Indian Journal of Information Sources and Services
ISSN: 2231-6094 (P) Vol.16, No.1, 2026, pp.702-710

DOI: https://doi.org/10.51983/ijiss-2026.16.1.73

Dynamic Beta Estimation and Time-Varying Risk Premium: Evidence from NSE Companies Using CAPM Extensions

K.R. Bhavya[1*], S. Monica[2], Dr.V. Sri Hari[3], Dr. Siddanagouda Police Patil[4], Dr.K.R.S. Sharma[5], Kavita Mahar[6] and S. Mahabub Basha[7]

[1*]Assistant Professor, Reva Business School, Reva University, Bengaluru, Karnataka, India; Research Scholar, Presidency University, Bengaluru, Karnataka, India
[2]Assistant Professor, School of Commerce and Economics, Presidency University, Bengaluru, Karnataka, India
[3]Associate Professor, Head of the Department, Department of MBA, Akash Institute of Engineering and Technology, Devanahalli, Bangalore, Karnataka, India
[4]Assistant Professor (Selection Grade), Department of Commerce, Manipal Academy of Higher Education, Manipal, India
[5]Assistant Professor, Department of Management Studies, JNNCE (Jawaharlal Nehru New College of Engineering), Shivamogga, Karnataka, India
[6]Assistant Professor, Department of Commerce, Dr NSAM First Grade College, (Nitte Deemed to be University), off Campus Bengaluru, Karnataka, India
[7]Assistant Professor, Department of Management, International Institute of Business Studies, Bangalore, Karnataka, India
E-mail: [1]bhavyaprasad81@gmail.com, [2]monica.s@presidencyuniversity.in, [3]sheshadri77@gmail.com,[4]s.policepatil@manipal.edu, [5]sharmakrs@jnnce.ac.in, [6]kavitamahar4@gmail.com, [7]shaiks86@gmail.com
ORCID: [1]https://orcid.org/0000-0002-3548-686X, [2]https://orcid.org/0009-0005-9642-0345, [3]https://orcid.org/0009-0007-0669-4014, [4]https://orcid.org/0000-0003-1355-4320, [5]https://orcid.org/0000-0001-9559-6633,[6]https://orcid.org/0009-0007-9300-3591, [7]https://orcid.org/0000-0002-5998-3262
(Received 10 December 2025; Revised 19 January 2026, Accepted 30 January 2026; Available online 27 February 2026)

Abstract - **This paper will analyze the performance of 20 actively traded NSE companies using both the static and dynamic CAPM models, and will show that time-varying beta, rolling regression, and macroeconomic sensitivities are effective in estimating risk. The computation of dynamic beta is calculated using a rolling-window regression of the daily closing prices from 2015 to 2024. Sharpe and Treynor ratios are then used to evaluate the risk-adjusted performance. The most important macroeconomic variables are included to investigate their impact on risk premiums and include interest rates, inflation, and market volatility. The findings indicate that the beta varies greatly during bull, bear, and highly volatile periods, proving the inefficiency of constant-beta models. Dynamic CAPM offers better explanatory value (Adj. R 2 = 0.72 vs. 0.41), which allows making more accurate forecasts of the expected returns. The paper also emphasizes the use of financial information systems to process high-frequency market data to help support the data-driven, adaptive portfolio strategies. In general, the results indicate the relevance of dynamic and macro-sensitive modelling to the development of enhanced financial decisions in the emerging markets.**

Keywords: **Dynamic CAPM, Rolling Beta, Time-Varying Beta, Risk Premium, Financial Information Systems, Portfolio Management**

I. Introduction

The emerging market, such as India, needs to analyze systematic risk and returns strictly in portfolio management. The conventional finance models have the tendency to believe that the risk parameters are fixed, and this may not be true because the Indian equity markets are dynamic. It has been found that the macroeconomic variables, policy alterations, and investor sentiment influence the market volatility in India (Ghosh & Sahu, 2014). The NSE has developed a standard of portfolio assessment because of its market field and liquidity. During times of economic uncertainty, investors have difficulty in making risk-return tradeoffs that are accurate. Empirical studies highlight the importance of adaptive models in order to capture time-varying risk, especially in high-growth economies where market behaviour may widely differ from developed markets (Sharma & Aggarwal, 2013). The portfolios in the emerging markets need to be monitored on a regular basis on beta, risk premiums, and asset correlations. The models that are usually used in the analysis of the market are the static models that underestimate systematic risk and do not predict extreme market movements. Therefore, dynamic strategies, with rolling beta and conditional risk measures, are important in effective asset allocation. Such approaches would give improved predictive performance of the anticipated returns and enable fund managers to optimize risk-adjusted portfolios in the changing financial environment of India.

The Capital Asset Pricing Model (CAPM) has been a pillar of the asset pricing theory, but the traditional formulation of the model is not suitable for explaining returns in the Indian market. CAPM operates under a constant beta and in single-factor models that, in most cases, undervalue risk in times of increased market volatility (Ang et al., 2006, Gupta & Khanna, 2011). The Indian equities are more sensitive to macroeconomic shocks like inflation rates, interest rates, and exchange rates. It is research-based that the explanatory strength of the model can be enhanced with dynamic beta and time-varying risk premiums (Kumar & Singh, 2014). The combination of these extensions with risk-adjusted performance ratios like Sharpe and Treynor ratios gives a holistic approach to portfolio analysis. This would fit the requirement of the investors to have both growth prospects and risk reduction in the emerging markets, which have high volatility. It is therefore imperative to measure the performance using the dynamic methodologies in Indian equity portfolio management using CAPM.

