Risk and Return in Financial Markets: Evaluating Investment Strategies for Optimal Portfolio Management

Dr. Vanitha P[1], Dr A. Premavasumati[2], Dr. Pavithra H P[3], Dr. Muthulakshmi P[4], Dr S Sathyakala[5], Dr R Nithya[6]

[1]Associate Professor M. Kumarasamy College of Engineering, Karur email id: vanithamkce@gmail.com. orcid id: 0000-0002-8646-0432.

[2]Associate Professor K.Ramakrishnan College of Engineering Autonomous Samayapuram Tiruchirapalli. email : premavasumathi2003@gmail.com, 0000-0002-9595-9809.

[3]Assistant Professor Affiliation: Dayananda Sagar Business Academy email id: pavitra.hp@gmail.com. orcid id: 0009-0006-2773-0769.

[4]Assistant Professor CHRIST (Deemed to be University) email id: pmuthulakshmi10@gmail.com.orcid id: 0000-0003-0135-900X.

[5]Associate professor Sona college of technology email id: sathyakala@sonabusinessschool.com , orchid id :0000-0002-2750-0553 pin code:636005.

[6]Associate Professor AVS Engineering College email id: nithiroyappan@gmail.com orcid id: 0009-0003-2981-3694.

HOW TO CITE:

Vanitha P, A. Premavasumati, Pavithra H P, Muthulakshmi P, S Sathyakala, R Nithya (2026). Risk and Return in Financial Markets: Evaluating Investment Strategies for Optimal Portfolio Management. International Journal of Special Education, 41(9s), 933-941

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.

Open access publication underthe terms and conditions

ABSTRACT:

The analysis of risk and returns remains a very significant factor in investment management because it is necessary to consider the expected return on investments relative to systematic risk. The multi-factor model has a broader perspective than the single-factor model. This study examined investment strategies for optimal portfolio management by evaluating the influence of market, size, value, profitability, and investment factors on portfolio excess returns. A quantitative research design was employed using secondary monthly Fama–French Five-Factor data covering the period from July 1963 to March 2026. The analysis incorporated descriptive statistics, correlation analysis, variance inflation factor assessment, Ordinary Least Squares regression, Sharpe ratio estimation, and residual diagnostic tests to evaluate portfolio performance and model reliability. The findings showed that the model explained 88.5% of the variation in portfolio excess returns. Market excess return exerted the strongest positive influence on portfolio performance, while size, value, and profitability factors were also positive and statistically significant. In contrast, the investment factor was statistically insignificant. The constructed portfolio generated an annualized return of 5.22%, annualized volatility of 10.06%, and a Sharpe ratio of 0.519, indicating moderate risk-adjusted performance. Diagnostic tests further confirmed the statistical reliability of the estimated model. The findings demonstrate that portfolio returns are influenced by multiple systematic risk factors rather than market exposure alone. The study therefore supports the usefulness of factor-based portfolio analysis in improving

of the Creative CommonsAttribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

investment evaluation and portfolio management decisions.

Keywords: risk and return, portfolio management, Fama–French five-factor model, asset pricing, Sharpe ratio.

1. Introduction

Capital allocation, capital investment promotion, and wealth creation are the functions in which financial markets play a very crucial role in economic development. Investors are always looking out for any opportunity to make the highest profit with the least amount of risk. Therefore, the connection between risk and return is considered one of the basic concepts in finance, as investment decisions greatly depend on profitability and market volatility (Saunders & Cornett, 2021). As financial markets become more complex, new opportunities and risks have emerged for investors and institutions that are driving a shift in portfolio management approaches and increasing the demand for better investment appraisal frameworks (Gunjan & Bhattacharyya, 2023).

