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Analysis of the Momentum Investing Strategy and Volatility-Based Strategy in the Indian Stock Market

Prof. Amit Bathia
Assistant Professor, NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: amit.bathia@nmims.edu

Mr. Ishaane Bansal
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: ishaanebansal12@gmail.com

Mr. Kushagra Syal
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: syalkushagra@gmail.com

Ms. Lavanya Patil
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: lavanyap0409@gmail.com

Mr. Sarthhak Salwan
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: sarrthaksalwan1612@gmail.com

Ms. Suhani Jain
Bachelors of Business Administration,
NMIMS Anil Surendra Modi School of Commerce, Mumbai, India
Email: suhani.jain1712@gmail.com

Prof. Aditya Kasar*
(*Corresponding Author)
Assistant Professor, NMIMS School of Technology Management & Engineering, Navi Mumbai, India
Email: aditya.kasar@nmims.edu

Abstract

This study examines the influence of demographic factors—specifically age, experience, and risk tolerance—on investor preferences for stock investment strategies, focusing on momentum and volatility-based approaches. Using primary data from a survey of 300 investors and secondary data of top-performing companies in the Indian stock market from 2013 to 2024, we apply multinomial logistic regression to analyse stock preferences in relation to volatility. Additionally, we assess whether momentum and volatility-based investment strategies outperform the NIFTY 50 index between 2018 and 2024. The findings reveal that younger investors tend to favour high-risk, high-reward stocks, such as momentum and volatility stocks, while older investors exhibit a preference for low-volatility, safer investments. Our research confirms that both momentum and volatility strategies yielded superior returns compared to the NIFTY 50 index, driven by high-growth stocks like Adani Enterprises and Tata Steel. This study contributes valuable insights to financial advisors, suggesting that *investment strategies should be tailored based on investor age and risk appetite to optimise returns in a dynamic market environment.*

Keywords: Momentum Investing Strategy, Volatility based strategy, Investment Decision, Indian Stock Market, Nifty 50 Index, Multinomial logistic Regression.

Introduction

In the actual operation of stock market investment, investors are presented with numerous options, plans, and risks. Two out of the many investment strategies that have emerged recently include the momentum investment strategy and the volatility investment strategy. Momentum investing depends on the idea that those stocks with good past performance are likely to be good this year while volatility trading concentrates on the pure risks and returns related to fluctuating stocks.

It is critical to grasp these approaches specifically when it comes to investing in the Indian stock market, as demonstrated in this research paper – a market that has in the recent past been known for its high growth rate as well as high risks. It also studies the quantitative aspect by using NIFTY 50 index acting as a benchmark for the Indian equity market with a CAGR of 12.97% between 2018 to 2024. The scope of this report is to appraise whether the two momentum and volatility strategies are capable of delivering a better return than this benchmark so as for the investors to get an insight on the amount of return and the amount of risk they are exposed to.

In regards to the effectiveness of the above strategies, it has been found out that there exists a disparity and that it depends on the following factors; age, experience and the level of risk taking propensity of the investment maker. Newer investors are more risky compared to older investors and tend to invest in short-term powerful companies such as momentum stocks. On the other hand, the older investors require lower risk as well as more consistent returns. Knowledge of how these demographics affect investment decisions may be useful in developing strategies that would suit those investors in the existing market.

Literature Review

The momentum technique was originally expounded by Jegadeesh and Titman (1993) and they showed that buying past winners and selling current losers can generate abnormal returns during periods of three to twelve months. According to their research, the authors confirmed that value stocks follow the same short-term characteristics as growth stocks, which do not correspond to efficient market theories.

The GARCH model of modelling market fluctuations was developed by Bollerslev (1986) with the full name of 'Generalised Autoregressive Conditional Heteroskedasticity'. It helps in making a price prediction and is particularly valuable when used in combination with the overwhelming momentum in unstable markets. This is important for all trade volatile based strategies.

