Impact of Using Short-Term Trading Strategies on Securities' Returns: Evidence from Djia Securities Market

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ABSTRACT

The purpose of this study was to analyze short-term trend following trading strategies to understand their impact on returns of securities trading at the Dow Jones Industrial Average (DJIA). It achieved the objectives by analyzing the impact of momentum and moving average strategies, as well as a combined alpha strategy, and then comparing their returns with the market returns and buy-and-hold returns. Recently, scholars have questioned the consistency of the efficient market hypothesis after the claims of superior returns emerged. Publications have shown both agreement and disagreement with the concept of delivering abnormal returns by traders and other participants. While the Efficient Market Hypothesis asserts no one can beat the market by utilizing technical or fundamental analysis, empirical results of technical traders have shown it is possible to deliver superior returns. In view of these conflicting claims, empirical research in a well-developed securities market like the Dow Jones Industrial Average (DJIA) was useful in assessing the returns of securities. A quantitative research methodology was adopted in this study, together with an experimental research design. Historical price and volume data from Yahoo Finance for the Dow Jones Industrial Average as the market index, and its constituent stocks as equity data were used. One stock was randomly picked from each strata (high vs low performing stocks), making a total of 2 stocks selected to be studied. Specifically, Cisco (CSCO) (high performing) and Walgreens Boots Alliance Inc (WBA) (low performing) data for a period of two years was studied. The beginning period was set 2 years from the date of the analysis (August 2023 to August 2025). The downloaded data was analyzed using Python 3.12.7 using Jupyter Notebook. From the empirical results, the momentum strategy can consistently deliver better returns than the market (CSCO 32.46% and WBA 49.95% vs the DJIA Market 12.32%). Moving averages did not deliver better returns than the market (CSCO 5.07% and WBA -1.10%, vs DJIA Market 12.32%). Combined strategy showed mixed results (CSCO 9.56%, 42.75% vs DJIA Market 12.32%). The Efficiency Market Hypothesis does not hold true for all the securities tested. The DJIA market exhibited a weak form of efficiency. Trend following strategies have been shown to have the power to assist the trader in entering and exiting trades at the right time and generate superior returns. Combining these two strategies gives the trader a chance to choose the best-performing one at that particular time. Using the right signals in short-term trading can be profitable both in the bullish and the bearish markets. The researcher recommended the use of active portfolio management strategies such as technical analysis to maximize returns for investors and create more wealth. Use of predictive computing techniques such as machine learning is highly recommended to consistently beat the market as trading data and methods become more complex.

Keywords: Trading strategies, Momentum, Moving averages, Market returns, Superior returns, Efficient Market Hypothesis.

INTRODUCTION

Background To the Study

Short-term trading strategies involve a technical analysis strategy of buying and selling securities, considering short-term profit movements. The movements are occasioned by price movements that could last from a few seconds to a few days or months (Fischer & Krauss, 2018; Zhao & Yang, 2023). For a market participant to benefit from using short-term trading strategies, they must understand and master basic concepts (Fischer & Krauss, 2018; Jogani, 2024). Such concepts include trading rules and indicators that inform the trader when to go long or short, as well as hold the securities. According to Chourmouziadis and Chatzoglou (2016), short-term trading can be very profitable and very risky at the same time. This phenomenon is occasioned by the volatility in prices of securities. Alhashel et al. (2018) claimed that using short-term strategies in a technical analysis approach can help to generate superior returns. The trade entry and exit times are of the essence; thus, a trader must remain active to reap the benefits.

Claims of achieving superior returns and investigations on the role of trading strategies in its achievement have gained attention of late. According to Baumann (2022), while this field has been popular since the 1960s, it was not until the early 2000s that it gained more prominence. Profitable trading strategies were attributed to information asymmetry in the securities markets, the psychology of the investor, and the semi-structured, nonlinear stock market nature (Baumann, 2022; Charoenwong, 2012). Technical trading strategies were highly popularized by John Murphy in the 1990s, when he carried out extensive empirical investigations in this field. Price, volume, and open interests are the most fundamental information sources in technical analysis (Murphy, 2009). Other scholars, such as Lee et al. (2021), have urged that a combination of technical and fundamental analysis gives the best results in delivering superior returns. This area has been receiving attention of late, as it has gone against the well-known theory in finance of the Efficient Market Hypothesis.

