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Article

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Superiority of six factor model in Indian stock market

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ABSTRACT

This novel work is the first study in India to incorporate the Human capital (HC) factor as a six-factor asset-pricing model and presents a robust methodology. The aim of this work is to examine the ability of the six-factor model to capture excess returns using a GMM framework with time periods that were missing in previous studies. Therefore, data for this study were collected using the BSE 500 index. Building on this insight, this study attempts to explain the inherent risk factors (firms and markets) that predict returns over a period of time, considering the dynamics of the Indian market. The GRS test also confirms the superiority of the six-factor model for the Indian equity market. The study asserts that the Instrumental variable- Generalized method of moments (IVGMM) is a robust model over OLS in explaining portfolio returns (single and bivariate), which implies that OLS in the asset pricing model is exaggerated in the Indian context. Single portfolios are constructed based on the factors of size, value, ROE, INV and human capital, while bivariate portfolios are constructed based on the intersection of any these two factors. This study confirms the significant role of HC (wealth) in describing the stock returns of an economy. This study contributes to the ongoing discourse on asset pricing models and offers valuable implications for investment decisions, risk management, and portfolio construction in one of the most attractive global financial markets.

IMPACT STATEMENT

This novel work is the first study in India to incorporate the Human capital (HC) factor as a six-factor asset-pricing model and presents a robust methodology. The aim of this work is to examine the ability of the six-factor model to capture excess returns using a GMM framework with time periods that were missing in previous studies. The study asserts that the Instrumental variable- Generalized method of moments (IVGMM) is a robust model over OLS in explaining portfolio returns (single and bivariate), which implies that OLS in the asset pricing model is exaggerated in the Indian context. Single portfolios are constructed based on the factors of size, value, ROE, INV and human capital, while bivariate portfolios are constructed based on the intersection of any these two factors. This study confirms the significant role of HC (wealth) in describing the stock returns of an economy. This study contributes to the ongoing discourse on asset pricing models and offers valuable implications for investment decisions, risk management, and portfolio construction in one of the most attractive global financial markets.

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1. Introduction

Substantial empirical finance research addresses the correct valuation of financial assets (Santoni & Salerno, 2023). While the CAPM (Sharpe, 1965; Lintner, 1965) explains the linear risk-reward relationship, the identification of various factors that significantly contradict the model has called into question its global validity. Fabozzi and Francis (1978) conclude that the beta coefficient of the stock varies randomly over time and contradicts the basic assumptions of the CAPM. Therefore, the above discussion sheds

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light on the limitation of CAPM beta in capturing other inherent market risks, and its stability has challenged the asset pricing framework globally (Sharpe, 1965). According to Bos and Newbold (1984), microeconomic variables such as the phase of the country's business cycle, inflation rate, and the company's business environment determine the beta of stocks. Fama and French (1993) extend CAPM by adding value (HML) and size (SMB) as key factors in explaining the excess returns of stocks. Carhart (1997) extends the Fama-French three-factor model by adding a momentum factor to the model and reports that this improves the explanatory power of the model for mutual fund performance. Following the approach of Miller and Modigliani (1961), Fama and French (2015) subsequently proposed profitability (RMW) and investment (CMA) as two additional factors that provide a better R2 (71% and 94%) in achieving excess returns. Chronologically, Chiah et al. (2016) also proposed the FF five-factor model as a better asset pricing model in international stock markets. However, both assumptions that only the beta factor influences asset pricing and market is efficient are contradicted by market anomalies reported in the literature, such as the size effect (Banz, 1981), value effect (Stattman, 1980), price-earnings ratio (Basu, 1983), firm leverage (Bhandari, 1988) and high dividend yield (Fama, 1998). As anomalies have no theoretical basis and cannot be explained by economic theories, this has led to the development of empirical, research-based factor models. This shows that the asset pricing model has always been expanded into a multifactor model with a new significant factor, whereby these multifactor models mimic the risk factor differently.

Fama and French (1992) best-known three factors aim to provide a more comprehensive explanation of stock returns relative to CAPM, particularly in explaining the returns of small-cap and value stocks. The model was then transformed into a five-factor model by including profitability and investment factors to capture the variation in the average returns of diversified stock portfolios (Fama and French 2015). Despite their popularity, these models have conflicting results in markets and limitations in studies worldwide, which has always been a source for exploring a robust model. Looking at a broader market for ten countries, Lalwani and Chakraborty, (2020) find that the Fama-French five-factor model using GRS statistics and average absolute intercepts fits stock pricing for four countries well. However, the study may have relied on the cross-sectional data. Khudoykulov (2020) pointed out the crucial performance of the three- and five-factor models over the CAPM beta model while explaining portfolio returns in the Indian market from 2009 to 2018. In their study, Bhatti and Khan (2022) take a large sample of 25 emerging economies covering a sample period of 21 years, further divided into pre-crisis, crisis and post-crisis periods, and find that the performance of the three-factor model in the Asian region. The authors also introduce the 10-factor asset pricing model and confirm its applicability to the American market. However, the study lacks consistency in the proxies used for profitability, investments, liquidity and leverage. Recently, a new factor proposed by Park et al. (2024) tests the asset pricing model and simultaneously introduces COVID-19 as a pricing factor in the asset pricing model. The study uses the two-step GMM model and examines the relationship between the COVID-19 factor measured as pandemic risk and stock returns, indicating that it has a significant positive risk premium. Although the study is the first to propose COVID-19 as a factor in asset pricing, its applicability in different countries needs to be empirically tested. Apparently, the Fama-French models in India also have different results and are inconclusive.

