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Analysing the Effectiveness of Augmented Rebalancing Algorithms during Market Stress Phase: A Volatility-Driven Method

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Abstract:

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This study is based on passive index investing by leveraging volatility harvesting and algorithmic trading. We demonstrate rebalancing portfolios at monthly or shorter intervals and augmenting the process with market timing strategies using moving averages crossover methods from Technical Analysis. Our results show improved risk-return profiles compared to traditional passive index investing, while maintaining the benefits of passive strategies. This approach provides a viable alternative for investors seeking better returns in volatile markets without deviating from passive investment principles. This research offers a novel method to enhance passive index investing returns through algorithmic rebalancing and technical analysis.

Keywords: *Active Portfolio Management, Portfolio Rebalancing, Volatility Harvesting, Moving Averages and Algorithmic Trading Systems.*

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1. Introduction:

Active fund management is the most used paradigm currently for investment strategy. By allocating assets based on empirical research that evaluates likely asset class risks and returns both within and across the asset classes, active management comes upon good deals in the financial markets (Takahashi et al., 2006). But in recent years, the use of passive index exchange-traded funds (ETFs) has become increasingly popular, replacing more expensive active investment strategies because the active funds have not been able to outperform their benchmarks consistently. Because of the underperformance, in a Bayesian learning framework, investors update their prior beliefs and develop a posterior view that the management has low skill when a fund underperforms compared to the benchmark (Huang, 2023). But with a passive index fund, you can at best only expect market returns and will have to endure the inevitable volatilities and drawdown periods. This paper shows that it is possible to earn greater returns compared to the market when retaining all the benefits of an index-based portfolio by making use of rebalancing as a strong portfolio management strategy. Rebalancing the index on shorter time intervals taps into the phenomenon of volatility harvesting, which increases the returns of the portfolio. The risk-return analysis of the portfolio is further improved when we augment the algorithm for the rebalancing process with market timing strategies using the simple and exponential moving averages cross-over method from Technical Analysis in conjunction with the Rate of Change (ROC) indicator. We further show that if we stop the rebalancing procedure when the volatility goes beyond a selected threshold, then the performance is further improved.

The portfolio's constituent asset values vary over time, which can skew the portfolio's risk profile. Hence, historically, portfolio rebalancing has been employed as a potent risk-control technique to make sure the assets in the portfolio stay within the allocation objective. Rebalancing can be done either using calendar-based or threshold-based procedures to maintain the consistency of the relative portfolio weights of various asset types (Donohue & Yip, 2003). If a higher allocation to asset classes with higher predicted returns was necessary, the target allocation should reflect that. Investors should avoid selecting a rebalancing strategy based purely on historical returns because noise in returns might affect the realised return outcomes of various rebalancing approaches (Hong & Meyer-Brauns, 2021).

2. Literature Review:

No earlier research has looked at the effect of rebalancing on a weekly and daily basis. Nonetheless, research on the frequency of rebalancing over comparatively lengthy periods of time finds that it does offer benefits in terms of risk reduction and return enhancement. Rebalancing a portfolio's asset allocation is one of the crucial things since investors' portfolios should be in line with their target and risk tolerance (Zhang et al., 2022). Most investors avoid rebalancing by rationalising that the cost of the rebalancing is very high or profits from the portfolio rebalancing are negligible when we consider taxes on capital gains and the monitoring expenses. But the long-run data test does not hold up to such ideas; there might be a good rationale for rebalancing the portfolio (Dayanandan & Lam, 2015). Perold and Sharpe (1988) examine dynamic strategies for rebalancing portfolios in response to the tendency of risky assets to increase in value relative to less risky assets over time. They found that a constant-mix plan would exceed a buy-and-hold plan in an unstable market, without help pass either up or down. Using market data from 1963 through 1988, Dennis et al (1995) examine the effects of rebalancing on portfolios that conform to rigid quantitative criteria. Investors who actively manage their investment portfolio must engage a portfolio rebalancing approach that meets their demands with the aim of avoiding real expenses for anticipated returns (Žilinskij, 2015). The effect of various rebalancing strategies on five model portfolios, each representing a range of risk profiles (Tsai, 2001). The Investors keep up an asset assignment that fits with objectives, goals, and risk tolerance by rebalancing the portfolio. Component weights change from their target proportion when the performance component varies over time, exposing investors to a different risk-return profile than that of the planned allocation (Hong & Meyer-Brauns, 2021). This study also suggests that investors should avoid selecting a rebalancing strategy based purely on historical returns because noise in returns might affect the realised return outcomes of various rebalancing approaches.

