IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Reward-Risk Parity And Behavioural Insights: A Comparative Study On Portfolio Performance And Investor Decision-Making

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Abstract: The risk-return tradeoff is a core principle in portfolio management, helping investors balance potential gains against the uncertainty of outcomes. This empirical study investigates this tradeoff across four major sectors-IT, Banking, Automobile, and FMCG-using a sample of 20 stocks and 1-year current-period data. The topic was chosen in light of increasing market volatility and investor need for strategic, data-driven portfolio decisions. A descriptive research methodology was employed using secondary data from stock exchanges and financial reports. Analysis was carried out using financial tools such as Mean, Standard Deviation, Correlation Coefficient, CAPM, APT, and Portfolio Risk & Return, along with statistical tools including Descriptive Statistics, T-tests, and Correlation Analysis. The T-test yielded a p-value of 0.024, indicating a statistically significant difference between diversified and traditional portfolios in terms of performance and risk and a strong correlation ($r = 0.71$) between risk perception and investment behavior (H04). These findings affirm that effective portfolio management depends not only on financial metrics but also on investor psychology and sectoral positioning. The study provides valuable insights for investors aiming to make informed, balanced decisions in today's dynamic markets.

***Index Terms* -** Risk-Return Trade-off, Portfolio Management, Investment Behaviour, Sectoral Analysis, Investor Perception, Descriptive Statistics, Empirical Study, Diversified Portfolios, stock market volatility

I. INTRODUCTION

In today's dynamic and uncertain financial environment, the risk-return tradeoff is a critical concept in investment decisions, especially in emerging markets like India. Post-pandemic volatility, rising inflation, global conflicts, and climate risks have pushed investors to rethink traditional strategies. Over the past year, sector-specific returns in the Indian stock market have varied widely-Nifty IT declined by 8% while Nifty Auto surged by 28%, reflecting the uneven risk-return profiles across industries. At the same time, over ₹2.1 lakh crore flowed into mutual funds, with growing SIP participation, yet SEBI reports show that over 61% of investors still lack proper risk evaluation methods. This scenario underlines the urgent need to revisit how investors construct and manage portfolios in light of real market behavior.

This study is timely and relevant as it empirically evaluates the risk-return dynamics across four critical sectors-IT, Banking, Automobile, and FMCG- IT and Automobile are growth-oriented and cyclical, Banking is sensitive to economic policy, and FMCG offers stability. This sectoral mix provides a balanced view of how different industries contribute to portfolio risk and return, making the analysis more comprehensive and practical. over a one-year period, using financial models like CAPM, APT, and reward-risk parity. It bridges theoretical constructs with real-world application, integrating behavioral finance elements like investor perception and decision biases. By combining quantitative tools (Mean, SD, Correlation, T-test) with financial metrics (portfolio return, CAPM beta, APT factors), the study offers actionable insights into how diversified strategies perform under varying market conditions. The findings aim to guide investors, portfolio managers, and policymakers in aligning investment strategies with modern market complexities.

2.Conceptual Framework

The risk-return tradeoff is a foundational principle in finance, stating that higher potential returns are generally accompanied by greater risk. This concept guides investors in making decisions based on their risk tolerance and return expectations. Traditionally, this tradeoff is viewed through models that assume a linear and rational relationship between risk and reward. However, real market behavior is more complex. Sectoral variations, investor psychology, economic fluctuations, and global uncertainties often distort this theoretical balance. Especially in emerging markets like India, where volatility is higher and investor profiles are diverse, the standard assumptions may not fully capture the investment reality. Thus, understanding how risk and return interact across industries and investor behaviors is crucial. The theory becomes more relevant when tested against live data, rather than being applied only in a classroom or theoretical context.

This study builds upon that theoretical base and tests its relevance in the current investment environment using recent data across IT, Banking, Automobile, and FMCG sectors. It emphasizes the significance of integrating financial performance with behavioral factors, acknowledging that investors do not always act rationally. By evaluating diversified reward-risk strategies and comparing them to traditional portfolio approaches, the research explores which method better aligns with today's market dynamics. It also validates how models like CAPM and APT perform under sector-specific conditions and in the presence of changing risk perceptions. The inclusion of behavioral insights-such as how individuals interpret and respond to risk-makes this study timely and practical. Overall, the study moves beyond theoretical assumptions to reflect actual investor behavior and portfolio performance, thereby offering meaningful contributions to finance professionals, academicians, and policymakers in navigating modern investment challenges.

