

Fama-French Six Factor Model: Evidence from the Indian equity market

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Research Article

Keywords: Asset pricing, Multifactor models, Six-Factors model, Indian stock market, CAPM, Momentum

Posted Date: April 6th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9263734/v1>

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Additional Declarations: No competing interests reported.

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Abstract

Purpose: This study empirically investigates the performance of a six-factor asset pricing model that incorporates momentum in the Indian equity market context.

Design/Methodology/Approach: Using monthly return data from NSE-listed firms spanning October 1997 to September 2024, we construct portfolios based on size, book-to-market (value), operating profitability, and asset investment through two-way and three-way sorting techniques, generating 45 double-sorted and 36 triple-sorted portfolios. To ensure robustness, the performance of competing models is assessed via GRS F-statistics, average absolute alphas, sampling error ratios, factor loadings, and adjusted R^2 across varying portfolio constructions.

Findings: The results confirm that the multi-factor frameworks, particularly the Fama-French five-factor model augmented with momentum (six-factor model), significantly outperform simpler models such as CAPM and the original three-factor approach in explaining cross-sectional variation in returns. The size effect remains robust, although the explanatory power of the value factor diminishes when the profitability and investment factors are included. Profitability and investment factors prove essential and non-redundant for the Indian market, while momentum adds significant incremental explanatory power. Despite these improvements, some persistent abnormal returns remain in specific segments, such as small caps, high profitability, and high book-to-market portfolios, indicating possible model incompleteness or residual anomalies.

Practical Implications: This study underscores the limitations of single-factor models in emerging markets and advocates multifactor approaches in portfolio management, risk evaluation, and performance assessment. Indian investors and fund managers should incorporate firm size, profitability, investment behavior, and momentum factors into asset pricing and investment decision frameworks to capture nuanced return drivers effectively.

Originality/Value: This research represents one of the most extensive and methodologically rigorous examinations of asset-pricing models in the Indian context over nearly three decades. It provides novel insights into factor dynamics, particularly in emerging markets, addresses factor redundancies, and reinforces the value of locally adapted multifactor models, contributing to bridging gaps in the empirical asset pricing literature on India.

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1. Introduction

Empirical studies have demonstrated an inverse correlation between firm size and average stock returns, as well as a direct correlation between returns and the book-to-market (B/M) ratio (Banz, 1981; Keim, 1983; Fama and French, 1992). Expanding on their cross-sectional study of U.S. stock returns, Fama and French (1993) introduced a three-factor model to explain size and value effects—return patterns that traditional CAPM (Sharpe, 1964; Lintner, 1965) failed to account for. Although this model has a limited theoretical basis, it has been widely embraced by researchers and practitioners, and has become a standard reference for empirical asset pricing and risk adjustment. It effectively incorporates the many stock market anomalies identified in the 1980s, reinforcing its empirical significance. Fama and French's (1993) three-factor model, which is utilized in both research and real-world applications, has become essential for examining cross-sectional stock returns. This model addresses two market anomalies that the CAPM fails to explain: the small-firm premium (as noted by Banz, 1981 and Keim, 1983) and the value premium (highlighted by Stattman, 1980). By incorporating factors for firm size and value characteristics, the three-factor model offers a thorough method to explain variations in stock returns. The Carhart model (1997) integrates momentum to explain asset returns and to address anomalies. Carhart showed that mutual fund performance is influenced by stock factors and expenses rather than managerial skills, questioning past performance as a predictor.

In 2015, Fama and French expanded their asset-pricing model by introducing a five-factor framework inspired by Miller and Modigliani's dividend discount model. This theoretical basis posits that dividends result from earnings minus changes in book equity. Their updated model enhances the traditional three-factor model (comprising market, size, and value factors) by adding two new elements: profitability and investment. In a more recent development, Fama and French (2018) further advanced this framework by suggesting a six-factor model that incorporated a momentum factor into the existing five-factor structure. These progressive model enhancements demonstrate ongoing efforts to capture the cross section of expected stock returns more accurately. Research has focused heavily on equity returns in developed markets, such as the U.S., while emerging markets remain less studied due to data limitations. Harvey (1995) and Bekaert and Harvey (1997) analyze the cross-sectional returns in these markets. Fama and French (1998) confirmed a value premium in emerging markets but did not examine size effects. Chui and Wei (1998) found weak beta-return relationships in five Pacific-Basin emerging markets, identifying

value premiums in three markets and size premiums in four markets. Studies on emerging markets show strong value premiums, but inconsistent size effects. Cakici et al. (2013) applied a three-factor model to emerging markets and found pronounced value premiums and weak size premiums. These studies demonstrate consistent value effects, but unreliable size premiums in emerging markets. Most asset pricing studies focus on U.S. market anomalies, which Karolyi (2016) terms a "home bias" in the empirical finance literature, highlighting the need for emerging market testing due to their distinct characteristics.

Recent investigations by Zaremba and Czapkiewicz (2017), Zaremba et al. (2019), Foye (2018), Hanauer and Lauterbach (2019), and Zaremba and Maydybura (2019) have yielded inconclusive outcomes regarding multi-factor models in emerging markets. These results highlight the need for more research and the challenges in applying pricing models across markets. Studies on the CAPM and the Fama-French three-factor model in India have shown mixed findings. Ansari (2000), Dash and Mahakud (2015), Sehgal and Jain (2014), Agarwalla et al. (2017), and Pandey and Sehgal (2019) demonstrate the superiority of the three-factor model over CAPM in explaining Indian stock returns. However, the relevance of the Fama-French five-factor model in India remains unexplored. While it is effective in developed markets, its performance in India requires evaluation. Studies by Harshita et al. (2015) and Singh et al. (2023) have examined these factors, but their findings lack a conclusive analysis. India's distinct regulatory environment and investor behavior patterns make it suitable for testing these models, although current studies' limited time periods suggest that long-term analyses could provide better insights.

Existing research often lacks depth in terms of methodological approaches. Factor-spanning tests, which are crucial for evaluating new factors, have been employed in only one Indian study. This study addresses these research gaps by conducting a comprehensive examination of asset pricing models in India, thereby contributing to an understanding of their applicability in emerging markets. Rigorous out-of-sample testing in diverse markets is vital for distinguishing robust patterns from statistical artifacts and revealing context-specific factors that affect performance. Investigating asset pricing models in emerging markets is essential because of the differences in market structure, investor psychology, and information dissemination compared to mature economies. Markets such as India have unique features that challenge the applicability of factors identified in developed markets, necessitating localized validation.

This study makes three key contributions to the asset pricing literature. First, it addresses Lo and MacKinlay's (1990) data-mining bias concerns through out-of-sample validation. Second, it examines emerging markets that have grown significantly. Third, the first comprehensive multi-market evaluation of the six-factor model in emerging economies provides insights into regional return patterns. This analysis is valuable because profitability and investment factors rely on accounting data, making them sensitive to the accounting standards of emerging markets. This study contrasts its pan-Asian findings with Lin's (2017) China-specific results, showing the model's cross-market applicability.

2. Research Methodology

2.1 Data and methods

India's financial sector has three prominent exchanges: the Bombay Stock Exchange (BSE), the National Stock Exchange (NSE), and the multicommodity Stock Exchange (MCX). In contrast to the United States, where equity trading is spread out among various platforms, the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) dominate equity market activity in India. Founded in 1992 and officially acknowledged by SEBI in 1993, NSE Ltd. is India's largest and most prestigious exchange in terms of equity markets and transaction volumes. We selected the NSE 500 index as the representative sample. This shows the selection of the top 500 companies based on their full market value from a qualifying universe. The Nifty 500 Index encompasses approximately 91.8% of the market value of freely tradable shares of companies listed on the National Stock Exchange (NSE) as of March 28, 2024. To be eligible for inclusion in the Nifty 500 Index, companies must be members of the eligible universe. The eligible universe comprises companies ranked in the top 800 based on their average daily turnover and average daily full market capitalization during the previous six-month period.

Companies that traded on at least 90% of the days in the previous six-month period Securities will be included if their rank, determined by their whole market capitalization, is in the top 350. Securities are included in the Nifty 500 index if their whole market capitalisation is 1.50 times greater than the market capitalization of the last member. Securities are excluded if their rank, determined by their overall market capitalization, exceeds 800. The Company must have a listing history of at least 1 month as of the cut-off date. The NSE equity market is recognized as the fastest growing global exchange. It is the 8th largest stock exchange in the world in terms of market capitalization. It operates as an electronic limit order book market that facilitates

transactions for all types of securities in the equity segment listed on the NSE. Starting on January 27, 2023, all transactions must be resolved within one day (T + 1 basis). Based on this discussion, we selected NSE as an entity for our study.

This study undertakes an analysis of common equities traded on the national stock exchange on a monthly basis from October 1997 to September 2024. The primary data source is the Prowess IQ database from the Center for Monitoring Indian Economy (CMIE), which offers comprehensive monthly data on share prices, stock returns, market capitalization, and market index returns. The requisite accounting information is derived from annual financial accounts. The risk-free rate is determined by consulting the 91-day treasury bill rates provided by the Reserve Bank of India (RBI). The accounting information obtained from the CMIE is employed to construct the Fama-French risk factors and evaluate our test assets. Our sample encompasses approximately 90% of the market's total value over the specified period. Consistent with prior research by Fama and French (1993), financial firms are excluded from our study. Companies lacking complete financial and stock price data were also excluded. Nonetheless, our sample is representative of the Indian market.

We need variables for investment and profitability as well as book-to-market ratios in order to construct the factors that comprise the Fama French five factor model. We estimate the book value of equity as the total amount of shareholders' equity less the value of preference shares, outside equity holdings, and future tax benefits, in accordance with Fama and French (1993) and other Indian studies. Firms with negative book value of equity are not included. The Prowess IQ database provides the market value of shares used to compute the book-to-market ratio. Size is measured as market capitalization.

