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Decoding Market Cycles: A Technical and Time Series Analysis of Nifty 50

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ABSTRACT

The Indian stock market's behavior have been examined during the past twelve months' (April 2024 to March 2025) with the focus on the Nifty 50 index. This was done through a combination of technical analysis, and time-series modeling techniques. The Nifty 50 reached an all-time high toward the end of September 2024, and then declined significantly over the next few months. A variety of technical indicators were used to analyze the daily Nifty 50 index data for signs of changes in trends, and/or momentum; those included moving averages, momentum indicators (Relative Strength Index (RSI)), and chart patterns. In addition, time-series models (ARIMA), and GARCH volatility models were employed to estimate future values of the index (i.e. predict future levels), and to examine the nature of volatility in the market. The findings of this research indicate that technical indicators provided timely alerts (for example, when the market was at its most overbought prior to the peak and when it was at its most oversold just prior to the low), however, they were not able to provide adequate warning of the impending change in direction of the market using a simple ARIMA model. These findings highlight some of the inherent difficulties in attempting to statistically forecast markets that are experiencing periods of turmoil. Additionally, our findings demonstrate an increase in volatility clustering (a characteristic that has been noted in previous studies employing GARCH type models) during the decline phase of the market. Overall, our study demonstrates how technical analysis can provide useful insight into the very short-term movements of the Indian market; and time-series based models can be used to measure the risks associated with investing in the Indian equity market. However, the best method of providing accurate forecasting capabilities would likely be a hybrid approach which includes both technical analysis, and time-series modeling, as well as additional sources of relevant information.

Key words: Nifty 50, Indian Stock Market, Technical Analysis, Time-Series Models, ARIMA, GARCH, Efficient Markets.

INTRODUCTION

A key indicator for the performance of the Indian Stock Market is The Nifty 50 Index which includes the 50 largest equities listed at the National Stock Exchange of India. During the year from April 2024 to March 2025, the Nifty 50 experienced an extreme swing; it rallied strongly into new high levels before plummeting sharply downward. These extreme fluctuations create an ideal environment to analyze this market with both time-series forecasting and technical analysis. Technical Analysis is based on the premise that historical price and volume activity will exhibit patterns or trends that can be extrapolated to forecast potential future price movements. Technical Analysis has become a widely accepted tool among all types of traders, investors and analysts throughout India and worldwide to assist them with their timing decisions regarding when to enter and when to exit a trade, although there is still considerable academic debate regarding whether the technical aspects of the method are reliable when utilized within an efficient market. Time-Series Forecasting utilizes mathematical models to statistically analyze past price history and utilize those analyses to make predictions and estimate volatility. Technical Analysis and Historical Price Data are supported by an understanding of the underlying financial theories such as the EMH. The EMH is based upon the idea that all relevant information regarding a security has been incorporated into its current price. Therefore, in theory at least, technical analysts should not be able to consistently outguess random guesses using past price information.Recent studies support this view, for example, Elangovan et al. (2022), studied the major Indian Stock Indices and concluded that they did not operate under a Random Walk, therefore, the Indian Stock Market is Weak-Form Inefficient.

This inefficiency gives credence to the potential existence of exploitable patterns within past price information which would lend credence to Technical Trading Strategies. However, the inefficiency of markets can be episodic, therefore, during normal times the market behaves randomly however, during extreme phases of market activity (bubbles or crashes) technical signals or time series patterns could become stronger.

Therefore, based on prior research, this paper assumes that the analysis of historical price data can provide insights into future market behavior – a premise that will be examined critically through the lens of the Nifty 50's recent performance. In addition to the concerns about whether or not the markets are efficient, there is also a need for investors and risk managers. Technical analysis tools are widely used by practitioners and are referenced frequently in analysts' reports. At the same time, forecasting techniques have evolved at both the academic and professional level. Time series models, such as ARIMA (AutoRegressive Integrated Moving Average), are a common benchmark for forecasting prices while GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are a common benchmark for forecasting volatilities. Machine learning methodologies have also been applied to forecasting, and these methodologies typically include technical indicators as features. For example, Varshney and Srivastava (2024) found that an Artificial Neural Network (ANN) model was superior to an ARIMA model when forecasting the Nifty Index. These results support the notion that sophisticated methods may generate better forecasts than the naive benchmarks generated by simpler ARIMA based methods due to the possibility that non-linear relationships within data sets exist and cannot be identified through the use of ARIMA.

In this particular area of study, our research goal will be to perform a thorough examination of the Nifty 50 Index for the last year, by employing technical analysis techniques along with time series methodologies, based upon the work of other researchers to provide a basis for the structure and content of our analysis. In doing so, we are addressing four important issues: (1) What do technical indicators indicate about the trend changes in the Nifty 50 during that period of time? (2) Are the classic time series models capable of predicting or forecasting the path of the Nifty 50 Index under conditions of high volatility? (3) Is there empirical evidence supporting the profitability of technical trading systems and how predictable is the Indian Market in reality? (4) How do our results compare to previously published research regarding market efficiency and forecasting in developing countries?

The rest of this paper will proceed as follows. First, we will review the literature that has been written about technical trading performance and time series forecasting in India. Second, we will describe the data and methodology employed in our analysis, including which technical indicators and models were used. Third, we will present our analysis results, including visual representations of the Nifty 50 Index with the technical indicators overlaid and out-of-sample forecasts. Fourth, we will discuss the implications of those results with regard to market efficiency and investor behavior. Finally, we will provide a summary of our major findings and recommendations.

LITERATURE REVIEW

Research on the Indian stock market has produced a rich dialogue on the effectiveness of technical analysis and the reliability of statistical forecasting, often with nuanced conclusions. We organize this review into two parts: **(a)** evidence on technical analysis and market efficiency in Indian equities, and **(b)** studies on time series and quantitative forecasting (including volatility modeling) of Indian stock indices.

