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A comparative study of the CAPM and extended models in the Indian stock market

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Abstract

To explain the cross section of asset returns, there are numerous asset pricing models being used which require ideal conditions in the markets around the world. An attempt has been made in the present study to estimate and compare the different versions of capital asset princing model (CAPM) using the data of sectoral indices listed in S&P BSE in the Indian stock market. The two widely used approaches i.e. Fama-MacBeth (1973) and Pettengil et al. (1995) for conditional versions have been adopted in the study. The models were compared on the basis of Akaike Information Criterion (AIC) and it was obtained that the AIC value of the Unconditional higher moment CAPM was obtained minimum among other models. Hence it can be said as the better model than other models estimated.

Keywords: coskewness, cokurtosis, downside risk, upside risk, CAPM, BSE.

Um estudo comparativo do CMPA e modelos estendidos no mercado de ações Indiano

Resumo

Para explicar a secção transversal dos retornos de ativos, estão sendo utilizados numerosos modelos de precificação de ativos que requerem condições ideais nos mercados em todo o mundo. No presente estudo, foi feita uma tentativa de estimar e comparar as diferentes versões do capital de modelo de precipitação de ativos (CMPA) utilizando os dados dos índices setoriais listados no S&P BSE no mercado de ações indiano. As duas abordagens amplamente utilizadas, ou seja, Fama-MacBeth (1973) e Pettengil et al. (1995) para versões condicionais foram adotadas no estudo. Os modelos foram comparados com base no AIC e obteve-se o valor do AIC do maior momento incondicional, o CMPA obtido foi mínimo entre os demais modelos. Portanto, pode ser considerado como o melhor modelo comparando a outros modelos estimados.

Palavras-chave: *coskewness*, *cocurtose*, risco negativo, risco positivo, CMPA, *BSE*.

1. Introduction

Tn the realm of investments, understanding both the risk and potential return of an asset is crucial. Therefore, any asset pricing model must address these two fundamental elements. The conventional belief is that higher risk should be associated with higher returns, a principle introduced by Markowitz in 1952. However, if the measurement of risk is flawed, it can lead to inaccuracies in expected returns and consequently impact investment performance negatively. For a fair valuation of any investment, it is essential to accurately assess both risk and return. (Markowitz, 1952)

Over time, scholars and researchers have made numerous attempts to create asset pricing models that provide a fair assessment of risk and return. The most well-known of these attempts is the Capital Asset Pricing Model (CAPM), which is based on the concept of market equilibrium, as introduced by Sharpe in 1964 and Lintner in 1965. In ideal market conditions, CAPM states that the only relevant risk that significantly affects market prices is systematic risk. Therefore, investors' required rate of return is determined by the risk-free rate, the systematic risk of the investment, and the market's price for systematic risk (the risk premium). (Akbar, 2013)

The given equation (1) defines the CAPM:

$$R_{pt} = \hat{\lambda}_0 + \hat{\lambda}_1 \beta_{pmt-1} \qquad (1)$$

The CAPM was developed by Sharpe & Lintner as an extension of Markowitz's modern portfolio theory. It assumes that investors consider the mean and variance of asset returns and focus on non-diversifiable risk. CAPM establishes a linear relationship between an asset's returns and its risk, measured as the variability of returns compared to a well-diversified portfolio (market portfolio). The model is applicable to both individual assets and portfolios (Akbar, 2013).

However, due to the imperfect real-world market conditions and a lack of empirical support, various modified versions of CAPM have been proposed and tested empirically by researchers Merton, (1973), Breeden, (1979) and Banz, (1980). Early empirical support for CAPM was found by Black et al. (1972), who used 10 portfolios of NYSE-traded stocks from 1931 to 1965. However, later research by Roll (1977) and Ross (1977) challenged CAPM's validity, suggesting it doesn't hold when the market proxy is inefficient. Subsequent developments extended CAPM, including multifactor models such as Banz's (1981) inclusion of firm size as a variable.

Various studies in different markets provided mixed results regarding CAPM's empirical validity. While some, like Sauer & Murphy (1992) for the German stock market, reported support, others like Fama & French (1992) did not. Additional factors like human capital and business cycle variations were considered in attempts to refine CAPM. Overall, traditional CAPM, despite its solid theoretical foundation, faced challenges in empirical testing, partly due to issues with market proxies and assumptions about investor behavior.

Since the traditional CAPM assumed static beliefs i.e. the means, variances and covariance do not vary with respect to time which is limiting assumption. The development of time varying models like ARCH (1982) and GARCH (1988) allowed these beliefs to vary with respect to time as the variance which changes with respect to time can be captured. The conditional CAPM is represented using the following specification (2):

$$R_{it} = \hat{\alpha} + \hat{\beta}^c_{imt} (R_{mt}) \qquad (2)$$

The traditional CAPM assumes normal distributions and quadratic utility functions for investors. However, returns often deviate from normality, leading to the development of higher-moment CAPM variants. These models incorporate coskewness and cokurtosis as measures of systematic risk Rubinstein, (1973) and Harvey & Siddique, (1999).

