Comparative study of Traditional Technical Analysis and Machine Learning in stock prediction

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Executive Summary

Problem Statement: Predicting stock market movements has been a long-standing challenge for investors and researchers. Traditional technical analysis and machine learning techniques have been employed to forecast price changes, but their effectiveness, particularly in the context of highly volatile stocks like Tesla, Inc., remains debatable. Moreover, the profitability of these methods is often questioned due to the presence of data snooping bias.

Approach: This study addresses the problem by comparing the performance of technical trading rules and machine learning algorithms, namely Long Short-Term Memory (LSTM) and Support Vector Machines (SVM), in predicting Tesla's stock prices. We analyze the profitability of many parameterized technical trading rules based on four popular indicators: Bollinger Bands, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Moving Averages. Additionally, we employ White's Reality Check to control for data snooping bias. We use the same set of four technical indicators as input features for the machine learning models, along with lagged returns based on the buy and sell signal parameters of the best in-sample technical trading rules. We compare the performance of LSTM and SVM models with the best technical trading rules and evaluate their ability to generate profitable trading signals.

Findings: Our analysis reveals that while many technical trading rules appear profitable in the sample, controlling for data snooping bias substantially reduces the number of profitable strategies. After accounting for data snooping, none of the trading rules remains profitable at the 5% significance level. We find that, contrary to many recent studies, our rules perform better in out-of-sample periods.
The machine learning models, particularly the LSTM-based approaches, demonstrate superior performance compared to the best technical trading rules in the out-of-sample period. The LSTM-RSI-MACD and LSTM-BB-MA combinations generate higher annualized and cumulative returns and better Sharpe ratios than the technical rules alone. The outperformance of the LSTM-RSI-MACD combination over the RSI2 rule is statistically significant using the Wilcoxon rank-sum test.

Recommendations: Based on our findings, we recommend that investors and traders exercise caution when using technical trading rules to predict stock prices, particularly in the case of highly volatile stocks like Tesla. Data snooping bias and their simplicity may limit long-term use cases.

Machine learning techniques, especially LSTM-based models, show promise in predicting stock market movements and generating profitable trading signals. However, it is crucial to employ rigorous statistical methods to validate these models' performance and be aware of the challenges associated with their implementation, such as overfitting and interpretability.

We suggest that future research explore the potential of hybrid strategies that combine technical indicators with machine learning algorithms to leverage the strengths of both approaches. Additionally, investigating the performance of these methods across a broader range of stocks and market conditions could provide valuable insights into their generalizability and practical applicability.

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1 Introduction

In the late 19th century, Charles Dow laid the foundations for what is now known as technical analysis (Hamilton 1922). This approach involves forecasting the direction of prices by studying past market data, primarily price and volume. While (Fama 1970) argued that such historical data cannot be successfully used to predict future prices in an efficient market, recent evidence has challenged this. Since the late 1980s, machine learning (ML) models have also become prevalent in stock market predictions; these models aim to uncover hidden patterns in past market data to predict future price movements.

In this dissertation, we first investigate the performance of four technical trading rules based on indicators, including Bollinger bands (BB), Relative Strength Index (RSI), Moving Average (MA), and Moving Average tConvergence Divergence (MACD) to predict the prices of Tesla, Inc., which represents a highly volatile and difficult-to-predict stock. We analyze the profitability of many parameterized technical trading rules and utilize a novel approach to control for data snooping bias (White 2000; Sullivan et al. 1999).

Next, we compare the performance of two state-of-the-art machine learning algorithms, namely Long Short-Term Memory (LSTM) and Support Vector Machines (SVM), in predicting the direction of Tesla's stock price movements. We use the same set of four technical indicators (BB, RSI, MA, and MACD) as input features for the ML models, along with lagged returns based on the buy and sell signal parameters of the best in-sample technical trading rules. This approach ensures a fair comparison between the performance of traditional technical analysis and modern machine learning techniques.

The main objectives of this study are threefold:

1. Evaluate the profitability of a wide range of technical trading rules based on popular indicators, while rigorously controlling for data snooping bias using White's Reality Check.

2. Investigate the predictive power of cutting-edge machine learning models, specifically LSTM and SVM, in forecasting the direction of Tesla's stock price movements.

3. Compare the performance of the best technical trading rules with the integrated ML models to determine which approach is more effective in generating profitable trading signals for a highly volatile stock like Tesla.

By addressing these objectives, we aim to contribute to the ongoing debate on the efficacy of technical analysis and machine learning in stock market prediction. The findings of this study can provide valuable insights for investors and traders seeking to optimize their strategies in the face of market inefficiencies and the challenges posed by highly volatile stocks.

The rest of this dissertation is structured as follows: Section 2 presents a comprehensive literature review, discussing literature on technical analysis and machine learning in stock market prediction. Section 3 describes this study's data, methodology, and performance evaluation metrics. Section 4 presents the results and discussion, including the in-sample and out-of-sample performance of technical trading rules, the impact of data snooping bias, and the comparative analysis of integrated ML models. Finally, Section 5 concludes the dissertation, summarizing the main findings and offering suggestions for future research.

2 Literature Review

Numerous studies have demonstrated that technical analysis can be profitable in both stock markets (Brock et al. 1992; Sullivan et al. 1999; P.-H. Hsu and Kuan 2005; P.-H. Hsu, Y.-C. Hsu, et al. 2010; Metghalchi et al. 2012; Jiang et al. 2019) and foreign exchange market (Frankel and Froot 1990; Taylor and H. Allen 1992; P.-H. Hsu, Taylor, et al. 2016; Coakley et al. 2016). Some studies also find evidence supporting the effectiveness of simple technical trading rules in Western equity markets (Alexander 1961; Bessembinder and Chan 1995; P.-H. Hsu and Kuan 2005). However, notable studies such as(F. Allen and Karjalainen 1999; Fama and Blume 1966; Bajgrowicz and Scaillet 2012), among others, have found negative empirical findings and argued against technical analysis.

Despite the mixed consensus, the profitability of technical trading rules remains a topic of intense debate in the academic community. Proponents argue that technical analysis can capture market inefficiencies and provide valuable signals for profitable trades. For example, (Brock et al. 1992) found that simple moving average and trading range breakout rules could generate significant returns in the U.S. stock market. Their seminal study tested 26 simple technical trading rules, including moving averages and trading range breakout rules, on the Dow Jones Industrial Average (DJIA) from 1897 to 1986. Importantly, they used a bootstrap methodology to assess the statistical significance of their results, which was a novel approach at the time for dealing with potential data snooping biases. Similarly, (Sullivan et al. 1999) demonstrated the profitability of technical trading rules in various international markets, even after accounting for data snooping bias. (Sullivan et al. 1999) extended the work of (Brock et al. 1992) by examining a more comprehensive set of 7,846 technical trading rules on the DJIA from 1897 to 1996. They employed (White 2000) to account for data snooping bias, which had not been addressed in the original study by (Brock et al. 1992). Despite the stricter statistical tests, (Sullivan et al. 1999) found that the best-performing technical trading rule could generate significant returns, even after considering transaction costs.

Another recent study by (Coakley et al. 2016) provided a comprehensive empirical investigation of the profitability of foreign exchange technical trading rules over the 1996–2015 period for 22 currencies quoted in US dollars. They analyzed a universe of 113,148 trading rules, including traditional moving average rules and those constructed based on technical indicators such as Bollinger bands and the relative strength index (RSI). Interestingly, after controlling for data snooping bias using the Step-SPA test, (Coakley et al. 2016) found a sharp divergence in the performance of traditional and newer trading rules based on technical indicators (RSI, MACD and BB). Virtually none of the traditional trading rules remained significant, with p-values close to 1. This is consistent with the literature suggesting a decline in the performance of traditional trading rules over the past two decades (Chuang et al. 2024; Rink 2023).

Therefore, sceptics contend that the apparent success of technical analysis may be largely due to data snooping and the selective reporting of positive results. (Fama and Blume 1966) and (F. Allen and Karjalainen 1999) argued that the profitability of technical trading rules could be attributed to chance rather than any inherent forecasting ability. Moreover, (Bajgrowicz and Scaillet 2012) found that the performance of technical trading rules has declined over time, suggesting that any market inefficiencies exploited by these strategies may be gradually disappearing.

In light of these conflicting findings, evaluating the effectiveness of technical trading rules using rigorous statistical methods that account for data snooping bias is crucial. White's Reality Check (2000) and the Superior Predictive Ability test proposed by (Hansen 2005) emerged as popular tools for addressing this issue. By applying these methods to a large universe of technical trading rules, researchers can identify strategies that generate statistically significant returns while controlling for the effects of multiple hypothesis testing (P.-H. Hsu, Taylor, et al. 2016; Chen et al. 2009; Coakley et al. 2016).

Furthermore, machine learning techniques have opened up new avenues for predicting stock market movements. Unlike traditional technical analysis, which relies on predefined rules and human interpretation, machine learning algorithms can automatically learn from data and adapt to changing market conditions. Studies by (Takeuchi and Lee 2013; Huck 2009; Nelson et al. 2017) have shown that machine learning models, such as neural networks and support vector machines, can generate profitable trading signals in various financial markets.

(Huck 2010) investigated the profitability of support vector machines (SVM) in the context of stock market prediction. The study focused on the German stock market, using data from the DAX 30 index. The author employed a combination of technical and fundamental indicators as input features for the SVM model, including moving averages, momentum, and price-to-earnings ratios. The SVM model was trained to predict the direction of stock price movements (up or down) daily. The study used a sliding window approach to generate trading signals, with the model being retrained every 20 trading days. The results showed that the SVM-based trading strategies could generate significant abnormal returns, outperforming a passive buy-and-hold strategy and a benchmark trading rule based on moving average crossovers.

(Yıldırım et al. 2021) proposed a hybrid LSTM model for forecasting the directional movement of the EUR/USD currency pair using both macroeconomic and technical indicators. The model consists of two LSTM models, one trained with macroeconomic indicators and the other with technical ones. The authors introduced a third class, "no-action," to label instances where the price change was below a predefined threshold, enabling the model to avoid making predictions in uncertain cases. The outputs of the two LSTMs were combined using a rule-based decision mechanism. The hybrid model outperformed individual LSTMs and a simple combination of both feature sets, achieving an average accuracy of 73.61% for one-day predictiom.

3 Methodology

In this study, we are concerned with analyzing the excess profitability of quantitative technical trading rules as they are objective and readily computable.

3.1 Data and Preliminary Analysis

The dataset comprises historical stock data for Tesla, Inc. (NASDAQ: TSLA) sourced from the Yahoo Finance platform using the 'yfinance' API, which offers extensive financial data for research purposes. The dataset spans from June 29, 2010, to March 15, 2024, encompassing nearly 14 years. It contains 3,452 data points, each representing the Tesla stock's trading activity for a single day. Table 1 below presents a dataset sample, displaying the first two and last entries to provide an overview of the data structure and the range of dates covered.

The dataset covers daily trading data, including open, high, low, and close prices and volume, with close prices used for analysis. There are no missing values or anomalies. The data spans nearly 13 years, divided into an 80% training set and a 20% testing set

Table 1: Tesla Stock closing price sample data

Date	Open	High	Low	Close	Volume
2010-06-29 00:00:00-04:00	1.266667	1.666667	1.169333	1.592667	281494500
2010-06-30 00:00:00-04:00	1.719333	2.028000	1.553333	1.588667	257806500
—	—	—	—	—	—
2024-03-15 00:00:00-04:00	163.160004	165.179993	160.759995	163.570007	96971900

for evaluating trading strategies and machine learning models.