Daniel & Moskowitz (2016) coined the term 'momentum crashes', defining them as bear market phenomena. They urged the use of volatility risk management coupled with momentum especially in the downtimes in which momentum returns are less so pronounced.

In stocks, non-systematic risk often leads to high future returns as established by the research conducted by Bali, Cakici and Whitelaw 2011. While acknowledging the potential of reaping handsome returns, their study alerts investors about the risks lurking in high fluctuation stocks, especially equity, and provides insights into how equities' volatility influences investment returns.

Using both momentum and volatility approaches in conjunction with each other was found to provide better results than benchmarks, by Barroso and Santa-Clara (2015). They claimed that while one gets much better protection during the volatile regime, the other is more suited in stagnant or even expanding markets.

Recent enhancement into momentum methods by Ryou et al. (2020) incorporate Hidden Markov Models (HMM) for stock selection from preferable market conditions. In so doing they show that trading based on HMM operations can outperform conventional momentum models and get optimum results when applied to cutting down risk and increasing profit in instances where holding periods are restricted to roughly one month.

SS Dani Kumar and Tiwari (2023) consider the issue of momentum investment strategies. The authors analyze the outcomes for various types of momentum strategies over the past years, looking at the psychological factors that can affect such strategies namely herding and overreaction.

The Indian stock market may generate extraordinary returns using momentum techniques and this is true as earlier pointed out, but its possibilities depend on several factors including character and costs of the market, and its volatility varying with the cycles of market as newly emerging findings on Indian markets demonstrate. With these issues in mind it is worthwhile to overview some successful applications of quantitative models. .

According to the behavioural finance theories it is argued that actual deviation arises due to investors' tendency to rely more on the high point of the fiscal year rather than recent data in determining their perception of past returns (Barberis et al., 1998; Saurav et al., 2023). One of the used strategies, namely 52-week high strategy, reveals a slight downtrend, however, both patterns indicate the long-term reversal of market behaviour

As observed by Tobias Wiest in June 2022, the ignorance derived from applying moment techniques is ginormous in multiple types of assets. Its causes and its birth are still a subject to debate, however. Subsequent research should focus on enhancing the construct of momentum strategies and gaining greater insight into the reasons behind it.

As today's machine learning enhances quantitative investment techniques significantly, especially in China's capital markets, Xu (2023) explains as follows. Employing the techniques of artificial neural networks, he indicates higher mean accuracy and returns compared to traditional fundamental analytic models.

In the context of the COVID-19, Papathanasiou et al. (2022) reviewed different strategies to understand how the market shape investors portfolio. It also emphasises correlation between so many stock types – value, momentum, growth, etc. In this article, the author compared the behaviour of value stocks and other types of stock.

Momentum techniques were also examined by Chan et al. (2000) in order to assess the ability of those methods to support country choosing. It further investigated the proposition that the international momentum profits are related and lastly tested the hypothesis that volume of trade also impacted the profitability.

Mean returns tested with t-test for a month formation period and several holding periods were used for testing the momentum approach to built a portfolio out of the best equities (Thomas & Dileep Kumar, 2014). From the analysis of the momentum method for various holding periods of the Indian capital market, the study established that investors do not make profits.

Freibauer and Grawert (2022) suggested strategies at the population risk level for some population like how rebalancing often causes unpredictable asset distribution, how volatile predictions and behavioral preferences affect portfolio sustainability.

Shumway and Stambaugh (2004) examined several methodologies for momentum trading and Lesmond, Schill, and Zhou (2004) found that trading cost are often greater than the returns from momentum leading to doubt on the ability to sustain such gains.

Pástor and Stambaugh (2003) investigate how market-wide liquidity affects asset pricing and show that high sensitivity to this factor yields 7, 5% annualised outperformance in stock returns.

Thomas & Dileep Kumar (2014) opted for a mean returns and t-test on a momentum strategy of the Turn of the Year & a momentum strategy for the Indian capital market that offered no gains for investors over several holding periods.

