Project 8:
Strategy Evaluation

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1 INTRODUCTION

Machine learning (ML) excels at learning patterns in large datasets and making predictions of future outcomes. This power of ML holds great promise in stock trading application. However, the question remains whether ML-based methods can really deliver better performance than traditional rule-based methods. In this project, a rule-based Manual Strategy and ML-based Strategy Learner are developed and compared for their performances in trading. The Manual Strategy is devised from rules created from human-learnt indicator and return patterns. The Strategy Learner is developed from machine-learnt relationship between indicators and returns. Both strategies use the same indicators. Their performance is benchmarked against a passive buy-and-hold strategy. The alternative hypothesis tested is that ML-based Strategy Learner outperforms rule-based Manual Strategy. The null hypothesis is that there is no difference in performance.

2 INDICATOR OVERVIEW

In this project, the Manual Strategy and Strategy Learner are developed using 3 technical indicators. They are Percentage Price Oscillator (PPO), Price-SMA ratio (P-SMA) and Percent B (%B). They are implemented as described below.

2.1.1 *Percentage Price Oscillator (PPO)*

PPO is an oscillator that quantifies how far apart 2 exponential moving averages (EMA), one fast-moving and one slow-moving, are at any given time as a percentage of the slow-moving EMA. The PPO at time t, is given by the following (ChartSchool, 2025a), where n is the number of time periods chosen for each of the EMAs and $n_{fast} < n_{slow}$:

$$PPO_t = \left(\frac{fast\ EMA_t - slow\ EMA_t}{slow\ EMA_t}\right) \times 100$$

$$EMA_t = (adj\ close_t - EMA_{t-1}) \times \left(\frac{smoothing}{1+n}\right) + EMA_{t-1}$$

Adjusted closing price is used as the price input for the EMA calculations. Key parameters are n for both EMAs and smoothing constant. The choice of n depends on the trading time horizon and style. Smaller n generates more frequent but noisier signals than larger n. In general, smaller n is suitable for frequent trading on shorter-term trend, and vice versa. The smoothing constant controls the weight given to most recent data. Increasing it gives more weight to the recent data (ChartSchool, 2025b), making the indicator less lagging. PPO is used to identify trends and their turning points based on the relative movement of the two EMAs. The additional EMA signal line, often included, **is not used** here.

2.1.2 *Price-SMA ratio (P-SMA)*

P-SMA ratio measures how far the stock price at any given time deviates from the simple moving average (SMA) of a specified n periods. The P-SMA at time t, is given by the following (Quant Investing, 2020), where n is the number of time periods chosen for the SMA:

$$price/sma_t = \frac{adj\ close_t}{SMA_t}$$

$$SMA_t = \frac{adj\ close_t}{\frac{\sum_{i=t-n+1}^{t} adj\ close_i}{n}}$$

Adjusted closing price is used as the price input for the above calculations. Key parameter is n for the SMA. The choice of n depends on the trading time horizon and style. Smaller n generates more frequent but noisier signals than larger n. In general, smaller n is suitable for trader who trades frequently on shorter-term trend, and vice versa. Hence, n must be optimized accordingly.

2.1.3 *Percent B (%B)*

%B is an indicator that measures the stock price's position relative to the Bollinger Bands. It encapsulates in a single number the price action in the context of the Bollinger Bands. Before calculating the %B, the Bollinger Bands need to be constructed first. The middle, upper and lower bands at time t of the Bollinger Bands can be computed as follows (ChartSchool, 2025c), where n is the number of time periods, and σ is number of standard deviations from the middle band:

$$Middle\ Band_t = SMA_t$$

$$Upper\ Band_t = SMA_t + \sigma \times \sqrt{\frac{\sum_{i=t-n+1}^{t} (adj\ close_i - SMA_t)^2}{n}}$$

$$Lower\ Band_t = SMA_t - \sigma \times \sqrt{\frac{\sum_{i=t-n+1}^{t} (adj\ close_i - SMA_t)^2}{n}}$$

%B can then be found by the following formula (Fidelity.com, 2025):

$$\%B_t = \left(\frac{adj\ close_t - Lower\ band_t}{Upper\ band_t - Lower\ Band_t}\right) \times 100$$

Adjusted closing price is used as the price input for the calculations. Key parameters are n and σ. As with the 2 indicators described above, the choice of n depends on the trading time horizon and style. The parameter, σ, is used to control the number of prices that fall outside the "normal" range. It is a cut-off that decides what prices are considered as extreme. Smaller σ produces more frequent but noisier signals than larger σ. At $\sigma = 2$, 95% of the prices fall within the upper and lower bands (Thompson, 2024).