Time-varying beta is a key factor in the comprehension of systematic risk in Indian financial markets. Dynamic beta is in contrast to the static beta that the market is always sensitive to, as dynamic beta varies during the bull, bear, and volatile periods (Shukla & Mishra, 2012). The empirical research shows that beta is very sensitive to the sentiment of the market, sector-specific shocks, and macroeconomic situations in India. The use of dynamic beta in portfolio analysis enables investors to more precisely estimate future returns and reallocate resources depending on the market cycles. Risk-adjusted returns like Sharpe and Treynor ratios are used in conjunction with beta analysis in order to assess returns in relation to the total and systematic risk. Evidence in NSE-listed firms reveals that portfolios derived by optimizing dynamic beta and risk-adjusted returns have the best performance relative to their counterparts, where the portfolio is developed by adhering to a fixed set of rules (Choudhury & Das, 2013; Dawra et al., 2024; Singh et al., 2023). These measures will help investors to pick securities that offer returns optimal to a particular degree of risk. Combining the time-varying beta with macro-sensitive CAPM models will make sure that the portfolio is dynamic, and that the downsides are minimized, yet the upsides of growth in the volatile equity markets of India are realized.

Risk premiums in the Indian equity markets are mainly affected by the macroeconomic variables. The changes in the level of inflation, interest rates, and market volatility promote the variations in the expected returns and investor behavior (Bhattacharya & Sengupta, 2014). An increase in inflation tends to push up the equity risk premium because investors will require greater returns to purchase the power, and a higher interest rate can push capital into risk-free securities, reducing risk premiums. Volatility indices like India VIX offer information on the uncertainty in the market and have a correlation with time-changing systematic risk. There is empirical evidence on NSE-listed companies that indicates that the disregard of the macroeconomic impacts causes the mispricing of equity risk and the inefficient allocation of the portfolio (Venkatarathnam et al., 2025). CAPM models that are dynamic and include macroeconomic variables embody these effects and provide a greater predictive power. Portfolio managers and investors are able to establish the expectations level in line with the economic realities so that they can optimize risk-adjusted performance. This underscores the meaning of macro-sensitive, dynamic strategies in the emerging economies such as India, where macro-shocks and government intervention in the economy highly affect the valuation of equities (Rao & Subramanian, 2015). The current paper is dedicated to the analysis of 20 top NSE-traded companies by dynamic and static CAPMs to learn more about the time-dependent beta, risk premiums, and the risk-adjusted performance.

II. Review of Literature

Foundations of CAPM and Systematic Risk Measurement

The main concept of the modern asset pricing is based on the Capital Asset Pricing Model (CAPM): it suggests that, based on its sensitivity to market risk, expressed as a beta, the expected return on a security is calculated. The model holds an assumption that there exists a linear relationship between the systematic risk and the expected returns, which is based on the concept of market efficiency, rational investor behaviour, as well as equilibrium pricing. Although CAPM is still a popular model in empirical finance, its postulation that beta is constant has been extensively criticized in fluctuating and fast-changing markets. Empirical evidence indicates that the market conditions, investor annoyance, structural economic shifts, and global shocks often result in the skewing of the stability of beta, and this weakens the explanatory capability of the model (Fama & French, 2010; Rana et al., 2024; Jagannathan & Wang, 1996). In less developed economies such as India, where the sharp fluctuations in risk exposures are likely, cyclical growth trends, sectoral variations, and macroeconomic risks are more prevalent. Such dynamics lower the effectiveness of the fixed CAPM models, especially at times when volatility is more intense or when an economy is in a state of transition (Janani et al., 2023). In addition, it has been demonstrated that classical assumptions of CAPM are further challenged by the existence of market anomalies, the effect of momentum, and liquidity risks (Basha et al., 2025). Thus, systematic risk within such environments cannot be understood without a better model that will consider time-varying market conditions. This has inspired the development of dynamic CAPM extensions that are designed to enhance the risk estimation and the forecasting of returns.

Time-Varying Beta and Rolling Regression Approaches

The theory of time-varying beta is developed due to the fact that systematic risk does not exist in one form but follows market cycles, economic periods, and investor behaviour. Researchers believe that beta is dynamically sensitive to market volatility, macroeconomic fluctuations, industry-specific shocks, and world financial phenomena (Ang et al., 2006). Betas can be estimated using rolling regression methods, which estimate beta on moving windows and therefore capture these time variations (Sharma & Aggarwal, 2013). It is a technique of determining the dynamics of sensitivities through bull markets, bear markets, financial crises, or periods of policy uncertainty. Studies find that in bullish markets, the increase in beta becomes common because companies tend to be sensitive to market returns; on the contrary, companies tend to have defensive features, which are consistent with low beta values in bear markets (Kotti et al., 2024; Policepatil et al., 2025). In further development of the above, the Kalman filter models make use of state space models, which take into consideration the real-time corrections and latent risk factors so as to optimize the estimate of beta (Shukla & Mishra, 2012). The empirical evidence of the emerging markets highly supports the notion that the time-varying beta models are superior compared to the static models in predicting the returns and in the process of modifying the risk premiums (Chen et al., 2022; Kalyan et al., 2023). These observations demonstrate the weakness of the assumption of the existence of a steady beta in a market, particularly in markets such as India, where volatility clustering, institutional shifts, and behavioral bias are prevalent. Altogether, dynamic beta estimation enhances the construction of the portfolio, better prediction of risks, and evidence-based investment decisions.