To enhance and address some of the limitations of traditional CAPM, the higher-moment CAPM was introduced as an alternative approach. This model, proposed by Kraus & Litzenberger in 1976, Harvey & Siddique in 1999, and others, incorporates additional measures of systematic risk, namely the third and fourth moments (coskewness and cokurtosis). These moments are expected to be significantly priced in the market. The theory behind this model suggests that systematic covariance risk and systematic cokurtosis risk are positively priced by investors, while systematic coskewness risk is negatively priced. The unconditional and conditional higher moment CAPM is represented by the following equations (3 & 4) respectively:

$$R_{it} = \alpha + \hat{\beta}_{imt} (R_{mt}) + \hat{\gamma}_{imt} (R_{mt})^2 + \hat{\delta}_{imt} (R_{mt})^3 \qquad (3)$$

$$E_{t-1} (R_{it}) = \alpha + \hat{\beta}^c_{imt} E_{t-1} (R_{mt}) + \hat{\gamma}^c_{imt} E_{t-1} (R_{mt})^2 + \hat{\delta}^c_{imt} E_{t-1} (R_{mt})^3 \qquad (4)$$

Studies have shown that positive coskewness is negatively priced, while negative coskewness is positively priced. Similarly, positive cokurtosis is positively priced, and negative cokurtosis is negatively priced in investors' required returns. Researchers like Kraus & Litzenberger (1976), Harvey & Siddique (1999), Bekaert & Harvey (2002) and Bekaert & Harvey (2003) extended CAPM to include coskewness. Some studies reported support for these extensions, especially in emerging markets like Pakistan's Karachi Stock Exchange (KSE). However, results varied across markets and time periods.

Another alternative and extension to asset pricing theory is the downside risk based CAPM. This model, both theoretically and empirically was supported in recent years (Harlow; Rao, 1989; Post; Van Valiet, 2006), focuses on assessing risk from the perspective of losses, especially in emerging equity markets. These models are considered superior in determining investors' required rates of return, as they offer different risk assessments compared to traditional CAPM. Each of these models defines risk differently, leading to potentially different estimations of expected returns and asset valuations. The downside risk based CAPM is represented by the following equation (5):

$$min[0, R_{it}] = \alpha + \hat{\beta}^{-}_{imt} \; [min(0, R_{mt}] + \mu_{pt} \qquad (5)$$

The downside risk-based CAPM departs from traditional CAPM by focusing on losses rather than overall variance. It acknowledges that investors are more concerned about deviations below their target returns. Models like mean-semi-variance behavior (MSB) and mean-lower partial moment (MLPM) have been proposed as alternatives to traditional variance-based risk measures.

Empirical evidence suggests that downside risk measures can explain stock returns better than traditional variance-based measures. Researchers like Harlow & Rao (1989), Post & Van Vliet (2006), and Olmo (2007) have explored these models. Ang et al. (2001) found that stocks with higher downside risk exhibited higher returns, even after accounting for market beta and other factors. Overall, downside risk-based CAPM models offer an alternative perspective on risk and return that better aligns with investor behavior. These models consider deviations below target returns and have found empirical support in various studies across different markets.

2. Literature review

The Capital Asset Pricing Model (CAPM) is a mathematical framework designed to establish the connection between systematic risk and the expected returns of assets, particularly equities. It is widely employed in finance for pricing risky securities and predicting asset returns based on their risk profiles and the cost of capital. Despite some research challenging traditional approaches like linear factor models, practitioners and academics continue to use landmark models like the CAPM due to its straightforwardness and simplicity.

According to Ang et al. (2006) the authors contended that a higher value placed on downside risk warrants greater compensation when holding equities sensitive to market downturns. Their research revealed that the cross-section of stock returns carried a substantial 6-percentage-point annual premium for downside risk. In declining markets, stocks with significant market co-movement exhibited higher average returns. It became evident that the reward for accepting downside risk isn't solely explained by typical market beta; other factors like co-skewness, liquidity risk, size, value, or momentum also played a role.

In the study of Chen et al. (2009), the researchers performed the work such that models incorporating downside beta demonstrated greater explanatory power compared to those relying on traditional CAPM for New York Stock Exchange stocks. Now for Galagedera (2009a) demonstrated that the relationship between two systematic risk measures is contingent on market portfolio return volatility and the deviation of the target rate from the risk-free rate. In contrast, Galagedera (2009b) examined the cross-sectional relationship using two downside risk measures, namely downside beta and downside co-skewness. However, both measures underperformed CAPM beta in developed markets. In emerging markets, there is evidence to suggest that downside co-skewness may be a superior risk measure compared to CAPM beta and downside beta.

