Efficiency of Trading Strategies in Portfolio Optimization

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Abstract. This study investigates three commonly used methods for timing stock trades and assesses their performance over a decade. The advent of new technologies has sparked a surge in the development of diverse trading strategies tailored for investment portfolio management. Nevertheless, the suitability of these strategies for portfolio integration varies, and some may yield adverse outcomes. For instance, a speculative trading approach might lead to significant losses. Using data spanning ten years, we evaluate the effectiveness of three main trading strategies that identify when stocks are likely to rise or fall, considering metrics such as return rate, Sharpe ratio, and maximum drawdown. Additionally, we explore potential improvements and the optimal scenarios for applying each strategy. Through this comprehensive analysis, our goal is to offer insights into how these strategies perform and when they're most effective. This information can be valuable for undergraduate-level investors in making informed decisions about managing their investment portfolios.

Keywords: Portfolio Optimization, Trading Strategies, Moving Average Crossover (MAC), Relative Strength Index (RSI).

1. Introduction

Portfolio optimization is now a key strategy for investors coming from the complexity of the financial markets as well as the goal of high returns at low risk. With the advancement of advanced algorithms and artificial intelligence technologies, sophisticated trading strategies have been created that have dramatically changed the landscape of investment management. These advanced and emerging technologies continue to more accurately identify the optimal mix of assets and market realities to dramatically increase portfolio returns.

Recent advancements in computational finance have introduced efficient algorithms for constructing trading strategies that optimize total return, the Sterling ratio, and the Sharpe ratio, offering new insights into market profitability and benchmarks for real trading [1]. Furthermore, the application of singular stochastic control approaches in pairs trading has demonstrated the potential to optimize both trade timing and the number of shares, considering transaction costs, thereby enhancing strategy efficiency. [2]

The significance of exploring the efficiency of trading strategies in portfolio optimization cannot be overstated. In an era where market dynamics are increasingly influenced by algorithmic trading and global economic uncertainties, understanding the effectiveness of these strategies becomes paramount. It not only contributes to the academic discourse on financial optimization but also offers practical insights for investors seeking to navigate the complexities of the modern financial markets. Moreover, as the financial industry evolves with technological advancements, evaluating these strategies' performance helps in refining them, thus driving innovation, and potentially leading to more robust investment management practices.

Innovative approaches such as multi-agent reinforcement learning have been applied to optimize trading strategies in quantitative markets, showing significant improvements over traditional methods [3]. Additionally, deep differentiable reinforcement learning has been utilized to find optimal trading strategies in complex market models, highlighting the potential for more accurate and stable solutions [4]. These developments underscore the importance of leveraging advanced computational techniques in trading strategy optimization.

Furthermore, the representation of trade strategies in the context of high-frequency trading challenges traditional asset pricing models and suggests the possibility of achieving positive alpha, indicating robust performance measurement and portfolio management strategies in turbulent markets[5].

This study focuses on the "Efficiency of Trading Strategy in Portfolio Optimization." It delves into the comparative analysis of various trading strategies, examining their effectiveness in optimizing investment portfolios. The study aims to bridge the gap between theoretical financial models and practical investment outcomes, providing a comprehensive understanding of how different trading strategies perform in real-world scenarios.

Our approach involves a quantitative analysis of historical market data to evaluate the performance of selected trading strategies in portfolio optimization. By employing statistical and computational methods, including machine learning algorithms, we aim to assess the strategies' returns, risk-adjusted returns, and their ability to diversify risk effectively. This analysis will be grounded in established financial theories, such as Modern Portfolio Theory (MPT) and the Efficient Market Hypothesis (EMH), while also exploring the implications of behavioral finance.

The target of this research is twofold: to contribute to the academic body of knowledge in finance by providing empirical evidence on the efficiency of various trading strategies in portfolio optimization and to offer actionable insights for investors and portfolio managers. By identifying the strengths and limitations of these strategies, the study aims to guide investment decisions, enhance portfolio performance, and contribute to advancements of investment management.

2. Data Collection

2.1. Data Sources And Time Frame

For the empirical analysis of the selected trading strategies—Moving Average Crossover, Relative Strength Index (RSI), and Mean Reversion—we sourced historical market data from Alpha Vantage, focusing on the period from January 1, 2010, to December 31, 2019.We also calculate the standard metric for SP500, to refer as a comparable target for each trading strategy’s performance. The return rate in 10 years is 264.68%, and the sharp-ratio is 0.2758, and there is now maximum drawdown since we assume there is only one trade for SP500 (buy at the first time and sell at the end). Moreover, this ten-year period provides a understandable view of market behaviors, and it excludes the unexpectable economics recessions such as 2007-2008 finance crisis and Covid-19 pandemic. Therefore, this 10-year is economically relative stable and we can more focos on the factor of trading strategies.

2.2. Company Selection

In this study, we have precisely selected 10 companies, each a leader in its respective industry, to evaluate the efficiency of trading strategies for portfolio optimization. These companies were chosen for their significant market presence, historical data availability, and the diverse industry sectors they represent, ensuring a comprehensive analysis across varying market conditions. Below is an overview of the companies selected and the rationale behind their inclusion:

2.2.1. Company Name

1). Apple Inc. (AAPL) - Technology: A titan in the technology sector, Apple is renowned for its disruptive technology such as iPhone and air pods, and growing power of Apple’s M chips in recent years. As of the end of 2019, Apple reported an annual revenue of approximately $260.17 billion, with a net income of about $55.26 billion, and total assets were valued at $338.52 billion.

2). JPMorgan Chase & Co. (JPM) - Financial Services: One of the world's largest financial institutions. JPM reporting an annual revenue of $115.63 billion, with a net income of $36.43 billion and assets totaling $2.687 trillion in 2019.

3). Amazon.com Inc. (AMZN) - E-commerce/Retail: Dominant company in the e-conmerce in the United State before 2020, also consume part of entertainment field such as Amazon Music and

Amazon video. In 2019, Amazon posted an annual revenue of $280.52 billion, net income of $11.59 billion, and held assets worth $225.25 billion.

4). Exxon Mobil Corporation (XOM) - Energy: Representing the energy sector, Exxon Mobil's financials are closely watched indicators of the industry's health. XOM reported revenue of $264.94 billion, a net income of $14.34 billion, and total assets of $362.60 billion for the year 2019.

5). Pfizer Inc. (PFE) - Healthcare/Pharmaceuticals: A leader in pharmaceuticals. The company's 2019 financials show a revenue of $51.75 billion, net income of $16.27 billion, and assets totaling $167.53 billion.

6). Tesla, Inc. (TSLA) - Automotive/Energy: Represent part of energy and automobile sector. Its innovative product also serves as this era’s disruptive technology in 21th century. With a 2019 revenue of $24.58 billion, a net income of $-862 million (highlighting its aggressive investment in growth), and total assets of $34.31 billion.

7). The Boeing Company (BA) - Boeing's role in aerospace provides insights into the industry's challenges and achievements. Reporting $76.56 billion in revenue, a net income of -$636 million due to unprecedented challenges in 2019, and assets of $133.62 billion

8). Alphabet Inc. (GOOGL) - Internet/Technology: lphabet's leadership in internet services and technology ventures underscores the digital economy's growth. The company achieved $161.86 billion in revenue for 2019, with a net income of $34.34 billion and assets worth $275.91 billion

9). Walmart Inc. (WMT) - Retail: Global retail empire. WMT reported $524.00 billion in revenue, a net income of $14.88 billion, and assets of $236.50 billion in 2019.

10). The Goldman Sachs Group, Inc. (GS) - Investment Banking: A leading investment banking firm. The firm reported $36.55 billion in revenue, with a net income of $8.47 billion and assets totaling $992 billion in 2019.