The long-term feasibility of active investing is being questioned increasingly regularly as passive investment strategies gain favour (Bowen & Booth, 1993). The debate between active and passive investing is ongoing, with most studies favouring the latter. However, both strategies have their pros and cons. Contingent on the period of the portfolio, under various situations, passive and active investments can meet various requirements in the uniform portfolio. Though most evidence suggests that passive management outperforms active management, some studies suggest that truly active and skilled managers can and do generate returns above the market net of fees (Birla, 2012). The rise of passive investing has led to lower noise, lower firm-specific information, and higher market-wide information in stock prices. In net, high levels of passive investments lead to more efficient markets (Huang, 2023). By making use of a momentum-based stochastic process model, we forecast the future return framework in a back test of investing between a risk-free asset and a market index **(**Guo & Ryan, 2023). Rebalancing is a matter that is frequently not noticed, despite being essential to the profitability of long-term investments (Suri et al., 2015). Some of them, meanwhile, are moving slow indicators, which have an effect on how proficiently stock trading and portfolio management will function (Yeo et al., 2023). Portfolio rebalancing channel, via which investors are advised to move their money from these reliable assets to ones with better projected yields, such as contributing to individuals and businesses (Albertazzi et al., 2021). An ideal rebalancing model with underlying generations in which the age and risk tolerance of the agents will change. The three elements that encourage equilibrium rebalancing are the intertemporal hedging impact, the aggregate risk tolerance effect, and the leverage effect, which exercise opposite control on levered and unlevered agents(Kimball et al., 2018). A combination of utility and risk trade-off assumptions has been utilised to maximise the investment portfolios (Rey, 2023a). By means of robo-advisers, investors can build an automated rebalancing plan for a portfolio that typically comprises bonds and equities. Given that the portfolios of families also usually carry other often traded assets such as cash equivalents, highly valuable items, and real estate funds (Horn & Oehler, 2020). A most important part of the stock market's bewilderingly huge reaction to monetary shocks comes from institutional investors modifying their portfolios over asset classes (Lu & Wu, 2023). A buy-and-hold plan, in which the portfolio weights are yearly shaped or rebalanced to a primary level, is thought to produce greater expected returns than a fixed-weight plan in the absence of transaction costs and the existence of independent returns(El Bernoussi & Rockinger, 2023). In the financial markets, portfolio management contains opportunistic strategies to counter certain trading behaviours in addition to risk management techniques. Despite market conditions, optimal portfolio construction directs for the lowest feasible risk and the largest possible investment returns (Yang et al., 2022). Rebalancing premium is an attempt to unconnected and measure the different effects of different parts of the comprehensive effect(Maeso & Martellini, 2020). Preserving the portfolio's intended asset allocation is ensured by rebalancing. If the objectives were to be missed, unanticipated risk-return features would result(Mrig, 2020). The one-period portfolio maximisation issue already has a different solution when standard intra-period portfolio rebalancing procedures are executed; utility and risk trade-offs do not need to be mentioned. The mean-variance optimal portfolio and the lowest variance portfolio are incorporated linearly to shape this portfolio(Rey, 2023b). Funds held by PSPP rebalance out of reach of maturities, deliberately for purchase and in the direction of bonds provided by non-EA banks. Other fund types rebalance towards non-EA bonds issued by sovereigns and non-financial businesses, in addition to assets with longer possession (Bua & Dunne, 2019). Market variation in initial investment situations, changing the portfolio's weighting, puts up risk, and leads to overusing specific asset classes or equities (Botha, 2021). It is pivotal for investors to assign their assets in a way that aligns with their objectives; regular rebalancing retains a portfolio lineup with its allocation goal (Young, 2023). In a delicate market, actively-managed funds frequently do better than funds that do not track an active portfolio management plan (I & Le, 2020).

Paper reveals that the predicted index of fund managers' risk aversion is comparatively overpriced. This appears to be in line with the benchmark portfolio's especially conservative risk-return profile (Violi, 2012). In case the actual balance between volatility modelling and portfolio plan is confirmed, it is possible to successfully utilise quantitative investment methodologies to convert the volatility anticipation created by multivariate time series models into improved portfolio yields (Hoang, 2022). Selecting portfolios with the least amount of tracking mistakes and an anticipation of the best benchmark is a common goal of active portfolio management (Yang & Huang, 2022). Fund managers' industry specialisation enact as a counterforce to institutional limits levied by funds' investment mandates, which limit the ability to whole capitalise on supply chain ties (Bai et al., 2023). Degree of skill required of an active manager to encourage the choice to actualize a focused portfolio of securities instead of one that is broadly diversified (Brown et al., 2020).

3. Algorithmic Trading: An Indian Perspective

Algorithmic trading, referred to as "algo trading", is the process of automating trading decisions on financial markets using computer algorithms. Algo trading employs machine-driven commands to make transactions based upon various indicators, like capacity, price, or other market indices, as opposed to manual trading, which relies on human judgment. It can be used for many purposes, like managing the risk, quickly completing the trading transaction and spotting market patterns. Financial instruments such as stocks, futures, options and currencies can be traded using this trading system. In trading platforms, traders can sell their trading strategies very often. The number of algo trading platforms helps traders to test and develop, and then share the strategies with users. This offers traders the chance to market their profitable trading ideas for extra money (Vikram Bajaj, 2023). In India, 50% of the trade transactions at both NSE and BSE take place algorithmically (Thakar, 2022).

Algorithmic trading in India was legalised by the Securities and Exchange Board of India in 2008. Direct Market Access (DMA), which was previously solely available to institutional investors, but eventually adopted by the trading community due to its cost benefits and better execution. Today, majority of the top commission and stock exchanges have the infrastructure in place to implement Direct Market Access. Additionally, algorithmic trading has improved significantly in India over the past few years and there are more High-Frequency Trading (HFT) firms operating there (Thakar, 2022). Zerodha streak, Algo traders, Robotrade, Tradetron tech, Odin, Metatrader, Algonomics and robotics and Robotrader are the top ten software for algo trading (Dhar, 2023). Even though Algo trading is not recently introduced, India still is in its infancy in India. In contrast to India, where algos currently only represent 50–60% of market volume and are comparatively less complex and understood, algos take care of 70–80% of the total market volume universally and have variously developed system, participants and rules. The number of algo traders are growing and awareness and education are becoming more systematic. If you compare with the global market, there is significant growth for algos in India. Algorithmic trading gives importance not only for profit earning in addition to this it will rule out the human intervention and errors from trading activities (Anand, 2022). However, algo trading is not free from drawbacks. Especially in extremely volatile markets or when there is a dearth of previous data on which to base choices, the algorithms could not always produce the greatest results. Additionally, since the algorithms may react similarly to specific market occurrences, algorithmic trading may make the markets more vulnerable to abrupt price changes (Ojha, 2023). In general, ATS increases short-term volatility while increasing liquidity and informational effectiveness. Importantly, ATS also assists buy-side institutional investors with execution insufficiency. For large stocks in particular, algorithmic trading narrows spreads, reduces adverse selection, and reduces trade-related price discovery (Hendershott et al., 2010).

