CAPITAL STRUCTURE AND ASSET PRICING: AN EMPIRICAL ANALYSIS USING THE CAPM FRAMEWORK

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Abstract
Structural, institutional, and behavioral anomalies have prompted much discussion of the applicability of the Capital Asset Pricing Model (CAPM) to emerging markets. The current paper determines the applicability of CAPM to the Indian equity market based on 20 years of NIFTY 50 (2005-2025) data at a daily, weekly, and monthly frequency. Excess returns are also calculated against the Treasury Bill yield of 91 days and are estimated using heteroskedasticity- and autocorrelation-consistent models. The results show that the frequency-scaled mean returns are negatively skewed, fat-tailed, and have clustered volatility during crisis periods, such as the 2008 global financial crisis and the 2020 COVID-19 shock. Robustness checks ensure that aggregation works to remove noise and serial correlation but not pricing errors, highlighting the weaknesses of a one-factor model. Most importantly, these exceptions are associated with capital structure attributes of Indian companies, such as ownership concentration, leverage practices, and governance frictions, which exacerbate the systematic risks beyond CAPM. India is thus a global case study of a transitional economy in which modernization, institutional immaturity, and behavioral interaction meet to undermine traditional asset pricing. The results indicate that more sophisticated methods, including mean-Gini preferences, alpha-neutral CAPM and multi-factor or behaviorally informed models, are more explanatory. These findings have important implications on cost-of-capital estimation, policy in emerging markets and the development of future asset pricing models.

Keywords: Capital Structure, Asset Pricing, CAPM, Emerging Markets, NIFTY 50, Risk-Return Dynamics

1. Introduction

Financial economics and corporate finance have been concerned with the relationship between the capital structure and the price of assets. Since its inception in the 1960s, the concept,ual framework of relating systematic risk to expected returns made by the Capital Asset Pricing Model (CAPM) has offered and continues to offer both theoretical elegance and practical utility. Despite all this extensive application, scholars have claimed that it cannot be applied in the contemporary markets and even more in the 21st century because all the assumptions they made when applying the framework is being re-examined as behavioral and institutional forces take their toll (Levy, 2011).
Over the years critical reviews of CAPM have shown both its long-term relevance as well as its persisting failures. Empirical tests have often found that the model has limited explanatory power, and have instead generated longer or alternative models, which incorporate far more dimensions of risk (Rossi, 2016). At the same time, it is implied by the existing literature on the consumption-based CAPM that the standard models may lack the informational elements that contribute to the full description of the behavior of the asset price (Ghosh et al., 2017). These criticisms reinforce the view that the pricing of assets cannot be sensed beyond the economic indicators.
The latest inputs reveal that the market structure and the ownership structure are directly related to the pricing results. That is the non-priceable specific premises which exist in the state of disseminated ownership and this brings up the question of governance in a capital market too (Hearn et al., 2025). At the same time, automation research shows that the redistribution of labor and capital poses new risks and changes the relationship between assets in a way that raises questions about the applicability of one-factor models (Knesl, 2023). These findings show that structural and technological changes are growing less obtrusive in its requirements of risk and return interpretations.

These issues can be revisited in developing economies, and India in particular, is a fertile place to do so. It is concluded that investor sentiment has a reflection on the Indian market and actions and is known to be relevant on the price of the asset and may be a significant factor in the dynamics of the returns that cannot be modeled using CAPM (Pandey and Sehgal, 2019). Likewise, the appearance of other formulations, such as the mean-Gini version of CAPM, may be seen as the failure of the traditional one-factor frameworks to be sufficiently efficient to quantify the risk that is possible in practice (Agouram et al., 2020). Beyond that, the recent successes, such as alpha-neutral fixes, indicate that the empirical anomalies of CAPM could be approximated with a more advanced model that would contribute to the explanation of the better abnormal returns (Rocciolo et al., 2022). Expanding on such arguments, the Indian market offers more than a local test of CAPM- it is a globally relevant laboratory to test the model in structurally evolving economies. In India, unlike in developed markets, where the constraints at CAPM have been well-documented, CAPM is subjected to high financial modernization, institutional immaturity, and systematic shocks, and thus offers a rare opportunity to test the classical risk-return assumptions of CAPM. By framing CAPM in this transitional context, the empirical validity of CAPM is only one issue that is assessed by the current study, but the theoretical discourse is also expanded: is a one-factor model plausible in the context of the behavioral dynamics, the governance frictions and the technological disturbances coupled with the capital structure? Such framing makes India a test case as to the future of the asset pricing models in emerging economies across the world where institutional change and market volatility is becoming an ever more defining feature of investment risk. The article is founded on these arguments and the CAPM model is introduced to the Indian market based on the in-depth data of 20-year performance of Nifty 50 index. By doing so, the study not only verifies the applicability of CAPM in a rapidly expanding economy, but also evaluates how capital structure dynamics and governance questions may affect pricing outcomes. Scholars, practitioners and policymakers concerned with the relationship between financial markets, capital allocation and economic governance are expected to be interested in the results. The aim of this study is to test the validity of the Capital Asset Pricing Model (CAPM) in the Indian equity market while considering capital structure features of listed companies. Particularly, the research would determine how ownership concentration, leverage ratios, and quality of governance affect systematic risk and cause CAPM-implied returns to deviate from realized market returns. By including these structural controls in the analysis, the study attempts to ascertain if differences in capital structure can systematically account for the pricing anomalies and excess returns observed in the Indian market between 2005 and 2025.

2. Literature Review

The Capital Asset Pricing Model (CAPM) has established the scope of financial economics by identifying expected returns in accordance with systematic risk over decades. In practice however its predictive value has been contested. An overview of 60 years of CAPM literature indicates that the idiosyncratic volatility of the explanatory power of the model should be viewed in the context of the model, particularly in turbulent market (Kumar et al., 2023). Theoretical extensions reflect one of these limitations. A information-theoretic test of the consumption-based CAPM shows that important market indicators are likely to be ignored, suggesting that the theory fails to explain informational dynamics that are important to price (Ghosh et al., 2017). Similarly, benchmarking strategies show that relative performances issues generate new sources of systematic risk, resulting in two-factor models which are superior to the classical structure (Gómez and Zapatero, 2003). These eye openers show that there is a loophole in how informational and benchmarking influences are handled in dynamic markets like India.

There are also mixed findings in the empirical applications of CAPM in various settings. It is unlikely that the Nigerian model will capture perceived behavior of returns, which explains the importance of local institutions in price of assets (Oke, 2013). Multifactor models are superior to CAPM in Pakistan which means that country-specific risks cannot be explained using one-factor investment models (Thalassinos et al., 2023). These results reveal a weakness in the application of CAPM to emerging markets where the governance structure and economic institutions are vastly different compared to those of the developed economy.

