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# News sentiment as a determinant of stock market technical analysis patterns

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**Abstract**
Prompted by flaws in the Efficient Market Hypothesis, this paper investigates the relationship between informational manifestations in news title sentiments and technical analysis activities. Thereupon, the paper measures the means and variances of the returns of five technical analysis strategies, Stochastic Relative Strength Index (RSI), Bollinger-Band, Moving Average Convergence/Divergence (MACD), MACD Breakout, and Volatility Breakout, on randomly selected thirty-day periods in 2016, and compares them in different informational contexts identified by sentiment analysis of Google News article titles. This study's findings indicate that technical analysis strategy means do not significantly deviate from the benchmark strategy in neutral and negative sentiments. However, under positive sentiments, the findings indicate that technical analysis strategy means all significantly deviate from the benchmark. Furthermore, this study identifies that the variances of technical analysis returns do not significantly differ across sentiments. By analyzing a variety of technical analysis strategies and their relationship with news sentiments, the study offers practical implications for investors in different market sentiments. Its findings highlight the importance of considering news sentiment when implementing technical analysis strategies, particularly in positive market conditions.

**Keywords**
Efficient Market Hypothesis, News sentiment, Technical analysis, Stochastic Relative Strength Index (RSI), Market conditions, Moving Average Convergence Divergence (MACD), Bollinger band, Volatility, Market strategy, Stock exchange

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## 1. Introduction

Since Eugene Fama's seminal proposal in 1970, the Efficient Market Hypothesis (EMH) has garnered widespread acceptance in the field of finance as the fundamental principle that governs market behavior. The theory posits that unexpected information 1] governs price movements and 2] elicits immediate and rational responses from investors, a notion that has found favor among many due to the perceived unpredictability of markets (1). Technical indicators stood in opposition to the doctrine of the EMH as past price trends could not apply to future price trends if only the unpredictability of information mattered. As a result, technical indicator algorithms, which rely on historical data to identify mispriced stocks, were discredited, particularly pronounced in the Dow Jones Industrial Average (DJIA) market.

However, this apparent theoretical conflict is resolved when the EMH's premise of immediate and rational stock prices is debunked. Empirical studies that investigated the efficiency of stocks often revealed significant inefficiencies, in apparent contradiction of the EMH. Ozkan (2) Mnif et al. (3) Van Oort (4) provided a prominent case in point in their examination of the 2016 DIJA market using Geographical Market Segmentations. The results of their models identified "prolific" and "persistent" inefficiencies in the period selected, revealing that market efficiency changed over time and under different circumstances. This discovery negated the presumption that investors cannot benefit from market timing strategies. If markets were inefficient, that is, the aggregate of investors failed to react to information instantly and correctly, stock prices would undergo adjustment periods, during which mispriced stocks would lag to correctly represent information (5). Consequently, technical analysis strategies can exploit these adjustment periods and generate profits by identifying footprints in price movements, using historical data to trade at optimal prices.

However, practical applications do not always attest to the predictability of technical analysis during adjustment periods. In fact, several studies have documented the relative under-performance of different technical analysis strategies across various markets (6).

Li et al. (7), Alfonso and Ramirez (8), Alusabaie et al. (9), Lahmiri (10), Rech et tal. (11), Naik (12), Ozturk et al. (13), Oliveira et al. (14) hypothesized that the performance of technical indicator algorithms varied due to the different affinities of stocks with various properties towards technical indicators. In this belief, Yao employed the non-linear method of neural networks as a model to forecast stock prices in the Kuala Lumpur Stock Exchange (15). Further, Alfonso and Ramirez developed a distinctive non-linear method to combine technical indicators, addressing the limitations of neural networks that lacked sufficient generalization power in high dimensional markets (8).
Similarly, machine learning studies have experimented with algorithms to deconstruct markets into combinations of variables and

develop technical indicators accordingly, which include tech naïve Bayes (NB), fine-tuned naïve Bayes (FTNB), support vector machine (SVM) (9, 10), MetaCost wrapper (9), cost-sensitive fine-tuned naïve Bayes (CSFTNB) (9), and Technical Trading Indicator Optimization (TTIO) (7). One noteworthy study was by Lahmiri (10), which modeled entropy in the international stock market to optimize technical indicator combinations using the SVM. More attempts at finding technical indicators in relation to the market include the Boruta feature selection (12), heuristic methods (13), tuning, and parameters (14).

Additionally, a few studies have focused on time horizons as determinants of technical indicator performances. Using fuzzy systems, Chourmouziadis proposed a short-term horizon to technical analysis trading (16). A study by Shynkevich et al. determined that the predictive performance of technical analysis peaked when the forecast horizon equaled the time frame (17).

However, insufficient attention has been devoted to the impact of information on the efficacy of technical indicators. Studies have consistently adhered to the presupposition that technical indicator algorithms operate independently of information awareness, neglecting the possibility that prevailing market information could greatly influence the varied returns of technical indicators as posited by the EMH.

This paper examines how technical analysis strategies perform in relation to prevailing informational trends. To quantitatively represent information, polarity scores of news title sentiments are employed, which capture both investor interpretations of information and the factual market context (18, 19). The constants derive from a sentimental analysis of news titles collected on Google News, which provides news articles from various investment communities (20). Specifically, the focus is on the Dow Jones Industrial Average market during 2016, a period previously established as inefficient by Van Oort (4). This precondition increases the theoretical possibility for technical analysis to generate profit by its predictive ability over the randomness of the market (5).

This study offers practical implications for practitioners of technical analysis. It identifies general sentimental circumstances for which technical analysis may outperform or underperform the Dow Jones Industrial Average market. This may help the practitioners enhance their profitability by avoiding return losses relative to the market. Furthermore, the study sets a direction for forthcoming technical analysis studies. By further examining how the contents of information determine the returns of technical indicators, future academics may develop technical analysis strategies that predominantly warrant consistent alpha generation.