This extensive period was chosen to capture various market conditions, including bull and bear markets, economic cycles, and significant company-specific events, allowing for a thorough analysis of the performance of technical indicators and machine learning models across different market regimes

To gain a better understanding of the data, we performed a preliminary analysis. Figure 1 below presents a time series plot of Tesla's closing price from 2010 to 2024 and its 30-day rolling standard deviation. The plot reveals a significant upward trend in the stock price, particularly from 2020 onwards, with notable volatility. This observation suggests that the dataset captures a range of market conditions, including periods of rapid growth and increased market fluctuations.

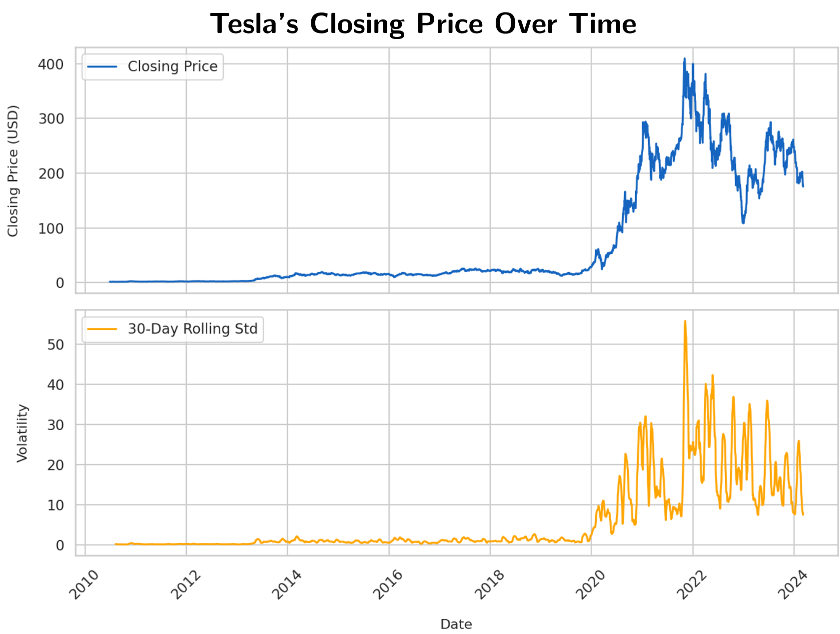


Figure 1: Tesla Stock closing price from 2010 to 2024

The rolling standard deviation measures volatility, and the plot highlights periods of heightened volatility, such as the spikes observed around 2020-2024. We observe that

Tesla's stock price can be categorized into two major periods, one before 2020 with more stable annual returns and one post-2020 with high volatility.

We calculated descriptive statistics for the closing price to summarise the dataset further, as shown in Table 2 below. The results indicate a wide range of prices, with a minimum of \$1.05 and a maximum of \$409.97. The mean closing price over the period is \$72.27, with a standard deviation of \$101.96, confirming the presence of significant volatility. The skewness value of 1.35 suggests that the distribution of closing prices is positively skewed, which is consistent with the observed upward trend in the time series plot.

Table 2: Descriptive Statistics

Statistic	**Value**
Count	3447
Mean	72.27
Standard Deviation	101.96
Minimum	1.05
25% Quantile	11.08
50% Quantile (Median)	17.07
75% Quantile	135.50
Maximum	409.97
Variance	10395.94
Skewness	1.35

It is important to acknowledge the limitations and considerations associated with the data. Firstly, the dataset is specific to Tesla Inc. and may not represent other stocks or market indices. The characteristics and dynamics of Tesla's stock price may differ from other companies or the broader market, limiting the generalizability of the findings. Secondly, the data is based on daily closing prices and does not capture intraday price movements or volatility. This limitation may affect the performance of certain technical indicators or machine learning model-based strategies that rely on high-frequency data or real-time price updates.

Despite these limitations, the chosen dataset provides a solid foundation for evaluating the effectiveness of technical analysis and machine learning approaches in predicting stock price movements. The long timeframe, diverse market conditions, and the inclusion of relevant variables enhance the analysis's robustness and allow for a comprehensive assessment of the performance of different strategies and models.

3.2 Technical Indicators for trading strategies

We employ MA, RSI, MACD and BB indicators to construct our technical strategies for Tesla stock. These indicators are selected based on their popularity among traders and their potential to capture different aspects of market dynamics (Wilder 1978; Murphy 1999; Appel 2005; Bollinger 2001; Coakley et al. 2016; Rink 2023; Mitchell 2024).

3.2.1 Moving Average (MA)

Moving Average (MA) is a widely used technical analysis tool that helps smooth out price fluctuations and identify trends in financial markets (Murphy 1999). It calculates the average price of a security over a specified number of periods, creating a constantly updating trend-following indicator. This study employs two common types of MAs: Simple Moving Averages and Exponential Moving Averages.

Simple Moving Average (SMA):

The SMA is calculated by taking the arithmetic mean of a security's closing prices over specific periods (Achelis 2000). The formula for SMA is:

$$SMA_t = \frac{1}{n} \sum_{i=0}^{n-1} P_{t-i} \tag{1}$$

where SMA_t is the simple moving average at time t, n is the number of periods, and P_{t-i} is the closing price at time $t - i$.

Exponential Moving Average (EMA):

The EMA is a weighted moving average that gives more importance to recent prices, making it more responsive to new information than the SMA (Appel 2005). The formula for EMA is:

$$EMA_t = (P_t \times \frac{S}{1+d}) + EMA_{t-1} \times (1 - \frac{S}{1+d}) \tag{2}$$

where EMA_t is the exponential moving average at time t, P_t is the closing price at time t, S is the smoothing factor (typically $2/(n+1)$), d is the number of periods, and EMA_{t-1} is the EMA of the previous period.

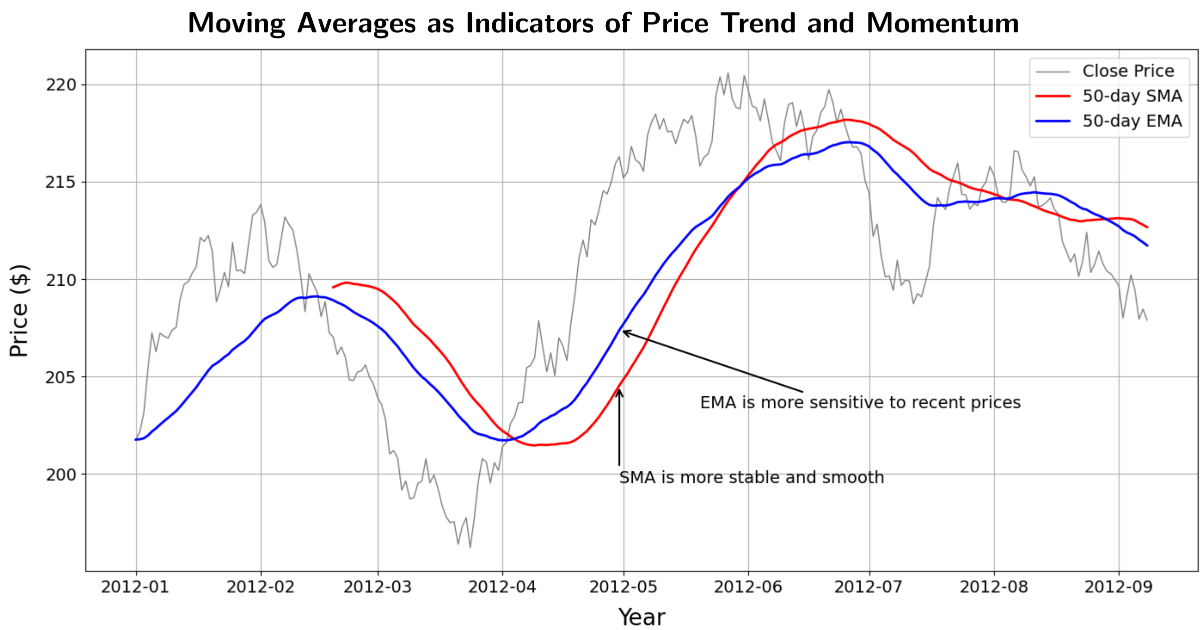


Figure 2: Tesla Stock closing price annual percentage change

Interpretation of MA as a trend-following indicator

Moving averages are primarily used to identify trends and potential support and resistance levels (Murphy 1999; Appel 2005). When the price is above the moving average, it indicates an uptrend; when it is below the moving average, it suggests a downtrend. Crossovers between short-term and long-term moving averages can signal trend changes, with a short-term MA crossing above a long-term MA indicating a bullish trend and a short-term MA crossing below a long-term MA signalling a bearish trend (Pring 2014).

3.2.2 Moving Average Convergence Divergence (MACD)

The Moving Average Convergence Divergence (MACD) is a trend-following momentum indicator developed by Gerald Appel that highlights the relationship between two moving averages of a security's price (Appel 1979; Appel 2005). In this study, the MACD is calculated using the 26-day and 12-day Exponential Moving Averages (EMAs) to identify market momentum and signal potential trade entry and exit points, following the method used by (Murphy 1999). The MACD consists of three main components:

MACD Line:

The difference between the 12-day and 26-day EMAs:

$$\text{MACD Line} = EMA_{12}(P) - EMA_{26}(P) \tag{3}$$

where $EMA_{12}(P)$ and $EMA_{26}(P)$ are the 12-period and 26-period exponential moving averages of the price P, respectively. The EMA is calculated using the formula in the previous section.

Signal Line:

The 9-day EMA of the MACD Line, acting as a trigger for buy and sell decisions:

$$\text{Signal Line} = EMA_9(\text{MACD Line}) \tag{4}$$

where $EMA_9(\text{MACD Line})$ is the 9-period exponential moving average of the MACD Line.

MACD Histogram:

Represents the difference between the MACD Line and the Signal Line:

$$\text{MACD Histogram} = \text{MACD Line} - \text{Signal Line} \tag{5}$$

The histogram indicates momentum shifts. It is positive when the MACD Line is above the Signal Line (bullish momentum) and negative when it is below (bearish momentum).

Interpretation of MACD as a momentum and trend-following indicator

The MACD is used to assess momentum and identify potential trend changes (Appel 2005). When the MACD line crosses above the signal line, it generates a bullish signal, suggesting a positive momentum shift and a potential uptrend (potential buy signal). Conversely, when the MACD line crosses below the signal line, it generates a bearish signal, indicating a negative momentum shift and a potential downtrend (potential sell signal). Divergences between the MACD and price action can also signal potential trend reversals (Pring 2014).

