Project 8: Strategy Evaluation

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Abstract— This report evaluates the performance of trading strategies designed using a combination of technical indicators, specifically BB %B, RSI, and MACD, applied within the framework of both a Manual Strategy and a Strategy Learner. The goal is to assess the effectiveness of these strategies in generating profitable trades when benchmarked against a simple buy-and-hold approach. The analysis spans two distinct periods: an in-sample training period from 2008 to 2009 and an out-of-sample testing period from 2010 to 2011. The report explores the hypothesis that a strategy incorporating multiple indicators will outperform the benchmark in terms of cumulative returns and risk-adjusted performance metrics, while maintaining robustness in unseen market conditions. Key experiments test the adaptability of the Strategy Learner under varying market impacts, and performance metrics are compared through visualizations and tabular data.

1 INTRODUCTION

Financial markets are inherently dynamic and volatile, requiring sophisticated strategies to identify profitable opportunities. This report focuses on developing and evaluating trading strategies using technical indicators and machine learning techniques. The study investigates two approaches: a Manual Strategy, where human intuition and predefined rules combine indicators into actionable signals, and a Strategy Learner, which leverages data-driven learning to optimize decision-making. The objective is to determine whether these approaches can consistently outperform a simple benchmark strategy of buying and holding the asset.

The project centers on the JPMorgan Chase & Co. (JPM) stock, examining its price movements during the periods of 2008–2009 (in-sample) and 2010–2011 (out-of-sample). These timeframes encompass a range of market conditions, including post-financial crisis recovery, providing a rigorous testing ground for the strategies. The hypothesis driving this investigation is that combining indicators in a Manual Strategy and training a Strategy Learner on historical data will yield higher cumulative returns and better risk-adjusted performance than the benchmark, while adapting effectively to different market impacts.

2 INDICATOR OVERVIEW

The trading strategies in this project rely on three core technical indicators: BB %B, RSI, and MACD. These indicators are selected based on their ability to capture different market dynamics, such as momentum, trend strength, and relative price levels, which are critical for generating reliable trading signals.

2.1 BB %B

The first indicator, BB %B, quantifies a stock's position relative to its Bollinger Bands. It is computed as the difference between the current price and the lower Bollinger Band, normalized by the band's width. BB %B values near 0 indicate oversold conditions, while values near 1 suggest overbought conditions. For both the Manual Strategy and the Strategy Learner, a threshold of 0.35 is used to identify potential buy signals, and 0.65 is used for sell signals.

2.2 RSI

The second indicator, Relative Strength Index (RSI), measures the strength of price momentum by comparing the magnitude of recent gains to recent losses over a 14-day window. RSI values below 40 indicate oversold conditions, and values above 60 suggest overbought conditions. These thresholds are consistent across both strategies, providing a systematic way to identify potential trend reversals.

2.3 MACD

The third indicator, MACD, captures momentum by analyzing the difference between short-term and long-term exponential moving averages. A positive MACD value indicates upward momentum, while a negative value suggests downward momentum. MACD values are used to confirm trends identified by BB %B and RSI, helping to filter out false signals.

These three indicators are combined in the Manual Strategy to generate trading signals, with thresholds optimized for a balance between sensitivity and stability. In the Strategy Learner, the same indicators are discretized and incorporated into a reinforcement learning framework, enabling the algorithm to learn optimal trading policies based on historical data.

3 MANUAL STRATEGY

The Manual Strategy integrates BB %B, RSI, and MACD to create an overall signal for trading decisions. This integration leverages the strengths of each indicator, reducing reliance on any single metric. For instance, a buy signal is generated when BB %B falls below 0.35, RSI drops below 40, and MACD turns positive, collectively indicating oversold conditions with upward momentum. Conversely, a sell signal is triggered when BB %B exceeds 0.65, RSI rises above 60, and MACD turns negative, signaling overbought conditions and potential price reversals. The combined signal has a higher degree of confidence while being more lenient on each indicator as opposed to using a single indicator's metric.