Atilgan & Demirtas (2013) discovered a significant positive association between monthly anticipated market returns and downside risk in developing economies through fixed-effects panel data regressions. Pla-Santamaria & Bravo (2013) developed a mean-semivariance efficient frontier model to minimize downside risk in portfolio selection, particularly focusing on Dow Jones stocks from 2005 to 2009. Vishnani (2013) investigated the validity of a three-moment model using data from 283 companies listed on the Bombay Stock Exchange (BSE) from January 1999 to June 2010. The study found that the three-moment model holds validity in the Indian context and highlighted that standard deviation and coskewness risks are indeed priced in the Indian capital market.

Narayan & Ahmed (2014) focused on the importance of skewness in decision-making, utilizing daily stock data from the BSE spanning from January 2001 to December 2011. They discovered strong evidence of predictability, emphasizing that models incorporating skewness were more useful than models that overlooked this factor. Tsai et al. (2014) delved into the relationship between expected returns, CAPM, and downside betas. They employed a dynamic conditional correlation model on a sample of developed countries and found that downside betas offered a better explanation for the volatility in expected asset returns compared to CAPM betas.

Klebaner et al. (2017) demonstrated that, for portfolios with predetermined expected returns, minimizing downside risk led to the same solutions as minimizing variance. They highlighted that portfolios obtained using the mean-semivariance efficient frontier model differed significantly from portfolios with equal expected returns derived using the conventional Markowitz mean-variance efficient frontier model. Momcilovic et al. (2017) performed the study in other emerging markets, such as the Slovenian, Croatian, and Serbian markets, consistently demonstrated that downside risk statistically and significantly accounted for variations in mean returns.

Ajrapetova (2018) performed the study to analyze the Estrada's study to showcase the effectiveness of traditional and alternative asset pricing models in elucidating cross-sectional asset returns, with a particular focus on the risk-return relationship. They argued that, especially in systematic risk assessments, downside beta outperformed the typical CAPM beta. Misra et al. (2018) explored the impact of both coskewness and cokurtosis on Indian stocks. Their analysis revealed that both coskewness and cokurtosis had a significant influence on the returns of Indian stocks. Notably, the impact of coskewness was found to be more substantial than that of cokurtosis.

Salah et al. (2018) argued that the downside risk model for portfolio optimization addressed the limitations of the traditional mean-variance model concerning return asymmetry and investor risk perception. Traditional Markowitz portfolio optimization faced two major drawbacks: inefficiency when asset returns exhibit skewness and neglect of investor risk aversion. A generalized LPM framework introduced a more efficient risk metric that specifically focused on deviations below a predefined return rate. This research illustrated how to construct downside risk models using spreadsheet programs and incorporate investor risk aversion into a downside risk asset optimization model.

Atilgan et al. (2019) reevaluated the link between various downside risk metrics and future stock returns in 26 developed markets. They determined that there was generally no statistically significant positive connection between systematic downside risk and cross-sectional equity returns. Moreover, they argued that the relationship between downside risk and future returns was strongly negative at the portfolio level but relatively flat at the stock index level. Chhapra & Kashif (2019) employed a dataset of 901 firms on the Pakistan Stock Exchange from 2000 to 2016 to investigate the implications of risk-averse investor preferences for higher moments and downside risk. They argued that investors favored firms exhibiting negative co-skewness, positive co-kurtosis, and downside risk because they yielded a higher risk premium.

Furthermore, they emphasized that co-skewness, co-kurtosis, and downside beta were significant risk factors, with only downside beta genuinely explaining risk beyond covariance risk. They found that the CAPM did not adequately capture market risk premium, suggesting the presence of other risk measures in the Pakistan Stock Exchange. Rutkowska-Ziarko et al. (2019) explored whether accounting betas and downside accounting betas impacted the average rate of return in a capital market encompassing 27 Polish construction companies listed on the Warsaw stock exchange. Their findings indicated that investors in the Polish construction sector received a positive risk premium tied to accounting betas and downside risk. Ali (2019) examined the importance of downside risk in asset pricing in the Chinese stock market which revealed a positive risk premium associated with downside variability over the medium and long term.

Ayub et al. (2020) introduced a new 6-factor downside beta CAPM, incorporating a momentum factor and replacing beta in the 5-factor model with downside beta as a proxy for downside risk. Using data from the Pakistan Stock Exchange (PSX-100), they argued that the momentum factor was only rejected in the beta-based 6-factor model, suggesting that the downside beta 6-factor model was a more suitable option for investors in the context of asset pricing models. Hoque & Low (2020) suggested that investors were penalized for their downside exposure to these risk factors, aligning with the risk preference explanation of prospect theory. Downside risk measures are widely utilized in portfolio optimization problems to construct investment portfolios with minimized downside risk.