Factors influencing investment decisions are not only market-related, but also behavioral and psychological aspects. According to Raut (2020), financial literacy and past investment experience impact on the investment decision-making of individual investors in uncertain market conditions. Almansour et al. (2023) reported similar results, which describe how behavioral finance influences investment decisions through investors' risk perception. Such results suggest that the investor reaction to uncertainty depends on personal understanding and behavioral traits and, hence, make risk assessment an essential element of the portfolio management process.

In the conventional finance theory, higher returns lead to higher risks. Empirical evidence, however, shows that the relation between risk and return may not be persistent in financial markets. For example, Fifield et al. (2020) remarked on the inconsistent relationship between risk and return in the traditional theory of market behavior. Van Dinh (2023) emphasized that expectations of return and risk are affected by the change of market conditions. Hence, it seems that there are other factors besides the traditional ones that influence risk and return, and these factors cannot be captured by single-factor analysis.

The principle of portfolio diversification is used in investment management due to the reduced unsystematic risks and improved portfolio efficiency. Cesarone et al. (2020) suggest that an optimization and diversification strategy might be used to identify efficient portfolios in different market conditions. Further, computational finance developments have made it possible to enhance portfolio optimization methods. Gunjan and Bhattacharyya (2023) emphasized on the growing use of artificial intelligence and quantitative techniques for portfolio optimization and investment analysis. As such, the demand for sophisticated finance models that can assess investment performance is growing.

Classical financial models have not been able to keep pace with the development of empirical asset pricing theories. The Capital Asset Pricing Model (CAPM) was traditionally considered the dominant model that explains asset returns based on market risk exposure. However, empirical research shows that market beta is insufficient for explaining differences in asset return. Hu (2022) noted that despite being important in the analysis of stock markets, modern financial theory faces certain limitations in dynamic and constantly changing financial environments. Therefore, multi-factor asset pricing theories emerged to address such issues.

Modern empirical asset pricing approaches have increasingly focused on factor-based analysis in finance. As Ferson (2025) states, modern models of empirical asset pricing utilize multiple risk factors to increase explanatory power. In line with Giglio et al. (2022), recent trends in finance show more use of factor models and machine

learning approaches that can identify systematic return patterns in financial markets. It, thus, becomes obvious that factor investing is widely adopted by many portfolio managers.

Multi-factor asset pricing approaches include such models as the famous Fama–French three-factor and five-factor model. This model is based on the CAPM, but it includes additional factors that represent firm size, value, profitability, and investments. Results obtained by Chahuán-Jiménez et al. (2025) show that multi-factor asset pricing models outperform traditional single-factor specifications in terms of explaining return behavior. Diallo et al. (2023) concluded that the Fama–French five-factor model outperforms the three-factor model in predicting portfolio return.

Although a large body of literature is available on the issue of portfolio optimization and asset pricing, there are still a number of gaps that need to be addressed. First, most existing papers either focus on CAPM or Fama–French three-factor framework without analyzing impact of profitability and investment factors on returns. Additionally, studies pay attention to stock valuation, but portfolio management applications require further consideration. Lastly, empirical results related to investment factors are inconsistent and controversial. Yaseen and Mohammed (2023) argue that numerous factors are involved in asset valuation, which implies that portfolio performance cannot be attributed to separate factors.

In view of these considerations, the current study aims to analyze the link between risk and return in financial markets through the Fama–French Five-Factor Model. The study aims to examine the effects of market, size, value, profitability, and investment factors on portfolio return, along with the effectiveness of the multi-factor approach in portfolio management.

2. Methodology

2.1 Research Design

A quantitative research methodology was applied in the current research in order to explore the relationship between risk factors and returns on portfolios. An explanatory type of research methodology was used for the purpose of the study, as the aim was to assess the impact of changes in various market risk factors on returns from the portfolio. A methodology based on secondary data analysis was chosen in order to establish the impact of the above-mentioned financial factors on the returns of the portfolio. Time series analysis methodology was used in order to study the pattern of variables over a long period of time.

