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Empirical analysis of adaptive market hypothesis using Sharpe Ratio for buy and sell opportunities in global indices

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ABSTRACT

This study aims to investigate market efficiency and compare the profitability of the Sharpe Ratio Minimae and Maximae trading strategies with the buy-and-hold strategy across indices in different global markets. It tests the prevalence of the Adaptive Market Hypothesis (AMH) by analyzing cyclical variations in strategy performance. The research covers stock indices from six countries, analyzing monthly data spanning January 1998 to December 2023. A rolling window approach is adopted to evaluate time-varying performance and explore potential correlations with market inefficiency. Statistical tests are employed to examine the dynamics of the Sharpe Ratio and its role in investment decision-making and risk assessment. The findings reveal that the Sharpe Ratio Minimae and Maximae strategies consistently outperformed the buy-and-hold strategy across all indices. These strategies achieved higher returns per unit of risk, validating the Adaptive Market Hypothesis by highlighting cyclical variations in market profitability. The results confirm the superior performance of Sharpe Ratio-based strategies over the buy-and-hold approach, supporting the presence of evolving market efficiency in line with the Adaptive Market Hypothesis. The study provides actionable insights for investors and portfolio managers, emphasizing the importance of recognizing market inefficiencies and adopting adaptive strategies. Adjusting investment approaches based on changing market conditions can significantly improve risk-adjusted returns.

Contribution/Originality: This study integrates performance metrics with adaptive trading strategies, offering actionable insights for investors. This research bridges the critical gap in comprehending the dynamic nature of market efficiency over time.

1. INTRODUCTION

Extensive research has been conducted on stock return predictability, a topic of significant interest due to its direct relevance to the weak-form Efficient Markets Hypothesis (EMH). The EMH posits that stock prices incorporate complete information present in the historical price movements of the market (Fama, 1965, 1970). According to the EMH, prices adhere to a "random walk" pattern, meaning that changes are inherently unpredictable and random. Consequently, investors are unable to achieve consistently higher returns over a period of time. Investors prioritise allocating time and resources toward seeking new information only when they perceive it to be valuable (Grossman & Stiglitz, 1980). Under such circumstances, they stand a chance to attain higher returns on investment. Fama (1970) proposed the categorisation of market efficiency into three broad categories, that is, weak, semi-strong, and strong, with efficiency levels differing in different markets. In recent times, behavioural finance has emerged to explore the rationality of market participants and the efficiency of financial markets.

Yen and Lee (2008) gave a historical overview of the last six decades' worth of empirical research on the EMH. Their investigation illustrates a notable decline in the strong support the EMH garnered during the 1960s, with increasing scrutiny and challenges emerging from behavioural finance during the 1990s. Malkiel, Mullainathan, and Stangle (2005) explicitly support the prevalence of the EMH and advocate that behavioural finance remain steadfast in their respective positions. Moreover, the supporters of the EMH frequently critique behavioural finance for its predominantly observational nature, asserting that it lacks explanatory principles for their counterexamples.

To bridge the gap between conflicting viewpoints, Lo (2004) and Lo (2005) stated that a biological viewpoint can yield insightful conclusions, supporting an evolutionary substitute for conventional ideas of market efficiency. Specifically, he introduced the adaptive markets hypothesis (AMH), which allows for the coexistence of EMH and behavioural finance coherently. Within this framework, market efficiency is viewed not as a binary condition but as a continuum that evolves and varies across different markets. Lo (2004) supported the AMH and argued that market efficiency is not an all-or-nothing case. Rather, efficiency is not constant but rather varies over time and across markets in response to shifting market dynamics. Consequently, market efficiency is characterised as greatly context-dependent and vigorous, rooted in evolutionary principles. Kian-Ping Lim and Brooks (2011) emphasized how the AMH's tenets are derived from a number of disciplines, including complex systems theory, behavioural ecology, evolutionary psychology, and bounded rationality in economics. Specifically, it suggested that concepts such as competition, modification, reproduction, and natural selection serve as fundamental determinants of market efficiency, influencing the moments in the financial markets (Lo, 2005). Cruz-Hernández and Mora-Valencia (2024) study analyzes the Adaptive Market Hypothesis in five major Latin American stock indices, using various predictability tests and a GARCH-M model to assess time-varying efficiency. The findings confirm that these markets exhibit shifting periods of efficiency and inefficiency, consistent with the Adaptive Market Hypothesis. Raju and Jagannathan (2024) analyzes major global indices (1998–2023) to evaluate the Adaptive Market Hypothesis through simple moving average strategies, revealing superior returns over buy-and-hold during periods of market inefficiency. The findings support AMH as a more effective framework than EMH for understanding emerging market dynamics.

By combining the Simon (1955) conceptualised bounded rationality and 'satisfying with evolutionary dynamics, the guiding principles of the AMH, as outlined by Lo (2005) are (1) People behave in their own best interests; (2) People make mistakes; (3) People grow and adapt; (4) Competition spurs innovation and adaptation; (5) Natural selection forms the ecology of markets; and (6) Evolution establishes the dynamics of markets. AMH has a number of useful ramifications for managing the portfolio. First of all, the state of the stock market defines the equity risk premium, which varies over time. Second, there are sporadic possibilities for arbitrage in the financial markets. Thirdly, fluctuations in industry competitiveness, investor adaptability, company environment, and profit potential lead to cycles of both strong and poor performance. Ultimately, survival stands as the sole objective, crucial for the progression of the security market.

The AMH emphasises the significance of timing when it comes to adopting advantageous investment strategies. This is predominantly important as the opportunities for profitability change over time, highlighting the practical application of AMH in navigating dynamic market efficiency. In line with an evolutionary viewpoint on the market, opportunities to generate super-normal profits are observed occasionally; however, they vanish as soon as they are exploited. The unique market conditions stimulate the emergence of profitable tactics. Therefore, the AMH is in favour of active portfolio management, contrary to the EMH's argument stating that it is impractical and cannot beat the buy-and-hold strategy. The AMH argues that efficiency of the market is dynamic over time, with the sporadic emergence of profit opportunities. The effectiveness and profitability of trading tactics are contingent on the prevailing market conditions.

The present study aims to examine the effects of the AMH on multiple indices over the period from January 1, 1998, to December 31, 2023. While previous research has predominantly employed linear and non-linear tests, these approaches often fail to capture the dynamic and evolving nature of market efficiency as posited by the AMH. This study addresses these limitations by incorporating a more comprehensive framework that better aligns with the adaptive and time-varying characteristics of financial markets. Hiremath and Kumari (2014); Lekhal and El Oubani (2020); Mandaci, Taşkın Yeşilova, and Ergün (2019); Numapau Gyamfi (2018); Obalade and Muzindutsi (2018) and Urquhart and McGroarty (2016) our empirical findings reveal that employing strategies such as Sharpe Ratio (SR) Minimae and Maximae leads to episodic momentum. Additionally, comparing the returns from these strategies with a simple buy-and-hold approach indicates that investors may need to adopt different strategies to outperform the market, contradicting the principles of the EMH (Fama, 1965).

Our research adds to the body of literature in the following ways. Firstly, to the best of our knowledge, this is the initial investigation to systematically monitor and elucidate the transient opportunities for earning abnormal returns, which emerge intermittently across multiple global indices, using the maximae and minimae strategy. Secondly, we employed the Sharpe ratio (SR) to compute the anticipated (excessive) returns to prove active management of the portfolio is better than the buy-and-hold strategy.

The rest of the paper is structured as follows: The second section delves into the related literature, including literature on the SR; the third section offers insights into the methodology employed; the fourth section of the study reports empirical results, while the final section discusses the study's conclusions, discussion, and implications.

2. LITERATURE REVIEW

The extant literature provides two distinct empirical methodologies that are commonly employed to investigate the AMH. The first approach, known as the "time-varying model" approach, focuses on analysing market efficiency (Ito, Noda, & Wada, 2014, 2016). These studies demonstrated that the level of market efficiency varies over time. The second approach uses the rolling window method to look into market efficiency. Since we used SR to test the efficiency in different indices, we provide an in-depth review of research in this domain.

Financial experts rely extensively on risk-adjusted return indicators commonly referred to as performance measures to choose among the available investment funds. Sharpe (1966) developed the reward-to-variability ratio, or SR as it is most often known. It swiftly garnered broad popular approval and now boasts nearly universal adoption across the financial realm. Since its inception in Sharpe (1966) pioneering work has been widely referenced and utilised in the literature. The SR quantifies the association between a portfolio's anticipated return and the standard deviation of its return series. It is a well-known indicator used to assess the success of portfolios. Meyer and Rasche (1992) studied that the SR proves to be a suitable performance metric when an investor intends to consolidate multiple assets into a single investment avenue. They argued that the return on the investment ensures alignment between the mean and standard deviation along with the expected utility. Eling and Schuhmacher (2007) provided evidence that the use of the SR may yield nearly identical returns compared to alternative performance measures. Lo (2002) demonstrated that the SR has its roots in mean-variance analysis and is used in various contexts, such as risk management, market efficiency assessments, and performance attribution; hence, it may be considered better than other performance metrics. Schuster and Auer (2012) investigated the dynamics of the empirical SR, and shed light on its temporal evolution and variations in different market conditions. The researchers analysed how these SR dynamics influence investment decision-making and risk assessment strategies. Noreen, Shafique, Ayub, and Saeed (2022) test the Adaptive Market Hypothesis using investor myopia as a proxy, analyzing NYSE data from 1994–2020. It finds that the Sharpe ratio and Lower partial moment ratio yield similar results, with investor behavior switching between myopic and non-myopic phases, indicating time-varying market efficiency.

Cooper, Gutierrez, and Marcum (2005) argued that the real-time predictability of stock returns may highlight the SR's advantage in assessing risk-adjusted performance. It likely emphasises the ratio's ability to provide a comprehensive measure by incorporating both return and risk considerations. The study delved into how the SR, in real-time analysis, aids investors in making informed decisions by factoring in the trade-off between return and volatility. Bailey and López de Prado (2012) stated that the SR will surpass a given level of threshold in case of non-normal yields. McLeod and Van Vuuren (2004) underscored the potential for market outperformance, reinforcing the significance of active portfolio management. Yet, the findings affirmed that both active and passive portfolio managers should refer to distinct SR variations for outperforming the market. Modigliani and Modigliani (1997) emphasises the importance of risk adjustment and discuss the application of risk-adjusted measures. Using SR, they provided a comprehensive assessment of portfolio performance, ensuring a balanced consideration of risk and returns. Van Heerden (2020) focused on enhancing the risk assessment component within the SR framework for selecting shares, particularly within the context of a momentum investment strategy. The study explored methodologies for adeptly integrating momentum strategies into the evaluation of risk-adjusted performance. The authors' primary goal was to provide valuable insights that can improve the process of share selection by giving due consideration to the risk element within the SR. According to Darolles and Gourieroux (2010) in a mean-variance portfolio context, interpreting Sharpe's performance is straightforward, allowing for coherent rankings based on diverse information sets, benchmark portfolios, and horizons. The ease of implementation involves performing regressions and calculating Sharpe performance measures, as demonstrated in hedge fund applications. Particularly for retail hedge fund investors, analysing a variety of Sharpe performances stands out as the primary and essential approach.

While many researchers have expressed appreciation for the SR, it is worth mentioning that some studies have voiced opinions against its application. Scholz (2007) evaluated and compared refinements to the SR against the original, aiming to determine the most suitable measure for ranking mutual funds in various market conditions. The study revealed that the original SR can yield misleading rankings during bear markets. They additionally proposed the refinements for exhibited flaws, emphasising the importance of theoretically derived solutions. The study recommended employing the normalised SR for accurate ex-post-performance measurement, particularly in atypical market conditions, highlighting its relevance over the original and other modified versions. Auer (2013) addressed issues related to low return scenarios with the SR framework. The study explored how the SR is affected when confronted with low returns, offering insights into potential distortions in risk-adjusted performance measures. Understanding these distortions is crucial for a comprehensive assessment of investment strategies, particularly during periods of diminished returns. Auer and Schuhmacher (2013) pinpointed the limitations, stressing the need for a more holistic hypothesis-testing approach that extends beyond the SR. The authors maintained that SR inadequately captures the intricate dynamics of hedge fund performance, advocating for a more nuanced evaluation framework. Bao and Ullah (2006) estimated SR's second-order bias and variance analytically in situations where the return series wasn't independently and identically distributed. Interestingly, they demonstrated that variance and bias expressions that are created depend on the covariance structure that is present during the process of creating the data. Christie (2005) researched that SR may mislead due to sampling errors in return mean and variance estimates. The SR exhibited less informative distributions compared to mean and variance estimators, potentially rendering less reliable conclusions. The sizable error in SR estimates may undermine their utility in making robust investment decisions.