3 MANUAL STRATEGY

The manual strategy uses PPO to identify short-term trends (1-3 months) and their turning points. Within these trends, P-SMA and %B are used to identify potential long/short entry and exit points. Entry or exit is executed only when signals from P-SMA and %B align. Regardless of trend direction, long trade is placed on dip while short trade is placed on surge. However, the triggers for long and short differ depending on the trend direction. In an uptrend, short trade is placed only after a strong surge, while long trade is entered on a mere pullback. In contrast, in a downtrend, long trade is placed only after a deep plunge, while short trade is entered on retracement. This is believed to be effective as it trades with, instead of against, the trends, thus increasing the winning probability.

To determine the effectiveness of this strategy, rules on entry and exit of long/short position are created using JPM stock's price data from Jan 2008 to Dec 2009. The rule's performance is assessed relative to a buy-and-hold benchmark. Commission ($9.95 per transaction) and impact (0.005 of price slippage) are taken into account. To optimize it, the n periods parameters of the indicators are tuned by varying one at a time while keeping others fixed. For P-SMA and %B, values tested are 10, 15, 20, 25 and 30. For PPO, the value pairs tested are (6, 20), (12, 26), (15, 29) and (21, 35). To avoid overfitting, the tuning seeks only to achieve a reasonable outperformance. It does not aim to maximize outperformance. Table 1 shows the values of these parameters that yield good results. These values are used in all experiments throughout this project. The exact rules for executing this strategy are detailed in Table 2. The rules are designed to make good predictions of return 31 days ahead at any point in time.

Table 1 — Values of parameters of the indicators used to build strategies.

PPO	P-SMA	%B
Period 1: 12	Period: 20	Period: 20
Period 2: 26		Std Dev: 2
Smoothing: 2		

Table 2 — Rules for generating long and short triggers, created from the complementary use of the 3 technical indicators.

PPO	P-SMA	%B	Action
< 0	<= 0.90	<= 10	1: Long
	> 1.02	>= 50	-1: Short
> 0	<= 0.98	<= 50	1: Long
	>= 1.10	>= 90	-1: Short

Figure 1 shows the performance after tuning. The strategy outperforms the benchmark throughout the entire period, ending with a cumulative return of about 6.2% against the benchmark's -8.3% (Table 3). The results suggest that the strategy fits well to the data from which the rules are created. To validate the strategy's predictive power for future price actions, it is back-tested to an unseen dataset from a different period (Out-Sample), Jan 2010 to Dec 2011. Figure 2 shows that the strategy's predictive power weakens considerably when it is applied to data it has not seen before. It underperforms the passive benchmark for most of the period till Sept 2011. It also ends in a loss of -3.5% (Table 3). Although it manages to end the period with a smaller cumulative loss than the benchmark (Table 3), the outperformance is smaller than that of the In-Sample. Its Sharpe ratio is also lower than the In-Sample's one. The results suggest that the rules may have captured patterns that exist only in the In-Sample dataset. Given human's limited ability to process large amounts of data, the rules may have missed patterns that exist in both the In-Sample and Out-Sample datasets. The rules may have also picked up random noises that could have been mistaken by the human learner as authentic patterns in the training data. Taken together, human-learnt manual strategy's predictive power does not generalize well to predict the unknown future