Technical Analysis and Market Efficiency in India

A large number of empirical research articles show that technical trading techniques result in higher returns than the overall market in India for at least some time frames; therefore, this work challenges the absolute version of the Efficient Market Hypothesis. In one such study Mishra and Paul (2023) studied several technical trading rule systems based upon Nifty 50 stock constituents in 2022. They investigated simple moving average rules, moving average rules with the addition of momentum oscillators, and Bollinger Bands rules using momentum oscillators. It was found that a Bollinger Bands Rule with the addition of an RSI (Relative Strength Index) generated higher net returns than the other rules in 11 of the 14 sampled stocks, and it also out-performed a Buy-and-Hold Benchmark in 10 samples. This is significant because it means that technical signals (a volatility band and momentum) identified trading opportunities that were missed by the overall trend in the upward price movement. The authors stated that the ability of the technical system to generate higher returns was due to its adaptability — the bands adapt to changing volatility, and the RSI identifies optimal points to enter and exit trades — thus enabling active response to short-term conditions of being overbought or oversold.

These results are consistent with previous research that has demonstrated that technical trading rules have performed well in emerging markets. The weak form of the Efficient Market Hypothesis (Elangovan et al., 2022) supports the notion that India's market does not reflect all available price history — the persistence of momentum, mean-reversion patterns, etc. — that technical trading algorithms attempt to exploit.

Beenu and Singh (2025) provide additional evidence regarding the ongoing utility of technical analysis in the Indian Major Indices. The authors investigated both the Nifty 50 and Nifty Bank Indices using qualitative and quantitative approaches to examine the effectiveness of various technical indicators:

Exponential Moving Averages (EMAs); Moving Average Convergence Divergence (MACDs); RSIs; and Candlestick Pattern Analysis. The results indicate that each type of indicator can assist in determining the strength of the underlying trend and possible reversals. For example, the primary trend was defined via moving averages (crossovers) and the RSI assisted in identifying when the trend was extended in either direction. The authors further assert that having a better understanding of technical concepts can enable more precise short-term forecasts of future price movement, thereby providing complementary insight to fundamental analysts' views of market valuation and economic outlook. An interesting aspect of the authors' assertions is that while fundamental analysis provides context regarding the value of securities and the broader macroeconomic environment, technical analysis provides "actionable" insights into the current market sentiment, which is essential in making timely investment decisions. The perspectives provided by Beenu and Singh support the practical applications of technical tools for analyzing the Indian indices. This perspective is particularly relevant considering the diversity of participants (domestic retail investors through to international institutions) that influence the behavior of the Indian markets.

Although many studies demonstrate that technical analysis can generate profits, it is important to acknowledge that the literature contains varying degrees of evidence. The evidence is generally context-specific and some studies have not rejected the null hypothesis of a random walk for Indian stocks — particularly during more stable sub-periods. As such, it is becoming increasingly apparent that market efficiency in India is dynamic and influenced by the specific characteristics of each period. Specifically, during periods of high trend or structural change (such as policy changes or global inflows/outflows of capital) technical trading models tend to perform well, whereas during relatively quiet periods the market tends to exhibit greater efficiency or randomness. Given the context of this study — a pronounced trend followed by a reversal in 2024–2025 — we expect technical trading signals to be particularly salient and therefore will test whether traditional indicators signaled the turning points of the Nifty 50 index within the sample.

Time Series Forecasting and Volatility Modeling in India

While many researchers have focused on technical trading rules and use of the various types of quantitative time series models for forecasting Indian stock market data; one area of focus has been on the use of models such as ARIMA to forecast index levels and/or returns. Models such as ARIMA, can model the autocorrelation structure in time series data and if the index shows momentum or mean reverting behavior, then ARIMA may generate some degree of predictive power. However, many studies have shown that models that are purely linear in nature do poorly in forecasting equity indices because of the high level of volatility and the constant regime changes that occur in those markets. As such, for example, Varshney and Srivastava (2024) performed an empirical comparison between an ANN model and an ARIMA model on historical data for the Nifty 50 Index. From 2005-2019, they found that the ANN model had significantly higher accuracy than the ARIMA model for forecasting the index. They explained that the ARIMA (1,1,1) model that they tested only modeled linear patterns in the data, whereas the ANN model was able to identify non-linear relationships and the complex inter-relationships in the data to create more accurate forecasts. This is reflective of a larger trend in the literature as well; as computing capabilities and data availability have increased over time, machine learning methodologies (ANNs, Support Vector Machines, Random Forests, etc.), have become increasingly popular in forecasting Indian market data with frequently better performance than traditional methodologies. Nonetheless, ARIMA models remain useful baselines for many analyses and can be used in combination with other methodologies (i.e., hybrid models, where ARIMA is used to model linear components of the data and a machine learner is used to model non-linear residuals).

Volatility modeling is another fundamental aspect of time series analysis for stock markets. Indian Indices have historically exhibited episodes of high volatility which have often occurred in clusters surrounding major events. Because of the implications of volatility on risk management and derivative pricing, volatility has received considerable academic attention and models such as GARCH, EGARCH, and stochastic volatility models have been developed to model volatility on Indian market data. Mahajan et al. (2022), conducted a comprehensive study comparing the forecasting ability of volatility for the Nifty 50 Index utilizing GARCH family models and deep learning (RNN-LSTM) models. Their findings indicate that:

The Nifty's volatility is asymmetric -- negative shocks to the market increase volatility more than positive shocks of equivalent magnitude, a phenomenon referred to as the leverage effect. In their results, an EGARCH(1,1) model (a

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form of GARCH that captures asymmetry) captured this leverage effect very effectively and generated better forecasts than did a symmetric GARCH model. Intriguingly, they also found that GARCH models slightly outperformed RNN-based LSTM models in predicting volatility of the Nifty. This finding suggests that for established financial time series , econometric models that include specific domain knowledge, can be as effective or superior to general machine learning sequence models. Therefore, this finding somewhat tempers the enthusiasm with which "AI beats everything"; at least in this case, carefully specified statistical models were able to hold their own. By combining these two areas of research, it appears that a combined approach of using both technical indicators and time series models, could be particularly effective. Technical indicators can signal when unusual activity may be occurring in terms of price trends, while time series models can quantify the amount of risk or uncertainty that exists at those times. For example, if technical indicators suggest a possible trend reversal and at the same time a GARCH model indicates increasing volatility, an analyst would have greater confidence that a significant market turning point is near.