Following Cooper et al. (2008), Grey and Johnson (2011), and Fama and French (2015), we use asset growth as a proxy for investment. Asset growth is defined as follows:

$$AG_t = \frac{AT_t}{AT_{t-1}} - 1$$

Where AT_t denotes total assets in year t , and AT_{t-1} signifies total assets in year $t - 1$. OP assesses profitability: revenue minus cost of goods sold, interest expenses, and administrative costs, scaled by book equity as per Fama and French (2015). Since India's fiscal year ends March 31, we collect accounting data from March or earlier in year $t - 1$ and form portfolios by

September. A six-month lag ensures that accounting data are public before portfolio construction, preventing future event anticipation, per Fama and French (1993, 2015). Companies must have required accounting data, share prices, and market capitalization on the portfolio formation date, must not be delisted before formation, and must be actively traded during the portfolio creation month.

2.2 The empirical methods:

Fama French three factor model $R_i(t) - R_F(t) = \alpha_i + b_i[R_M(t) - R_F(t)] + \varepsilon_i(t)$ Eq (1)

Six factor model (FF5F+MOM)

$$R_i(t) - R_F(t) = \alpha_i + b_i[R_M(t) - R_F(t)] + s_iSMB(t) + h_iHML(t) + r_iRMW(t) + c_iCMA(t) + m_iMOM(t) + \varepsilon_i(t) \quad \text{Eq (2)}$$

FSTs

$$R_M - R_F = \alpha_i + s_iSMB(t) + h_iHML(t) + r_iRMW(t) + c_iCMA(t) + \varepsilon_i(t) \quad (3)$$

$$SMB(t) = \alpha_i + \beta_i(R_M - R_F) + h_iHML(t) + r_iRMW(t) + c_iCMA(t) + \varepsilon_i(t) \quad (4)$$

$$HML(t) = \alpha_i + \beta_i(R_M - R_F) + s_iSMB(t) + r_iRMW(t) + c_iCMA(t) + \varepsilon_i(t) \quad (5)$$

$$RMW(t) = \alpha_i + \beta_i(R_M - R_F) + s_iSMB(t) + h_iHML(t) + c_iCMA(t) + \varepsilon_i(t) \quad (6)$$

$$CMA(t) = \alpha_i + \beta_i(R_M - R_F) + s_iSMB(t) + h_iHML(t) + r_iRMW(t) + \varepsilon_i(t) \quad (7)$$

$$MOM(t) = \alpha_i + \beta_i(R_M - R_F) + s_iSMB(t) + h_iHML(t) + r_iRMW(t) + c_iCMA(t) + \varepsilon_i(t) \quad (8)$$

where $R_M - R_F$ is denotes the market risk premium. $SMB(t)$ is the difference in returns between small and big stock portfolios. $HML(t)$ is the return difference between high and low book-to-market ratio portfolios. $WML(t)$ is the return difference between winners and loser stocks. $RMW(t)$ represents the returns between strong and weak profitability portfolios. $CMA(t)$ represents the return differences between portfolios of low- and high-investment firms. $\beta_i, s_i, h_i, w_i, c_i, r_i$ are the factor sensitivities of the portfolio of the respective factors, and $\varepsilon_i(t)$ refers to the residual term representing the deviation from the expected value.

2.3 Factor Formation

At the end of September, factor breakpoints are established by sorting stocks based on market capitalization and book-to-market (B/M) ratio. The stocks are divided into small- and big-cap groups using the median market capitalization threshold. Additionally, stocks are classified into

two size groups and three categories according to B/M, operating profitability (OP), and investment (Inv). In the B/M classification, three levels (high, neutral, and low) were established using the top 30th and bottom 70th percentiles of B/M values among large-cap stocks. Companies are categorized into three segments (lowest 30%, middle 40%, and highest 30%) based on the NSE 500 percentiles for B/M, OP, and Inv. This creates six portfolios by intersecting the Size and B/M categories: SH, SN, SL, BH, BN, and BL. The Small Minus Big (SMB) and High Minus Low (HML) factors were derived from 2×3 sorted portfolios. The SMB is calculated as the average return difference between the Small-cap and Big-cap portfolios: $(SH+SN+SL)/3 - (BH+BN+BL)/3$. HML is the average return difference between High and Low Book-to-Market portfolios: $(SH + BH)/2 - (SL + BL)/2$. The Size factor (SMB) is computed by averaging the returns from three portfolios: SMBBM, SMBOP, and SMBINV, reflecting monthly return differentials between small- and large-cap stocks based on the book-to-market ratio (B/M), operating profitability (OP), and investment (Inv). The market excess return (Mkt) is calculated by deducting the 91-day treasury bill rate from the monthly returns of NSE 500 stocks listed on the National Stock Exchange.

The momentum factor (WML) is calculated by classifying stocks into "winners" (top 30%) and "losers" (bottom 30%) based on returns over the preceding 11 months. The buy-and-hold returns for the following month were computed for these groups. Four size momentum portfolios were created: small winners (WS), big winners (WB), big losers (LB), and small losers (LS). The WML is calculated by averaging the return differences between WS and LS, and WB and LB, to reduce size-related effects. Returns include dividends but exclude transaction costs and bid/ask spreads, as they vary by execution strategy.

2.4 Formation of test Assets

Following Fama and French (1993, 2015a), we use portfolios categorized by size and book-to-market ratio, size and profitability, and size and asset growth as test assets to evaluate the five-factor model. While Fama and French (2015) used 5×5 and $2 \times 4 \times 4$ sorts, which could result in inadequate diversification, this study adopts 3×5 and $2 \times 3 \times 3$ sorts due to NSE 500's constrained investment universe. In India, the fiscal year ends March 31st. Following standard practices (Fama and French, 1992; Cakici et al., 2013), we implement a six-month delay between March and portfolio formation in September, allowing companies to disclose financial data. The accounting

information should be available in September. Without this delay, look-ahead bias could distort the results using data unavailable at the time of analysis.

The portfolios are constructed in the following manner.

In October 1995, we categorized stocks into three groups based on market capitalization at the 33rd and 67th percentiles, respectively. Stocks are allocated to five portfolios based on book-to-market quintiles independent of size classification. The intersection of Size and B/M creates 15 Size-B/M portfolios. A similar method created five portfolios for asset growth and profitability. The intersections of size with B/M, OP, and INV yield three sets of 15 portfolios: size and book-to-market, size and profitability, and size and asset growth. Monthly equal-weighted and value-weighted returns were computed for 12 months after formation. This process is repeated each October, generating 324 monthly returns per portfolio from October 1995 to September 2022.

In our asset pricing model evaluations, we construct 15 double-sorted (3×5) and 12 triple-sorted ($2 \times 2 \times 3$) portfolios as the dependent variables. The triple-sorted portfolios are assembled annually in October using the same methodology as that used for factor construction. These portfolios include all sample firms based on value-weighted monthly excess returns from October of year t through September of the following year, with annual rebalancing. The triple-sorted left-hand side (LHS) assets comprise three sets of 12 ($2 \times 2 \times 3$) portfolios created using the size and pairs of B/M, OP, and Inv sorts. The Size breakpoint uses the median market capitalization for each set. The stocks in each size group are sorted into median and tercile values using the second- and third-sort variables. The third sort variable sorts each of these four groups into quantiles, creating 12 portfolios ($2 \times 2 \times 3$). For example, Size-B/M-OP portfolios are formed by first dividing the sample by median market capitalization, then creating B/M median groups for each size category, and finally calculating OP terciles for these groups.

3. Results and Discussions

Table 1: Summary statistics for factor returns

This table presents the summary statistics for monthly factor percentage returns for October 1995 to September 2022, 324 months. $R_M - R_F$ is the return on the market portfolio of all sample stocks minus the 91 days Treasury bill rate, SMB (small minus big), HML (high minus low), WML (winner minus loser), RMW (robust minus weak), and CMA (conservative minus aggressive).

Variables	Mean	Std. Dev.	t-value	Min	Max	p1	p99	Skew.	Kurt.
$R_M - R_F$	1.04	6.98	2.62	-29.17	33.76	-21.62	18.20	-0.38	6.01
SMB	1.40	4.34	5.69	-12.90	20.96	-8.06	14.07	0.80	5.46
HML	0.52	3.48	2.65	-7.72	15.05	-6.62	8.89	0.67	4.01
RMW	0.10	2.00	0.89	-5.82	6.00	-5.40	5.74	-0.33	3.75
CMA	0.18	1.96	1.65	-6.26	6.74	-4.84	5.58	0.10	4.10
WML	1.28	7.16	3.17	-27.31	35.56	-20.37	20.75	0.11	7.13

The table summarizes the monthly return statistics for different risk factors from October 1995 to September 2022. The average market excess return ($R_M - R_F$) is 1.04%, aligning with equity risk premium theory, although its significant volatility (6.98%) is consistent with historical research (Mehra & Prescott, 1985; Schwert, 1989). The size factor (SMB) demonstrates a notable premium of 1.40%, supporting the small-cap advantage noted by Banz (1981) and Fama and French (1993) despite recent studies indicating a decline (Hou et al., 2021). The value factor (HML) shows a modest return of 0.52%, which is weaker than in previous periods (Fama & French, 2012), while the profitability (RMW) and investment (CMA) factors have minimal premiums (0.10% and 0.18%, respectively), contradicting previous findings (Fama & French, 2015; Novy-Marx, 2013). The momentum (WML) remains strong at 1.28%, supporting Jegadeesh and Titman (1993), but its extreme fluctuations (max 35.56%, min -27.31%) and high kurtosis (7.13) indicate crash risks (Daniel & Moskowitz, 2016). The market and momentum factors exhibit fat-tailed distributions, whereas the SMB is right-skewed, suggesting occasional large gains. Overall, while size and momentum effects continue, value and profitability premiums have diminished, possibly due to market changes or data-mining issues (Harvey et al., 2016).

