Evaluating the Effectiveness of a Filter Rule Trading Strategy: A Case Study on Microsoft (MSFT)

YUKE LI

Abstract: This study evaluates the effectiveness of a filter rule trading strategy applied to Microsoft (MSFT) stock over a five-year period, leveraging an AR(1) model and Bootstrap resampling to assess its robustness. The filter rule trading strategy identifies buy and sell signals based on rolling-window price extremes, aiming to capture short-term trends while mitigating downside risk. Our findings indicate that while the strategy consistently generates positive returns, its overall profitability remains lower than a buy-and-hold approach. However, a higher sharpe ratio suggests that it provides better risk-adjusted returns. Bootstrapped simulations confirm the statistical significance of the strategy's performance, revealing a right-skewed return distribution with higher kurtosis. The study concludes that filter rule trading strategies can yield positive results and their performance could be further refinement.

Keywords: Algorithmic Trading, Filter Rule Trading Strategy, AR(1) Model, Bootstrap.

1. Introduction

Technical analysis has been widely used in financial markets as a tool for identifying trading opportunities based on historical price patterns. Among various technical trading strategies, the filter rule method has been extensively studied due to its simplicity and potential to capitalize on price trends. This study focuses on implementing and evaluating a filter rule trading strategy applied to Microsoft (MSFT) stock from January 1, 2020, to January 1, 2025. The primary objective of this research is to assess the strategy's effectiveness in generating positive returns while ensuring at least four round-trip trades within the chosen time frame. The strategy employs a systematic approach where buy and sell signals are triggered based on price movements exceeding predefined filter thresholds. To ensure robustness, we utilize bootstrap resampling under the assumption of an AR(1) process, allowing us to evaluate the strategy's performance across 100+ simulated price paths. Key financial metrics, including total return, sharpe ratio, and maximum drawdown, are analyzed to determine the profitability and risk characteristics of the approach. Furthermore, we compare the distribution of bootstrapped returns with a normal distribution to test for statistical significance. By examining both historical and simulated data, this study aims to provide insights into the viability of filter rule trading in real-market conditions and identify potential areas for optimization.

2. Data Description

In this study, we analyze the historical stock price data of Microsoft Corporation (MSFT), one of the largest technology companies in the world. Microsoft is a key player in the software, cloud computing, and artificial intelligence sectors, making it a widely traded stock with significant market influence. Given its stability over the past decade, MSFT provides a suitable candidate for evaluating the effectiveness of systematic trading strategies.
The dataset was retrieved from Yahoo Finance using the yfinance Python library and spans from January 1, 2020, to January 1, 2025, covering a period of five years. Daily adjusted closing prices are used as the primary metric for analysis, as they account for stock splits and dividend adjustments, making them more suitable for performance evaluation.
To gain an initial understanding of the stock's performance over the selected time period, the adjusted closing prices were plotted over time. As shown in Figure 1, MSFT experienced a general upward trend, reflecting its overall growth in stock value.