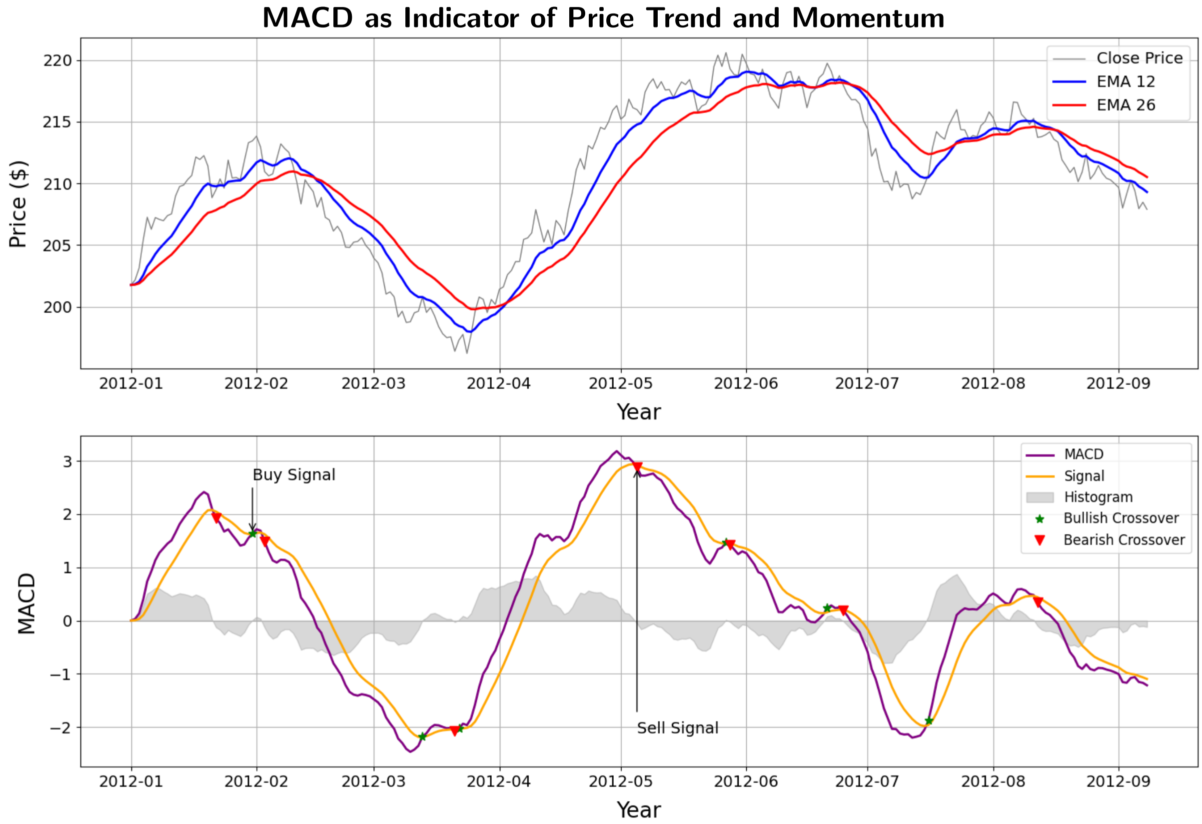


Figure 3: MACD

3.2.3 Relative Strength Index (RSI)

The RSI is a popular momentum oscillator J. Welles Wilder Jr. developed that measures the speed and change of price movements (Wilder 1978). RSI oscillates between 0 and 100, helping to identify overbought and oversold conditions in the market. This study employs the traditional 14-period RSI used by practitioners (Achelis 2000).

RSI Calculation

The RSI is calculated using the following steps:

Step 1: Calculate the average gain and loss

First, calculate the daily price change for each period. If the change is positive, it is considered a gain; if negative, it is considered a loss. Then, calculate the average gain and loss over the specified periods (14).

$$AG = \frac{1}{n}\sum_{i=0}^{n-1} Gain_i \tag{6}$$

$$AL = \frac{1}{n} \sum_{i=0}^{n-1} Loss_i \tag{7}$$

where AG is the average gain, AL is the average loss, n is the number of periods (14), and $Gain_i$ and $Loss_i$ are the gains and losses for each period i.

Step 2: Calculate the Relative Strength (RS)

The Relative Strength is the ratio of the average gain to the average loss:

$$RS = \frac{AG}{AL} \tag{8}$$

Step 3: Calculate the RSI

The RSI is then calculated using the Relative Strength:

$$RSI = 100 - \frac{100}{1 + RS} \tag{9}$$

Interpretation of RSI as a momentum oscillator and overbought/oversold indicator:

According to (Wilder 1978; Henderson 2002), the RSI indicator can be interpreted as follows:

- An RSI above 70 is considered overbought, indicating that the asset may be overvalued and a potential corrective pullback could occur.
- An RSI below 30 is considered oversold, suggesting that the asset may be undervalued and a potential bullish rally could develop.
- The RSI can also be used to identify the general trend:
  - An RSI consistently above 50 indicates an overall bullish trend.
  - An RSI consistently below 50 suggests an overall bearish trend.

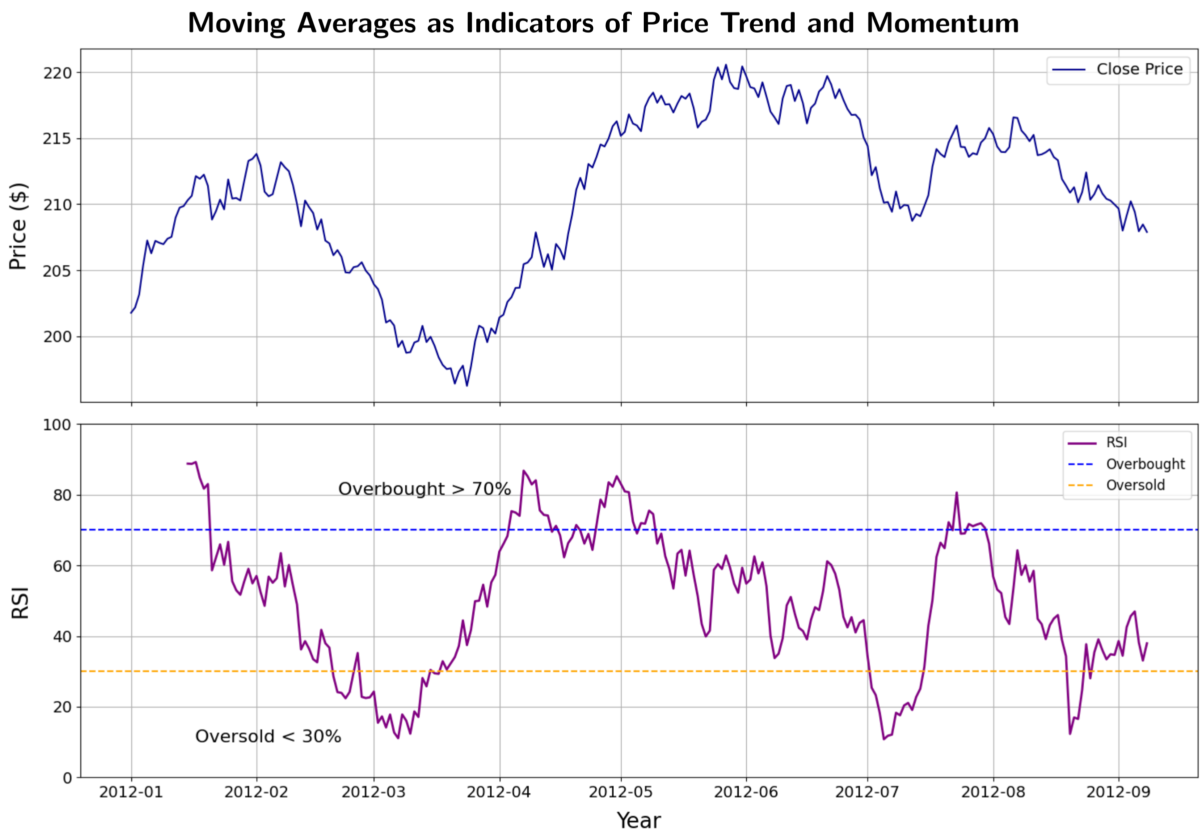


Figure 4: MACD

3.2.4 Bollinger Bands (BB):

Bollinger Bands (BB) is a technical analysis tool developed by John Bollinger in the 1980s to measure market volatility and provide dynamic support and resistance levels (Bollinger 2001). The bands consist of a middle band (typically a 20-period Simple Moving Average) and an upper and lower band, usually set 2 standard deviations above and below the middle band.

Bollinger Bands Calculation:

The Bollinger Bands are calculated using the following steps:

Step 1: Calculate the middle band (MB):

The middle band is a simple moving average (SMA) of the closing prices over a specified number of periods (usually 20).

$$MB = SMA_{20}(P) \tag{10}$$

where MB is the middle band, $SMA_{20}(P)$ is the 20-period simple moving average of the closing prices P.

Step 2: Calculate the standard deviation (SD):

The standard deviation measures the dispersion of the closing prices from the middle band over the specified period.

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - MB)^2} \tag{11}$$

where SD is the standard deviation, n is the number of periods (20), P_i is the closing price at period i, and MB is the middle band.

Step 3: Calculate the upper and lower bands:

The upper band (UB) and lower band (LB) are typically set 2 standard deviations above and below the middle band.

$$UB = MB + (2 \times SD) \tag{12}$$

$$LB = MB - (2 \times SD) \tag{13}$$

Figure 5 below show a plot to clarify the concept of Bollinger Bands:

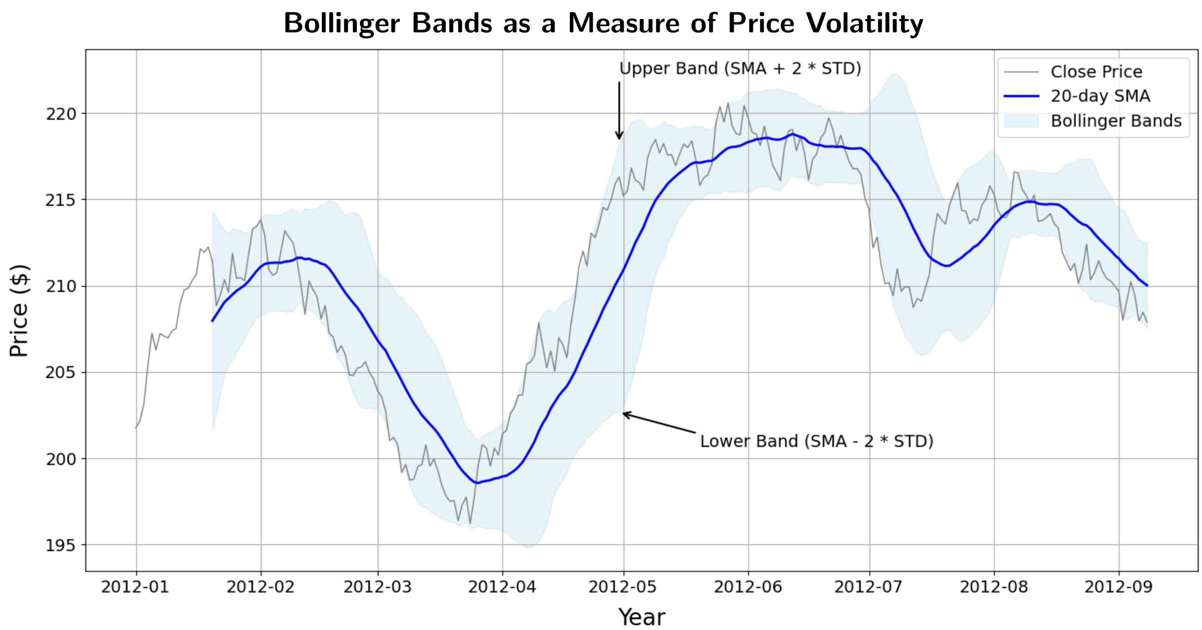


Figure 5: Bollinger Bands applied to simulated stock data over one year. The plot displays the closing prices (grey line), the 20-day Simple Moving Average (blue line), and the Bollinger Bands (light blue shaded area)

Interpretation of Bollinger Bands as a volatility and trend-following indicator

Bollinger Bands measure price volatility and identify potential overbought or oversold conditions (Bollinger 2001). When the price moves close to the upper Bollinger Band, it suggests that the price is overbought and may be due for a pullback. When the price moves close to the lower Bollinger Band, the price is oversold and may be due for a bounce (Murphy 1999). The width of the Bollinger Bands also provides insights into price volatility, with wider bands indicating higher volatility and narrower bands indicating lower volatility (Bollinger 2001).

3.3 Technical Trading Strategies

We present our study's specific trading strategies based on the technical indicators discussed in the previous section. These strategies are designed to generate buy and sell signals based on the indicators' values and predefined criteria to capitalize on potential market opportunities.

Each trading strategy incorporates a unique combination of technical indicators and trading filters (criteria for buy and sell signals) to capture different aspects of Tesla's market dynamics and improve the robustness of the generated signals. The range of parameters for each strategy is selected based on Tesla's high volatility, significant upward trend, and momentum shifts, as observed in the preliminary analysis (See Section 3.1).

