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Robo-Advisors, Algorithmic Trading, And Their Impact On Portfolio Diversification And Herding Behavior: Evidence From The Indian Retail Investment Market

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Abstract - The rapid evolution of financial technology (fintech) has brought about revolutionary changes in investment management through robo-advisors and algorithmic trading. The current research seeks to examine the effect of these technologies on portfolio diversification and herding behavior among investors in the Indian retail stock market. Applying a quantitative deductive research methodology, the study uses secondary financial data collected from National Stock Exchange (NSE), Bombay Stock Exchange (BSE), and popular robo-advisory platforms in the time span 2019–2024. To assess portfolio diversification, the Herfindahl-Hirschman Index (HHI) and the correlation analysis among the assets held by investors will be used. On the other hand, the Cross- Sectional Absolute Deviation (CSAD) model and the Lakonishok-Shleifer-Vishny (LSV) index will be applied to measure herding behavior among investors. The research findings demonstrate that portfolios advised by robots have much lower HHI (0.21) than portfolios managed by traditional methods (0.39), which shows higher levels of diversification. At the same time, herding behavior was proved to exist based on the negative value of the CSAD model's squared market return coefficient (β= -0.35; p=0.02), with LSV figures rising from 0.07 in relatively stable market periods to 0.19 when markets become highly volatile. Furthermore, regression analysis proves the existence of a significant negative relationship between algorithmic trading and portfolio concentration (β=-0.28; p=0.01). Thus, robo-advisors have been proved not only to lead to more effective diversification but also to generate herding risk due to their similarity. These findings have important implications for investors, fintech companies, government authorities, and financial regulation bodies.

***Keywords*:** Robo-advisors, algorithmic trading, portfolio diversification, herding behavior, Herfindahl-Hirschman Index, CSAD, LSV index, Indian financial market, behavioral finance, fintech

1. Introduction

In the past decade, we have seen dramatic shifts in the way the finance industry operates, driven by digital innovations, artificial intelligence (AI), automation, and big data analytics. All of these have significantly democratized the accessibility of financial markets and led to two revolutionary developments: robo-advisors and algorithmic trading systems.

Robo-advisors refer to automated algorithm-driven platforms providing portfolio management services through analyzing the needs, preferences, and time frames of each user to create and balance a diverse portfolio. On the other hand, an algorithmic trading system is characterized by automated execution of trades based on pre-set instructions without any manual intervention, processing data significantly faster than any individual trader can.

Both types of innovations operate within the framework of modern portfolio theory developed by Markowitz in 1952. By allocating investments across assets having low or even negative correlation with each other, algorithms try to reduce unsystematic risks.

However, there is a fundamental issue associated with these technologies which requires more attention from the scholarly community. With many traders making decisions based on algorithmically generated portfolios, is not the market becoming too uniform and dependent on a few similar algorithms and recommendations, thus exhibiting herd behavior? This concept refers to the imitation of dominant trends and patterns, leading to distorted prices and increased risk.

The case of India is particularly relevant for exploring this problem since it offers a unique perspective and setting for conducting research in this area. In the past decade, its number of retail investors has skyrocketed due to high smartphone ownership rates, widespread digital payments, migration caused

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by the coronavirus pandemic, and the appearance of zero-commission trading platforms such as Groww, Zerodha, and INDmoney. Despite being an important and rapidly developing market, the empirical evidence regarding behavioral effects of adopting fintech innovations in it is surprisingly rare.

The present paper intends to address this issue by examining the extent to which robo-advisors and algorithmic trading systems encourage risk-reducing portfolio diversification or herding behavior.

2. Review of Literature

2.1 Robo-Advisors and Portfolio Diversification

Literature about robo-advisory platforms largely focuses on their ability to democratize portfolio construction. In their work, Jung et al. (2018) showed that algorithmic platforms enable ordinary users with no professional skills in finance to build diversified portfolios with the help of automated asset allocation processes. D'Acunto et al. (2019) proved that using these platforms allows significantly reducing behavioral biases as investors change their strategy from reactive to systematic one. Belanche et al. (2019) identified trust and perceived usefulness as the key elements for the acceptance of robo- advisors due to the importance of personalized user experience. Bianchi & Brière (2021) highlighted the use of ETFs by robo-advisors in the process of cross-sector and cross-geographic diversification as well as in the maintenance of portfolio allocations with the help of automatic rebalancing. Cost efficiency, scalability, and disciplined rebalancing were pointed out by Sironi (2016) as key characteristics of these platforms.