2.2 Data Source

This research work involved the use of secondary data that was collected from the Kenneth R. French Data Library (French, 2026). This dataset comprises monthly observations of the Fama-French Five Factor Model (2x3) that includes the following factors: market excess return, size factor, value factor, profitability factor, investment factor, and the risk-free interest rate. The time frame of the collected data ranges from July 1963 to March 2026, which implies that there are 753 monthly observations. This dataset can be utilized in many research works in the field of empirical finance due to its vast coverage of risk-return behavior.

2.3 Variable Description

Portfolio excess return was used as the dependent variable in the analysis and was measured by deducting the risk-free return from the portfolio return. The five independent variables used in the research were the five explanatory variables identified by the Fama–French Five-Factor Model: market excess return (Mkt-RF), small-minus-big effect (SMB), book-to-market ratio (HML), profitability (RMW), and investment (CMA). The diversification of the portfolio needed the generation of portfolio returns by taking into account exposure to the five

explanatory variables together with the random error term.

2.4 Data Processing Procedure

The data in the original compressed file was extracted and reorganized in a time-series format. The date variables were converted into a datetime object with a monthly frequency. All factor returns were converted from percentage values to decimals.

Observations with missing data were deleted to maintain consistency in the regression model. This cleaned database was then used to conduct descriptive analysis, correlation analysis, regression, diagnostics, and portfolio analysis.

2.5 Analytical Techniques

Descriptive statistics were utilized to measure the central tendency, spread, and distribution properties of the variables. Variables such as average returns, standard deviations, skewness, kurtosis, yearly returns, and yearly volatilities were measured to analyze the risk-return properties of the factors. Second, correlation statistics were carried out to examine the relationships between the explanatory variables and detect possible multicollinearity issues. The Variance Inflation Factor (VIF) statistics were also computed to confirm that there is no serious multicollinearity problem in the regression equation.

The empirical relation between portfolio returns and the factors was measured through the Ordinary Least Squares (OLS) regression method within the Fama–French Five-Factor Model:

$$R_t - R_f = \alpha + \beta_1(Mkt - RF) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \varepsilon_t$$

where R_t represents portfolio return, R_f denotes the risk-free rate, α represents abnormal return, and ε_t is the error term.

In order to evaluate portfolio performance, the Sharpe ratio, annual returns, and annual volatility were calculated. Residual diagnostics of Jarque-Bera, Breusch-Pagan, and Durbin-Watson statistics were undertaken to check whether the assumption about normal distribution, homoscedasticity, and no autocorrelation held for the regression.

3. Results

3.1 Descriptive Statistics and Risk–Return Characteristics

The descriptive statistics show considerable dispersion of the behaviors of the five factors analyzed throughout the research period between July 1963 and March 2026. Excess returns of the market (Mkt-RF) had the highest mean monthly return (0.58%) and highest volatility (4.46%), meaning that investments in the market performed better compared to others but exposed investors to higher systematic risk. Profitability (RMW) and investment (CMA) factors had low volatility, meaning their returns were relatively stable.

Annualized returns further show that the market factor had a higher performance than other factors, with a higher annualized return (7.25%). From the descriptive statistics on skewness and kurtosis, it is clear that the variables were not normally distributed, especially the profitability factor, with a very high kurtosis value. This means that there are some extreme returns of the profitability factor at certain times. Descriptive statistics and annualized risk-return of the factors are provided in Table 1.

Table 1. Descriptive Statistics and Risk–Return Measures

Variable	Mean Monthly Return	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis	Annualized Return	Annualized Volatility
Mkt-RF	0.0058	0.0446	-0.2319	0.1610	-0.4990	1.7410	0.0725	0.1544
SMB	0.0018	0.0302	-0.1554	0.1846	0.3592	3.0792	0.0224	0.1047
HML	0.0030	0.0297	-0.1383	0.1286	0.0899	2.1775	0.0364	0.1029
RMW	0.0026	0.0222	-0.1895	0.1305	-0.3263	11.0575	0.0320	0.0770
CMA	0.0025	0.0207	-0.0708	0.0901	0.2723	1.3724	0.0303	0.0716

Growth pattern of the artificial portfolio exhibits a steady growth pattern, despite the presence of any dips that occur due to market shocks. In the case of this artificial portfolio, a period of accelerated growth followed the beginning of the 1990s, while the years of strong financial downturns saw significant contractions (Figure 1).