The subsequent sections of this study are organized as follows. Section 2 discusses the methods. Section 2.1 Period randomization, establishes the premise of market inefficiencies and outlines the criteria for data collection, while Section 2.2 Stock data collection, explains how this study obtained stock price movement data. Section 2.3 Technical analysis simulation, delineates the processes of technical analysis algorithms simulated in the study. Section 2.4 News article title collection, discusses ways in which this study obtains news article title data. Section 2.5 Sentiment analysis, details how this study converts news article titles into quantitative polarity scores, leading to section 2.6 Data analysis. Section 3 primarily focuses on the results and significance of the study's findings. Section 3.1 displays and evaluates the overall performances of trading strategies. Section 3.2 demonstrates the sentiment data of news article titles and defines negative, neutral, and positive sentiments accordingly. Section 3.3 evaluates the performance of technical trading strategies in relation to sentimental patterns. Finally, Section 4 presents the conclusion of this paper, summarizing the key findings and implications derived from the study.

## 2. Methods

This study aims to examine the effects of sentiments on the performance of technical indicator algorithms. To assess the technical analysis performance, five widely recognized strategies are selected: Stochastic Relative Strength Index (RSI), Bollinger-Band, Moving Average Convergence/Divergence (MACD), MACD Breakout, and Volatility Breakout (Breakout). These strategies are then applied to all stocks listed in the Dow Jones Industrial Average (DJIA) during 360 randomly chosen sixty-four-day periods, spanning from November 1st of 2015 to December 30th of 2016. These periods correspond to the thirty-day intervals starting January 1st of 2016, providing a representative sample of the stocks' performances.

Given the algorithms' objectives of generating buy and sell signals within a thirty-day time frame based on evaluating past trends, it was necessary to include a comprehensive sixty-four-day data set to accurately represent the employed data.

The data collected and represented in this study exhibited variations due to specific data requirements for the Bollinger-Band, Volatility Breakout, MACD, and MACD Breakout algorithms. These variations were considered during the analysis to ensure the accuracy of the technical analysis performances computed. This study's selection of technical indicators derived from Pheng et al (21), who identified optimal models that produced statistically significantly different returns compared to the non-involvement in stock markets. This increased the likelihood that technical analysis performances followed their predictive movements more so than the general market trend, so as to ideally maximize profit margins.

Through the application of natural language processing techniques, the study quantitatively assessed the sentimentality of these titles and assigned polarity scores accordingly. Each polarity score enabled the classification of titles into distinct sentiment categories of “negative”, “neutral”, and “positive”. The division of sentiments relied on the distribution of sentiments observed in the 360 randomly selected sixty-four-day periods, following the succeeding directive: The lowest 120 stocks set the range for negative sentiments, the middle 120 stocks set the range for neutral sentiments, and the upper 120 stocks set the range for positive sentiments. Subsequently, each polarity score was paired with its corresponding technical analysis performance to establish a relationship between sentiment and performance. The study then proceeded to evaluate the variances and means of the trading strategies across different sentiment categories, while examining their statistical significance.

*2.1 Period randomization*

To investigate the performance of technical analysis and sentiment patterns, this study focused on thirty Dow Jones Industrial Average (DJIA) stocks and their corresponding Google News article titles from November 1st of 2015 to December 30th of 2016. The selection of this specific market and time period followed the approach employed by Van Oort (2018), which identified extended durations of market inefficiency across the Dow Jones Industrial Average stocks in 2016. While the performances of stocks and sentiments during this year long period may not necessarily represent the same performances of other periods, they were crucial in establishing the premise of market inefficiency, which formed the foundation for exploring the potential utilization of implied informational patterns through technical indicator algorithms.

Within the said period, the study randomly selected 360 sixty-four-day subperiods, with each subperiod dedicated to one of the thirty DJIA stocks. This approach ensured the availability of diverse market data and news titles that reflected information trends. The chosen quantity of subperiods was designed to meet the statistical requirements of the Central Limit Theorem and normality, even with the presence of abnormally distributed data points. The thirty-day parametrization of each subperiod allowed for the study of short-term trading performances that included multiple buying and selling activities. This emphasis on short-term horizons aligned with the trading practices commonly observed among technical analysis practitioners Chourmouziadis (16) and Taylor et al. (22). The randomization processes were implemented *via* a random module in Python, ensuring the unbiased selection of variables.

*2.2 Stock data collection*

Once the randomization of subintervals for analysis was completed, the study proceeded to collect price movement data for the selected DJIA stocks. This data collection included the highest, lowest, closing, and opening prices of the stocks on a daily basis, all of which pertained to the trading mechanisms of the benchmark and different technical analysis strategies, as outlined in Section 2.4. To collect the price data, the study employed Pandas DataReader, a data analysis tool from Panda used to facilitate data extraction from Yahoo Finance. As an online stock data API platform, Yahoo Finance presents comprehensive historical price data for all 30 DJIA stocks. No alternative platform was considered as the documentation of stock pricing remained consistent across platforms.

*2.3 Technical analysis simulation*

Although the benchmark and technical analysis strategies all exhibited distinct methods in arranging trading cues, they shared the fundamental algorithmic framework of buying stocks at buy signals and divesting stocks at sell signals. Hence, it was possible to simulate the application of various technical analysis strategies under a unified procedure (23). The study undertook the processing of all technical analysis calculations by implementing four sets of commands, 1] Start thirty-day trading intervals from January 1st of 2016 to November 18th of 2016 with a money value of $1,000,000. 2] For every business day, add the factor of the number of stocks owned and the recorded day's closing price plus the remaining money value and append this value as an asset. If no stock is held, append the remaining money value. 3] When a trading strategy generated a buy response, divide the money value by the recorded day's closing price to calculate the number of stocks bought to the nearest whole number. Then, update the amount of money by subtracting the product of the number of stocks purchased and their closing prices. 4] When a trading strategy cued a sell signal, multiply the number of purchased stocks by the closing price. Add the resulting number to the amount of money value. Further, fix the number of purchased stocks to zero.