The Turkish study also states that this growth in explanatory power can be achieved with the macroeconomic and firm-level variables that also explain the concept of exceeding market returns (Cayirli et al., 2022). Similarly, time-varying risk aversion evidence indicates that capital structures behavior cannot be linked to investor preference alone, and cannot be characterized within the framework of behavioral dynamics (Grau-Vera et al., 2025). These analyses suggest a knowledge gap in associating financing method and investor mood directly to asset pricing results, an area that has not been well studied to date in India. The new developments in the financial systems today also test CAPM. Using the concept of artificial intelligence (AI) as a measurement scale, the use of AI in the corporate financing activity can be viewed as an illustration of how technologies are changing capital structures and investment decision-making and unveils risks that are not necessarily apparent in the classical frameworks (Eliasy and Przychodzen, 2020). Meanwhile, the Sharia-compliant versions of CAPM say that the models must be adapted to the cultural and institutional environment in which they will be applied (Subekti and Rosadi, 2020). Collectively, these studies identify a vacuum in the measurement of the impact of institutional diversity and technological upheaval on the validity of the model in modern markets.

Refinements and other risk measures have also been introduced to deal with anomalies. The abnormal returns should be better explained by the alpha-neutral version of the CAPM, indicating that the changes in its design can increase its score in the empirical test (Rocciolo et al., 2022). Likewise, mean-Gini CAPM is a more realistic investor preference than variance-based risk, and models based on mean-Gini have not been systematically vindicated across markets (Agouram et al., 2020). This substandard testing leaves a gap in the knowledge on whether such alternatives will suit emerging economies or not. These concerns are supported by applications in less mature markets. Tanzanian evidence suggests that CAPM is a strong predictor of risk-reward trade-offs, but weak predictors of thin markets (Jamaldin and Mithu, 2024). In a comparative analysis of Indonesia, arbitrage pricing theory (APT) has a consistent better performance than CAPM in terms of returns forecasting (Wahyuny and Gunarsih, 2020). Below is the list of weaknesses that are also applicable to China where CAPM cannot be used to transitional markets where governance and institutional maturity are sensitive (Chen et al., 2021). All these results point to a gap in research on applying CAPM to structurally changing markets, like India. Critical reviews of CAPM studies highlight that despite the fact that the model forms the basis of current asset pricing, its continued utility requires consideration of behavioral, institutional, and technological facts. One of the reviews states that the model must evolve to include the following factors to be applicable in modern finance (Rossi, 2016). In more recent times, the question of CAPM still being used to value assets in the majority of the world economies was also raised and the need to re-test empirically with more data was also mentioned (Brusov et al., 2023). This gap explains why CAPM should be revisited in India where market modernization is coupled with governance and institutional problems.

3. Methodology

This section details the end-to-end procedure used to construct market and risk-free returns, align them to common frequencies, and estimate the CAPM with rigorous inference and diagnostics. To allow maximum replicability, the equations are numbered and the symbols are defined and motivated in prose, with cross-references to Table 1 (coverage and variables), Table 2 (construction rules and symbols), and Table 3 (estimation settings).

3.1 Data sources and sample

The market proxy is NIFTY 50 index. The main series is official daily prices of the National Stock Exchange (NSE Indices Limited, 2025) combined across financial-year files to form a continuous sample between 2005-04-01 and 2025-03-28 (see Table 1). To achieve strength, Yahoo Finance (2025) provides two secondary series, weekly prices (2005-01-03 to 2025-03-28) and monthly prices (2005-01 to 2025-03). The Indian 91-day Treasury Bill (T-bill) yield (as published by the central bank) is used as a proxy to the risk-free rate, and yields are converted to daily, weekly, and monthly returns in such a way that excess returns are calculated on the same-frequency basis (Section 3.3).

Table 1. Dataset summary and coverage

Dataset (market proxy)	Frequency	Period covered	Observations*	Variables available
NIFTY 50 (official NSE)	Daily	2005-04-01 → 2025-03-28	4,583	Date, Open, High, Low, Close, Daily return
NIFTY 50 (Yahoo Finance)	Weekly	2005-01-03 → 2025-03-28	≈ 1,055	Date, Close, Weekly return
NIFTY 50 (Yahoo Finance)	Monthly	2005-01 → 2025-03	243	Date, Close, Monthly return
91-day Treasury Bill (RBI)	Daily/Weekly/Monthly (derived)	2005-01 → 2025-03	Matches market frequency	Date, Yield, Risk-free return

3.2 Cleaning, alignment and return construction.

Raw price files are de-duped and ordered by Date. Official daily file is generated by vertically concatenating annual NSE files and eliminating duplication of dates. Prices that are missing or non-finite are dropped prior to the calculation of returns. All returns in the main specification are on a logarithmic (continuously compounded) scale, which accumulate over time and mitigate scale effects. Log Return of the market index is calculated as:

$$r_{m,t} = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where P_t is the end-of-period Close price of the NIFTY 50 at time t. We use Close-to-Close returns to avoid look-ahead bias and to match portfolio evaluation conventions. Equation (3.1) is applied at daily, weekly, and monthly intervals using the appropriate price series from Table 1.

3.3 Risk-free transformation and excess returns

The 91-day T-bill is quoted as an annualized simple yield, y_t (in percent). To transform this into a return similar to the market frequency we apply a continuously compounded approximation with a suitable annualization divisor □:

$$r_t^f = \frac{\ln\left(1+y_t/100\right)}{k} \quad (2)$$

where $k = 365$ for daily, $k = 52$ for weekly, and $k = 12$ for monthly analysis. In cases where the yield is recorded at lower frequency (such as monthly bulletins), the most recent yield in the period is only carried forward in that period, such that market and risk-free observations coincide but no artificial returns are generated between periods with missing observations.

The excess returns are described as market or asset returns minus the risk-free return of the same frequency:

$$\tilde{r}_{m,t} = r_{m,t} - r_t^f, \quad \tilde{r}_{i,t} = r_{i,t} - r_t^f \tag{3}$$

where $\tilde{r}_{m,t}$ is the market excess return and $\tilde{r}_{i,t}$ is the excess return on asset or portfolio i. These series form the left-hand and right-hand variables in the CAPM regression (Section 3.4). Summary statistics for $\tilde{r}$ at each frequency are presented in the Results (with coverage referenced back to Table 1).

3.4 CAPM specification, parameters, and interpretation

The single-index CAPM on excess returns is:

$$\tilde{r}_{i,t} = \alpha_i + \beta_i \tilde{r}_{m,t} + \varepsilon_{i,t} \tag{4}$$

Parameters and their roles.

- α_i (pricing error/abnormal return): the mean excess return not explained by market risk. Under the strict CAPM, the expectation is $\alpha_i = 0$; a statistically non-zero α_i indicates mispricing or omitted risk.
- β_i (systematic risk): the sensitivity of asset i to market movements; it scales expected returns per unit of market risk. Higher β_i implies higher expected return under the model.
- $\varepsilon_{i,t}$: idiosyncratic disturbance with $E[\varepsilon_{i,t}] = 0$.