The trading strategies employed in this study include:

1. MA Crossover Strategy
2. MACD Crossover Strategy (Standard and Zero Cross)
3. RSI Overbought/Oversold Strategy
4. BB Breakout Strategy

In the following subsections, we will discuss the details of each of our trading strategy, including the specific indicators used, the trading filters applied, and the rules for generating buy and sell signals. We will also present the parameter ranges and the number of unique trading rules generated by each strategy.

3.3.1 Trading Filters

To enhance the robustness and efficacy of our trading strategies, we incorporate three types of filters: band filters, time-delay filters, and fixed-length filters. These filters are designed to reduce the impact of market noise, confirm the strength of trading signals, and provide a structured framework for position management.

Band filters effectively filter out minor fluctuations and focus on significant price movements. Time-delay filters introduce a waiting period before executing a trade, allowing for additional signal confirmation and mitigating the risk of acting on false or premature signals. Fixed-length filters are used for discipline and consistency in executing our trading strategies, allowing us to assess the trading performance systematically.

In our study, band filters are omitted for RSI and BB as these indicators inherently generate signals for key market conditions—overbought/oversold levels and volatility shifts, respectively. Conversely, band filters are applied to MA and MACD strategies to ensure their signals reflect significant market movements, aligning more accurately with trend signal generation.

3.3.2 MA Crossover Strategy

The MA crossover strategy generates buy and sell signals based on the intersection of two moving averages with different periods. This strategy aims to identify shifts in the stock's trend by comparing the short-term and long-term moving averages. We separate the strategy into two distinct rules:

MA1: If $MA_t(m)$ crosses above $MA_t(n)$ by at least f_b percent, go long the stock until $MA_t(m)$ crosses below $MA_t(n)$ by at least f_b percent, at which time go short the stock. If $MA_t(m)$ crosses below $MA_t(n)$ by at least f_b per cent, go short the stock until $MA_t(m)$ crosses above $MA_t(n)$ by at least f_b per cent, at which time go long the stock. m is less than n.

MA2: If $MA_t(m)$ crosses above $MA_t(n)$ by at least f_b per cent, go long the stock for f_h days and neutralize the position. If $MA_t(m)$ crosses below $MA_t(n)$ by at least f_b per cent, go short the stock for f_h days and neutralize the position. m is less than n.

Table 3 presents the parameters used for constructing the MA trading rules in this study.

Table 3: Parameters of technical trading rules for Moving Average

Parameters	Description	Value
m	Short-term moving average	1, 2, 5, 10, 20
n	Long-term moving average	50, 100, 150, 200
f_b	Fixed band multiplicative filter	0, 0.01, 0.1, 0.2, 0.3
f_d	Number of days for the delay filter	0, 1, 2, 4, 5
f_h	Fixed number of days position is held	1, 2, 4, 6, 8

Including longer-term moving averages (50, 100, 150, 200) helps identify more significant price movements and reduces the impact of short-term fluctuations. The total number of unique trading rules for the MA crossover strategy, considering the specified parameters and the $m < n$ condition, is 1000. This comprehensive set of rules thoroughly evaluates the strategy's performance and robustness across various parameter combinations.

3.3.3 MACD Crossover Strategy

The MACD crossover strategy generates buy and sell signals based on the MACD line and the signal line crossover. This strategy aims to capture changes in the stock's price momentum by comparing the MACD line, which represents the difference between two moving averages, and the signal line, which is a moving average of the MACD line.

MACD1: If $MACD_t$ crosses above $Signal_t$ by at least f_b percent, go long the stock until $MACD_t$ crosses below $Signal_t$ by at least f_b percent, at which time go short the stock. If $MACD_t$ crosses below $Signal_t$ by at least f_b per cent, go short the stock until $MACD_t$ crosses above $Signal_t$ by at least f_b per cent, at which time go long the stock.

MACD2: If $MACD_t$ crosses above $Signal_t$ by at least f_b per cent, go long the stock for f_h days and neutralize the position. If $MACD_t$ crosses below $Signal_t$ by at least f_b percent, go short the stock for f_h days and neutralize the position.

3.3.4 MACD Zero-Cross Strategy

The MACD Zero-Cross strategy generates buy and sell signals based on the MACD line crossing the zero line. This strategy aims to identify potential trend reversals by focusing on the MACD line's movement above or below the zero line.

MACD3: If $MACD_t$ crosses above zero by at least f_b percent, go long the stock until $MACD_t$ crosses below zero by at least f_b percent, at which time go short the stock. If $MACD_t$ crosses below zero by at least f_b percent, go short the stock until $MACD_t$ crosses above zero by at least f_b percent, at which time go long the stock.

MACD4: If $MACD_t$ crosses above zero by at least f_b percent, go long the stock for f_h days and then neutralize the position. If $MACD_t$ crosses below zero by at least f_b percent, go short the stock for f_h days and neutralize the position.

Table 4 presents the parameters for constructing the MACD trading rules.

Table 4: Parameters of technical trading rules for MACD

Parameters	Description	Value
s	Short-term EMA periods	6, 10, 15, 20, 25
l	Long-term EMA periods	13, 26, 30, 40
g	Signal periods	3, 9, 15, 20
f_b	Fixed band multiplicative value	0, 0.01, 0.05, 0.1
f_d	Number of days for the delay filter	0, 1, 2, 3
f_h	Number of days position is held	1, 5, 10, 15

The selected parameters for the MACD strategy aim to capture both short-term and medium-term price momentum while considering the stock's volatility. Including MACD Crossover and MACD Zero-Cross strategies allows for a more comprehensive assessment of the MACD's predictive capabilities. The MACD strategy generates 10880 unique trading rules.

3.3.5 RSI Overbought/Oversold Strategy

The RSI overbought/oversold strategy aims to identify potential trend reversals by measuring the magnitude of recent price changes. This strategy uses the RSI indicator, which compares the average gain and loss over a specified period, to identify overbought (potentially overvalued) and oversold (potentially undervalued) conditions.

RSI1: If $RSI_t(h)$ moves above $50 + v$ for at least f_d days and then subsequently moves below $50 + v$, go short the stock. If $RSI_t(h)$ moves below $50 - v$ for at least f_d days and then moves above $50 - v$, go long the stock. Positions are held until an opposite signal is generated.

RSI2: If $RSI_t(h)$ moves above $50 + v$ for at least d days and then subsequently moves below $50 + v$, go short the stock for f_h fixed days and then neutralize the position. If $RSI_t(h)$ moves below $50 - v$ for at least d days and then moves above $50 - v$, go long the stock for f_h fixed days and neutralize the position.

Table 5 presents the parameters for constructing the RSI trading rules.

Table 5: Parameters of technical trading rules for RSI

Parameters	Description	Value
n	Look-back period	1, 2, 3, 5, 10, 14, 20, 25, 30, 40, 50
v	Deviation from RSI = 50	5, 10, 15, 20, 25, 30, 35, 40, 50, 60
f_d	Minimum number of days in overbought/oversold levels	0, 1, 2, 3, 4, 5, 6, 7, 8, 10
f_h	Number of days position is held	1, 2, 4, 8, 10, 12, 20, 30

The RSI parameters are chosen to identify overbought and oversold conditions more effectively in the context of the Tesla stock's high volatility. Using look-back periods (5, 10, 15) and higher deviations from RSI = 50 (25, 30) can help capture more significant price reversals. We note that very low look-back periods (1,2,3,5) are included, which might skew results.

The RSI strategy encompasses 9900 unique trading rules based on the specified parameters. This wide range of parameters allows for a comprehensive assessment of the strategy's effectiveness in capturing overbought and oversold conditions.

3.3.6 BB Breakout Strategy

The BB breakout strategy identifies potential trading opportunities based on the stock's price movement relative to its Bollinger Bands. The bands are set a certain number of standard deviations (n_{std}) above and below the moving average, creating upper (UB_t) and lower (LB_t) bounds.

BB1: The BB1 strategy generates a buy signal when the price (P_t) crosses above $LB_t(e, n_{std})$ and remains above for f_d days. The long position is maintained until the price has crossed above the middle band for f_d days at which point the position is neutralized. Conversely, a sell signal is generated when the price crosses below $UB_t(e, n_{std})$ and remains below for f_d days. The short position is maintained until the price crosses below $MB_t(e)$ for f_d days at which point the position is neutralized.

BB2: A buy signal is generated when the price (P_t) has crosses above $LB_t(e, n_{std})$ for f_d days. The long position is held for f_h days, at which time the position is neutralized. Similarly, a sell signal is generated when the price has crossed below $UB_t(e, n_{std})$ for f_d days. The short position is held for f_h days, and the position is neutralized.

Table 6 presents the parameters for constructing the BB trading rules.

Table 6: Parameters of technical trading rules for Bollinger Bands

Parameters	Description	Value
e	Evaluation period	10, 15, 20, 25, 30, 35, 50
n_{std}	Number of standard deviations	1, 2, 3, 4
f_d	Number of days for the delay filter	0, 1, 2, 3, 4, 5, 8, 10, 15
f_h	Fixed number of days position is held	0, 1, 2, 5, 10, 15, 20, 25

The BB strategy captures potential price breakouts while accounting for the stock's high volatility. Shorter evaluation periods (10, 20) and a higher number of standard deviations

(2, 3) can help identify more significant price movements and reduce the impact of minor fluctuations.

The BB strategy generates 2268 unique trading rules, allowing for a thorough evaluation of its performance across various parameter combinations. This extensive set of rules enables us to assess the strategy's ability to capitalize on potential price breakouts while considering the trading filters' confirmation and risk management benefits.

3.4 Addressing Data Snooping Bias

In the pursuit of identifying profitable trading strategies, researchers often face the challenge of data snooping bias, which arises when the same dataset is used repeatedly to test multiple hypotheses or models (White 2000). This bias can lead to the discovery of seemingly significant relationships or patterns that are, in fact, spurious and do not generalize well to out-of-sample data. To mitigate this issue and ensure the robustness of our findings, we employ White's Reality Check (WRC) as a rigorous statistical framework for testing the significance of our best-performing trading rule among a large set of alternatives. We compared the best strategies based on either the highest Sharpe Ratio, Annualized Return, or Cumulative Return against those of the benchmark and performed bootstrap resampling to calculate p-values. We use the buy-and-hold strategy as our benchmark.

WRC is a comprehensive methodology that accounts for the entire universe of trading rules, thereby controlling for the adverse effects of data snooping (Sullivan et al. 1999). The procedure involves comparing the performance of the best trading rule to the performance of a benchmark, typically a buy-and-hold strategy while accounting for the fact that the best rule has been selected from a large pool of candidates.

Formally, let $\{r_{t,i}\}_{t=1}^{T}$ denote the returns of the i-th trading rule, where T is the total number of observations, and $i = 1, \ldots, M$, with M being the total number of trading rules considered. The performance of each trading rule is measured by its average return relative to the benchmark:

$$\bar{r}_i = \frac{1}{T} \sum_{t=1}^{T} (r_{t,i} - r_{t,b}) \tag{14}$$

where $r_{t,b}$ is the return of the benchmark at time t. The null hypothesis of WRC states that the best trading rule does not outperform the benchmark:

$$H_0 : \max_{i=1,\ldots,M} \mathbb{E}[\bar{r}_i] \leq 0 \tag{15}$$

To test this hypothesis, WRC employs a stationary bootstrap procedure (Politis and Romano 1994) to generate many resampled return series under the null hypothesis. The bootstrapped returns are then used to construct the empirical distribution of the test statistic, which is the maximum average return across all trading rules:

$$V^* = \max_{i=1,\ldots,M} \bar{r}_i^* \tag{16}$$

where $\bar{r}_i^*$ is the average return of the i-th trading rule in the bootstrapped sample. The p-value of the test is computed as the proportion of bootstrapped test statistics that exceed the observed test statistic:

$$p = \frac{1}{B} \sum_{b=1}^{B} 1\{V_b^* > V\} \tag{17}$$

where B is the total number of bootstrap replications, V_b^* is the test statistic for the b-th bootstrap sample, and V is the observed test statistic in the original data.