As an exception to Procedure 3, when the Breakout strategy generated a buy signal, the algorithm divides the money value by the sum of the recorded day's opening price and Volatility Score to calculate the number of stocks bought to the nearest whole number. It subtracts the product of the number of stocks purchased and the sum of the recorded day's opening price and Volatility Score from the previous day's money value to update the money value.

The aforementioned procedure provided an overarching algorithm for technical analysis simulations that predicated on signal generations. Below, this paper details the signal generation mechanisms of the Stochastic Relative Strength Index (RSI), Moving Average Convergence/Divergence (MACD), Bollinger-Band, and Breakout in addition to the benchmark. All of the below technical indicators were selected based on Pheng et al. (21), who identified the optimal models that reject the null hypothesis of equality of the mean returns between buy signals and sell signals.

*2.3.1 RSI*

The stochastic RSI Relative Strength Index (RSI) is a technical indicator that measures the speed, velocity, and momentum of price movements in a market (25). RSI employs a specific formula to generate buy and sell signals:

$$RSI = 100 - 100/(1 + RS)$$

In the formula, RS refers to Relative Strength. It is derived by dividing the average gain by the average loss over a 14-day period. Both average gain and loss are expressed as positive numbers. The study implements a 14-day period as its parameter, which aligns with the prevailing preference among RSI traders.

The paper followed three different RSI rules, 1] A buy signal is triggered when RSI crosses the centerline (RSI=50) from below, while sell signal is generated when RSI crosses the centerline from above (25). 2] The RSI algorithm identifies two zones (oversold and overbought zones) utilizing its RSI values. When the RSI value falls below 30 (RSI<30), stocks are considered oversold. Conversely, when RSI rises above 70 (RSI>70), stocks are considered overbought (25). 3] A buy signal is produced when RSI value, after having fallen to the oversold zone rises back above 30, and a sell signal is obtained when RSI rises above then falls below 70 (25).

*2.3.2 Bollinger-Band*

Bollinger-Band is a trading strategy that assesses volatility of securities, encompassing both price and volatility characteristics by indicating a relative definition of high and low prices of the market. The paper followed two set rules, 1] Entry and Exit signals of the stock purchase are generated by comparing price movements to their corresponding upper and lower Bollinger-Bands (26). 2] The upper and lower Bollinger-Band is expressed by the equations below:

Upper Bollinger Band = $^{20}$day SMA + [2 X ($^{20}$day price standard deviation)]
Lower Bollinger Band = $^{20}$day SMA – [2 X ($^{20}$day price standard deviation)]

In the equations above, the 20-day SMA represents a simple moving average value computed from the twenty most recent price data points. The implementation of a 20-day parameter aligns with the prevalent Bollinger-Band practice (26).

The paper followed three different Bollinger-Band rules, 1] The Bollinger-Band algorithm generates a sell signal when the equity price falls below the lower Bollinger-Band and triggers buy signals when the same metric reaches above the upper band. 2] Volatility level must be acknowledged when considering Bollinger Bands: Low volatility is suggested when upper and lower bands lie close together and market volatility increases as bands expand. 3] When volatility levels are high and Bollinger bands are far apart, a sell signal is generated. A Buy signal is produced as the difference between upper and lower bands decreases.

*2.3.3 MACD*

The Moving Average Convergence/ Divergence (MACD) indicates the relationship between exponential moving averages (EMA) of security prices by comparing the movement of the MACD line and the Signal line to derive trading signals (27). The MACD line is computed as below:

$$\text{MACD} = {}^{12}\text{Period EMA} - {}^{26}\text{Period EMA}$$

The 12-Period EMA signifies the exponential moving average for twelve recent price data, and the 26-Period EMA is an exponential moving average for twenty-six recent price data. The study selected 12-Period EMA and 26-Period EMA for its exponential moving average settings to reflect the conventional MACD practice (27). The Signal line is computed as below

$$\text{Signal} = {}^{9}\text{Period MACD EMA}$$

In this equation, the 9-Period EMA represents a nine-day exponential moving average for a MACD line. The choice of a nine-day parameter aligns with the general practices associated with MACD. (28)

The study indicated two MACD rules, 1] MACD value is positive when the 12-period EMA is above the 26-period EMA, and negative when 12-period EMA is below the 26-period EMA. 2] The MACD trading algorithm elicits a buy signal when the MACD line surpasses the signal line and a sell response when the MACD line falls below the signal line.

### *2.3.4 Breakout*

Volatility Breakout (Breakout) is a technical analysis strategy that relies on the volatility of a previous price point to trade to reflect the momentum of the market. By calculating the Volatility Score, this paper focused on quantifying the daily returns of the price to measure the stock volatility (28). The Volatility Score is calculated as follows:

$$Volatility_{Score} = P_{highest} - P_{lowest} \vee 0.5$$

where $P_{highest}$ represents the highest stock price observed during the preceding business day and $P_{lowest}$ represents the lowest stock price observed during the preceding business day. Two Volatility Breakout rules were followed in this paper, 1] Volatility Score implies how volatility of stocks impact future price movements of the market. 2] Breakout algorithm produces a buy signal when a price value rises by the Volatility Score from the opening price. A sell signal is triggered at the end of each day that produces the buy signal when the price value drops below the breakout range.