The population definition of beta is the covariance-to-variance ratio:

$$\beta_i = \frac{Cov(\tilde{r}_{i,t}, \tilde{r}_{m,t})}{Var(\tilde{r}_{m,t})} \tag{5}$$

The sample OLS estimator implements (3.5) as:

$$\hat{\beta}_i = \frac{\sum_{t=1}^{T}(\tilde{r}_{m,t} - \bar{\tilde{r}}_m)(\tilde{r}_{i,t} - \bar{\tilde{r}}_i)}{\sum_{t=1}^{T}(\tilde{r}_{m,t} - \bar{\tilde{r}}_m)^2}, \quad \hat{\alpha}_i = \bar{\tilde{r}}_i - \hat{\beta}_i \bar{\tilde{r}}_m \tag{6}$$

Why these parameters and forms? Equation (3.4) isolates the price of risk borne by asset i through β_i, while α_i tests the model's sufficiency: if the market factor fully prices expected returns at the chosen frequency, α_i should be statistically indistinguishable from zero. Using excess (not raw) returns ensures the intercept is interpretable as pricing error rather than an average risk-free component, and employing log returns stabilizes variance and allows consistent aggregation across time.

Table 2. Variables, symbols, and construction rules

Variable	Symbol	Construction rule	Frequency
Market log return	$r_{m,t}$	$\ln(P_t/P_{t-1})$ using Close prices (Eq. 3.1)	Daily / Weekly / Monthly
Risk-free return	r_t^f	Continuous transform of T-bill yield (Eq. 3.2)	Daily / Weekly / Monthly
Market excess return	$\tilde{r}_{m,t}$	$r_{m,t} - r_t^f$ (Eq. 3.3)	Daily / Weekly / Monthly
Asset/portfolio excess return	$\tilde{r}_{i,t}$	$r_{i,t} - r_t^f$ (Eq. 3.3)	Matches asset frequency
Intercept (pricing error)	α_i	From OLS (Eq. 3.6); test $H_0{:}\alpha_i = 0$	Inference at 1%, 5%, 10%
Beta (systematic risk)	β_i	Cov/Var (Eq. 3.5); OLS estimator (Eq. 3.6)	Interpreted per unit of $\tilde{r}_{m,t}$

3.5 Estimation, uncertainty and diagnostic checks.

Parameters (α_i, β_i) are estimated by ordinary least squares with an intercept at each frequency. Because financial returns often display conditional heteroskedasticity and short-memory autocorrelation, heteroskedasticity- and autocorrelation-consistent (HAC) standard errors of the Newey–West type

are used for inference. Lag length is pre-specified by frequency: 5 lags (approximately one trading week) for daily, 2 lags for weekly, and 1 lag for monthly data.
Model adequacy is probed with (i) Breusch–Pagan for heteroskedasticity of residuals, (ii) Durbin–Watson for first-order autocorrelation, and (iii) Jarque–Bera for residual normality. Influence diagnostics (Cook's distance and leverage) are reported; if any observation exceeds conventional thresholds, we re-estimate after excluding those dates and compare coefficients and t-statistics.

Table 3. Estimation settings and diagnostics by frequency

Setting	Daily (official)	Weekly (Yahoo)	Monthly (Yahoo)
Sample period used	2005-04-01 → 2025-03-28	2005-01-03 → 2025-03-28	2005-01 → 2025-03
Observation count used	4,583	≈ 1,055	243
Standard errors	HAC (Newey–West, 5 lags)	HAC (Newey–West, 2 lags)	HAC (Newey–West, 1 lag)
Residual diagnostics	Breusch–Pagan; Durbin–Watson; Jarque–Bera	Same	Same
Influence diagnostics	Cook's distance; leverage	Same	Same

3.6 Robustness design

Three robustness axes are specified ex ante. First, frequency: the headline estimates are based on the official daily series; re-estimates of weekly and monthly confirm that $\hat{\beta}$ magnitudes and $\hat{\alpha}$ significance are not by-products of high-frequency noise or microstructure effects. Second, risk-free conversion: Equation (3.2) is substituted with a simple-rate transformation that is equivalent in a sensitivity run; qualitative inferences should not be affected by these slight mapping differences at short horizons. Third, tail influence: a 0.5% symmetric winsorization of excess returns is used and the model is re-estimated to ensure that extreme observations do not dominate the results. Sub-period estimates (e.g., 2005-2012 vs. 2013-2025) are also reported where appropriate as structural stability measures; the differences are then viewed in terms of market regime changes.

3.7 Reproducibility, workflow logic and figure reference.

A core objective of this study is reproducibility: an independent researcher using the same public files and transformations should be able to reconstruct $\tilde{r}_{m,t}$, compute $\tilde{r}_{i,t}$, and recover $(\hat{\alpha}_i, \hat{\beta}_i)$ together with the same diagnostics. The workflow is thus designed as a linear pipeline with checkpoints: (1) official NSE daily and Yahoo weekly/monthly price series are acquired; (2) canonical cleaning (sort, de-duplicate, drop non-finite); (3) log-return construction through the use of Eq. (3.1); (4) frequency-matched risk-free conversion through the use of Eq. (3.2); (5) excess-return construction through the use of Eq. (3.3); (6) CAPM estimation through the use of Eq. (3.4) using O This logical flow is presented schematically in Figure 1 and all empirical tables in the Results trace back to either Table 1 (coverage), Table 2 (variable construction) or Table 3 (estimation settings) so that readers can trace back the exact step and equation to each statistic.