Against this backdrop, we integrate Minimae and Maximae's strategy with the SR to assess market efficiency or adaptability. Moreover, we compare the returns of this approach with buy-and-hold strategy. This is accomplished through the application of rolling window analysis, allowing us to compare returns between passive and active trading strategies. According to Zivot, Wang, Zivot, and Wang (2003) rolling window analysis is a more appropriate way for evaluating the stability and predictive accuracy of a time series model. This method involves systematically conducting back-testing on historical data to assess the model's performance over time. The back-testing process typically involves dividing the data into an estimation sample and a prediction sample, allowing for a comprehensive evaluation of the model's effectiveness across different periods. Lim and Brooks (2006) and Lim (2007) also evaluated the frequency with which the test statistic fails the random walk hypothesis using the rolling window approach. Taking this into account, we investigate the market's efficiency using various statistical measures employing the rolling window approach (Kian-Ping Lim & Brooks, 2011; Lim, Luo, & Kim, 2013; Lo, 2004).

3. DATA AND METHODOLOGY

This paper explores the changing dynamics of market efficiency by conducting tests of SR Minimae and Maximae strategies in comparison to the buy-and-hold strategy. The paper utilises a more widely recognised and accepted methodology as we rely on monthly data and also back-tested the SR Minimae and Maximae strategy on several indices, including the Bombay Stock Exchange (BSE)[1], Dow Jones Industrial Average (DJI), Nikkei 225, German DAX, Hang Seng Index, and Financial Times Stock Exchange. This study covers 26 years, starting from 1st January 1998 and 31st December 2023.

Moreover, for assessing the annual predictability metrics, we utilise a rolling window analysis with a fixed duration of 10 years. The test statistics are computed by considering data from January 1, 1998, to December 31, 2007. Subsequently, the window is rolled by one year, encompassing the period from 1 January 1999 to 31 December 2008. This process is iterated until the conclusion of the dataset, yielding predictability measures for returns up to December 31, 2023. The choice of a 10-year window ensured an adequate number of observations for generating robust and reliable results.

The study employs SR Minimae and Maximae strategies in comparison to the buy-and-hold strategy to reflect changes in market efficiency, consistent with the Adaptive Market Hypothesis (AMH). Monthly data is used to reduce noise and capture meaningful trends, while a selection of global indices ensures representation of diverse market conditions. A 10-year rolling window is chosen to capture dynamic shifts in predictability, balancing robust data and adaptability. The study spans 1998-2023, covering key economic cycles to provide a comprehensive view of evolving market behavior. This approach enables reliable insights into AMH across varying economic environments. Figure 1 illustrates the process of implementing a Sharpe ratio-based trading strategy using rolling windows.

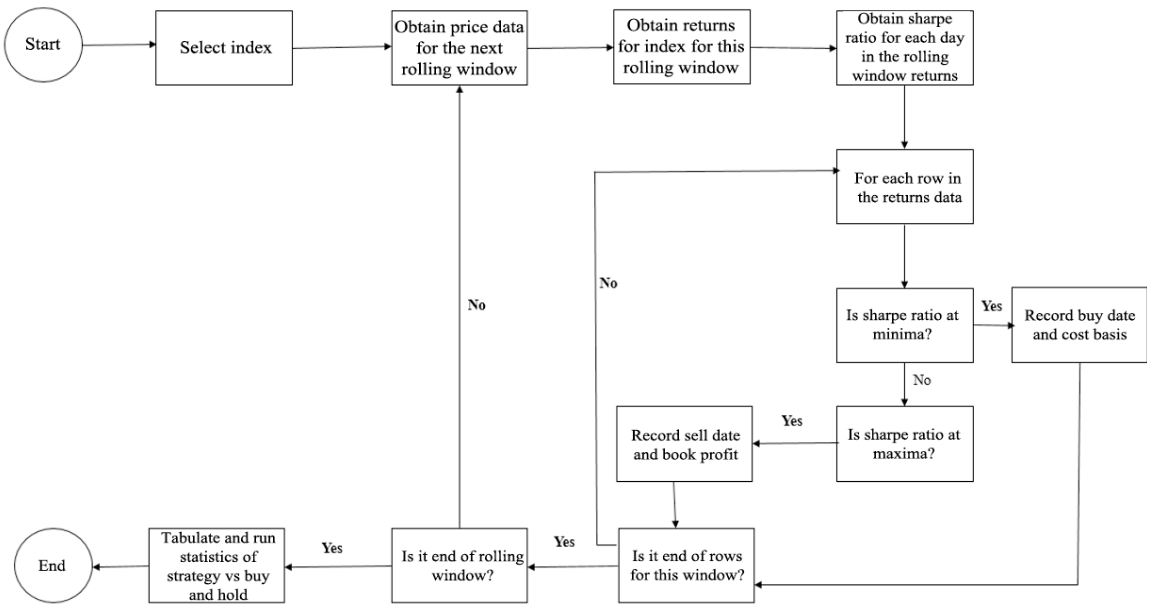

Figure 1. Conceptual framework of Sharpe ratio maxima and minima strategy.

For the strategy, the formulation for the SR would be:

[1] The Bombay Stock Exchange (BSE) is Asia's oldest stock exchange established in 1875.

$$R_t = \frac{ln(P_{t+1})}{ln(P_t)}, \quad (1)$$

Where P_t = Index Price in time t.

$$SR_t = \frac{R_t}{\sigma_t}, \quad (2)$$

Where R_t = Return in time t, σ_t is the standard deviation in time t.

$$SR_{t-1} < SR_t \text{ and } SR_{t+1} < SR_t, \quad (3)$$

For the Maxima to be reached in the SR where $1 < t < m$ and there are m time periods and indicates a sell.

$$SR_{t-1} > SR_t \text{ and } SR_t < SR_{t+1}, \quad (4)$$

For the Minima to be reached in the SR where $1 < t < m$ and there are m time periods and indicates a buy.

$$\text{Total Profit} = \sum_{i=1}^{N}(P_{sell,i} - P_{buy,i}), \quad (5)$$

Where N = Total number of transactions in the strategy.

$$Profit\ percent = \left(\left(\frac{Total\ Profit}{P_{buy,i=0}}\right)\right) * 100, \quad (6)$$

$$Passive\ Profit\ percent = \left(\left(\frac{P_{final}}{P_{buy,i=0}}\right) - 1\right) * 100. \quad (7)$$

Equation 1: Shows the geometric return of the index being analysed.

Equation 2: Is the formation of the SR.

Equation 3: Defines the Maximae condition for the SR.

Equation 4: Defines the Minimae for the SR.

Equation 5: Formulates the total profit per transaction and the SR as per strategy.

Equation 6: Formulates the profit percent derived from the strategy for the entire period.

Equation 7: Formulates the profit percent for passive strategy.

Important assumption: Transaction costs are assumed to be zero in this entire research paper.

4. EMPIRICAL RESULTS

This section provides a detailed discussion of the empirical findings of the study. First, we provide a discussion on the descriptive statistics. Descriptive statistics provide insights into market efficiency and the Adaptive Market Hypothesis (AMH) by comparing the buy-and-hold strategy with portfolios created using Sharpe Ratio (SR) Minimae and Maximae strategies across six major indices from 1998 to 2023. In Table 1, buy-and-hold returns show low mean values (e.g., 0.01 for BSE Sensex, 0.01 for DJI), suggesting relatively stable yet limited profitability and a certain degree of market efficiency in the long term.

In contrast, Table 2 shows that SR-based strategies yield higher mean returns (e.g., 0.07 for BSE Sensex, 0.05 for DJI), indicating potential opportunities for excess returns, which aligns with AMH's premise that market efficiency fluctuates over time. Higher standard deviations (e.g., 0.07 for BSE Sensex, 0.06 for DJI) in Table 2 also suggest increased volatility, reflecting that adaptive strategies may expose portfolios to greater risk as they exploit inefficiencies. The Jarque-Bera (JB) test statistics are significant across both tables, with values (e.g., 38.89 for BSE Sensex in Table 1, 267.74 for DJI in Table 2), indicating non-normal distributions of returns, which further supports AMH by showing that markets may not consistently adhere to efficiency assumptions. Notable differences in skewness and kurtosis demonstrate shifts in return distributions, suggesting changing market dynamics.

Overall, the results show that buy-and-hold strategies are consistent with stable efficiency, while SR-based strategies are more in line with AMH's view of evolving efficiency. This is because adaptive strategies change with the market over time, resulting in different levels of risk and profitability.

Table 1. Descriptive statistics for buy and hold for the sample period i.e. 1-1-1998 to 31-12-2023.

	Index	Count	Mean (μ)	S.D (σ)	Min.	25%	50%	75%	Max.	J B t-stat	p-value J B test	Skewness	Kurtosis
Return	BSE sensitive index (BSESN)	312	0.01	0.07	-0.24	-0.03	0.01	0.06	0.28	38.89	0.0000***	-0.20	4.68
	Dow Jones industrial average (DJI)	312	0.01	0.04	-0.15	-0.02	0.01	0.03	0.14	23.48	0.0000***	-0.40	4.06
	Nikkei 225 (N225)	312	0.004	0.05	-0.24	-0.03	0.01	0.04	0.15	19.86	0.0000***	-0.48	3.76
	German DAX (GDAXI)	312	0.01	0.06	-0.25	-0.03	0.01	0.04	0.21	59.62	0.0000***	-0.48	4.91
	Hang Seng index (HSI)	312	0.004	0.07	-0.22	-0.03	0.01	0.04	0.29	58.63	0.0000***	0.39	4.97
	Financial times stock exchange (FTMC)	312	0.01	0.05	-0.22	-0.02	0.01	0.04	0.18	135.68	0.0000***	-0.80	5.81

Note: *** represent 1 percent level of significance, Python version 3.12.1, and scipy library were used to compute the statistics.

Table 2. Descriptive statistics for portfolios created from Sharpe ratio minimae and maximae for the sample period i.e. 1-1-1998 to 31-12-2023.

	Index	Count	Mean (μ)	S.D (σ)	Min.	25%	50%	75%	Max.	J B t-stat	p-value J B test	Skewness	Kurtosis
Return	BSE sensitive index (BSESN)	75	0.07	0.07	-0.14	0.02	0.06	0.10	0.33	30.08	0.0000***	0.76	5.70
	Dow Jones industrial average (DJI)	72	0.05	0.06	-0.25	0.02	0.05	0.07	0.21	267.74	0.0000***	-1.37	12.04
	Nikkei 225 (N225)	67	0.05	0.07	-0.22	0.01	0.05	0.07	0.25	12.88	0.0015***	-0.15	5.12
	German DAX (GDAXI)	72	0.05	0.08	-0.27	0.01	0.05	0.08	0.28	65.20	0.0000***	-0.69	7.44
	Hang Seng index (HSI)	77	0.05	0.08	-0.18	0.01	0.05	0.09	0.33	15.70	0.0003***	0.38	5.07
	Financial times stock exchange (FTMC)	68	0.04	0.07	-0.22	0.01	0.04	0.08	0.29	54.79	0.0000***	-0.02	7.39

Note: *** represent 1 percent level of significance, Python version 3.12.1, and scipy library were used to compute the statistics.

Table 3. Comparison of return per unit risk of buy and hold versus strategy using actual holding period values for strategy.