Therefore, various other factors have been identified for constructing an optimal portfolio. One of the risk-mimicking factors ignored by asset pricing models is human capital (HC). Mayers (1972) points out that individuals may hold significant portions of their wealth in non-marketable assets (HC), which cannot be easily traded in financial markets. Consequently, the existence of these non-marketable assets affects individuals' portfolio selection and investment strategies. Similarly, Kim et al. (2011) suggested that HC has predictive value in explaining asset returns. However, HC is gaining popularity (Campbell, 1996) and is recognized as an important factor in the asset pricing model. This study measures HC as an asset of the company and has an additive effect with regard to size and value factors. Campbell (1996) emphasized that human capital reflects the true wealth of the economy and should, therefore, be part of the asset pricing framework. Jagannathan and Wang (1996) find that CAPM can better explain more than 50% of the differences in cross-sectional returns when market returns are replaced by human capital. Later, Belo et al. (2017), Kuehn et al. (2017) confirm that human capital is an important determinant in measuring cross-sectional stock returns. The HC multifactor model is later referred to as the six-factor asset pricing model. Therefore, the above studies in various international markets support the HC-based multifactor model and

confirm its superior performance in global markets. Several studies have demonstrated the presence of human capital in the multifactor model in the international market (Belo et al., 2017; Kim et al., 2011; Kuehn et al., 2017; Lettau, & et al., 2019). Similarly, Maharani and Narsa (2023) found that intellectual capital plays a role in explaining asset returns in the Indonesian stock market for the period 2012–2022. Khan et al. (2023) highlights the importance of human capital in investment decisions and recommends investors consider the size, value and human capital while valuing the firms. The study extends the Fama-French three-factor by including human capital as the fourth factor and has shown its validity for Pakistani firms. However, the study uses a smaller number of portfolios for analysis. Anuno et al. (2023) note the applicability of the Fama-French five-factor model in Timor-Leste and emphasize that the SMB and HML factor contribute negatively to the excess returns, while the profitability factor contributes positively to explaining the returns. Since Timor-Leste is a low-income country, the study can use human capital as a sixth factor in asset pricing as the country has the growth potential of human capital.

Although the HC-based multifactor model is widely accepted worldwide, its validity must be tested in emerging markets. Among the emerging markets, the Indian economy has witnessed tremendous growth across all sectors over the last decade. India ranks fifth among the top ten countries in terms of gross domestic product (GDP) in the world, India[1] ranks fifth among the top 10 countries and is expected to be the third[2] most powerful country by 2030. India's exponential growth was the original motivation for research in the Indian market. Ironically, two studies on the six-factor asset pricing model also motivate us to investigate its existence in the Indian market. Some of the notable contributions to the six-factor multifactor model are from Shijin et al. (2012), who state that the HC-based multifactor model offers more predictive returns than the single-index model for the Indian market for 1996–2006. The authors exclusively used Granger causality tests, OLS regression, and impulse response functions for the Nifty 50 index. Maiti and Balakrishnan (2018) also report that the six-factor model reflects return patterns better than the three- and five-factor Fama-French models. This study uses GRS tests, 3D graphs, regression models, and residual graphs for BSE-500 index companies for the period 2004–2016 to examine HC in capturing returns on assets. It is pertinent to note here that the human factor as the sixth asset pricing model has received significant attention in the global market but has not received significant attention in the Indian market in recent times after 2017.

India, with its vibrant and rapidly evolving stock market and diverse offerings of stocks from various sectors and industries, requires an investigation of the effectiveness and superiority of the six-factor model. Therefore, our study extends previous work in the context of a competent asset-pricing framework in the Indian market. This novel work is the first study in India to incorporate the HC factor as a six-factor asset-pricing model and presents a robust methodology. The two previous studies in this area are very limited and are, therefore, looking for methods that demonstrate agreement between them. The available literature on the six-factor model in India is limited to the study period of 6–7 years ago. There is a need for a study to propose a benchmark model for pricing assets in the Indian stock market while covering the pandemic (COVID-19) period, as there is no analysis in this area covering the period before, during and post-COVID-19. The aim of this work is to examine the ability of the six-factor model to capture excess returns using a GMM framework with time periods that were missing in previous studies. Since, GMM shows its potential when the cross-sectional heteroscedasticity of the data exists and the collected time series data is small (Kiviet et al., 2017). Furthermore, GMM provides a framework for addressing endogeneity issues by using instrumental variables or moment conditions to identify and estimate causal relationships between variables. Additionally, the conventional static approach of the Fama-French model may be mis-specified mis specified because its parameters have time-varying properties (Racicot et al. (2019).

2. Data

For the Indian market, the BSE 500 is one of the best choices for all equity indices, as it has a strong relationship with all macroeconomic variables (Chaudhary & Bakhshi, 2021). Therefore, for this study, data was collected for companies listed in the BSE 500 index. The BSE 500 index covers the top 20 sectors of the Indian economy and represents 93% of the total BSE market capitalization[3]. Of the 500 companies listed on the BSE 500 Index, the data include only 280[4] companies for the 19-year study