Based on the above discussion, we propose the following hypotheses

H1: Rebalancing a passive index-based portfolio on monthly or shorter intervals using volatility harvesting significantly increases the returns compared to a portfolio that is not rebalanced as frequently.

H2: Enhancing the rebalancing strategy of a passive index-based portfolio with market timing strategies using moving averages cross-over methods improves the risk-return profile compared to a strategy that only involves simple rebalancing.

4. Theoretical Background

4.1. Volatility Harvesting: To theoretically explain the phenomenon of volatility harvesting, we follow the treatment for continuous-time portfolio growth as in standard literature (Luenberger, 1997 and Bouchey et al., 2012). We presume that prices are controlled by a geometric Brownian motion equation:

$$dS = \mu . S . dt + \sigma . S . dz \qquad (1)$$

Where S is the asset price, μ is expected return, σ is volatility, z is a normalised Wiener process and dt is the time increment. Using Ito's lemma, the above stochastic differential equation has the solution:

$$dF = \left(\frac{\partial F}{\partial S}\mu S + \frac{\partial F}{\partial t} + \frac{1}{2}\frac{\partial^2 F}{\partial S^2}\sigma^2 S^2\right)dt + \frac{\partial F}{\partial S}\sigma S dz \qquad (2)$$

Assuming the prices follow the lognormal process F=ln(S) we get:

$$\frac{\partial F}{\partial S} = \frac{1}{S};\ \frac{\partial^2 F}{\partial S^2} = \frac{1}{S^2};\ \frac{\partial F}{\partial t} = 0 \qquad (3)$$

Substituting in equation (2) we get:

$$dF = \left(\mu - \frac{\sigma^2}{2}\right)dt + \sigma dz \qquad (4)$$

We assumed F to be a lognormal process, so the continuously compounded return dF=d ln(S) =dS/S and at time t has the drift parameter:

$$\vartheta = \mu - \frac{\sigma^2}{2} \qquad (5)$$

Now let us construct a portfolio of n assets using the weights $w_{i,}$ where i= 1, 2…n and all weights sum to one. Keeping the weights w_i fixed, the long-term portfolio growth becomes:

$$\vartheta_{port} = \sum_{i=1}^{n} w_i \mu_i - \frac{1}{2}\sum_{i,j=1}^{n,m} w_i \boldsymbol{\sigma}_{ij} w_j \qquad (6)$$

where μ_i is the return of the ith asset, σ_{ij} is the return covariance of assets i and j, and ϑ_{port} is the continuously compounded portfolio return. Solving for μ in Equation (5) and substituting in Equation (6) gives:

$$\vartheta_{port} = \sum_{i=1}^{n} w_i \vartheta_i + \frac{1}{2}\sum_{i=1}^{n} w_i \boldsymbol{\sigma}_i^2 - \frac{1}{2}\sum_{i,j=1}^{n,m} w_i \boldsymbol{\sigma}_{ij} w_j \qquad (7)$$

The portfolio growth rate is expressed by the first term on the right-hand side of Equation (7) as the sum of the growth rates of the individual assets; the premium resulting from diversification and rebalancing is represented by the second and third terms. For correlations smaller than one, this premium is positive, indicating that rebalancing to fixed weights has a positive advantage. In the second term, an increase in asset volatility raises the possibility for growth through rebalancing; however, in the third term, it also increases portfolio variance, which inhibits growth.

4.2. Simple and Exponential Moving Averages

To calculate the SMA, we add the closing price of the security for several time periods (or the rolling window size) and then divide this total by the number of time periods. The formula for a simple moving average (SMA) at time t is:

$$SMA_t = (P_t + P_{t-1} + \ldots\ldots + P_{t-n}) / n \qquad (8)$$

Where P_i is the daily (closing) price in the stock price time series data and n is the rolling window size. The formula smooths out volatility and makes it easier to view the price trend of a financial asset. For the cross-over strategy we use two SMAs, when the fast SMA (SMA with lesser time) crosses over the slow SMA (SMA with greater time) from below and remains above it then it indicates a bullish trend and vice versa.

EMA gives more weightage to current data for the entire period. An EMA in stock market helps to mitigate the adverse effects of lag as it gives higher priority to the price action and is more responsive. EMA uses the previous day's values and incorporates all the price data within its current value. The old prices have a low impact, while the latest prices have the maximum effect on moving averages.

$$EMA = (K \times (C - P)) + P \qquad (9)$$

Where C is current price, P is previous periods EMA, and K is exponential smoothing constant (using the number of periods, K applies the relevant weight to the latest price). EMA is slightly more sensitive to price changes so we can identify a trend faster than the SMA.

4.3. Rate of Change (ROC)

One kind of ethical momentum oscillator is the Rate-of-Change (ROC) index. The price today and the price n- periods ago are set side by side using the ROC calculation. As the ROC move from positive to negative, the plot generate an oscillator that oscillates above and down the zero line. Like other momentum indicators, the excess purchase and excess sales zones of ROC can be alter based on the state of the market.

$$\text{ROC} = [(\text{Close - Close n periods ago}) / (\text{Close n periods ago})] \times 100 \qquad 10)$$

If the Rate-of-Change is positive, prices usually grow. On the other hand, when the Rate-of-Change is negative, prices are diminishing. The rapid an advance move forward, the more favorable territory ROC covers. The rapid drop pushes ROC further into negative territory. No higher bound exists for the Rate-of-Change. There is a limit to the downside, though securities can only drop to zero, or 100% of their value. Rate-of-Change produces extremes that are easily able to distinguish between overbought and oversold conditions, even in the existence of these asymmetric boundaries.