	Index	Return per unit of risk from buy and hold μ/σ	Return per unit of risk from strategy μ/σ
Return	BSE sensitive index (BSESN)	0.1428	1.0000
	Dow jones industrial average (DJI)	0.2500	0.8333
	Nikkei 225 (N225)	0.0800	0.7142
	German DAX (GDAXI)	0.1666	0.6250
	Hang Seng index (HSI)	0.0571	0.6250
	Financial times stock exchange (FTMC)	0.2000	0.5715

Table 3 compares the return per unit of risk (μ/σ) for the buy-and-hold strategy versus the SR-based strategy across six major indices. The strategy outperforms buy-and-hold in risk-adjusted returns for all indices, with values such as 1.000 for BSE Sensex and 0.8333 for DJI, compared to 0.1428 and 0.2500, respectively, for buy-and-hold. This suggests that the strategy generates higher returns relative to risk, supporting the Adaptive Market Hypothesis (AMH) by showing that adaptive strategies can exploit market inefficiencies. The higher μ/σ ratios for the strategy indicate it is more efficient in terms of risk-return trade-off, especially in indices like BSE Sensex and DJI. This aligns with AMH's perspective that market efficiency is not static and can be leveraged through dynamic strategies.

This section discusses the empirical findings from the test presented in the previous part. We test whether the return from the SR supports the AMH and beats the buy-and-hold strategy. For that, we rely on the rolling window approach. Tables 4 to 9 represents the returns from the strategy and compare the returns from the strategy with the returns from the buy and hold using the t-test for comparison of sample means. Table 4 represent BSE Sensitive Index (BSESN); it depicts returns from the AMH strategy generally outperforming the buy-and-hold returns, indicating dynamic adjustments to market efficiency over the period analyzed. The consistently significant p-values at 1% suggest robust statistical evidence of the strategy's efficacy over buy-and-hold. This implies that market efficiency fluctuated, with the AMH strategy capturing transient inefficiencies. A stronger t-statistic over time points to increasing deviations from market efficiency, possibly reflecting varying investor behavior and market adaptability. The years with the highest t-statistics reflect market phases with greater inefficiency exploitable by the AMH strategy. Table 5 symbolise DJIA, here AMH strategy yields higher returns than buy-and-hold, particularly in later windows, such as 2012-2021, where returns are 2.29% compared to 1.93%. The p-values are significant for all periods, affirming the superiority of the AMH strategy. These findings suggest that market efficiency adapts over time, aligning with the Adaptive Market Hypothesis, as evidenced by shifting Sharpe ratios.

Table 6 denotes results of Nikkei 225. The AMH strategy shows consistent outperformance, especially in periods like 2012-2021, where the returns are 2.63% against 2.36%. Statistical significance is demonstrated across most periods ($p < 0.05$), highlighting that the Nikkei 225 market efficiency is not static but evolves with time. The improvement in Sharpe ratios underscores adaptive behavior in market participants.

Table 7 exemplifies GDAXI index, and it confirms that strategy significantly outperforms the buy-and-hold strategy, particularly in windows such as 2009-2018, where returns are 2.86% versus 1.12%. All p-values are below 0.01, affirming the robustness of the results. These findings suggest that the German market exhibits periods of inefficiency, which the AMH strategy exploits, supporting dynamic efficiency concepts.

Table 8 shows results of HSI, particularly strong results in 2003-2012, where returns are 3.60% compared to 1.42% for buy-and-hold. P-values indicate statistical significance at the 1% level, supporting the premise of evolving market efficiency. The significant t-statistics confirm the potential to exploit inefficiencies in the Hang Seng market through adaptive strategies. Table 9 displays results of FTMC index; it also confirms that in 2003-2012 (2.84% vs. 1.84%). The p-values are significant at 1% for most periods, affirming the hypothesis of time-varying market efficiency. This implies that FTMC market participants adapt their strategies based on changing conditions, supporting the core tenets of the Adaptive Market Hypothesis.

Lastly, Table 10 compares the performance of an Active AMH strategy versus the traditional buy-and-hold approach for six indices from 1998 to 2023, focusing on market efficiency. The Active AMH strategy consistently outperformed the buy-and-hold approach across all indices, with higher returns and statistically significant results ($p < 0.01$). This suggests periods of inefficiency in these markets, as superior returns contradict the Efficient Market Hypothesis (EMH). The low p-values and significant t-statistics reinforce the presence of adaptive behavior, indicating that market efficiency is time-varying. The BSE Sensex showed the highest excess returns (31.45% vs. 18.55%). The results highlight that adaptive strategies can exploit inefficiencies in various market conditions.

Table 4. Rolling window analysis for active AMH strategy with Sharpe ratio returns versus returns from traditional buy and hold strategy and *p*-value for the BSE sensitive index (BSESN).

Year	Returns from strategy	Returns from buy and hold	p-value	DF	t-statistic
1998-2007	4.85	4.46	0.0042***	35	-2.78
1999-2008	4.37	2.11	0.0019***	41	-3.07
2000-2009	3.89	2.22	0.0039***	44	-2.78
2001-2010	5.21	4.07	0.0033***	44	-2.84
2002-2011	7.91	3.72	0.0001***	52	-3.97
2003-2012	9.32	4.77	0.0000***	53	-4.34
2004-2013	6.15	2.50	0.0000***	53	-4.39
2005-2014	5.35	3.10	0.0000***	56	-4.86
2006-2015	3.28	1.76	0.0000***	55	-4.61
2007-2016	2.70	0.90	0.0000***	50	-4.61
2008-2017	2.12	0.67	0.0000***	74	-5.51
2009-2018	2.54	2.62	0.0000***	66	-5.54
2010-2019	2.31	1.36	0.0000***	52	-6.43
2011-2020	2.22	1.32	0.0000***	50	-5.78
2012-2021	3.47	2.63	0.0000***	36	-5.15
2013-2022	3.45	2.08	0.0000***	35	-5.26
2014-2023	2.94	2.41	0.0000***	31	-4.91

Note: *** represent the significance level at 1 percent respectively.

Table 5. Rolling window analysis for active AMH strategy with Sharpe ratio returns versus returns from traditional buy and hold strategy and *p*-value for the Dow Jones industrial average (DJIA) index.

Year	Returns from strategy	Returns from buy and hold	p-value	DF	t-statistic
1998-2007	1.74	0.67	0.0001***	30	-4.09
1999-2008	1.00	-0.05	0.0000***	39	-4.45
2000-2009	0.75	-0.07	0.0238**	31	-2.06
2001-2010	0.71	0.08	0.0284**	31	-1.97
2002-2011	0.90	0.21	0.0173**	32	-2.20
2003-2012	1.26	0.50	0.0141**	30	-2.30
2004-2013	0.95	0.58	0.0202**	29	-2.14
2005-2014	1.03	0.67	0.0191**	29	-2.17
2006-2015	1.00	0.62	0.0185**	29	-2.18
2007-2016	0.93	0.58	0.0210**	31	-2.12
2008-2017	1.08	0.89	0.0186**	31	-2.17
2009-2018	2.14	1.55	0.0000***	39	-5.12
2010-2019	2.08	1.68	0.0000***	41	-5.21
2011-2020	2.04	1.60	0.0000***	42	-5.31
2012-2021	2.29	1.93	0.0000***	43	-5.37
2013-2022	2.32	1.47	0.0000***	47	-5.38
2014-2023	2.06	1.29	0.0000***	47	-4.77

Note: ***,** represent the significance level at 1 and 5 percent respectively.

Table 6. Rolling window analysis for active AMH strategy with Sharpe ratio returns versus returns from traditional buy and hold strategy and P-value for the Nikkei 225 (N225) index.

Year	Returns from strategy	Returns from buy and hold	p-value	DF	t-statistic
1998-2007	0.92	0.02	0.0018***	38	-3.08
1999-2008	0.82	-0.33	0.0022***	39	-3.02
2000-2009	0.49	-0.44	0.0542*	33	-1.64
2001-2010	0.59	-0.25	0.0692*	32	-1.51
2002-2011	0.87	-0.22	0.0442**	33	-1.75
2003-2012	1.38	0.19	0.0191**	33	-2.15
2004-2013	1.00	0.50	0.0292**	32	-1.96
2005-2014	0.94	0.52	0.0349**	30	-1.87
2006-2015	0.76	0.16	0.0229**	28	-2.08
2007-2016	0.86	0.10	0.0125**	27	-2.37
2008-2017	1.29	0.54	0.0120**	27	-2.39
2009-2018	2.02	1.21	0.0005***	26	-3.67
2010-2019	1.95	1.22	0.0015***	26	-3.25
2011-2020	2.18	1.63	0.0007***	25	-3.56
2012-2021	2.63	2.36	0.0014***	25	-3.29
2013-2022	1.71	1.44	0.0005***	28	-3.61
2014-2023	1.96	1.10	0.0006***	26	-3.62

Note: ***,**,* represent the significance level at 1, 5 and 10 percent respectively.

Table 7. Rolling window analysis for active AMH strategy with Sharpe ratio returns versus returns from traditional buy and hold strategy and P-value for the German DAX (GDAXI) index.

Year	Returns from strategy	Returns from buy and hold	p-value	DF	t-statistic
1998-2007	1.33	0.84	0.0043***	38	-2.76
1999-2008	1.19	-0.09	0.0053***	39	-2.68
2000-2009	0.51	-0.11	0.0464**	35	-1.72
2001-2010	0.69	0.09	0.0345**	35	-1.87
2002-2011	1.09	0.14	0.0143**	35	-2.28
2003-2012	3.04	1.45	0.0005***	39	-3.50
2004-2013	2.04	1.37	0.0009***	36	-3.36
2005-2014	1.82	1.28	0.0019***	36	-3.08
2006-2015	1.76	0.97	0.0024***	31	-3.02
2007-2016	1.82	0.71	0.0014***	32	-3.21
2008-2017	1.93	0.62	0.0020***	30	-3.10
2009-2018	2.86	1.12	0.0001***	31	-4.02
2010-2019	2.16	1.19	0.0012***	31	-3.28
2011-2020	2.08	0.96	0.0007***	30	-3.50
2012-2021	2.41	1.61	0.0010***	29	-3.16
2013-2022	1.89	0.78	0.0027***	31	-2.99
2014-2023	1.52	0.78	0.0041***	29	-2.83

Note: ***,** represent the significance level at 1 and 5 percent respectively.

Table 8. Rolling window analysis for active AMH strategy with Sharpe ratio returns versus returns from traditional buy and hold strategy and P-value for the Hang Seng index (HSI) index.

Year	Returns from strategy	Returns from buy and hold	p-value	DF	t-statistic
1998-2007	2.63	1.56	0.0105**	35	-2.41
1999-2008	2.43	0.45	0.0007***	41	-3.38
2000-2009	1.68	0.23	0.0068***	39	-2.58
2001-2010	1.54	0.54	0.0147**	41	-2.25
2002-2011	2.43	0.62	0.0082***	45	-2.49
2003-2012	3.60	1.42	0.0021***	44	-3.00
2004-2013	2.62	0.81	0.0019***	43	-3.04
2005-2014	2.31	0.65	0.0031***	39	-2.89
2006-2015	2.17	0.46	0.0026***	38	-2.96
2007-2016	1.82	0.08	0.0016***	40	-3.13
2008-2017	1.29	0.08	0.0021***	41	-3.03
2009-2018	1.74	0.69	0.0005***	39	-3.51
2010-2019	1.72	0.29	0.0001***	38	-4.01
2011-2020	1.34	0.15	0.0004***	38	-3.58
2012-2021	1.53	0.22	0.0011***	35	-3.28
2013-2022	1.00	-0.15	0.0057***	35	-2.66
2014-2023	1.22	-0.26	0.0010***	36	-3.31

Note: ***,** represent the significance level at 1 and 5 percent respectively.

Table 9. Rolling window analysis for active AMH strategy with Sharpe ratio returns versus returns from traditional buy and hold strategy and P-value for the financial times stock exchange (FTMC) index.