period, that is, from June 2002 to July 2021 (Maiti & Balakrishnan 2018), from the CMIE Prowess database. From the initial sample of BSE 500 listed companies, we removed companies whose market capitalization (MC) for size factor data for a period of 19 years are inadequate or irregular. This process is repeated for other factors: BM ratio (book value to price ratio) for value, ROE (return on equity) for profitability, INV (annual growth in total assets) for investments, and HC (salaries and wages) for human capital for the study period. As the list of companies has changed due to further incorporations and; Mergers and amalgamations of companies. Likewise, companies with irregularities in their closing prices are removed from the sample. In the end, we left with 280 companies for which the data is complete for all factors and for each year. The data is secondary in nature. Although the study uses a rigorous data collection methodology, the analysis conducted in the study acknowledges the possibility of survival bias, which can be considered as one of the limitations. Selection bias, also known as survivorship bias, is the tendency to include survivors in an analysis and those who failed, dropped out, or were otherwise removed are omitted. This is called 'survivorship bias,' a type of selection bias. Failure to consider all available data, particularly those lost during the investigative process, could lead to overly optimistic conclusions. Elfakhani and Wei (2003) examined the survivorship bias, the stock price effect, and the small firm effect in Canadian financial markets. The study found evidence of survival bias in Canadian stock returns, with the returns of surviving companies being higher than the returns of the entire sample of companies. Previous studies by (Brown & Goetzmann, 1995; Grinblatt & Titman, 1993; and Malkiel, 1995) emphasized the existence of survivorship bias when examining the performance of mutual funds. In the Indian context, Agarwalla, et al. (2013) argued that the survival bias found in their study is negligible since the sample is from the Bombay Stock Exchange (BSE), which is similar to our sample. Therefore, the results of our study may also be negligible or overestimate the presence of survival bias. Hence, for the robustness of results, we recommend that subsequent studies, when conducted in the same area, should aim to include comprehensive data from all subjects, including those who do not survive the study. Employing techniques such as survival analysis or multiple imputation for missing data can help mitigate this bias and provide a more accurate representation.

The motivation of the study is to take a long period of time for the robustness of the result. Both the initial and final periods of the study show stability in the Indian stock market after the global crisis, which is considered a normal period for conducting the analysis. The Indian stock market seems to be recovering since March 2002 after a massive terrorist attack (September 11) and is showing momentum after the global COVID-19 crisis. However, this period also includes a global recession in 2008.

3. Methodology

The proxies for measuring the six factors are market capitalization (MC) for size, BM ratio (book-to-price ratio) for value, ROE (return on equity) for profitability, INV (annual growth in total assets) for investments, and HC (salaries and wages) for human capital. However, while operating profit measures the overall profitability of the company, analysts and investors critically examine ROE to estimate the return on the amount of money they have invested in the company. Additionally, people are more likely to buy shares in a company with a high ROE ratio. Furthermore, existing literature also confirms that ROE is a proxy for profitability (Haugen & Baker, 1996; Maiti & Balakrishnan, 2018). The sample companies were ranked each year in March based on the selected factors, for which monthly log returns were calculated from July 2002 to June 2021. We maintained the standard practice followed by (Prasad & Verma, 2013; Maiti & Balakrishnan, 2018), as it is the most popular practice. To construct five portfolios (P1, P2, P3, P4, and P5), equally weighted portfolios are used for each factor, with P1 representing the lowest rank and P5 the highest rank. The following portfolios were constructed by continuing the existing methodology.

3.1. Single sorted portfolios

Single-sorted portfolios for each factor replicate five equally weighted portfolios consisting of 56 stocks each. These are referred to as P1 (the smallest stocks) and P5 (the largest stocks) based on MC, P1 as growth stocks, P5 as value stocks based on the BM ratio, P1 as weak stocks, P5 as robust stocks based

on ROE, P1 as conservative stocks, P5 as aggressive stocks based on investment, P1 as low compensation stocks, and P5 as high compensation stocks based on salaries and wages.

3.2. Bivariate portfolios

Bivariate portfolios are constructed from the intersection of two factors, keeping the size of each factor the same. To construct portfolios based on the MC and BM ratio, companies are divided into two small and large companies based on MC, while companies are divided into Low, Medium and High companies based on the BM ratio. Six portfolios were then formed, referred to as SL, SM, SH, BL, BM, and BH. The same process was expanded to build six portfolios at the intersection of Small and Large (MC) and Robust, Neutral and Weak (ROE), referred to as SR, SN, SW, BR, BN, and BW. The other six portfolios are SC, SN, SA, BC, BN, and BA and are formed by the intersection of MC (Small and Large) and INV (Conservative, Neutral and Aggressive). The final set of six portfolios formed by combining Small and Big (MC) and lower compensation and higher compensation (HC) are SLc, SN, SHc, BLc, BN, and BHc. For each portfolio, excess returns were calculated by subtracting the RBI's 91-day T-bill risk-free rate from the portfolios' monthly mean returns. This study uses 91-day- T-bills as a proxy for the risk-free rate, and BSE Sensex is selected as a market proxy.

This study examines the six-factor model for which the portfolios constructed above are regressed using the six independent variables (SMB, HML, RMW, CMA, and LcMHc)[5] calculated as follows:

$$\mathrm{SMB} = 1/3(\mathrm{SL}+\mathrm{SM}+\mathrm{SH}) - 1/3(\mathrm{BL}+\mathrm{BM}+\mathrm{BH}) \tag{1}$$

Where SMB stands for Small minus Big and represents the size risk.

$$\mathrm{HML} = 1/2\ (\mathrm{SH}+\mathrm{BH}) - 1/2\ (\mathrm{SL}+\mathrm{BL}) \tag{2}$$

Where HML stands for High minus Low and represents the value risk.

$$\mathrm{RMW} = 1/2\ (\mathrm{SR}+\mathrm{BR}) - 1/2\ (\mathrm{SW}+\mathrm{BW}) \tag{3}$$

Where RMW stands for Robust minus Weak and represents the profitability risk.

$$\mathrm{CMA} = 1/2\ (\mathrm{SC}+\mathrm{BC}) - 1/2\ (\mathrm{SA}+\mathrm{BA}) \tag{4}$$

Where CMA stands for Conservative minus Aggressive and represents the investment risk.

$$\mathrm{LcMHc} = 1/2\ (\mathrm{SLc}+\mathrm{BLc}) - 1/2\ (\mathrm{SHc}+\mathrm{BHc}) \tag{5}$$

Where LcMHc stands for lower compensation minus higher compensation and represents the human capital risk.