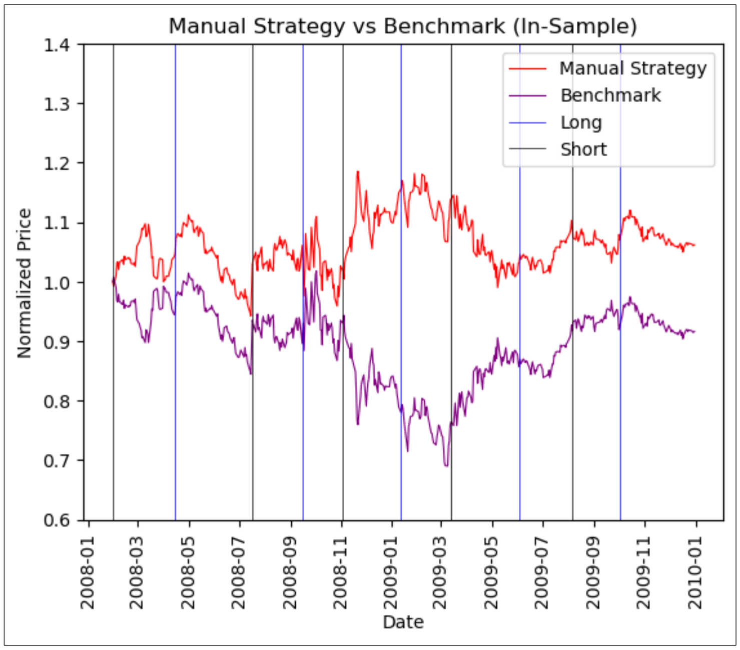

Figure 1 — Comparison of Manual Strategy against benchmark when back-tested on the same training data. Manual Strategy outperforms the passive benchmark.

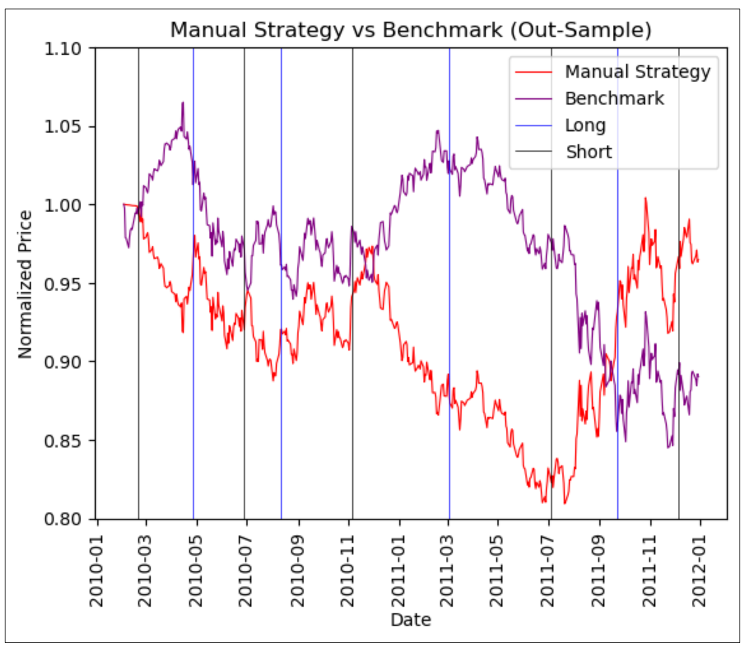

Figure 2 — Comparison of Manual Strategy against benchmark when back-tested on unseen data. Manual Strategy ends with higher cumulative return than the benchmark.

Table 3 — Comparison of Manual Strategy's performance relative to the benchmark's on several metrics when back-tested on In-Sample and Our-Sample datasets.

	In-Sample		**Out-Sample**	
Metrics	**Manual Strategy**	**Benchmark**	**Manual Strategy**	**Benchmark**
Cumulative Return	0.062056	-0.083747	-0.035245	-0.109782
Average Daily Return	0.000240	-0.000010	-0.000037	-0.000204
Std Dev of Daily Return	0.015230	0.018504	0.008710	0.008546
Sharpe Ratio	0.250156	-0.008579	-0.067435	-0.378937

4 STRATEGY LEARNER

Given the Manual Strategy's performance shown above, a ML-based learner is employed to see if it can do a better job than the rules-based strategy in learning patterns in the dataset and making predictions of future outcomes. To do this, the task is modelled as a classification problem, where it is the aim of the learner to classify any future data point into Long, Short or No Action based on the learnt relationship (if any) between the indicators and the 31-days returns. Using the JPM stock's price data from Jan 2008 to Dec 2009 as the training dataset, each row is labelled as 1, 0 or -1 (denoting Long, No Action or Short) according to its 31-days rate of return. The values of the 3 indicators are computed from the prices. Parameter values used are given in Table 1. The learner is then trained with this labelled dataset. The learner is a Random Forest classifier made up of a Random Decision Tree wrapped inside an ensemble Bag Learner. Key parameters of this learner are leaf size and bag number. Leaf size defines the minimum number of samples required for a potential split. It controls the tradeoff between variance and bias, and thus, overfitting and underfitting. The learner will overfit if leaf size is too small, and vice versa. Bag number indicates the number of learners to be trained using bootstrap aggregation. Increasing bag numbers mitigate overfitting and improve prediction accuracy. To determine the optimal leaf size and bag number to use, leaf size and bag number are varied from 5 – 20 and 20 – 35 respectively. Values are tested one at a time, keeping the other parameters constant, to find a pair that produces good performance on the training dataset. Leaf size, 17, and bag number, 30, are found to yield good performance. Since q-learner is not used here, discretization of data is not required. As the indicators values are either in percentages or ratio, no further normalization is required.