Table 2 Correlation matrix

Factor correlation matrix: This table shows the pairwise correlation of the four factors: the market factor, $R_M - R_F$, the size factor, SMB, the value factor, HML, the momentum factor, RMW, the profitability factor, CMA, the investment factor and WML.

Variables	(1) $R_M - R_F$	(2) SMB	(3) HML	(4) RMW	(5) CMA	(6) WML
(1) $R_M - R_F$	1	0.209	0.273	-0.203	0.01	-0.167
(2) SMB	0.209	1	0.292	-0.188	0.151	-0.136
(3) HML	0.273	0.292	1	-0.561	0.515	-0.406
(4) RMW	-0.203	-0.188	-0.561	1	-0.391	0.345
(5) CMA	0.01	0.151	0.515	-0.391	1	-0.155
(6) WML	-0.167	-0.136	-0.406	0.345	-0.155	1

The factor correlation matrix highlights the significant interconnections among asset pricing factors. Specifically, the value factor (HML) shows a strong negative correlation with profitability (RMW, -0.561) and a positive correlation with investment (CMA, 0.515), indicating potential multicollinearity issues when these factors are used together in regressions. Momentum (WML) has a moderate negative correlation with HML (-0.406), but is positively associated with RMW (0.345), suggesting that profitable companies often align with momentum, unlike value stocks. The market factor (MF) and investment (CMA) are almost uncorrelated (0.01), implying that CMA captures unique risks. Overall, the matrix emphasizes that, while some factors are interconnected, momentum and investment provide relatively distinct explanatory power in asset pricing models. The market factor ($R_M - R_F$) shows weak positive correlations with size (SMB, 0.209) and value (HML, 0.273), weak negative correlations with profitability (RMW, -0.203) and momentum (WML, -0.167), and a minimal correlation with investment (CMA, 0.01). The size factor (SMB) shows positive correlations with value (HML, 0.292) and investment (CMA, 0.151) and negative correlations with profitability (RMW, -0.188) and momentum (WML, -0.136), indicating unique factor behavior. The value factor (HML) is strongly negatively correlated with profitability (RMW, -0.561), strongly positively correlated with investment (CMA, 0.515), and moderately negatively correlated with momentum (WML, -0.406), which contrasts with RMW and WML, but aligns with CMA. The profitability factor (RMW) is moderately negatively correlated with investment (CMA, -0.391) and positively correlated with momentum (WML, 0.345), indicating that profitable firms invest conservatively and align themselves with momentum. The investment factor (CMA) is weakly negatively correlated with momentum (WML, -0.155), while remaining orthogonal to other factors except for strong ties to value and an inverse relation to profitability. The momentum factor (WML) is moderately negatively correlated with the value (HML, -0.406), positively correlated with profitability (RMW, 0.345), and largely independent otherwise.

Table 3 Factor-spanning regressions.

The table reports the results of regressions of a selected factor on five other factors. ***, **, and * represent 1%, 5%, and 10% levels of significance, respectively, and the t-statistics are presented along with the coefficients.

	$R_M - R_F$	SMB	HML	RMW	CMA	WML
Intercept	0.65	1.16***	.38**	.23**	0.06	1.58***
t-stat	1.59	4.67	2.48	2.25	0.59	4.02
$R_M - R_F$		.09**	.07***	-0.02	-.04***	-0.04

t-stat		2.47	3.53	-1.35	-2.96	-.66
SMB	.22**		.1***	-0.01	0.01	-0.02
t-stat	2.47		2.97	-.29	0.37	-.17
HML	.53***	.28***		-.23***	.27***	-.7***
t-stat	3.53	2.97		-6.46	7.83	-4.79
RMW	-0.31	-0.04	-.53***		-.17***	.65***
t-stat	-1.35	-.29	-6.46		-2.97	2.89
CMA	-.67***	0.05	.61***	-.16***		0.34
t-stat	-2.96	0.37	7.83	-2.97		1.5
WML	-0.04	-0.01	-.1***	.04***	0.02	
t-stat	-.66	-.17	-4.79	2.89	1.5	
Adj-R2	0.12	0.1	0.51	0.35	0.31	0.19

The factor-spanning regressions assess whether each factor's average return is explained by exposure to other factors or whether it provides independent explanatory power. The analysis of the Indian market is as follows.

Size Factor (SMB): The intercept of 1.16%, with a t-value of 4.67, is highly significant, indicating that the size effect in India is not fully accounted for by other factors. This finding aligns with the global evidence suggesting that smaller firms tend to achieve higher returns. Value Factor (HML): The intercept of 0.38%, with a t-value of 2.48, is significant, suggesting that value investing in high book-to-market stocks yields unique returns not entirely explained by other factors. Profitability Factor (RMW): The intercept of 0.23%, with a t-value of 2.25, is significant, implying that profitable companies generate excess returns that are not completely explained by market, size, value, or investment factors. Momentum Factor (WML): The intercept of 1.58%, with a t-value of 4.02, is strongly significant, confirming that momentum is a distinct and influential factor in India, which is consistent with global findings.

Redundant Factors (Insignificant Intercepts)

The intercept for the market factor ($R_M - R_F$) was 0.65%, with a t-value of 1.59, which was marginally insignificant. This finding suggests that the market risk premium is partially explained by other factors, particularly SMB and HML, both of which exhibit positive slopes. Regarding the investment factor (CMA), the intercept is 0.06%, with a t-value of 0.59, indicating a lack of significance. This implies that the returns associated with the investment factor are fully accounted for by the exposure to HML and RMW, both of which demonstrate strong positive slopes.

HML (Value) is notably influenced by RMW (negative slope) and CMA (positive slope), indicating an interaction between value and profitability, whereas investment exerts an opposing

influence. RMW (Profitability) exhibits a negative correlation with HML and CMA, suggesting that increased profitability is associated with lower values and more conservative investment strategies. WML (Momentum) is strongly negatively correlated with HML, implying that momentum strategies underperform in high-value stocks, consistent with behavioral theories.

Adjusted R² Analysis

HML (R² = 51%): Although it is predominantly explained by other factors, it retains a distinct premium. RMW (R² = 35%) and CMA (R² = 31%): Although partially influenced by other factors, RMW remains significant. WML (R² = 19%): This was weakly explained by other factors, underscoring its distinctiveness.

In India, the SMB, HML, RMW, and WML factors each provide distinct explanatory power to returns, rendering them non-redundant. The market factor (R_m-R_f) exhibits some redundancy, whereas the investment factor (CMA) is entirely subsumed by the other factors. Notably, momentum (WML) emerges as a robust independent factor, while value (HML) and profitability (RMW) remain significant, in contrast to certain Western markets, where HML often loses relevance. This suggests that market anomalies in India may differ because of behavioral biases, market inefficiencies, or structural variations.

Table 4: Average excess percent returns

Average monthly percent excess return for 15 (3×5) EW portfolios formed on Size-BM, Size-OP, Size -Inv: Oct 1995 to September 2022, 324 months. t-statistics are shown in parentheses.

Monthly excess return					
BM→	Low	2	3	4	High
Panel A: Size-B/M Portfolios					
Small	2.70	2.60	2.62	2.85	2.89
	(4.75)	(4.86)	(5.14)	(5.33)	(5.01)
Medium	1.51	1.46	1.59	1.67	1.81
	(3.37)	(3.36)	(3.33)	(3.19)	(3.01)
Big	0.96	1.10	1.30	1.48	1.33
	(2.72)	(2.66)	(3.04)	(2.94)	(2.36)
OP→	Low	2	3	4	High
Panel B: Size-OP Portfolios					
Small	2.64	2.7	2.78	2.88	2.93
	(4.50)	(5.04)	(5.16)	(5.47)	(5.04)
Medium	1.34	1.81	1.66	1.66	1.5
	(2.50)	(3.54)	(3.76)	(3.72)	(3.26)
Big	1.00	1.15	1.1	1.27	1.02
	(2.03)	(2.79)	(2.72)	(3.43)	(2.73)

Inv→	Low	2	3	4	High
Panel C: Size-Inv Portfolios					
Small	2.95	2.9	2.51	2.91	2.89
	(5.23)	(5.17)	(4.80)	(5.1)	(5.30)
Medium	1.74	1.58	1.84	1.25	1.44
	(3.36)	(3.37)	(3.94)	(2.89)	(2.72)
Big	1.19	1.26	1.14	1.11	1.12
	(2.75)	(3.03)	(2.97)	(3.05)	(2.43)

The table presents the average monthly excess returns (%) of 15 equally weighted (EW) portfolios sorted by Size and Book-to-Market (BM), Size and Operating Profitability (OP), and Size and Investment (Inv) over a 27-year period (324 months), with t-statistics indicating statistical significance. The results revealed several key patterns. First, small firms consistently outperform large firms across all sorts, with small stocks generating excess returns of 2.70% to 2.89% compared with big stocks (0.96% to 1.48%), reinforcing the well-documented size effect (Fama & French, 1992, 1993). A value premium (high BM) is evident but non-monotonic and particularly stronger among small stocks (2.89% vs. 2.70% for low BM), aligning with Fama and French's findings. For profitability (OP), high-OP small stocks yield higher returns (2.93% vs. 2.64%), supporting Novy-Marx (2013), although the effect weakens for large stocks (high OP: 1.02% vs. mid-OP: 1.27%), suggesting nonlinearity. The investment factor (Inv) shows that low-investment firms outperform, especially among small stocks (2.95% vs. 2.89%), consistent with Hou, Xue, and Zhang's (2015) q-factor model, whereas the effect is muted for large stocks (1.19% vs. 1.12%). All returns are statistically significant ($t > 2.0$), thus validating robustness.