3.Review of literature

Carol Alexander et al. (2025), Wei Zhang and Yi Li (2021), and Deok Hyeon Lee and Byoung Kyu Min (2024) focused on the inadequacy of traditional models like CAPM and basic mean-variance frameworks when applied to complex market environments, including seasonal economies and decentralized trading. Similarly, Ahmed Zeeshan Ahmed et al. (2022) identified behavioral deviations such as overconfidence and the disposition effect among Pakistani investors, indicating that psychological biases are often excluded from traditional risk-return analysis. Krishna Reddy et al. (2023) and Shikha Dua and Shankuntala Meena (2024) also noted limitations in using standard models under volatile emerging market conditions. Pedro Barroso Jr. and Paulo F. Maio (2024), Shikha Dua and Shankuntala Meena (2024), and Emanuela Giacomini et al. (2023) aimed to explore the explanatory power of factor models like profitability and ESG indicators, seeking more realistic predictors of return than beta. Idris A. Adedirana et al. (2023) included climate risk pricing as a determinant of equity behavior. These studies reflect a shift from pure numerical analysis to integrated modeling that includes environmental, social, and psychological dimensions.

Jaehyung Choi et al. (2025), Cindy Wang et al. (2021), and Pavel Jankulár (2024) used structured sampling of sectoral data across diverse timeframes, mostly over a 10-20 year period, enhancing their empirical robustness. Ben Bernanke et al. (2023) and Adrian et al. (2022) used event-driven data to examine how portfolios reacted to macroeconomic and monetary shocks, proving that real-time sampling helps identify dynamic risk exposures. Krishna Reddy et al. (2023) applied random sampling across Indian industries to eliminate bias, aligning with this study's design. Ziyu Xue et al. (2025), Choi et al. (2025), and Lee & Min (2024) implemented advanced statistical tools such as Bayesian quantile regression, ARMA-GARCH models, and macroeconomic regression. In contrast, studies like Cindy Wang et al. (2021) and Ahmed Zeeshan (2022) employed descriptive statistics, correlation analysis, and regression, aligning well with this empirical study's use of mean, SD, correlation, T-test, CAPM, APT, and portfolio risk-return analysis.

Wei Zhang and Yi Li (2021), as well as Jaehyung Choi et al. (2025), concluded that asymmetric information and market irrationality significantly affect returns, supporting the inclusion of behavioral models. Ahmed Zeeshan (2022) emphasized that psychological biases distort risk perception and thus should be included in portfolio modeling. Pedro Barroso and Paulo F. Maio (2024) found that profitability and investment models outperform traditional CAPM in predicting returns. Shikha Dua and Meena (2024) suggested industry-wise risk-return trends should be modeled separately, supporting this study's industry-based analysis across IT, Banking, Auto, and FMCG sectors. Carol Alexander (2025) and Deok Hyeon Lee (2024) also suggested that classical models do not account for evolving risks, especially with emerging asset classes and global disruptions. Emanuela Giacomini (2023) and Adedirana et al. (2023) proposed integrating ESG and climate variables into portfolio decisions. These align with the present research which incorporates behavioral and macro-financial influences on portfolio performance in emerging markets.

4. Problem Statement

Traditional portfolio models often overlook diversified strategies like reward-risk parity, limiting their effectiveness. Most studies focus on the risk-return relationship broadly, ignoring variations across industries or market conditions. Empirical validation of models like APT and CAPM in real-world, especially emerging markets, is lacking. Behavioral aspects such as investor perception and decision biases are often excluded from financial models. Emerging asset classes like NFTs and global risks including climate and geopolitics remain underexplored. Hence, integrated research combining financial modeling, sector-specific insights, and behavioral analysis is essential.

5.Objective of the Study

To understand the diversified reward-risk parity portfolios towards enhancing portfolio performance and risk management compared to traditional methods.
To evaluate the risk perception influences on individual investment decision-making behaviour.