By applying WRC to our universe of trading rules, which includes various parameterizations of technical indicators and machine learning models, we ensure that the identified best-performing strategies do not result from data snooping bias. This rigorous statistical approach strengthens the reliability and generalizability of our findings, providing a more accurate assessment of the true predictive power of the selected trading rules.

Although superior methods exist that can identify ALL the outperforming rules, we only consider White's reality check to find the best-performing rule to compare against the machine learning models.

3.5 Modern machine learning-based trading strategies

3.5.1 Modelling Approach

Our study focuses on binary classification to predict Tesla stock price movements. The prediction problem can be formulated as exploring the relationship between an output y and a set of D inputs x, where $x = \{x_1, x_2, \ldots, x_D\}$, i.e., $y = F(x)$. The output y represents the direction of price movement (upward or downward) in the next trading day, and the function F is learned from in-sample training data, allowing for predictions on new, unseen out-of-sample data.

We consider the binary classification setting, where $y \in 0, 1$:

- $y = 1$ indicates an upward price movement (positive return)
- $y = 0$ indicates a downward price movement (negative return)

The input features x are composed of L lags of x, such that:

$$y_{t+1} = F(x_t) \tag{18}$$

where $x_t = \{x_{1t}, \ldots, x_{Dt}, x_{1t-1}, \ldots, x_{Dt-1}, \ldots, x_{1t-L}, \ldots, x_{Dt-L}\}$, and y_{t+1} is the direction of price movement for the next trading day.

We employ two machine learning models, SVM and LSTM networks, to learn the function F and predict Tesla stock price movements. See Appendix B for the algorithm describing the implementation of SVM and LSTM models for our binary classification problem.

3.5.2 Feature Selection and Data Preparation

To apply SVM and LSTM to our Tesla stock price prediction task, we preprocess the data as follows:

- Use the best-performing rules of all indicators (MA, MACD, RSI, and BB) determined in the previous section as input features.
- Standardize the input features to have a mean of 0 and a standard deviation of 1, effectively normalizing the distribution of each feature. This approach is particularly suitable for financial data, which often exhibits outliers and varying scales due to market volatility and diverse indicators. The standardization process is mathematically represented as:

  $$z = \frac{x - \mu}{\sigma}$$

  where x is the original value of the feature, μ is the mean of the feature, σ is the standard deviation of the feature, and z is the standardized value.
- Create a target variable representing the direction of price movement for the next day, with 1 for upward movement and -1 for downward movement.

We split the data into training (80%) and testing (20%) sets, reserving the most recent 20% for testing to evaluate the models' performance on unseen data. This split allows for sufficient data for training while providing a realistic assessment of the models' performance in real-time trading scenarios. Also, we ensure the ML models are applied to the same periods as the technical trading rules for a fair comparison.

To ensure a fair comparison between traditional technical trading strategies and machine learning (ML) models, our feature selection directly mirrors the critical data points used by traditional methods. This structured approach includes:

1. **Indicator-Specific Values**: Current values of technical indicators directly inform the traditional strategy's trading signals.
2. **Lagged Closing Prices**: A series of historical closing prices spanning the longest horizon considered by the trading rule. This ensures that the ML models access the same price information as the traditional strategies.
3. **Indicator Signals**: Binary features indicating the occurrence of technical signals that trigger trading actions in traditional strategies. We use 1 for buy and -1 for sell.

For the LSTM model, we use a 60-day sequence length to capture the medium-term dynamics and patterns in the Tesla stock price while considering the stock's high volatility. This sequence length aligns with the common practice of using 60-day moving averages in technical analysis. It provides sufficient historical context for the model to learn from without introducing excessive complexity or computational burden.

After preprocessing the data and aligning the feature selection process with traditional technical trading strategies, we train and evaluate the SVM model using this curated dataset. SVM, a powerful machine learning algorithm, is well-suited for handling the complexities of financial time series data, making it an ideal choice for our study.

3.5.3 Support Vector Machines (SVM)

Our study selects SVM for its proven classification, regression, and outlier detection effectiveness. They are particularly adept at navigating the complexities inherent in financial time series data, which include noise, non-linearity, and non-stationarity (Kumbure et al. 2022; Nazareth and Ramana Reddy 2023; Kim 2003). This makes SVM a fitting choice for predicting Tesla's stock prices, which display similar complex patterns.

Overview of SVM

The core idea behind SVM is to map the input data points into a higher-dimensional feature space where a separating hyperplane can be found. The optimal hyperplane is chosen to maximize the margin between the nearest data points of different classes, known as support vectors. By maximizing the margin, SVM achieves better generalization and reduces the risk of overfitting (Burges 1998).

SVM for Classification

We employ an SVM classifier to predict Tesla stock price movements. In classification tasks, SVM seeks to find a hyperplane that best separates the data points belonging to different classes. The objective is to minimize the classification error while maximizing the margin between the support vectors. The optimization problem can be formulated as follows:

$$\min_{w,b} \frac{1}{2}||w||^2 \quad \text{subject to} \quad y_i(w^T x_i + b) \geq 1, \quad i = 1, \ldots, n \tag{19}$$

where w is the weight vector, b is the bias term, x_i are the input data points, y_i are the corresponding class labels, and n is the number of data points.

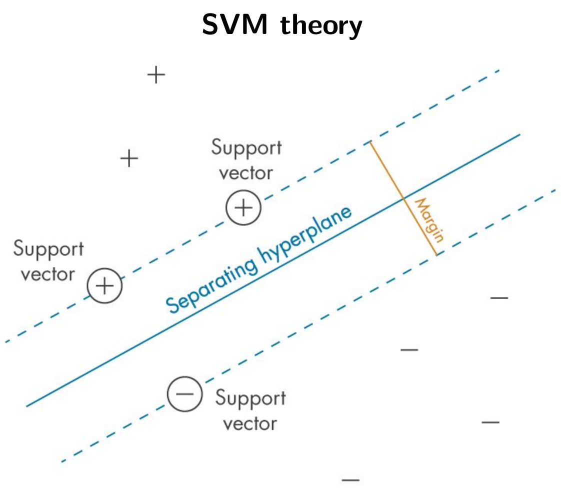


Figure 6: The separating hyperplane is optimized to maximize the margin between the two classes, denoted by plus and minus signs. The data points closest to the hyperplane, known as support vectors, define the margin.

Kernel Functions

SVM employs kernel functions that implicitly map the input data into a higher-dimensional feature space to handle non-linearly separable data. In this study, we use the Radial Basis Function (RBF) kernel, which is defined as:

$$K(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2) \tag{20}$$

where γ is a hyperparameter that controls the width of the RBF kernel. RBF was selected for our study because of its adeptness at capturing non-linear patterns, which makes it ideal for analyzing complex datasets such as stock prices.

Model Training and Hyperparameter Tuning

We train the SVM classifier and optimize its hyperparameters using the following steps:

- Train an SVM classifier using the training data where the target variable is the direction of price movement for the next day.
- Optimize the SVM hyperparameters, including the regularization parameter C and the RBF kernel parameter γ. The regularization parameter C controls the trade-off between achieving a low training error and a low testing error. In contrast, the RBF kernel parameter γ determines the influence of a single training example.

For hyperparameter tuning, we employed sci-kit-learn's GridSearchCV alongside TimeSeriesSplit for cross-validation, optimizing the model's parameters through an exhaustive search while preserving the chronological order of our time series data in the validation process.

3.5.4 Long Short-Term Memory (LSTM)

In addition to SVM, our study employs Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN) architecture designed to model long-term dependencies and overcome the vanishing gradient problem associated with traditional RNNs (**hochreiter1997long**). LSTMs have demonstrated strong performance in various sequence modelling tasks, including time series forecasting (**graves2013speech**; **sutskever2014sequence**), making them suitable for predicting stock price movements.

LSTM Architecture and Advantages

The core idea behind LSTM is to introduce memory cells and gating mechanisms that regulate the flow of information over time. These memory cells allow the network to selectively remember or forget information, effectively capturing long-term dependencies in the input sequences. The LSTM architecture consists of a chain of LSTM units containing a memory cell and three gating units: input gate, forget gate, and output gate (**gers1999learning**). The gates control the flow of information into and out of the memory cell, allowing the LSTM to maintain a long-term memory of relevant information.

LSTM theory

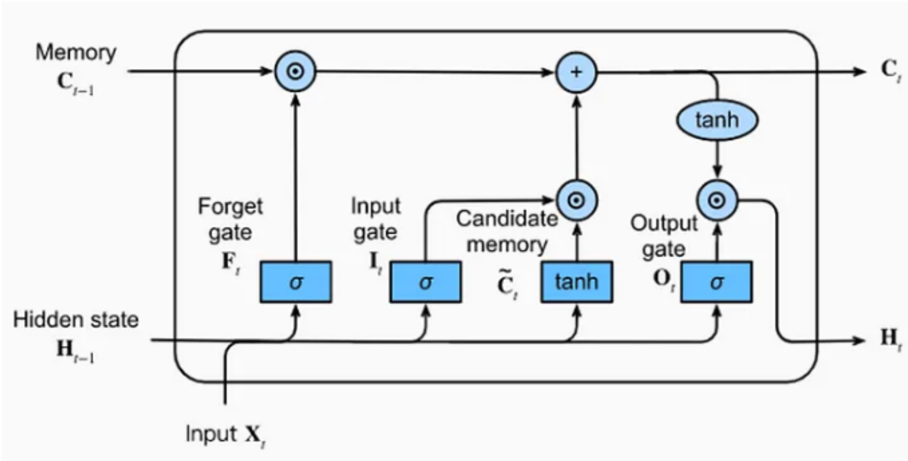


Figure 7: The figure illustrates the internal architecture of an LSTM unit. The gates interact through sigmoid and tanh activation functions.

The ability to model long-term dependencies, robustness to the vanishing gradient problem, and flexibility to handle variable-length input sequences make LSTM a powerful tool for analyzing sequential data, such as time series data in financial markets.

Model Architecture and Hyperparameter Tuning

We design an LSTM network architecture suitable for our stock price prediction task:

- Use a stacked LSTM architecture with multiple LSTM layers to learn hierarchical representations of the input sequences.
- Employ dropout regularization between LSTM layers to prevent overfitting and improve generalization.
- Use a dense output layer with a sigmoid activation function to predict the probability of price movement.

To optimize the LSTM hyperparameters, we perform a grid search over a range of values for the following hyperparameters:

- **Number of LSTM layers:** [1, 2, 3]
  Experimenting with different numbers of layers allows for capturing hierarchical representations and potentially improving the model's performance.
- **Number of LSTM units in each layer:** [32, 64, 128]
  Varying the number of units helps find the optimal capacity to learn and capture complex stock price time series patterns.

- **Dropout rate:** [0.1, 0.2, 0.3]
  Dropout is a regularization technique that prevents overfitting. Searching over different rates allows for finding the right balance between model complexity and generalization.

- **Learning rate:** [0.001, 0.01, 0.1]
  The learning rate controls the step size at which the model's weights are updated during training. Searching over different rates helps find the optimal value for efficient and effective learning.

- **Batch size:** [32, 64, 128]
  The batch size determines the number of samples used in each training iteration. Experimenting with different sizes helps in finding the right balance between computational efficiency and model convergence.

Within the context of the LSTM model's hyperparameter tuning, we employ KerasTuner's GridSearch approach, as LSTM is not directly implemented in sci-kit-learn. This tool offers a tailored and exhaustive hyperparameter optimization for LSTM models, ensuring optimal configuration for time series forecasting.