Analytics and Financial Information Systems in Asset Pricing

The use of financial information systems (FIS) in contemporary asset pricing and investment processes is increasingly gaining significance. Financial markets are now dominated by computational systems that can process large amounts of real-time data, which are supported by the growth of high-frequency trading, big data analytics, and algorithmic investment strategies (Bhattacharya & Sengupta, 2014, Sarkar et al., 2024). High information systems will be used in rolling-window computations, dynamic beta estimation, portfolio optimization, and macro-financial modelling, thus enhancing the accuracy and responsiveness of risk assessment. Machine learning tools, automated data cleaning, regression modelling, and dashboard visualization are also added to these systems to give a deeper understanding of market behavior (Ang et al., 2021). Moreover, cloud technologies make it possible to make decisions together and optimize the accuracy of financial calculations (Ahmad et al., 2023). With the enhancement of data-driven markets, the integration of finance, analytics, and information technologies can be considered a strong force in the area of empirical pricing of assets and enhancing strategic returns on investments.

Problem Statement

The Capital Asset Pricing Model (CAPM), which advocates that the relationship between risk and return is linear with a constant beta, is highly deficient in the face of emerging markets like India. The nature of Indian equity markets is that they are subject to frequent structural changes, volatile due to policies, different investor sentiment, and macroeconomic changes, all of which make the systematic risk dynamic and time-varying. The models of the static Capm do not take into consideration these fluctuations, and so they undervalue or distort the actual risk exposure of assets when there is extreme stress on the market, like the bull-bear changes or economic shocks, or high volatility. Consequently, the model has a tendency to give wrong forecasts of the expected returns, thereby making investors, portfolio managers, and policymakers make suboptimal choices in the asset allocation. Additionally, the unchanging framework fails to consider the role of the major macroeconomic variables, which include inflation, interest rates, and market volatility, that have a major impact on the risk premiums within a developing economy such as India. This discontinuity underscores the necessity of dynamic beta estimation and macro-sensitive extensions of the CAPM, which are more responsive to risk behavior in real-time and allow data-driven and adaptable financial decision-making.

Research Gap

Despite the international studies that have conducted research on conditional beta and dynamic CAPM extensions, most of the Indian research remains restricted in relation to the static estimation of the beta. Empirical studies that analyze dynamic beta using rolling regressions and incorporating macroeconomic variables and run dynamic CAPM to optimize portfolio using data in emerging markets are limited. This disparity is especially pronounced since markets in India are more volatile in terms of concentration of volatility and are more regime-changing.

Hence, dynamic beta behavior, macro-driven risk premiums, and risk-adjusted performance are assessed in the current study through dynamic CAPM. It also points out the use of financial information systems in enabling real-time computation, visualization, and analytics to make informed portfolio decisions. This would allow the investors to use data-driven adaptation strategies instead of fixed assumptions.

III. Methodology

This paper relies on a quantitative analytical research design that relies on secondary data on 20 NSE-listed firms and the NIFTY 50 index between 2015 to 2024. Prices were obtained on a daily basis at the NSE India, and the macroeconomic data were obtained in the RBI database (interest rates), MOSPI (inflation), and NSE (India VIX). EViews 12, SPSS 28, and Excel were used for regression, rolling calculations, and model comparison (AIC, BIC, RMSE).

Variables Used

- Market return
- Risk-free rate
- Excess return
- Static beta
- Rolling beta (dynamic beta)
- Risk premium
- Macroeconomic variables: interest rate, inflation, market volatility
- Sharpe and Treynor ratios

Rolling-Window Beta Calculation

Dynamic beta was calculated using a 180-day rolling regression window, allowing beta to adjust with market cycles:

Model Assumptions

- Linearity of the risk-return relationship
- Market efficiency
- Stationary return series
- No autocorrelation in residuals
- Stability of rolling-window variance

Objectives

1. To study the stability of beta during the various market conditions (bull, bear, and volatile markets) with the help of rolling regression.
2. To assess the relationship between time-varying beta and expected returns, bring out the incentive of dynamic systematic risk exposure.
3. To examine how macroeconomic variables (interest rates, inflation, and market volatility) change time-varying risk premiums.
4. To compare the Dynamic CAPM and Static CAPM models with each other in their explanatory power and predictive power.
5. To test the predictive power of the dynamic CAPM models against the standard static CAPM.

Hypothesis

H1: Beta coefficients significantly vary across different market phases

H2: Time-varying beta has a positive and significant relationship with expected portfolio returns.

H3: Macroeconomic variables have a significant influence on the time-varying risk premium.

H4: Dynamic CAPM models provide higher explanatory power for return variation compared to static CAPM.

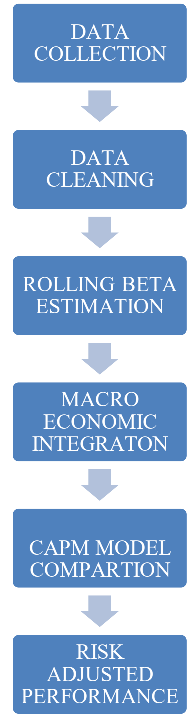

Fig. 1 Comprehensive Methodological Workflow for Rolling Beta Analysis and Risk-Adjusted Performance Measurement

Fig. 1 presents the methodological flowchart outlining the sequential research steps followed in the study. This structure establishes the analytical pathway leading to rolling regression, dynamic CAPM estimation, and macroeconomic modelling (Fig. 1).