According to Gârleanu and Pedersen (2013), superior returns have been enabled fundamentally by growth in computing and its application in portfolio management. Hedge funds and mutual funds are the most common securities that have shown consistency in beating the market by delivering abnormal profits (Agarwal & Ren, 2023). Active management and predicting prices using modern computing tools and techniques to accurately predict securities returns is the primary reason these asset managers have achieved the goal of delivering better returns than the market. The common predictors used include momentum strategies, Bollinger bands, and moving averages, among other methods (Precious & Marwa, 2023). Each technique has strengths and limitations to consider. Mean reversion in predictors is a crucial factor considered by portfolio managers as a general rule in managing transaction costs and increasing trading activity to deliver better returns. Technical and fundamental analysis are the primary tools used by portfolio managers to beat the market.

Fundamental analysis is the evaluation of securities by assessing their intrinsic value. The assessment considers, among other factors, financial information, economic, qualitative, and quantitative information (Amiri et al., 2016). Analysts of fundamental data look at conditions of macroeconomic and microeconomic nature to gauge the relative value of securities (Abuselidze & Slobodianyk, 2021). According to Baumann (2022), this approach aims to give a quantitative value of the security that can be used by an investor to compare the security's current price. This approach helps in understanding if the security is undervalued or overvalued. Additionally, it helps in the identification of fundamentally strong or weak firms and industries. It can fuel speculation by investors taking positions depending on the expectation of the value change in the companies and industries. Investors purchase securities (go long) of those firms perceived as underpriced or strong and sell (go short) on firms that are overpriced or are weak.

Technical analysis, on the other hand, focuses on the price direction using historical market data such as volume and price. Trend following strategies are primarily integral technical analysis methods (Baumann, 2022; Fischer & Krauss, 2018; Jogani, 2024). Trend following strategies have been widely used by technical analysts to predict the price movement and inform trading rules (Fischer & Krauss, 2018). These strategies include momentum and moving average strategies, among others, that show a direction of prices or volume movement. This study utilizes technical analysis to analyze momentum and moving average trend following strategies.

Statement Of the Problem

The problem addressed by this study is that it is not known to what extent, if any, the short-term trading strategies contribute to delivering superior returns in the Dow Jones Industrial Average (DJIA) market. In the past, scholars have questioned the consistency of the efficient market hypothesis after the claims of superior returns emerged (Jogani, 2024; Malkiel, 2003; Omar et al., 2025). Publications have shown both agreement and disagreement with the concept of delivering abnormal returns by traders and other participants. While the Efficient Market Hypothesis asserts no one can beat the market by utilizing technical or fundamental analysis, empirical results of technical traders have shown it is possible to deliver superior returns (Murphy, 2009). Gunawan (2024) demonstrated that the fact that some market participants have in the past been able to consistently beat the market, especially high-frequency traders or hedge funds, indicates that trading strategies could be of significant impact in achieving this goal. To understand their role, it necessitates an investigation

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into the impact of the trading strategies in achieving superior returns. The abnormal returns from technical analysts and short-term traders are a confirmation that the concept of EMH may not always hold true (Nazário et. al. 2017). In view of these conflicting claims, empirical research in a well-developed and efficient securities market like the Dow Jones Industrial Average (DJIA) was useful.

Research Objectives

The purpose of this study was to analyze short-term trend following trading strategies to understand their contribution to returns of securities trading at the Dow Jones Industrial Average (DJIA). It achieved the objectives by analyzing the impact of momentum and moving average strategies, as well as combining strategies and then comparing their returns with the market returns, as well as buy-and-hold returns.

1. To assess the influence of momentum strategy on returns of securities trading at the Dow Jones Industrial Average (DJIA).
2. To assess the contribution of the moving averages strategy to the returns of securities trading at the Dow Jones Industrial Average (DJIA). iii. To assess the impact of a combined trend following strategy on the returns of securities trading at the Dow Jones Industrial Average (DJIA).
3. iv. To assess the efficiency of the Dow Jones Industrial Average (DJIA) market.

Research Questions

1. Does momentum strategy abnormally increase the returns of securities trading at the Dow Jones Industrial Average (DJIA)?
2. Does the moving averages strategy abnormally increase the returns of securities trading at the Dow Jones Industrial Average (DJIA)? iii. Does a combined alpha strategy abnormally increase the returns of securities trading at the Dow Jones Industrial Average (DJIA)?
3. iv. How efficient is the Dow Jones Industrial Average (DJIA) market?