2.3. Plot for Stock Trend

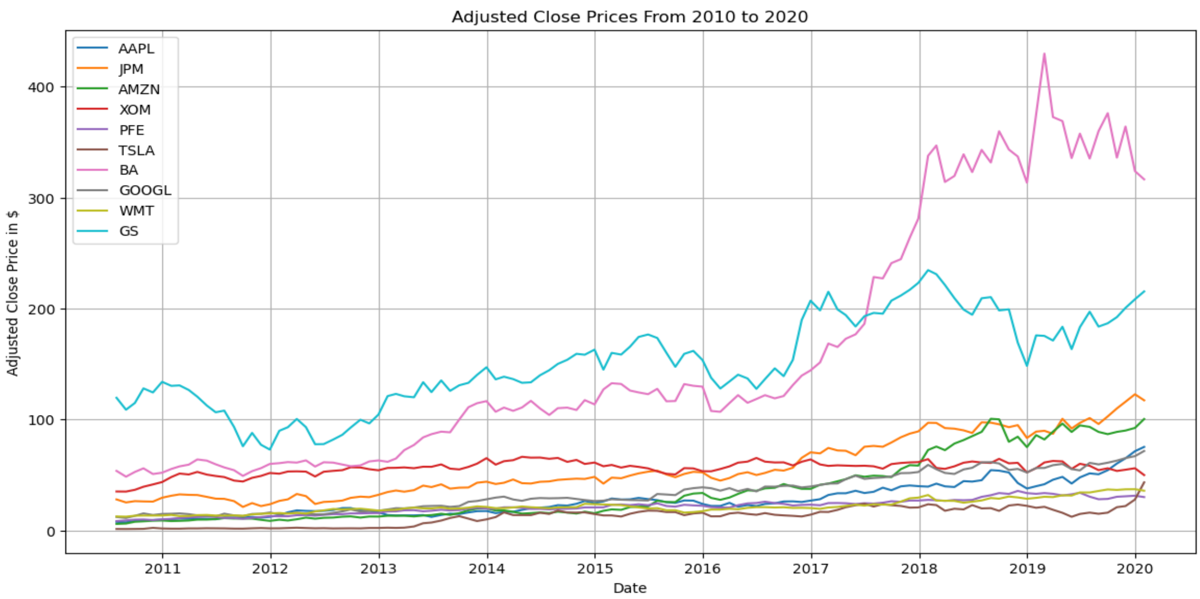

Fig 1. Portfolio adjusted price from 2010 to 2020 (Picture Credit: Original).

As Fig.1 depicts, we can see an uptrend for these 10 companies’ stock price, and there is a huge increment during 2016 to 2018. For example, BA increases nearly 200% and everyone except XOM increases significantly as economically succession.

3. Method Description(Reference)

3.1. Moving Average Crossover (MAC)

3.1.1. Definition

A technique widely used in financial markets to measure the dynamics and identify potential entry and exit points in a trading strategy. The MAC strategy relies on the intersection of two moving averages - a short-term moving average and a long-term moving average - of the stock price.

3.1.2. Calculation

Short-term moving averages (STMAs) are commonly calculated based on shorter time frames, such as 10 or 20 days, while long-term moving averages (LTMAs) span longer time periods, such as 50 or 200 days. These averages smooth out price data by creating a continuously flowing line, making it easier to identify the direction of a trend. A crossover occurs when the STMA crosses the LTMA. When the STMA moves up through the LTMA, a bullish signal is generated, indicating upward momentum, and possibly indicating a buying opportunity. Conversely, when the STMA moves down through the LTMA, a bearish signal is generated, indicating downward momentum and possibly a sell signal.

In this analysis, instead of using daily period to define short-term and long-term, we are using monthly period for it because of monthly adjusted close price that we subtracted. As a result, we define 3-month time frame for STMAs and 12-month time frame LTMAs.

3.1.3. Advantage

Its popularity lies in its simplicity and effectiveness in deciding buy and sell signal, can show a significant trend difference between short-term moving average and long-term moving average. his strategy is predicated on the idea that financial markets exhibit trends over time, and that these trends can be profitably exploited.

3.2. Relative Strength Index (RSI)

3.2.1. Definition

In the context of portfolio management, RSI serves as a momentum indicator for overbought and oversold signal from the scale of 0 to 100. It measures the speed of price change of assets within portfolio. Overall, RSI can used as a decision-making tool for buy or sell choice, thereby potentially improve portfolio performance and risk-control. The indicator was developed by J. Welles Wilder Jr. and introduced in his seminal 1978 book, New Concepts in Technical Trading Systems.[6] Mathematically, it is a bullish sign when RSI bypass 30, as well as it is a bearish sign bearish sign. In other words, it indicates the assets are overvalued if RSI is equal or above 70 which states a sell sign and undervalue if RSI is equal or below 30 which states a buy sign. [7]

3.2.2. Calculation

The RSI uses a two-part calculation that starts with the following formula: [7]

$$\text{RSI(step1)} = 100 - \left[\frac{100}{1+\frac{\text{Average Gain}}{Average\ Loss}}\right] \tag{1}$$

The formula used a positive value for Average Loss. The standard number of period used to calculate the initial RSI value is 14. [7] Once there are 14 periods of data available, the second calculation can be done. Its purpose is to smooth the results so that the RSI only nears 100 or zero in a strongly trending market.

$$RSI(step2) = 100 - \left[\frac{100}{1+\frac{(Previous\ Average\ Gain \times 13)+Current\ Gain}{(Previous\ Avaerage\ Loss \times 13)+Current\ Loss}}\right] \tag{2}$$

3.2.3. Importance

Trader can use RSI to predict price behavior of a security, also for identification of buy or sell signal.

3.3. Moving Average Convergence/Divergence(MACD)

3.3.1. Definition

Moving Average Convergence/Divergence (MACD) is a technical indicator to identify price trend, measure trend momentum, and identify market entry points for buying and selling, which indicating the relationship between two exponential moving averages (EMA) of assets' price.

3.3.2. Calculation

$$\text{MACD} = \text{12-period EMA} - \text{26-period EMA} \tag{3}$$

MACD is calculated by subtracting 26-period EMA from 12-period EMA. An EMA is a moving average (MA) that places greater weight and significance on the most recent data points.

MACD has a positive value when 12-period EMA is above 26-period EMA, otherwise, negative value when 12-period EMA is below 26-period EMA.

3.3.3. Crossover

The MACD falls below the signal line, which indicate the time to sell, marked as bearish signal. Moreover, if MACD rise above signal line, it may designate bullish signal, suggesting the price may experience uptrend momentum.

3.3.4. Confirmation for Crossover

If MACD whenever faced a short-term downtrend within a generally rising trend in relative long-standing rises above signal line, it works as the confirmation of bullish signal. Otherwise, if MACD that faced a short-term uptrend within a generally dropping trend in relative long-term drops below signal line, it serves as the confirmation of bearish signal.

4. Analysis

4.1. Introduction

As the exponentially growth of technology, the popularity of different trading strategies grows simultaneously [8] It is critical for trader to decide which strategy to use depend on diverse situation. For instance, investor should consider factors like timeframe, trading frequency, trading amount, portfolio construction, and expectation as well as transaction cost to decide which trading strategies or strategies to use. In the real life, investors typically combine multiple strategies 'result to analyze some preference or conclusions. Since different methods can differ a lot, so it is imperative for us to discuss the efficiency of trading strategies.

In this study, we will compare the result of metric with S&P500, if it will above SP500, we consider the method is good for the given portfolio, otherwise, we consider it is not promising strategy. And for all calculations, we assume zero transaction cost and zero free risk rate, in order to focus solely on the performance of strategies during a relative stable 10-year period.