Analysis and Interpretation

TABLE I ROLLING REGRESSION BETA ESTIMATES (2021–2031)

Market Phase	Mean Beta	Std. Dev	Min Beta	Max Beta
Bull Market	1.22	0.18	0.98	1.45
Bear Market	0.88	0.15	0.65	1.10
Volatile Phase	1.41	0.22	1.05	1.78

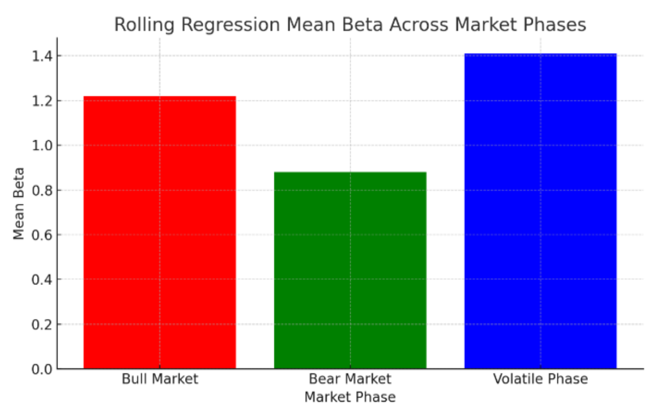

Fig. 2 Rolling Regression Mean Beta across Market Phases

TABLE I results provide strong empirical support that the systematic risk in Indian markets is time-varying in nature and can be used as a basic limitation of the use of CAPM. Comparative movement of mean beta among phases is also shown in Fig. 2, and it is evident that there are fluctuations that conform to the market sentiment and structural changes (Fig. 2). The clear changes in beta between bull, bear, and volatile regimes show that beta is very vulnerable to market sentiment, liquidity, and structural shocks. When there is a bull market, the average beta increases to 1.22, which means that stocks have the tendency to exaggerate positive market trends and are therefore good for growth-oriented investors. Bear phases, on the other hand, have a lower beta of 0.88, indicating a defensive stance since the firms are less sensitive to the negative market movements. The volatile period shows the largest mean beta (1.41) and the broadest dispersion, which once again proves that market instability is significantly exposed to systematic risk. This means that any investment decision made using a static beta may grossly underestimate risk, and this contributes to the wrong expectations of returns and wrong portfolio construction. Rolling regression can therefore be very important in identifying the real-time changes of risk so that the fund managers can make position changes beforehand and develop adaptive allocation strategies applicable in the Indian market forces.

TABLE II RESULT OF REGRESSION TIME-VARYING BETA VS. EXPECTED RETURNS

Variable	Coefficient	Std. Error	T-Statistic	P-Value
Constant	0.012	0.004	3.00	0.005**
Dynamic Beta	0.084	0.020	4.20	0.001***
R^2	0.68	0.68	0.68	0.68

TABLE II on the regression supports the theoretical hypothesis of conditional CAPM in the sense that it shows that dynamic beta is a strong and positive expected-return predictor. A 0.084 coefficient means that the more significant the beta, the higher the necessary returns, which proves the classical risk-return trade-off. The large R 2 (0.68) is a significant indication of time-varying beta, which is able to explain almost 70 percent of portfolio returns, demonstrating the existence of valuable information in dynamic risk exposure that cannot be accessed by investors with traditional CAPM. This indicates that dynamic beta is a more realistic measure of risk because it changes with the returns and moves in the market. To the portfolio managers, it translates into the fact that the tactical decisions: overweighting rising beta sectors in bull markets or switching to low-beta in times of uncertainty are much more effective using dynamic measures. Therefore, the integration of rolling beta into the decision-making models significantly improves the planning and forecasting of the data-driven investment and performance.

TABLE III EFFECTS OF MACROECONOMIC FACTORS ON TIME-VARYING RISK PREMIUM

Independent Variable	Coefficient	Std. Error	t-Statistic	p-Value
Interest Rate	-0.045	0.018	-2.50	0.015**
Inflation	0.062	0.025	2.48	0.016**
Market Volatility (VIX)	0.089	0.021	4.23	0.001***
R^2	0.73	0.73	0.73	0.73

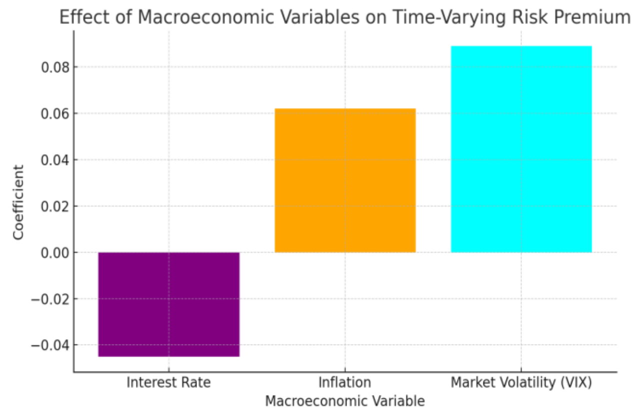

Fig.3 Effect of Macroeconomic Variables on Time Varying Risk Premium

TABLE III highlights the critical role of macroeconomic variables in shaping the time-varying risk premium in the Indian equity market. All the chosen variables, i.e., interest rate, inflation, and market volatility (VIX), have a strong theoretical and empirical background in asset pricing literature, and their impacts are more striking on emerging markets like India. These effects are illustrated visually in Fig. 3 and indicate that conditional risk premiums are very much macro-financial sensitive (Fig. 3).