### *2.3.5 MACD breakout*

The MACD Breakout strategy is a trading strategy that combines the MACD and Breakout strategies, specifically developed for this study. The trading mechanism of MACD Breakout strategy is outlined as below,

MACD Breakout first traces the MACD line and the Signal line according to the equation introduced in Section 2.3.3. It signals buy cues when the MACD line crosses above the Signal line. If this method does not detect a buy signal, MACD Breakout operates the Breakout strategy outlined in Section 2.3.4.

MACD Breakout generates sell signals according to Volatility Breakout rules outlined in Section 2.3.4.

*2.3.6 Benchmark*

The benchmark strategy, often referred to as the buy-and-hold strategy, is an investment technique in which investors purchase stocks and hold onto them for an extended period, regardless of short term price fluctuations. This strategy is based on the belief that over time, the stock market tends to exhibit an upward trend, leading to an increase in the value of investments purchased and held by investors. Unlike technical indicator algorithms, the benchmark strategy primarily focuses on long term investment growth and does not generate buy and sell signals.

*2.4 News article title collection*

Information is a type of qualitative data that holds differing implications depending on how its readers assess it. Expressed through human language, information cannot convert into a single quantitative value that encapsulates all its contents. As such, scholars often quantitatively assess information to only demonstrate the specific details they need. One such assessment is sentiments, the connotative positivity or negativity expressed by words that characterize information (20). To obtain market information, the study crawled through news titles from Google News during 2016 for subintervals selected in 3.1. The study used news titles as its sentiment dataset because they summarized the news contents that display information and offered writers' interpretations of news information.

*2.5 Sentimental analysis*

The study analyzed sentiments from Google News titles through the Natural Language Toolkit (NLTK). Using the NLTK, the study first tokenized words included in news article titles. This process separated all words from news articles. Then, the stop words were removed. The stop words are negligible words that do not convey any sentiment, such as 'is' and 'a’. After removing stop words, the analysis proceeded to lemmatization. This process combines words with the same roots. It ensures that the sentiment analyzer does not process overlapping meanings in the next step.

For the last phase of sentimental analysis, the study utilized the Sentiment Intensity Analyzer from NLTK to assign news titles polarity scores between -1 and 1. A negative polarity score implied that the collected news title offers a negative interpretation of the stock it discussed. A news title expressed increasing negativity as its polarity score approaches -1. A Polarity score of zero indicated that the news title did not mention any overarching information of sentimental value. Proximity to a zero polarity score suggested that a news article conveyed a mild sentiment. A news title with positive implications for a stock manifested positive polarity scores. A news title with the most positive stock performance understanding would yield a polarity score of 1 (24).

*2.6 Data analysis*

This study collected the data using two major steps. First, it collected 360 thirty day resulting returns of the benchmark and the five technical analysis performances from 2016 for the 30 Dow Jones Industrial Average (DJIA) stocks. The quantity of collected returns guaranteed that the Central Limit Theorem and normality requirement were met for statistical tests, despite the abnormally distributed balance data points. This study executed Levene's test to the six resulting returns to check the similarity of variance. Subsequently, the study performed a One-way ANOVA test to determine whether a significant difference of average existed among all the trading strategies. If the ANOVA result indicated the existence of difference in mean among all the strategies, a t-test was performed to determine which of the strategies was responsible for the difference. If the variances were equal by Levene's test, the study either used the Student's t-test or the Welch's t-test. The two tests decided whether the technical analysis strategies yielded statistically significant different returns from the benchmark strategy.

## 3. Results

*3.1 Technical analysis performance*

The study evaluated the rates of returns for benchmark and technical analysis strategies to analyze their respective profitability. The rates of returns measure the net change in investment assets as percentages of the initial costs. To derive this metric, the study divided resulting investment outcomes by initial investment capital for each of the trading strategies. The results are summarized in Figure 1 and Table 1.

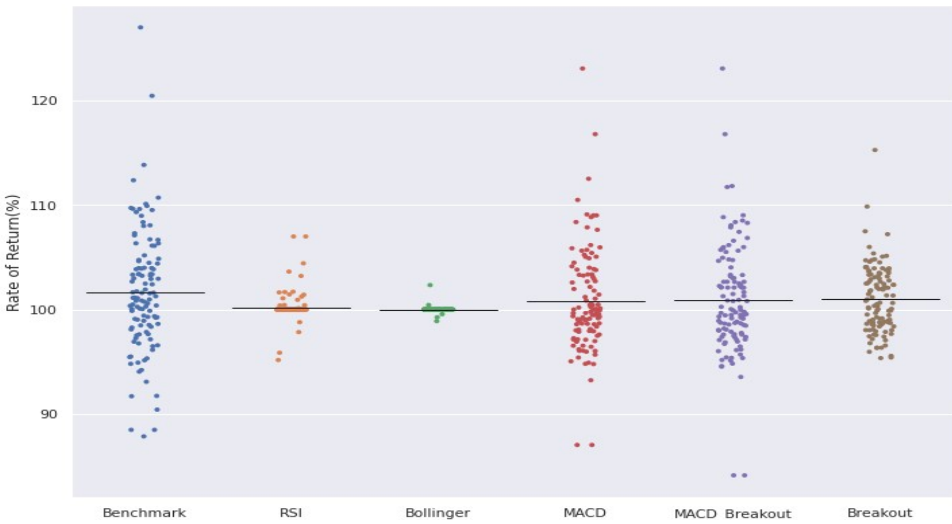


Figure 1. Benchmark and technical analysis rate of return scatter plot

Table 1.Benchmark and technical analysis average rate of return table trading strategy

| Trading strategy | Average rate of return |
|---|---|
| Benchmark | 101.68 |
| RSI | 100.22 |
| Bollinger-Band | 100.00 |
| MACD | 100.80 |
| MACD Breakout | 100.88 |
| Breakout | 101.00 |

Figure 1 illustrates the rate of returns for both benchmark and technical indicators during the studies designated test periods. The graph shows that two of the trading strategies– Bollinger-band and RSI–exhibited rates of returns closely centered around 100%. This suggested that their algorithms failed to identify substantial price movements for entry in many of the reading intervals.