4.2. Methodology/Metric

We evaluate portfolio performance by sharp-ratio, return rate, and maximum-drawdown.

4.3. Moving Average Crossover Analysis

4.3.1. Back testing

First, we define the buy and sell signal for back-testing by find the crossover between STMAs and LTMAs, then we generate the signals. When we catch a buy signal for each stock within the portfolio, we invest all the initial money ($10,000) to buy maximum shares, and we set the position to 1 which states the condition invested. Otherwise, if the condition is 1 (invested) and we encounter a sell signal. We sell all the shares of the stock by the adjusted close price and set the position back to 0 (default).

4.3.2. Performance metric evaluation

We used total return in percentage, calculated by the following formula:

$$Total\ Return\ (each\ company) = \frac{Earning - Initial\ Investment}{Initial\ Investment} \times 100\% \tag{4}$$

4.3.3. Graph Illustration

For each ten companies, here lists the graph for their own LTMAs, STMAs and their unique signal, compare to adjusted close price line:

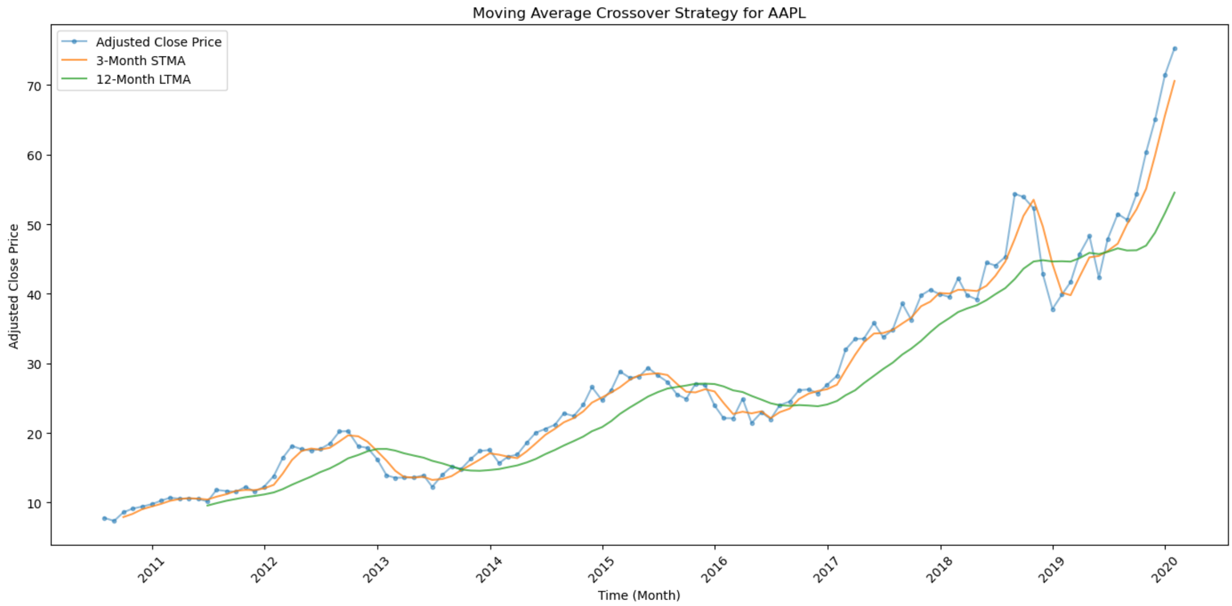

Fig 2. Apple Moving Average Crossover (Picture Credit: Original).

Fig 3. J.P Morgan MAC (Picture Credit: Original).

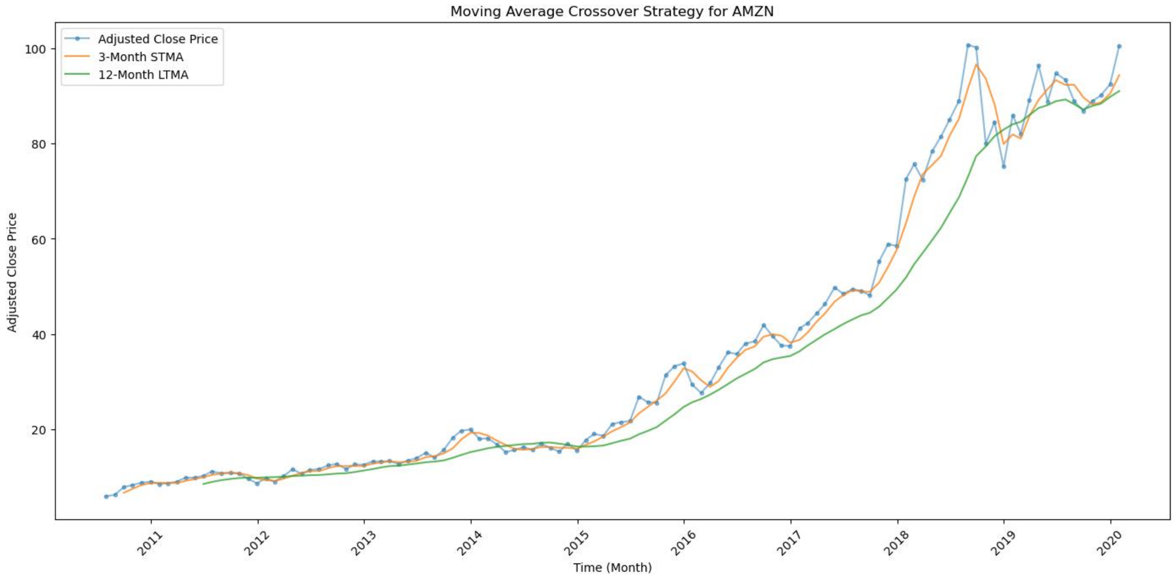

Fig 4. Amazon MAC (Picture Credit: Original).

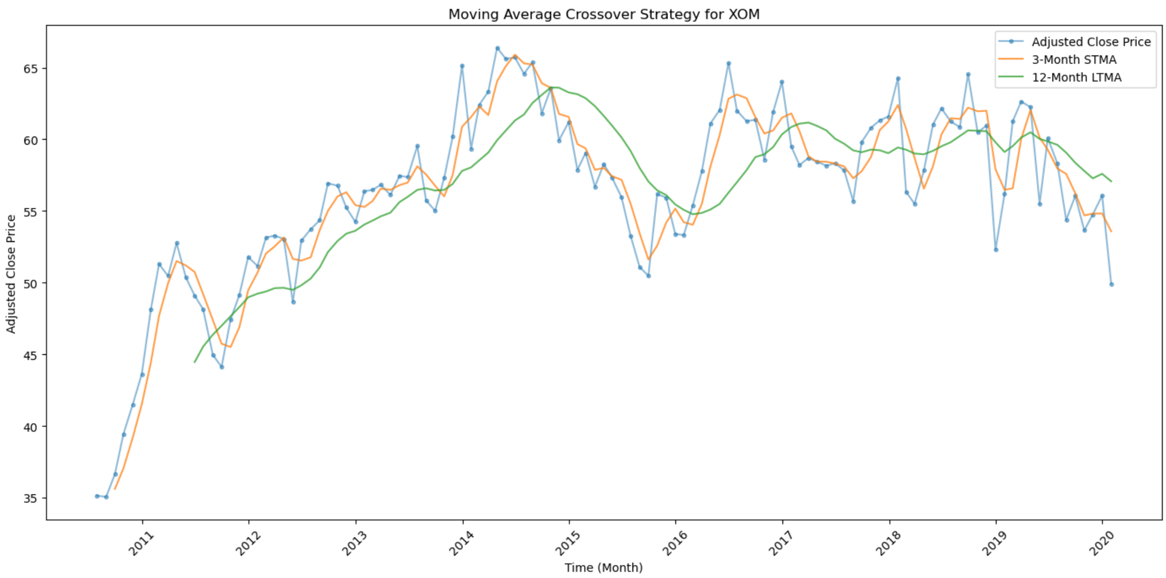

Fig 5. Exxon Mobile Corp. MAC (Picture Credit: Original).