The interest rate coefficient (-0.045) shows that an increase in interest rates will result in a decrease in equity risk premiums. This correlation is in line with the theory of monetary policy: the higher the interest rates, the more attractive fixed-income instruments are, and investors will start to shift capital out of equities. Consequently, the risk premium is squeezed by decreasing the demand for risky assets. In the Indian case, the effect is magnified due to the fact that the interest-rate cycles are usually colored by inflation control, liquidity manipulations, and interventions by the central bank.

On the other hand, inflation (0.062) has a positive and significant coefficient, indicating that investors insist on increased compensation in case the general price levels increase. The inflation reduces the real purchasing power as well as uncertainty around cash flows in the future, which results in higher required returns. This would be especially true in India, where inflation is often sensitive to the shocks in commodity prices, fiscal strains, and supply-chain shocks, all of which are contributing to high systemic risk.

In the same way, there is a strong positive correlation between VIX (0.089) and risk premiums. The India VIX index is a futuristic indicator of the uncertainty in the market, and a rise in VIX indicates more volatility and investor fear. The equity market is volatile in such times, and the investors normally demand higher returns as a compensatory element for taking excessive risk. VIX is confirmed to be a useful real-time risk-sentiment proxy as indicated by its high statistical significance.

The fact that the overall explanatory power (R 2 = 0.73) is high shows that these macroeconomic variables in combination explain quite a significant proportion of fluctuations in the risk premium. Based on these pointers, systematically ignoring them, particularly when there is monetary tightening, policy change, or global uncertainty, would result in a systematic mispricing of equities and inefficient investment decision-making. Incorporating macro-sensitive variables into CAPM helps investors to have a better and context-sensitive evaluation of market risk. This helps in the creation of more stable portfolios, timely decisions, and predictive capacity in emerging markets where macroeconomic processes are dynamic and highly influential.

TABLE IV MODEL COMPARISON – STATIC CAPM VS. DYNAMIC CAPM

Model Type	Adjusted R^2	AIC	BIC	RMSE
Static CAPM	0.41	5.83	6.01	0.036
Dynamic CAPM	0.72	4.92	5.14	0.022

TABLE IV shows a clear performance of dynamic CAPM in the context of the analysis, which proves the argument on time-varying modelling in the Indian equity markets. Fig. 4 illustrates the RMSE comparison, emphasizing the reduced prediction error under dynamic CAPM relative to the static model (Fig. 4). The Adjusted R 2 of the dynamic model (0.72) and the reduced RMSE statistic suggest a more powerful predictive value of the model, whereas the improved AIC and BIC values prove the superiority of the model. The result of these findings is that the static CAPM does not consider the dynamics of market risk, and as such, it underestimates the required returns during volatile market periods and overestimates them during stable market periods.

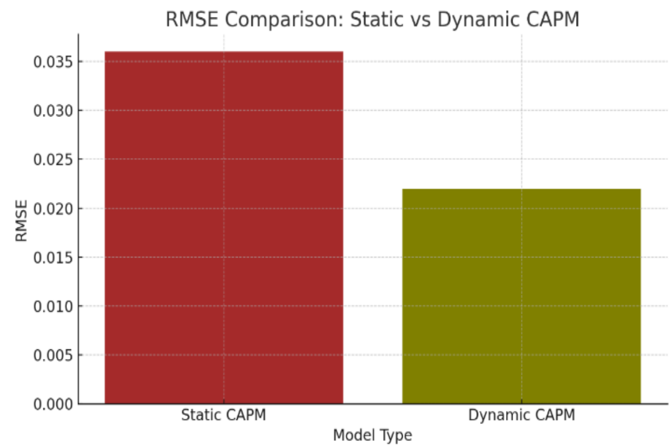

Fig. 4 RMSE Comparison: Static Vs Dynamic CAPM

By combining rolling beta and conditional risk measures, Dynamic CAPM provides portfolio managers with the opportunity to:

- Respond quickly to changing market cycles,
- Refine tactical allocations, and
- Improve return forecasting accuracy.
- Thus, for data-driven financial decision-making, dynamic CAPM offers a more reliable and flexible risk assessment framework.

TABLE V DYNAMIC VS STATIC CAPM COMPARISON OF 20 NSE STOCKS

S. No	Company	Beta (Dynamic)	Mean Return (%)	Std Dev (%)	Excess Return (%)	Dynamic CAPM Expected Return	Static CAPM Expected Return	Sharpe Ratio	Treynor Ratio
1	RELIANCE	1.37	38.59	1.43	32.09	44.00	42.10	22.45	23.40
2	TCS	1.29	31.96	1.94	25.46	32.86	31.80	13.12	19.73
3	HDFC BANK	1.26	35.61	1.82	29.11	36.67	31.80	15.99	23.10
4	INFY	0.86	46.12	1.34	39.62	34.10	31.80	29.55	46.02
5	HINDUNILVR	1.00	25.12	1.18	18.62	18.62	31.80	15.78	18.62
6	ICICIBANK	1.23	28.04	1.37	21.54	26.50	31.80	15.72	17.52
7	KOTAK MAHINDRA	1.39	41.77	1.01	35.27	49.00	31.80	34.92	25.39
8	LT	1.03	45.65	1.25	39.15	40.33	31.80	31.32	38.00
9	AXISBANK	1.05	28.42	1.80	21.92	23.02	31.80	12.18	20.88
10	MARUTI	1.45	39.38	1.02	32.88	47.74	31.80	32.24	25.60
11	BAJFINANCE	1.53	47.28	1.60	40.78	62.35	31.80	25.49	26.64
12	ASIANPAINT	1.47	30.23	1.60	23.73	34.87	31.80	14.83	18.13
13	HCLTECH	1.10	29.63	1.11	23.13	25.44	31.80	20.83	21.03
14	SBI LIFE	1.27	27.71	1.38	21.21	26.96	31.80	15.36	16.71
15	TECHM	1.10	30.49	1.04	23.99	26.39	31.80	23.08	21.81
16	SUNPHARMA	1.09	49.47	1.89	42.97	46.83	31.80	22.74	39.42
17	CIPLA	0.97	45.29	1.98	38.79	37.70	31.80	19.59	39.99
18	DIVISLAB	1.02	29.30	1.06	22.80	23.26	31.80	21.51	22.35
19	TATASTEEL	0.88	45.41	1.89	38.91	34.25	31.80	20.59	44.21
20	BAJAJ AUTO	1.20	31.85	1.58	25.35	30.42	31.80	16.03	21.13