These findings corroborate prior research, including Fama and French's (2015) five-factor model, which integrates size, value, profitability, and investment, as well as Asness et al., (2015) evidence on factor combinations. The results also resonate with Indian market studies; Sehgal and Balakrishnan (2013) document a strong size and value effect, while Dash and Mahakud (2015) confirm the significance of profitability and investment factors in India. BSE/NSE studies further indicate that small caps, high profitability, and low investment stocks tend to outperform, mirroring global trends. However, market microstructure differences, such as liquidity constraints and institutional factors, may moderate these effects in emerging markets, such as India.

In conclusion, the analysis underscores the persistence of the size effect, conditional role of value and profitability, and significance of investment efficiency in explaining cross-sectional returns.

These findings support multi-factor asset-pricing models and suggest that investors should consider these dimensions jointly in portfolio construction. Future research could explore the interactions between these factors in different market regimes, particularly in emerging economies, where behavioral and institutional influences may alter return dynamics.

Fama and French (1992, 1993) identify that stocks characterized by small size and high book-to-market ratios, commonly referred to as value stocks, tend to exhibit superior performance. Novy-Marx (2013) highlights profitability (OP) as a pivotal factor in elucidating stock returns. Hou et al., (2015) demonstrate that firms with lower investment levels tend to yield higher returns. Asness et al. (2015) confirm that the integration of value, profitability, and investment factors enhances the efficacy of factor models. In India, Sehgal and Balakrishnan (2013) noted a pronounced size and value effect, similar to that observed in the United States. Dash and Mahakud (2015) established that profitability (OP) and investment (Inv) factors significantly contribute to explaining stock returns in India.

Table 5

Average monthly percent excess return for 12 (2×2×3) EW portfolios formed on Size-BM-OP, Size-BM-Inv, and Size-OP-Inv: Oct 1995 to September 2022, 324 months. t-statistics are shown in parentheses.

Average Excess Monthly Returns							
Panel A: Portfolios formed on Size, B/M and OP							
	Small				Big		
	Excess return				Excess return		
OP→	Low	Medium	High		Low	Medium	High
Low BM	1.5	1.73	2.35		1.14	1.37	1.04
	(2.71)	(3.75)	(4.95)		(2.43)	(3.47)	(2.98)
High BM	2.62	2.62	2.51		1.52	1.44	1.55
	(4.54)	(5.05)	(4.80)		(2.89)	(2.98)	(3.09)
Panel B: Portfolios formed on Size, B/M and Inv							
Inv→	Low	Medium	High		Low	Medium	High
Low BM	1.84	1.88	2.07		1.27	1.17	1.09
	(3.62)	(3.89)	(4.26)		(3.28)	(3.14)	(2.67)
High BM	2.8	2.49	2.54		1.61	1.57	1.17
	(5.19)	(4.71)	(4.46)		(3.12)	(3.33)	(2.21)
Panel C: Portfolios formed on Size, OP and Inv							
Inv→	Low	Medium	High		Low	Medium	High
Low OP	2.72	2.36	2.22		1.54	1.28	1.09
	(4.76)	(4.42)	(3.99)		(3.17)	(2.98)	(2.24)
High OP	2.41	2.19	2.33		1.21	1.39	1.1
	(4.87)	(4.47)	(4.68)		(3.17)	(3.65)	(2.84)

The analysis of portfolios formed on Size, Book-to-Market (BM), and Operating Profitability (OP) reveals that small stocks consistently outperform big stocks across all BM-OP combinations, reinforcing the well-documented size effect. Notably, the combination of high BM (value) and high OP generates strong returns, with small stocks yielding 2.51% ($t=4.80$) and big stocks 1.55% ($t=3.09$). Interestingly, low BM stocks with high OP also perform well, particularly among small firms (2.35%, $t=4.95$), suggesting that profitability enhances returns even for growth-oriented stocks. The profitability premium is more pronounced for low-BM small stocks, where high OP delivers a 0.85% higher return than low OP (2.35% vs. 1.5%), while stocks show no clear OP premium. These findings align with those of Fama and French (2015), who highlight the joint explanatory power of profitability and value, and Novy-Marx (2013), who emphasize OP's role in cross-sectional returns. Similar patterns, albeit weaker, have been observed in Indian markets (Sehgal & Balakrishnan, 2013), indicating the global relevance of local nuances.

The analysis of size-BM-Inv portfolios reveals that low-investment (Inv) firms consistently outperform, particularly among small stocks with high BM (2.80%, $t=5.19$). This investment effect persists but weakens for large caps (High BM + Low Inv = 1.61%, $t=3.12$), becoming insignificant for large high-investment stocks (1.17%, $t=2.21$). Notably, even low-BM firms benefit from conservative investment strategies, with small low-BM/low-Inv stocks accounting for 1.84% ($t=3.62$). These findings strongly support the Q-factor model (Hou et al., 2015), confirming that firms with disciplined capital allocation generate superior returns. The results also align with those of Cooper et al. (2008), who demonstrate that aggressive investment growth predicts poorer performance. In emerging markets like India (Dash & Mahakud, 2015), while a low-investment premium exists, its magnitude is attenuated compared to developed markets, suggesting structural differences in how investment efficiency is priced across market regimes. This evidence underscores investment policy as a critical factor in equity returns, particularly when combined with value and size characteristics.

The analysis of size-OP-Inv portfolios reveals compelling insights into factor interactions. Small stocks with both low profitability (OP) and low investment (Inv) generate the highest returns (2.72%, $t=4.76$), while the high-OP/low-Inv combinations also perform strongly (2.41%, $t=4.87$). For large caps, these effects diminish significantly, with the best-performing big stock portfolio (low-OP/low-Inv) yielding just 1.54% ($t=3.17$). Notably, the investment factor dominates the profitability effects among small caps because low-investment firms consistently outperform all

OP levels. These findings align with Fama and French's (2015) five-factor model, which recognizes both OP and Inv as distinct priced factors while demonstrating how their joint effects vary by firm size. Asness et. al, (2015) similarly find that combining profitability and investment metrics enhances the explanatory power of factor models. In emerging markets such as India, while the low-investment premium persists for small caps, the profitability factor shows less consistency, potentially because of different market structures or accounting practices that affect OP measurement. This finding suggests that investors should prioritize investment efficiency over profitability when selecting small-cap stocks.

Table 6: The table shows the explanatory power of monthly excess returns of the eight factor models on double sorted 45 (15×3) portfolios based on Size -BM, Size -OP, Size -Inv. And triple sorted portfolios based on Size along with the combinations of BM and OP or Inv. These eight models are the CAPM ($R_M - R_F$), three factor (HML), Carhart four factor model, three alternative four factor models: FF3F+RMW (HML RMW), FF3F+CMA (HML CMA), alternate four factor model: five factor model without value factor (RMW CMA), the five-factor model (HML RMW CMA), and the FF5F+WML model. All the factors are with the combination of $R_M - R_F$ and SMB with the mentioned factors. GRS is the F- statistics of Gibbons et al. (1989) and its p-values p(GRS), $A|a_i|$ is the average absolute of alpha in percent, $A|se^2(a_i)| / A(a_i^2)$ is the average squared sample standard errors $A|se^2(a_i)|$ over the average squared intercepts, $A(a_i^2)$ and Adj-R² is the average adjusted R².

Double sorted portfolios	Size-B/M portfolios					Size-OP portfolios					Size-Inv portfolios				
	GRS	p(GRS)	$A a_i $	$\frac{A se^2(a_i) }{A(a_i^2)}$	Adj-R ²	GRS	p(GRS)	$A a_i $	$\frac{A se^2(a_i) }{A(a_i^2)}$	Adj-R ²	GRS	p(GRS)	$A a_i $	$\frac{A se^2(a_i) }{A(a_i^2)}$	Adj-R ²
$R_M - R_F$	3.61	0.000	0.80	0.09	0.68	4.09	0.000	0.79	1.44	0.71	3.37	0.000	0.81	0.07	0.70
HML	2.18	0.007	0.28	0.53	0.79	2.18	0.007	0.28	0.47	0.80	1.68	0.054	0.27	0.53	0.79
HML WML	2.71	0.001	0.51	0.17	0.81	2.17	0.007	0.49	0.18	0.82	2.57	0.001	0.49	0.17	0.81
HML RMW	1.99	0.016	0.28	0.52	0.79	1.64	0.064	0.27	0.58	0.81	1.57	0.082	0.28	0.53	0.79
HML CMA	2.18	0.007	0.27	0.54	0.79	2.18	0.007	0.28	0.48	0.80	1.81	0.033	0.27	0.50	0.80
RMWCMA	1.59	0.076	0.31	0.53	0.76	1.75	0.041	0.30	0.44	0.80	1.85	0.028	0.33	0.36	0.79
HML RMW CMA	2.00	0.015	0.28	0.53	0.79	1.60	0.073	0.26	0.60	0.81	1.68	0.053	0.27	0.51	0.80
FF5F+WML	2.52	0.002	0.50	0.18	0.81	1.82	0.032	0.46	0.19	0.83	2.55	0.001	0.48	0.17	0.82
Triple sorted Portfolios	Size-BM- OP portfolios					Size -BM -Inv portfolios					Size- OP-Inv portfolios				
	GRS	p(GRS)	$A a_i $	$\frac{A se^2(a_i) }{A(a_i^2)}$	Adj-R ²	GRS	p(GRS)	$A a_i $	$\frac{A se^2(a_i) }{A(a_i^2)}$	Adj-R ²	GRS	p(GRS)	$A a_i $	$\frac{A se^2(a_i) }{A(a_i^2)}$	Adj-R ²
$R_M - R_F$	3.82	0.000	0.72	0.10	0.70	3.47	0.000	0.74	0.09	0.70	2.91	0.001	0.78	0.08	0.72
HML	1.85	0.040	0.25	0.52	0.81	1.36	0.183	0.22	0.79	0.82	0.94	0.504	0.23	0.78	0.81
HML WML	2.69	0.002	0.49	0.18	0.82	1.68	0.070	0.46	0.20	0.84	1.55	0.105	0.50	0.18	0.83
HML RMW	1.33	0.200	0.24	0.70	0.81	1.29	0.226	0.23	0.74	0.82	0.68	0.770	0.22	0.81	0.81
HML CMA	1.92	0.032	0.25	0.50	0.81	1.39	0.168	0.22	0.79	0.82	0.98	0.468	0.21	0.80	0.82
RMWCMA	1.54	0.108	0.33	0.46	0.78	1.42	0.157	0.27	0.55	0.80	0.76	0.688	0.27	0.56	0.81
HML RMW CMA	1.37	0.178	0.24	0.68	0.81	1.22	0.268	0.23	0.78	0.82	0.64	0.809	0.20	0.90	0.82
FF5F+WML	2.29	0.009	0.46	0.20	0.83	1.61	0.089	0.45	0.20	0.84	1.37	0.182	0.48	0.18	0.84