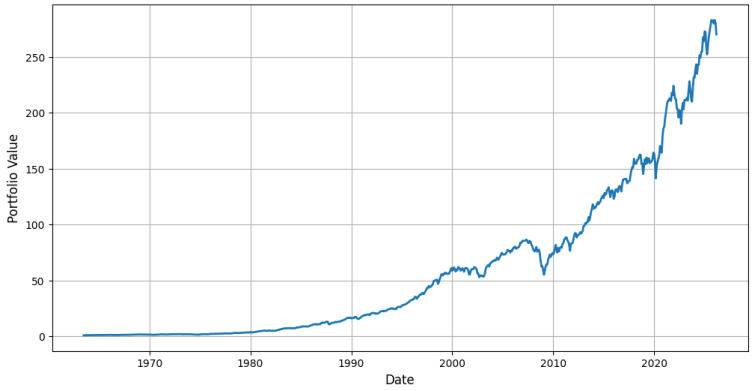

Figure 1. Cumulative Portfolio Growth

3.2 Correlation Analysis

The correlation test was performed to investigate the relationships among the independent variables and determine whether multicollinearity existed. From the result, there are moderate relationships among some variables, with the highest positive correlation existing between the value variable (HML) and investment variable (CMA) (r = 0.6809). There is a moderate negative correlation between the market variable (Mkt-RF) and investment variable (CMA) (r = -0.3523).

Generally, the correlation values were not above the critical multicollinearity levels, implying that each variable offers unique information about the model. This is further buttressed by the already established Variance Inflation Factor (VIF) values, which were all low, below the acceptable level of 5. Table 2 presents the correlation matrix of the five explanatory factors.

Table 2. Correlation Matrix

Variable	Mkt-RF	SMB	HML	RMW	CMA
Mkt-RF	1.0000	0.2747	-0.2079	-0.1876	-0.3523
SMB	0.2747	1.0000	0.0135	-0.3402	-0.0801
HML	-0.2079	0.0135	1.0000	0.0900	0.6809
RMW	-0.1876	-0.3402	0.0900	1.0000	0.0079

CMA	-0.3523	-0.0801	0.6809	0.0079	1.0000

The graph depicting the correlation structure not only supports the presence of positive and negative relationships but also highlights that there is no problem of multicollinearity (Figure 2).

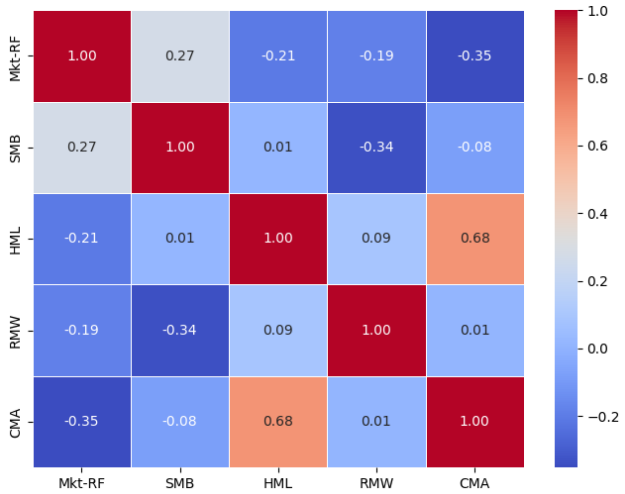

Figure 2. Factor Correlation Matrix

3.3 Regression Analysis of the Fama–French Five-Factor Model

Multiple regression analysis was used to examine the impact of these five risk factors on the return of portfolios. As can be seen, an adjusted R^2 of 0.885 was calculated from the estimated model. In other words, the variance of portfolio excess return was explained approximately 88.5% by the selected risk factors. The model was statistically significant at the 1% level, which confirmed the explanatory ability of the Fama–French Five-Factor approach.