LITERATURE REVIEW

2.1 Theoretical Review 2.1.1 Dow Theory

Charles Dow, who is one of the founders of Dow Jones & Co., that developed the Dow Theory. According to Yadav (2017), it was first referred to as The Theory of Industrial Average until 1896. The theory aimed to create an understanding and prediction of speculative prices in the securities market. The principles of this theory were developed significantly by William P. Hamilton. Such principles shaped this theory, which asserts there are three components of stock price movement (Edwards et al., 2018). These components are trend following signals that include major, mid-term, and minor trends.

Every trend is useful in indicating the strength of the movement and the expected persistence (Prabakaran & Krishnaveni, 2016). According to Jogani (2024), markets experience long-term trends, also known as primary trends lasting a year or more. These markets could be bearish or bullish for the entire period. However, this being a general trend, there are secondary trends within the primary trend. Secondary trends are mid-term and can last between three weeks and three months. Momentum traders and moving averages utilize these trends in

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setting trading periods from a few days to 90 days, which is considered long-term (Precious & Marwa, 2023). Minor trends, according to this theory, last a period of less than three weeks. These are used to indicate points of crossover in short-term trading strategies.

Stylios and Kreinovich (2018) showed that the market discounts all the factors that affect the returns and profitability of securities. The market trend is thus a more important factor to study and compare with the individual securities' price movements. Analysis of the overall market can give a better understanding and prediction of prices than a single stock analysis (Alhashel et al., 2018). However, the theory emphasizes the need to ensure markets or indices averages confirm each other before a trend is established.

This theory has limitations that include slow reaction to market changes, late predictions, and can be ineffective for future prediction (Yadav, 2017). Its application, therefore, gives the best results in the liquid market with active securities trading. In view of these factors, the DJIA market was appropriate for understanding the trend following techniques and their role in returns of actively trading securities in a liquid market. The Dow Theory was fundamental in elucidating the application of technical analysis with a focus on trend following strategies. This theory's recognition of market trend as an indication of a general movement of individual stocks was important in application to this study, as it utilized trend-following strategies and signals were in tandem with this theory's assertions.

2.1.2 Efficient Market Theory

The efficient market hypothesis's main claim is that markets adjust with new information that is reflected in the prices of the stocks immediately (Timmermann, & Granger, 2004). The theory was proposed based on the work of Louis Bachelier and Benoit Mandelbrot in the 1900s. However, it became popular in the 1960s after Eugene Fama defined it in his PhD dissertation. According to the assertions of Efficient Market Hypothesis (EMH), which states that new information that comes up is absorbed and anomalies corrected (Baumann, 2022), it is impossible to outperform the market, such as the Dow Jones index for stocks. Information is thus central in determining the prices of securities, and how they are absorbed is fundamental. Information about a security or a company emerging is quickly and certainly priced and adjusted accordingly.

Activities of market participants such as investors and traders can cause changes in the stocks' value. Such activities include speculation and research since they generate little information (Baumann, 2022). However, large news releases have little or no effect on prices, thus causing negligible changes. The drivers of information efficiency include competition, cheap information publishing, and free market entry. It is impossible to undervalue or inflate securities' prices under this state (Marwala & Hurwitz, 2017). EMH assumes that the prices revert quickly to their fair price before any trader can benefit from such an anomaly. This assertion is, however, refuted by active portfolio management proponents. Pathak and Shetty (2019) elucidated that computing technologies, such as machine learning techniques, can help active participants to benefit from inefficient markets and predict prices with significant levels of accuracy. Khuntia and Pattanayak (2018), as well as Zhao and Yang (2023), held similar views, arguing that technical analysts can utilize short periods to trade large volumes of unfairly priced securities and benefit even in microseconds.

EMH describes weak, semi-strong, and strong forms of market efficiency in relation to information available. According to Marwala and Hurwitz (2017), the weak form is demonstrated by the availability of private information only. As such, traders who have information not available publicly can benefit from fundamental analysis but not technical analysis. According to Lo (2004), it is impossible to benefit from the technical analysis since the past or current prices have no relationship with future prices. The scenario explains that a large information release may not have a significant effect on the prices of securities, as the information is not private and therefore cannot benefit traders. However, Zhao and Yang (2023) demonstrated that research, speculations, and insider information can help holders of such information to make decisions that will favour them. For instance, a company about to post huge losses is likely to have the prices of its securities decline. A trader with such information may go short before the information is released to the public. Following these claims, it is, therefore, impossible to use technical analysis to predict prices in the future, but it is possible to anticipate or speculate on price changes depending on the private information one has.