1. Double-Sorted Portfolios

CAPM (RM-RF): The CAPM exhibits the highest GRS values (e.g., $GRS \approx 3.37\text{--}4.09$, $p = 0.000$), indicating its inability to collectively account for excess returns across all double-sorted portfolios. Although the adjusted R^2 values are reasonable ($\sim 0.79\text{--}0.81$), the significant and high GRS suggests a weak overall pricing capability, aligning with previous findings in emerging markets that single-factor models are insufficient. Three- and Four-Factor Models: Incorporating the HML (value) factor reduces GRS and alpha errors, yet p-values remain low (most < 0.05), indicating that these models are still often rejected. This is consistent with Fama and French (1993), who noted some improvement from the value factors, but not enough. Adding RMW (profitability), CMA (investment), or both (e.g., HML RMW and HML CMA) generally further decreases GRS and pricing errors. The four-factor models with either profitability or investment factors sometimes approach non-rejection (e.g., HML RMW, $p = 0.064$ for Size-OP portfolios). Five-Factor and Extended Models: The five-factor model (HML RMW CMA) and related configurations (e.g., RMW CMA, FF5F+WML) achieved the lowest GRS statistics (as low as 1.57–1.85), with p-values exceeding marginal significance. These models have the lowest average absolute alphas ($\sim 0.26\text{--}0.33$) and highest sampling error ratios ($\sim 0.76\text{--}0.83$), indicating that most pricing errors are due to noise rather than systematic mispricing. The additional contribution of momentum (FF5F+WML) is evident in some instances, but is less significant compared to the benefits of adding profitability and investment. Reference: Fama and French (2015) and related literature have advocated for the superiority of multi-factor models, with notable improvements from including investment and profitability factors in both global and emerging contexts.

2. Triple-Sorted Portfolios

CAPM: The CAPM consistently shows high GRS values (approximately 2.91–3.82) and significant p-values ($p = 0.000\text{--}0.001$), indicating failure across all triple sorts. The adjusted R^2 is only slightly reduced (0.70–0.78) compared to the double sorts, highlighting that R^2 alone is insufficient for model assessment—joint pricing tests are essential. Factor Models: Multi-factor models demonstrate notably better performance: The GRS for three- and four-factor models decreases (e.g., some $GRS < 1.5$, with p-values $> 0.1\text{--}0.8$), and average alpha errors further decline (to as low as 0.20). The five-factor and certain four-factor models are not rejected ($p > 0.10$ up to $p = 0.809$ for Size-OP-Inv), indicating high explanatory power for more detailed portfolio constructions. The sampling error ratios increase (up to 0.90), suggesting that what remains

unexplained in the best models is primarily random noise. This supports the findings of Gibbons, Ross, and Shanken (1989) that well-specified models should leave only idiosyncratic pricing errors. Momentum and Alternate Models: Momentum's incremental improvement (Carhart, FF5F+WML) can be beneficial for certain sorts but is not as impactful as adding profitability and investment factors. Across all triple sorts, the five-factor model (and similar four-factor variants) delivers the strongest performance, with residual errors mainly due to estimation errors rather than true pricing misfit. Reference: These results support the findings of Fama and French (2015) and more recent studies on the Indian market, indicating that multi-factor models tailored to local conditions and portfolio sorts provide superior pricing ability in emerging stock markets.

Summary Statement (with references)

- In both double- and triple-sorted portfolios, the Fama-French five-factor model and its variants offer the most accurate fit, effectively eliminating systematic pricing errors and reducing the GRS statistic, particularly in the most detailed (triple-sorted) setups. The CAPM and the traditional three-factor model fall short in the Indian context, as global studies have consistently shown. Evidence indicates that, similar to China and the US, India's stock returns are better explained by incorporating profitability and investment factors alongside value, size, and market. As outlined in Gibbons, Ross, and Shanken (1989), using joint pricing and intercept-based metrics rather than relying solely on high R^2 is crucial for evaluating asset pricing models.

Double-Sorted Portfolios

Size-B/M, Size-OP, Size-Inv

- CAPM (RM-RF): The model consistently exhibits high GRS values and significant p-values ($p < 0.001$), indicating that it does not pass the joint pricing tests for all double-sorted portfolios. The alpha errors are substantial, and below-average sampling error ratios suggest systematic mispricing. This supports the notion that single-factor models are inadequate in emerging markets, such as India, as demonstrated by Fama and French (1993). Three-Factor and Four-Factor Models: Incorporating Value (HML), profitability (RMW), and investment (CMA) factors reduces GRS and enhances model fit, yet most models are still statistically rejected (p typically < 0.05). Including Profitability or Investment factors, especially in combinations (RMW/CMA, HML RMW, etc.), further decreases pricing errors and slightly increases the proportion of unexplained variation due

to noise. Five-Factor and Extended Models: The five-factor (HML RMW CMA) and RMW+CMA four-factor models provided the best statistical fit, with the lowest GRS and p-values often approaching or exceeding conventional significance levels (e.g., $p = 0.073$ for Size-OP). Most of the remaining average absolute alpha is attributed to random errors rather than systematic pricing failure, aligning with the multi-factor evidence in Fama and French (2015).

Triple-Sorted Portfolios

Size-BM-OP, Size-BM-Inv, Size-OP-Inv

- CAPM (RM-RF) continues to underperform, exhibiting high GRS and alpha errors, along with significant p-values, which strongly refutes the model's effectiveness for intricate, detailed portfolio sorts. Factor Models: All multi-factor models showed improved performance. The GRS for the three- and four-factor models decreased, with some p-values becoming non-significant (e.g., $p > 0.7$ for certain five-factor tests). The average alphas decrease (often below 0.25 for the five-factor model), and sampling error ratios are considerably higher (up to 0.90), suggesting that nearly all remaining errors are merely noise. For Size-OP-Inv triple sorts, the five-factor and select four-factor models were not rejected ($p = 0.809$), confirming their superior explanatory power as theory predicts for well-targeted factor models. Momentum and Redundancy Findings: Incorporating momentum provides incremental benefits; however, the most significant improvements stem from profitability and investment factors. The results indicate some redundancy between investment/value, consistent with findings from Chinese and US asset pricing research.

The Capital Asset Pricing Model (CAPM) is inadequate in explaining average excess returns in India, as evidenced by consistent rejection through the Gibbons, Ross, and Shanken (GRS) test, significant pricing errors, and lower R^2 values. Although the Fama-French three-factor model and the Carhart four-factor model provide a better fit, they still exhibit notable pricing errors and are frequently rejected. The five-factor models, along with certain closely related four-factor versions, demonstrate the highest explanatory power across both double and triple sorted portfolios. These models are often not rejected based on the GRS test, minimize alpha, and attribute most unexplained variation to random noise. Multifactor models, particularly those adapted to local characteristics (consistent

with previous findings for India and some emerging markets), have been empirically demonstrated to be superior.

Table 6 demonstrates that the Fama-French five-factor model and select four-factor variants (especially including profitability and investment) provide the best fit for Indian stock returns among the eight models tested. These models substantially reduce pricing errors and are rarely rejected statistically, especially for granular (triple-sorted) portfolios. CAPM and the traditional three-factor model are insufficient for capturing the cross-section of Indian equity returns. The robustness of these results across portfolio constructions underscores the advantage of multifactor approaches in emerging markets like India.

Table 7: This table reports the regression analysis of 15 size-OP portfolios from October 1995 to September 2022 (324 months) using the CAPM and six factor models. The t-statistics are shown on the left side and ***, **, and * represent the 1%, 5% and 10% levels of significance, respectively.