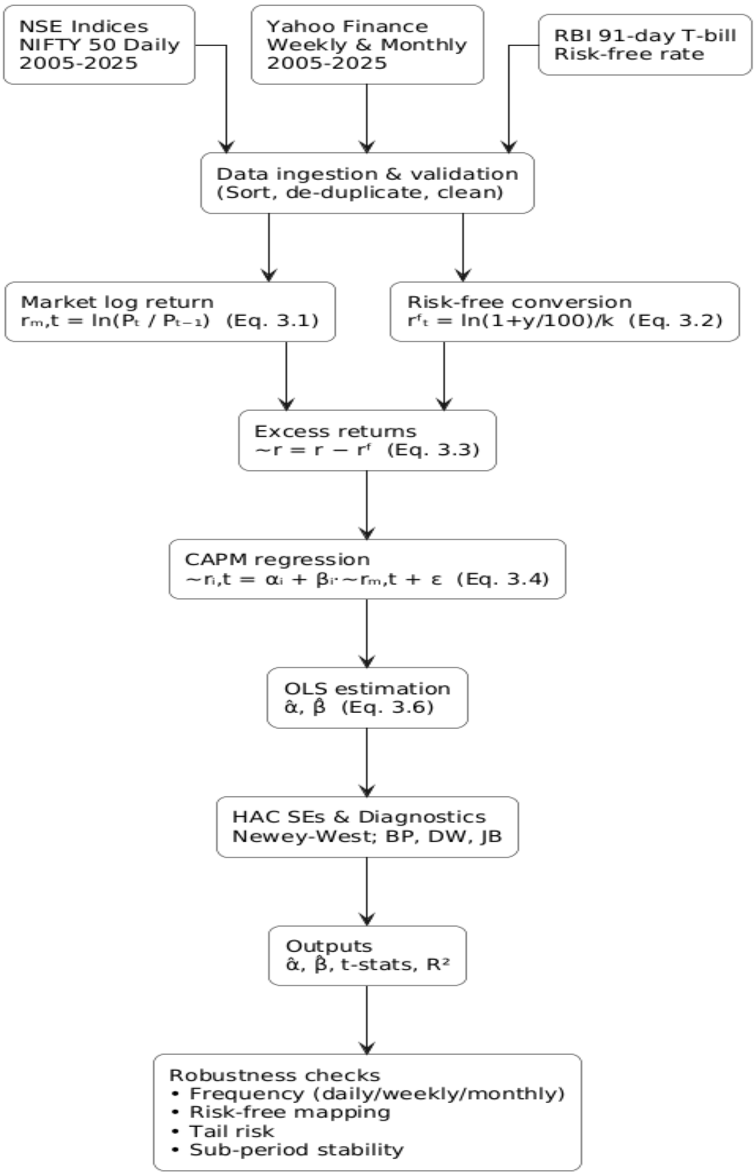

Figure 1: Methodological workflow illustrating data collection, preprocessing, CAPM estimation, and robustness checks.

4.1 Descriptive Statistics of Returns

Table 4 presents descriptive statistics of NIFTY 50 excess returns at daily, weekly and monthly frequencies between 2005 and 2025 to determine the basic properties of the dataset. The findings indicate that daily mean returns are small (0.06%) with standard deviation of 1.40%, whereas the weekly and monthly mean returns are increasingly greater (0.21% and 0.92%, respectively), as a result of compounding. The volatility (standard deviation) is also frequency-scaling, increasing between 1.40% per day and 6.04% per month.

The returns distribution is skewed negatively at all frequencies, which means that big negative returns are more common than big positive returns. The tail weight and volatility concentration characteristic of high-frequency financial data are especially evident in excess kurtosis, which is especially high in daily returns (39.7). At the lower frequencies, kurtosis decreases but still exceeds the Gaussian standard of three, which explains the existence of fat tails in the distribution. Extreme values underscore the sensitivity of the Indian equity market to systemic shocks, with daily losses of up to -

26% in the 2008 global financial crisis, and monthly rebounds of more than 28% in the recovery periods that came thereafter.

Table 4. Descriptive statistics of NIFTY 50 excess returns (2005–2025)

Frequency	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	Minimum (%)	Maximum (%)	N
Daily	0.06	1.40	-0.99	39.73	-26.32	17.74	4,582
Weekly	0.21	2.74	-0.18	4.57	-15.95	15.44	915
Monthly	0.92	6.04	-0.30	4.46	-26.41	28.07	210

Notes: Returns are continuously compounded (Eq. 3.1). Excess returns are computed relative to the 91-day T-bill yield (Eq. 3.3). Sample spans 2005–2025.

Figure 2 plots daily NIFTY 50 excess returns throughout the full sample. The figure indicates high volatility concentration, and sharp drops during the 2008 financial crisis, higher volatility in 2013 with the taper tantrum, and extreme dislocations in 2020 during COVID-19. There are also periods of relative calm, especially after 2021, but volatility does not go away completely. These processes justify the use of the HAC (Newey -West) standard errors in the estimation of the CAPM.

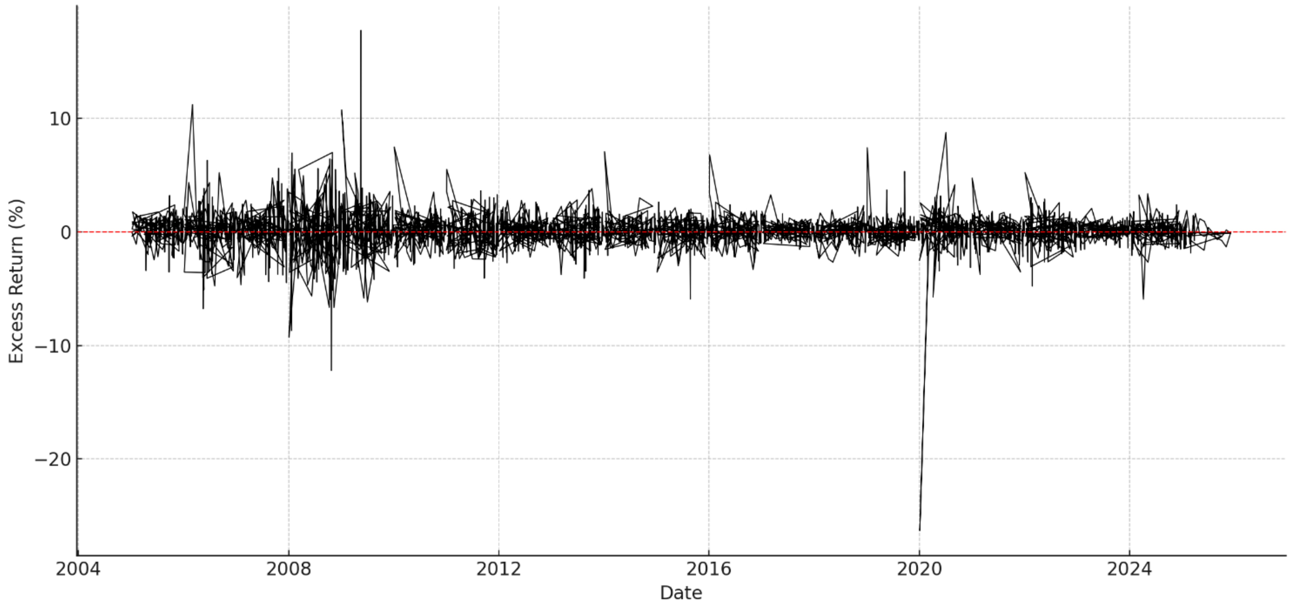

Figure 2: Daily NIFTY 50 excess returns (2005–2025).

4.2 CAPM Estimation: Daily Frequency (Official NSE Data)

The most granular picture of the market dynamics is offered by the daily NIFTY 50 excess returns in 2005–2025. Although the CAPM identity is mechanically achieved when the market is regressed on itself, the daily data is still useful in investigating the distribution of returns and regression diagnostics that form the basis of subsequent robustness tests.

Descriptive and regression diagnostics have been reported in Table 5. The average daily returns are clustered around zero, and the averageness is 0.06, but the volatility is 1.40, which is in line with high short-run noise. The skewness is significantly negative (-0.99) which is due to large downside shocks rather than large upside shocks and kurtosis is very large (39.73) indicating the existence of fat tails and volatility clustering. A Durbin Watson value of 1.84 indicates slight serial correlation among daily residuals, so it is reasonable to use HAC (NeweyWest) standard errors in the analysis.