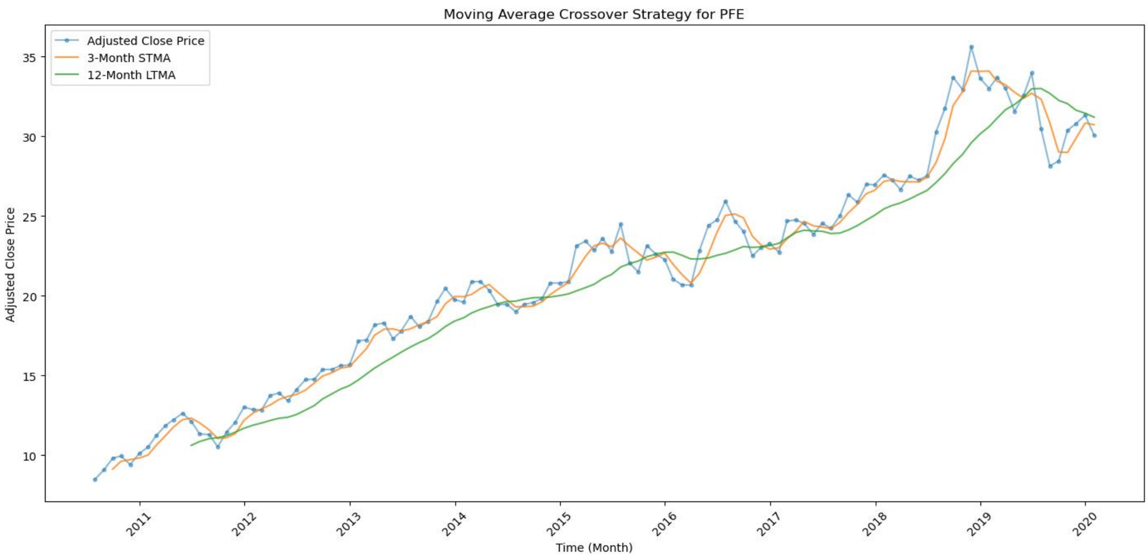

Fig 6. Pfizer MAC (Picture Credit: Original).

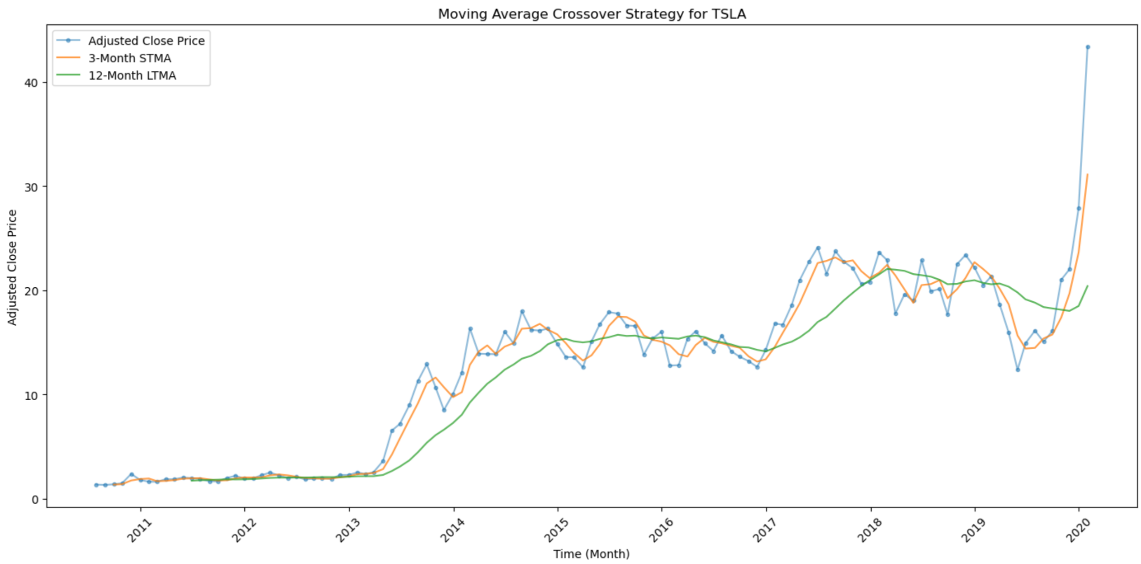

Fig 7. Tesla MAC (Picture Credit: Original).

Fig 8. Boing MAC (Picture Credit: Original).

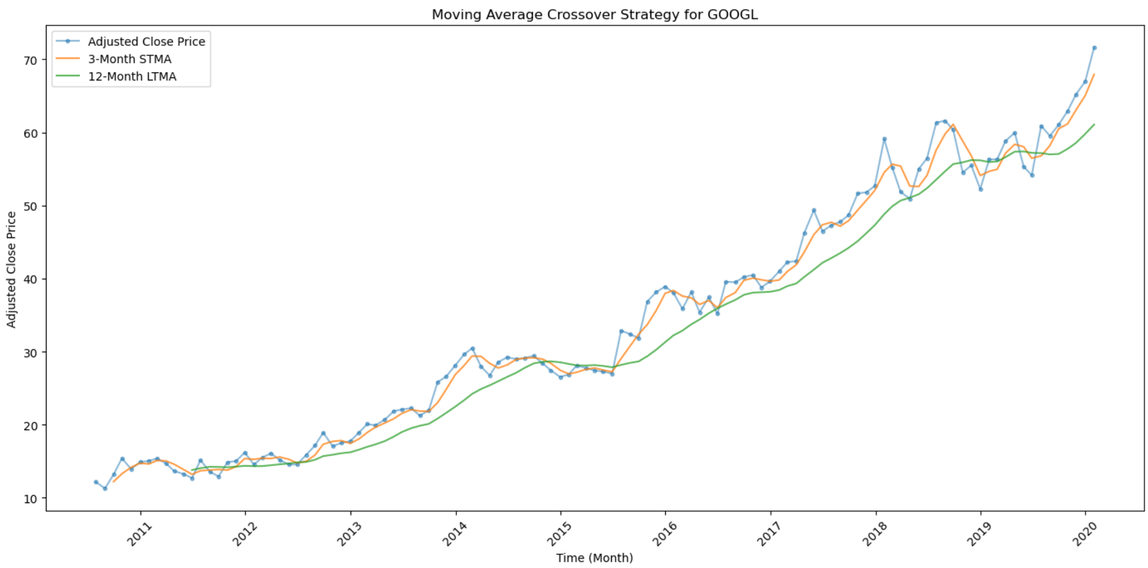

Fig 9. Google MAC (Picture Credit: Original).

Fig 10. Walmart MAC (Picture Credit: Original).