Year	Returns from strategy	Returns from buy and hold	p-value	DF	t-statistic
1998-2007	1.25	1.21	0.0100***	28	-2.46
1999-2008	0.97	0.32	0.0074***	41	-2.54
2000-2009	0.77	0.44	0.0292**	41	-1.94
2001-2010	0.87	0.77	0.0288**	37	-1.96
2002-2011	1.39	0.69	0.0019***	40	-3.05
2003-2012	2.84	1.84	0.0002***	36	-3.88
2004-2013	2.06	1.72	0.0002***	32	-3.87
2005-2014	1.89	1.28	0.0002***	34	-3.86
2006-2015	1.45	0.96	0.0004***	36	-3.64
2007-2016	1.16	0.59	0.0008***	35	-3.40
2008-2017	1.58	0.94	0.0003***	37	-3.68
2009-2018	2.22	1.63	0.0000***	32	-4.38
2010-2019	1.91	1.30	0.0000***	33	-4.35
2011-2020	1.10	0.76	0.0163**	29	-2.24
2012-2021	1.55	1.27	0.0167**	28	-2.23
2013-2022	0.96	0.49	0.0368**	31	-1.85
2014-2023	0.86	0.23	0.0341**	29	-1.89

Note: ***,** represent the significance level at 1 and 5 percent respectively.

Table 10. Rolling window analysis for active AMH strategy with Sharpe ratio returns versus returns from traditional buy and hold strategy and P-value for all indices for the entire sample period i.e. 1-1-1998 to 31-12-2023.

Ticker	Year	Returns from strategy	Returns from buy and hold	p-value	DF	t-statistic
BSESN	1998-2023	31.45	18.55	0.0000***	103	-6.02
DJI	1998-2023	7.24	3.73	0.0000***	92	-5.66
N225	1998-2023	3.09	1.23	0.0000***	82	-4.42
GDAXI	1998-2023	5.03	2.83	0.0000***	92	-4.52
HSI	1998-2023	6.63	0.59	0.0000***	102	-4.29
FTMC	1998-2023	5.73	3.09	0.0000***	83	-4.16

Note: *** represent the significance level at 1 percent respectively, Python version 3.12.1, and scipy library were used to compute the statistics.

Figures 2 to 7 depict the variations in the SR across the time for different indices. The ● indicates the buy points and the Minimae in the SR, while the + indicates the sell points and the Maximae in the SR.

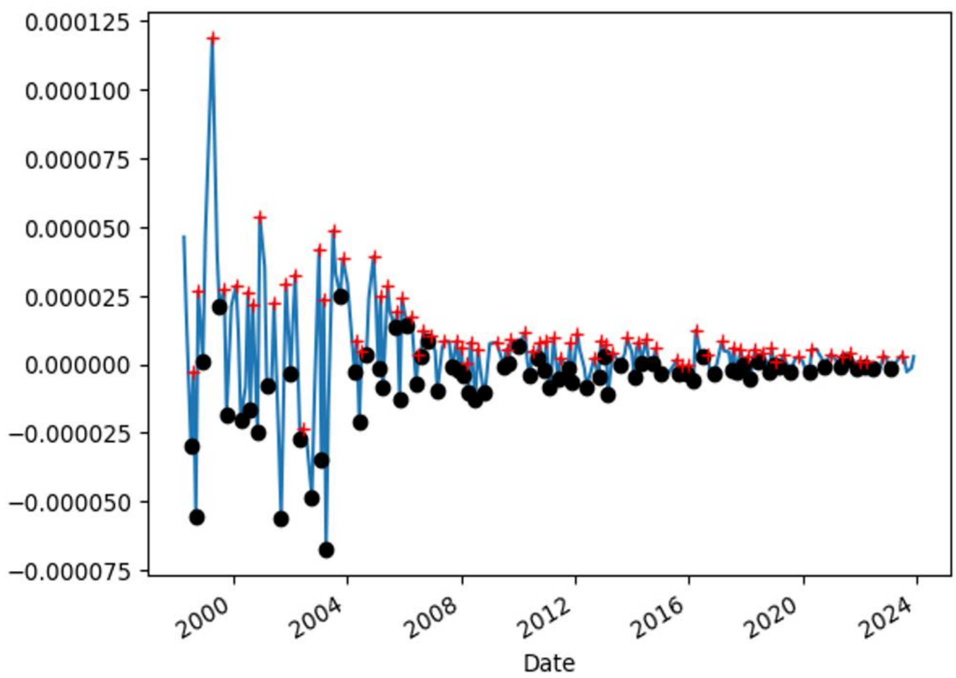

Figure 2. Trend in Sharpe ratio return in BSE sensitive index (BSESN).

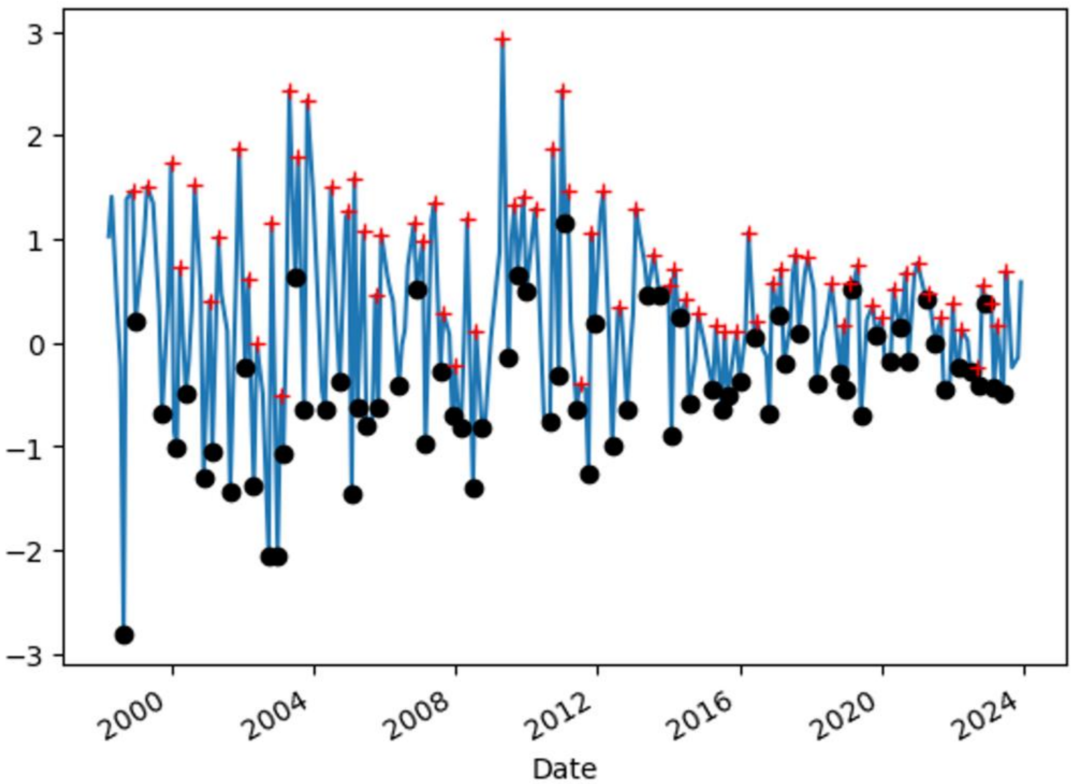

Figure 3. Trend in Sharpe ratio return in Dow Jones industrial average (DJI).

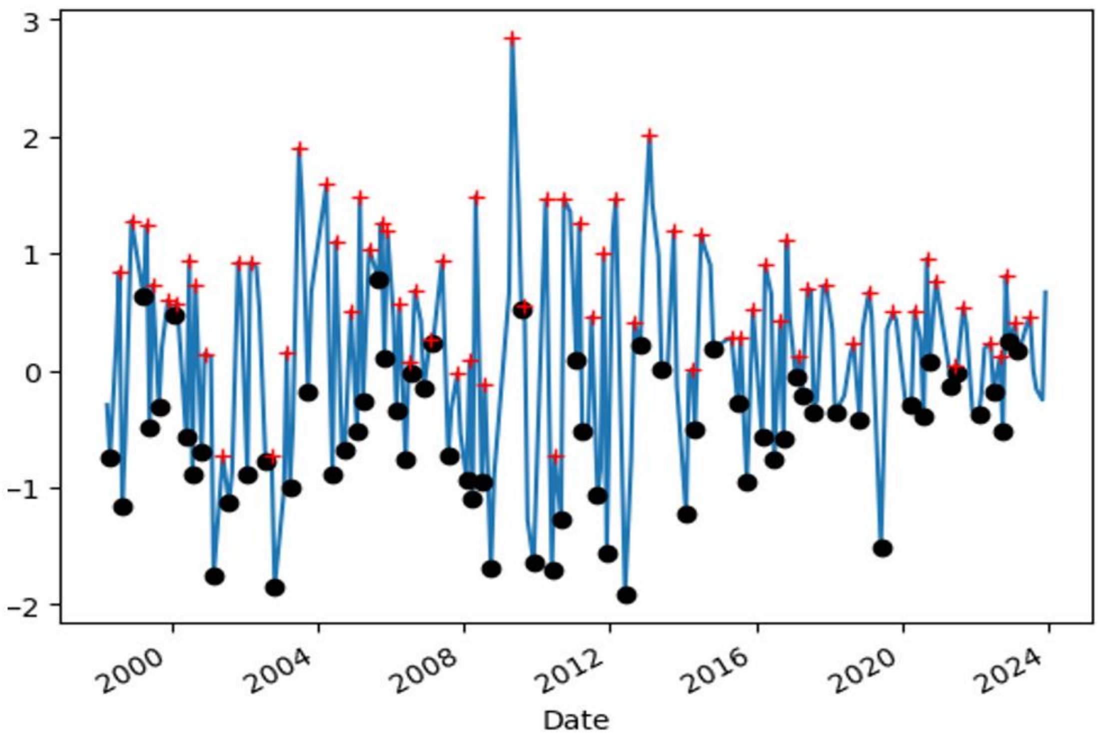

Figure 4. Trend in Sharpe ratio return in Nikkei 225 (N225) index.

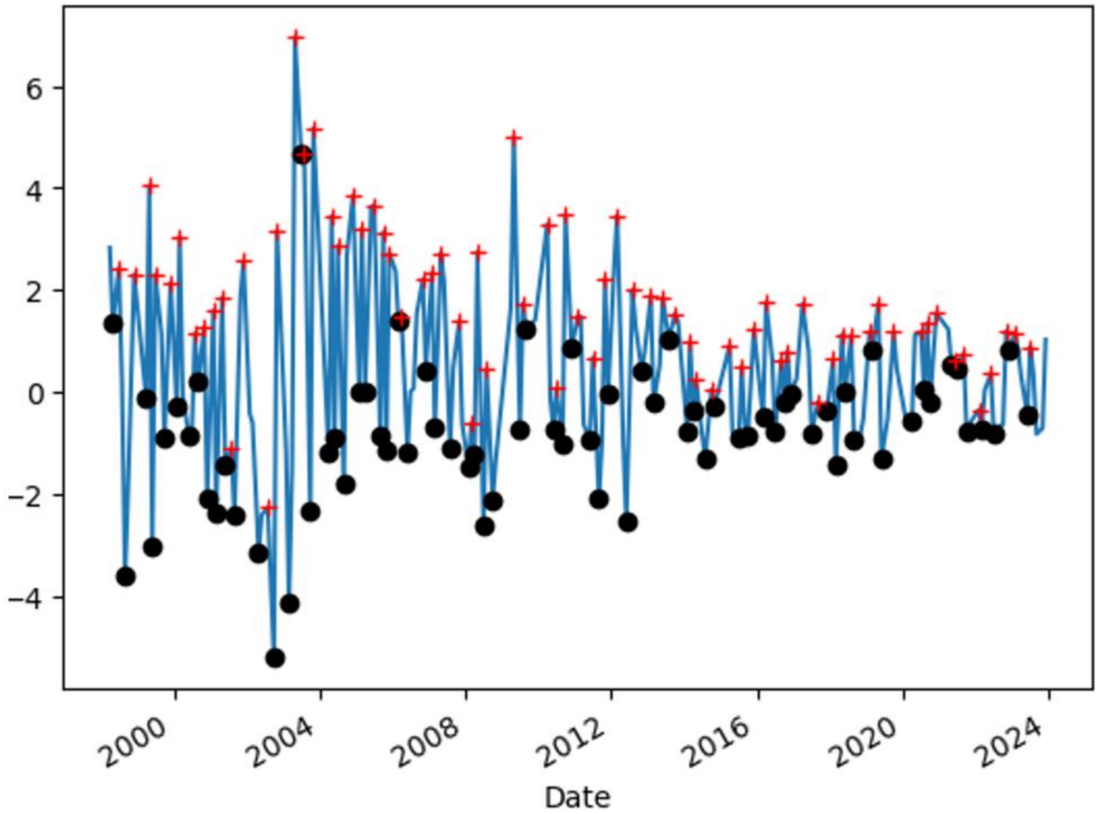

Figure 5. Trend in Sharpe ratio return in German DAX (GDAXI) index.