5 EXPERIMENT 1

It is hypothesized that the Strategy Learner outperforms the Manual Strategy due to its better ability in learning patterns from large datasets. To test this hypothesis, the Strategy Learner is trained to learn the relationship between the values of the 3 indicators and the 31-days returns computed from the JPM stock prices dataset from Jan 2008 to Dec 2009. It is the same dataset from which the Manual Strategy's rules are created. Both strategies use the same indicators with the same parameter values. The leaf size and bag number used are 17 and 30 respectively. These values are found to work well as described above. The performances of both strategies relative to how much they outperform the buy-and-hold benchmark are compared by back-testing them on the training (In-Sample) and unseen test (Out-Sample) datasets.

Figure 3 shows that the Strategy Learner performs better than the Manual Strategy when back-tested on In-Sample dataset. The results suggest that the Strategy Learner is better in picking up patterns in the dataset on which it is trained. This is expected given that machine learning can identify complex, subtle and non-linear relationships between variables in large datasets which humans are incapable of. Rules created from human-learnt patterns may not capture the full complexity of patterns between indicators and price actions. However, the In-Sample results should not be taken to mean that the Strategy Learner can perform as well when predicting future outcomes. It needs to be back-tested on an unseen dataset.

Figure 4 shows that the Strategy Learner continues to outperform the Manual Strategy when back-tested on a dataset (JPM stock prices, Jan 2010 – Dec 2011) it is not trained on before. The size of outperformance relative to the benchmark is similar to that of the In-Sample results (*Appendix 8.1: Experiment 1's Performance Metrics*). In contrast, the performance of Manual Strategy deteriorates significantly. The size of its outperformance relative to the benchmark narrows considerably, compared to that in the In-Sample results (*Appendix 8.1: Experiment 1's Performance Metrics*).

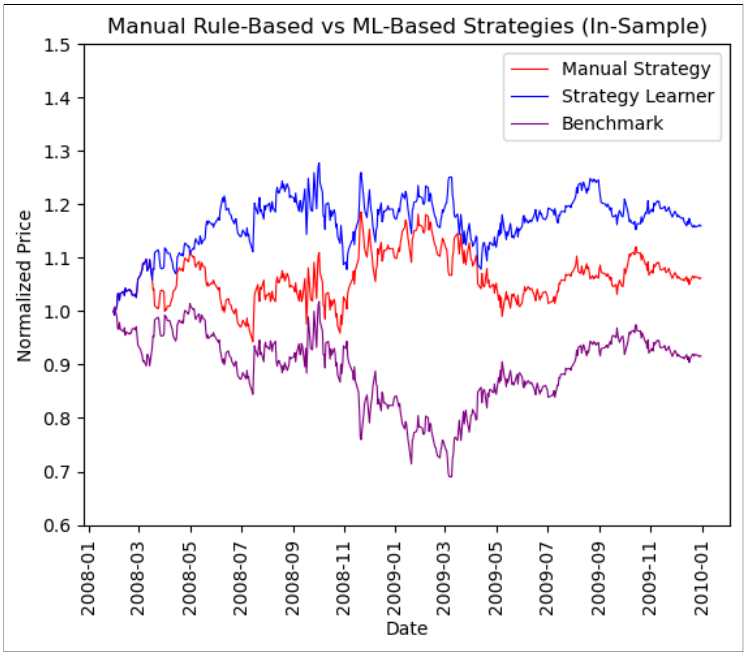

Figure 3—Comparison of Manual Strategy and Strategy Learner performances, back-tested on training dataset (In-Sample). Strategy Learner outperforms Manual Strategy.