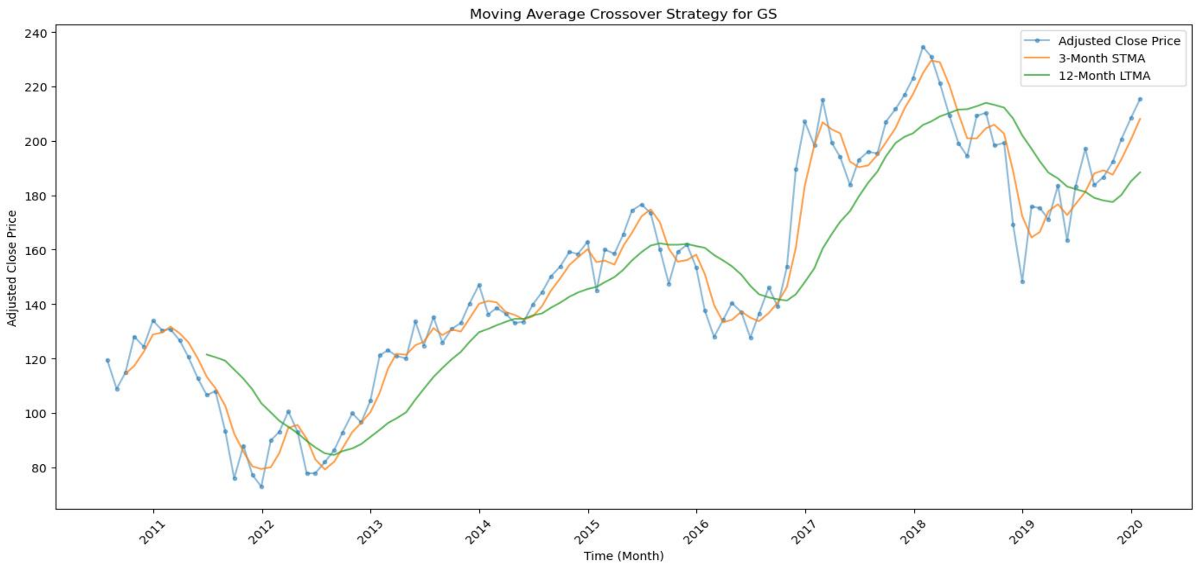

Fig 11. Golden Sachs Mac (Picture Credit: Original).

Table 1. 10 companies in portfolio and portfolio's performance. (Table Credit: Original).

	Return Rate (%)	Sharpe Ratio	Max Drawdown (%)	Standard Deviation
AAPL	192.46	0.0991	-146.39	6.71
JPM	152.81	0.0452	-165.81	7.81
AMZN	361.09	0.1203	-160.44	8.04
XOM	-14.00	-0.0957	-178.31	7.99
PFE	87.98	0.2284	-109.94	3.23
TSLA	2995.11	0.2388	-146.80	14.13
BA	399.02	0.0661	-196.77	10.42
GOOGL	160.15	0.0256	-179.96	8.57
WMT	45.77	-0.0198	-161.56	6.92
GS	86.55	0.0683	-131.40	5.59
Total Portfolio	446.69			

Based on its return rate of the portfolio (Table 1), we can conclude that if we invest $1 at the beginning, using Moving Average Crossover Method, we will be rewarded around $447 after a decade, specifically from 2010 to 2020 (Fig2-11).

Our analysis aligns with findings by Attia, who demonstrated that Moving Average Crossovers not only mitigated losses in stocks exhibiting strong overall downward trends but also outperformed a continuous investment approach, albeit introducing greater volatility into the investment [9].

4.4. Relative Strength Index (RSI) Analysis

4.4.1. Back Testing

We first define a function to calculate the RSI with a fixed common period of 14, generating buying signal when RSI is crossing below 30 and selling signals when RSI is augmenting across 70. When a buying signal is detected, investing all initial investment ($10,000) to buy as many as possible shares for each 10 stocks in portfolio, which assuming equal weighted within portfolio for simplicity. Meanwhile, marked the position as 1(already invested). Otherwise, if we detected a selling signal if the position is invested, we sell the shares we had at current price and set back the position at 0(default).

4.4.2. Performance metric evaluation

We used total return in percentage, calculated by the following formula:

$$Total\ Return\ (each\ company) = \frac{Earning - Initial\ Investment}{Initial\ Investment} \times 100\% \tag{5}$$

4.4.3. Graph Illustration For RSI

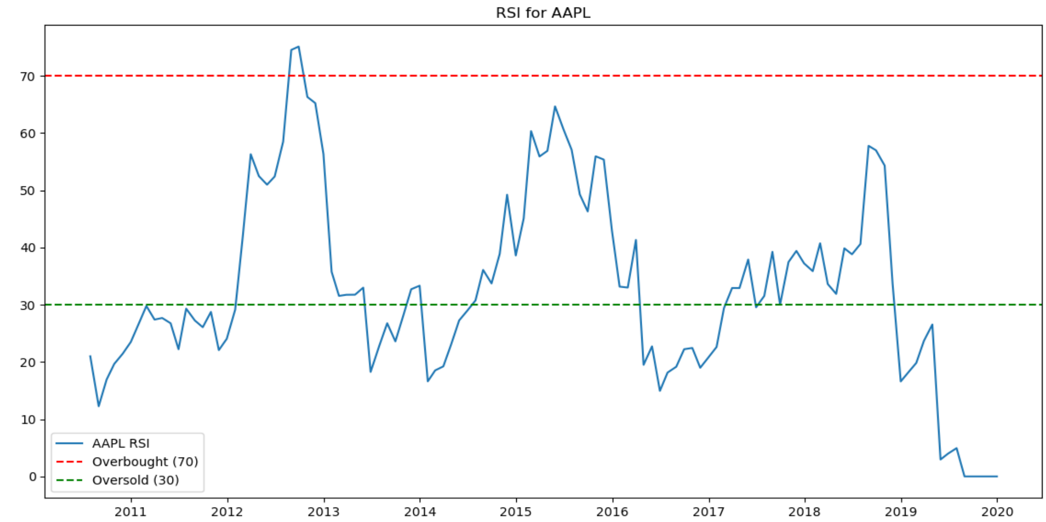

Fig 12. RSI for AAPL(Picture Credit: Original).

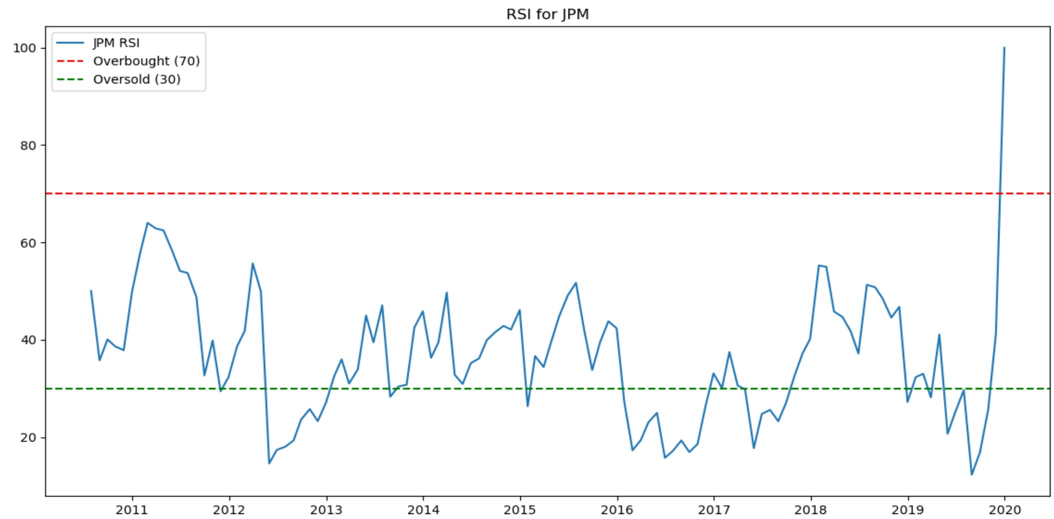

Fig 13. RSI for JPM(Picture Credit: Original).

