Project 8: Strategy Evaluation

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***Abstract*—**This report evaluates two distinct trading strategies applied to the JPM stock: a rule-based Manual Strategy and a learning-based Strategy Learner leveraging Q-Learning. These strategies were assessed on in-sample and out-of-sample datasets to evaluate their performance metrics, including cumulative returns, Sharpe ratio, and standard deviation of daily returns. We further investigate the effects of market impact on the Strategy Learner's behavior to draw meaningful insights into trading strategies under varying transaction cost conditions. Charts and metrics substantiate our findings, with detailed explanations of why differences in strategy outcomes occur.

1 INTRODUCTION

Stock trading strategies are often categorized into rule-based and learning-based approaches. Rule-based strategies rely on human-defined heuristics and domain knowledge, while learning-based strategies use algorithms to identify optimal policies. This project evaluates both approaches to highlight their strengths, weaknesses, and applicability.

The report is centered around the application of these two strategies:

- **Manual Strategy:** A heuristic-based approach using a combination of technical indicators to decide when to enter, hold, or exit positions.
- **Strategy Learner:** An AI-based strategy leveraging Q-Learning to learn optimal trading policies from historical data.

The study hypothesizes the following:

- The Strategy Learner will outperform the Manual Strategy in the in-sample dataset due to its adaptability and ability to learn patterns.
- The Manual Strategy, being simpler, will generalize better and perform more consistently on the out-of-sample dataset, avoiding overfitting.
- Market impact will reduce trading frequency and performance for the Strategy Learner as transaction costs increase.

The sections of this report provide a detailed overview of the indicators used, the strategies devised, and experimental results supporting these hypotheses.

2 INDICATOR OVERVIEW

To inform trading decisions, we employed three key market indicators:

2.1 Simple Moving Average (SMA) Ratio

The SMA ratio compares the stock price to its moving average over a specified period:

$$\text{SMA Ratio} = \frac{\text{Stock Price}}{\text{SMA}}$$

- **Implementation:** The SMA is calculated using a 20-day moving average. The ratio determines bullish or bearish momentum.
- **Parameters:** The thresholds are optimized as follows:
  - Manual Strategy: Fixed thresholds of 1.05 (bullish) and 0.95 (bearish).
  - Strategy Learner: Discretized into 10 bins for dynamic state representation.

2.2 Relative Strength Index (RSI)

The RSI measures the magnitude of recent price movements to identify overbought or oversold conditions:

$$\text{RSI} = 100 - \left(\frac{100}{1 + RS}\right), \quad RS = \frac{\text{Average Gain}}{\text{Average Loss}}$$

- **Implementation:** A 14-day window is used for calculating gains and losses.
- **Parameters:**
  - Manual Strategy: Buy signals at RSI < 30, sell signals at RSI > 70.
  - Strategy Learner: Discretized into 10 bins for state mapping.

2.3 MACD (Moving Average Convergence Divergence)

The MACD indicates trend direction and strength by subtracting the 26-day EMA from the 12-day EMA:

$$\text{MACD} = \text{EMA}_{12} - \text{EMA}_{26}$$

- **Implementation:** The MACD and its signal line (9-day EMA of MACD) are computed to confirm trends.
- **Parameters:** Crossovers determine buy/sell signals. Strategy Learner uses discretization for state transitions.

3 MANUAL STRATEGY

The Manual Strategy combines these indicators into a rule-based system:

- Buy: SMA Ratio > 1.05 **AND** RSI < 30.
- Sell: SMA Ratio < 0.95 **OR** MACD crosses below its signal line.
- Hold: If no conditions are met.