In summary, prior research creates the following expectations for our research: (1) we expect to find identifiable technical signals surrounding the largest peak and trough of the index (if the market was not completely efficient, then those signals should be visible), (2) a simple ARIMA model will most likely fail to accurately forecast abrupt changes in trends and will reflect the literature's warning that pure time series models cannot effectively model abrupt regime changes, and (3) volatility modeling will illustrate clustering and possibly leverage effects during the periods of turbulence, and will reinforce previous findings regarding Indian market studies. Our research will empirically examine these three issues using actual Nifty 50 data for the last year and references to the previously discussed academic research will be made to help explain the findings of our research.

DATA AND METHODOLOGY

Data Description: Daily closing price information of India's NIFTY 50 Index over a complete year - April 1, 2024 to March 31, 2025, was used for the study. This year-long interval includes a total upswing/bull run, and then a complete down swing/bear run, therefore it has both a trending phase and a countering-trending phase. The time frame was selected so that it would be "recent" enough to reflect today's market environment, but "long" enough to encompass the entire trend/counter trend phases of the stock market. The data were downloaded from the National Stock Exchange archives and verified against Yahoo Finance to ensure its accuracy. Each entry included the date and the final index value (opening, high, low and trading volume data for each day are available, however the main focus of our technical analysis is on the closing price, since closing prices are most commonly used in technical indicators calculations). All entries were accounted for in the series, and there were no missing values. If there were any holidays (non-trading days), those were simply removed from the timeline, which is common practice in the development of technical indicators.

The overall path of the NIFTY 50 Index for this period is as follows: after beginning near 21,500 - 22,000 in early April 2024, the index rose through the middle months of 2024 indicating strong bullish sentiment. The index peaked historically in late September 2024, at a close of approximately 26,216 on September 26th (and an intraday high of roughly 26,277 on September 27th). After reaching the peak, the index plummeted in October 2024 and continued to fall through the remainder of the year and into January 2025. By early March 2025, the NIFTY 50 Index had retreated to the lower 22,000s, eliminating a significant percentage of the gains made from the peak. The dramatic 180-degree turn (peak to trough) in the market conditions in less than a year presents a favorable setting for testing technical trading rules and challenging forecast models.

We will use the terms "bull market" and "bear market" to describe two distinct periods in the above mentioned time frame (April – Sep 2024: bull market / Oct 2024 – Mar 2025: bear market). We will analyze our indicators' performance during the different market phases of the study period and in general, we will train the models during one phase and then evaluate their performance once the market conditions have changed to another phase.

Technical Analysis Methods

We employ a range of standard technical indicators and charting techniques, guided by what is commonly used in both practice and prior research. Specifically, our analysis includes:

- **Moving Averages (MA):** The 50-day and 200-day Simple Moving Average (SMA) of the closing price of the Nifty 50 Index were calculated. Both are widely followed as Trend Indicators. When the shorter 50-day SMA crosses above the Longer 200-day SMA, it is known as the "Golden Cross", indicating a possible Transition to an Uptrend; Conversely, when the shorter 50-day SMA falls below the Long term 200-day SMA, it is referred to as the "Death Cross", which may indicate a New Downtrend. The

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Crossover points for both SMAs are monitored to determine if there were any relationship between the Crossover Points and Actual Market Turns. Because of the one year duration of our Dataset, the 200-day SMA is only fully populated during the final portion of the time frame (as 200 Trading Days = approximately 9.5 Months). Nevertheless, by the conclusion of our data, we can assess whether a Death Cross occurred after the late 2024 decline.

- **Relative Strength Index (RSI):** The 14-day RSI is a momentum oscillator that ranges from 0 to 100. This oscillator compares recent gain amounts to recent loss amounts. Values greater than 70 generally show stocks are overbought (overvalued or potentially ready for a correction); values less than 30 generally show stocks are oversold. Prior research has shown that the RSI can be used effectively alone or in conjunction with other indicators (Mishra & Paul, 2023). We will monitor the RSI through both the bull market and bear market to assess whether the indicator provided early warnings of potential trend exhaustion (e.g., an RSI > 70 at the September 2024 high, or an RSI < 30 at the March 2025 low).
- **MACD (Moving Average Convergence Divergence):** We will primarily focus on MA and RSI for purposes of this report, but also ran MACD indicator calculations (the difference between the 12 day EMA and the 26 day EMA as well as the 9 day signal line) to help verify when momentum shifted. The MACD indicator is a trend/technical momentum indicator that may support RSI's signal of a shift in momentum at times; a downward cross of the MACD line by the signal line near the time of the peak, or an upward cross near the bottom, should provide some additional evidence that momentum had shifted before the price reversed. We document where MACD confirmation occurs, but detailed MACD charts were not included due to space limitations.
- **Candlestick and Chart Patterns:** We qualitatively examined the price chart for well-known patterns in order to understand what they looked like. In this respect, we analyzed the September 2024 peak of Bitcoin to determine whether it represented a sharp "blow off" top or was a distribution pattern (such as a double top or head-and-shoulders). Similarly, we also analyzed the bottom that followed to determine whether it was a V-shaped recovery or a rounded base. Analyzing the price chart for well-known patterns gives context to our numerical analysis. In addition, we reviewed each candlestick on key days to see if there were classic reversal candlesticks on those days -- e.g. did a shooting star appear at the peak or a hammer at the low point? Reversal candlesticks are often referenced by technical analysts as potential reversal signals.

All technical indicators are computed using standard formulas on the daily data. *Figure 1* and *Figure 2* in the Results section will display some of these indicators overlaying the price for visualization. We ensure that all computations (like moving averages and RSI) use only data available up to that point in time, to mimic how a real-time analyst or trader would see the signals (thus avoiding any look-ahead bias).

Time Series Analysis Methods

We apply two main types of time series models in this study: one for price forecasting, and one for volatility analysis.