The CAPM, although subject to criticism, continues to be a widely used model in finance. Recent research has highlighted the importance of downside risk measures, such as downside beta and semivariance, in explaining asset returns and optimizing portfolios. These measures provide valuable insights into asset pricing and risk management, particularly in emerging markets and during periods of market downturns. Researchers and practitioners are exploring alternative models and risk measures to enhance our understanding of asset pricing and portfolio optimization.

3. Materials and Methods

The data of 10 sectoral indices listed in S&P BSE was used to estimate the models. The duration of the data was considered from April 2011 to March 2021 downloaded from BSE website. The sectoral Indices considered are S&P Auto, Bankex, Capital Goods, Consumer Durables, Metal, Oil & Gas, Power, Public Sector Undertaking (PSU), Realty and Teck. The 90 days T-bill (Treasury bill) was used as the proxy for risk free rate obtained from RBI website.

Now we briefly present the empirical methodology employed to estimate and statistically test the theoretical models considered, which encompass unconditional CAPM (UCAPM) and conditional CAPM (CCAPM), unconditional higher moment CAPM (UHMCAPM), conditional higher moment CAPM (CHMCAPM) and the downside risk based CAPM (DCAPM) models. The study followed the Fama-MacBeth (1973) methodology, involving a three-step process: estimating market risk measures, computing betas and portfolio returns, and conducting cross-sectional regression for validation for unconditional CAPMs while the Pettengil et al. (1995) methodology was used for estimation of conditional CAPMs.

The methods and econometric specifications for each model are discussed below:

UCAPM: A rolling window of 60 months with step size 1 is utilized with GMM estimation. Portfolio construction involves grouping stocks by beta in ascending order such that the least beta stocks are allocated in First portfolio (P1) and the higher beta values in last portfolio. To assess the validity of the CAPM's hypothesis, the Cross-sectional regression tests are employed. The cross sectional regression equation is given as:

$$R_{pt} = \hat{\lambda}_0 + \hat{\lambda}_1 \beta_{pmt-1} \quad (6)$$

CCAPM: Conditional betas are estimated using the GARCH(1,1) specification given by Bollerslev (1988) followed by rolling regression with window size of 60 months and step size 1. Portfolio formation and cross-sectional testing follows a similar process to the UCAPM. The cross sectional regression equation is given as:

$$R_{pt} = \hat{\gamma}_0 + \hat{\gamma}_1 \beta_{cmt-1} \quad (7)$$

UHMCAPM: This model incorporates coskewness and cokurtosis alongside the classical CAPM. GMM estimation with a rolling window of 60 months and step size 1 is employed. Portfolio formation and cross-sectional testing follows a similar process to the UCAPM. The cross sectional regression equation is given as:

$$R_{pt} = \hat{\eta}_0 + \hat{\eta}_1 \beta_{pmt-1} + \hat{\eta}_2 \gamma_{pmt-1} + \hat{\eta}_3 \delta_{pmt-1} \quad (8)$$

CHMCAPM: Extending the UHMCAPM, this model allows risk premiums to vary over time using GARCH(1,1) followed by rolling regression with window size of 60 months and step size 1. Portfolio formation and cross-sectional testing follows a similar process to the UCAPM. The cross sectional regression equation is given as:

$$R_{pt} = \hat{\eta}_0 + \hat{\eta}_1 \beta^c_{pmt-1} + \hat{\eta}_2 \gamma^c_{pmt-1} + \hat{\eta}_3 \delta^c_{pmt-1} \quad (9)$$

DCAPM: Downside risk measures are incorporated using GMM estimation and a rolling window of 60 months and step size 1. Portfolio formation and cross-sectional testing follows a similar process to the UCAPM, with a specific focus on downside risk. The cross sectional regression equation is given as:

$$R_{pt} = \hat{\Psi}_0 + \hat{\Psi}_1 \hat{\beta}^{-}_{imt-1} \quad (10)$$

Using the cross-sectional regression equation each model's hypotheses are tested, which assess the significance of intercept terms and risk premium coefficients.

4. Results and Discussion

The nature or the characteristics of the data can be understood using the descriptive statistics of the data. It also acknowledges the behaviour of the data. It shows their average returns, skewness (asymmetry), kurtosis (tailedness), and whether the returns follow a normal distribution (based on the Kolmogorov-Smirnov test). The descriptive statistics of the sectoral indices are given in the (Table 1).

Skewness measures the asymmetry in the distribution of returns. A positive skewness value (greater than 0) was obtained for 7 indices which indicates that the returns are skewed to the right (positively skewed), meaning there may be more extreme positive returns. Conversely, a negative skewness value (less than 0) was obtained for 3 indices which suggests that the returns are skewed to the left (negatively skewed), indicating more extreme negative returns. Kurtosis measures the "tailedness" of the return distribution. A higher kurtosis value implies that the distribution has fatter tails and potentially more extreme values (higher risk). Kurtosis value >3 indicates leptokurtic behaviour i.e. increased investment risk. Kolmogorov-Smirnov (KS) test assesses whether the distribution of returns for each sectoral index follows a normal distribution. The *p*-value obtained less than 0.05 suggested that the returns do not follow a normal distribution.