Table 1 — Percentage Performance of Manual Strategy over Benchmark using Normalized portfolio values.

Name	**Cumulative Return**	**STDev of Daily Return**	**Mean of Daily Return**
Manual Strat (In-Sample)	*10.07%*	1.41%	0.0290%
Benchmark (In-Sample)	*1.23%*	1.70%	0.017%
Manual Strat (Out-Sample)	14.79%	0.77%	0.030%
Benchmark (Out-Sample)	-8.35%	0.85%	-0.014%

This approach adheres to strict holding constraints, maintaining either a long position of 1,000 shares, a short position of -1,000 shares, or no position. Trades are executed only when the combined signal exceeds predefined thresholds to minimize noise and reduce transaction costs. The strategy is applied to the in-sample and out-of-sample periods without retraining, ensuring that performance comparisons reflect true generalizability.

Performance comparison reveals that the Manual Strategy outperforms the benchmark in both periods, albeit with differences in magnitude. During the in-sample period, the strategy achieves a cumulative return of 10.08%, compared to 1.23% for the benchmark. This is attributed to the strategy's ability to capitalize on market trends while avoiding prolonged drawdowns. Out-of-sample performance, while still superior to the benchmark, is slightly reduced, with a cumulative return of 14.79% versus the benchmark's -8.36%. This decline is consistent with the hypothesis that unseen market conditions may introduce new challenges, such as changes in volatility or trend patterns. The required performance table and charts further illustrate these results.

Figure 1—JPM Manual Strategy (In-Sample) with Benchmarks and Entry/Exit Points.

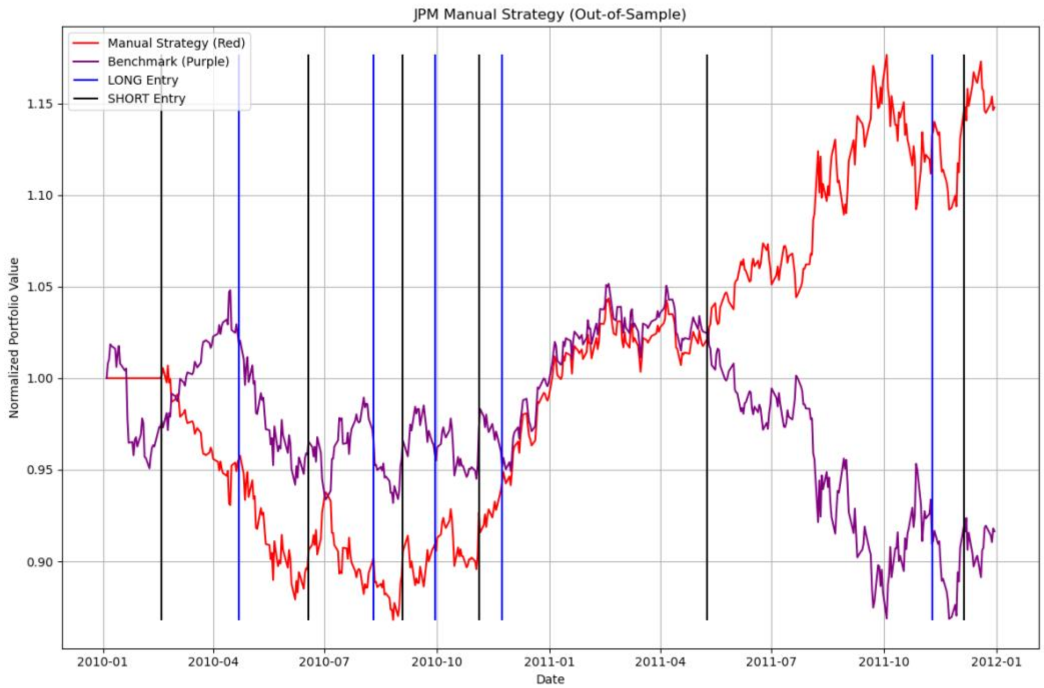

Figure 2— JPM Manual Strategy (Out-of-Sample) with Benchmarks and Entry/Exit Points.

