatory buffers and safety nets are weaker, making financial firms more vulnerable to downside shocks.

Conclusion

This study examines the role of firm-level downside risk in shaping crash risk and equity return dynamics using a strongly balanced monthly panel from 2014 to 2024. The results provide clear evidence that downside risk is not priced in average returns but plays a critical role in extreme negative return outcomes, particularly in the lower tail of the return distribution. Quantile regression estimates reveal pronounced return asymmetries, with downside risk exerting a strong and economically meaningful impact during adverse states while remaining irrelevant under normal conditions.

Moreover, the analysis uncovers significant heterogeneity between financial and non-financial firms and highlights that financial institutions are particularly exposed to downside risk in extreme market downturns. These findings underscore the importance of moving beyond mean-based models and adopting distribution-sensitive approaches when assessing risk and return relationships.

The findings have several important policy implications. First, regulators and market participants should recognise that downside risk materialises primarily during extreme market conditions, implying that stress testing frameworks should explicitly incorporate downside risk measures rather than relying solely on average volatility metrics. Second, the heightened sensitivity of financial firms to downside risk highlights the need for stronger capital buffers and liquidity requirements, particularly in emerging markets where systemic vulnerabilities are more pronounced. For investors, the results suggest that traditional diversification strategies based on mean returns may be insufficient to mitigate tail risk. Portfolio construction frameworks should therefore incorporate downside risk metrics to better manage exposure to extreme losses.

Despite its contributions, this study has several limitations. First, downside risk is measured using historical return realisations, which may not fully capture forward-looking expectations. Future research could incorporate option-implied downside measures. Second, the analysis focuses on a single emerging market, limiting generalizability. Cross-country studies could examine whether institutional quality moderates the effect of downside risk. Third, while quantile regression captures distributional heterogeneity, it remains static. Future work could employ dynamic tail risk models to explore the temporal evolution of downside risk.

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Author contribution

All authors contributed to the conception and design of the study, data collection, analysis and interpretation of the results, and the writing of the manuscript. All authors read and approved the final version of the manuscript.

Use of AI tools declaration

The authors confirm adherence to all ethical research and publishing standards. This work is original, and all sources have been duly acknowledged. The authors also disclose that ChatGPT was utilized solely for language editing, grammar improvement, and structural refinement of the manuscript.

Conflict of interest

The authors declare that there are no competing interests related to this manuscript.

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