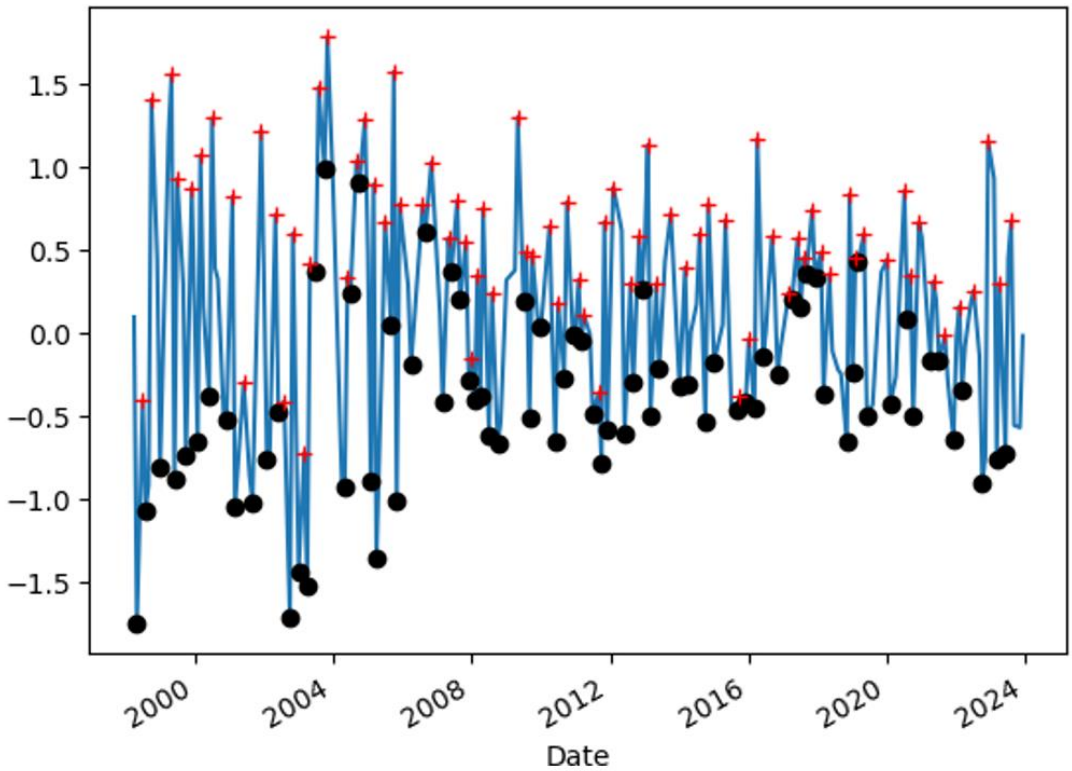

Figure 6. Trend in Sharpe ratio return in Hang Seng index (HSI) index.

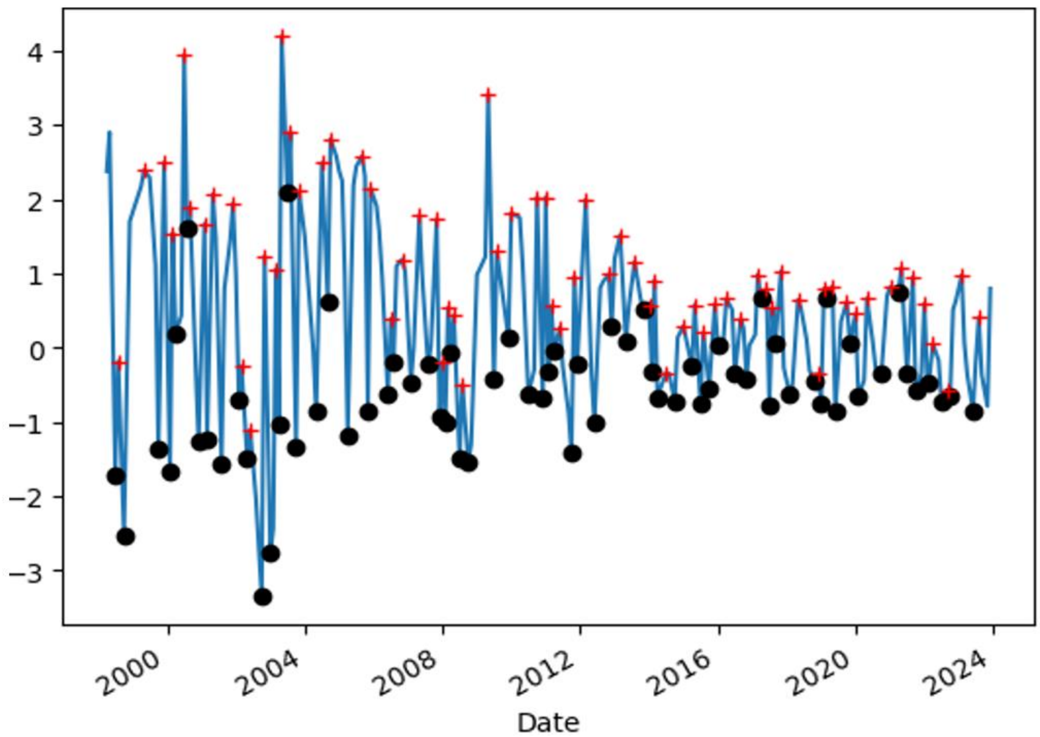

Figure 7. Trend in Sharpe ratio return in financial times stock exchange (FTMC) index.

Figures 8, 10, 12, 14, 16, and 18 depict the returns for the buy-and-hold strategy for each of the indices. The histograms show a near-normal distribution in each of the indices. The mean return for the buy and hold is depicted with the blue line. These figures are plotted in conjunction with the data in Table 1, which contains the descriptive statistics for the buy-and-hold strategy.

Figures 9, 11, 13, 15, 17, and 19 depict the returns for the strategy generated with the SR Maximae and Minimae, for each of the indices. The histograms show a near-normal distribution in each of the indices. The mean return for the strategy is depicted with the blue line. These figures are plotted in conjunction with the data in Table 2, which contains the descriptive statistics for the strategy generated using SR Maximae and Minimae.

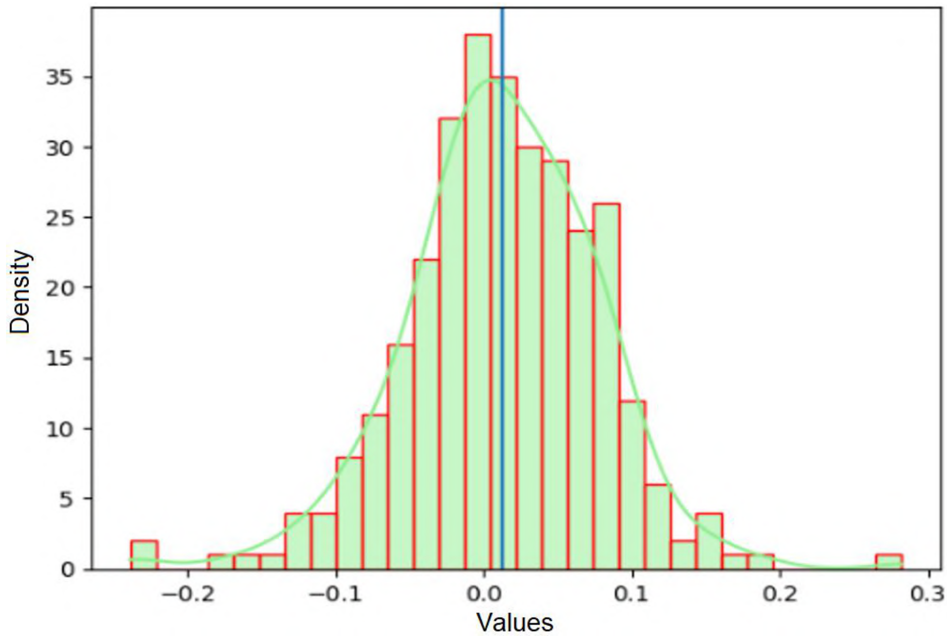

Figure 8. Histogram with density plot of descriptive statistics of buy and hold analysis of BSESN.

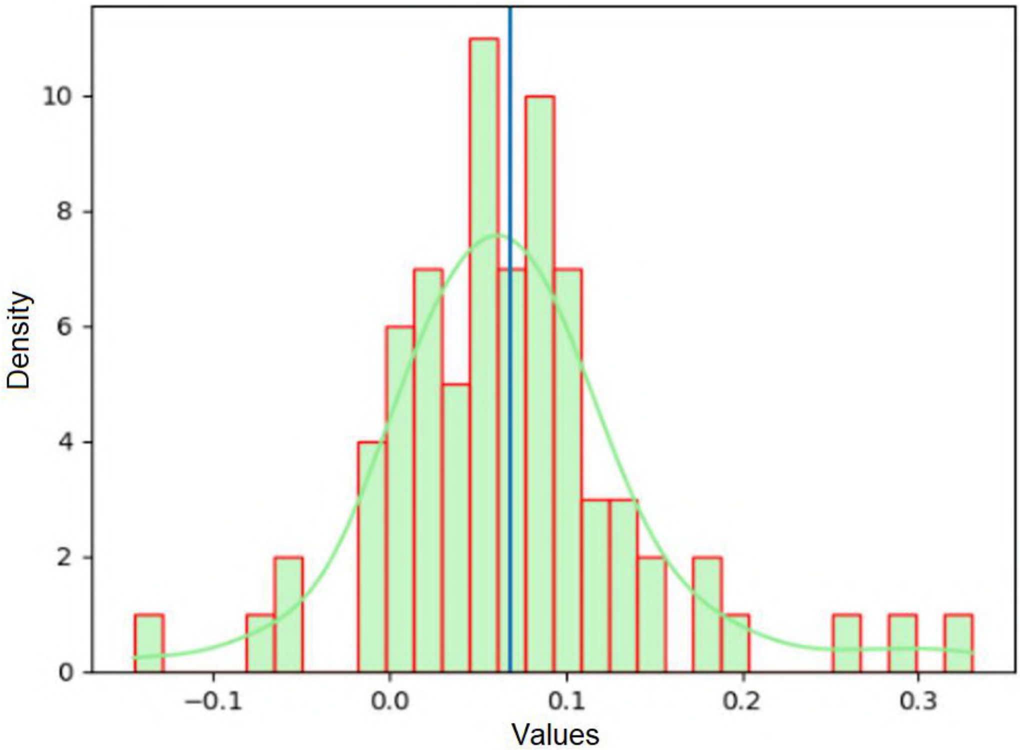

Figure 9. Histogram with density plot of descriptive statistics of strategy analysis of BSESN.