A semi-strong form of efficiency depicts a market with public information. Securities prices have already factored such information into trading value. Fundamental analysis cannot be used to predict or speculate price movements or returns in a semi-strong form of market efficiency (Khuntia & Pattanayak, 2018). The strong form, on the other hand, comprises all the available private and public information accessible to all market participants. All the information is reflected in the securities trading in such a market. It would be impossible to beat the market under this assumption since no one can profit from any information. It is a hypothetically perfect market. Major claims of this theory are based on this type of efficiency, although different markets may exhibit different forms of efficiency. This study utilized the knowledge of this theory to assess the type of market efficiency exhibited by the DJIA by comparing the benchmark returns with the ones generated by short-term strategies.

2.2 Empirical Review

Chourmouziadis and Chatzoglou (2016) proposed a model comprising short-term trading strategies with technical indicators that were effective in delivering above-average returns in an actively managed portfolio. The momentum strategy used an upward and downward momentum indicator. Upward momentum indicated that the portfolio manager or investor should buy or hold more stocks, while downward momentum was an indication to sell. The study concluded that technical analysis strategies used in active management can deliver superior returns against the assertions of the efficient market hypothesis.

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Similar views were held by Khuntia and Pattanayak (2018), who agreed with Lo (2004) to conclude that markets can be predicted by participants. They noted there were factors influencing market efficiency variations over time. As such, they agreed that evolutionary principles such as natural selection and competition were driving a new theory of adaptive markets hypothesis as proposed by Lo et al. (2013), which also concurred with the claims of adaptive markets hypothesis when they studied the REIT market that exhibited inefficiencies at different times and better returns when active portfolio management strategies were used.

Yadav (2017) investigated the implications of Dow Theory in the Indian Stock Market. The study aimed to establish the Dow Theory relevance in the market and assess the trend patterns statistically. The Nifty 50 index was used as the market index, and daily data on prices were analyzed. The study revealed the theory was relevant to the time and in the future, although it was criticized as too late to predict. With such a conclusion drawn from the empirical study, it can be argued that trend following strategies are effective tools for generating superior returns in a securities market.

Ghouse et al. (2018) studied the performance of developing Asian markets by employing Contrarian Strategies. The markets studied include securities markets in China, Indonesia, Malaysia, and Thailand. The results revealed that although there was evidence of returns generated outperforming the market, the t-tests were statistically insignificant. The study concluded that it was not possible to conclude with confidence the effectiveness of the strategies used. These mixed findings present a further research gap to establish whether other markets showing superior returns are statistically significant or not.