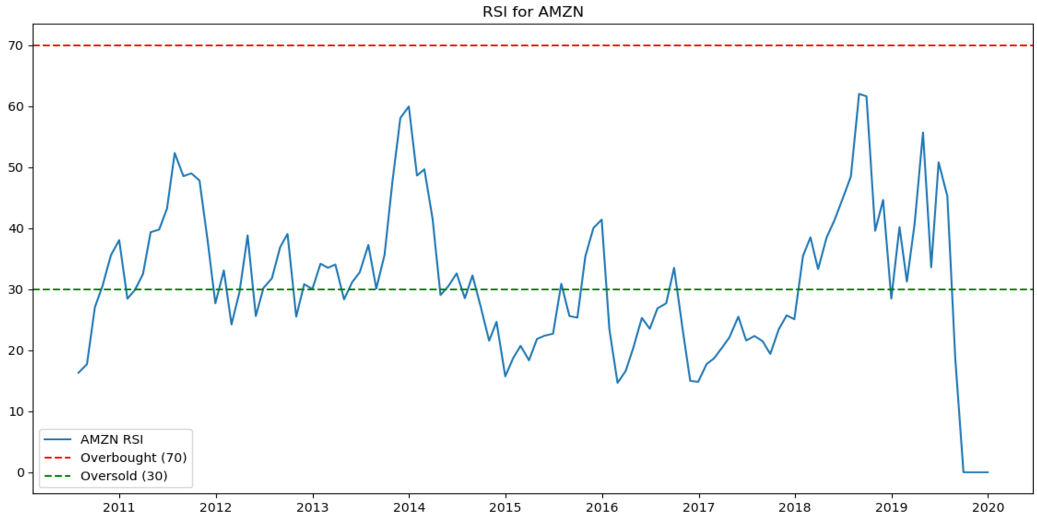

Fig 14. RSI for AMZN(Picture Credit: Original).

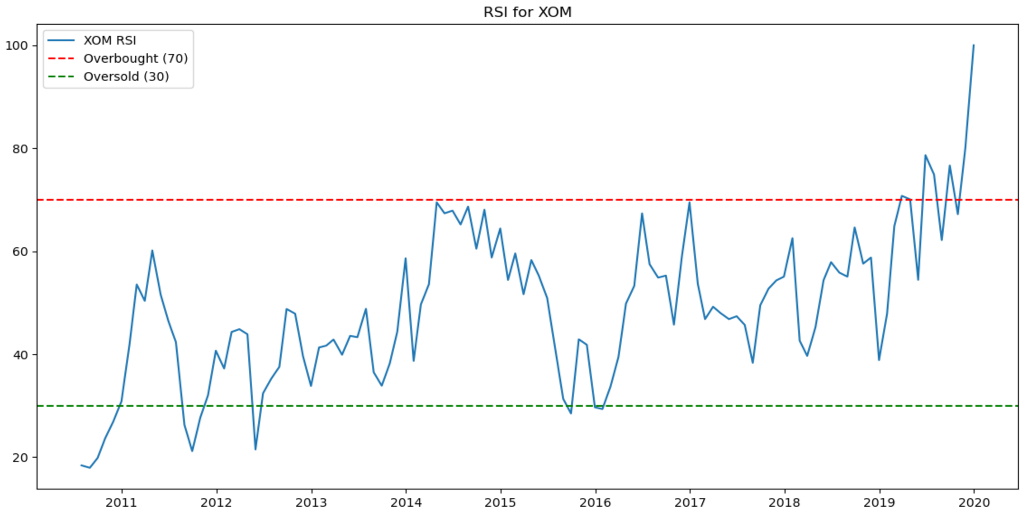

Fig 15. RSI for XOM(Picture Credit : Original).

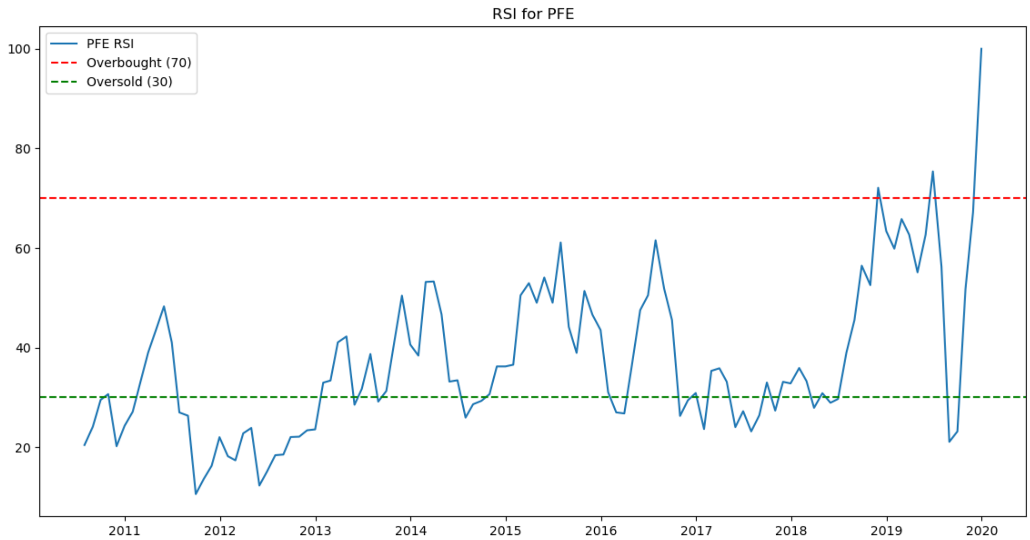

Fig 16. RSI for PFE(Picture Credit: Original).

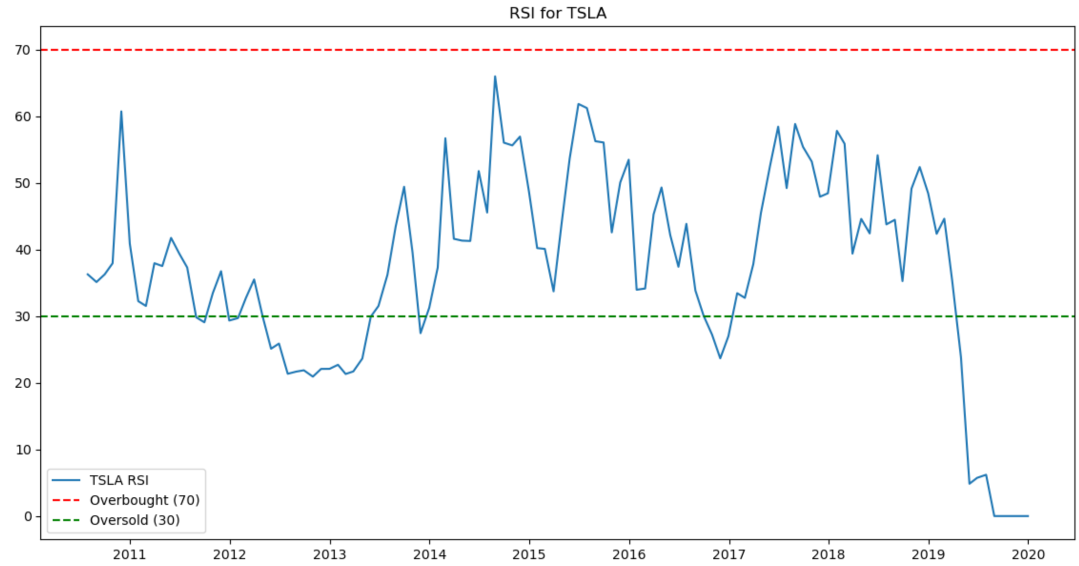

Fig 17. RSI for TSLA(Picture Credit: Original).