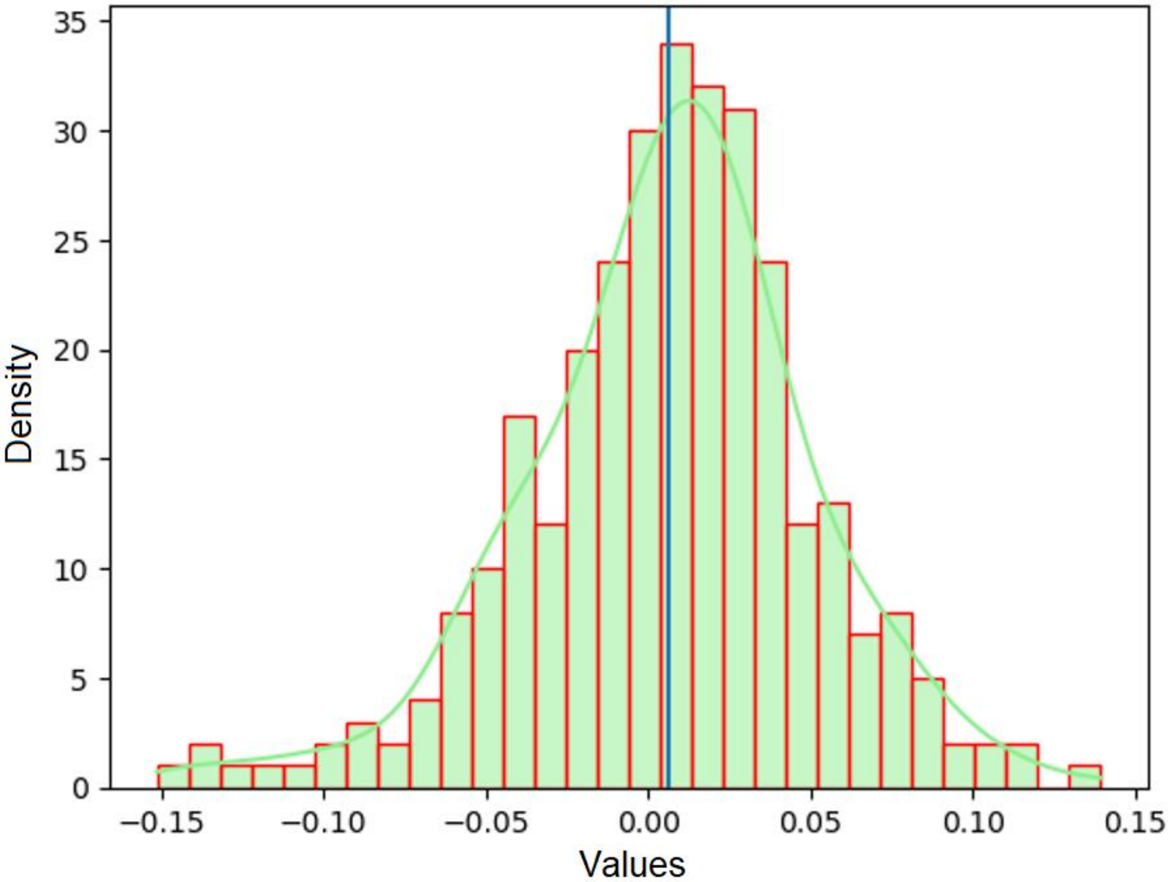

Figure 10. Histogram with density plot of descriptive statistics of buy and hold analysis of DJI.

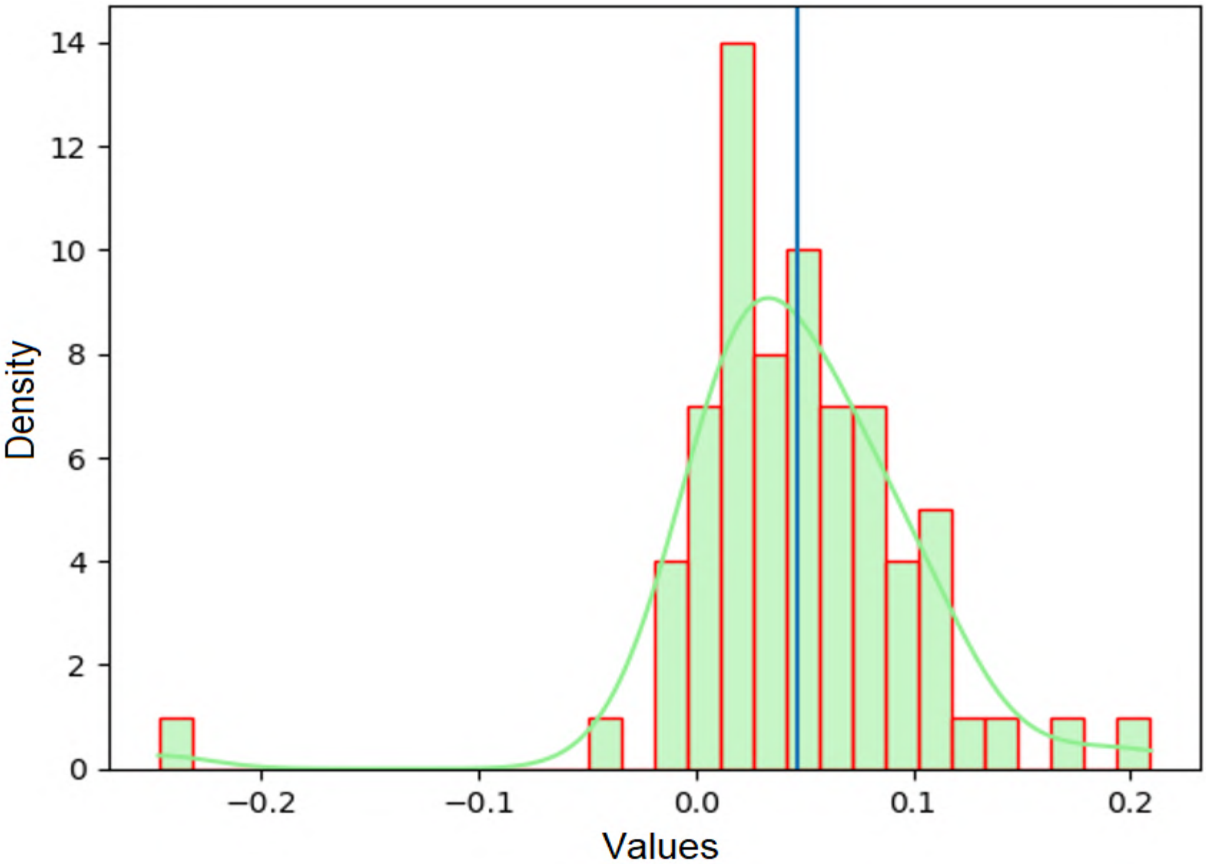

Figure 11. Histogram with density plot of descriptive statistics of strategy analysis of DJI.

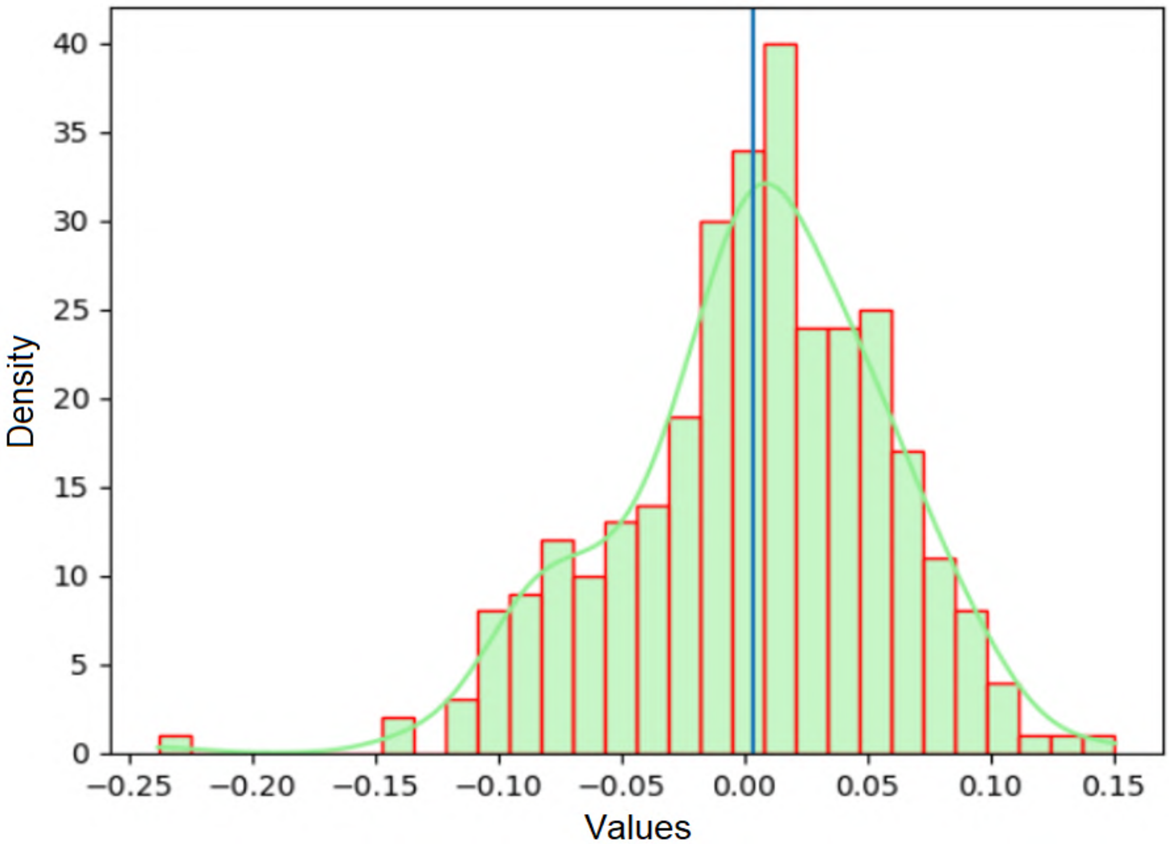

Figure 12. Histogram with density plot of descriptive statistics of buy and hold analysis of N225.

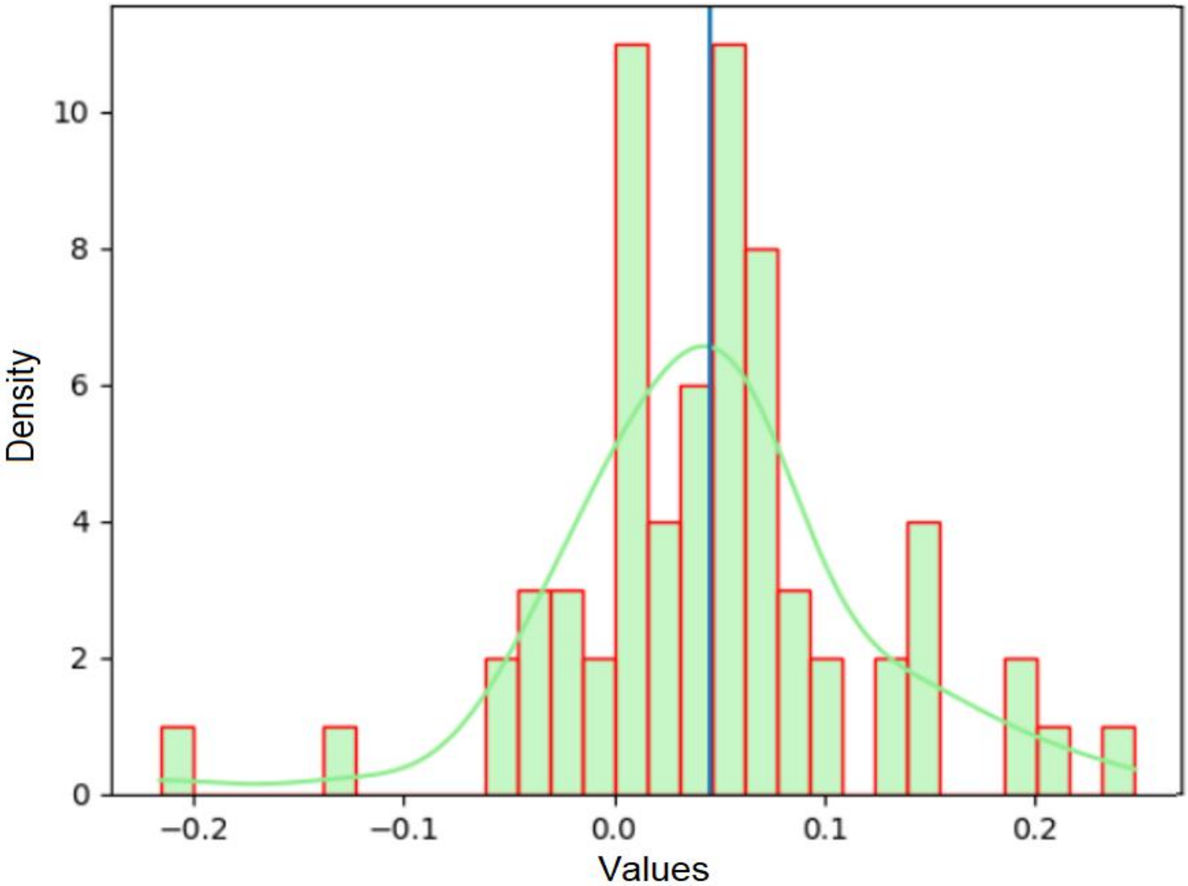

Figure 13. Histogram with density plot of descriptive statistics of strategy analysis of N225.