2.3 Conceptual Framework

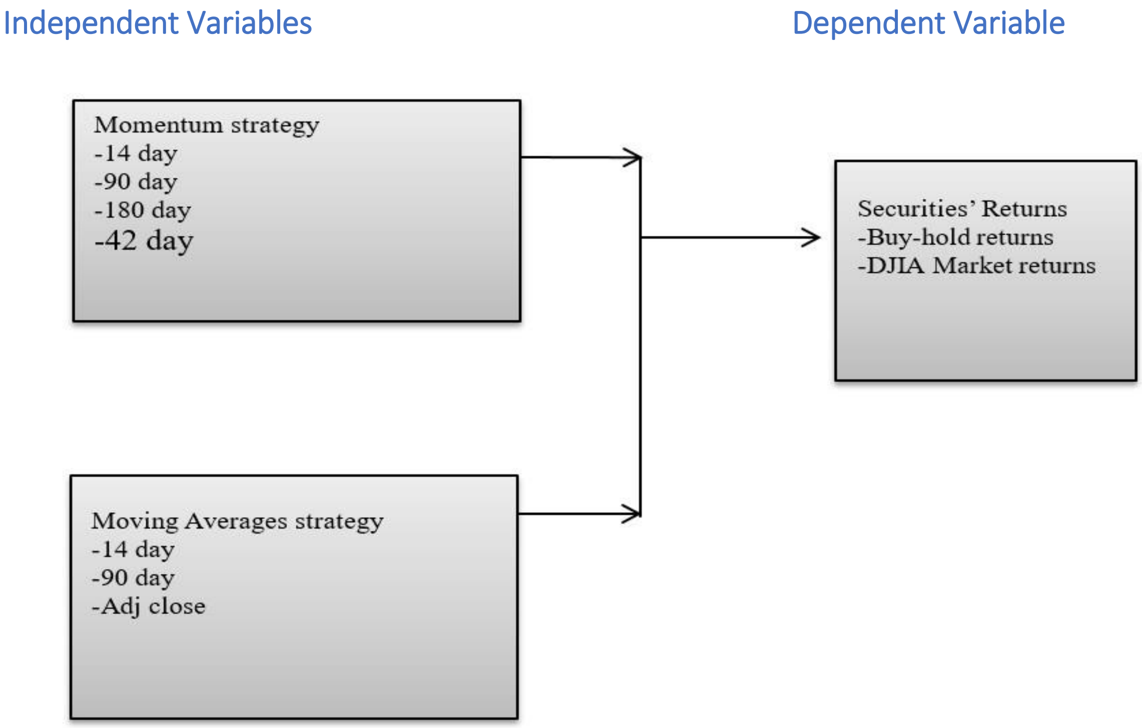

Figure 1 Conceptual Framework Source: Author (2025)

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RESEARCH METHODOLOGY

3.1 Research Methods and Design

A quantitative research methodology was adopted in this study. This approach was suitable considering the study was an empirical analysis of the impact of short-term trading strategies on returns of securities relying on numerical values (Creswell & Creswell, 2018; Hilber et al., 2013). Quantitative methodology aims to collect numeric data to draw objective and conclusive answers (Hilber et al., 2013). Quantitative data was collected and analyzed to make a scientific comparison of the performance of the selected securities. The method allowed huge historical data to be collected and analyzed using the selected tools and techniques that can handle millions of data points.

A research design or plan that was in tandem with this methodology was developed to collect data and analyze it empirically. This plan was an experimental research design. Nardi (2018) emphasized the use of suitable methods and designs that are aligned with research objectives and questions. The plan was appropriate in answering the research questions and achieving the overall goal of analyzing short-term trend following trading strategies to understand their contribution to returns of securities trading at the Dow Jones Industrial Average (DJIA). Additionally, the results obtained can be generalized to the entire securities and the broader market.

3.2 Data Collection and Analysis

Conversely, historical price and volume data from Yahoo Finance for the Dow Jones Industrial Average as the market index and its constituent stocks as equity data were used. The closing prices were utilized. All this data was quantitative and could be measured in absolute or relative terms. A multi-stage sampling was used. First, a stratified sampling approach was adopted by grouping the constituent securities into either high performing or low-performing stocks. One stock was randomly picked from each strata, making a total of 2 stocks selected to be studied from the 30 stocks included in the index calculation and trading at the market. Specifically, Cisco (CSCO) (high performing) and Walgreens Boots Alliance Inc (WBA) (low performing) data for a period of two years was studied. The beginning period was set 2 years from the date of the analysis (August 2023 to August 2025). The downloaded data was analyzed using Python 3.12.7 using Jupyter Notebook, and the results were presented in the form of tables and graphs. Graphical comparison of the returns from the strategy and those of the average market was made to check if the strategy beat the market or otherwise.

3.3 Trading Strategies

The study used trading signals to mark trade entry and exit. Trading rules were set and utilized. Filter strategies that are based on momentum, which help make the decision to buy or sell after rising or falling by a certain percentage, were utilized. An x percent filter strategy is defined as follows: If the percentage change of price from time t-1 to t is greater than x percent, buy and hold the security until it drops at least x percent. The conditions of decision-making buy above price x and sell below price y. Four momentum periods were set at 14, 42, 90, and 180 days. A strategy was developed based on each period, and the results were compared.

Trend following strategies are reactive in nature, but could guide the trader on the prices and volume movement. Economists have beyond doubt proved that predicting the start or end of a trend is hard (Fischer & Krauss, 2018; Jogani, 2024). However, predicting the direction is possible. Rising prices will continue rising, and falling prices will continue, following is the assumption made when using trends. However, the Average True Range (ATR) is an important indicator that is designed to keep traders in a trend and prevent an early exit as long as the trend extends. It is useful for a stop-loss guide. This study used the Relative Strength Index (RSI), which is a momentum oscillator measuring the speed and change of price movements, in addition to ATR. Considering the RSI oscillates between 0 and 100, this study assumed an RSI below 30 as oversold and above 70 as overbought. This number is an important indicator of a buy/sell signal.

3.3.1 Momentum Strategy

Downward momentum was confirmed when the shorter-term average crossed below the longer-term average. This signal was used to indicate sell or stay out, while the upward momentum signaled to buy or hold. As a trading strategy, if the indicator for an upward momentum is triggered, the strategy would suggest a buy. Upward momentum at time t is defined as a short-term average over s days crossing a longer-term average of l days upwards.