On the contrary, MACD, MACD Breakout, and Volatility Breakout generated a diverse range of returns, scattered across various points. This trend implied that at least one of the following was true: 1] The DJIA stock price movements were diverse enough to generate a wide range of return values, and 2] The strategies had low thresholds for buy signals. Infrequently, MACD, MACD Breakout, and Breakout have been shown to generate rates of returns exceeding 110%.

The Benchmark strategy displayed a similar pattern, generating slightly higher rates of returns above 110% compared to other technical analysis strategies. Returns ranging from 100% to 110% are fairly evenly distributed among the mentioned strategies, indicating a diverse range of return rates. Returns below 100% were more sparsely distributed for the benchmark than for other strategies. Moreover, the benchmark strategy experienced significantly greater negative rates of returns than MACD, MACD Breakout, and Breakout strategies. The return rates below 100% did not converge towards 100% as closely as those observed in other technical indicators. This suggested that MACD, MACD Breakout, and Breakout may offer more stability than the benchmark strategy in under-performing markets.

Table 1 presents the average rate of return for the benchmark and the five technical analysis strategies. The table shows that all strategies achieved average rates of return exceeding 100%. This trend suggests that the DJIA stock market proved to be profitable for these strategies in 2016. Furthermore, the table demonstrates that, on average, the benchmark strategy outperformed all technical analysis algorithms used in this study. Combining this finding with the implication that benchmark under-performance generally carries more risk than under-performance of other technical analysis strategies, it can be seen that the high-risk, high-return principle held true for DJIA stock trading in 2016. The comparative over-performance of the benchmark over technical analysis strategies could be attributed to the widely accepted knowledge that the benchmark tends to outperform technical analysis in bullish markets (29). In 2016, the Dow Jones Industrial Average experienced a significant increase from 17,148.94 to 19,762.60; a growth of 15.24% (30). Under the assumption that bullish markets support benchmarks over technical analysis, such growth may account for a significant portion of the observed trend. Another factor that could explain the relative under-performance of technical analysis strategies is that the market inefficiencies in adjustment periods in the 2016 DJIA market mentioned in (4) were not long enough for daily technical algorithms to effectively detect.

*3.1.1 Technical analysis performance mean and variance data analysis*

To determine whether a pair of dataset with different mean exists, this study performed the One-way Analysis of Variance (ANOVA) test. The test yielded a p-value of 0.03, signifying that the mean rate of return for at least one strategy differed significantly from another strategy at a 95% confidence level.

Furthermore, this study used Levene's test to identify which datasets exhibited different means when compared to the benchmark strategy. Levene's test, a statistical tool to check the homogeneity of variance, can determine whether a Welch's t-test or a Student's t-test should be employed to analyze the disparity in mean between two datasets.

The result of Levene's test on the benchmark and the five technical analysis algorithms indicated a p-value of 0.00, which falls below the critical threshold value of 0.05 required to reject the null hypothesis; *viz*. that at least one pair of datasets possesses equal variance at a 95% confidence level. This p-value demonstrated that the variances of datasets statistically and significantly differ from the benchmark. Accordingly, Welch's t-test, which requires a nonhomogeneous variance, was appropriate to determine whether technical analysis strategies statistically significantly differ from the benchmark strategy.

Table 2. Results of Welch's t-test on the Five Technical Analysis Strategies Compared to the Benchmark

| **Technical Analysis Strategy** | **T-statistic** | **p-value** |
|---|---|---|
| RSI | 3.20 | 0.00 |
| Bollinger-Band | 3.65 | 0.00 |
| MACD | 1.79 | 0.07 |
| MACD Breakout | 1.29 | 0.20 |
| Breakout | 2.34 | 0.02 |

Table 2 summarizes the results of the Welch's t-test conducted on each technical analysis strategy. The p-value for MACD and MACD Breakout were respectively 0.07 and 0.20, both over 0.05. The p-value of greater than 0.05 indicated that the differences in means were statistically insignificant and hence the null hypothesis that the two datasets have unequal means could not be rejected. Therefore, at a 95% confidence level, it was not possible to conclude that neither MACD Breakout nor MACD exhibited a significant difference in mean compared to the benchmark.

On the contrary, RSI, Bollinger-Band, and Breakout yielded p-values of 0.00, 0.00, and 0.02, respectively, all below the 0.05 threshold. The corresponding t-statistics were greater than the critical value of 1.96, providing substantial evidence to reject the null hypothesis and conclude that the mean difference was statistically significant. These findings validate that RSI, Bollinger-Band, and Breakout perform differently from the benchmark at a 95% confidence level.

A plausible explanation for the resemblance between MACD and MACD Breakout and the benchmark is that the two technical analysis algorithms have low thresholds for buy signals and high thresholds for sell signals. This approach ensures that MACD and MACD Breakout hold stocks for longer durations, aligning their respective price movements with those of benchmark. On the other hand, RSI and Bollinger-Bands both set relatively high thresholds for buy signals, leading to minimal engagement in the market, which contrasts with how the benchmark synchronizes to market price movements.

The experiment results that highlight significant differences between the rate of returns for Breakout and the benchmark shed light on how the technical analysis algorithm liquidates all of its holdings at the end of business days.

*3.2 Sentiment analysis*

The goal of this study was to compare the variability of technical analysis performance based on different sentiments. As such, the study first outlined the qualifications for different sentiment categories and arranged the six trading strategies' rates of returns accordingly.

During the process of sentiment analysis, news headlines were quantitatively expressed into polarity scores between -1 to 1. For example, a title that read "[Stock] expects [an] uptrend as its dividends double from the previous year" converts into a polarity score of 0.371, denoting a moderately neutral sentiment.