Of the risk factors chosen, the market excess return factor had the most positive impact on portfolio returns (β=0.5964, $p<0.001$). Other risk factors, such as SMB, HML, and RMW, also showed significant positive relationships with portfolio returns. However, the CMA risk factor is not statistically significant, meaning that the conservative and aggressive styles of investment activities do not affect the portfolios created by us.

Regression diagnostics, in turn, support the reliability of the estimated model. Thus, the Durbin-Watson test statistic of 2.049 shows no autocorrelation among the residuals, while the Jarque-Bera and Breusch-Pagan tests show that the residuals have a normal distribution and homoscedasticity. Table 3 displays the estimated regression coefficients and their statistical significance.

Table 3. Fama–French Five-Factor Regression Results

Variable	Coefficient	Std. Error	t-Statistic	p-Value	Lower 95% CI	Upper 95% CI
Constant	-0.0000	0.0004	-0.1145	0.9089	-0.0008	0.0007
Mkt-RF	0.5964	0.0090	66.3558	0.0000	0.5787	0.6140
SMB	0.1451	0.0131	11.1030	0.0000	0.1194	0.1707
HML	0.1146	0.0168	6.8316	0.0000	0.0817	0.1475
RMW	0.0780	0.0175	4.4538	0.0000	0.0436	0.1124
CMA	-0.0039	0.0251	-0.1573	0.8750	-0.0532	0.0453

The properties of the portfolio return suggest that the majority of the returns for each month lie near the average with a symmetric nature, although some extreme values exist when market volatility is high (Figure 3).