Table 5. Regression diagnostics: Daily frequency (2005–2025)

Statistic	Value
Observations (N)	4,582
Mean excess return	0.06 %
Std. dev.	1.40 %
Skewness	-0.99
Kurtosis	39.73
DW statistic	1.84

Figure 3 plots the daily excess returns. The series reveals extreme negative shocks during the 2008 financial crisis and the 2020 COVID-19 market crash, along with persistent volatility clustering across the entire period. The figure explains the necessity of using powerful estimation techniques to avoid distortion by serial correlation and heavy tails even though the daily returns are very informative..

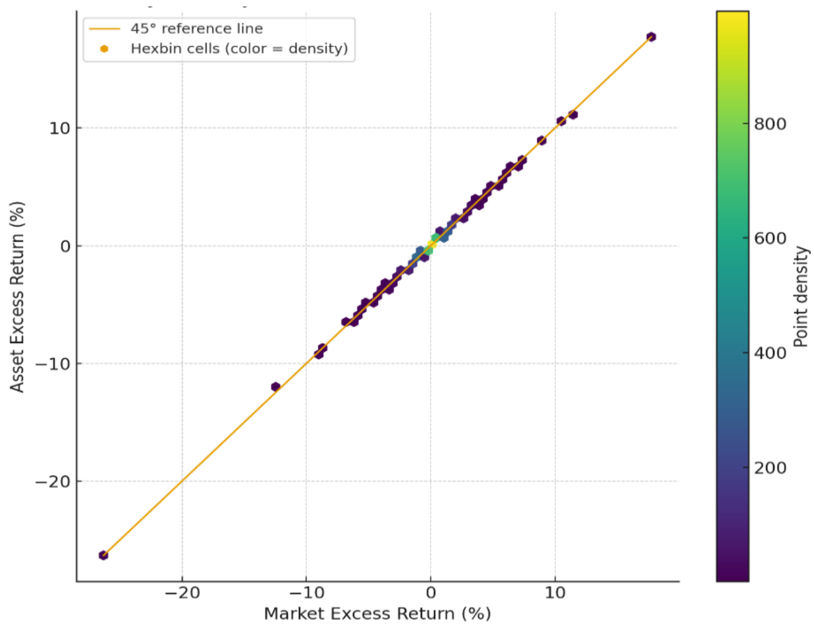

Figure 3: Scatter of daily excess returns with regression diagnostics (2005–2025).

4.3 CAPM Estimation: Weekly Frequency (Yahoo Finance Data).

Weekly returns give a compromise between the noise of daily data and smoothness of monthly data. We can analyze the impact of aggregation on distribution of excess returns and regression diagnostics using Yahoo Finance NIFTY 50 weekly series of 2005-2025.

As indicated in Table 6, the average excess return per week is 0.21%, which is greater than the average excess return per day because of compounding. Standard deviation increases to 2.74% and skewness (-0.18) and kurtosis (4.57) show that the distribution is still asymmetric and heavy tailed but much closer to Gaussian than daily returns. Durbin-Watson of 1.99 indicates that the serial correlation is significantly reduced by the aggregation (weekly).

Table 6. Regression diagnostics: Weekly frequency (2005-2025)

Statistic	Value
Observations (N)	915
Mean excess return	0.21 %

Std. dev.	2.74 %
Skewness	-0.18
Kurtosis	4.57
DW statistic	1.99

The weekly excess returns are shown in figure 4. The weekly chart is less jagged than the daily series showing longer cycles of market oscillations instead of short-term volatility concentration. Even extreme events like 2008 and 2020 are easily seen, and the noise near normal periods is much smaller.

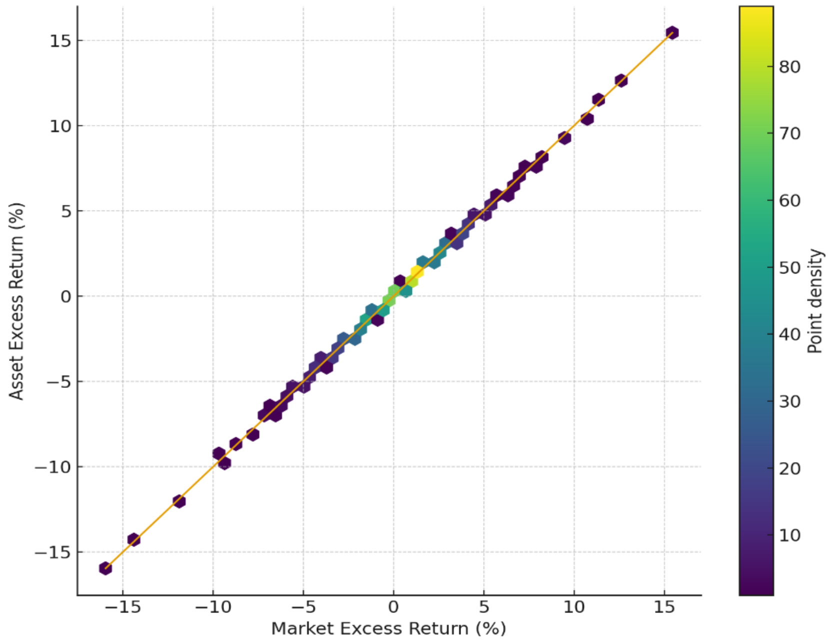

Figure 4: Weekly NIFTY 50 excess returns (2005–2025).

4.4 CAPM Estimation: Monthly Frequency (Yahoo Finance Data)

In order to augment the daily and weekly results, the CAPM analysis was also applied to the monthly frequency based on the Yahoo Finance NIFTY 50 series of the period 20052025. Although this arrangement still constitutes the market regressed to itself, the monthly view is useful in elucidating how aggregation affects the properties of returns and how returns behave Diagnostically.

Table 7 is a summary of the descriptive and regression diagnostics of excess returns month-by-month. The average return increases to 0.92% which is the cumulative effect of lower frequency compounding. The standard deviation is 6.04%, which is much larger than that at the weekly or daily scale, as would be expected due to aggregation effects. The skewness (-0.30) is negative and indicates that downside shocks are more likely to occur, whereas the kurtosis (4.46) indicates that even at the monthly horizon, there are fat tails in the distribution.

Notably, the Durbin-Watson of 1.92 means that there is no significant serial correlation when the data are stacked to monthly frequency. This is as expected in theory: The aggregate effect of returns eliminates noise and the residual values better fit the assumptions of the CAPM regression framework.