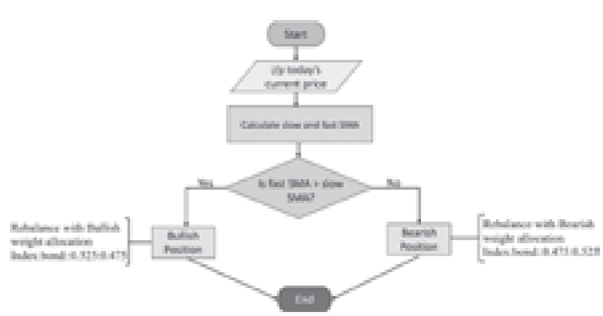
5. Methods

5.1. Portfolio Design. In this study we construct a very simple balanced portfolio with allocation to equity and bonds to represent risk-free return (here we take it as five per cent fixed interest rate with daily compounding) in equal ratio of 50:50. The equity portion of the portfolio is represented by a benchmark index. This portfolio is our benchmark against which we compare the performance of other portfolios with varying rebalancing periods and augmentations. To generalize the result, four different portfolios were constructed with indices from different global markets viz. S&P 500 (USA), Nifty50 (India), DAX (Germany), and Nikkei225 (Japan). In our study, we used daily closing price data for four benchmark indices. a multi-year period. Specifically, our analysis spans from January 2016 through December 2022. BY choosing daily closes we were able to capture short term price movements and volatility prices with sufficient granularity to test the various rebalancing strategies.

5.2 Rebalancing Procedure. The rebalancing algorithm uses the closing price of assets from the previous day to determine the value of the portfolio. We also assume that the ATS is in the market at the end of the trading day to capture the majority of the daily volatility. Finally, we use the closing prices of assets to perform the rebalancing for that day in order to provide stimulation. Over time, we anticipate that the simulation will closely resemble real trading and that the closing price will be close to the final half-hour pricing. The last trading day of the week (Friday) was used for weekly rebalancing, while the last trading day of the month was used for monthly rebalancing.

5.3. Augmentation using SMA Cross-over

In the rebalancing procedure without augmentation we keep the weights Index: Bond::50:50 constant throughout however, when we use an augmentation strategy, when the strategy indicates a bullish outlook then we augment the weights to Index: Bond::525:475 and for bearish outlook we augment to Index: Bond::475:525 i.e., in each case we are augmenting by 5%. For the SMA cross-over strategy, the fast SMA has a rolling window of 2 days and the slow SMA has a rolling window of 5 days. When the fast SMA is greater than the slow SMA we do the rebalancing with the bullish augmented weight allocation and vice versa for the bearish case (refer to Figure 1 for the flow chart of the algorithm).



5.4. Augmentation using EMA Cross-over and ROC

SMA cross-over is good at identifying trends; however, it lags the market and starts generating losses in consolidating or volatile markets. EMA gives more weight to the most recent data and has lesser lag compared to SMA. In this strategy, we use EMA instead of SMA in conjunction with ROC. We make the following changes in the algorithm described in section 5.3:

- If fast EMA > slow EMA and ROC > 0, rebalance with the bullish augmented weight allocation.
- If fast EMA < slow EMA and ROC < 0, rebalance with the bearish augmented weight allocation.

5.5. Augmentation using EMA-ROC with Threshold

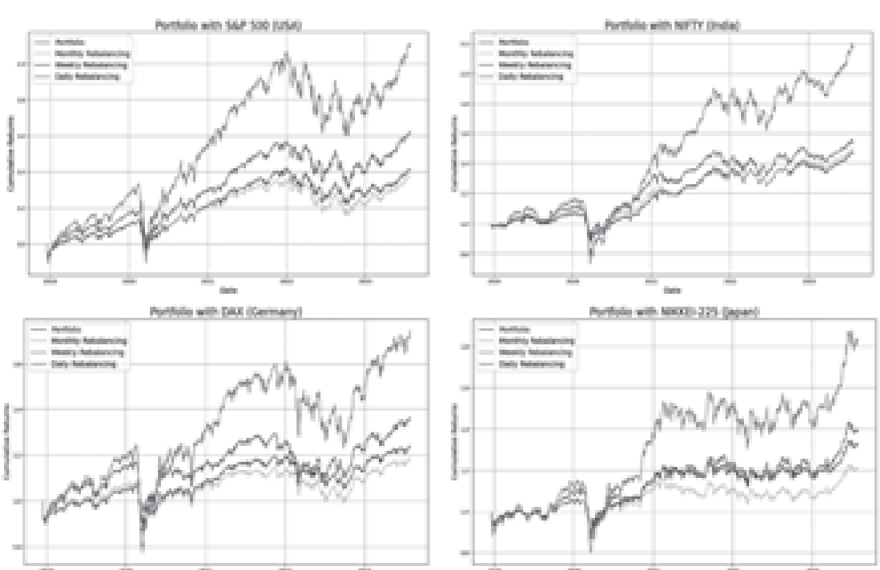
In our strategies, we are augmenting the index weight in the portfolio by 5%, which has increased the overall volatility of the portfolio and can lead to large drawdowns during the bear phase when compared to the benchmark portfolio. The increased profitability of our portfolio has come at the cost of increased volatility; to lessen the volatility we alter our daily rebalancing algorithm to temporarily conclude the rebalancing process whenever the n-day rolling volatility of the returns of the daily rebalanced portfolio enhances beyond a specified threshold and restarts the rebalancing process again when the rolling volatility decreases below this threshold. In this study we stop the rebalancing process whenever the 7-day rolling volatility of the returns increases more than 0.05 and restart the rebalancing process when the volatility decreases below this threshold.