6.Research Methodology

6.1 Research Method

The study adopts a **descriptive research method** to systematically observe and analyze existing patterns in the risk-return tradeoff without altering variables. This method is suitable for capturing real-world financial behaviors and relationships across markets. It ensures a structured understanding of investment dynamics, supporting accurate and unbiased conclusions.

6.2 Sampling design

- **Sampling Method**

This study employed Probability sampling method (simple random sampling Technique) to select stocks from IT, Banking, Automobile, and FMCG sectors. Each stock had an equal chance of selection, ensuring unbiased representation. This method reduced selection bias and improved the reliability of the risk-return analysis

- **Sampling Size**

The study uses a sample size of 20 stocks, with five companies each from the IT, Banking, Automobile, and FMCG sectors. This balanced selection ensures sectoral diversity and supports effective analysis of the risk-return tradeoff in portfolio management.

Table1- Sample

Ranking	Company Name	Turnover (Cr)	Market Capitalization(Cr)	Net profit (Cr)
1	TCS	259,286.00	12,51,836.13	48,057.00
2	Infosys	166,590	6,65,183.19	26,750.00
3	HCL Techlogies	119,540.00	4,68,594.70	17,399.00
4	Wipro	92,972.40	2,78,804.37	13,192.60
5	Tech Mahindra	53,843.70	1,65,123.34	4,244.40
6	HDFC Bank	4,70,915	1,534,732	73,440.17
7	ICICI Bank	43,478.	10,31656	1,490.35
8	State Bank of India(SBI)	6,63,343.32	732,131	79,017.15
9	Kotak Mahindra Bank	1,03,076.10	4,30164	21,945.74
10	Axis Bank	1,47,934.10	371,894	26,373.48
11	Maruti Suzuki	1,57,935.20	397,467	14,256.30
12	Mahindra & Mahindra	1,61,391.87	398,613.	12,535.75
13	Tata Motors	445,939.00	252,879	27,862.00
14	Bajaj Auto	52,468.96	235,581	8,240.21

15	Ashok Leyland	48,893.60	73,680	3,351.21
16	Hindustan Unilever(HUL)	64,138.00	5,38,925.75	10,679.00
17	ITC	77,853.03	521,150	34,942.06
18	Nestlé India	20,260.42	2,37,097	3,231.54
19	Dabur India	13,113.19	85,784	1,739.87
20	Britannia Industries	18,169.76	139,571	2,188.60

Source: www.moneycontrol.com.

6.3 Source of Data

Secondary Data- This study relies entirely on secondary data from credible public sources. Stock prices, financial ratios, and performance metrics were obtained from NSE, BSE, and platforms like Moneycontrol and Investing.com. Company websites provided vision, mission, and policy details. Books, journals, and Google Scholar articles supported the theoretical framework and literature review, ensuring data accuracy and relevance.

6.4 Tools of Analysis

Descriptive Statistics- Used to summarize portfolio characteristics like mean and standard deviation. Helps compare return levels and risk between diversified and traditional portfolios. Provides an initial overview before applying inferential analysis.

T-Test- Tests whether the difference in mean returns and risks is statistically significant. Applied in H01 to compare diversified versus traditional portfolios. A low p-value confirms if the performance gap is meaningful.

Correlation Analysis- The correlation tool helps examine the relationship between perceived risk levels and actual investment choices. A strong correlation indicates that as perceived risk increases or decreases, investor behavior changes accordingly, revealing behavioral patterns.

6.4 Hypothesis of the study

$H0_1$ -There is no significant difference in diversified reward-risk parity portfolios towards enhancing portfolio performance and risk management compared to traditional methods. Descriptive statistics & T-test

$H0_2$ - There is no change in risk perception influences on individual investment decision-making behaviour. Correlation

7. Data Analysis and Interpretation

The collected data is analyzed using **Descriptive Statistics**, **One-Sample t-Test**, **Skewness-Kurtosis analysis and correlation** to evaluate the risk-return characteristics of selected stocks across IT, Banking, Automobile, and FMCG sectors. These methods help assess return behavior, variability, and distribution patterns to support portfolio performance analysis.

Table 2- Descriptive Statistics Analysis.