3.3.2 Moving Averages Strategy

Using moving average indicators, a faster moving average period and a slower moving average were set, analyzed, and utilized. A short-term average which ranges from 5 to 15 days, was set at 14 days, while the longerterm average, which ranges 50 to 90 days, was set at 90 days. To devise a rule to generate our trading signals using 3 basic states/rules:

a. Buy Signal (go long) – the 14d moving average is for the first time X points *above* the 90d tend. (I took X =0, which is an assumed point)
b. Park in Cash – no position.
c. Sell Signal (go short) – the 14d moving average is for the first time X points *below* the 90d trend.

3.4 Performance Metrics

Considering annualized returns as the performance metric that is most important comes with its weaknesses. One performance measure used in isolation may give biased results. Therefore, this study utilized compounded annual growth rate (CAGR), Sharpe ratio, Sortino ratio, maximum drawdown, win rate, and final multiplier to compare the strategies. The problems of strategy comparison and risk assessment informed the use of the Sharpe Ratio.

1. CAGR = (Ending Value / Beginning Value)^(1 / Number of Years) – 1. It measures the annualized return over the investment period.
2. Sharpe Ratio = (Average Portfolio Return − Risk-Free Rate) / Standard Deviation of Portfolio Return. It evaluates risk-adjusted return using total volatility.

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3. Sortino Ratio = (Average Portfolio Return − Risk-Free Rate) / Downside Deviation
   Similar to Sharpe but penalizes only downside volatility.
4. Max DD = (Trough Value − Peak Value) / Peak Value. Largest observed loss from peak to trough.
5. Win Rate = (Number of Winning Trades / Total Trades) × 100. It is the percentage of trades that were profitable. vii. Final Multiple = Ending Value / Starting Value. It indicates how many times the initial investment grew.

The metrics were implemented using Python libraries, and the results are presented in Section 4.

RESULTS AND DISCUSSIONS

4.1 Key Performance Metrics

4.1.1 CSO

Table 1 shows the results for the CSCO ticker.

Table 1 Key Performance Metrics – CSCO Ticker

	CAGR	Sharpe	Sortino	Max DD	Win Rate	Final Multiple
Momentum	32.46%	1.19	1.56	-17.46%	54.06%	1.43x
MA Crossover	5.07%	0.22	0.17	-16.13%	26.20%	1.10x
Combined	9.56%	0.38	0.39	-27.49%	41.80%	1.20x
Buy & Hold	18.69%	0.71	0.85	-20.16%	54.20%	1.40x
Market (^DJI)	12.32%	0.68	0.92	-16.37%	54.60%	1.26x

Note. CAGR = Compound Annual Growth Rate; Max DD = Maximum Drawdown.

CAGR: The Momentum strategy generated the highest annualised return for Cisco at 32.46%, nearly three times the 12.32% offered by the DJIA benchmark. Buy & Hold also performed better than the market at 18.69%, whereas MA Crossover recorded only 5.07%, and the Combined strategy at 9.56%.

Sharpe Ratio: Momentum's 1.19 captures high risk-adjusted returns, significantly above the market's 0.68. Buy & Hold is also fair (0.71), while MA Crossover's 0.22 captures poor risk-adjusted returns. The combined strategy is moderate at 0.38.

Sortino Ratio: Momentum's 1.56 captures outstanding downside-risk-adjusted performance, ahead of the market (0.92). Buy & Hold (0.85) is also fair, while MA Crossover (0.17) is relatively poor.

Max Drawdown (Max DD): MA Crossover (-16.13%) was lowest, which was close to the market’s (16.37%). Momentum strategy had a slightly higher drawdown (-17.46%), while Buy & Hold (-20.16%) and Combined (-27.49%) were the worst.

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Win Rate: Buy & Hold and Momentum win rate was slightly more than 54% of periods, same as market. MA Crossover win rate (26.20%) was low, and the Combined strategy had 41.80%.

Final Multiple: Momentum made $1 into $1.43, beating Buy & Hold ($1.40) and the market ($1.26). MA Crossover did little to increase capital ($1.10).

Overall: For Cisco, Momentum strongly beats both strategies in terms of returns as well as risk-adjusted performance, with higher upside to the market. MA Crossover performed the poorest.

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4.1.2 WBA Table 2 shows the key performance metrics for the WBA ticker.