Chan et al. (2000) examined the components of the momentum strategies to assess the country utilisation. It further analysed whether the international momentum profits are linked and lastly, whether trading volume also influences profitability.

In the study by Freibauer & Grawert (2022), they have used different strategies in an attempt to segregate assets in the two categories depending on the risk of the population's category. According to this paper, the behavioural preferences, rebalancing, and volatility forecasting explain the weighted allocation of assets and therefore the longevity of a portfolio.

Asness, Moskowitz, and Pedersen (2013) provide compelling evidence on the persistence of return premia associated with momentum and value signals in global equity, fixed income, commodities, and currencies markets. Their analysis weakens the conventional behavioural and rational asset pricing theories that dominated the academic work and focuses mostly on US equities by providing strong correlation structure between different methods.

Damodaran (2012) considers passive and contrarian, as well as activist strategies and defines what the global value investor's outcomes are; the author again notes that their profits coincide with other less methodical strategies.

Acharya and Pedersen (2005), demonstrate how expected liquidity and covariances with market returns of a security determine the required return on it. By using their model, they demonstrated that there are negative liquidity shocks that mean low present returns, which in return equal high future returns, meaning that liquidity risk has to be incorporated into asset pricing models.

Glenn N. Pettengilla, Susan M. Edwardsa, Dennis E. Schmitt (2006) in their paper look at the possibility of momentum investing being useful to the individual investor where this is investing in securities that have recently been good performers. Concerning momentum stocks, both analysts and individual investors select them; however, the former benefit from this strategy, but not the latter.

As stated by Lakonishok, Shleifer and Vishny (1994), market participants often overestimate future growth for glamour stocks; that's why the authors argue that it is not intrinsic risk that explains why value strategies outperform glamour strategies. In their study, they argue that value stocks have higher returns due to the cross-sectional low price to their corresponding risk and return levels.

Research Gap

Despite a large amount of research existing on the usage of momentum and volatility based strategies, literature that examines the influence which an investor's relevant characteristics, such as age, experience and personal risk taking propensity, have on their preference for such strategies, is scarce, particularly in developing markets including India. Previous studies have mostly focused on first order components including market risks for instance, market fluctuation (Barroso & Santa-Clara, 2015) and others are herding behaviour (Kumar & Tiwari, 2023). Nevertheless, no research has looked at all these traits of an investor at one time to assess their cumulative impact on choosing the most suitable strategy. In addition, studies from around the world have shown that it is possible to generate abnormal returns by using the momentum and the volatility indices (Jegadeesh & Titman, 1993; Barroso & Santa-Clara, 2015). But, practically speaking, very little is understood regarding the effectiveness of these strategies against major indices like the NIFTY 50, not to mention the current COVID-19 pandemic environment.

Additionally, the current studies often fail to consider the factors relevant to the Indian market including market oscillations, variations and fluctuations of market liquidity which are important factors that precipitate the effectiveness of these methods. Thomas & Dileep Kumar (2014) did not find Indian momentum strategies profitable in all the firms; however, they did not study the characteristics of the investors or did not also compare the performance, with benchmark indices helps to evaluate profitabilities in the present time market horizon (2018–2024).

The purpose of this study is to close this gap by:

1) Analyse how momentum and volatility strategy is affected by the configuration of the investor's characteristics: risk appetite, age, and experience.

2) Identification of whether these tactics have outperformed the NIFTY 50 index statistically for the time period between 2018 and 2024.

These gaps will be filled within the framework of the study and provide a broader understanding of the effectiveness of stock strategies in emerging markets, useful for market professionals and ordinary users., and risk tolerance affect their preference for these strategies, especially in emerging markets like India.

Research objectives

1) *To examine the connection between and investors preferred stock investment techniques and their level of risk tolerance*

   The objective is to determine whether investors who are more risk averse may adhere to regular methods, while those who have a higher risk tolerance may be more likely to choose momentum- or volatility-based strategies.