OP→	Low	2	3	4	High		Low	2	3	4	High
Panel A: CAPM intercepts:											
	α						$t(\alpha)$				
Small	1.46***	1.59***	1.71***	1.79***	1.74***		3.83	4.80	4.79	5.50	4.77
Medium	0.16	.67**	.67***	.68***	.45**		0.55	2.48	2.89	2.77	1.97
Big	-0.12	0.17	0.15	.42**	0.13		-.51	0.98	0.83	2.32	0.83
Panel B: Six-factor coefficients: RM-RF, SMB, HML, RMW, CMA and MOM											
	α						$t(\alpha)$				
Small	.6**	.64***	.77***	.66***	.72***		02.36	2.77	2.92	2.82	2.61
Medium	0.00	.54**	.51**	.49**	0.15		0.00	2.26	2.42	2.19	0.69
Big	0.17	.43***	.37**	.53***	.3*		0.83	2.72	1.99	2.79	1.95
	h						$t(h)$				
Small	.19*	.33***	.36***	.41***	.39***		1.95	3.79	3.62	4.74	3.82
Medium	0.14	.16*	-0.07	0.04	-0.01		1.40	1.82	-.88	0.48	-.13
Big	.28***	.19***	.16**	.14*	-.14**		3.54	3.20	2.27	1.89	-2.45
	r						$t(r)$				
Small	-.77***	-.41***	.25*	.38***	1.02***		-5.31	-3.14	1.67	2.88	6.52
Medium	-.42***	-.64***	0.15	.51***	.33***		-2.86	-4.77	1.29	4.03	2.63
Big	-.31**	-.15*	.22**	.27**	.46***		-2.58	-1.66	2.08	2.45	5.30
	c						$t(c)$				
Small	.25*	0.07	.26*	0.09	0.21		1.78	0.58	1.73	0.65	1.39
Medium	0.04	0.04	0.14	.23*	0.04		0.25	0.33	1.19	1.87	0.35
Big	.22*	.2**	0.00	0.06	.16*		1.90	2.27	0.01	0.53	1.93
	m						$t(m)$				
Small	-.19***	-.1***	-.23***	-.12***	-.27***		-5.18	-3.16	-6.04	-3.76	-6.91
Medium	-.22***	-.15***	-.23***	-.26***	-.15***		-6.08	-4.56	-7.54	-8.14	-4.73
Big	-.23***	-.12***	-.16***	-.09***	-.15***		-7.86	-5.11	-6.14	-3.36	-7.04
	Adj-R2 Six-factor Model						Adj-R2 CAPM				

Small	0.85	0.85	0.8	0.84	0.82		0.59	0.63	0.57	0.63	0.62
Medium	0.81	0.83	0.81	0.8	0.81		0.7	0.73	0.73	0.71	0.76
Big	0.85	0.88	0.83	0.78	0.86		0.76	0.83	0.8	0.77	0.83

Size-OP portfolios

Regression analysis of size-OP portfolios from 1995-2022 reveals important insights into asset pricing models and profitability effects. The CAPM demonstrates significant limitations, particularly for small-cap stocks that show economically meaningful monthly alphas of 1.46%-1.79% (all statistically significant at the 1% level). While medium-sized firms display smaller but still significant alphas (0.45%-0.68%), large caps generally show insignificant alphas except for mid-OP stocks, confirming Novy-Marx's (2013) finding that operating profitability contains independent pricing information beyond market beta. The expanded six-factor model shows substantial improvement in explanatory power, with adjusted R^2 values increasing from 0.57-0.83 under CAPM to 0.78-0.88, particularly for small caps where the improvement ranges from 22-26 percentage points. However, significant alphas persist across the profitability spectrum (0.60%-0.77% for small caps), suggesting either incomplete factor specifications or potential mispricing related to profitability characteristics.

Factor loadings revealed several noteworthy patterns. The value factor (HML) shows positive loadings for small caps (0.19-0.41) but turns negative for large high-OP caps (-0.14), indicating that the value premium interacts differently with profitability across size segments. The profitability factor (RMW) loads are strongly positive for high-OP firms (up to 1.02 for small caps), confirming Fama and French's (2015) five-factor model results. Interestingly, the investment factor (CMA) provides relatively weak explanatory power, while momentum (MOM) shows consistently negative loadings (-0.09 to -0.27) across all portfolios, aligning with Asness's (1997) findings on value-profitability strategies. These results collectively underscore operating profitability as a distinct pricing factor while highlighting the complex interactions between firm size, profitability, and other risk factors in equity markets. Persistent alphas, particularly for small profitable firms, suggest that current factor models may still be incomplete in capturing all systematic sources of return variation, pointing to opportunities for further model refinement and research into the underlying economic mechanisms driving these relationships.

Table 8: This table reports the regression analysis of 15 size-Inv portfolios from October 1995 to September 2022 (324 months) using the CAPM and six factor models. The t-statistics are shown on the left side and ***, **, and * represent the 1%,5% and 10% levels of significance, respectively.

INV→	Low	2	3	4	High		Low	2	3	4	High
Panel A: CAPM intercepts:											
	α						$t(\alpha)$				
Small	1.8***	1.73***	1.41***	1.79***	1.78***		5.04	5.01	4.45	4.67	5.13
Medium	.6**	.56**	.81***	0.27	0.23		2.12	2.13	3.18	1.23	0.89
Big	0.23	0.33	0.27	0.26	0.02		0.99	1.50	1.39	1.55	0.11
Panel B: Six-factor coefficients: RM-RF, SMB, HML, RMW, CMA and MOM											
	α						$t(\alpha)$				
Small	.65***	.66***	.53**	.86***	1.03***		2.75	2.93	2.32	2.92	3.77
Medium	.41*	0.24	.63***	0.01	0.09		1.70	1.13	2.64	0.06	0.39
Big	0.18	.43**	.54***	.44**	.48***		0.80	2.19	2.93	2.51	2.63
	h						$t(h)$				
Small	.25***	.32***	.32***	.47***	.38***		2.84	3.77	3.77	4.31	3.68
Medium	0.11	0.01	0.11	0.12	-.16*		1.16	0.06	1.29	1.45	-1.83
Big	.16**	.32***	.2***	.15**	-0.04		1.97	4.32	2.90	2.31	-.66
	r						$t(r)$				
Small	-0.07	.25*	0.11	0.07	0.06		-.52	1.93	0.84	0.40	0.41
Medium	-0.06	0.16	-0.11	0.05	-.23*		-.43	1.29	-.83	0.45	-1.67
Big	0.07	0.03	0.15	.29***	0.01		0.60	0.31	1.48	2.94	0.05
	c						$t(c)$				
Small	.68***	.74***	0.08	-.59***	-.61***		5.09	5.79	0.61	-3.57	-3.99
Medium	.55***	.64***	0.07	-0.18	-.74***		3.99	5.34	0.53	-1.47	-5.58
Big	.81***	.52***	.23**	-0.01	-.64***		6.60	4.72	2.20	-.08	-6.29
	m						$t(m)$				
Small	-.13***	-.19***	-.18***	-.21***	-.21***		-4.00	-5.89	-5.59	-5.08	-5.33
Medium	-.24***	-.25***	-.18***	-.11***	-.16***		-7.03	-8.23	-5.25	-3.51	-4.68
Big	-.12***	-.13***	-.16***	-.11***	-.2***		-3.92	-4.58	-6.18	-4.52	-7.88
	Adj-R2 Six-factor model						Adj-R2 CAPM				
Small	0.86	0.87	0.84	0.79	0.79		0.61	0.63	0.64	0.56	0.61
Medium	0.82	0.83	0.79	0.8	0.84		0.71	0.7	0.71	0.75	0.76
Big	0.79	0.82	0.81	0.82	0.88		0.71	0.73	0.76	0.79	0.83

Size-Inv portfolios

The regression analysis of size investment portfolios from to 1995-2022 provides compelling evidence of the role of investment efficiency in asset pricing. The CAPM shows significant limitations, particularly for small-cap stocks that exhibit large monthly alphas of 1.41%-1.80% (all statistically significant at the 1% level), while medium firms display smaller but still meaningful alphas (0.23%-0.81%) and large caps show mostly insignificant results. This pattern strongly

confirms Hou et al., (2015) q-factor model, finding that investment growth represents a distinct priced factor in equity markets. The expanded six-factor model demonstrates substantially improved explanatory power, with adjusted R^2 values increasing from 0.56-0.83 under CAPM to 0.79-0.88, particularly for small caps where improvements exceed 25 percentage points. However, significant alphas persist (0.53%-1.03% for small caps), with high-investment small firms showing the largest unexplained returns, suggesting either incomplete factor specifications or potential mispricing related to investment behavior.

The factor loadings reveal particularly interesting patterns in how investments interact with other firm characteristics. The investment factor (CMA) emerges as the strongest predictor, showing positive loadings for low-investment firms (0.68 for small caps, 0.81 for big caps) and negative loadings for high-investment firms (-0.61 to -0.74), supporting Cooper et al.'s (2008) findings about the negative relationship between asset growth and future returns. The value factor (HML) maintains positive loadings for small caps but turns negative for large high-investment firms, while profitability (RMW) shows relatively weak effects. The consistently negative momentum loads (-0.11 to -0.25) across all portfolios suggest that investment strategies tend to exhibit return reversal. These results collectively underscore investment efficiency as a crucial determinant of cross-sectional returns, potentially more important than profitability in explaining stock performance, as suggested by Fama and French's (2015) five-factor model. These findings have important implications for asset pricing theory and practice, particularly for understanding the performance characteristics of small firms and the interaction between investment behavior, firm size, and value effects in equity markets.

Table 9. This table reports the regression analysis of 15 Size-BM-OP portfolios from October 1995 to September 2022 (324 months) using the CAPM and six-factor models. The t-statistics are shown on the right side and ***, **, and * represent the 1%,5% and 10% levels of significance, respectively.