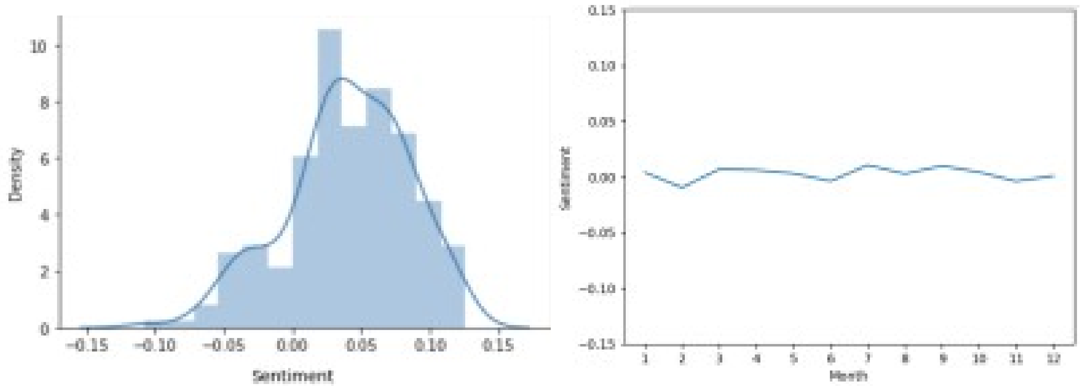


Figure 2. Distribution of 30-day Sentiment

This study established three distinct sentiment categories: negative, neutral, and positive. Negative sentiments encompassed the lower one-third of all sentiments from the comprehensive 30-day sentiment data collected from this study. Neutral sentiments comprised the middle one-third of the sentiments within the same dataset. Similarly, positive sentiments represented the upper one-third of the sentiment distribution. This categorization was based on the quantity of data points, which may lead to criticism that the distribution captures overall sentiment trends rather than sentiments that are inherently negative, neutral, and positive. However, this study deemed such an approach to be proper and necessary to account for the large concentration of 30-day sentiments around zero. Figure 2 illustrates the pronounced centralization of the 30-day sentiments' propensity near a single point.

Based on the collected 30-day polarity scores, this study defineed negative sentiments as polarity scores ranging from -1 to 0.0262, neutral sentiments as polarity scores ranging from 0.0262 to 0.0638, and positive sentiments as polarity scores ranging from 0.0638 to 1.

*3.3 Technical analysis rate of return in relation to sentiments*

The trading strategy results presented in Figure 3 highlighted a direct relationship between sentiments and the benchmark performance; the more positive the sentiments were, the higher the benchmark performance. However, findings in Table 3 suggest that this observed trend was not consistent. The variances of the benchmark strategy under negative, neutral, and positive sentiments were 13.20, 26.45, and 22.72, respectively. Comparing these three different values, it could be concluded that positive sentiments elicited more reliable growth than negative and neutral sentiments. However, it is important to note that even among positive sentiments, there is still a significant level of variability indicated by the difference in variance.

In terms of reliability, both the RSI and Bollinger-Band performances demonstrated consistent and stable change. The RSI variances under negative, neutral, and positive sentiments were 0.66, 0.72, and 1.08, respectively. Even less, the Bollinger-Band variances respectively measured 0.07, 0.07, and 0.02. While the returns of RSI and Bollinger-Band generally exhibited stability, they did not guarantee greater returns. Figure 3 indicates that both technical analysis strategies generated average rates of returns near 100 under all sentiments. However, the algorithms exhibited patterns in response to sentiments. For RSI, rates of returns under neutral sentiments generally showed an upward trend, while those under positive sentiments tended to fluctuate downwards. This resulted in RSI's profitability being arranged in a descending order as neutral, negative, and positive. The profitability of rates of returns for Bollinger-Band, far less versatile to indicate any fluctuation, ranged from negative to positive to neutral. These results suggested that the sentiment trends observed in both technical analysis strategies deviated from that of the benchmark. This underlines the importance of considering distinctive mechanisms of different technical analysis strategies in responding to price movements generated by incoming information trends.

Table 3. Variances of Each Trading Strategies by Sentiments

| **Sentiment** | **Benchmark** | **RSI** | **Bollinger-Band** | **MACD** | **MACD Breakout** | **Breakout** |
|---|---|---|---|---|---|---|
| Negative | 13.20 | 0.66 | 0.066 | 7.675 | 12.50 | 5.48 |
| Neutral | 26.45 | 0.72 | 0.07 | 16.58 | 21.17 | 7.98 |
| Positive | 22.72 | 1.08 | 0.02 | 12.92 | 18.60 | 6.42 |

Table 4. Average Rates of Returns for Each Trading Strategies by Sentiments

| **Sentiment** | **Benchmark** | **RSI** | **Bollinger-Band** | **MACD** | **MACD Breakout** | **Breakout** |
|---|---|---|---|---|---|---|
| Negative | 100.74 | 100.01 | 100.04 | 100.10 | 99.71 | 100.10 |
| Neutral | 100.91 | 100.04 | 99.99 | 100.37 | 100.43 | 100.22 |
| Positive | 101.25 | 99.94 | 100.00 | 100.27 | 100.23 | 99.79 |