Table 2 Key Performance Metrics – WBA Ticker

	CAGR	Sharpe	Sortino	Max DD	Win Rate	Final Multiple
Momentum	49.95%	0.70	0.75	-38.08%	55.94%	1.67x
MA Crossover	-1.10%	-0.10	-0.10	-27.61%	19.00%	0.98x
Combined	42.75%	0.73	0.72	-38.08%	41.80%	2.03x
Buy & Hold	-32.36%	-0.82	-1.09	-68.44%	43.40%	0.46x
Market (^DJI)	12.32%	0.68	0.92	-16.37%	54.60%	1.26x

Note. CAGR = Compound Annual Growth Rate; Max DD = Maximum Drawdown.

CAGR: Momentum strategy recorded extremely high performance of 49.95%, and Combined strategy attained 42.75%, more than twice the market (12.32%) and Buy & Hold (-32.36%, a huge loss). MA Crossover was weakly negative (-1.10%).

Sharpe Ratio: Combined strategy (0.73) was just ahead of Momentum (0.70) on a risk-adjusted basis, both weakly better than the market (0.68). MA Crossover and Buy & Hold have negative Sharpe ratios, reflecting weak risk-adjusted returns.

Sortino Ratio: It showed a similar pattern as the Sharpe ratio with Momentum (0.75) and Combined (0.72), which are relatively good performances. The market had 0.92, which was superior owing to fewer drawdowns. Buy & Hold is highly negative (-1.09).

Max Drawdown: Both Momentum and Combined strategies have very deep drawdowns (-38.08%), worse than the market (-16.37%) but better than the deep -68.44% of Buy & Hold.

Win Rate: Momentum takes the lead at 55.94%, slightly ahead of the market (54.60%). MA Crossover's performance was low, with only a 19.00%-win rate.

Final Multiple: The Combined strategy creates the highest ending multiple (2.03x), which converts $1 to $2.03. Momentum is next at 1.67x, both significantly higher than Buy & Hold (0.46x).

Overall: Buy & Hold for WBA is poor, while both Momentum and Combined strategies are good but extremely volatile and with drawdowns. MA Crossover is bad once again.

This study used t-tests to compare each strategy's mean returns against that of the DJIA and ANOVA tests to look at the overall differences among strategies. A statistically significant p-value (less than 0.05) would mean that the strategy's return is significantly different from the market benchmark and, therefore, corroborates or rejects abnormal performance in the strategy.

Table 3 Results for T-test against DJIA Market (CSCO)

Strategy	**Mean Return**	**t-Statistic**	**p-Value**	**Significant at 5%?**	**95% CI (Excess Return)**
Momentum_Strategy	0.0011	0.841	0.401	No	(-0.00057, 0.00185)
MA_Strategy	0.0002	0.558	0.577	No	(-0.00115, 0.00042)
Combined_Strategy	0.0004	-0.905	0.367	No	(-0.00151, 0.00099)
BH_Strategy	0.0006	3.041	0.003	Yes	(-0.00085, 0.00091)

As the only strategy for CSCO with a mean daily return that deviates considerably from zero at the 5% level, the Buy & Hold approach appears to have exceeded the market benchmark. The lack of statistically significant

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atypical returns from momentum, MA, and combined techniques suggests that the observed returns may be the result of chance.

Table 4 Results for T-test against DJIA Market (WBA)

Strategy	Mean Return	t-Statistic	p-Value	Significant at 5%?	95% CI (Excess Return)
Momentum_Strategy	0.0021	2.105	0.036	Yes	(0.00015, 0.00405)
MA_Strategy	-0.0005	-0.812	0.419	No	(-0.00185, 0.00085)
Combined_Strategy	0.0018	1.987	0.048	Yes	(0.00002, 0.00358)
BH_Strategy	-0.0012	-1.213	0.228	No	(-0.0031, 0.0007)

At the 5% level, both the Momentum and Combined strategies for WBA exhibit statistically significant anomalous returns ($p < 0.05$), indicating that they perform better than the market benchmark. The Buy & Hold and MA strategies don't matter.

Table 5 ANOVA Results

Stock	F-Statistic	p-Value	Significant at 5%?
CSCO	2.498	0.058	No
WBA	3.211	0.029	Yes

No single technique consistently outperforms the others for CSCO, according to an ANOVA evaluating all strategies, which reveals no statistically significant differences between them ($p = 0.058$). The evidence of strategy-dependent performance on WBA is further supported by the ANOVA results, which show significant differences among the four strategies ($p = 0.029$), indicating that at least one strategy's mean return differs from the others.