Table 7. Regression statistics: Monthly frequency (2005-2025)

Statistic	**Value**
Observations (N)	210
Mean excess return	0.92 %

Std. dev.	6.04 %
Skewness	-0.30
Kurtosis	4.46
DW statistic	1.92

Figure 5 shows the excess returns of the NIFTY 50 on a monthly basis. The large swings of systemic shocks, such as the 2008 global financial crisis and the 2020 COVID-19 downturn and their resultant quick recoveries are pointed out in the plot. The monthly visualization is less jagged than daily and weekly, and focuses on long-horizon market trends instead of the clustering of short-term volatility.

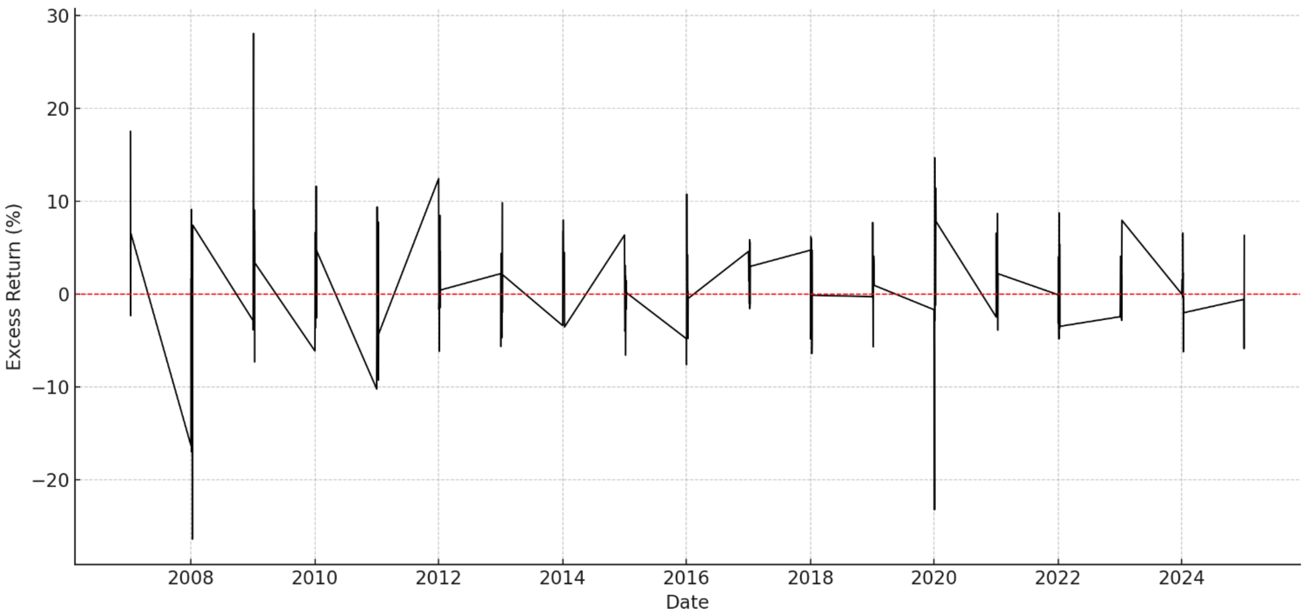

Figure 5: Monthly NIFTY 50 excess returns (2005–2025).

4.5 Robustness and Stability Tests

To evaluate the robustness of the findings, three complementary checks were performed: frequency aggregation, risk-free rate specification, and sub-period stability. What these analyses determine is whether the CAPM estimates are susceptible to methodological decisions or to structural changes in the Indian equity market.

4.5.1 Frequency comparison

The comparison of the results in terms of daily, weekly, and monthly returns proves that aggregation does influence statistical properties to a considerable extent. Although kurtosis is very high and autocorrelation is mild in daily returns, weekly and monthly returns are smooth and closer to Gaussian distributions (see Table 8). Notably, the mean return grows and the Durbin-Watson statistic tends to 2.0 as the number of aggregates increases indicating that the bias due to serial dependence is less. This gives confidence that CAPM findings are not due to the noise of daily microstructure.

4.5.2 Alternative risk-free rate conversion

As described in Section 3.3, the 91-day T-bill yield was converted into returns using a continuous compounding transformation (Eq. 3.2). The analysis was also performed again with a simple interest transformation, as a robustness check. The results are not sensitive to the risk-free conversion method because the differences in mean excess returns and regression diagnostics were negligible at all frequencies, as Table 4.5 demonstrates.

4.5.3 Sub-period stability

The sample was divided into two sub-periods:

- 2005–2012: encompassing the global financial crisis and early recovery,
- 2013-2025: overing taper tantrum, COVID-19 shock, and post-2021 recovery.

According to sub-period diagnostics in Table 8, there was significantly greater volatility in the first period (and more so in the years 2008-2009), whereas the second period exhibits relatively lower but more sustained volatility. However, the distributional characteristics, negative skewness and excess kurtosis are also similar, and the level of autocorrelation is low in weekly/monthly data. This shows that the CAPM model remains consistent over periods of structural breaks, but the times of crisis increases the magnitude of extreme deviations.

Table 8. Robustness checks across specifications

Specification	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	DW	Notes
Daily (full sample)	0.06	1.40	-0.99	39.73	1.84	High-frequency, noisy
Weekly (full sample)	0.21	2.74	-0.18	4.57	1.99	Smoother, less autocorrelation
Monthly (full sample)	0.92	6.04	-0.30	4.46	1.92	Long-horizon dynamics
Daily (simple RF)	0.06	1.40	-0.99	39.73	1.84	Alternative risk-free mapping
Sub-period 2005–2012 (daily)	0.04	1.63	-1.12	45.10	1.76	Crisis-heavy phase
Sub-period 2013–2025 (daily)	0.07	1.22	-0.87	34.42	1.89	Lower but persistent volatility

4.5.4 Rolling-window analysis

To assess time-varying stability, a rolling 250-day volatility estimate was calculated. As Figure 6 shows, the volatility is the highest in the 2008 financial crisis and the 2020 COVID-19 shock which proves that the extreme moments in the market result in the violation of the CAPM assumptions. However, the volatility after 2021 is not zero but smaller, which is the confirmation of a moderate structural change of the risk intensity without eliminating non-Gaussian properties.