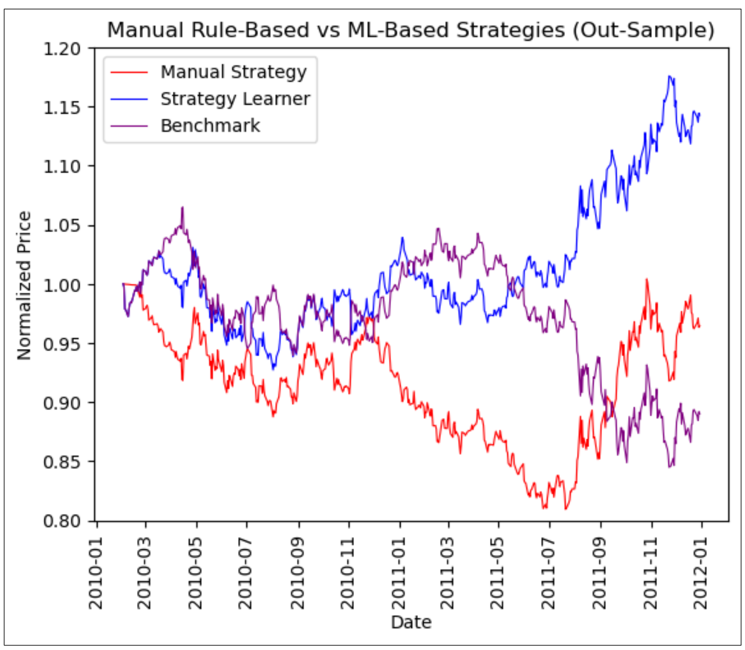

Figure 4—Comparison of Manual Strategy and Strategy Learner performances, back-tested on an unseen dataset (Out-Sample). Strategy Learner outperforms Manual Strategy.

These observations suggest that the Strategy Learner can generalize the relationships learnt from the training dataset to predicting future outcomes when provided with new indicator information. In contrast, rules derived from patterns learnt by human from the training dataset fail to generalize well. This is expected given that ML-based Strategy Learner can be tuned to distinguish true signals from noises by adjusting the leaf size and bag number. In contrast, rule-based Manual Strategy relies on human judgement which is less capable of differentiating true signals and noises. Furthermore, some patterns might have escaped the attention of the human learner due to its limited cognitive power. Despite the Strategy Learner's better performance in the Out-Sample results, signs of weakened performance can be observed. This is evident from Figure 4 which shows that the Learner does not convincing outperform the benchmark until June 2011.

6 EXPERIMENT 2

Given that the Strategy Learner takes impact into consideration in determining long/short entry and exit points, changing impact size is expected to affect trading behavior and profitability. Larger impact requires long/short entry and exit points to have higher predicted returns, and vice versa. Consequently, less signals and less frequent trading are expected when impact is larger. However, it is less straightforward in terms of profitability. More signals and frequent trading may not necessarily lead to higher profitability, as some signals may be low quality or simply noises. Nevertheless, we hypothesize that larger impact size reduces trading frequency and profitability, and vice versa. The null hypothesis is that impact size has no effect on trading frequency and profitability. To test the hypothesis, impact is varied while keeping other variables fixed. The Strategy Learner used here is the same as the one described in experiment 1, except for impact and commission values. Impact values tested are 0, 0.02, 0.05 and 0.07. Commission is set to 0. The Strategy Learner is evaluated on the same training data for its behavior and performance on several metrics (Figure 5 and 6). Figure 5 shows that cumulative return at the end of the study period decreases with increasing impact size. Average daily return also decreases with increasing impact (Figure 6). Bigger impact size increases performance volatility, as evidenced by the increase of standard deviation of daily return (Figure 6). Accordingly, impact size adversely affects profitability on a risk-adjusted basis, as indicated by the Sharp ratio (Figure 6). As expected, the total number of trades decreases with increasing impact. This suggests that the observed decrease in profitability is not the result of only slippage but also less frequent trading. Together, the results support our hypothesis that impact is inversely related to trading frequency and profitability.