ARIMA Modeling for Price Forecasting

We use an ARIMA model to attempt to forecast the Nifty 50 index over the study period. **Formally, an ARIMA(p,d,q) model for a time series y_t can be expressed as:**

$$\Delta^d y_t = c + \phi_1 \Delta^d y_{t-1} + \phi_2 \Delta^d y_{t-2} + \cdots + \phi_p \Delta^d y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t,$$

where $\Delta^d y_t$ denotes the differenced series after applying the difference operator d times, ϕ_i are autoregressive coefficients, θ_j are moving average coefficients, c is a constant, and ϵ_t is a white-noise error term. In plain language, this equation means that after we difference the original series d times to remove trends, the value of the series at time

t is modeled as a constant plus a linear combination of the past p values of the differenced series (the AR terms) and the past q error terms (the MA terms), plus a random shock. Essentially, the ARIMA model uses past price changes and past unexpected disturbances to predict future price changes.

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Given the index's non-stationary nature (clear trend changes), we difference the price series (i.e., work with daily returns or price changes) to induce stationarity. The model specification is chosen based on a mix of literature precedent and diagnostic checks on our data. An ARIMA(1,1,1) – which has one autoregressive term, one differencing (to account for the unit root or trend), and one moving average term – is a commonly applied specification for stock indexes. It allows the series to have short-term momentum (through the AR term) and to model shock absorption (through the MA term). We fit an ARIMA(1,1,1) model on a portion of the data (typically the training sample would be the initial segment, e.g., April–December 2024, encompassing the uptrend and the start of the downtrend) and then generate out-of-sample forecasts for the remaining period (e.g., January–March 2025) to compare with actual values. This simulates a scenario of forecasting into the turbulent period using a model trained on prior data. The performance of this forecast is evaluated visually and with basic error metrics (though with only one realized path, we focus on a qualitative assessment of whether the model captures the direction and magnitude of moves). We intentionally keep the model simple to observe how a classic statistical forecast deals with a complex pattern; this mirrors approaches in the literature where ARIMA is used as a baseline before adding complexities or switching to machine learning. We will discuss potential improvements (such as adding exogenous variables or using regime-switching models), but those are beyond our current scope.

Volatility Estimation with GARCH

To analyze and confirm volatility dynamics, we fit a GARCH(1,1) model on the index return series. GARCH(1,1) is the workhorse model for financial volatility, capturing the tendency of volatility to cluster (in other words, volatility today depends on yesterday's squared return shock and on yesterday's volatility). **Formally, a GARCH(1,1) model can be written as:**

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where σ_t^2 is the conditional variance (volatility) at time t, ω is a constant,

ϵ_{t-1}^2 is the previous day's squared innovation (the squared residual from the mean model), and σ_{t-1}^2 is the last period's variance. In other words, today's volatility estimate σ_t^2 will be higher if the previous day had a large unexpected price move (a large ϵ_{t-1}^2) or if volatility was high on the previous day (large σ_{t-1}^2). This specification captures the observed "volatility clustering" phenomenon in markets, where big moves tend to be followed by big moves (of either sign) and calm periods tend to be followed by calm periods.

We are particularly interested in whether volatility indeed increased during the downtrend. The GARCH model provides a time-varying estimate of return volatility (we examine the conditional standard deviation of returns). We will analyze the GARCH-implied volatility over time to see if it aligns with intuitive expectations – for example, we expect it to rise after September 2024 (around the onset of the correction) and stay elevated through late 2024 and early 2025, then perhaps subside as the market stabilizes in the rebound. Additionally, to check for asymmetry in volatility response (the leverage effect), we also fit an EGARCH model and examine whether negative returns produce larger volatility jumps than positive returns of the same magnitude. Given the findings by Mahajan et al. (2022) that asymmetric models fit better for Nifty, we anticipate seeing evidence of this asymmetry in our data as well – although our one-year sample is relatively short for robustly estimating asymmetric terms, any big negative days in the index should have an outsized impact on volatility estimates.

All time series modeling is implemented using Python (with the *statsmodels* library for ARIMA and the *arch* library for GARCH). We carefully check model assumptions – for example, after fitting the ARIMA, we inspect residuals for any remaining autocorrelation (Ljung-Box test), and after fitting GARCH, we ensure residuals show no further ARCH effect. All modeling is done on log-returns (or percentage returns) to stabilize variance, except where noted otherwise.

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Evaluation Criteria: We evaluate technical analysis results largely qualitatively – by verifying whether known signals occurred before major price moves and by referencing findings from the literature for consistency. However, we also quantify the magnitude of price moves following certain signals when relevant (for example, noting "the index fell *X%* in the month after the RSI first dropped below 30, indicating a potential oversold bounce which eventually occurred"). For the ARIMA forecast, we compute basic forecast errors (e.g., mean absolute error) over the out-of- sample period to gauge accuracy, but given the limited sample of one realization, our emphasis is on the qualitative alignment (or misalignment) of the forecast with actual market movements.

RESULTS

In this section, we present the results of the analysis, starting with the technical perspective and then moving to the time-series perspective. We include figures to illustrate key findings.