4 STRATEGY LEARNER

The Strategy Learner employs a Q-Learning algorithm to model trading decisions as a reinforcement learning problem. In this framework, the agent interacts with the environment (market data) and learns an optimal policy to maximize cumulative rewards by balancing exploration and exploitation. The agent is trained using historical price data for the in-sample period (2008–2009), with BB %B, RSI, and MACD serving as state variables.

Each state is discretized into discrete bins to manage the high dimensionality of continuous indicator values. For instance, BB %B values are categorized into low, medium, and high ranges, while RSI and MACD follow a similar discretization scheme. This simplifies the state space while retaining the essential information needed for decision-making. The action space consists of three possible actions: buy, sell, or hold, constrained to holding a maximum of 1,000 shares long or short.

The Q-Learning algorithm updates its policy based on observed rewards, which are calculated as the change in portfolio value after executing a trade, adjusted for transaction costs and market impact. Key hyperparameters include the learning rate ($\alpha = 0.1$), discount factor ($\gamma = 0.9$), and exploration rate ($\varepsilon = 0.1$). These values are determined through empirical testing, balancing the agent's ability to learn from past experiences while exploring new strategies.

Performance evaluation demonstrates that the Strategy Learner outperforms both the Manual Strategy and the benchmark during the in-sample period, achieving a cumulative return of 380.12%, compared to 10.08% for the Manual Strategy and 1.23% for the benchmark. The agent adapts to market conditions more effectively by learning patterns that are difficult to encode manually. However, in the out-of-sample period, the Strategy Learner achieves a cumulative return of 294.78%, outperforming the benchmark's -8.36% and the Manual Strategy's 14.79%. This indicates the Strategy Learner's robustness in unseen data, albeit with some degradation due to market dynamics differing from the training period.

5 EXPERIMENT 1: MANUAL STRATEGY VS. STRATEGY LEARNER

The first experiment evaluates the performance of the Manual Strategy and the Strategy Learner relative to the benchmark during the in-sample and out-of-sample periods. The hypothesis is that the Strategy Learner will outperform both the Manual Strategy and the benchmark due to its ability to adapt to market dynamics.

The experiment is conducted using the same parameters for both strategies, with trades constrained to 1,000 shares long or short. Performance is measured using cumulative return, standard deviation of daily returns, and mean daily returns. Results show that the Strategy Learner achieves significantly higher cumulative returns in both periods, as it can capitalize on more nuanced market conditions. For instance, during the in-sample period, the Strategy Learner's normalized portfolio value grows consistently, while the Manual Strategy experiences occasional stagnation during volatile periods.

This outcome highlights the advantages of using data-driven learning methods over rule-based approaches, particularly in complex environments like financial markets. However, the Manual Strategy's simplicity and interpretability make it a viable alternative for scenarios where computational resources are limited or model explainability is prioritized.