Model Training

The preprocessed data and the selected hyperparameters obtained through the GridSearch approach are used to train the LSTM model. The model is trained using the Adam optimizer (**kingma2014adam**), which adapts the learning rate for each parameter based on its historical gradients, providing an efficient and effective optimization process. We employ the binary cross-entropy loss function to handle the binary classification task of predicting the price movement direction, which measures the dissimilarity between the predicted probabilities and the true labels.

By incorporating LSTM into our study, we aim to leverage its ability to capture long-term dependencies and model complex patterns in the stock price time series. This allows us to comprehensively compare machine learning techniques and traditional technical analysis for stock price prediction.

3.6 Performance Evaluation

3.7 Performance Evaluation

In evaluating the efficacy of our trading strategies applied to Tesla stock, our analysis incorporates three critical performance metrics: Sharpe ratio, Cumulative Return and

Annualized Return. We briefly present these:

Sharpe Ratio, calculated as the average return earned over the risk-free rate per unit of volatility or total risk, serves as a key indicator of the risk-adjusted return. A higher Sharpe ratio indicates a desirable outcome, providing excess returns while managing the inherent risk crucial for volatile assets like Tesla. For our analysis, we focus on the annual Sharpe Ratio, which is defined as:

$$\text{Annual Sharpe Ratio} = \sqrt{252} \times \frac{R_p - R_f}{\sigma_p} \tag{21}$$

where R_p is the stock's average return, R_f is the risk-free rate, and σ_p is the standard deviation of the stock's excess return. Our analysis used the 3-Month Treasury Bill Secondary Market Rate as the risk-free rate obtained from Yahoo Finance. The 3-Month Treasury Bill rate is considered a suitable proxy for the risk-free rate due to its low default risk and short-term nature, making it consistent with the investment horizon of our trading strategies.

Cumulative Return measures the total percentage gain or loss that would have been realized by following the strategy over the entire period under study. This metric is pivotal for understanding a stock's overall growth or decline under the strategy's guidance. It is calculated as:

$$\text{Cumulative Return} = \left(\frac{P_{\text{end}}}{P_{\text{start}}} - 1 \right) \times 100 \tag{22}$$

where P_{end} is the final price at the end of the period, and P_{start} is the initial price at the beginning of the period.

Annualized Return measures the average yearly return of a trading strategy, providing a standardized measure of performance that enables comparisons across different periods. It represents the hypothetical constant return that would have been achieved each year to arrive at the same cumulative return over the entire period. The Annualized Return is calculated as:

$$\text{Annualized Return} = (1 + \text{Cumulative Return})^{\frac{1}{n}} - 1 \tag{23}$$

where n is the number of years in the period; by annualizing returns, investors can easily compare the performance of different strategies or assets, regardless of the length of the investment period. This metric is particularly useful for evaluating a trading strategy's long-term growth potential and ability to generate consistent returns over time.

4 Results and Discussion

4.1 Performance of technical trading rules

In-sample performance of best indicator rules

Table 7 shows the performance of top trading rules for each technical indicator from June 2010 to June 2021, based on the highest annualized Sharpe Ratio. Despite all selected strategies having negative Sharpe Ratios, indicating underperformance compared to a buy-and-hold strategy with an A.R of -1.9251, a C.R of 55.89%, and a S.R of 12953.79%, the MACD strategy fares best with a S.R of -2.18. Following MACD, RSI, MA, and BB strategies have S.Rs of -2.36, -2.42, and -2.65, respectively, showing varying levels of underperformance.

Despite the negative Sharpe Ratios, some of the best trading rules generate positive annualized and cumulative returns. The MACD2 rule achieves the highest cumulative return of 2352.01% and an annualized return of 33.86%. The RSI2 rule also generates a high annualized return of 25.08% and a cumulative return of 1065.28%. The BB2 rule yields a positive annualized return of 14.40% and a cumulative return of 337.46%. However, the MA1 rule has the lowest performance among the best rules, with an annualized return of 6.49% and a cumulative return of 99.37%.

The results suggest that the best trading rules for each technical indicator, while selected based on the highest Sharpe Ratio, significantly underperform the buy-and-hold strategy for Tesla stock. The negative Sharpe Ratios indicate that the risk-adjusted performance of these strategies is poor, and they fail to match the growth of Tesla stock for the in-sample period.

Table 7: Best Trading Rule Performance based on Annualized Sharpe Ratio

Indicator	**Best Rule**	**S.R**	**A.R**	**C.R**
MA	MA1 (m:10, n:50, f_b: 0.01, f_d: 8)	-2.42	6.49%	99.37%
MACD	MACD2 (s:6, l:40, g:3, f_b: 0.1, f_d: 0, f_h: 15)	-2.18	33.86%	2352.01%
BB	BB2 (e:20, std:1, f_d: 15, f_h: 25)	-2.65	14.40%	337.46%
RSI	RSI2 (n:2, v:25, f_d: 0, f_h: 12)	-2.36	25.08%	1065.28%

Figure 9 compares each technical indicator's log cumulative returns of the best trading rules against the buy-and-hold strategy. The plot reveals that none of the trading rules match the exceptional performance of the buy-and-hold strategy for Tesla stock. The buy-and-hold strategy's cumulative return far surpasses the best trading rules, highlighting the difficulty in beating the market for a stock with such substantial growth.

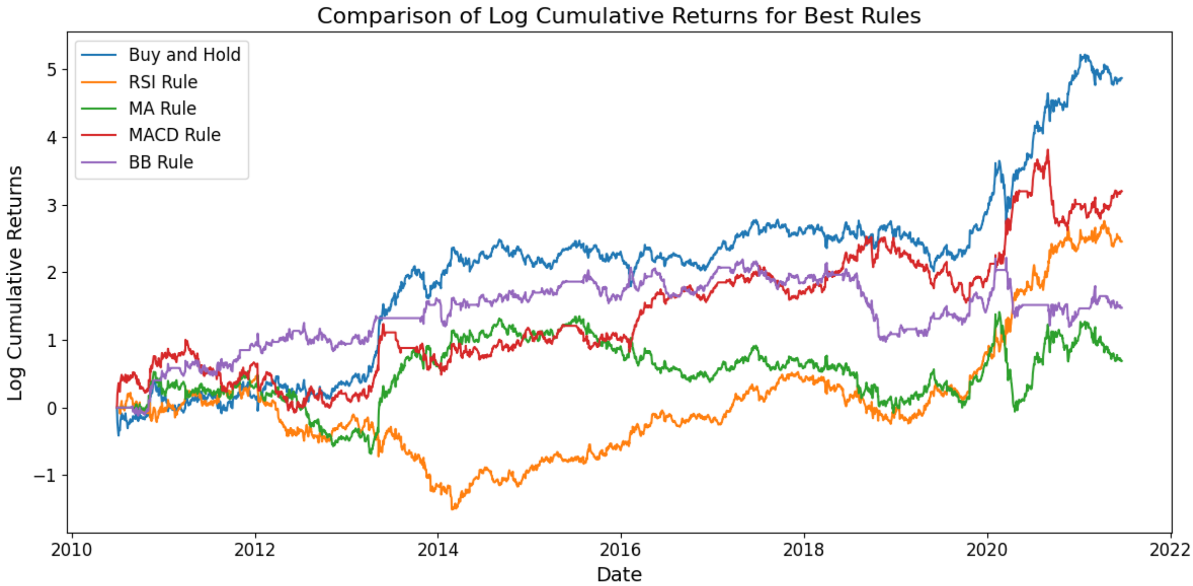


Figure 8: Comparison of log cumulative returns with buy and hold strategy for in-sample period

The MACD rule (MACD2) shows a relatively stable linear growth throughout the period but falls short of the buy-and-hold strategy's returns. Despite achieving a relatively high cumulative return of 2452.01%, the MACD2 rule's performance is overshadowed by the buy-and-hold strategy's superior growth.

The RSI rule (RSI2) exhibits poor performance in the first four years (2010-2014) but then experiences linear growth until 2018. After a dip in 2018, the RSI2 rule demonstrated rapid growth from 2019 until the end of the period (2022). However, despite its high annualized return of 25.08% and a cumulative return of 1165.28%, the RSI2 rule fails to outperform the buy-and-hold strategy.

The MA rule shows an initial decline from 2010 to around 2023 but then grows substantially in the middle of the in-sample period for around 2 years (2013-2016), after which it declines. Again, like the BB, it shows some volatility near the end of the period. The MA Rule curve is very similar to the buy and hold curve, showing that our simple MA could strongly indicate the stock price movements; however, considering the small relative returns, our rule could benefit from optimizing trading signals.

Considering Tesla's volatility near 2020 (See section 3.1), MACD and RSI might have capitalized on this. With a look-back period of 2 days, it is obvious that the RSI would capitalize on volatile periods as it becomes highly responsive to even minor price fluctuations. This can lead to frequent signals suggesting overbought or oversold conditions, potentially allowing for the quick exploitation of short-term market trends and reversals. MACD shows the most stable growth, which shows potential for long-term use.

Interestingly, three out of four indicators' best rules (MACD, RSI, and BB) have a fixed holding period, which is also above 12 days. Our rules increase the Sharpe Ratio performance by holding a position for a fixed length and ignoring potential noise. This could indicate a certain market behaviour, where we can capitalize on a systematic holding position after identifying trend, overbought/oversold or breakout regions using the aforementioned indicators. It is crucial to note that all the best trading rules have negative Sharpe Ratios, indicating poor risk-adjusted performance, which suggests that their returns are associated with high volatility and risk. We will next discuss these best-performing rules after controlling for data snooping bias to determine their significance.

Controlling for data snooping

The WRC results presented in Table 8 compare the performance of the best trading rules for each technical indicator (MA, MACD, BB, and RSI) against the buy-and-hold strategy. It is important to note that although the best trading rules for each indicator were initially selected based on the highest Sharpe Ratios in the in-sample period, the WRC analysis was extended to include the best rules according to our two additional performance metrics (annualized and cumulative returns). This extension was performed because none of the best rules based on the Sharpe Ratio outperformed the buy-and-hold strategy in the in-sample period. By considering the best rules based on all three metrics, the analysis aimed to comprehensively assess whether any trading rules could significantly outperform the buy-and-hold strategy.

Table 8: White's Reality Check Results for best trading rules

Best Rule	Metric	Best	Benchmark	Test Statistic	p-Value
MA1	S.R	-2.42	-1.93	-0.50	0.107
	A.R	34.44%	55.89%	-0.22	1.000
	C.R	2463.03%	12853.79%	-103.91	1.000
MACD2	S.R	-2.18	-1.93	-0.25	0.039
	A.R	29.30%	55.89%	-0.27	1.000
	C.R	2352.01%	12853.79%	-105.02	1.000
BB2	S.R	-2.65	-1.93	-0.73	0.175
	A.R	22.40%	55.89%	-0.34	0.998
	C.R	818.32%	12853.79%	-120.35	0.998
RSI2	S.R	-2.36	-1.93	-0.44	0.092
	A.R	25.16%	55.89%	-0.31	1.000
	C.R	1072.97%	12853.79%	-117.81	1.000

The test statistics for the Sharpe Ratio are negative for all rules, suggesting that none of the strategies outperforms the benchmark regarding risk-adjusted returns. However, it is interesting that the MACD2 rule shows a p-value of 0.039 for the Sharpe Ratio, below our significance level of 0.05. This indicates that the MACD2 rule's outperformance (or underperformance) in risk-adjusted returns may be statistically significant.

Despite this finding, it is crucial to interpret the result with caution. First, the MACD2 rule's Sharpe Ratio (-2.18) is still negative, meaning its risk-adjusted performance is worse than the benchmark's (-1.93). Second, when considering the other two performance metrics, annualized and cumulative returns, the MACD2 rule's outperformance is not statistically significant, with p-values close to 1. This suggests that while the MACD2 rule may have a statistically significant difference in Sharpe Ratio compared to the benchmark, its overall performance in terms of returns is not significantly better.