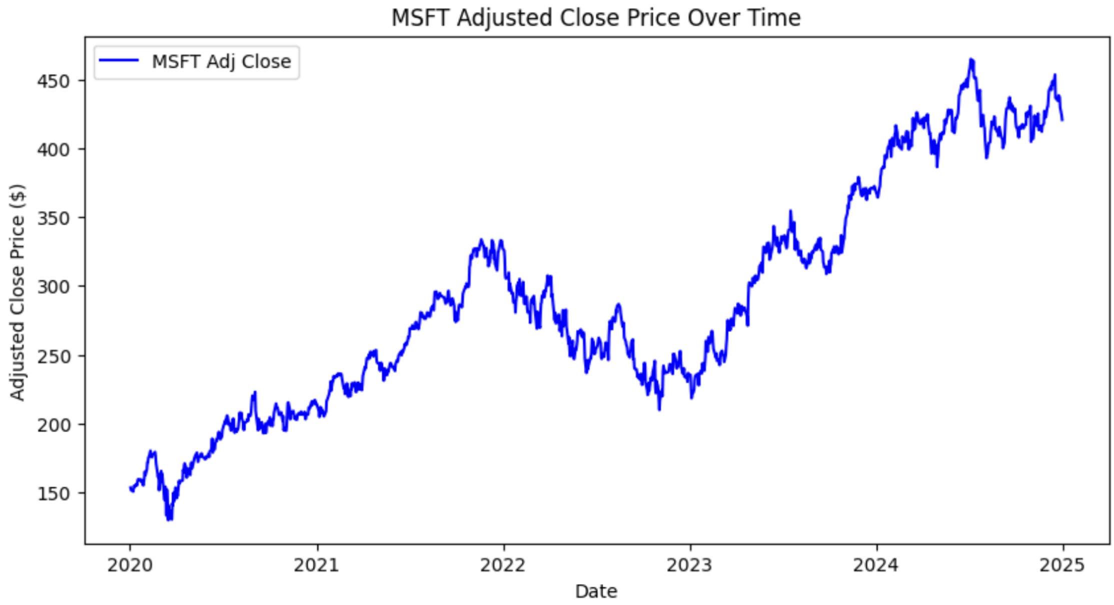

Fig. 1. MSFT Adjusted Close Price Over Time

3. Baseline Trading Strategy

This section presents the baseline trading strategy employed in this study, which is based on a filter rule approach. Filtering rules take advantage of the momentum effect or trend continuation characteristics of the market and may have profit potential under certain market conditions [5]. The strategy utilizes rolling-window price extremes to generate buy and sell signals, identifying potential breakout opportunities. By systematically entering and exiting trades based on predefined thresholds, this approach provides a rule-based mechanism for capturing short-term price movements.

The filter rule trading strategy in behavioral finance can be explained through investor biases, market inefficiencies, and emotions. It leverages trend-chasing bias, where investors believe trends will persist, fueling herding effects—buying in uptrends and panic selling in downtrends. Market inefficiencies, driven by noise traders, can cause price trends to persist, making the strategy profitable. Additionally, market emotions (Fear & Greed) influence breakouts, as greed drives buying in bull markets, while loss aversion and fear amplify sell-offs in bear markets.

3.1. Strategy Framework

The baseline trading strategy follows a systematic approach based on historical price movements. The key elements of the strategy are outlined as follows:

- Rolling Window Price Extremes
  - A 15-day rolling maximum price (M_k) is calculated as the highest closing price over the past 15 trading days.
  - A 15-day rolling minimum price (m_k) is computed as the lowest closing price over the past 15 trading days.
- Trading Signals and Execution Rules
  - A buy signal is triggered when the closing price exceeds 1.01 times (+1%) the previous period's maximum (M_k), indicating a potential breakout.
  - A sell signal is activated when the closing price falls below 0.99 times (-1%) the previous period's minimum (m_k), signaling a potential downward breakout.
    In previous studies, 1%, 2%, and 5% filter thresholds have been commonly used. Among them, the 1% filter rule has demonstrated superior performance in most cases [3]. Therefore, in this study, we select the 1% filter as the primary parameter for testing.
- Trade Execution and Position Management

- If a buy signal occurs and sufficient capital is available, shares are purchased at the market price, adjusted for a 0.05% slippage cost to account for transaction friction.
- If a sell signal is triggered while holding a position, all shares are liquidated at an adjusted execution price, incorporating dividend and stock split adjustments.
- No leverage or short selling is considered, ensuring a conservative approach to risk management.

- Risk Considerations and Transaction Costs
  - The strategy assumes a fixed initial capital of $100,000, with all trades executed using available cash.
  - A 0.05% slippage is introduced to simulate market impact and order execution delays.
  - A risk-free rate of 2% per annum is assumed, which is later used in performance evaluation.

3.2. Performance Evaluation Metrics

To assess the effectiveness of the baseline strategy, the following key performance indicators (KPIs) are computed:

- Total Return (%): Computed as

$$\text{Total Return} = \left(\frac{\text{Final Portfolio Value} - \text{Initial Capital}}{\text{Initial Capital}}\right) \times 100$$

- Buy-and-Hold Return (%): Represents the return of a simple buy-and-hold strategy using adjusted closing prices, given by

$$\text{B\&H Return} = \left(\frac{\text{Final Adj Close} - \text{Initial Adj Close}}{\text{Initial Adj Close}}\right) \times 100$$