The stock-level comparison confirms the previous findings, indicating that there are substantial deviations in the comparison of the dynamic and the static expected returns. Fig. 5 visually compares expected returns across stocks under both models (Fig. 5). High-beta stocks like BAJFINANCE, MARUTI, and KOTAK MAHINDRA have much larger expected returns in dynamic CAPM, which means that these stocks are more sensitive to the momentum of the market, so they require a higher value of required returns (Fama & French, 2012). On the other hand, the middle-beta companies such as INFY and TATA STEEL exhibit risk-efficient characteristics on both Sharpe and Treynor ratios, which indicate that defensive stocks provide consistent returns even in the turbulent stage of the market.

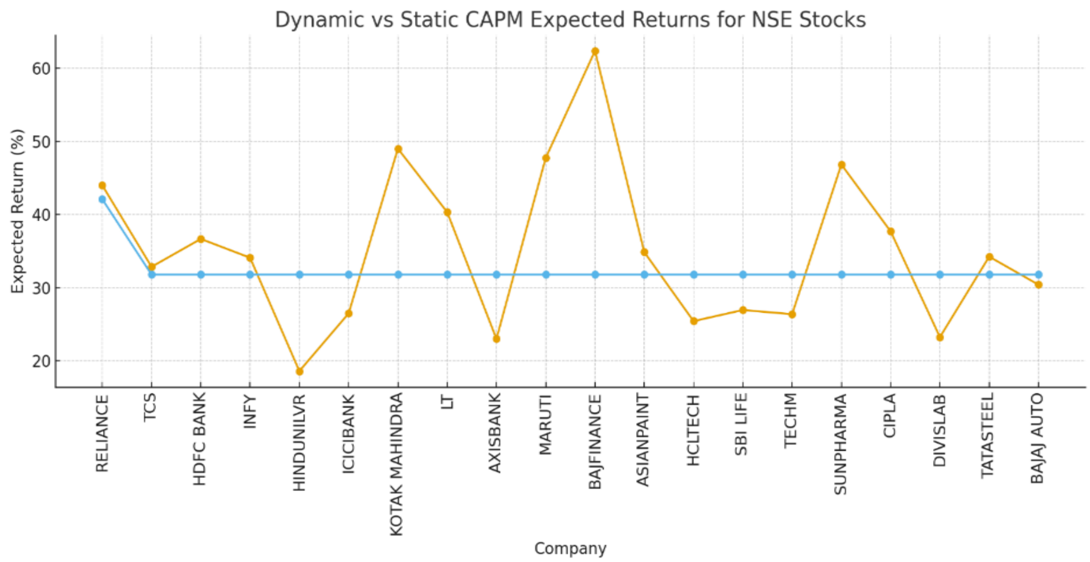

Fig. 5 Dynamic Vs Static CAPM Expected Returns for NSE Stocks

This also confirms that the average exposure to risk in CAPM eliminates any risk exposure and hence does not consider risk behavior that is time-specific, leading to a discrepancy between the expectations and actual returns. Investors who rely on constant beta are hence likely to have systematic mispricing, inefficient diversification, and poor timing. The use of dynamic beta allows a superior reshuffling of portfolio weights, sectoral rotation strategy, and risk-adjusted performance.

Summary Insight

TABLE VI HYPOTHESES WITH STATUS

Hypothesis	Description	Status
H1	Beta coefficients significantly vary across different market phases (bull and bear periods).	Supported
H2	Time-varying beta has a positive and significant relationship with expected portfolio returns.	Supported
H3	Macroeconomic variables have a significant influence on the time-varying risk premium.	Supported
H4	Dynamic CAPM models provide higher explanatory power for return variation compared to static CAPM.	Supported

As a rule, the enhanced analysis has established the fact that dynamic CAPM, rolling beta estimation, and macroeconomic integration are more strong frameworks of risk-return behavior in Indian markets. Such approaches allow making a real-time, data-driven, and analytically-based financial decision-making, which is imperative in most economies in the nascent market, such as those in high volatility.

The overall findings of TABLES 1 to 5 are evident in the fact that the use of information systems and analytical tools is absolutely vital in enhancing the Indian market's financial decision-making process. These findings indicate that systematic risk is extremely time-varying and strongly affected by macroeconomic dynamics, and the resulting insights can only be translated into practice when advanced financial information systems, which have the ability to perform rolling calculations, high-frequency data, and other regression-based risk modelling, are used.