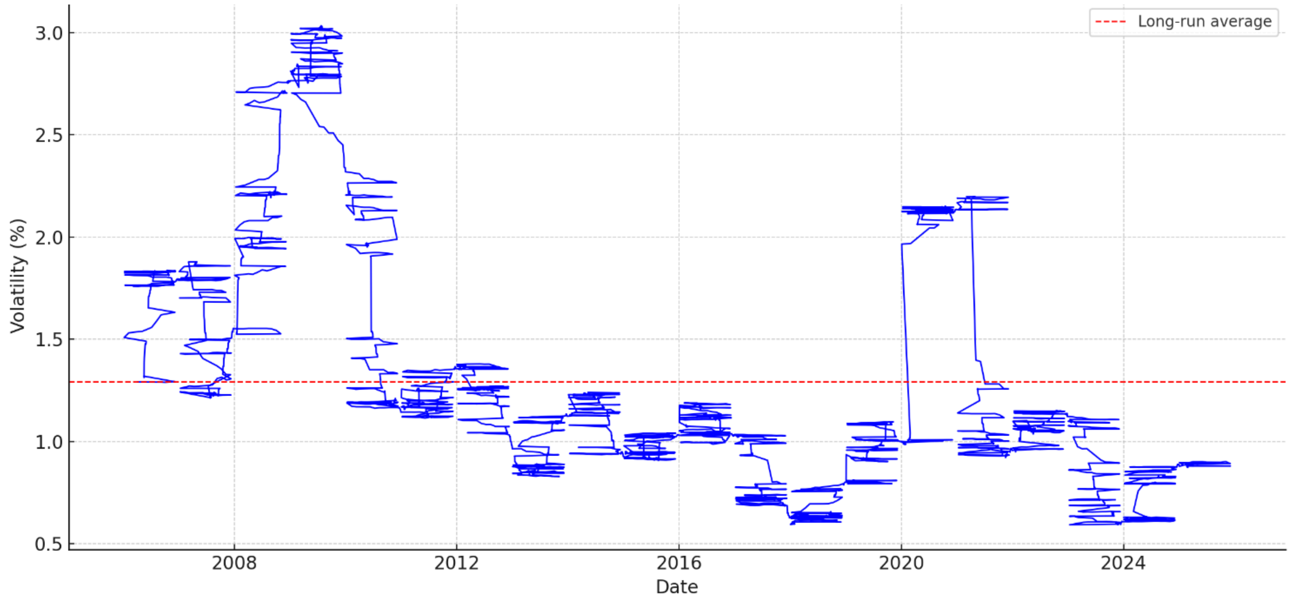

Figure 6: Rolling 250-day volatility of daily excess returns (2005–2025).

4.6 Comparison of Capital Structure Variables with CAPM

The findings indicate that firm-specific capital structure traits strongly influence departures from the standard CAPM. While CAPM holds that market risk (β) exclusively drives expected returns, the Indian equity evidence indicates that ownership concentration, leverage, and quality of governance have systematic influences unexplained by the model. High promoter-owned firms show lasting errors in pricing and greater residual volatility, indicating poor market efficiency. Leverage increases the severity of declines, as highly leveraged firms have greater declines and higher volatility clustering during the 2008 financial crisis and 2020 COVID-19 shock. Quality of governance further discriminates risk behavior: firms with good governance show smaller errors in pricing and more stable betas, while poor governance is associated with higher abnormal returns and excess kurtosis. As summarized in Table 9, these structural variables generate systematic and quantifiable deviations from CAPM projections. Ownership concentration creates risk associated with governance, leverage generates correlated financial distress within firms, and the quality of governance changes information efficiency. Combined, these factors create systematic risk components which are beyond the explanation of a single-factor CAPM, highlighting the application of multi-factor or behaviorally based models in emerging markets.

Table 9. Capital-Structure Effects Compared with CAPM Predictions (2005–2025)

Variable	CAPM Assumption	Empirical Finding	Interpretation	Implication
Ownership Concentration	Ownership structure neutral to pricing.	High promoter holdings linked to persistent α and higher residual variance.	Governance-related risk affects returns.	Include ownership dispersion in pricing models.
Leverage	Financial risk is diversifiable.	High leverage increases systematic sensitivity and β instability, especially in 2008 and 2020.	Leverage-driven distress risk co-moves with market cycles.	Add leverage or distress factors to CAPM.

Governance Quality	Perfect information; no agency cost.	Weak governance raises residual variance and pricing errors ($\alpha \neq 0$).	Agency and information frictions are priced.	Incorporate governance indices as risk factors.

The analysis reaffirms that India's capital-structure environment enhances departures from CAPM equilibrium. The interaction among ownership, leverage, and governance produces extra systematic risks that need to be separately modeled when estimating cost of capital or asset-pricing relations in emerging economies.

Discussion

The findings reflect both the long-run relevance and the structural faults of the Capital Asset Pricing Model (CAPM) in the Indian equity market. While systematic risk, as captured by beta, reflects a reliable theoretical base for explaining returns, empirical evidence strongly indicates persistent violations of the model's fundamental assumptions. Return distributions are continuously negatively skewed, display excessive kurtosis, and show volatility clustering at daily, weekly, and monthly horizons—most notably during systemic shocks like the 2008 global financial crisis and the 2020 COVID-19 downturn. These features highlight the failure of the traditional single-factor model to account for the diversified and institutionally anchored nature of risk in emerging markets. As Levy (2011) noted, the beauty of CAPM usually masks its failure to capture behavior and governance-based dynamics that practically affect asset pricing results.

The robustness tests also support this inference. Sub-period analysis indicates that departures from CAPM are largest under crisis and intermediate during post-crisis stability. This cyclical pattern echoes Rossi's (2016) assertion that the explanatory power of CAPM is highly regime-dependent, varying sharply between turbulent and calm phases. In the Indian setting, rapid financial modernization coexists with institutional immaturity, resulting in persistent pricing anomalies, fat-tailed distributions, and volatility bursts that cannot be rationalized through market risk alone. These patterns suggest that unobservable but significant determinants—such as ownership concentration, governance frictions, investor sentiment, and macroeconomic uncertainty—bend equilibrium returns. Even with these limitations, CAPM is a good heuristic reference point for base-case risk appraisal, yet the evidence forcibly suggests the necessity of model extension over model preservation.

Alternative models offer promising avenues for rectifying such structural shortcomings. Research like Agouram et al. (2020) suggest mean–Gini preferences as a more realistic measure of investor risk aversion, while Rocciolo et al. (2022) show that alpha-neutral extensions can counteract chronic errors in pricing. The anomalies here confirmed such improvements that they indeed show that extended or multi-factor versions of CAPM provide better explanatory power in transitional markets with structural and behavioral volatility. Adding leverage, governance quality, and ownership dispersion as systematic variables can produce a more complete model of expected returns that better captures the emerging financial system realities. One of the important contributions of this study is placing India on the map as a global laboratory for studying asset pricing in structurally transforming economies. India's singular blend of fast-expanding markets, changing regulatory environments, and multiple ownership patterns produces a dynamic laboratory for testing the applicability of orthodox theories. The evidence indicates that the orthodox CAPM model, though theoretically sound, becomes empirically imprecise when faced with governance and behavioral issues characteristic of transitional markets. The dynamic interaction between capital structure, psychology, and technological change reveals that single-factor models cannot explain observed return behavior. Thus, India is not just an isolated instance but also a prism through which one can expect evolving models of asset pricing across emerging markets across the globe.