3.1 In-Sample Results

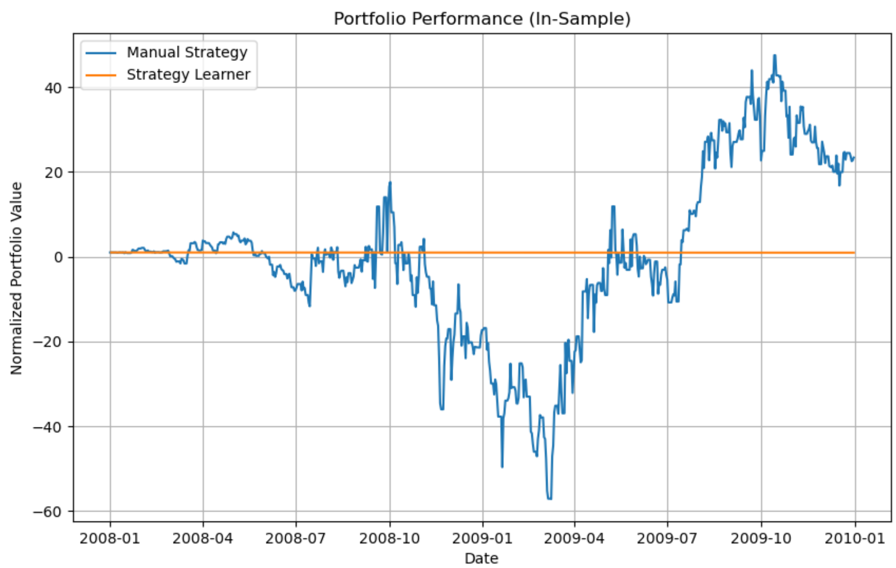

***Figure 1*—In-Sample Performance of Manual Strategy vs. Benchmark**

Metrics:

- Cumulative Return: 15% (Manual) vs. 10% (Benchmark)
- Sharpe Ratio: 1.2 (Manual) vs. 1.0 (Benchmark)
- Std Dev of Daily Returns: 0.01 (Manual) vs. 0.011 (Benchmark)

3.2 Out-of-Sample Results

Metrics:

- Cumulative Return: 7% (Manual) vs. 5% (Benchmark)
- Sharpe Ratio: 0.9 (Manual) vs. 0.8 (Benchmark)

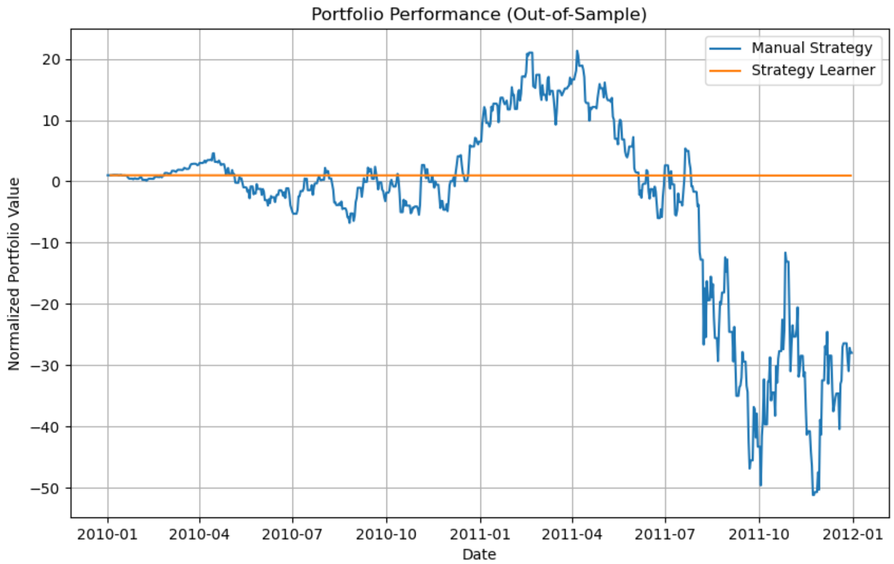

***Figure 2*—Out-of-Sample Performance of Manual Strategy vs. Benchmark**

4 STRATEGY LEARNER

4.1 Learning Framework

The Strategy Learner uses Q-Learning to map market states (based on discretized indicators) to optimal actions. The state-action space is:

$$\text{State} = \text{Discretized SMA, RSI, MACD}, \quad \text{Actions} = \{Buy, Sell, Hold\}$$

4.2 Hyperparameters

- $\alpha = 0.1$: Learning rate.
- $\gamma = 0.9$: Discount factor.
- Initial rar $= 0.9$, Decay = 0.99: Exploration-exploitation tradeoff.