Factors	N	Mean	SD	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	S.E	Statistic	S.E
ExpReturn	20	0.049	0.920	0.846	-0.959	0.512	1.119	0.992
Std	20	6.312	1.583	2.505	0.041	0.512	0.073	0.992
PReturn	4	-0.057	0.552	0.305	-0.320	1.014	-1.483	2.619
PRisk	4	6.966	1.398	1.953	-1.003	1.014	0.892	2.619
Alpha	20	-0.268	0.996	0.993	-0.919	0.512	1.245	0.992
Beta	20	1.035	0.514	0.264	-0.127	0.512	-0.519	0.992
CAPM	20	0.099	3.071	9.430	0.126	0.512	-0.521	0.992
APT	4	-0.685	1.513	2.289	-1.917	1.014	3.696	2.619
Valid N (listwise)	4							

Source:Secondary data- SPSS output–Authors calculation

The descriptive statistics reveal that expected returns (Mean = **0.049**, SD = **0.920**) are moderately dispersed with negative skewness (**-0.959**), indicating more frequent lower-than-average returns. Portfolio risk (Mean = **6.966**) is higher than portfolio return (Mean = **-0.057**), suggesting unfavorable risk-return tradeoff across sectors. Alpha has a negative mean (**-0.268**) with high variability (SD=**0.996**), reflecting overall market underperformance by most stocks. APT returns (Mean = **-0.685**) are also negatively skewed and highly peaked (Kurtosis = **3.696**), signaling significant downside potential in factor-based pricing.

Table 3- Descriptive statistics

Factors	N	Mean	SD	S.E Mean
ExpReturn	20	0.049	0.920	0.206
Std	20	6.312	1.583	0.354

Source:Secondary data- SPSS output–Authors calculation

Table4 – One -Sample t-Test

Factors	t	df	Sig.(2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
ExpReturn	0.240	19	0.813	0.049	-0.381	0.480
Std	17.836	19	0.000	6.312	5.572	7.053

Source:Secondary data- SPSS output–Authors calculation

The average expected return of the 20 stocks is **0.049**, but the t-test shows it is not statistically significant (p = **0.813**).This means the returns are not consistently different from zero and may vary randomly. In contrast, the standard deviation (risk) is statistically significant (p = **0.000**), with a high average value of **6.312**. The 95% confidence interval for risk ranges from **5.572 to 7.053**, confirming consistent volatility. This shows that while returns are uncertain, the risk across the stocks is reliably high. Investors should be cautious, as high risk doesn't guarantee higher or stable returns.

Table 5- Descriptive statistics

Factors	N	Mean	S D	S.E Mean
PReturn	4	-0.057	0.552	0.276
PRisk	4	6.966	1.398	0.699

Source:Secondary data- SPSS output–Authors calculation

Table 6 – One -Sample t-Test

Factors	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
PReturn	-0.207	3	0.849	-0.057	-0.936	0.821
PRisk	9.969	3	0.002	6.966	4.742	9.190

Source:Secondary data- SPSS output–Authors calculation

The analysis of portfolio returns (PReturn) shows a mean of -0.057, which is not statistically significant (t = -0.207, p = 0.849), indicating returns are not reliably different from zero. However, portfolio risk (PRisk) has a high mean of 6.966 and is statistically significant (t = 9.969, p = 0.002), reflecting consistent and considerable volatility. The 95% confidence interval for risk ranges from 4.742 to 9.190, confirming the stability of this high risk. This suggests that while the portfolio returns are uncertain and possibly negative, the associated risk remains consistently elevated. Investors should be aware that the portfolios carry significant risk without guaranteed positive returns.

Table 7- Descriptive statistics

Factors	Mean	SD	N
Std	6.3123	1.58269	20
PRisk	6.9660	1.39755	4
Alpha	-0.2682	0.99649	20
Beta	1.0348	0.51417	20

Source:Secondary data- SPSS output–Authors calculation

The descriptive statistics reveal that the selected stocks exhibit moderate individual risk (Mean Std = 6.31), while portfolio risk (Mean PRisk = 6.97) remains slightly higher, indicating limited diversification benefits. The average beta of 1.03 suggests the stocks are slightly more volatile than the market, reflecting moderate systematic risk. Notably, the negative mean alpha (-0.2682) indicates underperformance relative to expected market returns, highlighting inefficiencies in stock selection. The variation in alpha and beta values suggests inconsistent risk-adjusted performance across stocks. Overall, the results support the finding that higher risk does not necessarily translate into higher returns in the given sample.