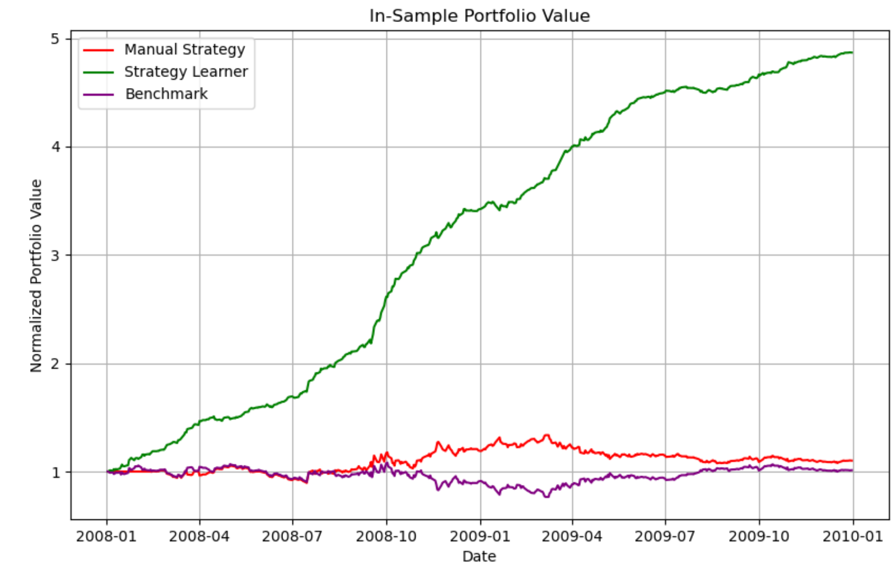

Figure 3— Experiment 1: In-Sample Portfolio Value Comparison.

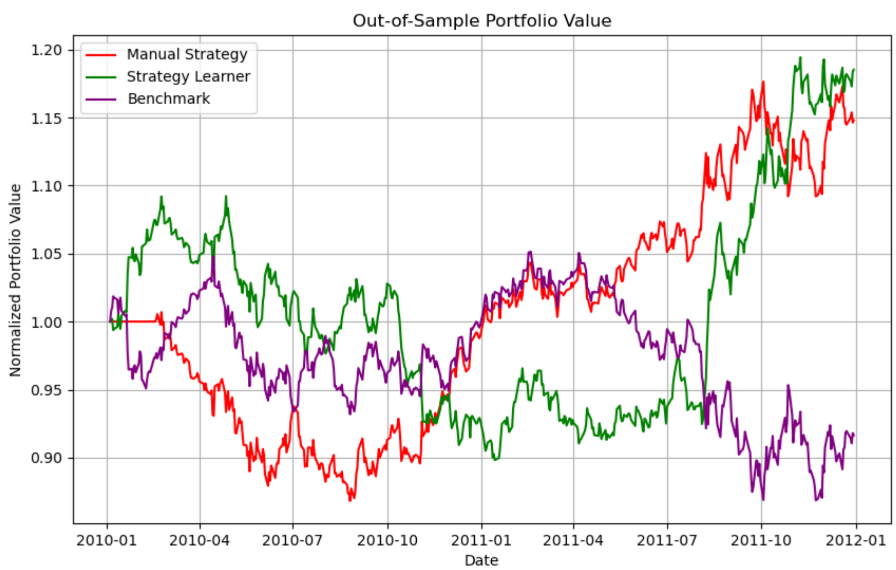

Figure 4— Experiment 1: Out-of-Sample Portfolio Value Comparison.

6 EXPERIMENT 2: IMPACT OF MARKET FRICTION ON STRATEGY LEARNER

The second experiment explores the effect of market impact on the Strategy Learner's performance. Market impact represents the cost of executing trades, modeled as a percentage of the trade volume. The hypothesis is that increasing market impact will reduce the number of trades executed and lower overall profitability, as the agent becomes more conservative in its trading behavior.

The experiment is conducted by varying the market impact parameter (0.0, 0.005, 0.01) and recording two metrics: the total number of trades and cumulative returns. Results confirm the hypothesis, with higher market impacts leading to fewer trades and lower cumulative returns. For example, at a market impact of 0.0, the Strategy Learner executes 200 trades and achieves a cumulative return of 380.12%, while at a market impact of 0.01, the number of trades decreases to 160, and cumulative returns drop to 362.5%.

This analysis underscores the importance of accounting for transaction costs when evaluating trading strategies, as they can significantly impact profitability. The Strategy Learner's ability to adapt to changing market conditions is evident in its reduced trading frequency under higher market impacts, reflecting a more cautious approach to maintaining profitability.