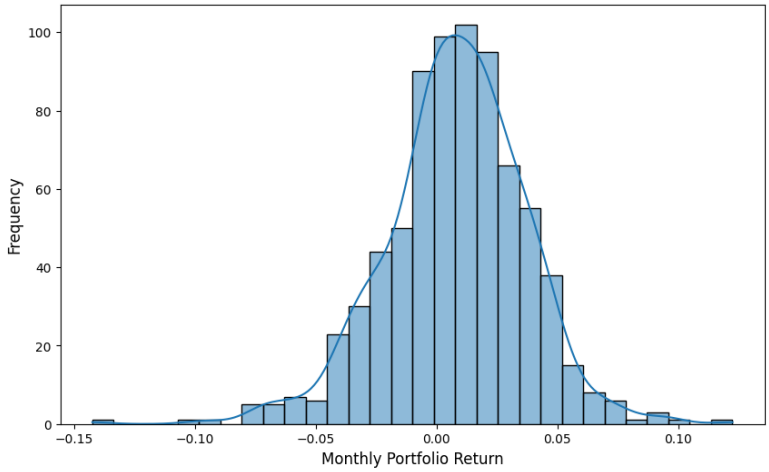

Figure 3. Distribution of Portfolio Returns

4. Discussion

The empirical results indicate that the Fama-French Five-Factor Model possesses high explanatory power regarding the constructed portfolio returns. The relatively high adjusted R^2 of 0.885 demonstrates that the considered set of variables explains a sufficiently large proportion of return variations, thus proving that the portfolio's success was affected by a number of systematic risk sources other than pure market risk. The strongest positive coefficient belonged to the market excess return variable, meaning that general market changes were the main reason for returns in the portfolio. It corresponds to the information provided in the descriptive statistics, where the largest annualized return and volatility were also observed for the market factor. Moreover, size, value, and profitability factors were also positive and statistically significant. It means that their influence on portfolio returns is also noteworthy, which allows concluding that being exposed to corresponding factors played an essential part in constructing the portfolio. More specifically, the significance of the SMB factor implies that size-related factor exposure positively affected portfolio performance, while the significant HML and RMW coefficients mean that exposure to such factors as value and profitability was also crucial in evaluating the portfolio's success. At the same time, the insignificance of the CMA factor coefficient implies that it did not play a major role in the constructed portfolio's performance. As a result, exposure to conservative investments rather than aggressive ones was less significant for explaining portfolio returns. The risk-adjusted portfolio performance may also be characterized as moderate. Thus, it returned a fairly high annualized return (5.22%), had relatively low volatility (10.06%) and a good Sharpe ratio (0.519), which means that it managed to generate positive excess returns. Residual diagnostics confirmed the lack of serious autocorrelation and non-normality and/or heteroskedasticity problems, thus proving the adequacy of the model.

The strong influence of the market factor on portfolio returns confirms that systematic risk plays an important role in asset pricing and portfolio returns. According to Pelger (2020), systematic risk holds important information regarding return variability, especially when there is a possibility to measure market risk more accurately. It corresponds to the findings of this paper since the market factor proved to be the most influential variable explaining portfolio returns. At the same time, they confirm the need for a move from a single-factor approach to evaluating portfolio performance to analyzing multiple factors that impact returns and affect

risks simultaneously. The work of Kumar & Misra (2019) proves the point in showing that liquidity-adjusted CAPM is a valuable tool for explaining asset price dynamics. Moreover, the influence of bankruptcy risk on portfolio performance shown in the study of Chhapra et al. (2020) proves that there are various types of systematic risk that can affect return behavior in a way similar to how market risk influences them.

The importance of size and value factors in the considered model aligns with the findings of several papers. Thus, Hu et al. (2019) state that Fama-French factors prove valuable for international investors in explaining returns of stocks in China. In addition, the results of Cox & Britten (2019) indicate that the five-factor model works well at the Johannesburg Stock Exchange. The significance of the profitability factor and the insignificance of the investment one may be interpreted according to the findings of Ali et al. (2021). They proved that there is no universal relationship between profitability and investment premiums and how they affect return behavior since they depend on the country's economic structure, sampling period, and portfolio construction technique. Consequently, the reason for the RMW significance in the paper and the insignificance of the CMA coefficient becomes obvious.

Portfolio performance results align with the findings concerning integrated risk management and return estimation uncertainty issues. The necessity of using integrated risk management as part of investment strategy formation was demonstrated by Tjiwidjaja (2025). The same point was made by Kan et al. (2022) concerning the impact of estimation error on portfolio choice decisions.

The findings have practical implications for investors and portfolio managers. The market factor's dominance proves the importance of market exposure in portfolio construction. The significance of size, value, and profitability factors shows that investors need to take into account several sources of systematic risk in assessing portfolio returns. Finally, the CMA's insignificant role in returns proves that each factor needs to be tested before being included in portfolios.

First, it should be admitted that there are a few limitations associated with the study. The main ones consist of using secondary returns data and a portfolio constructed by the author rather than investors' assets and real stock market data. In addition, the paper uses monthly data to evaluate portfolio returns and does not consider other variables in the regression analysis. Future research should focus on analyzing actual portfolio returns and stock returns, and comparing different portfolio constructions or analyzing other regions or asset classes. Furthermore, future research could add other factors to the model to improve its predictive power and portfolio returns and risk adjustment.

5. Conclusion

Factor-based analysis offers a helpful approach towards the assessment of the link between risks and investment returns. It appears that the Fama–French Five-Factor Model is able to explain a significant part of excess returns on portfolios due to its ability to account for several important factors. In particular, the study revealed that the most important factor determining portfolio returns was the market risk factor, followed by size, value, and profitability factors. It is therefore evident that there are other determinants affecting performance apart from exposure in the market, thus calling for an evaluation of the influence of these other determinants in the decision-making process. The absence of a statistically significant influence of the investment factor reinforces the hypothesis that all risks do not have an equal effect on investment performance. Analysis has proven the need to test the statistical significance of factors before using them in portfolio construction. A positive average return and a reasonable Sharpe ratio prove the efficacy of this approach.