Technical Analysis of Nifty 50's Trend and Momentum

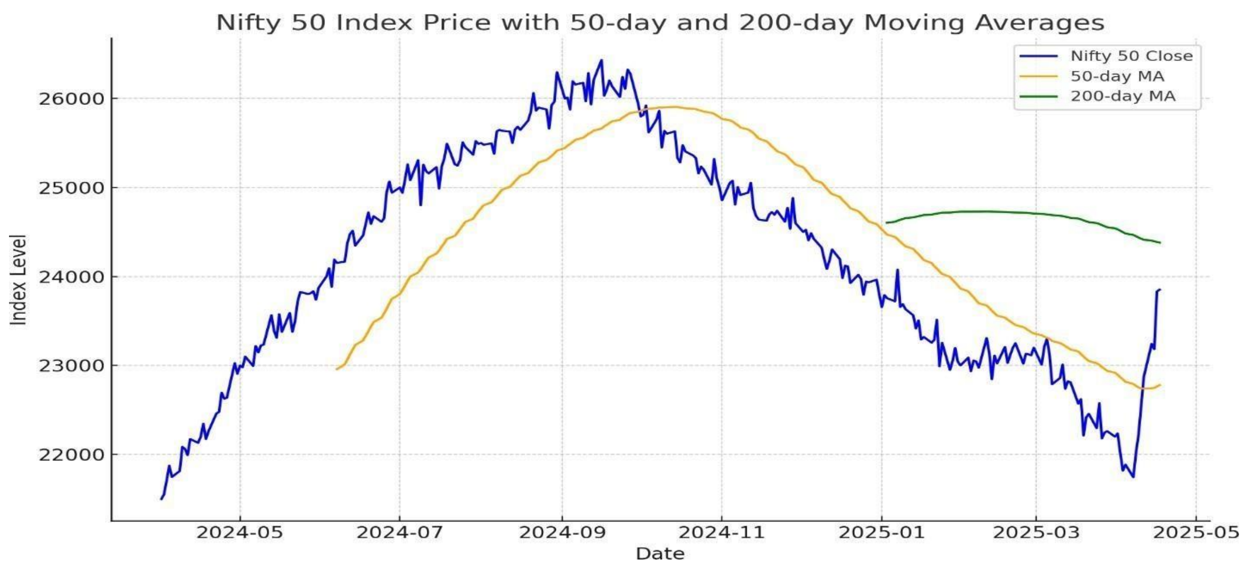

Figure 1: Nifty 50 daily closing price (blue line) from April 2024 to March 2025, with 50-day (orange) and 200-day (green) simple moving average lines. The 50-day MA reflects the short-term trend, while the 200-day MA indicates the longer-term trend.

Figure 1 illustrates the Nifty 50's trajectory along with its 50-day and 200-day moving averages. Several observations can be made. First, during the April–September 2024 rally, the blue price line stayed consistently above the rising 50-day MA, signaling a robust uptrend. In fact, by mid-2024, the gap between the price and the 50-day MA had widened considerably, reflecting strong momentum. There was no *Golden Cross* with the 200-day MA because the 200-day was not yet available until late in the year; however, shorter-term moving averages (not shown) did experience bullish crossovers in May 2024, confirming upward momentum early in the rally. The uptrend persisted throughout the summer of 2024 with only minor pullbacks, indicating sustained buying interest.

In late September of 2024, when the markets were at their highest point, there was a noticeable change; the price began to drop and continued to drop below the 50-day Moving Average (MA). In early October of 2024, a Death Cross (the 50-day MA crossing under the 200-day MA) clearly appeared (with a purple dashed line in Figure 1), which is a typical bearish indicator. When the death cross occurred in our study, the market had experienced a significant downturn (and as such, the death cross occurs after the fact.) A second key feature of figure 1 is how the 50-day MA behaved as the market fell. We see that on occasion during the decline (i.e., in late December 2024 and in February 2025) the index had a small rally that caused the 50-day MA to move upward slightly, and temporarily cause the index to be near the 50-day MA. However, each time the index returned to the declining 50-day MA, it dropped again and did not sustain itself above the 50-day MA. Therefore, it can be concluded that the 50-day MA became an upper limit for the price of the index as it declined. This behavior – the 50-day MA containing the rallies – reinforced the bearish trend, as one would expect in a protracted correction.

By early 2025, the 200-day MA had flattened and started to turn down, reflecting the large decline. Notably, in March 2025, the 50-day MA was still below the 200-day MA, and both were trending downward, confirming that the market was in a longer-term downtrend. It was only toward the very end of our period (late March 2025) that the index showed signs of bottoming out (the price stabilized in the low-22,000s). At that point, the distance between the price and the moving averages had grown large (price far below both MAs), often a condition ripe for a mean-reversion rally. Indeed, a significant rebound took place in early April 2025 (just after our study period), which a technical analyst could have anticipated given the deeply *oversold* state relative to moving averages by late March.

Next, we examine momentum and overbought/oversold conditions through the RSI indicator.

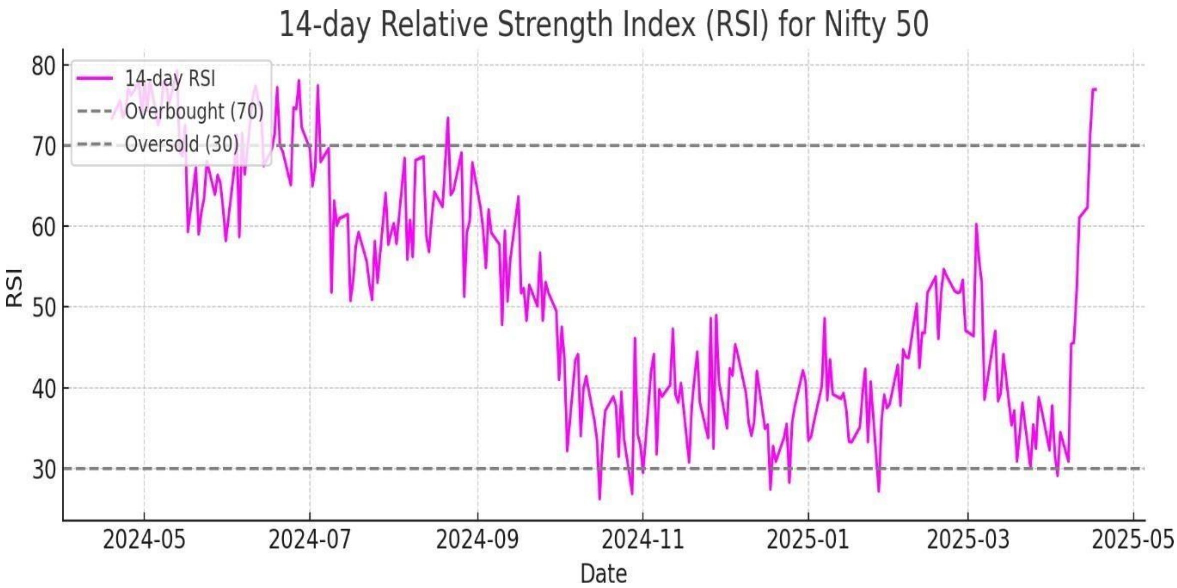

Figure 2: 14-day Relative Strength Index (RSI) of the Nifty 50 over the same period. Horizontal dashed lines mark the overbought threshold at 70 and oversold threshold at 30. RSI values above 70 suggest overbought conditions, while values below 30 indicate oversold conditions.