Agnew et al. (2020) and Rossi & Utkus (2020) proved that automation helps investors keep themselves on course and avoid impulsive trading typical for the majority of retail investors. Finally, Gupta & Pathak (2022) noted the high receptiveness of young Indian investors to digital services because of their benefits including lower fees and convenience.

2.2 Algorithmic Trading and Market Efficiency

The majority of studies conducted on algorithmic trading have concentrated on its positive effects on market microstructure. For example, Hendershott et al. (2011) showed that the introduction of algorithmic trading has substantially improved the efficiency of price discovery and transparency in the stock markets of the United States. In foreign exchange markets, Chaboud et al. (2014) confirmed that algorithms contribute to faster assimilation of information in prices.

Brogaard et al. (2014) considered the topic of high-frequency trading and found that high-frequency traders increase the liquidity of the market through tighter bid-ask spreads and rapid assimilation of information into prices. Similarly, Hasbrouck and Saar (2013) found that algorithmic trading decreases transaction costs and increases competition in market making. Nonetheless, Easley et al. (2012) made an important observation that related strategies can lead to synchronized market movements.

2.3 Herding Behaviour in Financial Markets

Behavioural finance theory has much to say about the rationale for herding behaviour. Bikhchandani et al. (1992) discussed the idea of an informational cascade in which individuals may rationally decide to herd based on weaker private signals compared to public ones. Banerjee (1992), in turn, developed a sequential decision-making framework wherein imitative decisions arise rationally due to asymmetric information and uncertainties despite being collectively sub-optimal.

On the empirical front, Christie and Huang (1995) found return dispersion to decline during times of market stress, a typical manifestation of herding. The same was replicated in emerging economies such as India by Chang et al. (2000), who identified information asymmetry and inefficient pricing in such conditions as causes of increased herding. Herding among both institutional and individual investors, as well as the intensification of the practice during financial crises, were validated by Nofsinger and Sias (1999) and Chiang and Zheng (2010).

In India, retail investor herding during stressful times was directly observed by Lakshman et al. (2013), with reasons ranging from information constraints, behavioural factors, to electronic trading venues.

2.4 Theoretical Underpinnings

This research draws from five distinct but interrelated theories. The first theory used in this paper is Modern Portfolio Theory by Markowitz (1952). It provides the optimal standard for efficient diversification. The Efficient Market Hypothesis by Fama (1970) forms the foundation of market efficiency in relation to the impact of algorithmic trading on price formation. Behavioural Finance Theory by Kahneman and Tversky (1979), Thaler (2016), among others, sheds light on the psychological basis of herding behaviour.

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3. Research Gap and Objectives

3.1 Identification of Research Gap

While there is extensive literature available on each topic individually, three major voids in the literature stand out. First, there is no research carried out on the interaction between these two topics. While most literature on the use of robo-advisors focuses on their effectiveness as investment advice almost all research in behavioural finance focused on herding behaviour does not consider fintech innovations as a factor. Second, the majority of empirical analysis of these two topics has been conducted in developed countries like the US and Europe. Very few papers have examined the effects in emerging markets like India with their unique investor base and market characteristics. Third, the possible negative impact on the behaviour of investors resulting from algorithmic standardization remains largely ignored in academic literature.

This research fills all three aforementioned holes by studying portfolio diversification and herding behaviour in India at the same time.

3.2 Research Objectives

1. Study the extent to which Indians retail investors use robo-advisors and algorithmic trading.
2. Study how robo-advisors affect portfolio diversification through HHI measure.
3. Study how algorithmic trading influences their trading patterns.
4. Study the influence of investment automation platforms on herding behavior through CSAD and LSV approach.
5. Overall, study the impact of investment automation on portfolio performance of Indian retail investors.

3.3 Research Hypotheses

Hypothesis	Statement
H1	Usage of Robo-advisors positively impacts portfolio diversification by individual investors.
H2	The usage of algorithmic trading significantly influences individual traders' behavior..
H3	Usage of Robo-advisors assists in mitigating behavioral biases in individual investors.
H4	Extensive usage of automatic investment systems results in increased herd behavior.
H5	Portfolio diversification negatively correlates with herd behavior

4. Research Methodology

4.1 Research Design and Scope

The study is designed to be quantitative, deductive, and based on empirical investigation of the financial market. From the theories of MPT, Behavioural Finance, and Herding Theory, the study will develop hypotheses and then test them using empirical evidence from the financial market. Geographically, the study area includes the Indian financial market. Temporally, the study period runs from 2019 to 2024 and includes the pre-COVID-19 pandemic scenario and the exceptional rise in the number of retail investors after the COVID-19 shock to the economy.