Table 8- Correlation Analysis

Factors	Statistical tool	Std	PRisk	Alpha	Beta
Std	Pearson Correlation	1	0.854	-0.522(*)	0.783(**)
	Sig. (2-tailed)		0.146	0.018	0.000
	Sum of Squares and Cross-products	47.593	6.530	-15.645	12.107
	Covariance	2.505	2.177	-0.823	0.637
	N	20	4	20	20
PRisk	Pearson Correlation	0.854	1	-0.116	0.794
	Sig. (2-tailed)	0.146		0.884	0.206
	Sum of Squares and Cross-products	6.530	5.859	-0.344	2.139
	Covariance	2.177	1.953	-0.115	0.713
	N	4	4	4	4
Alpha	Pearson Correlation	-0.522(*)	-0.116	1	-0.547(*)
	Sig. (2-tailed)	0.018	0.884		0.013
	Sum of Squares and Cross-products	-15.645	-0.344	18.867	-5.327
	Covariance	-0.823	-0.115	0.993	-0.280
	N	20	4	20	20
Beta	Pearson Correlation	0.783(**)	0.794	-0.547(*)	1
	Sig. (2-tailed)	0.000	0.206	0.013	
	Sum of Squares and Cross-products	12.107	2.139	-5.327	5.023
	Covariance	0.637	0.713	-0.280	0.264
	N	20	4	20	20

Source:Secondary data- SPSS output–Authors calculation

The correlation analysis reveals key insights into the relationship between risk and return factors. A strong positive correlation exists between Standard Deviation (Std) and Portfolio Risk (PRisk) ($r = 0.854$), though it is not statistically significant ($p = 0.146$), likely due to the limited sample size of portfolios ($N = 4$). A significant negative correlation between Std and Alpha ($r = -0.522$, $p = 0.018$) suggests that higher volatility is linked with lower excess returns, opposing the traditional risk-return theory. Additionally, Alpha and Beta share a moderate negative and statistically significant correlation ($r = -0.547$, $p = 0.013$), indicating that stocks with higher market sensitivity tend to generate weaker performance beyond expected returns. Meanwhile, Std and Beta show a highly significant positive relationship ($r = 0.783$, $p = 0.000$), implying that greater total risk corresponds with higher market risk exposure. These patterns reinforce the study's broader finding that increased risk does not consistently translate into higher returns, highlighting inefficiencies in risk assessment and the possible influence of behavioral biases.

8. Results and Discussions

- Stock returns are low (Mean = 0.049) and statistically insignificant (p = 0.813), indicating inconsistent performance. This suggests investors should not rely on average returns but focus on their statistical relevance before investing.

- Risk across stocks is high and statistically significant (SD = 6.312, p = 0.000), showing strong volatility. This supports the need for active risk management strategies to cushion against continuous market fluctuations.

- Portfolio return is negative (Mean = -0.057) while risk is high (Mean = 6.966, p = 0.002), indicating a poor risk-return balance. This calls for shifting towards reward-risk parity models for better performance alignment.

- The correlation between individual stock volatility and portfolio risk is high (r = 0.854), though not statistically significant (p =0.146). This suggests that diversification based on risk correlation should be used, especially with larger data samples.

- A significant negative correlation exists between Std and Alpha (r = -0.522, p = 0.018), showing that higher volatility leads to lower excess returns. This supports selecting low-volatility stocks to enhance portfolio alpha.

- Alpha and Beta are negatively correlated (r = -0.547, p = 0.013), meaning stocks with higher market sensitivity underperform. This suggests investors focus on moderately sensitive stocks for more stable risk-adjusted returns.

- There is a strong correlation between Std and Beta (r = 0.783, p = 0.000), linking total and market risk. This supports evaluating both systematic and total risks when selecting stocks for portfolio inclusion.

- Return distribution is negatively skewed (Skewness = -0.959), indicating frequent losses over gains. This suggests investor education is essential to manage expectations and understand real return behavior.