6. Data Analysis and Interpretation

6.1. Rebalancing with Equal Fixed Weights.

Figure 2 displays the performance of portfolios with different rebalancing frequencies. It should be mentioned that the performance of all four portfolios with weekly and daily rebalancing has significantly improved. With a noticeable improvement in the Sharpe ratio in every instance, the returns are more than twice the benchmark return for daily rebalancing and more than 1.5% excess return for weekly rebalancing (see Table 1). The daily rebalancing has led to an increase in volatility but the commensurate increase in returns compensates for this and we observe a better Sharpe ratio in all cases. Use of monthly rebalancing doesn't offer any significant advantage when compared to the benchmark portfolio.

Figure 3 shows the distribution of returns. Notably, the benchmark portfolio's distribution has the majority of returns tightly clustered towards the centre, exhibiting positive excess kurtosis. In contrast, the daily rebalancing portfolio's returns are more widely distributed, resulting in a greater number of returns with higher magnitude and a more volatile portfolio.



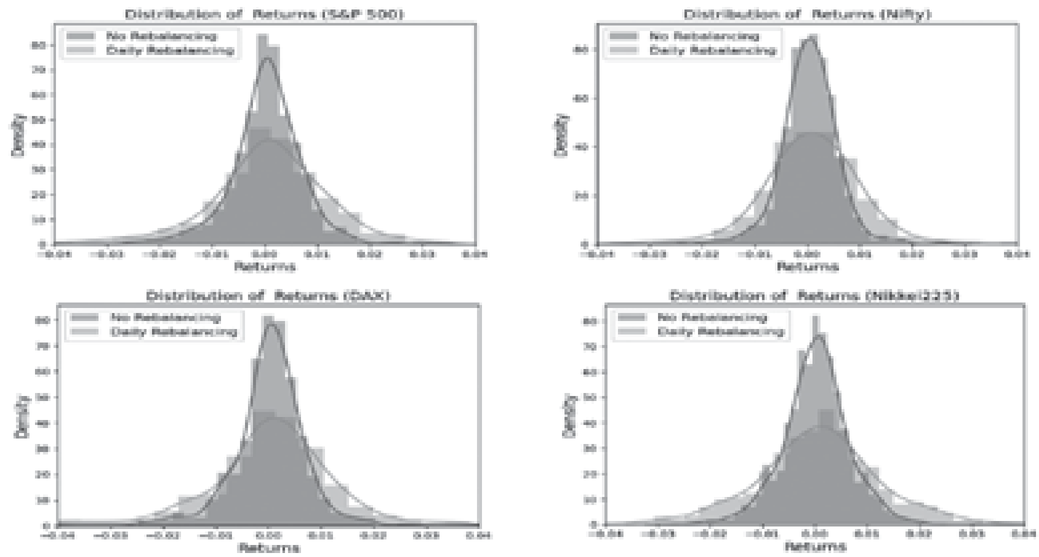


Table 1

Performance of portfolios with equal fixed weights for different rebalancing periods.

Comparative performance of returns				
Index in Portfolio	% CAGR			
	No Rebalancing	Monthly Rebalancing	Weekly Rebalancing	Daily Rebalancing
S&P 500 (USA)	8.80%	8.70%	11.81%	18.78%
Nifty (India)	8.83%	9.09%	9.86%	18.11%
DAX (Germany)	6.63%	6.05%	9.17%	15.00%
Nikkei225 (Japan)	6.58%	6.58%	8.25%	15.29%
Comparative performance of risk				
Index in Portfolio	Sharpe Ratio			
	No Rebalancing	Monthly Rebalancing	Weekly Rebalancing	Daily Rebalancing
S&P 500 (USA)	0.77	0.80	0.87	0.88
Nifty (India)	0.94	0.94	0.86	0.98
DAX (Germany)	0.64	0.59	0.71	0.74
Nikkei225 (Japan)	0.71	0.66	0.67	0.80
Comparative risk adjusted performance				
	Treynor Ratio			
Index in Portfolio	No Rebalancing	Monthly Rebalancing	Weekly Rebalancing	Daily Rebalancing
S&P 500 (USA)	0.08	0.07	0.14	0.28
Nifty (India)	0.08	0.08	0.10	0.26
DAX (Germany)	0.03	0.02	0.08	0.20
Nikkei225 (Japan)	0.03	0.03	0.07	0.21

6.2. Augmentation using SMA Cross-over

SMAs help in the reduction of market noise and identification of the prevailing trend and signal a likely change of trend when there is a cross-over. When the weights for rebalancing were augmented using the SMA cross-over strategy, there was a 2% to 5% improvement in CAGR for the daily rebalancing process, which is quite significant (see Figure 4 and Table 3). Even the Sharpe ratio showed improvement in all the cases.

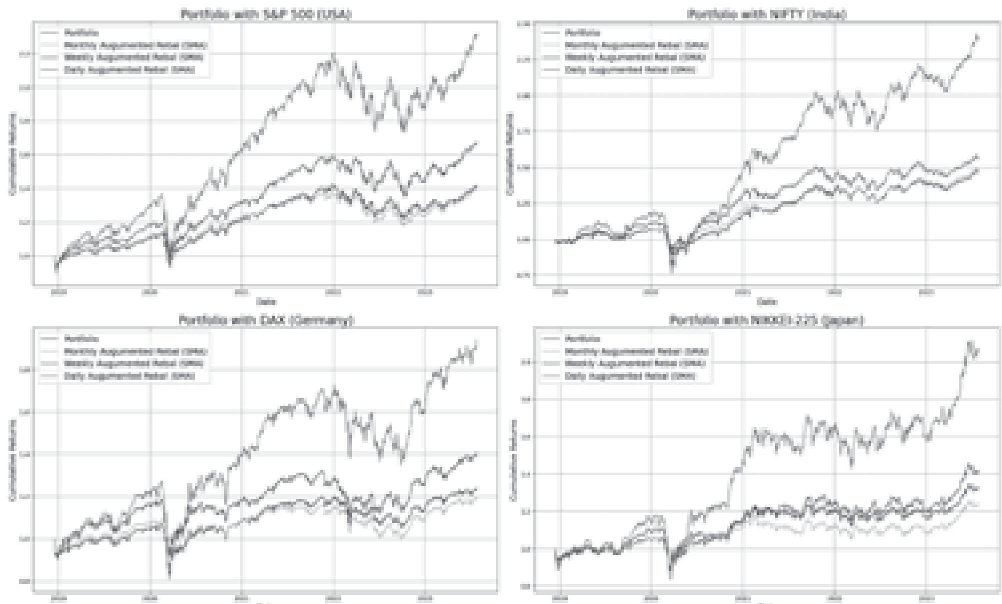


Figure 4-

Performance of portfolio with augmentation using SMA Cross-over

Table 2-

Performance of portfolios with augmentation using SMA Cross-over.