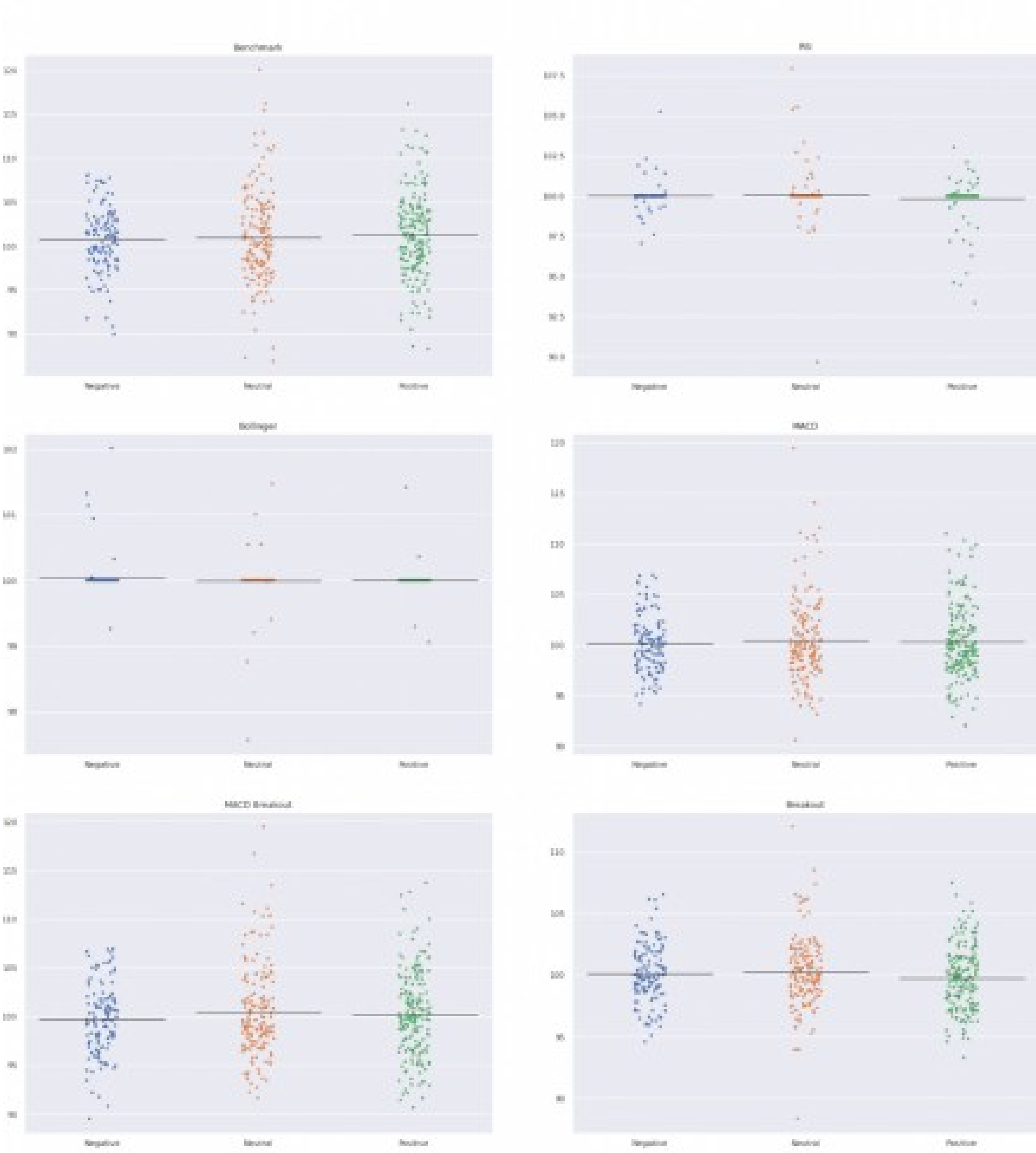

Figure 3. Trading Strategy Performance for Each Sentiment

Contrary to the benchmark strategy, MACD, MACD Breakout, and Breakout generated lower but more stable returns. According to Table 4, the rates of returns for negative, neutral, and positive sentiments were as follows: MACD (100.10, 100.37, 100.27), MACD Breakout (99.71, 100.43, 100.23), and Breakout (100.10, 100.22, 99.79). The corresponding variances for these strategies were as follows: MACD (7.67, 16.58, 12.92), MACD Breakout (12.50, 21.17, 18.60), and Breakout (5.47, 7.98, 6.41). Further, they exhibited sentiment to rate of return trends different from that of the benchmark. For instance, MACD and MACD Breakout generated the greatest average return under neutral sentiments and the lowest average return under negative sentiments. Moreover, the average rate of returns for Breakout demonstrated strong performance under neutral sentiments but weak performance under positive sentiments. It is also noteworthy that both MACD Breakout and Breakout experienced discernable declines when the sentiment was < 100%.

Overall, four out of six trading strategies generated the most stable rates of returns under negative sentiments. Furthermore, neutral sentiments resulted in the highest return volatility for five out of six trading strategies. These two recurring patterns indicate that sentiments associated with information influx influence market behavior differently for different technical indicators, subsequently impacting price movements and the corresponding technical analysis performances.

### *3.3.1 Technical analysis rate of return in relation to sentiments data analysis*

This study employed Levene's tests to assess the similarity of variance among trading strategy performances for each sentiment and trading strategy. The former evaluation examines the extent to which the five technical analysis performances vary over different sentiments. The latter underscores how the average rate of returns for each trading strategy differs based on sentiment patterns. Additionally, this study employed One-way ANOVA tests to determine whether the differences between the mean rates of returns for technical analysis strategies and the benchmark were statistically significant, considering each sentiment and trading strategy. If a positive response was obtained, a subsequent t-test was conducted to assess the significance of the mean difference between the benchmark and each technical analysis strategy.

Table 5. Results of Levene's Test on Trading Performance Variance for Each Strategy by Sentiments

| Sentiment | F-statistic | p-value |
| --- | --- | --- |
| Negative | 70.07 | 2.55e-60 |
| Neutral | 69.21 | 3.99e-62 |
| Positive | 104.56 | 1.15e-90 |

Table 5 presents the results of Levene's test on trading performance for each sentiment, as categorized by sentiment. The p-values for all sentiments are below 0.05, rejecting the null hypothesis that one or more technical analysis strategy performance data share the same variance as the benchmark performance data at a 95% confidence level.