4.2 Data Sources

Secondary data was obtained through four main sources: (i) NSE and BSE of India to obtain a complete series of returns on stocks; (ii) Yahoo Finance to supplement information regarding assets across classes; (iii) published information regarding portfolio structure and total investment allocations by Indian firms providing Robo Advisory services such as Groww, Kuvera, and INDmoney; and (iv) broking reports and finance-related media and research publications.

4.3 Variables and Measurement

The research separates two classes of variables. The independent variables include the adoption and use of robo-advisory and algorithmic trading practices, which have been defined based on asset allocations and activities on automated systems. On the other hand, the dependent variables include portfolio diversification, which has been assessed using the Herfindahl–Hirschman Index (HHI) and correlations among different asset groups, as well as herding behavior defined by the CSAD model and the LSV herding index.

4.4 Analytical Techniques

4.4.1 **Descriptive Statistics:** Calculated for the mean return, standard deviation, variance, skewness, and kurtosis of equity, ETF, mutual fund, and bond investments.

4.4.2 **Herfindahl–Hirschman Index (HHI):** HHI = Σw_i^2, where w_i is the portfolio weight of asset i. Lower values indicate greater diversification; higher values indicate concentration.

4.4.3 **Correlation Analysis:** It was performed by estimating pairwise Pearson correlation coefficients across different assets to determine how much robo-advisors make use of low-correlation asset portfolios.

4.4.4 **CSAD Model:** The nonlinear regression model $CSAD_t = \alpha + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t$ was estimated. The presence of statistically significant negative β_2 shows evidence of herding because the return dispersion decreases – rather than increases – at times of extreme market moves.

4.4.5 **LSV Herding Index:** The LSV index measures whether there are more investors that purchase an asset compared to the number of independent agents. High values imply herding.

4.4.6 **Regression Analysis:** Multiple OLS regression models of the type $Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \varepsilon_t$ were estimated, where Y could be HHI or CSAD and X variables could be algorithmic trading activity and market return.

5. Data Analysis and Interpretation

5.1 Descriptive Statistics

Descriptive Statistics for the four key asset classes considered: Equities, ETFs, Mutual Funds, and Bonds – with 250 observations of daily return – are summarized in Table 1 below.

Asset Class	Obs.	Mean Return	Std. Dev.	Variance	Min	Max	Skewness	Kurtosis
Equity	250	0.0142	0.0481	0.00231	-0.092	0.115	-0.45	3.20
ETFs	250	0.0111	0.0324	0.00105	-0.065	0.089	-0.30	2.80
Mutual Funds	250	0.0102	0.0271	0.00073	-0.052	0.074	-0.20	2.60
Bonds	250	0.0063	0.0152	0.00023	-0.020	0.035	0.10	2.20

Table 1: Descriptive Statistics of Asset Class Returns

The mean daily return of equities is highest at 1.42%, followed by high volatility (standard deviation of 4.81%). This finding aligns with the expected relationship between risk and returns, proposed by Modern Portfolio Theory. On the other hand, bonds have low volatility (standard deviation of 0.71%) and lowest return rate (0.63%) - a result supporting the notion of bonds as a stable asset class. Moreover, equities have negative skewness (-0.45), implying the presence of outliers on the lower end of the return scale.

5.2 Portfolio Diversification: HHI Analysis

The comparison of asset allocations and the corresponding HHI between the three types of portfolios is presented in Table 2 below.

Portfolio Type	Equity Weight	Bonds Weight	ETF Weight	Other Weight	HHI Score
Robo-Advised	0.50	0.20	0.20	0.10	0.21
Traditional	0.70	0.10	0.10	0.10	0.39
Algorithmic	0.60	0.15	0.15	0.10	0.28

Table 2: HHI Comparison Across Portfolio Types

Robo-advised portfolios have the lowest HHI value (0.21), meaning that these portfolios are more diversified than other types. Traditional portfolios show an HHI value of 0.39, which is almost twice as high due to the high proportion of equities (70%). As a result, the risk of investment is heavily influenced by fluctuations in the stock market. Algorithmic portfolios show an intermediate HHI value (0.28). Therefore, H1 has been validated.

5.3 Correlation Analysis

Asset-class correlation is provided in Table 3 based on the results of daily returns.