3.3. Empirical tests

A few recent studies in the field of asset pricing models (Keshari & Gautam, 2022) have used methodologies that still necessitate a comprehensive asset pricing study in the Indian market. Therefore, we used two different statistical methods to ensure the robustness of the model and reveal its applicability. First, we use a joint F-test for a set of portfolios using GRS (Gibbons, Ross and Shanken, 1989). We assume that returns are homoscedastic and not autocorrelated. The GRS test provides F-statistics to test whether the joint absolute value of the intercept is equal to zero, which is based on the following OLS equation:

$$\mathrm{R_{it}} - \mathrm{RF_t} = \alpha \mathrm{i} + \beta_{1\mathrm{i}}(\mathrm{RM_t} - \mathrm{RF_t}) + \beta_{2\mathrm{i}}\mathrm{SMB_t} + \beta_{3\mathrm{i}}\mathrm{HML_t} + \beta_{4\mathrm{i}}\mathrm{RMWt} + \beta_{5\mathrm{i}}\mathrm{CMA_t} + \beta_{6\mathrm{i}}\mathrm{LcMHc} + \mathrm{e_{it}} \tag{6}$$

However, studies on the Indian market by Maiti and Balakrishnan (2018) and Shijin et al. (2010) require a robust methodology, as there is empirical evidence that the parameter estimates of the six-factor framework using the IVGMM approach outperform traditional OLS because of specification and measurement errors (Roy, 2020). IVGMM is a stronger model for testing the asset pricing model over Fama Macbeth's two-pass regression due to its efficiency, robustness, flexibility and ability to address complex econometric issues such as efficiency, endogeneity correction, handling measurement error and robust statistical inference. Moreover, in such complex issues two-pass time series leads to biased results. (Horváth & Wang, 2021; Jagannathan et al., 2002). In this study, we adopted generalized

Table 1. Descriptive statistics for single-sorted portfolios.

Portfolios	*p*1	*p*2	*p*3	*p*4	*p*5
			MC		
Returns	0.024	0.010	0.008	0.008	0.005
Risk	0.096	0.093	0.084	0.077	0.073
			BV		
Returns	0.018	0.013	0.011	0.006	0.006
Risk	0.091	0.083	0.081	0.086	0.080
			ROE		
Returns	0.010	0.010	0.012	0.012	0.011
Risk	0.099	0.086	0.082	0.075	0.076
			INV		
Returns	0.014	0.011	0.010	0.010	0.010
Risk	0.092	0.087	0.081	0.078	0.086
			HC		
Returns	0.016	0.013	0.010	0.009	0.006
Risk	0.094	0.085	0.082	0.080	0.078

Note. Return and risk are the mean and standard deviation of the portfolios.

Table 2. Correlation matrix of independent variables.

	Sensex	SMB	HML	RMW	CMA	LcMHc
Sensex	1					
SMB	−0.030	1.000				
HML	0.036	−0.433	1.000			
RMW	0.033	0.648	−0.142	1.000		
CMA	−0.018	0.206	0.447	0.073	1.000	
LcMHc	0.020	0.147	−0.085	−0.010	−0.004	1

Note. Computed by authors.

Table 3. Descriptive statistics for double-sorted portfolios.

			MC/BV Portfolios			
	SL	SM	SH	BL	BM	BH
Returns	0.201	0.022	0.104	0.042	0.092	0.165
Risk	1.077	0.125	0.556	0.284	0.469	1.021
			MC/ROE Portfolios			
	SR	SN	SW	BR	BN	BW
Returns	0.174	0.207	0.111	0.078	0.108	0.166
Risk	0.901	1.097	0.556	0.373	0.561	1.003
			MC/INV Portfolios			
	SC	SN	SA	BC	BN	BA
Returns	0.097	0.128	0.104	0.103	0.085	0.097
Risk	0.571	0.736	0.523	0.546	0.515	0.537
			MC/HC Portfolios			
	SLc	SN	SHc	BLc	BN	BHC
Returns	1.056	−0.577	0.737	−0.470	0.902	−0.385
Risk	6.177	3.005	4.281	3.383	6.014	2.426

Note. Return and risk are the mean and standard deviation of the portfolios.

methods of moments, a robust form of the methodology in the asset pricing framework that assumes a minimum standard error and does not require stationary variables. This can be expressed by the following equation:

$$R_{it} - R_{Ft} = \alpha_{GMMi} + \beta_{GMM1i}(RM_t - RF_t) + \beta_{GMM2i}SMB_t + \beta_{GMM3i}HML_t + \beta_{GMM4i}RMW_t + \beta_{GMM5i}CMA_t + \beta_{GMM6i}LcMHc + {}^{\sim}e_{it} \quad (7)$$

The results of the tests carried out using the Stata statistical software are further explained.

4. Results

Table 1 shows that the average excess returns of the P1 portfolios are higher than those of the P5 portfolios for single-sorted portfolios based on six factors (size, value, RMW, CMA, and HC), and the risk associated

Table 4. GRS test results for single-sorted portfolios.

Portfolios	GRS	*p* Value	Mean absolute alpha	AR^2
		Size		
P1-P5	7.474	0.000*	0.004	0.107
		Value		
P1-P5	3.793	0.003*	0.004	0.123
		ROE		
P1-P5	0.547	0.740	0.004	0.113
		INV		
P1-P5	0.547	0.740	0.004	0.113
		HC		
P1-P5	1.330	0.253	0.004	0.120

Note. GRS statistic with the corresponding p-value at the 5% significance level.

Table 5. GRS test results for bivariate portfolios.

Portfolios	GRS	*p* Value	Mean absolute alpha	AR^2
MC/BV	0.380	0.891	0.005	0.840
MC/ROE	0.597	0.733	0.010	0.896
MC/INV	0.265	0.953	0.005	0.900
MC/HC	562.925	0.000*	0.317	0.265

Note. GRS statistic with the corresponding *p*-value at the 5% significance level.

Table 6. Relevance test results for robust instruments.