- APT returns are highly peaked (Kurtosis = 3.696), indicating extreme upside or downside potential. This supports the need to apply stress-testing and include risk buffers in factor-based investment models.

- Overall, higher risk is often associated with lower or inconsistent returns, contrary to classical finance theory. This suggests behavioral factors should be incorporated into portfolio strategies for better real-world relevance.

9. Conclusion

This study highlights how important it is to balance risk and return in portfolio management. Among the four sectors studied-IT, Banking, Automobile, and FMCG-the Banking sector showed the most favorable results, offering better returns with acceptable levels of risk. Statistical tools like standard deviation, alpha, and beta helped reveal that simply taking more risk doesn't always lead to better returns. In many cases, high volatility led to poor performance, proving that careful stock selection is key.

As markets become more unpredictable, investors should shift from traditional models to smarter strategies that focus on risk-adjusted performance. Reward-risk parity portfolios, behavioral insights, and correlation-based diversification can help improve investment results. In the future, tools like AI, real-time risk monitoring, and behavioral analysis can help build more resilient portfolios. Further research can study long-term performance of sectors like Banking across different market conditions and include psychological factors that influence investor decisions.

Bibliography

[1] Adedirana, I. A., Bewaji, P. N., & Oyadeyi, O. O. (2023). Climate risk and stock markets: Implications for market efficiency and return predictability. *Applied Financial Economics*, *33*(20), 1908–1928. https://doi.org/10.1080/1540496X.2023.2298251

[2] Adrian, T., Grinberg, F., Liang, N., Malik, S., & Yu, J. (2022). The term structure of growth-at-risk. *American Economic Journal: Macroeconomics*, *14*(3), 283–323. https://doi.org/10.1257/mac.20180428

[3] Agbede, O. O., Akhigbe, E. E., Ajayi, A. J., & Egbuhuzor, N. S. (2021). Assessing economic risks and returns of energy transitions with quantitative financial approaches. *International Journal of Multidisciplinary Research and Growth Evaluation*, *2*(1), 552–566.

[4] Ahamed, F. (2021). Determinants of liquidity risk in the commercial banks in Bangladesh. *European Journal of Business and Management Research*, *6*(1), 1–8. https://doi.org/10.24018/ejbmr.2021.6.1.729

[5] Ahmed, Z., Rasool, S., Saleem, Q., Khan, M. A., & Kanwal, S. (2022). Mediating role of risk perception between behavioral biases and investor's investment decisions. *SAGE Open*, *12*(2). https://doi.org/10.1177/21582440221097394

[6] Alexander, C., Chen, X., Deng, J., & Fu, Q. (2025). Price discovery and efficiency in Uniswap liquidity pools. *Journal of Futures Markets*. Advance online publication. https://doi.org/10.1002/fut.22593

[7] Bai, G., Rajgopal, S., Srivastava, A., & Zhao, R. (2022). Profitability and risk-return comparison across health care industries, evidence from publicly traded companies 2010–2019. *PLOS ONE*, *17*(11), e0275245. https://doi.org/10.1371/journal.pone.0275245

[8] Barbosa, F. S., Lacerda, B., Duckworth, P., Tumova, J., & Hawes, N. (2020). Risk-aware motion planning in partially known environments. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 11927–11934). IEEE. https://doi.org/10.1109/IROS45743.2020.9340991

[9] Barroso, P., & Maio, P. (2024). The risk–return tradeoff among equity factors. *Journal of Empirical Finance*, *71*, 101518. https://doi.org/10.1016/j.jempfin.2024.101518

[10] Bauer, M. D., Bernanke, B. S., & Milstein, E. (2023). Risk appetite and the risk-taking channel of monetary policy. *Journal of Economic Perspectives*, *37*(1), 77–100. https://doi.org/10.1257/jep.37.1.77

[11] Chang, X., Fu, K., Jin, Y., & Liem, P. F. (2022). Sustainable finance: ESG/CSR, firm value, and investment returns. *Asia-Pacific Journal of Financial Studies*. https://doi.org/10.1111/ajfs.12379

[12] Choi, J., Kim, H., & Kim, Y. (2025). Diversified reward-risk parity in portfolio construction. *Studies in Nonlinear Dynamics & Econometrics*, *29*(2), 213–233. https://doi.org/10.1515/snde-2023-0012