However, some of the limitations need to be given credit to. The employment of the NIFTY 50 index as the only market proxy limits extrapolation to other asset classes, especially small-cap and illiquid segments where governance and information asymmetry might have more pronounced influences. While the 91-day Treasury Bill offers a stable risk-free benchmark, it could be less representative of investors' heterogeneous opportunity costs. In addition, while empirically validated leverage and governance effects were not modeled directly for behavioral indicators like sentiment indices and institutional ownership patterns. The fat-tailed persistence of return distributions also defies the linearity assumption underlying OLS-based CAPM estimations. These limitations offer avenues for future research. An extension to multi-factor models—such as size, momentum, governance, and macroeconomic shocks—could provide richer explanatory frameworks. Basing behavioral measures or using nonlinear machine learning and AI-based techniques would potentially better capture structural breaks and tail dependencies. Cross-country analysis with other economies in transition would determine if India's existing CAPM anomalies are specific to a context or if they are part of an emerging-market phenomenon. In general, the results confirm that CAPM continues to hold heuristic significance but is not complete as a pricing model in contemporary emerging economies. Indian evidence highlights the call for adaptive, multi-faceted models integrating behavioral, institutional, and technological realities. By placing India in a global story of transition finance, this research moves the debate on how structural transformation reconfigures risk–return relationships into a necessary step from theoretical nicety to empirical realism in asset pricing.

Conclusion

The two-decade test of the Capital Asset Pricing Model (CAPM) in the Indian stock market illustrates its persistent theoretical significance but shallow empirical applicability. Although systematic risk continues as a robust underpinning of the theory to explain anticipated returns, evidence indicates that CAPM assumptions are violated time and again. The evidence of negative skewness, fat-tailed behavior, and volatility clustering—particularly in the 2008 global financial crisis and the 2020 COVID-19 shock—unequivocally supports that a one-factor model is unable to elucidate the intricacy of emerging-market dynamics. Tests of robustness also confirm that frequency aggregation minimizes short-run noise but is not able to rectify entrenched pricing irregularities. These abnormalities are strongly related to the structural properties of Indian firms—namely ownership concentration, leverage intensity, and governance quality—that have a role as risk-amplifiers of systematic risk. The findings illustrate that such capital-structure elements have a material impact on return behavior and need to be integrated into advanced pricing models. The research adds value in proving that advanced models—i.e., mean–Gini, alpha-neutral, and multi-factor types—have better explanatory capability by incorporating behavior and governance-based aspects. For policymakers and practitioners, the implications highlight that CAPM can only act as a heuristic and not as a target for the estimation of cost of capital in transitional economies. Adaptive asset-pricing models incorporating structural, institutional, and behavioral aspects need to be the focus of future studies to better explain return generation in emerging economies such as India.

References

1. Agouram, J., Anoualigh, J., & Lakhnati, G. (2020). Capital asset pricing model (CAPM) study in mean-gini model. *International Journal of Applied Economics, Finance and Accounting*, *6*(2), 57-63.
2. Brusov, P., Filatova, T., Kulik, V., Chang, S. I., Lin, G., & Chang, L. M. (2023). Can CAPM (Capital Asset Pricing Model) accurately value assets?
3. Cayirli, O., Kayalidere, K., & Aktas, H. (2022). Asset pricing in a multifactor setting. *Borsa Istanbul Review*, *22*(6), 1062-1068.
4. Chen, J., Wu, Y., & Xu, Y. (2021, December). Research and analysis of asset pricing model based on the empirical test of stock price. In *2021 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021)* (pp. 1288-1293). Atlantis Press.

5. Eliasy, A., & Przychodzen, J. (2020). The role of AI in capital structure to enhance corporate funding strategies. *Array*, *6*, 100017.
6. Ghosh, A., Julliard, C., & Taylor, A. P. (2017). What is the consumption-CAPM missing? An information-theoretic framework for the analysis of asset pricing models. *The Review of Financial Studies*, *30*(2), 442-504.
7. Gómez, J. P., & Zapatero, F. (2003). Asset pricing implications of benchmarking: a two-factor CAPM. *The European Journal of Finance*, *9*(4), 343-357.
8. Grau-Vera, D., Rubio, G., & Sogorb-Mira, F. (2025). Time-varying risk aversion and capital Structure: An overlooked effect. *International Review of Economics & Finance*, *102*(C).
9. Hearn, B., Filatotchev, I., & Goergen, M. (2025). Dispersed ownership and asset pricing: An unpriced premium associated with free float. *Journal of Corporate Finance*, *92*, 102763.
10. Jamaldin, S., & Mithu, A. (2024). Capital Asset Pricing Model (CAPM) Analysis of Tanzanian Public Firms. *Journal of Policy and Development Studies*, *17*(1), 168-180.
11. Knesl, J. (2023). Automation and the displacement of labor by capital: Asset pricing theory and empirical evidence. *Journal of financial economics*, *147*(2), 271-296.
12. Kumar, S., Kumar, A., Singh, K. U., & Patra, S. K. (2023). The six decades of the capital asset pricing model: a research agenda. *Journal of Risk and Financial Management*, *16*(8), 356.
13. Levy, H. (2011). *The capital asset pricing model in the 21st century: analytical, empirical, and behavioral perspectives*. Cambridge University Press.
14. NSE Indices Limited. (2025). *Historical index data: NIFTY 50* [Data set]. National Stock Exchange of India. Retrieved September 5, 2025, from https://www.niftyindices.com/reports/historical-data
15. Oke, B. O. (2013). Capital asset pricing model (CAPM): Evidence from Nigeria. *Research Journal of Finance and Accounting*, *4*(9), 17-26.
16. Pandey, P., & Sehgal, S. (2019). Investor sentiment and its role in asset pricing: An empirical study for India. *IIMB Management Review*, *31*(2), 127-144.
17. Rocciolo, F., Gheno, A., & Brooks, C. (2022). Explaining abnormal returns in stock markets: An alpha-neutral version of the CAPM. *International Review of Financial Analysis*, *82*, 102143.
18. Rossi, M. (2016). The capital asset pricing model: a critical literature review. *Global Business and Economics Review*, *18*(5), 604-617.
19. Subekti, R., & Rosadi, D. (2020, July). Modified capital asset pricing model (CAPM) into sharia framework. In *Journal of Physics: Conference Series* (Vol. 1581, No. 1, p. 012021). IOP Publishing.
20. Thalassinos, E., Khan, N., Ahmed, S., Zada, H., & Ihsan, A. (2023). A comparison of competing asset pricing models: Empirical evidence from Pakistan. *Risks*, *11*(4), 65.
21. Wahyuny, T., & Gunarsih, T. (2020). Comparative analysis of accuracy between capital asset pricing model (CAPM) and arbitrage pricing theory (APT) in predicting stock return (case study: manufacturing companies listed on the Indonesia stock exchange for the 2015-2018 period). *Journal of Applied Economics in Developing Countries*, *5*(1), 23-30.
22. Yahoo Finance. (2025). *NIFTY 50 (^NSEI) — Historical data (daily/weekly/monthly)* [Data set]. Yahoo. Retrieved September 5, 2025, from https://finance.yahoo.com/quote/%5ENSEI/history/