References

Ali, F., Khurram, M. U., & Jiang, Y. (2021). The five-factor asset pricing model tests and profitability and investment premiums: evidence from Pakistan. Emerging Markets Finance and Trade, 57(9), 2651-2673.

Almansour, B. Y., Elkrghli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. Cogent Economics & Finance, 11(2), 2239032.

Cesarone, F., Scozzari, A., & Tardella, F. (2020). An optimization–diversification approach to portfolio selection. Journal of Global Optimization, 76(2), 245-265.

Chahuán-Jiménez, K., Muñoz-Rojas, L., Muñoz-Pizarro, S., & Schulze-González, E. (2025). Comparison of the CAPM and Multi-Factor Fama–French Models for the Valuation of Assets in the Industries with the Highest Number of Transactions in the US Market. International Journal of Financial Studies, 13(3), 126.

Chhapra, I. U., Zehra, I., Kashif, M., & Rehan, R. (2020). Is bankruptcy risk a systematic risk? Evidence from Pakistan Stock Exchange. Etikonomi: Jurnal Ekonomi, 19(1), 51-62.

Cox, S., & Britten, J. (2019). The Fama-French five-factor model: evidence from the Johannesburg Stock Exchange. Investment Analysts Journal, 48(3), 240-261.

Diallo, B., Bagudu, A., & Zhang, Q. (2023). Fama–French three versus five, which model is better? A machine learning approach. Journal of Forecasting, 42(6), 1461-1475.

Ferson, W. (2025). Empirical asset pricing: Models and methods.

Fifield, S. G., McMillan, D. G., & McMillan, F. J. (2020). Is there a risk and return relation?. The European Journal of Finance, 26(11), 1075-1101.

Giglio, S., Kelly, B., & Xiu, D. (2022). Factor models, machine learning, and asset pricing. Annual Review of Financial Economics, 14(1), 337-368.

Gunjan, A., & Bhattacharyya, S. (2023). A brief review of portfolio optimization techniques. Artificial Intelligence Review, 56(5), 3847-3886.

Hu, G. X., Chen, C., Shao, Y., & Wang, J. (2019). Fama–French in China: size and value factors in Chinese stock returns. International Review of Finance, 19(1), 3-44.

Hu, J. (2022). Application of modern portfolio theory in stock market based on empirical analysis. In 2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022) (pp. 1561-1567). Atlantis Press.

Kan, R., Wang, X., & Zhou, G. (2022). Optimal portfolio choice with estimation risk: No risk-free asset case. Management Science, 68(3), 2047-2068.

Kumar, G., & Misra, A. K. (2019). Liquidity-adjusted CAPM—An empirical analysis on Indian stock market. Cogent Economics & Finance.

Pelger, M. (2020). Understanding systematic risk: A high-frequency approach. The Journal of Finance, 75(4), 2179-2220.

Raut, R. K. (2020). Past behaviour, financial literacy and investment decision-making process of individual investors. International Journal of Emerging Markets, 15(6), 1243-1263.

Saunders, A., & Cornett, M. M. (2021). financial-markets and institutions.

Tjiwidjaja, H. (2025). Optimization of Investment Portfolio Returns Through an Integrated Risk Management Approach. The Journal of Academic Science, 2(3), 853-863.

Van Dinh, D. (2023). Analyzed relationship between risks and expected returns. Journal of Economic and Administrative Sciences, 39(4), 749-759.

Yaseen, S. T., & Mohammed, S. B. (2023). Factors affecting the market value of the shares of a sample of companies working in the scientific field/an analytical study from 2015-2020. Res militaris, 13, 3137-3149.