Portfolios formed on Size, B/M and OP															
OP→	Low	Medium	High		Low	Medium	High		Low	Medium	High		Low	Medium	High
Panel A: CAPM intercepts:															
	α				t(α)				α				t(α)		
Low BM	0.34	.77***	1.3***		1.01	2.71	5.04		0.03	.43**	0.21		0.16	2.58	1.44
High BM	1.38***	1.51***	1.45***		4.11	4.95	4.33		0.37	0.38	0.50		1.27	1.42	1.65
Panel B: Six-factor coefficients: RM-RF, SMB, HML, RMW, CMA and MOM															
	α				t(α)				α				t(α)		
Low BM	-0.06	0.40	.79***		-.19	1.62	3.63		.39*	.69***	.37***		1.87	4.09	2.66
High BM	.44**	.58***	.51**		2.21	3.20	2.08		.45**	.51**	0.36		2.03	2.29	1.30
	h				t(h)				h				t(h)		
Low BM	-.67***	-.36***	-.34***		-6.07	-3.83	-4.16		-0.12	-.11*	-.24***		-1.48	-1.73	-4.66
High BM	.56***	.43***	.62***		7.47	6.36	6.72		.76***	.59***	.95***		9.26	7.08	9.27
	r				t(r)				r				t(r)		
Low BM	-.32*	-0.08	.34***		-1.95	-.54	2.76		-.37***	0.12	.26***		-3.13	1.31	3.27
High BM	-.34***	.26**	.78***		-3.00	2.48	5.57		-.23*	-0.03	.39**		-1.84	-.24	2.53
	c				t(c)				c				t(c)		
Low BM	.54***	0.10	-0.03		3.27	0.70	-.27		-.19*	0.08	.16**		-1.66	0.88	2.04
High BM	0.18	0.10	0.14		1.63	1.03	0.99		0.01	.29**	-0.05		0.11	2.37	-.35
	m				t(m)				m				t(m)		
Low BM	-.23***	-.21***	-.15***		-5.49	-5.97	-4.73		-.15***	-.17***	-.15***		-5.25	-7.22	-7.7
High BM	-.14***	-.21***	-.22***		-5.09	-8.13	-6.44		-.22***	-.19***	-.11***		-6.95	-6.17	-2.8
	Adj-R2 Six- factor model								Adj-R2 CAPM						
Low BM	0.77	0.76	0.83		0.84	0.85	0.87		0.64	0.63	0.71		0.82	0.83	0.83
High BM	0.9	0.9	0.82		0.86	0.83	0.76		0.67	0.66	0.6		0.7	0.7	0.64

Table 10. This table reports the regression analysis of 15 Size-BM-Inv portfolios; October 1995 to September 2022, (324 months) using CAPM and six factor models. The t-statistics are shown on the right side, ***, **, * represents 1%,5% and 10% level of significance.

Portfolios formed on Size, B/M and Inv															
	Small							Big							
Inv→	Low	Medium	High		Low	Medium	High		Low	Medium	High		Low	Medium	High
Panel A: CAPM intercepts:															
	α				$t(\alpha)$				α				$t(\alpha)$		
Low BM	.76**	.86***	1.03***		2.54	2.96	3.64		.37**	.32*	0.09		2.05	1.73	0.62
High BM	1.67***	1.35***	1.36***		5.10	4.45	3.86		.5*	.53**	0.02		1.68	2.06	0.07
Panel B: Six-factor coefficients: RM-RF, SMB, HML, RMW, CMA and MOM															
	α				$t(\alpha)$				α				$t(\alpha)$		
Low BM	0.32	.44*	.52**		1.45	1.81	2.16		.49***	.48**	.4***		2.83	2.57	2.86
High BM	.63***	.46**	.52**		3.18	2.39	2.26		.46**	.58***	0.09		2.11	2.95	0.35
	h				t(h)				h				t(h)		
Low BM	-.52***	-.45***	-.43***		-6.34	-4.93	-4.83		-.16**	-.13*	-.2***		-2.44	-1.81	-3.79
High BM	.43***	.57***	.65***		5.84	7.96	7.46		.69***	.79***	.85***		8.36	10.74	9.25
	r				t(r)				r				t(r)		
Low BM	0.04	0.01	-0.13		0.33	0.09	-93		-0.01	.24**	0.05		-.14	2.28	0.63
High BM	0.10	0.15	-0.03		0.88	1.41	-.25		-0.12	0.04	-0.06		-.97	0.39	-.46
	c				t(c)				c				t(c)		
Low BM	.9***	0.02	-.34**		7.27	0.12	-2.53		.59***	.25**	-.37***		6.08	2.36	-4.76
High BM	.57***	.19*	-.77***		5.20	1.77	-5.90		.59***	0.07	-.64***		4.84	0.65	-4.61
	m				t(m)				m				t(m)		
Low BM	-.29***	-.21***	-.1***		-9.21	-6.14	-2.88		-.14***	-.16***	-.15***		-5.83	-6.17	-7.86
High BM	-.16***	-.17***	-.22***		-5.82	-6.14	-6.75		-.18***	-.15***	-.22***		-5.81	-5.50	-6.43
	Adj-R2 Six-factor model								Adj-R2 CAPM						
Low BM	0.85	0.79	0.8		0.84	0.79	0.91		0.67	0.65	0.67		0.79	0.77	0.87
High BM	0.89	0.89	0.86		0.85	0.86	0.82		0.64	0.68	0.63		0.68	0.71	0.69

Size-BM-OP portfolios

This table presents the intercepts (α) and factor loadings (slopes) from the regression models estimating the performance of portfolios sorted on Size, Book-to-Market (BM), and Operating Profitability (OP).

The intercept α represents risk-adjusted excess returns that are not accounted for by the model. Panel A: CAPM Alphas. The Capital Asset Pricing Model (CAPM) is insufficient in explaining returns, as demonstrated by the consistently large and statistically significant alphas: low BM–high OP: $\alpha = 1.3^{***}$ with $t(\alpha) = 5.04$; high BM–low OP: $\alpha = 1.38^{***}$, $t = 4.11$. This indicates substantial abnormal returns that the CAPM model fails to capture. Panel B: Six-Factor Alphas reveal a significant reduction across all portfolios. For example, in the low BM–high OP category, α decreased from 1.3^{***} to 0.37^* ($t = 2.66$). Portfolios characterized by high BM exhibit even lower alphas, generally ranging from 0.44 to 0.58, with t-statistics approximately between 2.0 and 3.2. This suggests that the six-factor model accounts for the majority of the systematic risk. Although the remaining alphas were smaller, they remained significant in certain instances, indicating potential mispricing or overlooked risk factors.

The coefficients presented herein illustrate the sensitivity of portfolios to various risk factors. Specifically, the HML factor demonstrates a significant negative correlation with portfolios characterized by low book-to-market ratios (Growth Stocks), with coefficients ranging from $h = -0.67^{***}$ to -0.34^{***} and t-statistics reaching -6.07 . This indicates that these portfolios behave in opposition to the value stocks. Conversely, portfolios with high book-to-market ratios (Value Stocks) exhibit a strong positive correlation with the HML factor, with coefficients ranging from $h = 0.56^{***}$ to 0.95^{***} , and t-statistics up to 9.27 . This finding corroborates the expected behavior as value portfolios show substantial exposure to the HML factor. The HML factor effectively distinguishes between growth and value stock.

RMW: Profitability Factor low BM–low OP: Demonstrates a negative correlation with profitability, $r = -0.32^*$ ($t = -1.95$). High BM–high OP: Displays a strong positive correlation, $r = 0.78^{***}$ ($t = 5.57$). Overall, exposure tended to increase with higher OP levels. Interpretation: The profitability factor aligns with expectations, indicating that stocks with high OP benefit from the RMW. CMA: Investment Factor Low BM portfolios: The results are mixed, occasionally even negative (e.g., -0.19^* , $t = -1.66$). high BM portfolios: Loadings are near zero or slightly positive.

Overall, the results were not consistently significant with limited explanatory power. Interpretation: The CMA factor exhibits weak or inconsistent pricing.

The MOM analysis revealed a significant negative correlation across all portfolios. Specifically, low-BM portfolios exhibit momentum coefficients ranging from $m = -0.15^{***}$ to -0.23^{***} , with t-values as low as -7.7. High BM portfolios demonstrate similar patterns, with coefficients ranging from $m = -0.11^{***}$ to -0.22^{***} . This suggests that these portfolios generally underperform under high momentum conditions. Interpretation: The negative coefficients may indicate that these portfolios employ a contrarian strategy or lack momentum orientation.

The Six-Factor Model displayed notably high adjusted R^2 values, ranging from 0.76 to 0.90, indicating a robust explanatory power for the data. This is particularly pronounced in portfolios characterized by high BM and low OP. In contrast, the CAPM model yields lower R^2 values, between 0.60 and 0.87, and is particularly weak for portfolios with both low BM and OP. Interpretation: The Six-Factor Model significantly improves the model fit across all portfolio categories.

Size-BM-Inv portfolios

CAPM (Panel A): Most portfolios exhibit significant alphas, particularly those characterized by small size and high book-to-market (BM) ratios: Small–High BM–Low Investment: $\alpha = 1.67^{***}$, $t = 5.10$; Small–Low BM–High Investment: $\alpha = 1.03^{***}$, $t = 3.64$. Even larger portfolios tend to display positive alphas, although these are generally smaller in magnitude and less statistically significant: big–High BM–Low Investment: $\alpha = 0.50^*$, $t = 1.68$. Interpretation: The Capital Asset Pricing Model (CAPM) fails to adequately account for a substantial portion of returns, as evidenced by the high alphas, which suggest the presence of mispricing or omitted factors. Six-factor Model (Panel B): The application of the six-factor model resulted in a significant reduction in alpha values. For the Small–Low BM–High Inv portfolio, the alpha decreases from 1.03^{***} (CAPM) to 0.52, with a t-value of 2.16. In the case of the Small–High BM–Low Inv portfolio, the alpha is 0.63^{***} , with a t-value of 3.18. Portfolios of larger size also demonstrate lower, often statistically insignificant, alpha values. For instance, the big-high-BM-high-Inv portfolio exhibits an alpha of 0.09, with a t-value of 0.35, indicating that the model fully accounts for this variation. Interpretation: The six-factor model effectively explains the majority of return variation, particularly in large and high-BM portfolios. The remaining significant alphas are predominantly

observed in the small and low-BM portfolios, which may suggest the presence of residual mispricing.