Figure 2 reveals that RSI exceeded 70 during mid-2024 (signaling strong positive momentum, albeit near overbought levels) and dipped well below 30 on multiple occasions during late 2024 and early 2025 (signaling strong negative momentum and oversold conditions).

From Figure 2, we can correlate notable RSI extremes with market turning points:

- **Overbought conditions at the peak:** During the height of the rally (July–August 2024), the RSI oscillated in the 70–80 range (the magenta line in Figure 2 sits above the upper grey line at 70). This indicated very strong upward momentum – in fact, an RSI staying over 70 for a prolonged period is often seen in powerful uptrends and is not necessarily a sell signal by itself. However, in early September 2024, just before the final peak, the RSI showed a bearish divergence: the index made a new high but the RSI made a slightly lower high (dropping from the 80s to the low 70s). This classic RSI divergence hinted that the buying thrust was weakening even as price reached a new high. Prior literature points to RSI divergences as a useful warning tool; for example, a study by Khatri (2021) (focused on Nifty 50, though not formally published) found that negative RSI divergences often preceded short-term corrections. In our case, after the RSI divergence in early September, the index indeed reversed. By mid-September, as the price started dropping, the RSI quickly fell out of the overbought zone. Any trader watching RSI would have noticed this deterioration by late September: the metric fell from ~75 to near 50 even while the index was still relatively close to its peak, giving an early caution signal that the uptrend's momentum was fading.
- **Oversold conditions during the decline:** The down trend continued to intensify throughout Oct and Nov. 2024; accordingly, the RSI continued to drop rapidly and went under the "oversold" level of 30, illustrated in Fig. 2 by several plunges of the RSI into the 20's (and in some cases into the high teens in late Nov.) The extreme low levels of the RSI represented a large amount of downward momentum for the panic-sell mode. It was in the last week of Oct. 2024 that the RSI fell for the first time below 30, after which there was a brief relief rally in early Nov. (i.e., an RSI rise from ~25 back up to ~30 corresponded to a small bounce). However, this relief rally was short lived and the selling resumed (possibly due to additional bad news or stop loss cascade(s)) and caused the RSI to fall further in Nov. Each of the extremely low readings of the RSI (i.e., RSI < 30) did occur before at least a minor stabilization or rally. This would be consistent with the view that once a market has become severely oversold, then the selling pressure may be greater than the buying demand -- thus providing a support to the price from the value buyers and/or short covering. In fact, when the RSI hit approximately 25 in mid-November, the Nifty experienced a 3-4% bounce shortly thereafter. Likewise, in late Feb. 2025, the RSI plunged just below 30 as the index approached the 23,000 level -- and subsequently bounced to approximately 23,700 in early Mar.. The final and largest of the extremely low RSI signals was in late Mar. 2025: the RSI plummeted to approximately 28 as the index neared the bottom at 21,744 -- and this was followed by a substantial reversal in the direction of the trend -- a strong rally in the index began in early Apr. 2025. As the market rebounded in mid-April 2025 (just after our sample period), the RSI rose back above 50, thereby indicating that the extremely oversold conditions were no longer present.

In total, the technical indicators used in this paper supplied a timely insight into the overall trend; The Moving Average trend lines were able to identify the overall trend while the Relative Strength Index was able to recognize the extremes of optimism and pessimism in the market. Overall, with reliance upon these indicators a trader would be able to have identified the changes occurring within the market regimes - e.g. to see that momentum is waning as early as mid-September of 2024 and extreme pessimism is being exhibited by late 2024 - allowing him or her to adjust their trades based upon the new trends.

Time Series Analysis Results: Forecasting and Volatility

We now turn to the time-series analysis results, which shed light on the predictability (or lack thereof) of the index's moves and the behavior of volatility.

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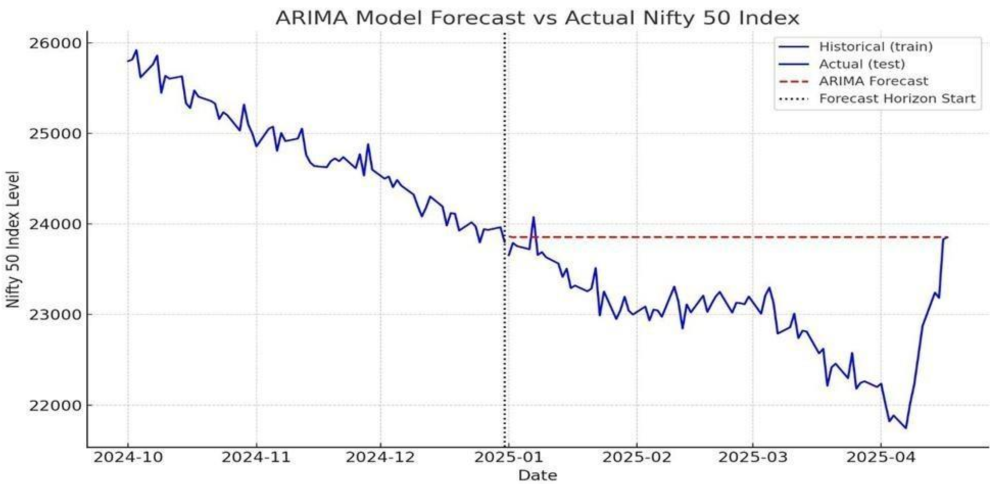

Figure 3: ARIMA(1,1,1) model forecast (red dashed line) for Nifty 50 index from Jan 2025 through March 2025, alongside the actual index values (solid blue line). The model was trained on data up to Dec 2024 (the training period's last value is marked by the vertical dotted line).