- Sharpe Ratio: Traditional Sharpe Ratio calculation is designed for buy-and-hold strategies, assuming that capital is always invested in the market. However, for active trading strategies, capital is not continuously exposed to market risk, necessitating an adjustment to the Sharpe Ratio for a more accurate risk-adjusted return measurement. Schmidt [1] proposed a modified Sharpe Ratio calculation tailored for active trading strategies, incorporating the actual number of trading days in the market T to ensure a more realistic assessment. If capital is only deployed on specific trading days, using the adjusted formula helps to provide a more reliable evaluation of risk-adjusted performance.

$$SR_{\text{ann}} = \frac{r_{\text{annt}} - r_f}{\sigma_d \sqrt{T}}$$

- Buy-and-Hold Sharpe Ratio:

$$SR_{\text{ann}} = \frac{(r_d - r_{fd})\sqrt{T}}{\sigma_d}$$

- Winning Trades (%): The proportion of round-trip trades that resulted in a profit, calculated as

$$\text{Win Rate} = \left(\frac{\text{Winning Trades}}{\text{Total Round-Trip Trades}}\right) \times 100$$

- Maximum Drawdown (%): The maximum observed decline in portfolio value from a peak, given by

$$\text{Max Drawdown} = \max(\text{Drawdown Series}) \times 100$$

- Calmar Ratio: A risk-adjusted return metric calculated as

$$\text{Calmar Ratio} = \frac{\text{Annualized Return}}{\text{Maximum Drawdown (MDD)}}$$

  Unlike the Sharpe Ratio, which uses return volatility as a risk measure, the Calmar Ratio focuses on the worst portfolio decline. It is particularly useful for evaluating hedge funds and trend-following strategies, where managing drawdowns is crucial.

  Since the trading strategy implemented in this study follows a trend-following breakout approach, it is exposed to potential large drawdowns if the market reverses after a breakout signal. As a result, relying solely on volatility-based risk measures like the Sharpe Ratio may not fully capture the downside risks. The Calmar Ratio provides a more comprehensive evaluation by assessing the trade-off between return and maximum drawdown, making it a more suitable performance metric for this strategy.

3.3. Backtesting Results

The backtesting results evaluate the performance of the baseline trading strategy over the selected period. The equity curve, shown in Figure 2, illustrates the growth of the portfolio value starting with an initial capital of $100,000. Table 1 presents the key performance metrics of the strategy:

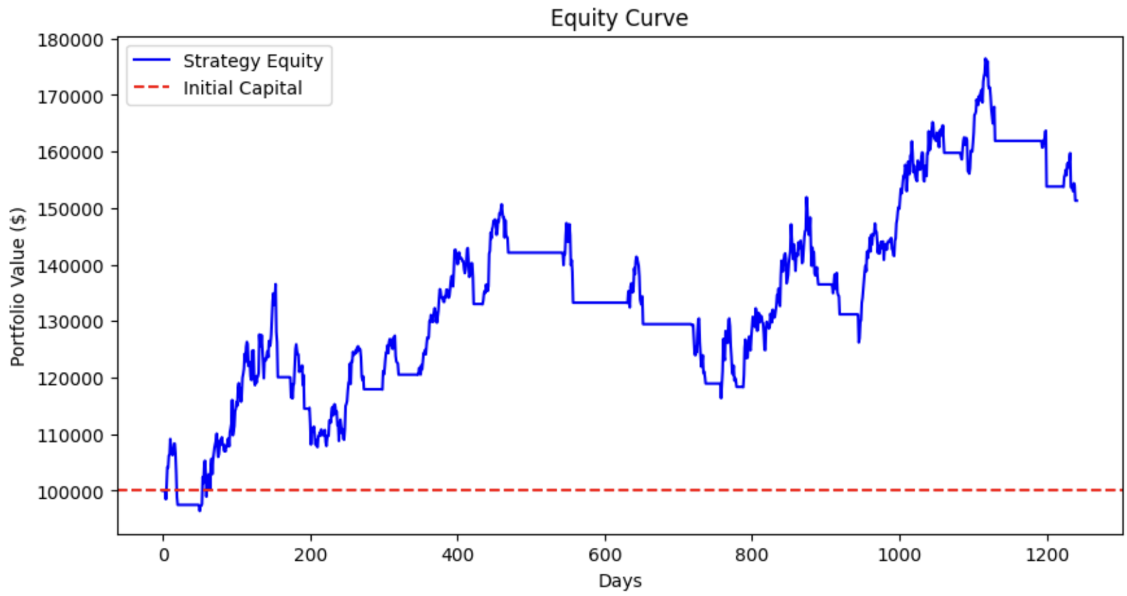

Fig. 2. Baseline Trading Strategy Backtesting Results

- Total Return: The strategy achieved a return of 51.32%, significantly lower than the Buy-and-Hold (B&H) strategy's 174.36%.
- Sharpe Ratio: The strategy's Sharpe ratio of 1.839 indicates a stronger risk-adjusted return compared to the B&H Sharpe ratio of 0.751.
- Winning Trade Percentage: The strategy maintains a win rate of 50.0%, suggesting that half of the trades were profitable.
- Maximum Drawdown: The maximum drawdown of 22.77% represents the largest peak-to-trough decline in portfolio value, highlighting potential downside risks.
- Calmar Ratio: The strategy's Calmar ratio of 0.379 measures return relative to the maximum drawdown, offering insight into drawdown efficiency.

# of round-trip trades	Total return, %	Sharpe ratio	B&H Return %
18	51.32	1.839	174.36
B & H Sharpe Ratio	Winning Rate, %	Max Drawdown, %	Calmar Ratio
0.751	50.0	22.77	0.379

Table 1. Baseline Trading Strategy Backtesting Results

While the Buy-and-Hold strategy significantly outperforms in terms of absolute return, the baseline strategy exhibits a better risk-adjusted return, as reflected in the higher Sharpe ratio. However, the drawdown remains substantial. In conclusion, baseline strategy can capture market trends, it may not be optimal for maximizing long-term returns.

4. Bootstrap and Resampling

In this section, we describe the bootstrap-based resampling method used to generate alternative price paths under the assumption that returns follow an AR(1) process. This technique enables the construction of simulated price series by resampling residuals from an autoregressive model, providing a robust way to assess the variability of trading strategy outcomes.

4.1. Model Assumption and Estimation

The bootstrap procedure begins by assuming that the log returns of the asset follow an AR(1) process:

$$r_t = \alpha + \beta r_{t-1} + \epsilon_t$$

Using historical data, we estimate the parameters α and β via ordinary least squares (OLS) regression. The residuals from this regression, defined as:

$$e_t = r_t - \alpha - \beta r_{t-1}$$

are then extracted for resampling.

4.2. Bootstrap Resampling of Residuals

To generate alternative price paths, we apply the bootstrap method to the estimated residuals. This involves randomly sampling (with replacement) from the residuals e_t, preserving their empirical distribution while breaking any time dependency. The resampled residuals, denoted as $\hat{e}_t$, are used to construct new returns:

$$\tilde{r}_t = \alpha + \beta \tilde{r}_{t-1} + \hat{e}_t$$

where $\tilde{r}_t$ represents the bootstrapped log returns.

4.3. Constructing Bootstrapped Price Paths

Once the bootstrapped returns are obtained, we recursively construct the corresponding price series. The initial price P_1 is taken from the historical dataset, and subsequent prices are generated using the exponential function:

$$\hat{P}_t = \hat{P}_{t-1} \times e^{\tilde{r}_t}$$

This ensures that the generated prices remain strictly positive while preserving the statistical characteristics of the original data.

4.4. Comparison with Historical Prices

To validate the effectiveness of the bootstrap method, we compare the simulated price paths with historical price movements. The fig 3 below illustrates the original price series alongside the bootstrapped paths.