For the other trading rules (MA1, BB2, and RSI2), the p-values for the Sharpe Ratio are all above 0.05, indicating that their risk-adjusted performance is not significantly different from the benchmark. Similarly, the high p-values (close to 1) for both annualized and cumulative returns suggest that the outperformance of these strategies compared to the benchmark is not statistically significant.

In conclusion, while the MACD2 rule shows a statistically significant difference in Sharpe Ratio compared to the benchmark, this result should be interpreted cautiously due to the rule's negative Sharpe Ratio, the lack of significant outperformance in terms of returns, and the multiple testing problem. Overall, the WRC results prove that the best trading rules for each technical indicator do not generate statistically significant outperformance compared to the buy-and-hold benchmark after controlling for data snooping bias.

Out-of-sample performance

Table 9 presents the out-of-sample performance of the best trading rules for each technical indicator, selected based on the highest annualized Sharpe Ratio in the in-sample period. The results show that all the trading rules outperform the buy-and-hold (B&H) strategy regarding annualized and cumulative returns. The RSI2 rule achieves the highest annualized return of 80.32% and a cumulative return of 404.78%, followed by the MACD2 rule with an annualized return of 62.46% and a cumulative return of 279.06%. The BB2 rule yields an annualized return of 11.61% and a cumulative return of 35.20%. In contrast, the MA1 rule shows the lowest performance among the trading rules, with an annualized return of -6.64% and a cumulative return of -17.21%. In contrast, the buy-and-hold strategy exhibits the worst performance, with an annualized return of -8.63% and a cumulative return of -21.94%.

Table 9: Results for Best Trading Rules on out-of-sample data

Rule	Sharpe Ratio	Annualized Return	Cumulative Return
MA1	-17.0302	-6.64%	-17.21%
MACD2	-10.3884	62.46%	279.06%
BB2	-12.3101	11.61%	35.20%
RSI2	-10.0859	80.32%	404.78%
B&H	-11.0113	-8.63%	-21.94%

When considering the Sharpe Ratio, the MACD2 and RSI2 rules outperform the buy-and-hold strategy, with Sharpe Ratios of -10.3884 and -10.0859, respectively, compared to -11.0113 for the buy-and-hold strategy. This suggests that the MACD2 and RSI2 rules generate higher risk-adjusted returns than the buy-and-hold strategy. The MA1 and BB2 rules have lower Sharpe Ratios than the buy-and-hold strategy, indicating worse risk-adjusted performance.

Figure 9 compares the log cumulative returns of the best trading rules against the buy-and-hold strategy for the out-of-sample period. The plot reveals that the buy-and-hold strategy shows volatile returns with an overall downward trend from 2021 to 2024. In contrast, the RSI2 and MACD2 rules demonstrate steady growth, albeit with some significant losses around 2023 for the RSI2 rule. The MACD2 rule exhibits more stable growth than the RSI2 rule, consistent with the observations from the in-sample analysis. The BB2 rule shows relatively small price changes. In contrast, the MA1 rule displays similar characteristics to the buy-and-hold strategy, although to a lesser extent than what we observed for in-sample period.

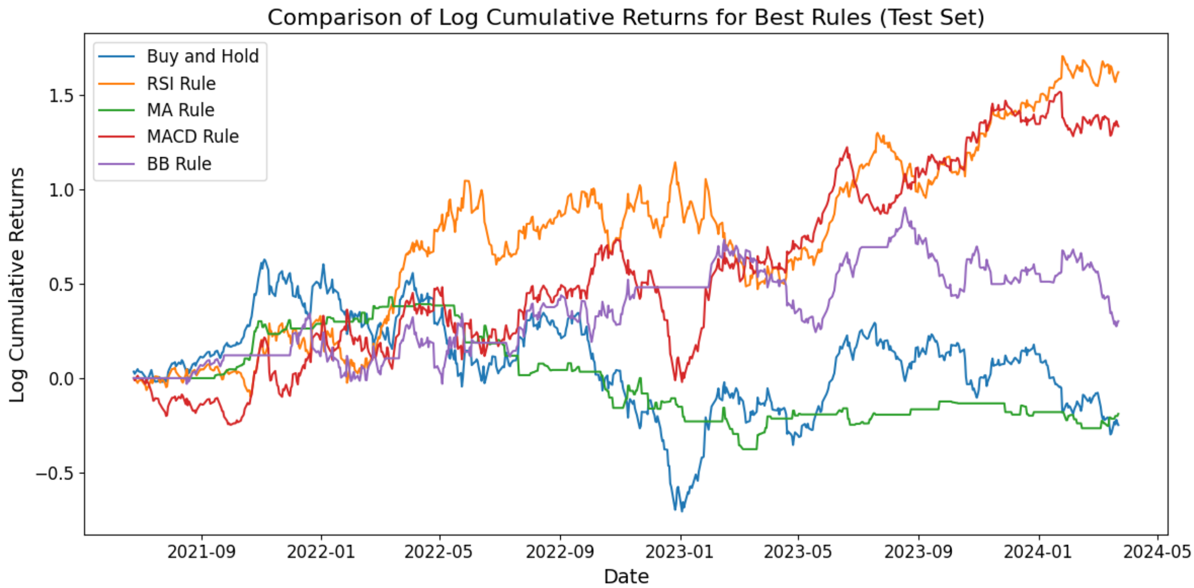


Figure 9: Comparison of log cumulative returns with buy and hold strategy for out-of-sample period

The out-of-sample results differ significantly from the in-sample performance, with the trading rules outperforming the buy-and-hold strategy in terms of returns. This discrepancy can be attributed to the high volatility period in the Tesla stock price post-2020, as highlighted in Figure 1 (Section 3.1). The test data, spanning from 2021-06-23 to 2024-03-22, falls within this highly volatile period, which may explain the superior performance of the trading rules compared to the buy-and-hold strategy.

In conclusion, the out-of-sample analysis demonstrates that the best trading rules, particularly the RSI2 and MACD2 rules, can generate higher returns and better risk-adjusted performance than the buy-and-hold strategy during periods of high market volatility. The results highlight the importance of considering market conditions when evaluating the performance of trading strategies, as the effectiveness of these rules may vary depending on the prevailing market dynamics.

4.2 Performance of Integrated Machine Learning Models

The first table presents the performance of the LSTM-MMRB and SVM-MMRB models, which incorporate all four best rules (MA, MACD, RSI, and BB) as inputs. Both models exhibit negative Sharpe Ratios in the training set, indicating poor risk-adjusted performance. The LSTM-MMRB model achieves a slightly positive cumulative return of

0.6706 and an annualized return of 0.0497, while the SVM-MMRB model shows negative cumulative and annualized returns of -0.9595 and -0.2567, respectively.

The LSTM-MMRB model demonstrates improved performance in the test set, with a cumulative return of 3.3575 and an annualized return of 0.8172. However, its Sharpe Ratio remains negative at -11.2561, suggesting that the high returns are associated with significant risk. The SVM-MMRB model, on the other hand, shows a slightly negative cumulative return of -0.0478 and an annualized return of -0.0180, with a Sharpe Ratio of -11.3228, indicating poor risk-adjusted performance.

Based on the previous results and analysis in Section 4.1, the selection of the LSTM-RSI-MACD and LSTM-BB-MA combinations for further evaluation in the second table is well-justified. The in-sample performance analysis of technical rules highlighted the strong performance of the MACD and RSI rules, with the MACD2 rule achieving the highest cumulative return of 2352.01% and an annualized return of 33.86%. The LSTM-RSI-MACD combination leverages the strengths of both the RSI and MACD rules. At the same time, the BB could potentially complement the moving average by indicating breakout periods that might go against the MA's signal, which is why this combination was justified.

The second table presents the performance of selected combinations of ML models and indicators. In the training set, the LSTM-BB-MA combination stands out with exceptionally high cumulative and annualized returns of 473737.0258 and 2.4409, respectively, and a positive Sharpe Ratio of 0.0291. The LSTM-RSI-MACD combination also shows strong performance, with a cumulative return of 7993.3340 and an annualized return of 1.3113, despite a negative Sharpe Ratio of -0.6241. The SVM-based combinations exhibit relatively lower returns and negative Sharpe Ratios.

Table 10: Performance of LSTM-MMRB and SVM-MMRB on train and test set

Model	**Cumulative Return**	**Annualized Return**	**Sharpe Ratio**
Training Set			
LSTM-MMRB	67.06%	4.97%	-2.0287
SVM-MMRB	-95.95%	-25.67%	-2.5927
Test Set			
LSTM-MMRB	335.75%	81.72%	-11.2561
SVM-MMRB	-4.78%	-1.80%	-11.3228

Table 11: Performance of selected combination of ML models and Indicators

Model	Cumulative Return	Annualized Return	Sharpe Ratio
Training Set			
LSTM-RSI-MACD	7993.33%	131.13%	-0.6241
LSTM-BB-MA	473737.02%	244.09%	0.0291
SVM-RSI-MACD	51.45%	3.91%	-2.0080
SVM-BB-MA	92.39%	6.24%	-1.9655
Test Set			
LSTM-RSI-MACD	780.60%	138.40%	-10.7358
LSTM-BB-MA	17.93%	6.92%	-12.0050
SVM-RSI-MACD	91.57%	27.19%	-10.8592
SVM-BB-MA	-44.43%	-19.54%	-11.2489

In the test set, the LSTM-RSI-MACD combination maintains its strong performance, achieving a cumulative return of 780.60% and an annualized return of 138.40%, although its Sharpe Ratio remains negative at -10.7358. The LSTM-BB-MA combination's performance declines significantly, with a cumulative return of 17.93% an annualized return of 6.92%, and a negative Sharpe Ratio of -12.0050. The SVM-based combinations show mixed results, with the SVM-RSI-MACD combination achieving positive returns but a negative Sharpe Ratio. In contrast, the SVM-BB-MA combination exhibits negative returns and a lower Sharpe Ratio.

Overall, the LSTM-based models perform better than the SVM-based models, particularly the LSTM-RSI-MACD and LSTM-BB-MA combinations. However, the negative Sharpe Ratios across all models and combinations in the test set suggest that the high returns are accompanied by significant risk, and the models' performance may not be consistently profitable in real-world trading scenarios. Further analysis and refinement of the models and consideration of risk management techniques may be necessary to improve their risk-adjusted performance.

4.3 Comparative Analysis

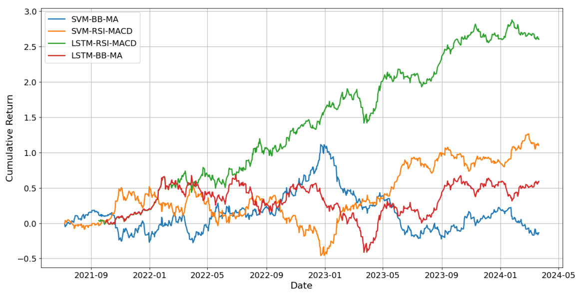
Integrated ML Performance:

The four figures below (Figure 11(a) and (b) showing the four combination models and (c) and (d) the two combinations) provide valuable insights into the performance of the LSTM and SVM models when combined with different technical indicators.