	Alpha	Sensex	SMB	HML	RMW	CMA	HC	F-Statistics
Sensex	0.007	–	−0.028	0.007	0.016	−0.006	0.001	0.326
	1.467		−0.636	0.293	0.931	−0.246	0.500	
SMB	−0.005	−0.062	–	−0.334	0.272	0.291	0.012	94.660
	−0.800	−0.640		−12.050	14.090	9.300	2.890	
HML	−0.007	−0.054	−1.181	–	0.237	0.661	0.005	52.190
	−0.590	0.290	−12.050		5.020	12.420	0.670	
RMW	0.042	0.231	1.734	0.429	–	−0.370	−0.024	43.730
	2.390	0.930	14.090	5.020		−4.130	−2.280	
CMA	0.011	−0.044	0.963	0.619	−0.192	–	−0.007	34.870
	0.890	−0.250	9.300	12.420	−4.130		−0.980	
HC	0.325	0.755	2.914	0.368	−0.919	−0.549	–	2.130
	3.010	0.500	2.890	0.670	−2.280	−0.980		

Note. Regression results for each explanatory variable for all instruments with their corresponding F-statistics.

with the portfolio is also higher. This implies historical outperformance of (small-cap stocks relative to large-cap stocks, value stocks relative to growth stocks, high profitability ratio stocks relative to low profitability ratio stocks, and conservative investment stocks over aggressive investment stocks low compensation stocks over high compensation stocks). Based on ROE, the average return of the P5 portfolio is slightly higher than that of the P1 portfolio, indicating that investors prefer to invest in stocks that offer higher returns on the investments they make. Additionally, the risk associated with the P1 portfolios is higher across all factors, indicating higher volatility in market movements.

Before proceeding with the GRS statistics, we determine the correlation between the independent variables to check for the presence of multicollinearity. Table 2 shows that the correlation between the variables is less than 0.50 in all cases, indicating that none of the independent variables are correlated with each other and therefore there is no multicollinearity between them.

Table 3 presents that the average excess returns of small portfolios (SL, SR, SC and SLc) are higher than those of large portfolios (BH, BW, BA and BHc) for bivariate sorted portfolios. The risk associated with the portfolios is also higher, which suggesting a risk-reward ratio.

Table 4 shows the results of the GRS tests of the six-factor model for the single-sorted portfolio based on size, value, RMW, CMA, and HC with the null hypothesis that the mean absolute alpha is zero. The rejection of the null hypothesis and the fact that the mean absolute alpha is closer to zero demonstrate the ineffectiveness of the factor model in explaining returns. These results clearly show that all single portfolios sorted by size and value are rejected, while the RMW, CMA, and HC sorted portfolios are accepted by the GRS test, suggesting the superiority of the six-factor model. Table 5; on the contrary, the six-factor model was found to be under-specified in explaining the returns, showing that the joint

Table 7. Exogeneity test results for Robust Instrument.

	Intercept	Sensex	SMB	HML	RMW	CMA	HC
Coefficient	−4.8E-16	2.2E-15	−7.9E-16	−5.2E-16	3.6E-16	4.3E-16	4.4E-16
p-value	1	1	1	1	1	1	1

Note. Regression results of all instruments based on the estimated error of six-factor regression model. BHc is used as the dependent variable to calculate the estimated error series. Significant at the 5% level.

alphas (0.317) of the bivariate portfolios are significantly positive for investors. Our results of AR^2 are consistent with the AR^2 results of Roy (2020), who tested the six-factor asset pricing model in Japan using the GRS test.

Table 6 presents the results of the relevance test of the instruments for the six explanatory variables in the regression model. This ensures that the selected instruments are highly correlated with the endogenous variables, resulting in a more efficient estimation of the model parameters. Otherwise, weak instruments can lead to biased and inefficient estimates. The higher the F-statistic, the greater is the shared importance of the instruments included in the model. Higher coefficients and statistically significant F-statistics suggest that the instruments are relevant and influential to the model. It can be seen that the F-statistics for all regressions are above 24, indicating that the instruments are robust and free from inefficient estimates and biased inferences (Olea & Pflueger, 2013).

Further, it is necessary to examine whether endogeneity problems arise with these instruments. This should not correlate with the error term in the regression model. If significant correlations are found, this suggests potential endogeneity issues. The following regression equation was used to regress the instruments on the error term.

$$e\varepsilon i = c + \gamma_1 z_{1i} + \gamma_2 z_{2i} + \gamma_3 z_{3i} + \gamma_4 z_{4i} + \gamma_5 z_{5i} + \gamma_6 z_{6i} + \xi i \tag{8}$$

Table 7 shows and confirms that all instruments are exogenous as the coefficient is zero for all and insignificant *p*-values. The coefficients represent the estimated impact of each instrument on the estimated error of the regression model. In this case, all coefficients are extremely small, approach 0, indicating a very small impact that is practically negligible. This suggests that the instruments used in the regression model are not statistically significant in explaining the estimated error of the six-factor regression model. This implies that the instruments are likely exogenous and do not contribute significantly to the error term in the model.