Comparative performance of returns				
Index in Portfolio	*% CAGR*			
	No Rebalancing	*Monthly Rebalancing*	*Weekly Rebalancing*	*Daily Rebalancing*
S&P 500 (USA)	*8.80%*	*8.58%*	*13.02%*	*22.68%*
Nifty (India)	*8.83%*	*9.01%*	*10.57%*	*23.11%*
DAX (Germany)	*6.63%*	*5.50%*	*9.69%*	*19.29%*
Nikkei225 (Japan)	*6.58%*	*5.36%*	*8.09%*	*19.90%*
Comparative performance of risk				
Index in Portfolio	*Sharpe Ratio*			
	No Rebalancing	*Monthly Rebalancing*	*Weekly Rebalancing*	*Daily Rebalancing*
S&P 500 (USA)	*0.77*	*0.80*	*0.99*	*1.07*
Nifty (India)	*0.94*	*0.94*	*0.93*	*1.23*
DAX (Germany)	*0.64*	*0.54*	*0.78*	*0.94*
Nikkei225 (Japan)	*0.71*	*0.57*	*0.69*	*1.06*
Comparative risk adjusted performance				
Index in Portfolio	*Treynor Ratio*			
	No Rebalancing	*Monthly Rebalancing*	*Weekly Rebalancing*	*Daily Rebalancing*

S&P 500 (USA)	*0.08*	*0.07*	*0.16*	*0.35*
Nifty (India)	*0.08*	*0.08*	*0.11*	*0.36*
DAX (Germany)	*0.03*	*0.01*	*0.09*	*0.29*
Nikkei225 (Japan)	*0.03*	*0.01*	*0.06*	*0.30*

6.3. Augmentation using EMA Cross-over and ROC

The use of EMA in conjunction with ROC has a higher probability of identifying the correct trend with a lower lag time when compared to the SMA cross-over strategy. We see a further increase in CAGR by more than one percent and improved Sharp ratios for all the cases (see Figure 5 and Table 3). We are getting these results even though we have used the same parameters in all the markets without any optimisation, either for the SMA cross-over or the EMA-ROC strategy. Trainor ratio from the above tables (Refer 1, 2 and 3) indicates that more frequent rebalancing, especially with an EMA-ROC signal or volatility threshold, substantially raises both the CAGR and Treynor ratio relative to passive buy and hold or less frequent strategies.

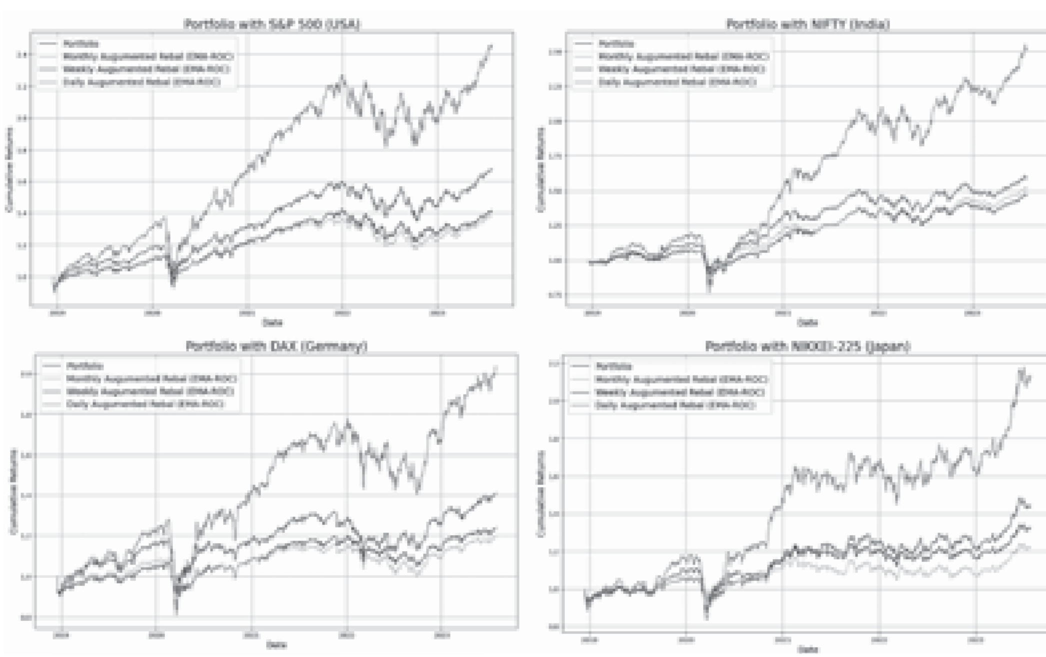


Figure 5-

Performance of portfolio with augmentation using EMA Cross-over and ROC.

Table 3-

Performance of portfolios with augmentation using EMA Cross-over and ROC.