Table 6. Results of Levene's Test on Trading Performance Variance for Each Sentiment by Trading Strategies

| Technical Analysis Strategy | F-statistic | p-value |
|---|---|---|
| Benchmark | 5.18 | 0.01 |
| RSI | 0.00 | 0.10 |
| Bollinger-Band | 1.30 | 0.27 |
| MACD | 2.97 | 0.05 |
| MACD Breakout | 1.81 | 0.17 |
| Breakout | 0.71 | 0.49 |

Table 6 shows the results of Levene's test on trading performance for each sentiment, categorized by trading strategies. It demonstrates that the variances for RSI, Bollinger-Band, MACD Breakout, and Breakout exceed the p-value of 0.05. This suggests that the behaviors of these technical analysis strategies do not significantly differ across sentiments. Conversely, the variance for MACD does not exceed the p-value of 0.05. On this note, it could be concluded that the variances of MACD exhibit statistically significant differences at a 95% confidence interval.

Table 7. Results of One-way ANOVA test on trading performance means for each sentiment by sentiments

| Sentiment | F-statistic | p-value |
|---|---|---|
| Negative | 2.22 | 0.05 |
| Neutral | 1.53 | 0.18 |
| Positive | 2.61 | 0.00 |

Table 7 demonstrates the results of the One-way ANOVA test on the mean values of technical analysis performance for each sentiment. Negative sentiments yield a respective p-value of 0.18, which is greater than 0.05. The results indicate that the mean rate of returns for technical analysis strategies did not significantly differ from the benchmark. Conversely, negative and positive sentiments yielded p-values of 0.00 and 0.05, respectively, indicating a statistically significant difference between the performance of technical analysis strategies and the benchmark.

Table 8. Results of One-way ANOVA test on trading performance mean for each sentiment by trading strategies

| Technical Analysis Strategy | F-statistic | p-value |
|---|---|---|
| Benchmark | 0.50 | 0.61 |
| RSI | 0.49 | 0.61 |
| Bollinger-Band | 1.84 | 0.16 |
| MACD | 0.22 | 0.80 |
| MACD Breakout | 1.07 | 0.34 |
| Breakout | 1.32 | 0.27 |

Table 8 summarizes the results of the One-way ANOVA test on trading performances for each sentiment based on a division of trading strategies. The p-values for all trading strategies are above 0.05, suggesting that the mean rate of return for each trading strategy does not statistically significantly differ across sentiments.

Table 9. Results of Welch's t-test on trading performance means for each sentiment by for positive sentiments

| Technical Analysis Strategy | T-statistic | p-value |
|---|---|---|
| RSI | 3.67 | 0.00 |
| Bollinger-Band | 3.59 | 0.00 |
| MACD | 2.25 | 0.03 |
| MACD Breakout | 2.18 | 0.03 |
| Breakout | 3.71 | 0.00 |

Elaborating on the conclusions drawn from the One-way ANOVA test documented in Table 7, this study employed t-tests to identify specific technical analysis strategies that generated statistically significant differences in means during positive sentiments. Since the rate of return variances for positive sentiments are essentially different across trading strategies, the t-tests operate in the form of a Welch's t-test. The results in Table 9 reveal that all technical analysis strategies bear accountability for the overall p-value of 0.00 for positive sentiments, with none of them exceeding 0.05. This provides evidence that the mean rate of return for all trading strategies significantly differ under the regime of positive sentiments.

## 4. Conclusion

This study analyzed the behaviors of technical analysis activities by categorizing market contexts based on their sentiment division. It observed the thirty-day rates of returns for the benchmark strategy as well as the five technical analysis strategies– Stochastic Relative Strength Index (RSI), Bollinger-Band, Moving Average

Convergence/Divergence (MACD), MACD Breakout, and Volatility Breakout (Breakout). These analyses were conducted on all 30 DJIA stocks in the year 2016. The study then employed various statistical tests to assess the means and variances of the strategies' performances in relation to market sentiments. Based on the empirical evidence, this study derived several conclusions.

This study provided insights into the relationship between technical indicator algorithms and market sentiments, suggesting that technical analysis strategies exhibited varying performances based on the prevailing market sentiments.The contrast was reflected in their variances, which refered to the differences in their performances. It determined that the mean returns of technical analysis did not significantly deviate from the benchmark under neutral sentiments, but varied significantly under negative and positive sentiments. Additionally, the study concluded that the benchmark and MACD strategies demonstrated contrasting behaviors in response to prevailing information trends, which was reflected in their variances.

While this study contributed to facilitating the understanding of technical analysis and market sentiments, it also acknowledged that relying solely on quantitative metrics like price and volume data may not always be sufficient in predicting market trends accurately.

Thus, further research could focus on integrating the information with technical indicator algorithms to enhance its capability to predict market trends more accurately and generate reliable alpha. This could be achieved by analyzing how qualitative and quantitative metrics govern technical analysis activities and identifying ways to deconstruct information to make it more useful in predicting market trends. For example, changes in government policy or corporate earnings reports can impact market behavior, but by incorporating both quantitative and qualitative analysis, investors can gain a more comprehensive understanding of the market and make more informed investment decisions.

Additionally, exploring how market inefficiency relates to the effectiveness of informational supplements in technical indicator algorithms could help identify the market contexts in which such supplements are most effective in changing alpha generation. Consequently, further research could explore how to deconstruct information to make it more useful in predicting market trends, ultimately leading to better investment decisions and outcomes for investors.

In conclusion, this study examined the Efficient Market Hypothesis and technical indicator algorithms to understand how information trends may supplement the profitability of technical analysis. The findings and conclusions of this study offer new perspectives that could guide future research and improve the reliability of alpha generation.

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