2) *To investigate the ways in which investor attributes (experience, age, and risk tolerance) work together to shape stock preference in both momentum- and volatility-based investing methods.*

   This goal incorporates all investor attributes in order to evaluate how these elements, taken as a whole, affect the choice of stock investment strategies. It looks to see if various mixes of expertise, age, and risk tolerance lead investors to favour particular approaches.

3) *To evaluate the possible strategic benefits of volatility- and momentum-based stock strategies in outperforming a market index that represents the entire market, such as the NIFTY 50.*

   The goal is to investigate ways that momentum and volatility strategies can leverage high-risk, high-reward situations or latch onto trends in high-growth equities to outperform the NIFTY 50 in returns between 2018 and 2024.

4) *To examine the premise that the volatility and momentum strategies' observed returns are statistically larger than the compound annual growth rate of the NIFTY 50 index*.

   The goal is to apply statistical techniques to determine whether the mean returns from volatility and momentum strategies are appreciably higher than the 12.97% CAGR of the NIFTY 50. If outperformance is verified, reject the null hypothesis.

Hypothesis

Hypothesis A: Impact of Age on Stock Preference

- Null Hypothesis (H0a): Age does not have a significant impact on investor preferences for types of stocks such as standard stock, momentum stock, or volatility stock.

Hypothesis B: Momentum and Volatility Strategies vs. NIFTY 50 Returns

- Null Hypothesis (H0b): The unweighted average returns from momentum and volatility stocks selected using respective strategies are less than or equal to the NIFTY 50 CAGR of 12.97% for a specified period

Methodology

The research has been conducted using both primary and secondary data. The primary data was collected by floating a google form to people with different age groups and experience in the stock market. Out of the 306 responses, 300 were error free, therefore our sample size is 300. The primary data was exported to Microsoft Excel and Multinomial Logistic Regression was conducted using Jamovi 2.6.2. The model compares different levels of volatility (low, moderate, high) using low volatility as the reference category.

Apart from this, Stock price data of the last 10 years was taken for the top 50 companies in 2013 according to Market Capitalization. This data was corrected to accommodate the stock splits and bonus issues. Then their Holding Period Return and Standard Deviation was calculated for the first 5 years, and the top 10 companies with highest returns and highest SD were selected. HPR helped select companies according to momentum and SD to select companies according to volatility. Returns for these companies were analysed for another 6 years to test whether the stock selection according to momentum strategies and volatility strategies could beat the benchmark.

Data Analysis and Findings

Primary Research (Qualitative)

For the primary research, this study used a multinomial logistic regression model to assess the relationship between age and stock volatility preferences from a survey (ref. Appendix) with a sample size of 300. The dependent variable, stock volatility, was divided into three categories: low, moderate, and high volatility. The independent variable was age (measured in years) which was categorised in groups of -4 for age groups of 18-24, 25-34, 35-44, and 45+ respectively.

Table no 1: Model Fit Measures

Model Fit Measures

			Overall Model Test		
Model	Deviance	R^2_{McF}	χ^2	df	p
1	588.53670	0.05851	36.57251	2	0.0000000114388176

Note. Models estimated using sample size of N=301

Source : Jamovi

The results of the multinomial logistic regression illuminate the relationship between age and stock volatility preference. The R^2 value of the McFadden model is equal 0.0585 that shows that 5.85% of the variability in stock volatility preference is explained by age, which indicates that while age has an effect, other factors besides age likely influence volatility preference among investors. In behavioural finance, preferences for stock volatility are often shaped by various factors, such as risk tolerance, investment experience, income, financial goals, and market conditions, which may exert stronger effects than age alone.

Table no. 2- Omnibus Likelihood Ratio Test

Omnibus Likelihood Ratio Tests

Predictor	χ^2	df	p
Age_Group	36.57251	2	0.0000000114388175

Source : Jamovi

In the Omnibus Likelihood Ratio Tests, the age predictor exhibited a Chi-square χ^2 value of 42.76, further confirming its significance with a p-value of 0.000000519, underscoring the substantial effect of age on stock volatility preferences.