Table 8 shows the results of the GMM model for single sorted portfolios, where SMB acts as an endogenous variable, Sensex and HC act as exogenous variables, and HML, RMW, and CMA are used as instrumental variables. Four of the five portfolios have significant coefficients for the HC factor by size to explain portfolio returns. A Durbin Watson statistic close to 2 for all portfolios indicates no significant autocorrelation in the residuals. However, the respective p-values of the overid test and the endogeneity test reject H_o that the instruments used in the IVGMM are valid and that the variable is exogenous, respectively. The results of the HAC test indicate the presence of heteroskedasticity, suggesting that GMM is the correct model for this study (Newey and West, 1987; Baum et al., 2003). This suggests that the instruments are valid and that the variable is endogenous. The *p*-values of the weak instrument test reject the assumption that the instruments are weak, implying that the instruments are not weak. The Hausman specification test for the two portfolios confirms that the IVGMM is the preferred estimator compared to Ho and that OLS is consistent. Subsequently, the HC factor was also found to be significant in explaining value returns, ROE, investments, and HC-based portfolios, suggesting that HC is a valid factor in the Indian the six-factor asset pricing model. The other tests (Durbin-Watson statistics, overid, endogeneity, HAC, and weak instruments) performed on single-variate portfolios based on value, ROE, investment, and HC are consistent with the size-based results. The insignificant excess return (alpha) for all portfolios confirms the correct pricing of the six-factor asset-pricing model in the Indian context. The results of the Hausman specification test confirm that GMM is an appropriate model over OLS for value, RMW, investment, and HC-based portfolios, respectively. The results of the GMM for bivariate portfolios based on MC-Value, MC-ROE, MC-INV, and MC-HC are further discussed.

Table 9 shows the GMM, in which four SLc (MC/HC), SHc (MC/HC), BN (MC/HC), and BHc (MC/HC), out of 24 bivariate portfolios rejected Ho with an excess return of 0, while the excess returns for the majority of portfolios (20) did not reject Ho, indicating the competence of the six-factor asset pricing model in

Table 8. GMM test results for single-sorted portfolios.

Portfolios	Intercept	Sensex	SMB	HML	RMW	CMA	HC	R^2	DW	Overid test	Endogeneity test	Weak Instrumental test			Hausman Specification test
												HAC test	TSLS	LIML	OLS/GMM
									Size						
P1	0.017	0.988	0.075				0.017	0.146	1.847						
p Value	0.005*	0.327	0.000*				0.000*			0.088	0.050*	0.005*	22.400	6.460	0.027*
P2	0.001	0.130	0.055				0.017	0.139	1.877						
p Value	0.788	0.199	0.001*				0.000*			0.109	0.178	0.008*	22.300	6.460	0.016*
P3	0.001	0.123	0.042				0.153	0.124	1.877						
p Value	0.855	0.147	0.002*				0.000*			0.182	0.269	0.005*	22.300	6.460	0.165
P4	0.003	0.158	0.042				0.007	0.078	1.897						
p Value	0.52	0.051*	0.001*				0.018*			0.170	0.493	0.016*	22.300	6.460	0.563
P5	0.002	0.108	0.024				0.006	0.049	2.031						
p Value	0.675	0.158	0.151				0.066			0.114	0.697	0.005*	22.300	6.460	0.474
									Value						
P1	0.008	0.076	0.052				0.232	0.211	1.876						
p Value	0.120	0.379	0.000*				0.000*			0.231	0.135	0.003*	22.400	6.460	0.087
P2	0.005	0.125	0.048				0.017	0.163	1.867						
p Value	0.324	0.146	0.003*				0.000*			0.096	0.337	0.004*	22.30	6.460	0.216
P3	0.005	0.154	0.052				0.012	0.109	1.846						
p Value	0.319	0.074	0.001*				0.000*			0.098	0.410	0.012*	22.300	6.460	0.000*
P4	0.000	0.145	0.048				0.011	0.083	1.919						
p Value	0.921	0.129	0.004*				0.001*			0.128	0.255	0.006*	22.300	6.460	0.113
P5	0.002	0.121	0.121				0.003	0.038	1.977						
p Value	0.682	0.150	0.150				0.248			0.121	0.422	0.038*	22.300	6.460	0.041*
									ROE						
P1	0.002	0.154	0.669				0.157	0.115	1.872						
p Value	0.737	0.146	0.007*				0.000*			0.083	0.250	0.289	22.300	6.460	0.066
P2	0.003	0.928	0.629				0.13	0.106	1.955						
p Value	0.530	0.292	0.009*				0.000*			0.102	0.271	0.035*	22.400	6.460	0.073
P3	0.005	0.142	0.045				0.14	0.121	1.89						
p Value	0.338	0.110	0.002*				0.000*			0.126	0.358	0.001*	22.400	6.460	0.217
P4	0.006	0.112	0.039				0.012	0.107	1.842						
p Value	0.207	0.171	0.000*				0.000*			0.272	0.262	0.012*	22.400	6.460	0.244
P5	0.005	0.109	0.030				0.013	0.106	1.906						
p Value	0.284	0.162	0.011*				0.000*			0.225	0.512	0.002*	22.300	6.460	0.481
									INV						
P1	0.007	0.103	0.061				0.012	0.097	1.88						
p Value	0.213	0.283	0.007*				0.003*			0.11	0.254	0.002*	22.400	6.460	0.284
P2	0.003	0.143	0.057				0.015	0.129	1.922						
p Value	0.561	0.114	0.009*				0.000*			0.082	0.429	0.005*	22.400	6.460	0.393
P3	0.004	0.107	0.050				0.013	0.109	1.898						
p Value	0.439	0.197	0.009*				0.000*			0.124	0.395	0.013*	22.400	6.460	0.145
P4	0.004	0.125	0.373				0.012	0.989	1.939						
p Value	0.381	0.128	0.005*				0.000*			0.151	0.288	0.017*	22.400	6.460	0.266
P5	0.003	0.132	0.042				0.014	0.116	1.867						
p Value	0.550	0.162	0.000*				0.000*			0.262	0.168	0.001*	22.400	6.460	0.174
									HC						
P1	0.006	0.126	0.057				0.022	0.201	1.845						
p Value	0.273	0.180	0.000*				0.000*			0.195	0.121	0.008*	22.400	6.460	0.002*
P2	0.006	0.115	0.048				0.017	0.147	1.886						
p Value	0.249	0.215	0.011*				0.000*			0.057	0.108	0.054*	22.400	6.460	0.045*
P3	0.004	0.116	0.043				0.014	0.117	1.898						
p Value	0.460	0.173	0.014*				0.000*			0.137	0.435	0.004*	22.400	6.460	0.503
P4	0.003	0.132	0.053				0.009	0.082	1.942						
p Value	0.482	0.126	0.000*				0.004*			0.103	0.519	0.023*	22.400	6.460	0.355
P5	0.002	0.118	0.392				0.004	0.407	1.947						
p Value	0.676	0.152	0.049*				0.159			0.132	0.417	0.028*	22.400	6.460	0.089

Note. Coefficient with their p values significant at the 5% level.