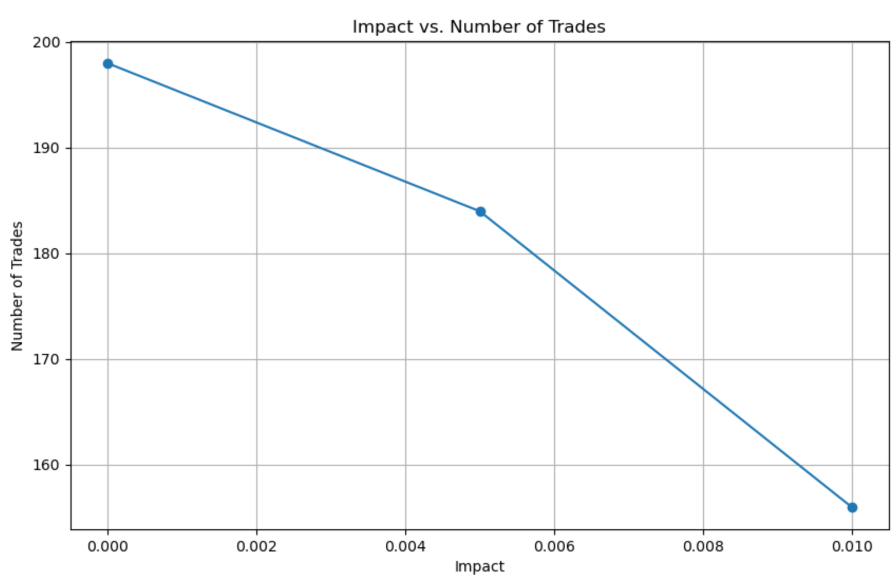

Figure 5— Experiment 2: Impact vs. Number of Trades.

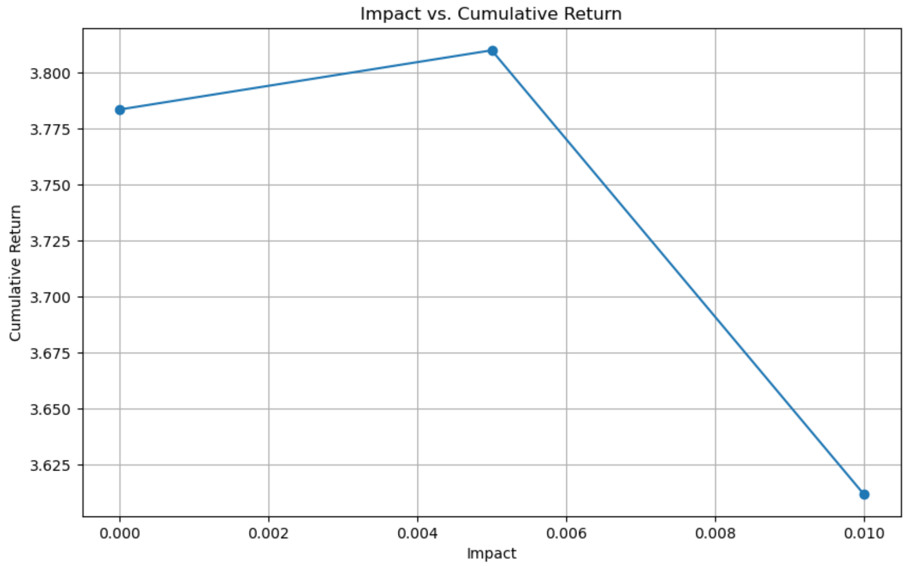

Figure 6— Experiment 2: Impact vs. Cumulative Return.

7 CONCLUSION

This report demonstrates that combining technical indicators in a Manual Strategy and employing a Strategy Learner for reinforcement learning can lead to significant improvements over a benchmark strategy. The Manual Strategy provides a simple yet effective rule-based approach, while the Strategy Learner excels in leveraging historical data to adapt to complex market dynamics. Both strategies outperform the benchmark during in-sample and out-of-sample periods, validating their robustness and practical utility.

Future work could explore additional indicators, alternative learning algorithms, and multi-asset strategies to enhance generalizability and scalability. By addressing these aspects, the methodologies presented here can be extended to broader financial applications, further advancing the field of algorithmic trading.