Table no. 3- Model Coefficients

Model Coefficients - Volatility_Pref

Volatility_Pref	Predictor	Estimate	SE	Z	p
Moderate - Low	Intercept	0.86463	0.34256	2.52402	0.0116022969345060
	Age_Group	−0.09933	0.11340	−0.87594	0.3810609586220206
High - Low	Intercept	1.55924	0.37197	4.19185	0.0000276684776384
	Age_Group	−0.78368	0.15148	−5.17352	0.0000002297238890

Source : Jamovi

Table no. 4- Odds Ratios

	95% Confidence Interval	
Odds ratio	Lower	Upper
2.37413	1.21315	4.64617
0.90544	0.72500	1.13080
4.75521	2.29377	9.85805
0.45672	0.33940	0.61460

Source : Jamovi

The analysis compares two main contrasts: Moderate Volatility vs. Low Volatility and High Volatility vs. Low Volatility, allowing us to explore how age impacts these preferences.

For the Moderate vs. Low Volatility comparison, the intercept estimate of 0.86463 is statistically significant (p = 0.0116), suggesting that, in general, there is a baseline tendency for moderate volatility over low volatility. However, the coefficient for age group (-0.09933) in this comparison has a p-value of 0.3811, which is not statistically significant. The corresponding odds ratio of 0.90544 (close to 1) further indicates that age has little effect on the likelihood of preferring moderate over low volatility. This lack of significant influence suggests that age alone may not be a strong determinant of whether investors choose moderate volatility over low, possibly because factors such as risk perception, financial literacy, or life circumstances may vary widely within age groups. This implies that older individuals tend to be more conservative in their stock preferences, avoiding moderate risk in favour of safer, low-volatility investments.

The comparison of High Volatility vs. Low Volatility yields even stronger results. The intercept estimate of 1.55924 is highly significant (p = 0.0000277), establishing a baseline preference for high over low volatility for younger investors in the reference group. More importantly, the age group coefficient of -0.78368 has a very low p-value (0.0000023), making it statistically significant. This negative coefficient indicates that as age increases by each group, the likelihood of preferring high volatility over low volatility significantly decreases by around 78.3%. The odds ratio of 0.45672 (less than 1) reflects that older investors are about 54% less likely to choose high volatility over low volatility with each incremental age group, supporting the hypothesis that older investors prefer lower volatility.

Interpretation of Results for age impact on stock choices

By including the variables, these findings imply that age has a serious influence on the volatility with regard to stock preference, especially high volatility stocks. This feature is in harmony with the postulated hypothesis of the generally lower risk-seeking tendency of older people, therefore, their aversion to more risky stocks. These results are in concordance with the general expectation that risk taking capability decreases as people grow older.

Secondary Research (Quantitative)

Dataset M: Momentum Stocks

This dataset ranks the top 10 stocks from the NIFTY 50 based on their Average HPR (Holding Period Return) up to 2018. Stocks with high HPR typically indicate positive momentum in the market, often due to strong performance over time. The top performers in this list are Maruti Suzuki India Ltd. and Adani Enterprises Ltd., with Average HPRs of 3.71% and 2.96%, respectively. The presence of companies like HDFC Bank and Reliance Industries suggests that both consumer-facing and industrial sectors are well-represented.

Momentum stocks like these often benefit from investor optimism and positive news flow.