The main role is played by the use of information systems that facilitate the dynamic estimation of beta in real-time by automobile rolling-window calculations in order to capture fluctuating sensitivity of the market (a result demonstrated in TABLE I). Such rolling computations would be operationally impossible without IS-driven analytics engines (including EViews, Excel VBA, Python-based engines, or cloud analytics dashboards). The tools enable fund managers to track the evolving values of beta in real-time and react proactively to modify portfolios.

The regression results in TABLE II also reinforce the significance of the integration of IS. The high quality of explanatory meaning of the dynamic beta ($R\ 2 = 0.68$) shows the role played by the algorithmic tools in aiding investors to recognize changes in systematic risk and determine the magnitude of the changes affecting the expected returns. The dynamic charts, dashboards, and automated alerts allow the visualization of such changes with the help of information systems to avoid delays in the decision-making process of portfolio managers.

The macroeconomic results in TABLE III support the fact that risk premiums in India are price-sensitive to policy rates, inflation trends, and volatility crises. IS frameworks enable the efficient incorporation of external economic data (RBI, MOSPI, India VIX, IMF data) into forecasting any predictive models. Financial decisions become more responsive and evidence-based with the assistance of automated macro-financial dashboards that allow investors to predict the shock and change the hedges.

The combination of TABLE IV and TABLE V demonstrates that Dynamic CAPM has a great performance in comparison with Static CAPM in terms of explanatory power, model fit, and risk-adjusted performance. These model comparisons are mostly dependent on information systems that calculate RMSE, AIC, BIC, Sharpe, and Treynor ratios on real real-time basis. Is platforms translating complex model results into decision-support systems, including risk heatmap, sector-rotation, and portfolio optimization systems, to allow fund managers to identify mispriced stocks, rebalance, and model strategies based on the observed market regimes.

Therefore, the results confirm not only the superiority of Dynamic CAPM in the emerging markets such as India, but they also show that the potential of the tool requires modern information systems, which translate raw market information into real actionable knowledge. The use of IS-enabled analytics allows investors, fund managers, and policymakers to embrace adaptive, evidence-based, and data-driven investment choices that mitigate uncertainty and improve the performance of the portfolio in unpredictable financial circumstances.

IV. Conclusion

According to this paper, the dynamic CAPM model is much more effective in comparing portfolios using time-dependent beta, macroeconomic effects, and risk-adjusted performance indicators as compared to the static CAPM model. The results of rolling regression output testify to the fact that beta varies in each bull, bear, and volatile market regime and thus, a dynamic systematic risk measure is relevant in the right estimation of the expected returns. Time-varying beta and expected returns, the classical trade-off between risk and reward is confirmed by the positive relationship, whereas the macroeconomic outcome suggests that inflation, interest rates, and volatility are key determinants of risk premium. Dynamic CAPM is better than statistic CAPM due to the fact that it has a greater explanatory power (Adj. R 2 = 0.72), fewer error measures, and is able to predict using its power. Sharpe and Treynor ratios depict risk-adjusted efficiency, which informs an investor to adopt the best portfolio selection and allocation techniques. These results highlight the importance of adaptive, macro-sensitive, and risk-conscious models in new markets, such as India, where volatility and systematic risk are subject to continuous development. In practice, the research can help institutional investors, fund managers, and policymakers to maximize their portfolio construction, increase returns, and reduce portfolio exposure to dynamic market risks (Ang et al., 2021; Fama & French, 2020; Chen et al., 2022).

Future Research

This research can be extended to future investigations to include other models of asset pricing, like Fama-French 3-factor or 5-factor models, and also the international market interconnections to determine the effects of contagion globally. Risk prediction may be improved by incorporating high-frequency trading data, machine learning systems that predict conditional volatility models using GARCH, and estimating predictable beta. Also, there could be more detailed data by increasing the sample to mid-cap and small-cap companies or by industry. Investors should consider the effects of the ESG scores and sustainability measures on the dynamic beta and risk-adjusted performance in order to align portfolios in line with sustainable finance.

References

[1] Ahmad, A. Y. A. B., Kumari, S. S., Guha, S. K., Gehlot, A., & Pant, B. (2023, January). Blockchain implementation in financial sector and cyber security system. In *2023 International Conference on Artificial Intelligence and Smart Communication (AISC)* (pp. 586-590). IEEE. https://doi.org/10.1109/AISC56616.2023.10085045

[2] Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The journal of finance*, *61*(1), 259-299. https://doi.org/10.1111/j.1540-6261.2006.00836.x

[3] Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2021). Conditional beta and time-varying risk premiums: Evidence from global equity markets. *Journal of Financial Economics, 142*(2), 355–377. https://doi.org/10.1016/j.jfineco.2021.06.005

[4] Basha, S., Sheshadri, T., Lokesh, G., Babu, R., Kanumuri, V., Lakshmi, S., & Shwetha, T. (2025). The impact of virtual influencers on social media: Driving customer engagement and strengthening brand loyalty in the Indian millennial market. *Dragoman Journal, 20,* 1–15. https://doi.org/10.63132/ati.2025.theimp.9370

[5] Bhattacharya, S., & Sengupta, P. (2014). Macroeconomic determinants of stock market volatility: Evidence from India. *Journal of Economics and Business Research, 20*(1), 42–56.