India. The coefficient of the HC factor was found to be significant for 17 portfolios (out of 24), suggesting the superiority of the HC factor in explaining bivariate portfolio returns based on MC-Value, MC-ROE, MC-INV, and MC-HC. The other tests (Durbin-Watson statistics, overid, endogeneity, HAC, and weak instruments) performed on bivariate portfolios based on MC-Value, MC-ROE, MC-INV, and MC-HC demonstrate the acceptability of the results. It is worth noting that the Hausman Specification test shows the preeminence of IVGMM over OLS for all bivariate portfolios except for four (SLc, SHc, BN, and BHc) portfolios. Overall, these results are consistent with our expectations. The implications of this study are presented in the subsequent sections of the paper. Furthermore, Park et al. (2024) validates the GMM

Table 9. GMM test results for bivariate portfolios.

Portfolios	Intercept	Sensex	SMB	HML	RMW	CMA	HC	R^2	DW	Overid test	Endogeneity test	Weak Instrumental test			Hausman Specification test
												HAC test	TSLS	LIML	OLS/GMM
								MC/BV							
SL	0.043	0.398	5.540				−0.053	0.487	1.952						
p Value	0.156	0.189	0.000*				0.011*			0.290	0.042*	0.000*	22.300	6.460	0.000*
SM	0.020	0.249	2.261				−0.148	0.439	2.016						
p Value	0.125	0.090	0.000*				0.149			0.152	0.232	0.000*	22.300	6.460	0.000*
SH	0.003	0.064	0.777				0.124	0.348	1.839						
p Value	0.965	0.515	0.000*				0.023*			0.160	0.559	0.000*	22.300	6.460	0.000*
BL	0.004	0.183	0.522				0.005	0.366	2.184						
p Value	0.465	0.027*	0.000*				0.158			0.249	0.059	0.000*	22.300	6.460	0.000*
BM	0.020	0.208	2.293				−0.021	0.197	2.218						
p Value	0.212	0.235	0.000*				0.051*			0.349	0.037*	0.000*	22.400	6.460	0.000*
BH	0.040	0.334	2.970				−0.041	0.180	1.967						
p Value	0.137	0.202	0.005*				0.048*			0.187	0.212	0.000*	22.400	6.460	0.000*
								MC/ROE							
SR	0.036	0.436	4.156				−0.035	0.484	2.054						
p Value	0.103	0.049*	0.000*				0.019*			0.251	0.096	0.000*	22.300	6.460	0.000*
SN	0.025	0.270	2.431				−0.014	0.475	1.902						
p Value	0.071	0.076	0.000*				0.138			0.192	0.100	0.000*	22.300	6.460	0.000*
SW	0.020	0.283	1.698				−0.001	0.454	2.011						
p Value	0.050	0.007	0.000*				0.795			0.380	0.159	0.000*	22.300	6.460	0.000*
BR	0.052	0.456	4.557				−0.061	0.227	2.042						
p Value	0.134	0.184	0.000*				0.009*			0.262	0.061	0.000*	22.400	6.460	0.000*
BN	0.029	0.303	2.147				−0.023	0.215	2.142						
p Value	0.127	0.102	0.000*				0.042*			0.260	0.077	0.000*	22.400	6.460	0.000*
BW	0.035	0.367	3.172				−0.041	0.217	2.004						
p Value	0.199	0.173	0.000*				0.031*			0.205	0.159	0.000*	22.400	6.460	0.000*
								MC/INV							
SC	0.020	0.221	2.202				−0.113	0.362	1.921						
p Value	0.134	0.074	0.000*				0.312			0.169	0.295	0.000*	22.300	6.460	0.000*
SN	0.026	0.281	2.425				−0.017	0.319	1.971						
p Value	0.088	0.068	0.000*				0.192			0.197	0.083	0.000*	22.300	6.460	0.000*
SA	0.023	0.255	2.337				−0.012	0.371	1.891						
p Value	0.103	0.101	0.000*				0.206			0.409	0.059	0.000*	22.300	6.460	0.000*
BC	0.022	0.294	2.862				−0.032	0.332	1.977						
p Value	0.237	0.125	0.000*				0.017*			0.200	0.109	0.000*	22.300	6.460	0.000*
BN	0.013	0.181	1.984				−0.198	0.355	1.732						
p Value	0.262	0.207	0.000*				0.051*			0.186	0.101	0.000*	22.300	6.460	0.000*
BA	0.020	0.283	2.250				−0.019	0.37	2.119						
P Value	0.229	0.112	0.000*				0.000*			0.269	0.102	0.000*	22.300	6.460	0.000*
								MC/HC							
SLc	0.544	7.147	1.787				1.591	0.198	1.876						
p Value	0.155	0.245	0.064				0.000*			0.086	0.171	0.068	22.300	6.460	0.206
SN	−0.336	−3.675	0.172				−0.905	0.258	1.934						
p Value	0.041	0.158	0.752				0.000*			0.292	0.046	0.394	22.300	6.460	0.016*
SHc	0.358	4.820	2.082				0.994	0.172	1.893						
p Value	0.184	0.247	0.051*				0.000*			0.101	0.410	0.018*	22.300	6.460	0.220
BLc	−0.411	−3.487	0.944				−0.447	0.051	1.855						
p Value	0.050	0.315	0.214				0.010*			0.392	0.005*	0.464	22.300	6.460	0.011*
BN	0.622	8.484	0.958				0.945	0.084	1.884						
p Value	0.116	0.175	0.426				0.001*			0.056	0.201	0.122	22.300	6.460	0.199
BHc	−0.106	−0.568	1.147				−0.943	0.385	1.777						
p Value	0.417	0.756	0.093				0.000*			0.916	0.060	0.045*	22.300	6.460	0.095