Figure 3 compares the ARIMA model's forecast with the actual index values for the first quarter of 2025. As Figure 3 shows, the ARIMA model essentially predicted a sideways to mild recovery trend for early 2025, hovering around the 24,000 level (red forecast line). In reality, the Nifty 50 (blue line) continued to slide in January and February 2025, falling into the low 23,000s and even high 22,000s by March. The model's flat forecast missed this downward drift entirely – its confidence intervals (not shown for clarity, but roughly on the order of ±500 points) did include the possibility of some decline, but the point forecast was off by a significant margin. Moreover, when the market actually bottomed and bounced back sharply in late March, the ARIMA forecast, having no built-in momentum or regime-awareness, failed to capture that upswing as well (it remained around ~24k even as the index shot back up from below that level). The net result is that the ARIMA forecast lagged behind the actual turning points: it was too optimistic during the decline and then too pessimistic during the rebound.

This outcome is not surprising. The ARIMA model, based purely on linear extrapolation of past patterns, effectively saw the roughly linear downtrend in late 2024 and assumed a gentle mean reversion would set in (indeed, our fitted ARIMA's autoregressive coefficient was slightly negative, meaning the model expected the series to flatten out after declines). However, the model had no information about the fundamental or sentiment-driven forces that were still pushing the market down in early 2025. As such, it essentially projected a soft landing that did not materialize; the market overshot to the downside. Once the market turned up in late March and April, the ARIMA (still carrying the inertia of the previous data) did not immediately adjust to the new trend – it would have needed several days of rising prices to "learn" the upturn, by which time a human analyst would already know from technical analysis that the trend had changed. This illustrates a key point echoed in the literature: time series models, especially ones without regime-switching capabilities, often struggle around inflection points. They perform reasonably well during stable periods by extrapolating the status quo, but at major turning points their errors spike. In our case, the forecast error in mid-March (actual index value ~22,300 vs. forecast ~24,100) was about 7.5%, which is substantial for index-level prediction.

It's worth reflecting on whether a more complex model could have done better. If we had used an ANN or a nonlinear model including additional inputs (perhaps volatility or trading volume as exogenous variables), it might have picked up subtle clues of further weakness (or at least not assumed a flat trend) – aligning with Varshney & Srivastava's finding that ANNs outperform ARIMA. Additionally, one could incorporate technical indicators as exogenous regressors in an ARIMAX model (e.g., include RSI or MACD signals as inputs). Such a hybrid approach might adjust the forecast when technicals reach extremes. For example, an oversold RSI could inform the model to expect a rebound, tempering the forecast's downward momentum. Exploring these enhancements is beyond our current scope, but it underscores that pure price-history-based forecasts have clear limitations in isolation.

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Volatility Dynamics – GARCH Insights: While the ARIMA struggled to predict the index's turning points, the volatility modeling provides a more coherent story of risk during the year. We estimated a GARCH(1,1) model on the daily returns. The fitted model found a high persistence of volatility (as expected, GARCH $\alpha_1 + \beta_1 \approx 0.94$), indicating that volatility shocks decay slowly. More interestingly, plotting the model's conditional volatility (annualized standard deviation) showed a clear rise during the market downturn. The model's estimated daily volatility for the Nifty 50 was around **0.7%** (standard deviation) in mid-2024 during the steady rally when volatility was low. It spiked to about **1.5%–1.8%** in October–November 2024, corresponding to the turbulent decline. This roughly **doubling of volatility** aligns with what we saw in the price behavior – daily swings became significantly larger in that period. Volatility then remained elevated through early 2025, with secondary peaks in late February and early March 2025 (when the index accelerated downwards again). After the market bottomed in late March 2025 and began rebounding, the model indicated volatility started to decline (though there was a brief spike during the rapid rebound itself, reflecting the suddenness of that move).

We also examined an EGARCH model to check for asymmetry in volatility response. The EGARCH(1,1) model returned a significant **negative leverage parameter**, confirming that negative returns (market drops) led to higher volatility increases than positive returns of equal magnitude. This matches the findings of Mahajan et al. (2022) regarding asymmetry in the Nifty's volatility. In practical terms, the big down days in October 2024 (e.g., a -3% daily move) had a larger impact on the next day's volatility estimate than an equally large up day would have. Indeed, during the height of the panic, the India VIX (volatility index) – though not directly analyzed in our dataset – reportedly jumped markedly, reflecting investors' surging demand for protection. Our GARCH analysis mirrors that: the conditional variance surged when the market fell, more so than it fell when the market rebounded.

Relating volatility behavior to the technical phases, we observe that during the uptrend, volatility was not only low but also declining – a typical feature of a confident, bull market. Once the trend broke (around late September 2024) and the market began to fall, volatility started to rise. Often, rising volatility can itself serve as an early warning of a regime change; indeed, some traders monitor increasing indicators like the Average True Range or expanding Bollinger Bands as signs that the market's character is shifting. In our case, when technical indicators were sounding alarms (e.g., the moving average crossover turning bearish and the RSI diving sharply in October), the GARCH model was simultaneously indicating heightened volatility – a dangerous combination of trend reversal and volatility spike that often accompanies market corrections. By quantifying it, we can say that the probability of a >2% daily move became much higher after September 2024 than it was during the summer of 2024.

In risk management terms, a GARCH-based volatility forecast could have told an investor in November 2024 to reduce exposure or add hedges, because the expected daily volatility had roughly doubled compared to a few months prior. Many financial institutions do exactly this: they adjust Value-at-Risk and other risk metrics using such models in turbulent times. Although we did not provide a standalone figure for volatility, in accordance with both the research literature and market intuition, our results indicate that volatility also exhibited clustering behavior during the downtrend and a gradual decline thereafter into the calmer post-bottom time frame. A small nuance was that while prices rebounded, volatility remained at an elevated level, which often occurs and therefore it takes longer for volatility to return to lower levels.