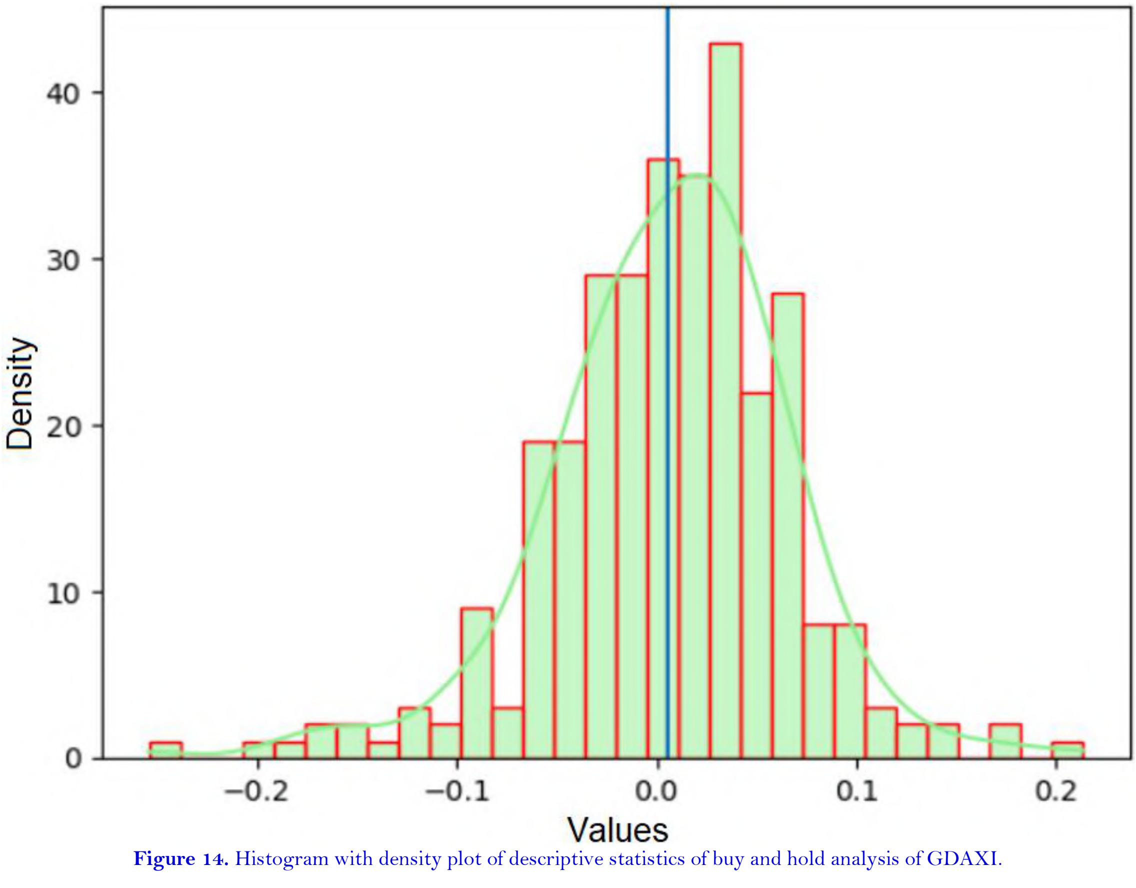

Figure 14. Histogram with density plot of descriptive statistics of buy and hold analysis of GDAXI.

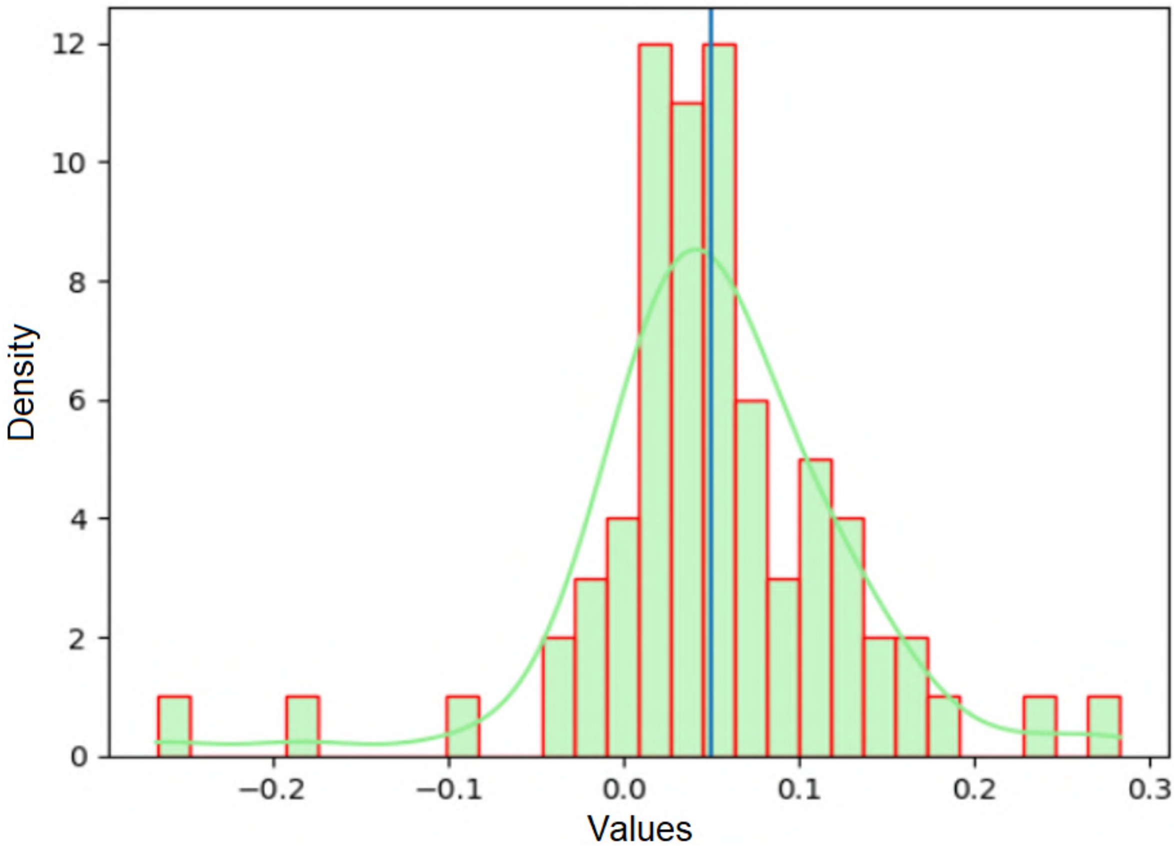

Figure 15. Histogram with density plot of descriptive statistics of strategy analysis of GDAXI.

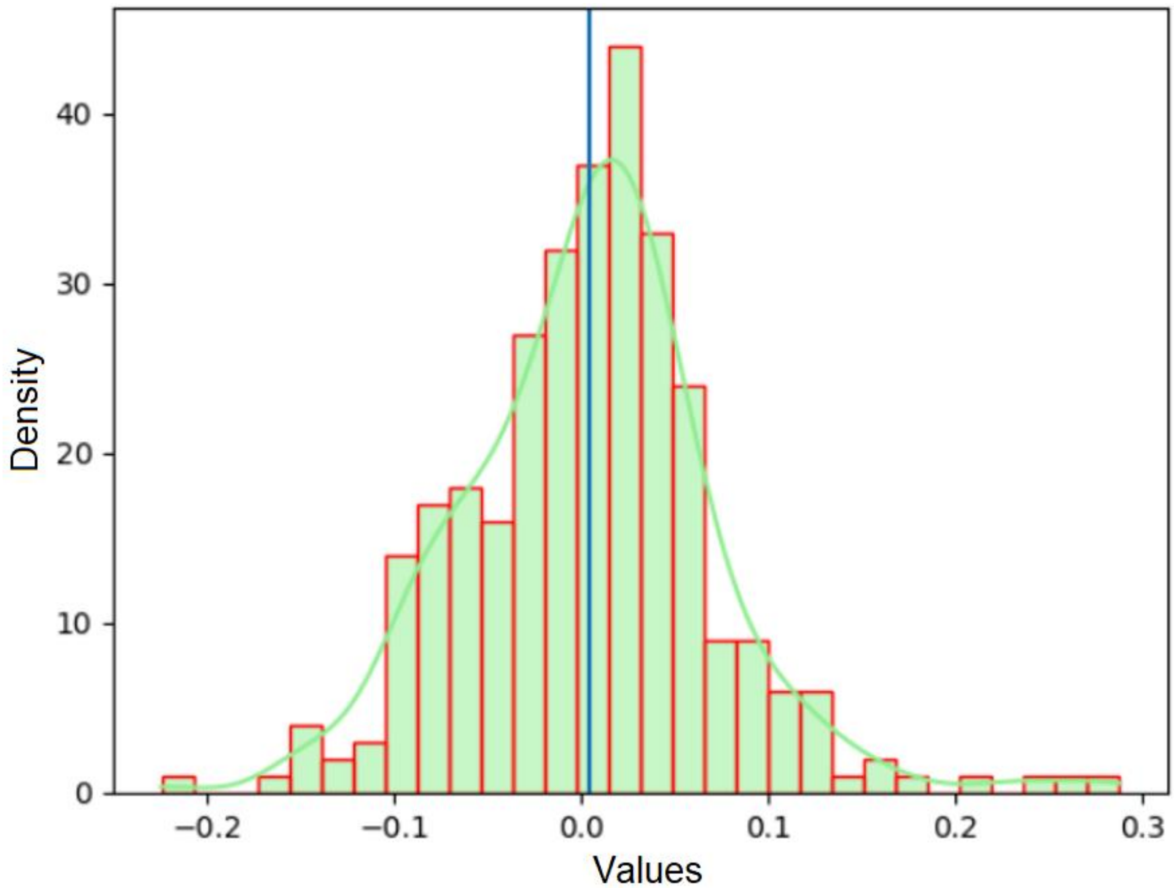

Figure 16. Histogram with density plot of descriptive statistics of buy and hold analysis of HSI.