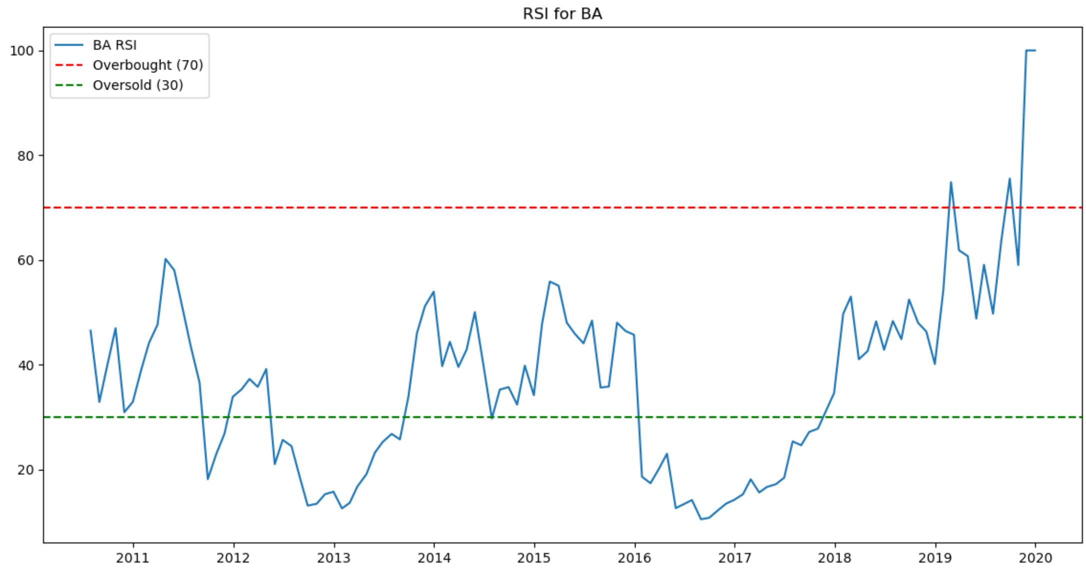

Fig 18. RSI for BA(Picture Credit: Original).

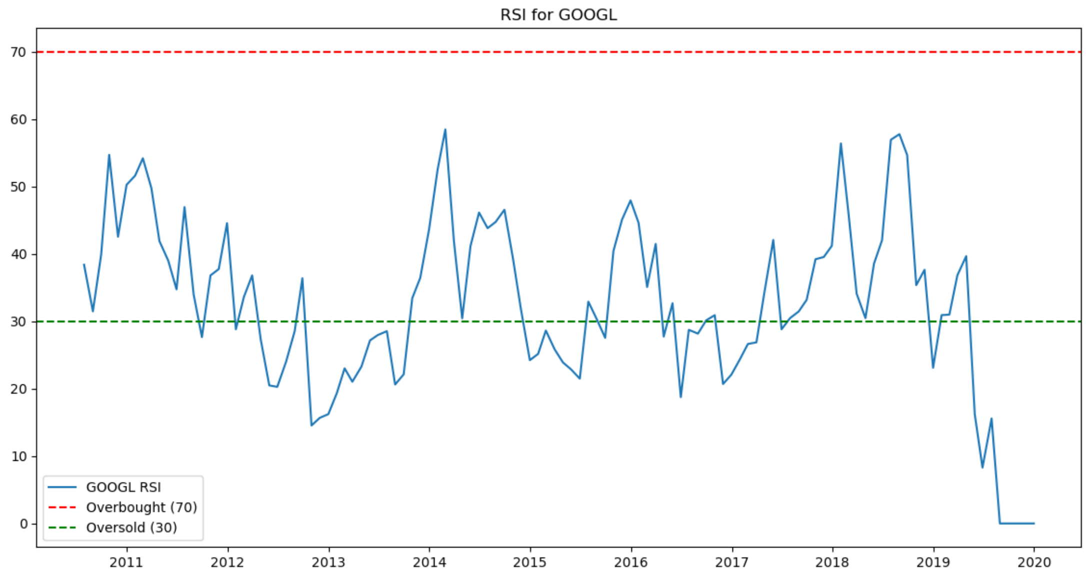

Fig 19. RSI for GOOGL(Picture Credit: Original).

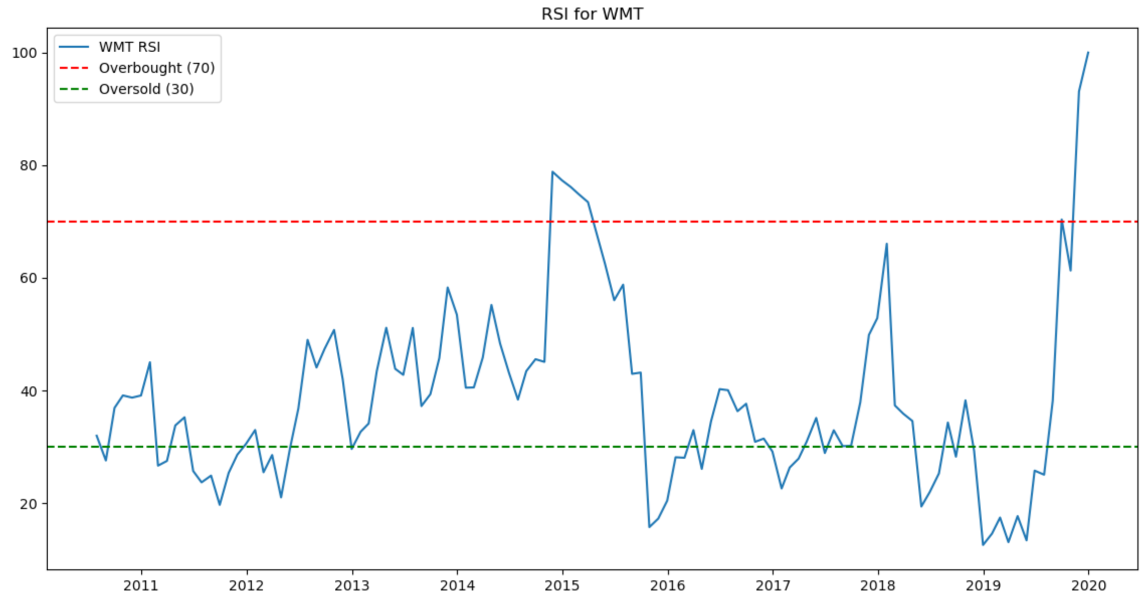

Fig 20. RSI for WMT(Picture Credit: Original).

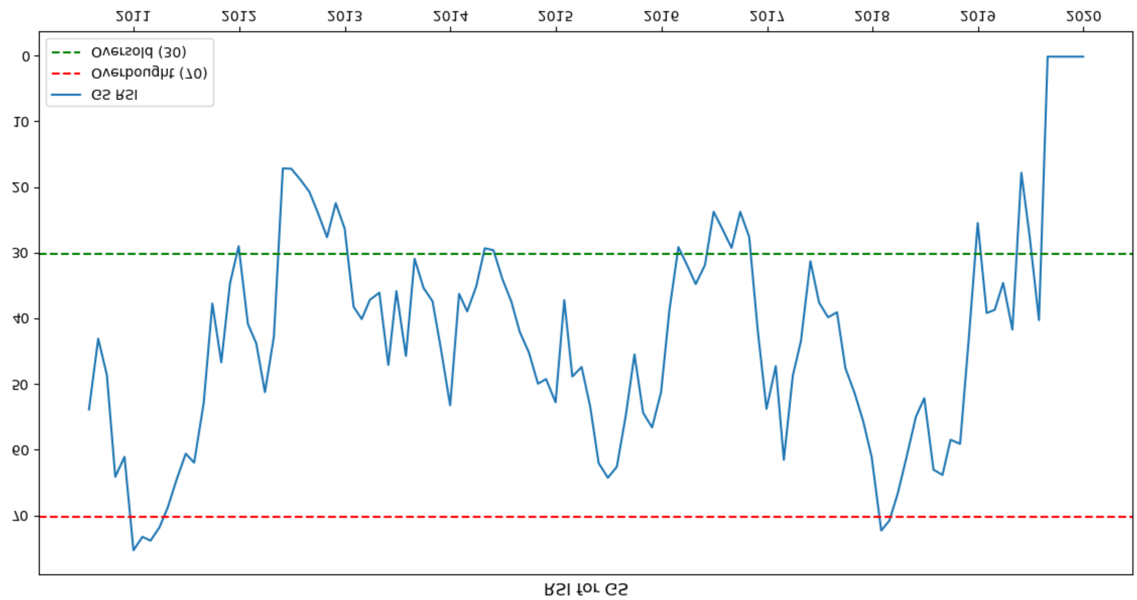

Fig 21. RSI for GS (Picture Credit: Original).