Table 5: Holding Period Return of Companies Selected using Momentum Strategy

Company	*Average HPR till 2018*
Maruti Suzuki India Ltd.	3.71%
Adani Enterprises Ltd.	2.96%
Adani Ports & Special Economic Zone Ltd.	2.23%
Hindustan Zinc Ltd.	2.03%
HDFC Bank Ltd.	1.99%
Hindustan Unilever Ltd.	1.95%
Godrej Consumer Products Ltd.	1.93%
Tata Steel Ltd.	1.86%
Reliance Industries Ltd.	1.76%
Tech Mahindra Ltd.	1.76%

Dataset V: Volatility Stocks

The second dataset focuses on the volatility of stocks, measured by the Standard Deviation (SD) of returns up to 2018. Reliance Communications Ltd. is by far the most volatile stock, with an SD of 30.18%, followed by Adani Enterprises Ltd. at 18.54%. Stocks with high volatility can experience large swings in their stock prices, which can represent both risk and opportunity for investors, especially those engaging in speculative or short-term trading.

Volatility here reflects the potential uncertainty around the future performance of these companies. For instance, stocks like DLF Ltd. and SAIL are affected by market and sector-specific factors, such as fluctuations in commodity prices, infrastructure spending, and policy changes.

Table 6: Standard Deviation of Companies Selected using Volatility Strategy

Company	*Standard Deviation till 2018*
Reliance Communications Ltd	30.18%
Adani Enterprises Ltd.	18.54%
DLF Ltd.	14.77%
Steel Authority of India (SAIL) Ltd.	13.07%
Bharat Heavy Electricals Ltd.	12.85%
Indian Oil Corporation Ltd.	11.18%
Tata Steel Ltd.	10.91%
Bank of Baroda	10.82%
Tata Motors Ltd.	10.30%
State Bank of India	9.84%

Further Analysis

- Intersection Between Momentum and Volatility: Interestingly, Adani Enterprises Ltd. and Tata Steel Ltd. appear in both lists. This suggests that these companies, while exhibiting high volatility, have also managed to maintain strong momentum in terms of their average holding period returns. This could imply that these stocks are particularly attractive to investors willing to embrace higher risk for potentially higher rewards.
- Sectoral Representation: The momentum stocks (Set M) are largely diversified across various industries like automotive (Maruti Suzuki, Tata Motors), banking (HDFC Bank), and consumer goods (Godrej Consumer Products, Hindustan Unilever). In contrast, the volatility set (Set V) includes many companies from infrastructure (DLF, SAIL) and heavy industries (Bharat Heavy Electricals, Indian Oil). This suggests that volatile industries tend to be cyclical or heavily impacted by macroeconomic factors, such as oil prices or government policies.

Going forward we will look at the performance of each of these stocks from April 2018 to March 2024, and see if their returns beat the index

To do this, we will look at the compounded annual growth rate for each of the stocks and see if these stocks or collection of stocks, beat the index returns.

The analysis involves examining the Compounded Annual Growth Rate (CAGR) from April 2018 to March 2024 for both momentum and volatility stocks and comparing them against the NIFTY 50 index's CAGR of 12.97%.

1. Momentum Stock Strategy Performance:

Momentum stocks typically rely on continued market optimism and strong past performance. Below is a comparison of the stocks from the momentum strategy, showing their CAGR values:

Table 7: HPR & CAGR of Companies Selected using Momentum Strategy

Company	*Average HPR till 2018*	*CAGR (2018-2024)*
Maruti Suzuki India Ltd.	3.71%	3.97%
Adani Enterprises Ltd.	2.96%	65.95%
Adani Ports & Special Economic Zone	2.23%	24.81%
Hindustan Zinc Ltd.	2.03%	0.29%
HDFC Bank Ltd.	1.99%	6.78%
Hindustan Unilever Ltd.	1.95%	10.39%
Godrej Consumer Products Ltd.	1.93%	9.35%
Tata Steel Ltd.	1.86%	16.27%
Reliance Industries Ltd.	1.76%	21.68%
Tech Mahindra Ltd.	1.76%	12.59%

Key Insights:

- Top Performers: Adani Enterprises Ltd. (65.95%), Adani Ports (24.81%), and Reliance Industries (21.68%) delivered outstanding returns, significantly surpassing the NIFTY 50's CAGR of 12.97%.
- Average Performance: Stocks like Tech Mahindra Ltd. (12.59%) nearly matched the index return.
- Underperformers: Maruti Suzuki (3.97%), HDFC Bank (6.78%), and Hindustan Zinc (0.29%) notably lagged behind.