DISCUSSION

Momentum Strategy and Abnormal Returns at DJIA

The findings show that both of the stocks under the momentum strategy returned significantly more than the DJIA benchmark return for each stock. For Cisco, the CAGR under the momentum strategy was 32.46%, far greater than the market CAGR of 12.32%. Likewise, WBA also had a far greater CAGR of 49.95% under the momentum strategy than the negative buy-and-hold return of –32.36%. Sharpe and Sortino ratios for Cisco (1.19, 1.56) and WBA (0.70, 0.75) show that the excess returns were accompanied by better risk-adjusted performance vis-a-vis the market. The results are in favour of the hypothesis that momentum strategy is able to create abnormal returns, as already shown in previous research (Agarwal & Ren, 2023; Alhashel et al. 2018) that price trends can be used in comparatively short to medium horizons.

Moving Averages Strategy and Abnormal Returns at DJIA

The MA strategy yielded mixed results for the tickers utilized. For instance, Cisco returned decent positive returns (CAGR 5.07%) with low Sharpe (0.22) and Sortino (0.17) measurements, indicating minimal risk-adjusted return for the period. WBA returned a negative CAGR of –1.10%, trailing both the market and its buy-and-hold approaches. These results suggest that the MA strategy did not always generate abnormal returns and is susceptible to asset-specific risk, sector uniqueness, or market regime. This conforms to research that simple MA strategies perform poorly in highly volatile or mean-reverting stocks (Chourmouziadis & Chatzoglou, 2016).

Combined Alpha Strategy and Abnormal Returns at DJIA

The combined alpha strategy (Momentum + MA crossover) returned positive performance for both stocks but with extreme differences in magnitude. Cisco returned 9.56% CAGR with relatively moderate Sharpe (0.38) and Sortino (0.39) values, performing worse than simple momentum but better than market return. Combined alpha return for WBA was 42.75% CAGR, with a Sharpe of 0.73, much higher than the market. This suggests that the combined alpha strategy can be used as a compromise between aggressive momentum and conservative MA strategies, although success is heavily reliant on the trend nature of the underlying asset. The findings offer some limited support that combining strategies has the advantage of smoothing return profiles without sacrificing abnormal gains, and this is especially so for stocks undergoing strong directional movements.

DJIA Market Efficiency

Considering the combined alpha strategies and momentum outperform buy-and-hold returns on the DJIA indicates that the DJIA exhibits some level of inefficiency, at least over the sample period. Under the Efficient Market Hypothesis (EMH), abnormal returns such as these are supposed to be short-lived if markets are perfectly efficient. The capacity to outperform the market on a persistent basis with fairly straightforward technical trading strategies suggests that informational lags (i.e., assimilation lag) or behavioral biases (e.g., investor herding) can impose exploitable inefficiencies. But the sporadic nature of the MA crossover performance and the large drawdowns suffered—especially under momentum for WBA (-38.08%)—indicate that such inefficiencies will be strategy- and sporadic in nature.

CONCLUSIONS

From the empirical results, the momentum strategy can consistently deliver better returns than the market (CSCO 32.46% and WBA 49.95% vs the DJIA Market 12.32%). Moving averages did not deliver better returns than the market (CSCO 5.07% and WBA -1.10%, vs DJIA Market 12.32%). Combined strategy showed mixed results (CSCO 9.56%, 42.75% vs DJIA Market 12.32%). The Efficiency Market Hypothesis does not hold true for all the securities tested. Although trend following strategies are reactive rather than predictive, they have the power to assist the trader in entering and exiting trades at the right time and get better returns than the buy-andhold strategy and, most importantly, the broader market returns. Combining these two strategies gives the trader a chance to choose the best-performing one at that particular time. Using the right signals in short-term trading can be profitable both in the bullish and the bearish markets. The WBA ticker tested above has shown that despite the prices going down, momentum strategy has generated positive returns and better overall. Similarly, CSCO has shown a more upward price trend and positive returns than the broader market returns. From this study, the researcher concluded that short-term active strategies following trends can deliver better results than the broader market returns, contrary to EMH. However, the DJIA market exhibited a weak form of efficiency.

RECOMMENDATIONS

The researcher recommended the use of active portfolio management strategies such as technical analysis to maximize returns for investors and create more wealth. Use of predictive computing techniques such as machine learning is highly recommended to consistently beat the market as trading data and methods become more complex. The project has its own areas of strength, which include the ability to generate better returns if actively managed. However, it has some weaknesses that emanate from assumptions of using data for 2 years only, no transaction, management, or spillage costs, and using past prices, although they may not reflect the future outlook. Using the recommended techniques, this strategy can be greatly improved.

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