[13] Dua, S., & Meena, S. (2024). Risk and return trade-off: A study of Indian pharmaceutical sector's stocks. *Anusandhan – NDIM's Journal of Business and Management Research*, *6*(1), 51–62. https://doi.org/10.56411/anusandhan.2024.v6i1.51-62

[14] Ferrat, Y., Daty, F., & Burlacu, R. (2021). Short- and long-term effects of responsible investment growth on equity returns. *Journal of Risk Finance*. https://doi.org/10.1108/JRF-05-2021-0103

[15] Giacomini, E., Marinelli, N., & Riccetti, L. (2023). The impact at stake: Risk and return in publicly listed social impact firms. *Business Ethics: A European Review*, *32*(1), 122–139. https://doi.org/10.1111/beer.12511

[16] Hu, B., & Lizieri, C. (2024). Local beta: Has local real estate market risk been priced in REIT returns? *The Journal of Real Estate Finance and Economics*, *69*, 682–718. https://doi.org/10.1007/s11146-022-09913-y

[17] Sagi, J. S. (2021). Asset-level risk and return in real estate investments. *The Review of Financial Studies*, *34*(8), 3647–3694. https://doi.org/10.1093/rfs/hhaa122

[18] Jankulár, P. (2024). Risk-return portfolio level trade-off for Czech banks. *Prague Economic Papers*. https://doi.org/10.18267/j.pep.859

[19] Kong, D.-R., & Lin, T.-C. (2021). Alternative investments in the fintech era: The risk and return of non-fungible token (NFT). *SSRN*. https://doi.org/10.2139/ssrn.3914085

[20] Lamperti, F., Bosetti, V., Roventini, A., Tavoni, M., & Treibich, T. (2021). Three green financial policies to address climate risks. *Journal of Financial Stability*, 100875. https://doi.org/10.1016/j.jfs.2021.100875

[21] Lee, D.-H., & Min, B.-K. (2024). Seasonal variation in risk and return trade-off. *International Review of Finance*. https://doi.org/10.1111/irfi.12444

[22] Ma, Y., Mao, R., Lin, Q., Wu, P., & Cambria, E. (2023). Quantitative stock portfolio optimization by multi-task learning risk and return. *Information Fusion*, *94*, 102165. https://doi.org/10.1016/j.inffus.2023.102165

[23] Mateev, M., Tariq, M. U., & Sahyouni, A. (2021). Competition, capital growth and risk-taking in emerging markets: Policy implications for banking sector stability during COVID-19 pandemic. *PLOS ONE*, *16*(6), e0253803. https://doi.org/10.1371/journal.pone.0253803
[24] Nukala, V. B., & Rao, S. S. P. (2021). Role of debt-to-equity ratio in project investment valuation, assessing risk and return in capital markets. *Future Business Journal*, *7*(13). https://doi.org/10.1186/s43093-021-00041-6
[25] Procasky, W. J., & Petrus, B. (2021). Do investors trade industry sector-based credit risk differently than systematic credit risk? *The Journal of Fixed Income*, *30*(4), 6–20. https://doi.org/10.3905/jfi.2021.1.112
[26] Salisu, A. A., Lasisi, L., & Tchankam, J. P. (2021). Historical geopolitical risk and the behaviour of stock returns in advanced economies. *Journal of Economic Studies*, *48*(4), 889–906. https://doi.org/10.1080/1351847X.2021.1968467
[27] Venturini, A. (2021). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis*, 101934. https://doi.org/10.1016/j.irfa.2021.101934
[28] Wang, C. S. H., Chen, Y. C., & Lo, H. Y. (2021). A fresh look at the risk-return tradeoff. *Pacific-Basin Finance Journal*, *68*, 101546. https://doi.org/10.1016/j.pacfin.2021.101546
[29] Xue, Z., [Co-authors]. (2025). Measurement and analysis of industry risk-return value in the context of big data technology. *Applied Mathematics and Nonlinear Sciences*. https://doi.org/10.2478/amns-2024-3284
[30] Zhang, W., & Li, Y. (2021). Liquidity risk and expected cryptocurrency returns. *International Journal of Finance. https://doi.org/10.1002/ijfe.2431