Conclusion (Momentum Strategy):

The momentum stock strategy overall outperformed the NIFTY 50 index, thanks to a few high-growth stocks. The average CAGR of the top performers significantly boosts the portfolio return.

2. Volatility Stock Strategy Performance:

Volatility stocks are often seen as riskier but provide opportunities for large swings. Here is the performance:

Table 8: SD and CAGR of Companies Selected using Momentum Strategy

Company	*SD till 2018*	*CAGR (2018-2024)*
Reliance Communications Ltd.	30.18%	-32.34%
Adani Enterprises Ltd.	18.54%	65.95%
DLF Ltd.	14.77%	28.19%

Steel Authority of India (SAIL) Ltd.	13.07%	9.35%
Bharat Heavy Electricals Ltd.	12.85%	18.84%
Indian Oil Corporation Ltd.	11.18%	6.09%
Tata Steel Ltd.	10.91%	16.27%
Bank of Baroda	10.82%	11.22%
Tata Motors Ltd.	10.30%	19.12%
State Bank of India	9.84%	20.12%

Key Insights:

- Top Performers: Adani Enterprises (65.95%), DLF Ltd. (28.19%), Tata Motors (19.12%), and State Bank of India (20.12%) significantly outperformed the NIFTY 50.
- Losses: Reliance Communications Ltd. (-32.34%) performed abysmally, weighing down the overall strategy.
- Solid Returns: Other stocks like Bharat Heavy Electricals (18.84%) and Tata Steel (16.27%) delivered strong, steady returns.

Conclusion (Volatility Strategy):

The volatility stock strategy also managed to beat the NIFTY 50 index return, with a few stocks generating stellar growth. However, the high-risk nature of this strategy is evident with major losses like those from Reliance Communications.

Findings

Table 9: Outperformance Determination of Companies Selected using Momentum Strategy w.r.t. NIFTY 50

Company	*CAGR (2018-2024)*	*Outperformance*
Maruti Suzuki India Ltd.	3.97%	No
Adani Enterprises Ltd.	65.95%	Yes
Adani Ports & Special Economic Zone	24.81%	Yes
Hindustan Zinc Ltd.	0.29%	No
HDFC Bank Ltd.	6.78%	No
Hindustan Unilever Ltd.	10.39%	No
Godrej Consumer Products Ltd.	9.35%	No
Tata Steel Ltd.	16.27%	Yes

Reliance Industries Ltd.	21.68%	Yes
Tech Mahindra Ltd.	12.59%	No (slightly less)

***Observation*:**

- Out of the 10 stocks in the momentum strategy, 5 outperformed the NIFTY 50 index's CAGR of 12.97%.
- Key outperformers: Adani Enterprises Ltd. (65.95%), Adani Ports (24.81%), and Reliance Industries (21.68%).
- Conclusion: Momentum strategy partially rejects the null hypothesis (H_0). The outperformance is driven by a few high-growth stocks, indicating that momentum investing captured these high-return opportunities.

Table 10: Outperformance Determination of Companies Selected using Momentum Strategy wr.t. NIFTY 50

Company	*CAGR (2018-2024)*	*Outperformance*
Reliance Communications Ltd.	-32.34%	No
Adani Enterprises Ltd.	65.95%	Yes
DLF Ltd.	28.19%	Yes
Steel Authority of India (SAIL) Ltd.	9.35%	No
Bharat Heavy Electricals Ltd.	18.84%	Yes
Indian Oil Corporation Ltd.	6.09%	No
Tata Steel Ltd.	16.27%	Yes
Bank of Baroda	11.22%	No
Tata Motors Ltd.	19.12%	Yes
State Bank of India	20.12%	Yes

Observation:

- Out of the 10 stocks in the volatility strategy, 6 outperformed the NIFTY 50 index's CAGR of 12.97%.
- Key outperformers: Adani Enterprises Ltd. (65.95%), DLF Ltd. (28.19%), and State Bank of India (20.12%).
- Conclusion: The volatility strategy largely rejects the null hypothesis (H_0). The strategy yielded more frequent outperformers despite being high-risk.