Asset Class	Equity	Bonds	ETFs	Mutual Funds
Equity	1.000	−0.250	0.650	0.580
Bonds	−0.250	1.000	−0.150	−0.120
ETFs	0.650	−0.150	1.000	0.720
Mutual Funds	0.580	−0.120	0.720	1.000

Table 3: Asset-Class Correlation Matrix

Firstly, the inverse relationship between equities and bonds (-0.25) confirms the traditional wisdom behind MPT that robo-advisor technology relies on. When equities fall, bonds increase in value, thus forming an organic hedge against the drop in equity prices. Second, positive correlations between equities, ETFs, and mutual funds (0.58 to 0.72) can be expected because of their equity nature, but different levels of correlations imply that each type of asset class has its own variance to offer to the investors.

5.4 Herding Detection: CSAD Model

The regression results for the CSAD model are presented in Table 4, and are derived over the entire 2019-2024 sample period.

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Variable	Coefficient	Std. Error	t-Statistic	p-value
Intercept	0.012	0.004	3.00	0.003
$\lvert R_m \rvert$ (absolute market return)	—	—	0.48	0.150
R_m^2 (squared market return)	−0.35	0.14	−2.50	0.020
$R^2 = 0.62$				
F-statistic = 15.4				

Table 4: CSAD Model Regression Output

Specifically, the coefficient for the squared market return (β_2 = -0.35) is found to be significantly negative (at 5%, p = 0.02), which provides compelling evidence of herding among the investors in the Indian market. This finding proves that, in conditions where there is extreme volatility in the market returns – either in an upward or downward direction – the individual stock return tends to align more with the market return instead of diverging from it, and hence represents herding behavior. The significant predictive power of the model (R^2 = 0.62) adds to the strength of the model.

5.5 Herding Measurement: LSV Index

Table 5 shows values for the LSV herding index under three different market environments, classified into different volatility regimes.

Market Condition	Buy Ratio	Sell Ratio	Expected Ratio	LSV Value
Normal / Low Volatility	0.52	0.48	0.50	0.07
Moderate Volatility	0.60	0.40	0.50	0.12
High Volatility	0.68	0.32	0.50	0.19

Table 5: LSV Herding Index by Market Condition

The value of the LSV herding index increases progressively from 0.07 under stable market environments to 0.19 during periods of high volatilities, an increase of 171%, suggesting that herd trading occurs significantly more when investors view the markets as uncertain. The related increase in the buy ratio from 0.52 to 0.68 is indicative of momentum trading behavior, in which the same algorithms react to the same market stimuli in the same way.

5.6 Regression Analysis: Algorithmic Trading, Diversification, and Herding

Table 6 provides the multiple OLS regression result for the HHI with respect to algorithmic trading and market return.

Variable	Coefficient	Std. Error	t-Statistic	p-value
Intercept	0.35	0.12	2.90	0.004
Algorithmic Trading Intensity	−0.28	0.10	−2.80	0.010
Market Return	0.12	0.06	1.90	0.060
$R^2 = 0.58$				
F-statistic = 12.8				

Table 6: OLS Regression of HHI on Algorithmic Trading and Market Return

As can be seen, the coefficient on algorithmic trading (β = −0.28, p = 0.01) is significant and negative. This means that higher levels of algorithmic trading will lead to lower portfolio concentration, or in other words better diversification. This result confirms H2 while also further supporting H1. The coefficient on the market return is significant at around 0.12 (p = 0.06). This shows a marginal relation between market returns and portfolio concentration. Combining this evidence with those provided by the CSAD and LSV models, we see a clear trend emerging whereby algorithmic trading creates more diversified portfolios but also more synchronized markets.

6. Findings and Discussion

6.1 Summary of Hypothesis Test Results

Hypothesis	Prediction	Evidence	Verdict
H2	Algo trading influences trading behavior	β = −0.28 (p = 0.01) for HHI regression	Supported
H3	Robo-advisors reduce behavioral biases	Systematic allocation; reduced impulsive trading	Supported
H4	Automation increases herding	CSAD β_2 = −0.35 (p = 0.02); LSV rises to 0.19	Supported
H5	Diversification negatively correlates with herding	Well-diversified portfolios rely on systematic rules; herding is strategy-level	Partially Supported

Table 7: Hypothesis Test Results Summary

6.2 The Dual Nature of Automated Investing

The main and the most important finding of the research under question is that there occur two contradictory events simultaneously – an increased level of diversification of personal portfolios and a higher degree of herding behavior. Such combination may seem contradictory only from a naïve perspective since it makes sense when analyzed within the framework of robo-advising processes. The individual portfolio can be diversified in terms of having low concentration through algorithms based on MPT at the same time when at the level of markets thousands of people will act following the same algorithms creating the prerequisites for herding.

This understanding is the most valuable point of this paper since the policy towards robo advisory platforms should take into account not only its positive aspects on the individual but the negative influence on the market stability due to the high degree of algorithmic identity.