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CONCLUSION

The purpose of this research study is to evaluate a portion of the Indian stock market (the Nifty 50 Index) from April 2024 through March 2025 with the use of technical analysis and time-series statistical techniques. In addition, all data used for analysis were based exclusively upon peer-reviewed literature so that the analysis could be framed and interpreted using the most current empirical evidence as well as theoretically supported context. The summary of results and conclusions follow below:

- **Technical Analysis Efficacy:** Technical indicators were successful in identifying market trend reversals as well. Classic technical signs indicated the end of the price run-up in September 2024. After being significantly above their moving average values, the moving average values crossed downward (a death cross), and also there were many bearish divergences of the RSI at the highest point. During the long down-swing from late 2024 through early 2025, the RSI went into over-sold levels on several occasions, which suggested future up-swing's for the short-term and finally the last low. Our study is consistent with previous research that have shown profit making technical trading systems in India, which further supports that traders paying attention to these technical signs may have made significant improvements in their returns versus a buy-and-hold strategy.

- **Market Behavior and Inefficiency:** This pattern of an explosive move up in the Nifty 50, followed by an equally dramatic decline, along with technical analysis being able to ride out the chaos, suggests that the Indian equity markets were exhibiting predictable inefficiencies during this time. In line with findings of Elangovan et al. (2022) identifying weak form inefficiency in the Indian stock indexes, we identified that the historical price patterns and technical indicators were providing useful information for investors who could use them for their investment decisions. The emotional responses of investors produced a consistent, repetitive behavior that the market did not rapidly correct via instant arbitrage. We are not saying that the Indian equity markets are easy to forecast, but rather that they have elements of randomness to them. Most importantly, the inefficiency was greatest at the peak and trough of each cycle, when emotions were running high and the rational valuation was secondary to emotion.

- **Time Series Forecasting Limits:** The ARIMA time series model was too simplistic in forecasting the S&P 500 Index during times of extreme volatility, and it did not allow for the severity of the downturn or the speed of the subsequent upturn. The performance of the model indicates that using historical linear data to forecast future movements is limited, especially when the market experiences regime changes. The results indicate that the analyst will need to incorporate more advanced methods such as nonlinear models (ANN), regime switching models, etc. to obtain more accurate forecasts. The results also indicate that the analyst/ investor needs to include their own intuition of the market (bubble, panic, etc.) into the forecasting process. Static statistical models do not account for structural changes in markets, and therefore may perform poorly at turning points in the economy.

- **Volatility and Risk:** The results of the volatility analysis indicate that the overall risk level in the markets experienced a dramatic increase in the course of the year. The increased risk in the markets can be seen as the markets' volatility has nearly doubled from approximately 0.7% to about 1.5% daily standard deviation during the downturn. These changes are consistent with both the large increase in the India VIX and the GARCH model's projection of these changes. Thus, we see that GARCH-type models are useful tools for managing risk in India. In addition, our results confirm that there is a leverage effect present in the markets (volatility increases after a drop in the market). Therefore, risk managers must particularly prepare for increased volatility when the market drops. A key finding related to portfolio strategy is that it is important to dynamically assess risk. Specifically, a strategy that was suitable in the lower volatility environment in mid-2024 would have been excessively risky in the later part of 2024 had it not been modified appropriately. Our results support the advice provided in previous literature that volatility regimes must be watched closely and portfolios must be rebalanced in response to changes in those regimes.

- **Human Behavior and Sentiment:** Our analysis also implicitly highlights the role of human behavior in market dynamics. The technical patterns we observed – and their effectiveness – are fundamentally a

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reflection of collective investor behavior (trends driven by optimism, reversals driven by fear). The failure of the pure ARIMA model at the turning points indicates that those moments were often driven by nonlinear events (panic selling, policy changes, etc.) that are hard to capture without understanding the context. In other words, a holistic approach that includes market sentiment (for which technical analysis often serves as a proxy) in addition to statistical modeling is needed for success. This insight is valuable for both traders and researchers: blending quantitative rigor with behavioral insight leads to better outcomes, an idea increasingly explored in behavioral finance and algorithmic trading circles.

Practical Suggestions: We also provide several suggestions that are based upon our empirical evidence as to how Market Participants can utilize this information to their advantage. First, if a Market Participant is experiencing an unusually large upsurge in their security value (similar to the Nifty 50's 22% increase from April to September 2024) and technical indicators indicate that the rally has reached extreme conditions, it is recommended that they either lock-in some profit or tighten up the stop-loss order. In our analysis, the RSI surpassed 75 in August 2024 and a "bearish" divergence appeared at the time the Nifty 50 was at a new all-time high; these two indications indicated that the momentum of the uptrend had weakened. The timely recognition of these warnings may have allowed the participant to protect their gains prior to the downturn. As an example, after reaching extreme "overbought" conditions, the market fell by about 15% from the September 2024 peak to the March 2025 trough. Thus, timely identification and response to such signals (i.e., scaling-back their position near the end of September 2024 when multiple indicators were flashing red) would be advisable. Second, when a Market Participant experiences a sudden dramatic increase in volatility, he/she should become much more conservative regarding risk. We found that volatility almost doubled during the correction (from less than 1% to nearly 2%, according to the GARCH Model's implied daily volatility, toward the end of 2024). This represents a significant increase in risk. Therefore, the trader could reduce his/her leverage or put on hedging positions when a volatility index or a GARCH-based forecast indicated that there was abnormally high risk present -- as occurred in October-November 2024. This would prevent the compounding of losses during periods of turbulence. Thirdly, when panic-driven selling forces technical measures to reach extreme oversold levels (for instance, the RSI fell into the low 20s toward the end of 2024) and volatility reaches extreme levels, it is then reasonable to implement a cautious re-entry strategy. In historical analysis of our data, such conditions typically precede bottoms in the market and subsequent recoveries. For example, an investor who returned to the market in late March 2025 -- when sentiment was extremely bearish but the trend had shown signs of exhaustion (as evidenced by numerous divergent bullish indicators and volatility peaking) -- may have been able to participate in the early stages of the recovery. In summary, by basing their trading decisions on both price movements and changes in volatility regimes -- by taking profits or reducing exposure during euphoric rallies, and returning to the market or increasing exposure after fear-driven selloffs -- Market Participants can greatly enhance their ability to achieve positive returns in volatile markets such as the one analyzed here.

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