Momentum Strategy: The null hypothesis (H0b) is rejected, as the unweighted average CAGR of the selected momentum stocks (17.21%) exceeded the NIFTY 50 CAGR of 12.97%. Out of 10 stocks, 5 outperformed the index, suggesting that momentum investing can yield superior returns, particularly when high-growth stocks are captured. For instance, Adani Enterprises (65.95%), Adani Ports (24.81%), and Reliance Industries (21.68%) significantly outpaced the NIFTY 50. However, there were also underperformers, such as Maruti Suzuki (3.97%) and Hindustan Zinc (0.29%), highlighting the selective nature of momentum's success.

Volatility Strategy: Similarly, the null hypothesis (H0b) is rejected for the volatility strategy, with 6 out of 10 stocks surpassing the NIFTY 50 index. Despite the inherent risks, the volatility strategy delivered higher returns, evidenced by stocks like Adani Enterprises (65.95%), DLF Ltd. (28.19%), and State Bank of India (20.12%). While some stocks, such as Reliance Communications (-32.34%), lagged significantly, the average return from the volatility-based stocks (16.28%) still exceeded the NIFTY 50 CAGR.

In conclusion, both momentum and volatility-based strategies demonstrated their potential to outperform the NIFTY 50 index, reinforcing the rejection of the null hypothesis (H0b) and supporting the effectiveness of these strategies over the specified period.

Conclusion

In conclusion, the research confirms that age significantly impacts stock preference, with younger investors showing a higher propensity for riskier, high-volatility stocks, while older investors tend to prefer low-volatility, stable investments. This is supported by the multinomial logistic regression results, where the likelihood of preferring high or moderate volatility stocks decreases with age, reflecting older investors' more conservative risk profiles. Furthermore, both momentum and volatility strategies outperformed the NIFTY 50 index, particularly driven by the exceptional growth of certain high-performing stocks like Adani Enterprises. These findings reject the null hypothesis (H0b) for both strategies, affirming the effectiveness of momentum and volatility-based investments in outperforming the benchmark.

Limitations and Future Scope

Future Scope:

Investment Strategies and Financial Advisory:

- Potential to guide investment strategies and financial advisory services, especially with the growing ageing population.
- Tailoring stock portfolio recommendations based on age-related risk preferences.

Expansion of the Model:

- Further exploration of the relationship between age and risk preferences across various market conditions.

Future Variables to Consider:

- Variables like income, education, and financial literacy could be incorporated to better explain stock volatility preferences across different age groups.

Broader Applications:

- The model could be expanded to predict stock prices and potentially outperform benchmarks.
- Can be tested on more companies, across different sectors, and during different time frames.

Adaptability to Different Trading Strategies:

- Modification to evaluate returns on intra-day trading, beyond long-term growth.

Sector and Region Specificity:

- Customization based on sectors, regions, demographics, and income levels for more targeted predictions.

Limitations:

- Whilst the current study is based on 300 responses, a larger sample size could denote higher precision and yield better outcomes.

- The study does not account for significant events which could impact the data like pandemics, financial crisis, investor sentiment etc.

- Paper does not consider sector specific companies to analyse the correlations between different sectors and how the strategies could be implemented on them.

- The study lacks a focus on regional differences, income levels, and education, which may influence investment behaviours across different populations.

- The analysis is limited to a specific time frame (2018-2024). The study may not account for long-term patterns or for short-term strategies like day trading.

- The analysis focuses on top-performing and volatile stocks but does not investigate outliers or extreme underperformers. Understanding these extreme cases could offer additional insights into the limitations of momentum and volatility strategies.

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