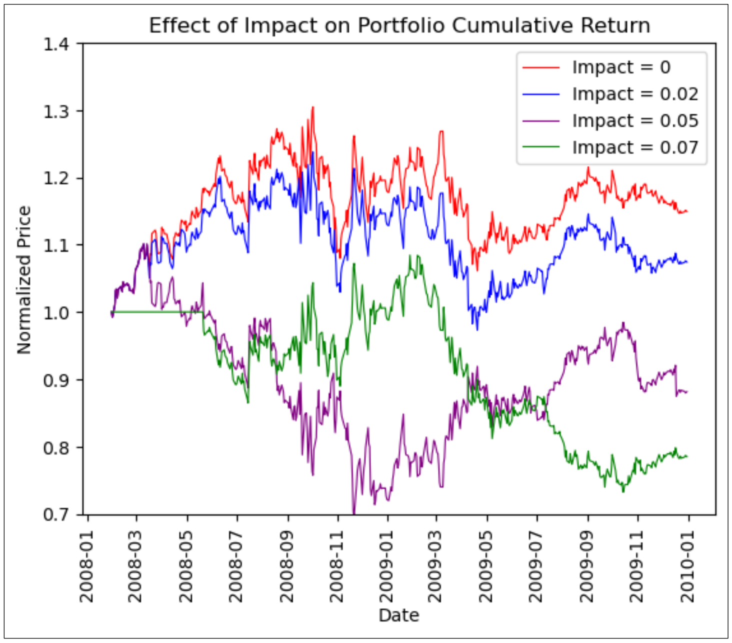

Figure 5 — Effect of impact size on cumulative return. Cumulative return decreases with increasing impact size

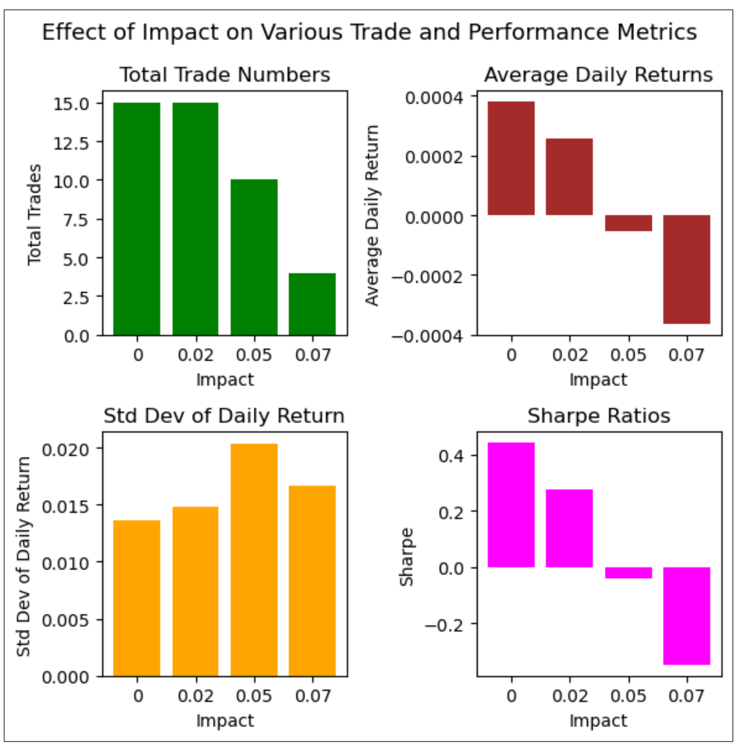

Figure 6 — Effect of impact size on trade frequency, average daily return, standard deviation of daily return and Sharpe ratio.

7 REFERENCES

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8 APPENDICES

8.1 Experiment 1's Performance Metrics

Table 4 — Manual Strategy's and Strategy Learner's performances relative to the benchmark's on several metrics when back-tested on In-Sample and Our-Sample datasets.

	In-Sample			Out-Sample		
Metrics	**Manual Strategy**	**Strategy Learner**	**Benchmark**	**Manual Strategy**	**Strategy Learner**	**Benchmark**
Cumulative Return	0.062056	0.159192	-0.083747	-0.035245	0.142686	-0.109782
Average Daily Return	0.000240	0.000400	-0.000010	-0.000037	0.000307	-0.000204
Std Dev of Daily Return	0.015230	0.013791	0.018504	0.008710	0.007834	0.008546
Sharpe Ratio	0.250156	0.460431	-0.008579	-0.067435	0.622093	-0.378937

8.2 Experiment 2's Performance Metrics

Table 5 — Effect of impact size on several performance metrics.

Metrics	**Impact 0**	**Impact 0.02**	**Impact 0.05**	**Impact 0.07**
Cumulative Return	0.149200	0.074056	-0.118522	-0.215139
Average Daily Return	0.000380	0.000257	-0.000053	-0.000363
Std Dev of Daily Return	0.013654	0.014824	0.020376	0.016615
Sharpe Ratio	0.441798	0.275212	-0.041291	-0.346822