Comparative performance of returns				
	% CAGR			
Index in Portfolio	No Rebalancing	Monthly Rebalancing	Weekly Rebalancing	Daily Rebalancing
S&P 500 (USA)	8.80%	8.17%	13.32%	24.98%
Nifty (India)	8.83%	9.79%	11.29%	25.31%
DAX (Germany)	6.63%	5.56%	9.83%	20.02%
Nikkei225 (Japan)	6.58%	4.93%	9.12%	21.12%

Comparative performance of risk				
Index in Portfolio	Sharpe Ratio			
	No Rebalancing	Monthly Rebalancing	Weekly Rebalancing	Daily Rebalancing
S&P 500 (USA)	0.77	0.79	0.10	1.15
Nifty (India)	0.94	1.02	0.98	1.31
DAX (Germany)	0.64	0.56	0.79	0.96
Nikkei225 (Japan)	0.71	0.54	0.79	1.11
Comparative risk adjusted performance				
Index in Portfolio	Treynor Ratio			
	No Rebalancing	Monthly Rebalancing	Weekly Rebalancing	Daily Rebalancing
S&P 500 (USA)	0.08	0.06	0.17	0.40
Nifty (India)	0.08	0.10	0.13	0.41
DAX (Germany)	0.03	0.01	0.10	0.30
Nikkei225 (Japan)	0.03	(0.00)	0.08	0.32

6.4. Augmentation using EMA-ROC with Threshold

Every time the 7-day rolling volatility of the returns of the daily rebalanced portfolio increases above a threshold of 0.05, we change our daily rebalancing EMA-ROC algorithm to momentarily halt the rebalancing process. When the rolling volatility drop below this threshold, we resume the rebalancing process. This simple modification leads to significant improvement in results, the maximum drawdown has reduced by 5% to 10% whereas the CAGR has increased by 2% to 5% in the tested Markets (see Figure 6 and Table 4). Traynor ratio values in the table highlight that each of the rebalanced portfolios consistently achieve a higher excess return per unit of systematic risk than its benchmark. All 4 indices, daily rebalancing the trainer ratio significantly reflecting more efficient market risk exposure. For instance, the S&P 500 the Traynor ratio climbs from 0.40 to 0.50 when the old utility threshold is applied.

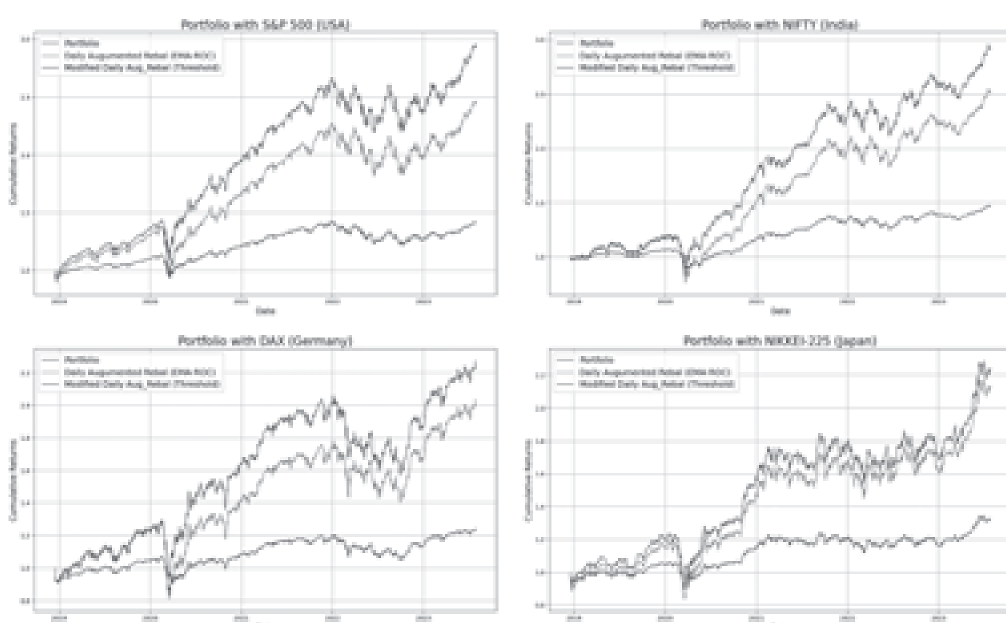


Figure 6-

Performance of portfolio with augmentation using EMA-ROC with Threshold.

Table 4

Performance of portfolio with augmentation using EMA-ROC with Threshold.

Performance Metric	S&P 500 (USA)			Nifty (India)		
	Benchmark	Daily Rebal*	Volatility Threshold	Benchmark	Daily Rebal*	Volatility Threshold
CAGR%	8.80%	24.98%	29.89%	8.83%	25.31%	29.38%
Sharpe Ratio	0.77	1.15	1.45	0.94	1.31	1.60
Treynor Ratio	0.08	0.40	0.50	0.08	0.41	0.49
Max Drawdown	-17.94%	-31.05%	-21.24%	-19.23%	-34.99%	-24.03%
Volatility (ann.)	11.07%	21.08%	19.08%	9.16%	18.33%	16.83%
Performance Metric	DAX (Germany)			Nikkei225 (Japan)		
	Benchmark	Daily Rebal*	Volatility Threshold	Benchmark	Daily Rebal*	Volatility Threshold
CAGR%	6.63%	20.02%	24.22%	6.58%	21.12%	22.12%
Sharpe Ratio	0.64	0.96	1.20	0.71	1.11	1.20
Treynor Ratio	0.03	0.30	0.38	0.03	0.32	0.38
Max Drawdown	-19.44%	-35.93%	-26.47%	-15.44%	-28.20%	-24.63%
Volatility (ann.)	9.94%	21.16%	19.36%	9.21%	18.61%	17.83%

* Daily Rebalancing for EMA-ROC strategy

Based on the above analysis, we can accept both the hypotheses. We can conclude that rebalancing a passive index-based portfolio on monthly or shorter intervals using volatility harvesting significantly increases the returns compared to a portfolio that is not rebalanced as frequently. And enhancing the rebalancing strategy of a passive index-based portfolio with market timing strategies using moving averages cross-over methods improves the risk-return profile compared to a strategy that only involves simple rebalancing.