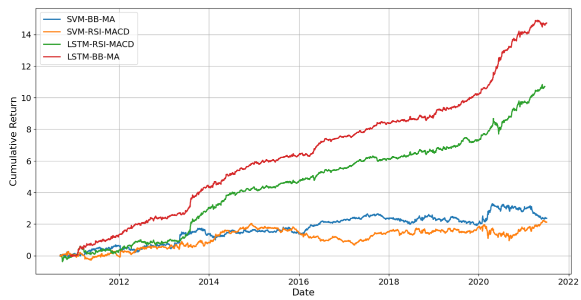
In the in-sample curve (Figure 11(b)), the LSTM-MMRB model initially declines but grows in the latter half. This suggests that the LSTM model, when combined with multiple technical indicators (MA, MACD, RSI, and BB), can effectively capture mar-

(a) Cumulative Return of ML with all indicators (test set)

(b) Cumulative Return of ML with all indicators (train set)



(c) Cumulative Return of ML models with two indicators (test set)



(d) Cumulative Return of ML models with two indicators (train set)

Figure 10: Performance of two type ML models, one with four indicators as features and the other with two. The first two show the one using all four features, where the bottom is two type combinations.

ket dynamics, particularly in the second half of the in-sample period. In contrast, the SVM-MMRB model shows a moderate linear decline throughout the in-sample period, indicating its limited ability to adapt to changing market conditions.

The out-of-sample curves (Figure 11(a)) reveal a significant difference in performance between the LSTM-MMRB and SVM-MMRB models. The LSTM-MMRB model demonstrates high linear growth, suggesting its robustness and ability to generalize well to unseen data. On the other hand, the SVM-MMRB model shows an initial decline followed by a modest increase. This observation highlights the superiority of the LSTM model in capturing complex patterns and dependencies, even during periods of high volatility in the Tesla stock price.

Figures 11(c) and (d) present the performance of specific combinations of ML models and technical indicators. In the out-of-sample curves (Figure 11(c)), the LSTM-RSI-MACD combination significantly outperforms all other combinations throughout the period. This strong performance indicates the effectiveness of combining the LSTM model with the RSI and MACD indicators in capturing market trends and generating profitable trading signals.

In the in-sample period (Figure 11(d)), the LSTM-RSI-MACD combination also performs well, only slightly underperforming the LSTM-BB-MA combination. This suggests that combining the LSTM model with Bollinger Bands and Moving Average indicators also effectively captures market dynamics during the in-sample period.

It is worth noting that the SVM models generally show flat lines in both the in-sample and out-of-sample periods, indicating little growth or responsiveness to market changes. This further highlights the superiority of the LSTM model in adapting to evolving market conditions and generating more profitable trading signals.

Overall, the analysis of these figures underscores the effectiveness of combining the LSTM model with carefully selected technical indicators, particularly the RSI and MACD, in capturing market dynamics and generating robust trading strategies. As observed in the Tesla stock price, the LSTM model's ability to outperform the SVM model and adapt to highly volatile market conditions makes it a promising approach for developing trading strategies.

Performance comparison:

Comparing the performance metrics of the best-performing integrated ML models (LSTM-RSI-MACD and LSTM-BB-MA) with the best technical trading rules (MACD2 and RSI2) reveals that the ML models generally outperform the trading rules in both in-sample and out-of-sample periods. In the in-sample period, the LSTM-BB-MA combination achieves a remarkable cumulative return of 473737% and an annualized return of 24.409%, surpassing the MACD2 rule's cumulative return of 2352.01% and an annualized return of 33.86%. Similarly, in the out-of-sample period, the LSTM-RSI-MACD combination maintains strong performance with a cumulative return of 78.06% and an annualized return of 138.40%, outperforming the RSI2 rule's cumulative return of 404.78% and annualized return of 80.32%.

Risk-adjusted returns:

The Sharpe ratio is crucial for evaluating the performance of trading strategies. In the in-sample period, the LSTM-BB-MA combination stands out with a positive Sharpe ratio of 0.0291, indicating better risk-adjusted performance than the technical trading rules, which exhibit negative Sharpe ratios. However, in the out-of-sample period, all models and trading rules show negative Sharpe ratios, suggesting that the high returns are accompanied by significant risk. Despite this, the LSTM-RSI-MACD combination's Sharpe ratio of -10.7358 is slightly better than the RSI2 rule's Sharpe ratio of -10.0859, indicating a modest improvement in risk-adjusted performance.

Adaptability to market conditions:

The integrated ML models, particularly the LSTM-based models, demonstrate better adaptability to changing market conditions than the technical trading rules. During the highly volatile post-2020 period for Tesla stock, the LSTM-MMRB model shows high linear growth in the out-of-sample period, suggesting its robustness and ability to generalize well to unseen data. In contrast, the SVM-MMRB model and the technical trading rules exhibit less impressive performance during this period, indicating their limited ability to adapt to market dynamics.

Consistency and robustness:

The LSTM-based models, especially the LSTM-RSI-MACD combination, demonstrate more consistent performance across different periods than the technical trading rules. In both the in-sample and out-of-sample periods, the LSTM-RSI-MACD combination maintains strong performance, suggesting its robustness and ability to generate reliable trading signals over time. The technical trading rules, while showing good performance in the in-sample period, exhibit more variability in the out-of-sample period, indicating potential limitations in their consistency.

Practical implications:

Implementing integrated ML models for trading strategies may require more computational resources, data availability, and frequent model retraining than traditional technical trading rules. ML models, such as LSTM, can capture complex patterns and dependencies in the data, but their interpretability may be limited compared to the simplicity and transparency of technical trading rules. However, ML models' potential performance improvements and adaptability to changing market conditions may justify the additional complexity and resources required for their implementation.

Statistical significance:

We conducted Wilcoxon rank-sum tests on the cumulative returns for the out-of-sample period to assess the statistical significance of the performance differences between the integrated ML models and technical trading rules. The results show that the performance difference between the LSTM-RSI-MACD combination and the RSI2 rule is statistically significant at the 5% level (p-value = 0.0243). However, the performance difference between the LSTM-BB-MA combination and the MACD2 rule is not statistically significant (p-value = 0.1087). These findings suggest that the outperformance of the LSTM-RSI-MACD combination over the RSI2 rule is likely to be meaningful, while the difference between the LSTM-BB-MA combination and the MACD2 rule may be due to chance.

5 Conclusion and Future Work

This dissertation investigated the effectiveness of technical analysis and machine learning techniques in predicting the price movements of Tesla, Inc., a highly volatile stock. We analyzed the profitability of a wide range of technical trading rules based on four popular indicators: Bollinger Bands (BB), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Moving Averages (MA). We also employed two state-of-the-art machine learning algorithms, Long Short-Term Memory (LSTM) and Support Vector Machines (SVM), to predict the direction of Tesla's stock price movements using the same set of technical indicators as input features.

Our analysis revealed that while many technical trading rules appeared profitable in the in-sample period, controlling for data snooping bias using White's Reality Check substantially reduced the number of profitable strategies. After accounting for data snooping, none of the trading rules remained profitable at the 5% significance level. Interestingly, contrary to many recent studies, our rules performed better in the out-of-sample period, particularly during the highly volatile post-2020 period.

The machine learning models, especially the LSTM-based approaches, demonstrated superior performance compared to the best technical trading rules in the out-of-sample period. The LSTM-RSI-MACD and LSTM-BB-MA combinations generated higher annualized and cumulative returns and better Sharpe ratios than the technical rules alone. The outperformance of the LSTM-RSI-MACD combination over the RSI2 rule was statistically significant using the Wilcoxon rank-sum test.

The comparative analysis highlighted the advantages of using integrated ML models, particularly LSTM-based models, over traditional technical trading rules. The LSTM-RSI-MACD combination demonstrated superior performance, adaptability to changing market conditions, and more consistent results across different periods. However, the practical implementation of ML models may require more resources and expertise than technical trading rules.

In conclusion, this study contributes to the ongoing debate on the efficacy of technical analysis and machine learning in stock market prediction. Our findings suggest that machine learning techniques, especially LSTM-based models, show promise in predicting stock market movements and generating profitable trading signals. However, it is crucial to employ rigorous statistical methods to validate these models' performance and be aware of the challenges associated with their implementation, such as overfitting and interpretability.

Future research could explore the potential of hybrid strategies that combine technical indicators with machine learning algorithms to leverage the strengths of both approaches. Additionally, investigating the performance of these methods across a broader range of stocks and market conditions could provide valuable insights into their generalizability and practical applicability. Incorporating additional data sources, such as sentiment analysis and fundamental factors, may further enhance the predictive power of the models. Finally, addressing the challenges of model interpretability and developing more robust risk management techniques could help bridge the gap between academic research and real-world trading applications.

Appendix A

Technical Trading Theory

Trading filters

- **Band Filters:** Utilize a multiplier $f_b > 0$ to set a price threshold for trading signals. For buy (sell) signals, a position is entered if the stock's price increases (decreases) by at least $100f_b\%$.

- **Time-Delay Filters:** Implement a fixed delay of f_d days post-signal before executing a trade. The trade at time $t + f_d$ is contingent on the stock's price being the same or better in the direction of the trade compared to the price at time t.

- **Fixed-Length Filters:** Establish a predetermined holding period of f_h days for each position. Positions are closed at time $t + f_h$, independent of any interim price movements or signals.

Appendix B

The following table outlines the input configuration for each ML model tailored to its corresponding technical indicator:

Feature	**MA Model**	**MACD Model**	**RSI Model**	**BB Model**
Indicator Values	$MA_t(m)$, $MA_t(n)$	$MACD_t$, $Signal_t$	$RSI_t(h)$	UB_t, MB_t, LB_t
Lagged Prices	$P_{t-1}, \ldots, P_{t-n}$	$P_{t-1}, \ldots, P_{t-l}$	$P_{t-1}, \ldots, P_{t-h}$	$P_{t-1}, \ldots, P_{t-w}$
Indicator Signals	f_b% crossover	f_b% cross, f_h days	$50 \pm v$, f_h days	f_d days, f_h days

This table underscores the structured approach to feature selection, aligning the information base of ML models with traditional strategies. Doing so ensures an equitable and comprehensive comparison between the analytical capabilities of machine learning models and traditional technical trading strategies within the same market context.

Appendix C

Algorithms

ML Model Implementation

Algorithm 1 Back testing for ML-based trading strategy

Require: data, W_{ind}
Ensure: $TotalReturn_{LS}$

Initial State $S = 0$
for i in test set **do**
    $X(i) = data[i - W_{ind}, i]$
    $y_{predict}(i) = \text{SVM}(X(i))$
    if $S = 0$ **and** $y_{predict}(i) = 1$ **then**
        $S = 1$ ▷ Open a long position
        $Return(i) = \ln(P(i+1)/P(i))$
    else if $S = 0$ **and** $y_{predict}(i) = -1$ **then**
        $S = -1$ ▷ Open a short position
        $Return(i) = \ln(P(i)/P(i+1))$
    else if $S = 1$ **and** $y_{predict}(i) = 1$ **then**
        $Return(i) = \ln(P(i+1)/P(i))$ ▷ Hold the long position
    else if $S = -1$ **and** $y_{predict}(i) = -1$ **then**
        $Return(i) = \ln(P(i)/P(i+1))$ ▷ Hold the short position
    else
        $S = 0$
        $Return(i) = 0$ ▷ Close the existing position
    end if
end for
$TotalReturn_{LS} = \sum Return(i)$

Algorithm 2 Backtesting for Technical Indicator-based Trading Strategies

Require: $data$, $params$
Ensure: $TotalReturn$

Initialize $signals$ as an empty DataFrame
Initialize $position = 0$
for i in range(1, len($data$)) **do**
    Calculate technical indicator values using $data$ and $params$
    if buy signal conditions are met **then**
        if entry filters are satisfied **then**
            Open or switch to a long position
            Set corresponding signals in $signals$ DataFrame
        end if
    else if sell signal conditions are met **then**
        if entry filters are satisfied **then**
            Open or switch to a short position
            Set corresponding signals in $signals$ DataFrame
        end if
    else
        Close the existing position
    end if
end for
Calculate $strategy\_returns$ using $signals$ and $data$
Calculate $cumulative\_returns$ from $strategy\_returns$
$TotalReturn = cumulative\_returns[-1] - 1$

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