The Value Factor (HML) demonstrates a consistently negative correlation with low book-to-market (BM) ratios, indicating growth portfolios. For example, the correlation for Small–Low BM–Low Investment is $h = -0.52^{***}$, with a t-value of -6.34. Conversely, high BM ratios, a characteristic of value portfolios, exhibit a strong positive correlation, as evidenced by the high BM–High Investment with $h = 0.85^{***}$ and a t-value of 9.25. This analysis suggests that HML effectively distinguishes value and growth portfolios across different sizes and investment categories. The Profitability Factor (RMW) demonstrates varying levels of significance across portfolios. Specifically, small-low BM portfolios generally show limited significance. However, some significance is observed in the big–Low BM–Medium Investment portfolios, with a correlation coefficient of $r = 0.24^{**}$ and a t-value of 2.28. By contrast, High BM portfolios exhibit minimal or no exposure to this factor. Thus, the profitability factor (RMW) does not substantially influence returns in most portfolios examined, particularly within high BM portfolios.

Investment Factor (CMA) Key Observations: Portfolios characterized by low investment levels (Low Inv) exhibit significantly positive loadings. For example, Small–Low BM–Low Inv: $c = 0.90^{***}$, $t = 7.27$. In contrast, portfolios with high investment levels display negative CMA loadings. For instance, Big–High BM–High Inv: $c = -0.64^{***}$, $t = -4.61$. Explanation: The CMA is closely associated with the investment dimension, suggesting that portfolios with higher investment levels tend to underperform compared to those that employ more conservative investment strategies.

Momentum (MOM) All portfolios exhibit a significant negative correlation: Small–Low BM–Low Inv: $m = -0.29^{***}$, $t = -9.21$; Big–High BM–High Inv: $m = -0.22^{***}$, $t = -6.43$. These portfolios might display contrarian behavior or include stocks that are losing momentum. The MOM has a major influence, albeit with a negative bias.

Adj-R² Model Fit Size BM CAPM R² for small low BM ranges from 0.65 to 0.67, while for big high BM, it spans from 0.63 to 0.69. In contrast, the six-factor model R² for small low BM is between 0.79 and 0.85, and for big high BM, it is between 0.82 and 0.89. Interpretation: The six-factor model offers significantly greater explanatory power, especially in portfolios with high BM and large sizes.

4. Conclusion

This study evaluates the applicability of the Fama-French six-factor model (FF5 + Momentum) in the Indian equity market from October 1995 to September 2022 using portfolios sorted on size, book-to-market (B/M), profitability (OP), and investment (Inv). The key findings reveal that size (SMB), value (HML), profitability (RMW), and momentum (WML) are non-redundant factors, with SMB (intercept = 1.16%, $t^* = 4.67$) and WML (intercept = 1.58%, $t^* = 4.02$) being particularly significant. In contrast, the investment factor (CMA) is redundant, as it is fully explained by exposure to HML and RMW, whereas the market factor ($R_m - R_f$) shows marginal insignificance. Portfolio-level analysis confirms strong size and value effects, with a small cap and high B/M portfolios delivering higher returns (e.g., small-high B/M: 2.89% monthly). Profitability (high-OP stocks) and low-investment firms also outperform, although RMW's explanatory power of RMW weakens among large caps. Notably, momentum exhibited negative loadings in small caps, suggesting contrarian tendencies. The six-factor model significantly outperforms CAPM, with adjusted R^2 improvements from 0.56–0.64 to 0.75–0.89 for small caps, though residual alphas (e.g., 0.58–1.11%) indicate unexplained risks. Unique to India, HML remains a priced factor, diverging from the U.S. and European markets, possibly due to inefficiencies or behavioral biases, while RMW's weaker impact may reflect accounting differences. The strong momentum effect aligns with India's anomaly driven market, although its negative correlation with HML points to complex factor interactions. These findings suggest that investors should prioritize size, value, and momentum while treating CMA as subsumed. Future research could refine the model by incorporating macroeconomic or liquidity factors to address residual alphas and develop localized asset-pricing frameworks, given India's distinct market dynamics.

Ethics approval: Not Required

Consent to participate: Not Required

Consent for publication: Not Required

Competing interests: The authors confirm that there are no conflicts of interest associated with this study

Funding: No funding was received for this study.

Data availability: The authors confirm that the data supporting the findings of this study are available upon request.

References

- Aggarwal, R. (2017). The Fama-French three factor model and the capital asset pricing model: Evidence from the Indian stock market. *Indian Journal of Research in Capital Markets*, 4(2), 36-47.
- Ansari, V. A. (2000). Capital asset pricing model: should we stop using it?. *Vikalpa*, 25(1), 55-64.
- Asness, C. S. (1997). The interaction of value and momentum strategies. *Financial Analysts Journal*, 53(2), 29-36.
- Asness, C. S., Frazzini, A., Israel, R., & Moskowitz, T. J. (2015). Fact, fiction, and value investing. *Published in Journal of Portfolio Management*, 42(1).
- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of financial economics*, 9(1), 3-18.
- Barillas, F., & Shanken, J. (2018). Comparing asset pricing models. *The Journal of Finance*, 73(2), 715-754.
- Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial economics*, 43(1), 29-77.
- Cakici, N., Fabozzi, F. J., & Tan, S. (2013). Size, value, and momentum in emerging market stock returns. *Emerging Markets Review*, 16, 46-65.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1), 57-82.
- Chui, A. C., & Wei, K. J. (1998). Book-to-market, firm size, and the turn-of-the-year effect: Evidence from Pacific-Basin emerging markets. *Pacific-Basin finance journal*, 6(3-4), 275-293.
- Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *the Journal of Finance*, 63(4), 1609-1651.
- Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial economics*, 122(2), 221-247.
- Dash, S. R., & Mahakud, J. (2015). Market anomalies, asset pricing models, and stock returns: evidence from the Indian stock market. *Journal of Asia Business Studies*, 9(3), 306-328.
- Efficiency, S. M. (1993). Returns to buying winners and selling losers: Implications for. *The Journal of Finance*, 48(1), 65-91.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, 47(2), 427-465.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1), 3-56.

Fama, E. F., & French, K. R. (1998). Value versus growth: The international evidence. *The journal of finance*, 53(6), 1975-1999.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of financial economics*, 105(3), 457-472.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, 116(1), 1-22.

Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of financial economics*, 128(2), 234-252.

Foye, J. (2018). A comprehensive test of the Fama-French five-factor model in emerging markets. *Emerging Markets Review*, 37, 199-222.

Gray, P., & Johnson, J. (2011). The relationship between asset growth and the cross-section of stock returns. *Journal of banking & Finance*, 35(3), 670-680.

Hanauer, M. X., & Lauterbach, J. G. (2019). The cross-section of emerging market stock returns. *Emerging Markets Review*, 38, 265-286.

Harvey, C. R. (1995). Predictable risk and returns in emerging markets. *The review of financial studies*, 8(3), 773-816.

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ... and the cross-section of expected returns. *The Review of Financial Studies*, 29(1), 5-68.

Hou, K., Mo, H., Xue, C., & Zhang, L. (2021). An augmented q-factor model with expected growth. *Review of Finance*, 25(1), 1-41.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3), 650-705.

Karolyi, G. A. (2016). The gravity of culture for finance. *Journal of Corporate Finance*, 41, 610-625.

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of financial economics*, 12(1), 13-32.

Leite, A. L., Klotzle, M. C., Pinto, A. C. F., & da Silva, A. F. (2018). Size, value, profitability, and investment: Evidence from emerging markets. *Emerging Markets Review*, 36, 45-59.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The journal of finance*, 20(4), 587-615.

Lo, A. W., & MacKinlay, A. C. (1990). An econometric analysis of nonsynchronous trading. *Journal of Econometrics*, 45(1-2), 181-211.

McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability?. *The Journal of Finance*, 71(1), 5-32.

- Mehra, R., & Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of monetary Economics*, 15(2), 145-161.
- Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of financial economics*, 108(1), 1-28.
- 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.
- Schwert, G. W. (1989). Why does stock market volatility change over time?. *The journal of finance*, 44(5), 1115-1153.
- Sehgal, S., & Balakrishnan, A. (2013). Robustness of Fama-French three factor model: Further evidence for Indian stock market. *Vision*, 17(2), 119-127.
- Sehgal, S., & Jain, S. (2014). Long-term prior return patterns in stock and sector returns in India. *Journal of Advances in Management Research*, 11(2), 192-210.
- Sehrawat, N., Kumar, A., Nigam, N. K., Singh, K., & Goyal, K. (2020). Test of capital market integration using Fama-French three-factor model: Empirical evidence from India. *Investment Management & Financial Innovations*, 17(2), 113.
- Sha, Y., & Gao, R. (2019). Which is the best: A comparison of asset pricing factor models in Chinese mutual fund industry. *Economic Modelling*, 83, 8-16.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3), 425-442.
- Singh, K., Singh, A., & Prakash, P. (2023). Testing factor models in an emerging market: evidence from India. *International Journal of Managerial Finance*, 19(1), 203-232.
- Singh, S., & Yadav, S. S. (2015). Indian stock market and the asset pricing models. *Procedia Economics and Finance*, 30, 294-304.
- Sobti, N. (2016). Revisiting Capm and Fama French Three Factor Model in Indian Equity Market. *Business Analyst*, ISSN, 31-46.
- Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A journal of selected papers*, 4(1), 25-45.
- Zaremba, A., & Czapkiewicz, A. (2017). Digesting anomalies in emerging European markets: A comparison of factor pricing models. *Emerging Markets Review*, 31, 1-15.
- Zaremba, A., & Maydybura, A. (2019). The cross-section of returns in frontier equity markets: Integrated or segmented pricing?. *Emerging Markets Review*, 38, 219-238.