Table 2. 10 companies in portfolio and portfolio's performance in new strategy. (Table Credit: Original).

	Return Rate (%)	Sharpe Ratio	Max Drawdown (%)
AAPL	-68.50	-0.4969	-71.84
JPM	-74.56	-0.4705	-80.90
AMZN	-93.62	-0.9053	-94.14
XOM	-34.30	-0.3204	-47.21
PFE	-59.80	-0.6546	-69.31
TSLA	-95.23	-0.4084	-92.77
BA	-78.04	-0.7779	-80.61
GOOGL	-80.56	-0.6276	-62.76
WMT	-55.23	-0.4536	-45.36
GS	12.32	0.1317	-58.73
Total Portfolio	-64.53		

4.5. Moving Average Convergence / Divergence (MACD)

4.5.1. Back Testing

The basis for interpreting MACD is by MACD line, Signal Line and Histogram. We first get MACD line by subtracting 26-period EMA by 12-period EMA, and then compared to Signal line, which is the 9-period EMA of MACD line. The difference between these two-line called histogram, which is an indicator for bullish and bearish points (Fig 12-21).

The analysis will be also based on this fact: invest all we can to buy the shares at the signal of buying, and sell all we have at the selling signal. The initial wealth is $10,000 for each stocks, and we assume zero transaction cost and zero risk-free rate like previous.

4.5.2. Metric performance evaluation

We used return rate and sharp ratio as well as max drawdown like previous section.

4.5.3. Graph illustration

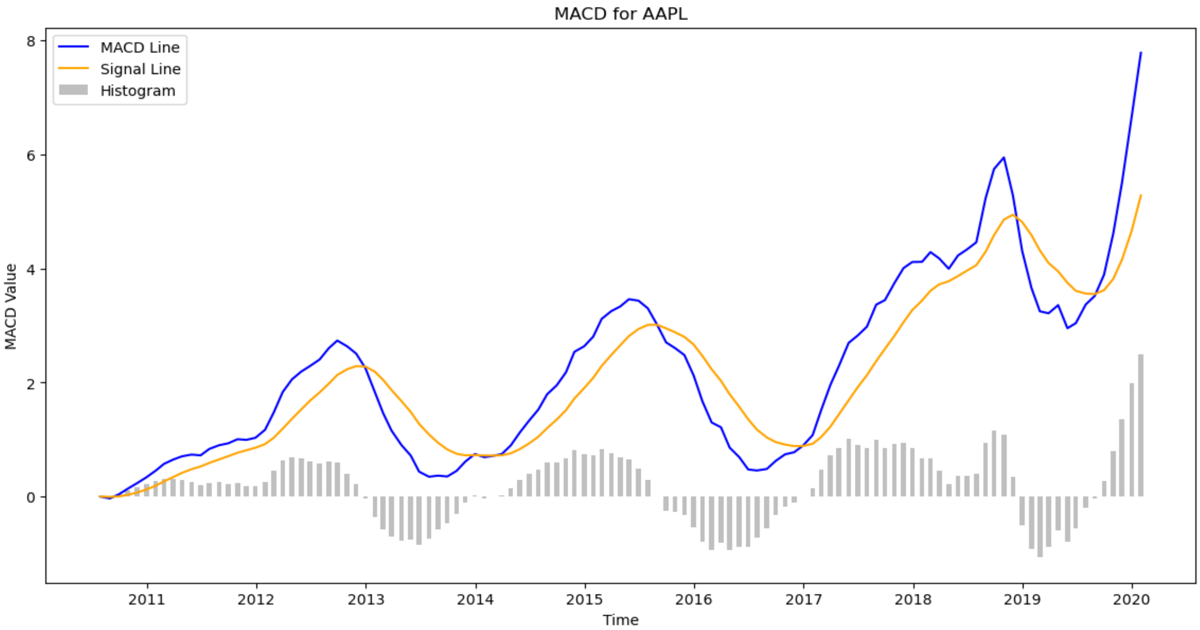

Fig 22. MACD line, Signal line and Histogram for Apple from 2010 to 2020 (Picture Credit: Original).

As the MACD for AAPL in Fig.22, we can state the fact that if MACD line and Signal line are intersected, then the histogram will be zero; also, as the difference between MACD line and Signal line increases, the histogram will also increase. Overall, the intersection serves as the bearish and bullish signals (Fig 22 and Table 3).

Table 3. 10 companies' performance on MACD from 2010 to 2020 (Table Credit: Original**).**

	Return Rate (%)	Sharp ratio	Maximum Drawdown(%)
AAPL	384.54	1.29	68.86
JPM	69.7	0.42	-29.87
AMZN	557.68	1.05	38.67
XOM	-24.94	-0.21	-24.94
PFE	113.58	0.58	72.7
TSLA	1147.64	0.63	11.60
BA	129.38	0.41	-23.06
GOOGL	129.35	0.50	-16.48
WMT	70.26	0.62	-0.42
GS	64.54	0.61	-12.06
Portfolio	264.17	0.64	nan

4.6. Comparison Among 3 Strategies

As we can clearly see, RSI is not promising for our portfolio management, because of its negative return rate. Also, by other evidence of study, found that while RSI rules generated significant abnormal returns in certain stock markets, they also highlighted the inconsistency of these results across different markets, suggesting that RSI may not always be a reliable indicator. [10] For other two method, MAC and MACD, from the definition of these two, there are very alike. However, if we expand them into 10-year investment with our portfolio, the outcome is significant different. Also, we compare with our standard comparison, SP500’s metric, to determine if the strategies are promising or not.

By Comparing with Table1 and Table 3 with SP500’s metric, we can conclude that both two methods, MAC and MACD are good trading strategies. They both process relatively high sharp ratio, representing high return by given risk, and high return rate which means under 10 year investing, they will gain much more than just simply investing sp500. In a word, these strategies under this portfolio, is doing better than no-strategies involved.

5. Conclusion

This study embarked on a comprehensive analysis of three distinct trading strategies – the Moving Average Crossover (MAC), the Relative Strength Index (RSI), and the Moving Average Convergence/Divergence (MACD) –1 to assess their efficiency in portfolio optimization within a ten-year frame from 2010 to 2020. The result indicate notably that MAC yield the highest return rate of 446%, showing a robust method for identifying buying and selling points. In constrast, RSI was less reliable for this portfolio, highlights that the importance of finding a nuanced trading strategies for each portfolio management.

For investor, this study can guild them to further development of algorithm trading models, combine multiple strategy to build a whole prediction and analysis. Academically, this study bridges the gap between theory and reality, offering evidence that emphasizes diversity and flexibility for portfolio optimization in financial industry.

Despite all, this study is affected by some limitations. First, for the selection of portfolio, only focus on large-cap companies within United States. It ignores the testing for small companies and international markets or digital market like crypto market. Additionally, the simple assumption of zero transaction cost is far from the reality. In real life, transaction cost for the stock market is a huge factor influence the investors and investing groups that can significantly affect return.

In our further study, it will focus on international market and alternative investment to validate the universality of trading strategies on portfolio optimization. Exploring the transaction cost to make our analysis more reliable in real life, thus make better references for readers and investors.

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