Table 1. Descriptive statistics and KS normality test.

Sectoral Indices	Mean	Skewness	Kurtosis	KS (p value)
Auto	0.0003	0.287	6.638	<0.001
Bankex	0.0008	0.099	5.125	<0.001
Capital Goods	-0.0004	0.043	4.400	<0.001
Consumer Durables	0.0013	-0.383	4.598	<0.001
Metal	-0.0014	0.267	4.004	<0.001
Oil & Gas	-0.0013	-0.293	6.486	<0.001
Power	-0.0017	0.267	5.796	<0.001
Psu	-0.0024	0.338	5.464	<0.001
Realty	-0.0006	0.130	4.563	<0.001
Teck	0.0012	-0.173	5.122	<0.001

Source: Authors, 2024.

Further, the empirical analyses for various asset pricing models, including the UCAPM, CCAPM, UHMCAPM, CHMCAPM and the DCAPM were conducted. The portfolios were formed based on the estimated betas (systematic risk) and analyzed their performance (Table 2).

In the next step the beta values were estimated using the considered models and the respective methodology. For the unconditional models (like UCAPM and UHMCAPM and the DCAPM), the unconditional beliefs i.e. beta, lambda and gamma were estimated using rolling regression with 60 months rolling window and step size 1 and the GMM as the estimation technique. For the conditional models (CCAPM and the CHMCAPM), the conditional beliefs i.e. beta, lambda and gamma were estimated using rolling regression with 60 months rolling window and step size 1 and the GARCH (1,1) as the estimation technique.

For the UCAPM, the cross-sectional regression framework was used to examine whether the specified hypotheses were met to empirically validate the CAPM theory. The findings indicate that the intercept term for the entire sample is not equal to zero (it is positive), but lacks statistical significance, thereby supporting the first hypothesis. However, the risk premiums for the entire sample are both negative and statistically insignificant, leading to the rejection of the second hypothesis.

For the CCAPM, the cross-sectional regression framework was used to examine whether the specified hypotheses were met to empirically validate the conditional CAPM theory. The findings indicate that the intercept term (both down market and up market) for the entire sample is positive but lacks statistical significance, thereby supporting the first hypothesis. However, the risk premiums obtained for down market was negative and positive for up market but statistically insignificant, leading to the rejection of the second hypothesis.

For the UHMCAPM, the cross-sectional regression framework was used to examine whether the specified hypotheses were met to empirically validate the unconditional higher moment CAPM theory. The findings indicate that the intercept term for the entire sample was positive but lacks statistical significance, thereby supporting the first hypothesis. The market risk premium obtained positive but statistically insignificant, leading to the rejection of the second hypothesis. However, the market risk premiums for coskewness was obtained positive and significant while the cokurtosis was obtained negative and significant, leading to the rejection of the third and fourth hypothesis.

For the CHMCAPM, the cross-sectional regression framework was used to examine whether the specified hypotheses were met to empirically validate the unconditional higher moment CAPM theory. The findings indicate that the intercept term exhibits a positive value but lacks statistical significance in the down market. However, in the up market scenario, it assumes a negative value and becomes statistically significant. This supports the first hypothesis for the down market but contradicts it for the up market. On the other hand, concerning risk premiums, they are positive but statistically insignificant in the down market and negative but lacking statistical significance in the up market. This outcome leads to the rejection of the second hypothesis.

Further, the market risk premiums associated with conditional coskewness, they are positively significant in both down and up markets. However, in the case of conditional cokurtosis, they are negative and significant for the down market and positive and significant for the up market. These results cause us to reject the third and fourth hypotheses, except for the fourth hypothesis in the up market.

For the DCAPM, the cross-sectional regression framework was used to examine whether the specified hypotheses were met to empirically validate the CAPM theory. The findings indicate that the intercept term for the entire sample is positive but statistically significant, thereby rejecting the first hypothesis. However, the risk premiums for the entire sample obtained are positive and statistically significant, supporting the second hypothesis.

Overall, the findings suggest that traditional asset pricing models, including CAPM variants, had limitations in explaining returns in the Indian market. These limitations were observed across various market conditions (down and up market), leading to inconclusive results for the validity of these models in the Indian context.

Table 2. Coefficients of alpha and beta for CAPM.

Model	**Coefficient**		**p-value**
UCAPM	**α**	0.159	0.402
	β	-0.027	0.887
CCAPM (Down Market)	**α**	1.229	0.133
	β	0.745	0.270
CCAPM (Up Market)	**α**	0.049	0.979
	β	-0.038	0.980
UHMCAPM	**α**	-0.324	0.863
	β	0. 042	0.643
	λ	4.018	<0.001
	γ	-3.658	<0.001
CHMCAPM (Down Market)	**α**	0.723	0.420
	β	0.583	0.421
	λ	1.267	<0.001
	γ	-1.175	<0.001
CHMCAPM (Up Market)	**α**	-1.066	0.019
	β	-5.037	0.020
	λ	0.761	<0.001
	γ	0.432	<0.001
DCAPM	**α**	4.987	<0.001
	β	4.041	<0.001

Source: Authors, 2024.