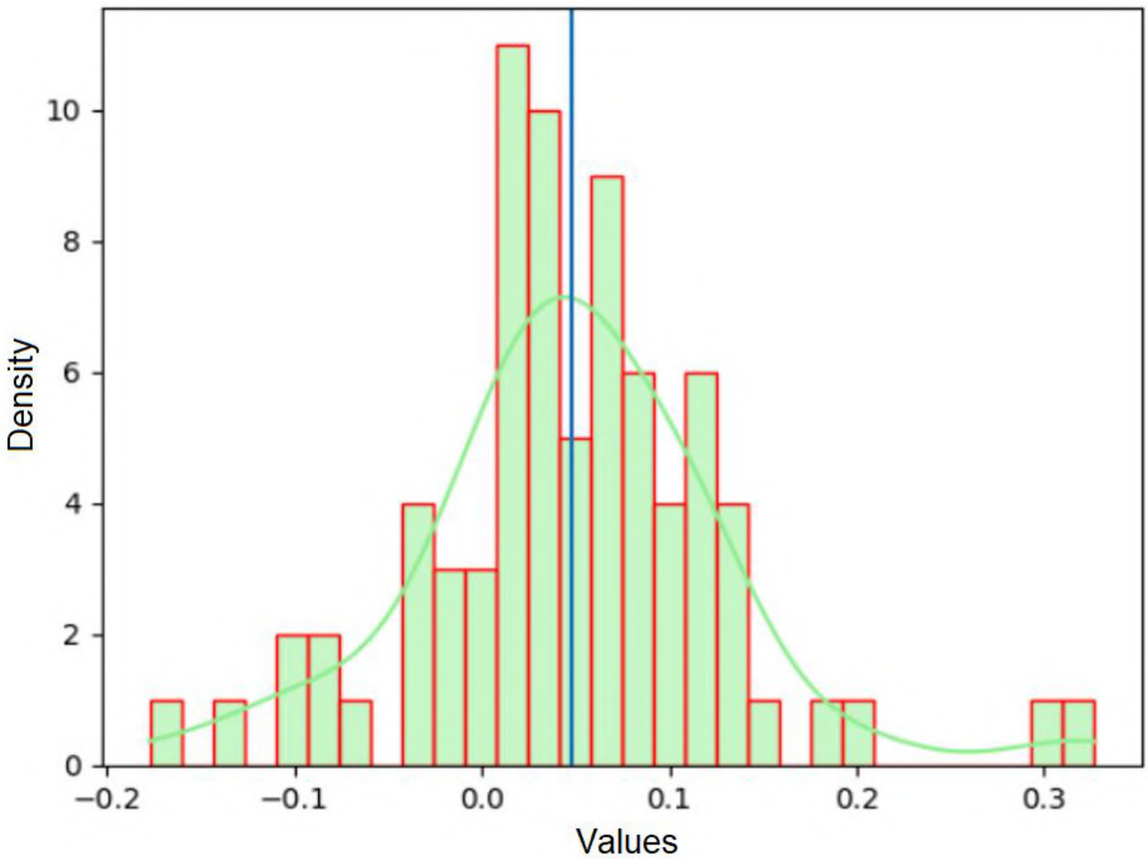

Figure 17. Histogram with density plot of descriptive statistics of strategy analysis of HSI.

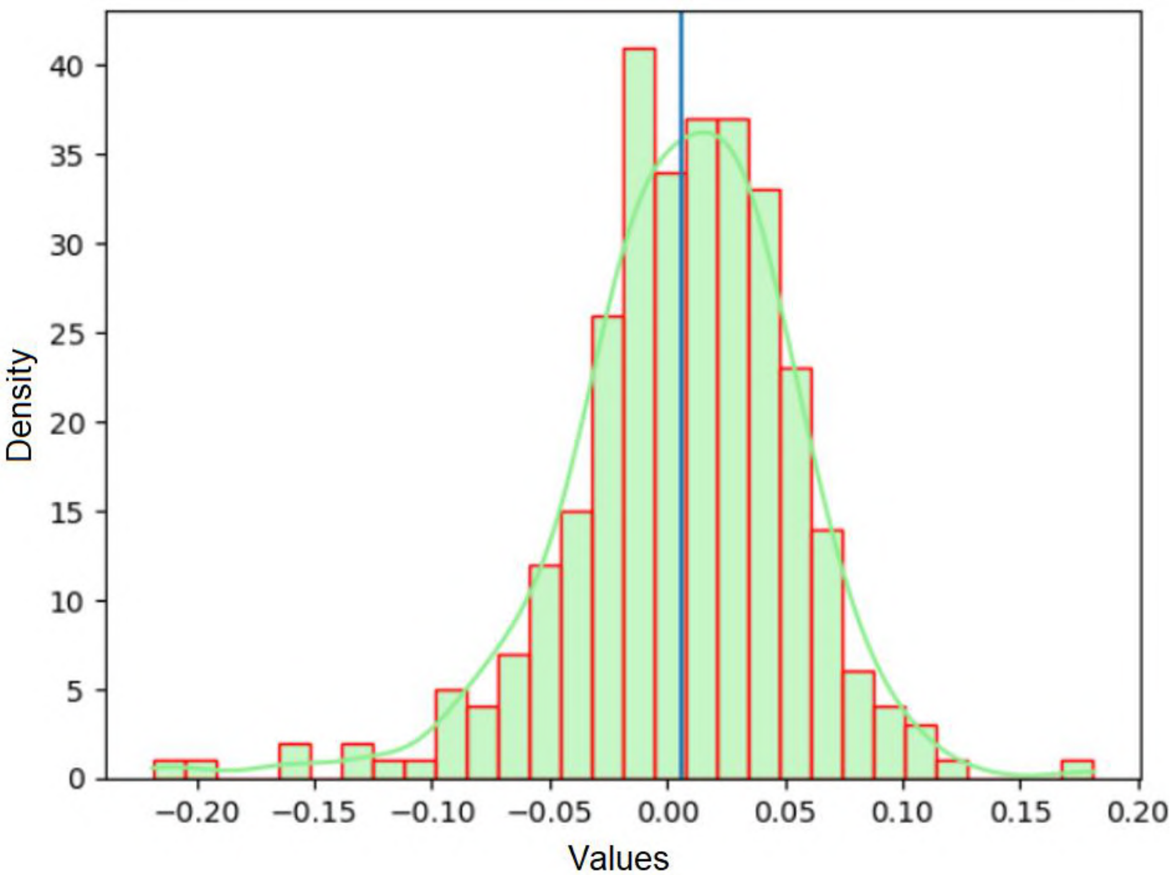

Figure 18. Histogram with density plot of descriptive statistics of buy and hold analysis of FTMC.

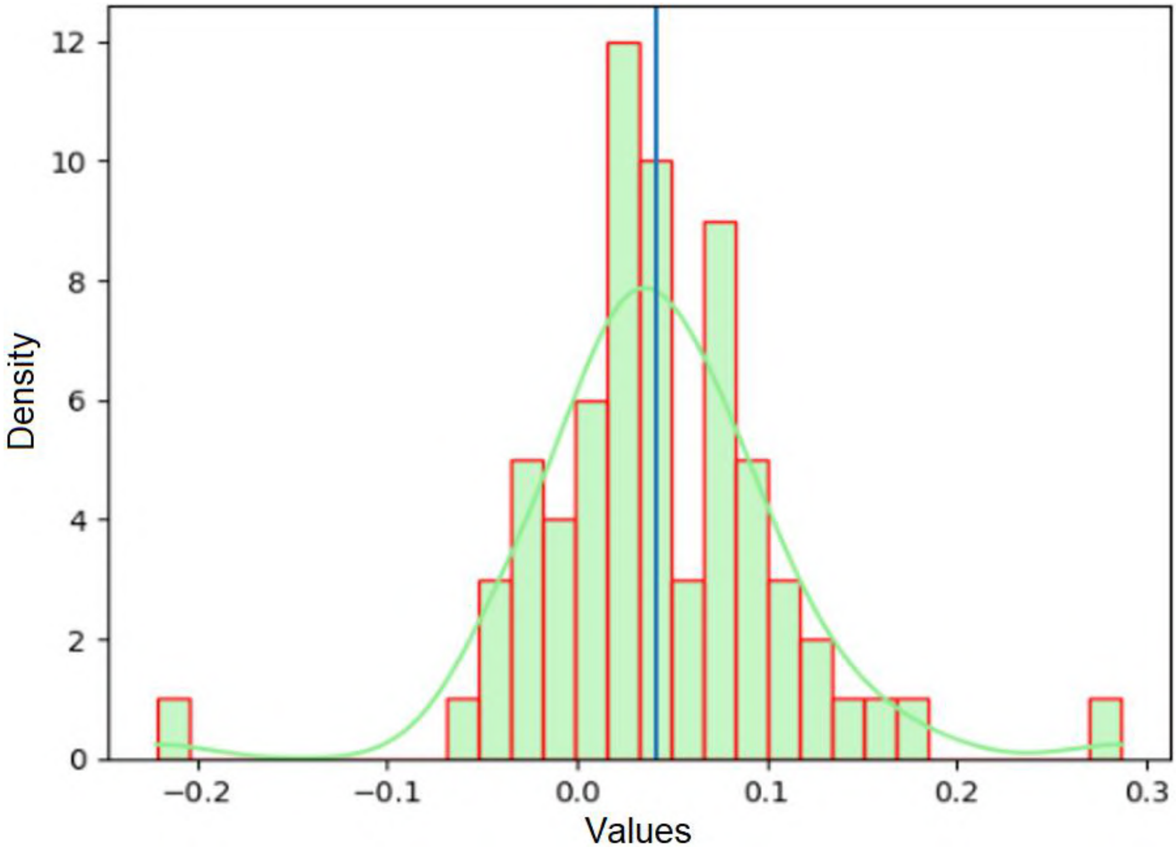

Figure 19. Histogram with density plot of descriptive statistics of strategy analysis of FTMC.

5. CONCLUSION, DISCUSSION AND IMPLICATIONS

This study delves into the performance of six global stock market indices—BSE Sensitive Index, Dow Jones Industrial Average (DJIA), Nikkei 225, German DAX, Hang Seng Index, and Financial Times Stock Exchange—over the period from January 1998 to December 2023. The analysis focused on evaluating the profitability and risk-adjusted returns of the SR Minimae and Maximae trading strategies, employing a rolling window methodology to capture the time-varying nature of market dynamics.

The results demonstrated a consistent outperformance of the AMH-based strategies over the traditional buy-and-hold approach across all indices. Notably, the Sharpe ratio returns from the adaptive strategies were significantly higher, indicating superior risk-adjusted performance. For instance, in the case of the German DAX, returns from the AMH strategy peaked at 3.04% for the 2003-2012 window compared to 1.45% from the buy-and-hold strategy. Similarly, the BSE Sensitive Index showed substantial gains, with adaptive strategy returns reaching 9.32% during the same period, highlighting the capacity of the AMH framework to capture inefficiencies in diverse markets.

Moreover, the rolling window approach revealed the dynamic nature of market efficiency, aligning with the Adaptive Market Hypothesis. The significant p-values and negative t-statistics across various periods confirmed that market efficiency is not static but evolves in response to changing market conditions. This adaptability underscores the practical relevance of incorporating AMH principles in portfolio management, particularly in volatile or transitional market phases. The findings contribute to the literature by bridging the gap between theoretical frameworks and real-world application. We highlight the efficacy of adaptive strategies in exploiting temporary inefficiencies, providing investors with tools to enhance returns while managing risk. Furthermore, the study reinforces the importance of continuous evaluation and adaptation of trading strategies in order to stay ahead in a constantly evolving financial environment.

The graphical analysis indicates that markets exhibit cycles of efficiency and inefficiency, with the SR strategy yielding better returns per unit of risk compared to buy and hold. Results for the rolling window analysis reported that the active trading strategy consistently outperforms buy and hold, corroborating the findings of Cooper et al. (2005); Lim and Brooks (2006); Lim (2007) and Feldman, Jung, and Klein (2015) moreover, the results are contradictory to those of Christie (2005) and Hiremath and Narayan (2016) in terms of SR and market efficiency, respectively. Our empirical findings reveal that investment strategies such as SR Minimae and Maximae lead to episodic momentum. Additionally, comparing the returns based on the SR with a buy-and-hold approach indicates that returns based on the SR always outperform the market, confirming the prevalence of AMH.

5.1. Discussion

The study demonstrates that adaptive trading strategies consistently outperform traditional buy-and-hold strategies across global markets, reinforcing the dynamic nature of market efficiency as posited by the Adaptive Market Hypothesis (AMH). The significant improvements in risk-adjusted returns across all indices highlight the practical utility of these strategies in exploiting time-varying inefficiencies. These findings suggest that investors and portfolio managers should adopt adaptive approaches to optimize returns under changing market conditions. Additionally, the research underscores the global applicability of AMH, offering valuable insights for both emerging and developed markets. Future studies could explore other asset classes or integrate behavioral factors to further understand adaptive market notions.

5.2. Implications

The findings of this study provide some important implications for framing investment strategies. Firstly, the AMH lodges itself as a viable and feasible alternative to the EMH, which purports that the markets can be predicted. The points at which the SR reaches a minimum represent a buying opportunity and could mean points at which the markets are either fearful or in an oversold condition; it represents the buying opportunity of that particular index. In contrast, the SR reaches a maximum, indicating a sell opportunity, and markets are in a fearless, overbought, or possibly even greedy state or overvalued. This research does not account for regulatory changes and geopolitical events, which could affect efficiency. Additionally, alternative strategies such as the Treynor measure or the Jensen measure may offer additional insights into the AMH; however, that is out of the scope of the current study.

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