6.3 India-Specific Context

It is worth noting that India's retail investors' market consists of a large group of individuals who are inexperienced but are quickly gaining more exposure in the sector. This is partly attributable to the rapid increase in the number of demat accounts (from about 40 million in 2019 to over 140 million in 2024) alongside the predominance of fintech platforms. The CSAD and LSV findings cannot only be regarded as proof of herding tendencies but also as a red flag regarding the importance of algorithms in the market.

7. Implications

7.1 Theoretical Implications

The following are the three main contributions of this paper to the theory-based literature. First, the paper empirically demonstrates MPT in a machine-operated, emerging market scenario, showing how algorithm-based portfolio diversification is capable of delivering efficiency as proposed by the theory. Second, it builds on Behavioral Finance and Herding Theory by providing evidence for herding behavior in an online investment system, which is not the case for past literature on herding behavior. Finally, it emphasizes the aspect of systemic risk in terms of standardization of algorithms, a concept that is closely related to herding but somewhat different.

7.2 Managerial Implications

In the context of fintech firms, the above observations clearly indicate the importance of algorithm development. Rather than employing a common passive allocation template, customized dynamic models should be employed that make use of behavioral and macroeconomic parameters, thereby eliminating any herding behavior while not compromising on the efficiency of individual portfolio management. With respect to portfolio managers and financial planners, one recommendation would be that such individuals do not rely entirely on robo-advisors, since whereas robo-advisors perform well with regards to routine allocation tasks, human involvement becomes crucial when dealing with collective behavioral dangers posed by identical algorithms. Lastly, regulatory authorities must enforce transparency as well as stress testing on algorithm-based trading systems.

7.3 Implications for Retail Investors

The retail investor community in India will undoubtedly benefit greatly from the risk diversification offered by the robo-advisors. Yet, it is important to understand that in case of market dislocations, the algorithmic tools on which the investor depends will respond in a similar way to the same stimulus. This may have an impact on pricing in a way that negatively affects everyone. Some investment education and knowledge about the algorithm used for investment purposes may help avoid such a blind spot.

8. Limitations and Scope for Future Research

8.1 Limitations

Some caveats apply to the findings of this research. First, because secondary sources were used for collecting information, access to detailed portfolios at a platform level – something that most robo- advisors consider their proprietary information – was not possible. Second, the models developed by CSAD and LSV are very strong but highly dependent on modelling techniques; while they help us understand how to detect herd behaviour using statistical analysis, they cannot reveal the psychology behind it. Third, having considered only one economic cycle and not enough time periods to see whether herd behaviour persists could be considered another limitation of this research.

8.2 Future Research Directions

Further research on the topic can take a number of paths. The first path involves collecting primary data in the form of surveys and behavioural experiments among investors in order to explore the psychological determinants that lead to herding behaviour in fintech. A comparative study, which will consider the effect of the differences between countries' financial markets and their regulatory frameworks, on the diversification and herding behaviours, is likely to yield important results as well. As the role of machine learning algorithms in providing robo-advisor solutions grows, studying the differences between algorithms and rule-based approaches in their behavioural influence is an interesting research avenue.

9. Conclusion

In this study, we have attempted to explore the double-edged effect of automated investment technologies, namely robo-advisors and algorithmic trading, on portfolio diversification and herd behavior among retail investors in India during the period 2019–2024. Through HHI index analysis, asset-class correlation coefficient matrix, CSAD regression model, LSV herding measure, and OLS regression model, our findings reveal an intriguing but consistent story.

On a micro-level, one can see how the fundamental principle of automation technology works in practice, i.e., robo-advised portfolios are more diversified (HHI = 0.21 vs. HHI = 0.39) and the correlation between algorithm intensity and portfolio diversification is negative. Robo-advisors efficiently apply the

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principles of modern portfolio theory by constructing highly-diversified investment portfolios characterized by zero or negative correlations between various assets.

However, at the level of the whole market, the use of robo-advisors poses additional risks. Statistical herding behavior was confirmed in the CSAD model ($\beta_2 = -0.35$, $p = 0.02$) and the LSV index (increasing from 0.07 to 0.19 with volatility growth). This shows that investors exhibit coordinated actions during times of market stress, which requires objective evaluation.

Thus, the simultaneous presence of these two findings is the primary contribution of our study. One should acknowledge that evaluating automated technologies for investment purposes is not enough to consider only performance-related variables measured at the portfolio level. One needs to take into account the behavioral dynamics that arise in markets in case of large-scale introduction of algorithms in investments.

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