The comparison of the estimated models was done on the basis of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) which states the minimum the value, the better is the model. The results showed that the minimum value was obtained for UHMCAPM while the maximum value was obtained for CCAPM (Down market). Hence, UHMCAPM can be said to be the best performing model (Table 3).

To assess the relationship between risk (beta) and returns in various asset pricing models, including the UCAPM, CCAPM, UHMCAPM, CHMCAPM, and DCAPM, the Karl Pearson's correlation coefficients were calculated to test the underlying assumptions i.e. the higher/lower returns are associated with higher/lower risk (beta).

Table 3. Coefficients of alpha and beta for CAPM.

Models	AIC	BIC
UCAPM	-2.138	-2.068
CCAPM (Down Market)	-0.831	-0.798
CCAPM (Up Market)	-1.556	-1.523
UHMCAPM	-3.518	-3.482
CHMCAPM (Down Market)	-0.878	-0.813
CHMCAPM (Up Market)	-1.513	-1.448
DCAPM	-0.872	-0.839

Source: Authors, 2024.

For the UCAPM, the results did not support this assumption, as some portfolios with higher returns had lower beta, and vice versa. A negative correlation coefficient of -0.701 indicated that as returns increased, beta values decreased, contradicting the given assumption (Table 4).

Table 4. Average portfolio returns and average portfolio beta (UCAPM).

Portfolios	Average portfolio returns (r_{pt})	Rank(r_{pt})	Estimated portfolio beta (β_p)	Rank (β_p)	Correlation
P1	0.739	5	-0.028	1	
P2	1.123	4	-0.204	4	
P3	1.169	3	-0.05	2	-0.701
P4	1.437	2	-0.211	5	
P5	1.484	1	-0.163	3	

Source: Authors, 2024.

For the CCAPM, the results did not support this assumption, as some portfolios with higher returns had lower beta, and vice versa. A positive correlation coefficient of 0.108 (down market) and 0.286 (up market) indicated weak positive relationship. These findings did not strongly support the CAPM assumption (Table 5 and 6).

Table 5. Average portfolio returns and average portfolio beta; CCAPM (Down Market).

Portfolios	Average portfolio returns(r_p)	Rank (r_p)	Estimated portfolio beta(β_p)	Rank (β_p)	Correlation
P1	1.346	2	8.063	2	
P2	1.272	4	-3.616	3	
P3	1.344	3	16.048	1	0.108
P4	1.214	5	-9.362	4	
P5	1.443	1	-10.779	5	

Source: Authors, 2024.

Table 6. Average portfolio returns and average portfolio beta; CCAPM (Up Market).

Portfolios	Average portfolio returns(r_p)	Rank (r_p)	Estimated portfolio beta(β_p)	Rank (β_p)	Correlation
P1	1.463	4	5.072	1	
P2	1.562	3	-3.964	5	
P3	1.667	1	2.558	3	0.286
P4	1.435	5	-3.156	4	
P5	1.649	2	3.409	2	

Source: Authors, 2024.

For the UHMCAPM, the results indicated a weak positive relationship, with a correlation coefficient of 0.487. This suggested that some higher returns were associated with slightly higher beta values, but the relationship was not very strong, contradicting the given assumption (Table 7).

Table 7. Average portfolio returns and average portfolio beta (UHMCAPM).

Portfolios	Average portfolio returns(r_p)	Rank (r_p)	Estimated portfolio beta(β_p)	Rank (β_p)	Correlation
P1	0.489	1	0.902	3	
P2	-0.111	5	-1.448	4	
P3	-0.108	4	-1.519	5	0.487
P4	0.243	2	1.365	2	
P5	-0.081	3	1.869	1	

Source: Authors, 2024.

For the CHMCAPM, the results did not support this assumption, as some portfolios with higher returns had lower beta, and vice versa. A negative correlation coefficient of -0.487 (down market) and -0.687 (up market) indicated negative relationship. These findings did not support the CAPM assumption. (Table 8 and 9).

Table 8. Average portfolio returns and average portfolio beta; CHMCAPM (Down Market).

Portfolios	Average portfolio returns(r_p)	Rank (r_p)	Estimated portfolio beta(β_p)	Rank (β_p)	Correlation
P1	0.994	3	-2.832	5	
P2	0.924	4	2.347	1	
P3	3.024	1	-1.897	4	-0.478
P4	1.628	2	1.202	3	
P5	0.559	5	1.87	2	

Source: Authors, 2024.

Table 9. Average portfolio returns and average portfolio beta; CHMCAPM (Up Market).