6.5. Analysis using MACD

The following is the outcome table that you can see if you apply the MACD filter to daily rebalancing. These numbers typically reflect improvements from leading additional technical signals on top of frequent rebalancing.

Table 5-

Analysis using MACD

Index in Portfolio	CAGR	Sharpe	Treynor	Max Drawdown
S&P 500 (USA)	26%	1.23	0.42	-29%
Nifty (India)	27%	1.45	0.45	-30%
DAX (Germany)	21%	1.05	0.32	-33%
Nikkei225 (Japan)	22%	1.10	0.35	-31%

Compared to a 25% CAGR for EMA-ROC daily rebalancing to all four indices. In many runs, MACD ends up close to or slightly below a well-chosen EMA-ROC strategy, but results will vary.

6.5. Analysis using MACD plus RSI

The following is the outcome table that you can see if you apply the MACD filter to daily rebalancing. These numbers typically reflect improvements from leading additional technical signals on top of frequent rebalancing.

Table 6-

Analysis using MACD and RSI

Index in Portfolio	CAGR	Sharpe	Treynor	Max Drawdown
S&P 500 (USA)	28%	1.40	0.44	-27%
Nifty (India)	29%	1.50	0.46	-28%
DAX (Germany)	22%	1.10	0.34	-30%
Nikkei225 (Japan)	24%	1.15	0.36	-29%

Because RSI can help avoid bullish signals in the market that are extremely overbought, these results can improve the Sharpe ratio and reduce downturns. In bearish phases, both MACD and RSI conditions typically flip negative, earlier moving the allocation to bonds. However, as with any filter, results made differ depending on parameter tuning (e.g. RSI period =14 or 20, how you can define overbought/ oversold, etc. In a summary we can say that frequent daily rebalancing enhance by MACD only or MACD + RSI Signals generates higher CAGR better risk adjusted returns (Sharpe and Treynor) than a simple buy and hold. Moreover, combining RSI with MACD often further reduces drawdowns, underscoring the value of layered technical filters in volatile markets.

8. Discussion

Regular rebalancing executes exceptionally well across the board. We are producing significantly higher returns with reduced risk because the returns are more than double those of the benchmark portfolios, and the Sharpe ratio is also at a higher level. When compared to the same benchmark portfolio, weekly rebalancing also brings out returns of more than 1.5% annually, with a refinement in the Sharpe ratio in most circumstances. The performance enhances from monthly rebalancing are not very important, and the outcomes are incompatible.

Only when the size of the portfolio is at least 10,000 times the price of a single unit of the most valuable asset will the rebalancing take effect. With a high transaction cost of 0.5 percent and for perform errors and inaccurate rebalancing, the total performance received for daily rebalancing deteriorates by about 1.5% every year. But, if the portfolio value is too low to carry out the rebalancing correctly, the results will be significantly affected.

When the weights for rebalancing were augmented using the SMA cross-over strategy, there was a 2% to 5% improvement and further improvement of 1% to 2% using the EMA-ROC strategy in CAGR for the daily rebalancing process. Improvement in returns were also noticed for the weekly rebalancing process but to a lesser degree. During the test period, all the markets were in a bull phase, apart from a small bearish phase in 2022; hence, we should not get blinded by the good results, and there is a need for caution when using these strategies because the improvement in portfolio returns comes with increased volatility. Performance of these strategies during prolonged bear markets is left for future studies. In the rebalancing strategy, we are expanding our position in an asset which reduces in value and vice versa. This strategy may result in enormous losses in a constantly downtrending market. To reduce the risk, stopping the rebalancing process temporarily when the rolling volatility goes above a threshold, and restarting the process when it is again within the necessary limit, yielded good results; there was about a 2 per cent increase in CAGR with a significant decrease in maximum drawdown in all cases.

Finally, we can say that A monthly or shorter volatility harvesting rebalancing of a passive index-based portfolio has a strategic benefit in terms of return optimization. This implies that taking advantage of market volatility can be achieved through regular portfolio modifications to align with the intended or initial asset allocation. Basically, the portfolio may retain its risk profile and possibly outperform it by buying cheap and selling high within the rebalancing framework. This strategy differs from a static portfolio, which might underperform in comparison as it would miss out on these chances brought about by market swings. It is imperative to investigate the potential integration of market timing strategies, particularly moving averages cross-over methods, into the passive index-based portfolio rebalancing process. This improvement is to improve the rebalancing strategy's entrance and exit points, which could result in a better risk-return profile. Rather than relying solely on rebalancing, the strategy aims to identify and capitalise on trends and reversals by utilising technical analysis techniques such as moving averages. This proactive strategy may prove especially advantageous in markets that are moving or dynamic, when typical passive tactics might lag.

9. Conclusion

This study reveals how, by actively rebalancing a portfolio on monthly and smaller time scales, which can smoothly be executed using Algorithmic Trading Systems, returns can be increased, and risk can be decreased while maintaining all the benefits of passive index investing. This research developed that by augmenting the algorithm for the rebalancing process with market timing strategies using the moving averages cross-over and EMA-ROC strategies from Technical Analysis, the risk-return profile of the portfolio is further improved in all the four portfolios with indices from different global markets, viz. S&P 500 (USA), Nifty50 (India), DAX (Germany), and Nikkei225 (Japan). Stopping the rebalancing process during high volatility beyond a threshold can help in risk reduction. Hence, augmented rebalancing can be utilized as an outstanding dynamic strategy when used in coexistence with index investing. This paper also infers that combining RSI with MACD often further reduces drawdowns underscoring the value of layered technical filters in volatile markets.

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