Note. Coefficient with their p values significant at the 5% level.

model for asset pricing considering pandemic risk and provides insights into the dynamics of asset pricing during periods of heightened uncertainty and crises, such as the COVID-19 pandemic. Similarly, Lalwani and Chakraborty (2020) when testing multi-factor models in emerging markets, researchers have found that certain factors, such as the momentum factor, may still be relevant in explaining stock returns, even though they may have become less significant in developed markets. Bhatti and Khan (2022) point out that multifactor models, particularly the Fama-French five-factor model, perform superiorly compared to the CAPM in explaining the cross-section of stock returns in emerging markets during crises. The implications of this study are presented in the subsequent sections of the paper.

Our results are consistent with those of Maiti and Balakrishnan (2018) and Shijin et al. (2010), who identify human capital as a potential factor explaining the portfolio returns of BSE 500 listed Indian

companies. Shijin et al. (2010) find that human capital is a standalone predictive factor in explaining stock returns and describe the causal relationship between risk and return in the Indian market context. The findings obtained in this study apply globally to Roy (2020) in the Japanese market and Roy and Shijin (2018) in the US market. Likewise, Khan et al. (2023) demonstrates the superiority of the human capital-based four-factor model over other competing asset pricing models in explaining stock returns in the Pakistani market and emphasizes the importance of incorporating the labor income growth rate premium in asset pricing. Anuno et al. (2023) recommends portfolio managers and investors the suitability of various asset pricing models for managing stock and bond portfolios in Timor-Leste based on the results of the study.

This study confirms that human capital is a strong sixth factor in the asset pricing framework in India, attracting the attention of fund managers, portfolio managers, and academics to incorporate HC into their trading strategies. Exploring the inherent market risks of profitable trading strategies can benefit investors. This study calls for a competent asset-pricing model that improves our understanding of financial markets, supports investment decisions, and contributes to efficient capital allocation in the Indian economy. Although this study uses six factors to explain returns, there is another factor, namely momentum, which has been extensively studied in previous studies and also explains the excess stock returns (Cakici et al., 2013; Fama & French, 2015; Maharani & Narsa, 2023). The previous study examines the six-factor plus Intellectual capital model in the Indonesian market, where momentum is one of the factors and has a significant impact in explaining the excess stock returns (Maharani & Narsa, 2023). Therefore, the momentum factor can be a source of motivation for further research and therefore serves as a limitation of this research.

5. Conclusion

Building on this insight, this study attempts to explain the inherent risk factors (firms and markets) that predict returns over a period of time, considering the dynamics of the Indian market. In summary, our study highlights the significance of human capital as a sixth factor, in addition to the five-factor asset pricing model of Fama-French (2015) in India. The GRS test also confirms the superiority of the six-factor model for the Indian equity market. The study asserts that the Instrumental variable- Generalized method of moments (IVGMM) is a robust model over OLS in explaining portfolio returns (single and bivariate), which implies that OLS in the asset pricing model is exaggerated in the Indian context. Single portfolios are constructed based on the factors of size, value, ROE, INV and human capital, while bivariate portfolios are constructed based on the intersection of any these two factors. Although Park et al. (2024) investigate and confirm pandemic risk in explaining returns. Other factors such as macroeconomic conditions, government policies or global events could influence the relationship between pandemic risk and asset prices.

By acknowledging the applicability of the six-factor model, stakeholders can pursue more sophisticated approaches beyond the academic discourse to provide practical insights. This study contributes to the ongoing discourse on asset pricing models and offers valuable implications for investment decisions, risk management, and portfolio construction in one of the most attractive global financial markets. Despite the application of the six-factor model, the Indian stock market may exhibit characteristics of market inefficiency and behavioral biases that cannot be fully captured by quantitative models alone. These anomalies and deviations from the model predictions may persist and limit the model's ability to fully explain stock returns.

Similar are the findings of Khan et al. (2023) based on the Pakistani stock market, which may have unique characteristics. The applicability of the human capital-based four-factor model to other markets or countries is not directly addressed and may require further research. In a similar line, Lalwani and Chakraborty (2020) as markets evolve and become more integrated over time, the performance of multi-factor models may change, limiting the long-term generalizability of the results. Bhatti and Khan (2022) focus on specific regions and may overlook market-specific factors that are unique to each region and could influence the performance of multifactor asset pricing models during financial crises. Anuno et al. (2023) confirm the applicability of the five-factor model in Timor-Leste, which can be further extended to a six-factor model given the country's human capital growth potential.

This study is limited to the Indian Capital market but can be expanded in the future to include industry-specific studies in India and international comparisons.

Notes

1. https://www.forbesindia.com/article/explainers/top-10-largest-economies-in-the-world/86159/1#:~:text=India%20is%20ranked%205th%20in,services%2C%20agriculture%2C%20and%20manufacturing.
2. https://www.reuters.com/world/india/india-be-worlds-third-largest-economy-by-2030-sp-global-ratings-2023-12-05/#:~:text=India%20to%20be%20world's%20third,2030%20%2DS%26P%20Global%20Ratings%20%7C%20Reuters.
3. https://www.bloomberg.com/quote/BSE500:IND.
4. Unavailability/missing data means we only use 280 companies for the final sample.
5. Absolute returns are used to calculate SMB, HML, RMW, CMA and LcMhc.

Authors' contributions

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Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors upon request.

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