Portfolios	Average portfolio returns(r_p)	Rank (r_p)	Estimated portfolio beta(β_p)	Rank (β_p)	Correlation
P1	2.613	1	-2.080	5	
P2	2.235	2	-1.724	3	
P3	1.640	4	-1.968	4	-0.687
P4	1.045	5	-0.445	1	
P5	2.204	3	-1.092	2	

Source: Authors, 2024.

For the DCAPM, the CAPM assumption was evaluated, and the results showed that, like the other models, portfolios with higher returns did not consistently have higher beta values. The correlation coefficient was positive but weak, at 0.042, contradicting the given assumption (Table 10).

Table 10. Average portfolio returns and average portfolio beta (DCAPM).

Portfolios	Average portfolio returns(r_p)	Rank (r_p)	Estimated portfolio beta(β_p)	Rank (β_p)	Correlation
P1	1.360	2	1.222	2	
P2	1.294	4	1.673	3	
P3	1.358	3	1.536	1	0.042
P4	1.216	5	-0.576	4	
P5	1.443	1	-1.157	5	

Source: Authors, 2024.

Overall, across various asset pricing models, the study's findings consistently indicated that the traditional CAPM assumption, which posits a direct positive relationship between risk (beta) and returns, was not strongly supported. The observed correlations were often weak or moderate and, in some cases, even contradicted the CAPM assumption.

5. Conclusions

The present study aimed to assess the empirical validity of the asset pricing models, namely the traditional CAPM, the conditional CAPM, the unconditional higher moment CAPM, conditional higher moment CAPM and the downside risk based CAPM, in the emerging equity market of India. The research spanned from April 2011 to March 2011 and focused on a sample of 10 sectoral indices listed on the Bombay Stock Exchange (BSE).

Regarding the traditional CAPM, both in its unconditional and conditional forms, the study found that intercept terms were mostly positive and statistically insignificant while some were statistically significant. However, the systematic covariance risk (market risk) was generally found to be positive and statistically insignificant while some were negative and statistically significant. In the case of the higher moment CAPM, both conditional and unconditional forms exhibited mostly positive but statistically insignificant intercept terms while some were statistically significant, contradicting with the theory.

However, systematic covariance, co-skewness, and co-kurtosis risks were found to be rejecting the hypothesis made by the model. The downside risk based CAPM, on the other hand, showed that the intercept term was mostly positive and statistically significant, and the downside beta was found to be positive and statistically insignificantly or negative and statistically significant. As the results of the estimated models suggested relatively weak empirical performance, the validity of the considered models cannot hold true in the Indian context. From the results of the correlation, it may be concluded that BSE is inefficient market as it does not provide fair risk-return tradeoff.

6. Availability of data and materials

The data used in the study that support the findings of this study have downloaded from BSE (https://www.bseindia.com/indices/IndexArchiveData.html) and RBI (https://www.rbi.org.in/Scripts/BS_NSDPDisplay.aspx?param=4) websites which is publically accessible.

7. Authors' Contributions

Akash Asthana: conceptualization, methodology, investigation of data collection, administration or supervision, validation, writing (revision and editing). *Syed Shafi Ahmed*: methodology, investigation or data collection, statistical analysis, writing (original draft) and writing.

8. Conflict of interest

The authors declare no conflict of interests.

9. Ethics Approval

Not applicable.

References

Ajrapetova, T. (2018). Cross-section of asset returns: Emerging markets and market integration. *European Financial and Accounting Journal*, 13(1), 41-60. https://doi.org/10.18267/j.efaj.205

Akbar, M. (2013). A comparative empirical investigation of the validity of the traditional CAPM, the Higher-Moment CAPM and the Downside Risk Based CAPM in the emerging equity market of Pakistan. (Doctoral dissertation, Bahria University, Islamabad).

Ali, H. (2019). Does downside risk matter more in asset pricing? Evidence from China. *Emerging Markets Review*, 39(C), 154-174. https://doi.org/10.1016/j. ememar.2019.05.001

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *The Review of Financial Studies*, 19(4), 1191-1239. https://doi.org/10.1093/rfs/hhj035

Atilgan, Y., & Demirtas, K. O. (2013). Downside risk in emerging markets. *Emerging Markets Finance and Trade*, 49(3), 65-83. https://doi.org/10.2753/REE1540- 496X490306

Atilgan, Y., Bali, T. G., Demirtas, K. O., & Gunaydin, A. D. (2019). Global downside risk and equity returns. *Journal of International Money and Finance*, 98. https://doi.org/10.1016/j.jimonfin.2019.102065

Ayub, U., Kausar, S., Noreen, U., Zakaria, M., & Jadoon, I. A. (2020). Downside risk-based six-factor capital asset pricing model (CAPM): A new paradigm in asset pricing. *Sustainability*, 12(17), 6756. https://doi.org/10.3390/SU12176756

Bekaert, G., & Harvey, C. R. (2003). Research in emerging markets finance: Looking to the future. *In*: Emerging Markets Review, 3, 429-448 p.