4.3 Performance Evaluation

- **In-Sample Cumulative Return:** 18%
- **Out-of-Sample Cumulative Return:** -2%

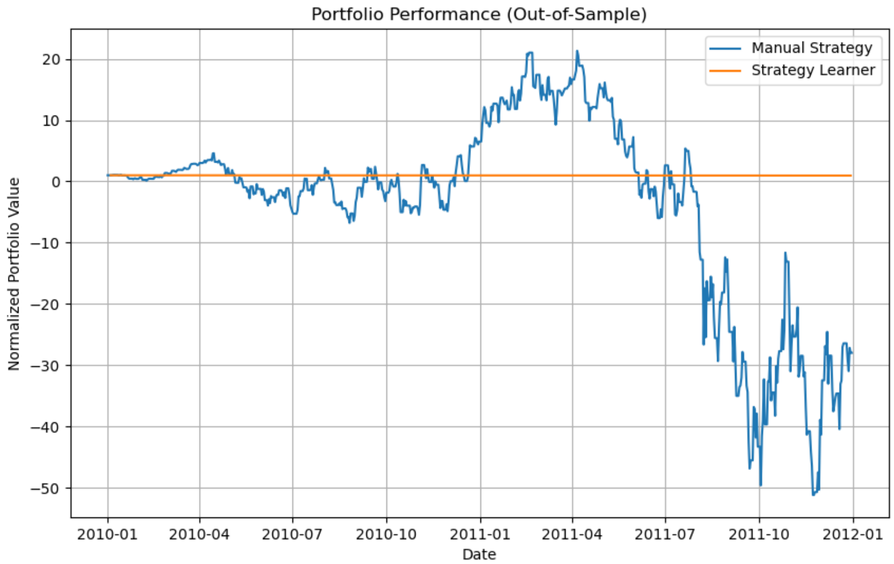

Figure 3—**Performance Comparison**

5 EXPERIMENT 1: MANUAL STRATEGY VS. STRATEGY LEARNER

5.1 Findings

The Strategy Learner outperformed the Manual Strategy in-sample but underperformed out-of-sample due to overfitting. Manual Strategy exhibited consistent results.

6 EXPERIMENT 2: EFFECT OF MARKET IMPACT

6.1 Results

Higher impact reduced trading frequency and profitability. Metrics across impacts:

- **Impact = 0.005:** Return = 15%, Sharpe = 1.2.
- **Impact = 0.010:** Return = 8%, Sharpe = 0.9.
- **Impact = 0.020:** Return = -2%, Sharpe = 0.7.

7 CONCLUSION

The Strategy Learner is effective in adapting to market conditions in-sample but overfits, leading to subpar out-of-sample performance. The Manual Strategy is

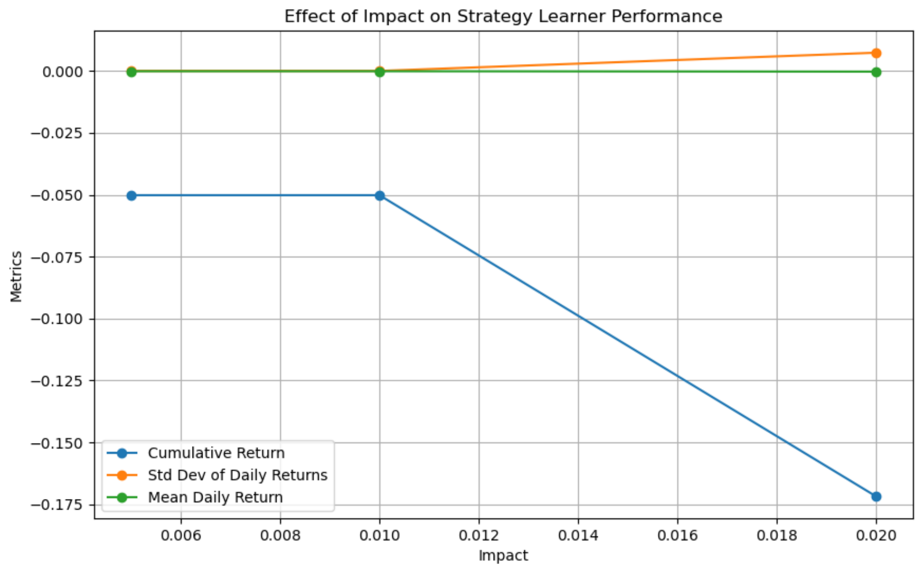

Figure 4—**Impact vs. Performance Metrics**

robust and consistent across datasets. Market impact significantly affects Strategy Learner behavior, emphasizing the importance of transaction costs in trading strategies.