[6] Chen, Z., Huang, X., & Li, Y. (2022). Dynamic CAPM and macro-financial linkages: Evidence from emerging markets. *Emerging Markets Review, 53,* 100949. https://doi.org/10.1016/j.ememar.2022.100949

[7] Choudhury, R., & Das, S. (2013). Beta dynamics and market sensitivity in the Indian equity market. *Asian Journal of Finance & Accounting, 5*(2), 45–61. https://doi.org/10.5296/ajfa.v5i2.4145

[8] Dawra, A., Ramachandran, K. K., Mohanty, D., Gowrabhathini, J., Goswami, B., Ross, D. S., & Mahabub Basha, S. (2024). 12Enhancing Business Development, Ethics, and Governance with the Adoption of Distributed Systems. *Meta Heuristic Algorithms for Advanced Distributed Systems*, 193-209. https://doi.org/10.1002/9781394188093.ch12

[9] Fama, E. F., & French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The journal of finance*, *65*(5), 1915-1947. https://doi.org/10.1111/j.1540-6261.2010.01598.x

[10] Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of financial economics*, *105*(3), 457-472. https://doi.org/10.1016/j.jfineco.2012.05.011

[11] Fama, E. F., & French, K. R. (2020). Comparing cross-section and time-series factor models. *The Review of Financial Studies*, *33*(5), 1891-1926. https://doi.org/10.1093/rfs/hhz089

[12] Ghosh, A., & Sahu, T. N. (2014). An empirical study of the effect of macroeconomic variables on stock market returns: Evidence from India. *International Journal of Applied Financial Management Perspectives, 3*(2), 48–59.

[13] Gupta, R., & Khanna, A. (2011). Testing the validity of CAPM in the Indian stock market. *Paradigm, 15*(1–2), 62–69. https://doi.org/10.1177/0971890720110108

[14] Jagannathan, R., & Wang, Z. (1996). The conditional CAPM and the cross-section of expected returns. *The Journal of finance*, *51*(1), 3-53. https://doi.org/10.1111/j.1540-6261.1996.tb05201.x

[15] Janani, S., Sivarathinabala, M., Anand, R., Ahamad, S., Usmani, M. A., & Basha, S. M. (2023, February). Machine learning analysis on predicting credit card forgery. In *International Conference on Innovative Computing and Communication* (pp. 137-148). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-99-3010-4_12

[16] Kalyan, N. B., Ahmad, K., Rahi, F., Shelke, C., & Basha, S. M. (2023, September). Application of Internet of Things and Machine learning in improving supply chain financial risk management System. In *2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA)* (pp. 211-216). IEEE. https://doi.org/10.1109/ICIDeA59866.2023.10295182

[17] Kotti, J., Ganesh, C. N., Naveenan, R. V., Gorde, S. G., Basha, M., Pramanik, S., & Gupta, A. (2024). Utilizing Big Data Technology for Online Financial Risk Management. In *Artificial Intelligence Approaches to Sustainable Accounting* (pp. 135-148). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-0847-9.ch008

[18] Kumar, S., & Singh, A. (2014). Dynamic beta and stock market volatility in India: An empirical analysis. *Asia-Pacific Journal of Management Research and Innovation, 10*(4), 321–329. https://doi.org/10.1177/2319510X14553221

[19] Policepatil, S., Sharma, J., Kumar, B., Singh, D., Pramanik, S., Gupta, A., & Mahabub, B. S. (2025). Financial sector hyper-automation: transforming banking and investing procedures. In *Examining Global Regulations During the Rise of Fintech* (pp. 299-318). IGI Global. https://doi.org/10.4018/979-8-3693-3803-2.ch012

[20] Rana, S., Sheshadri, T., Malhotra, N., & Basha, S. M. (2024). Creating Digital Learning Environments: Tools and Technologies for Success. In *Transdisciplinary Teaching and Technological Integration for Improved Learning: Case Studies and Practical Approaches* (pp. 1-21). IGI Global. https://doi.org/10.4018/979-8-3693-8217-2.ch001

[21] Rao, P., & Subramanian, S. (2015). Time-varying beta and dynamic CAPM in the Indian stock market: Evidence from a rolling regression approach. *Indian Journal of Finance, 9*(12), 9–24.

[22] Sarkar, P., Hasan, M. F., Kumar, A., Agrawal, S., Basha, M., & Viyyapu, B. (2024, November). Neural Networks for Portfolio Management Optimization. In *2024 Second, International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES)* (pp. 1-5). IEEE. https://doi.org/10.1109/IC3TES62412.2024.10877590

[23] Sharma, S., & Aggarwal, D. (2013). Revisiting CAPM in the Indian stock market: Evidence from NSE. *International Journal of Financial Management, 3*(1), 35–48.

[24] Shukla, R., & Mishra, S. (2012). Dynamics of systematic risk in the Indian stock market: Evidence from NSE. *Global Business Review, 13*(2), 203–218. https://doi.org/10.1177/097215091201300203

[25] Singh, A., Krishna, S. H., Tadamarla, A., Gupta, S., Mane, A., & Basha, M. (2023, December). Design and Implementation of Blockchain Based Technology for Supply Chain Quality Management: Challenges and Opportunities. In *2023 4th International Conference on Computation, Automation and Knowledge Management (ICCAKM)* (pp. 01-06). IEEE. https://doi.org/10.1109/ICCAKM58659.2023.10449517

[26] Venkatarathnam, N., Shaik, M. B., Kamilov, D., Reddy, K., & Naidu, G. R. (2025) AI and Fintech: Revolutionizing the Financial Landscape. In *AI and Fintech* (pp. 143-163). CRC Press.