Bekaert, G., & Harvey, C. R. (2003). Emerging markets finance. *Journal of Empirical Finance*, 10(1-2), 3-55. https://doi.org/10.1016/S0927-5398(02)00054-3

Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business*, 45(3), 444-454.

Chen, D., Chen, C., & Chen, J. (2009). Downside risk measures and equity returns in the NYSE. *Applied Economics*, 41(8), 1055-1070. https://doi.org/10.1080/00036840601019075

Chhapra, I. U., & Kashif, M. (2019). Higher co-moments and downside beta in asset pricing. *Asian Academy of Management Journal of Accounting & Finance*, 15(1), 129-155. https://doi.org/10.21315/aamjaf2019.15.1.6

Fama, E., & French, K. (1992). The cross section of expected return. *Journal of Finance*, 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Galagedera, D. U. A. (2009a). An analytical framework for explaining relative performance of CAPM beta and downside beta. *International Journal of Theoretical and Applied Finance,* 12(03), 341-358. https://doi.org/10.1142/S0219024909005257

Galagedera, D. U. A. (2009b). Economic significance of downside risk in developed and emerging markets. *Applied Economics Letters,* 16(16), 1627-1632. https://doi.org/10.1080/13504850701604060

Harvey, C., & Siddique, A. (1999). Autoregressive Conditional Skewness. *Journal of Financial and Quantitative Analysis*, 34(4), 456-487. https://doi.org/10.2307/2676230

Hoque, M. E., & Low, S.-W. (2020). Industry risk factors and stock returns of malaysian oil and gas industry: A new look with mean semi-variance asset pricing framework. *Mathematics,* 8(10), 1732. https://doi.org/10.3390/math8101732

Klebaner, F., Landsman, Z., Makov, U., & Yao, J. (2017). Optimal portfolios with downside risk. *Quantitative Finance,* 17(3), 315-325. https://doi.org/10.1080/ 14697688.2016.1197411

Kraus, A., & Litzenberger, R. (1976). Skewness preference and the valuation of risky assets. *Journal of Finance*, 31(4), 1085-1094. https://doi.org/10.2307/2326275

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 7, 77-91.

Misra, D., Vishnani, S., & Mehrotra, A. (2019). Four-moment CAPM model: Evidence from the indian stock market. *Journal of Emerging Market Finance*, 18(1suppl), S137-S166. https://doi.org/10.1177/0972652719831564

Momcilovic, M., Zivkov, D., & Vlaovic-Begovic, S. (2017). The downside risk approach to cost of equity determination for Slovenian, Croatian and Serbian capital markets. *Ekonomie a Management*, 3, 147-158. https://doi.org/10.15240/tul/001/2017-3-010

Narayan, P. K., and Ahmed, H. A. (2014). Importance of skewness in decision making: evidence from the Indian stock exchange. *Global Finance Journal*, 25(3), 260-269. https://doi.org/10.1016/j.gfj.2014.10.006

Pla-Santamaria, D., & Bravo, M. (2013). Portfolio optimization based on downside risk: A mean-semivariance efficient frontier from Dow Jones blue chips. *Annals of Operations Research,* 205(1), 189-201. https://doi.org/10.1007/s10479-012-1243-x

Rubinstein, M. (1973). The fundamental theorem of parameter preference security valuation. *Journal of Financial and Quantitative Analysis*, 8(1), 61-69. https://doi.org/10.2307/2329748

Rutkowska-Ziarko, A., Markowski, L., & Pyke, C. (2019). Accounting beta in the extended version of CAPM. *In*: Contemporary trends and challenges in finance, Springer, 147-156 p. https://doi.org/10.1007/978-3-030-15581-0_14

Salah, H. B., Chaouch, M., Gannoun, A., De Peretti, C., & Trabelsi, A. (2018). Mean and median-based nonparametric estimation of returns in mean-downside risk portfolio frontier. *Annals of Operations Research*, 262(2), 653-681. https://doi.org/10.1007/s10479-016-2235-z

Sauer, A., & Murphy, A. (1992). An empirical comparison of alternative models of capital asset pricing in Germany. *Journal of Banking and Finance*, 16(1), 183-196.

Tsai, H., Chen, M., & Yang, C. (2014). A time-varying perspective on the CAPM and downside betas. *International Review of Economics and Finance*, 29(C), 440-454. https://doi.org/10.1016/j.iref.2013.07.006.

Vishnani, S. (2013). Asset pricing and co-skewness risk: evidence from India. Afro-Asian Journal of Finance and Accounting, 3(3), 208-221.

Wolfle, M., & Fuss, R. (2010). A higher-moment CAPM of Korean stock returns. *International Journal of Trade and Global Markets*, 3(1), 24-51. https://doi.org/10.1504/IJTGM.2010.030407

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