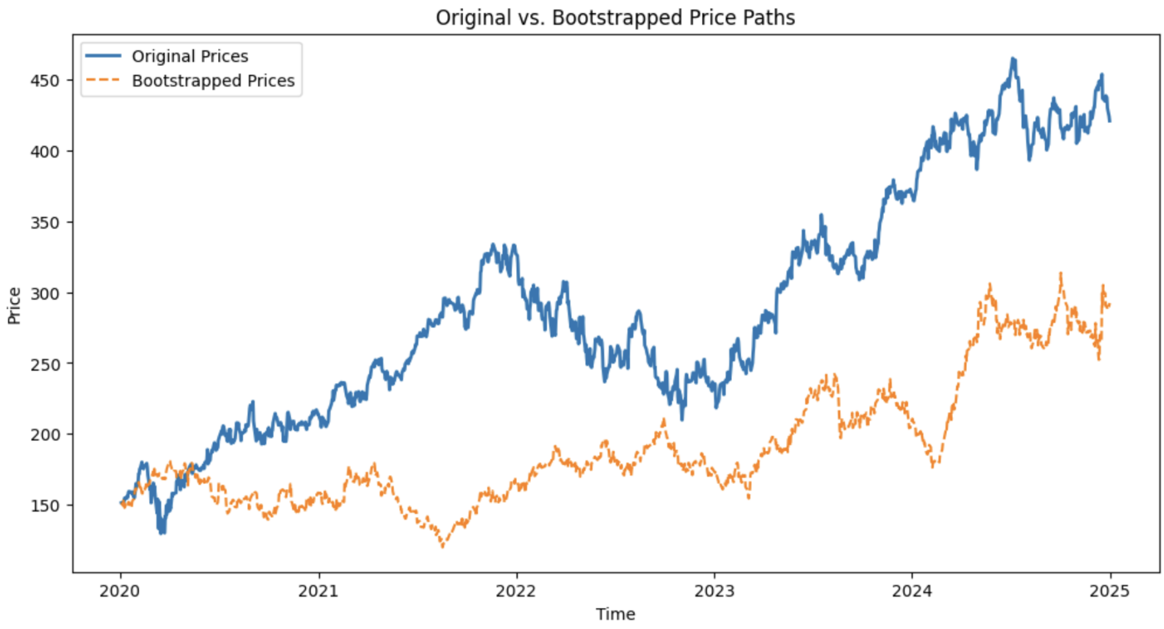

Fig. 3. Original vs. Bootstrapped Price Paths

The bootstrapped price series exhibit statistical properties similar to the historical data but allow for alternative realizations of market behavior, making them valuable for risk assessment and strategy robustness testing.

5. Bootstrapped Trading Strategy

To evaluate the robustness of the trading strategy under different market conditions, we employ a bootstrap-based approach. This method generates alternative price paths by resampling residuals from the AR(1) model, allowing us to assess the variability of strategy performance.

5.1. Methodology

We conduct 100 bootstrap simulations. Each simulation consists of the following steps:

1. Bootstrap Resampling of Residuals
    - Residuals from the AR(1) regression are resampled with replacement to construct new log returns and price paths.
2. Trading Strategy Implementation
    - The strategy generates buy and sell signals based on rolling maximum and minimum prices over a defined window.
    - Position sizing, capital allocation, and trade execution are determined according to predefined rules in Baseline Trading Strategy.
3. Performance Evaluation
    - Key performance metrics, including include # of round-trip trades, Total return (%), Sharpe ratio, B&H Return (%), B&H Sharpe Ratio, Winning Rate (%), Max Drawdown (%), and Calmar Ratio, are computed for each bootstrapped path.

5.2. Discussion

The results of the bootstrapped trading strategy provide insights into its overall performance under different market conditions. On average, the strategy achieves a total return of 71.5354%, which is lower than the buy-and-hold strategy (229.504%). However, its Sharpe ratio (1.8743) is significantly higher than that of buy-and-hold (0.7709), indicating superior risk-adjusted returns. In terms of trading frequency, the strategy executes an average of 18.11 round-trip trades, reflecting moderate trading activity. The winning trade percentage is 45.2327%, slightly below 50%. Hoewever, in some cases, a higher win rate is observed, suggesting that the strategy performs better under certain market conditions.

The average maximum drawdown is 31.8729%, indicating that the strategy may experience capital drawdowns during periods of market volatility. Additionally, the average Calmar ratio is 0.31, suggesting a balanced trade-off between returns and risk management.

In summary, although the bootstrapped trading strategy underperforms the buy-and-hold approach in terms of absolute returns, it achieves higher Sharpe, demonstrating a more attractive risk-adjusted return profile. The complete simulation results table is provided in the Appendix for further reference.

	# of round-trip trades	Total return, %	Sharpe ratio	B&H Return %
Historical	18	51.32	1.839	174.36
Average	18.03	71.5354	1.8743	229.504
	B & H Sharpe Ratio	Winning Rate, %	Max Drawdown, %	Calmar Ratio
Historical	0.751	50.0	22.77	0.379
Average	0.7709	45.2327	31.8729	0.3912

Table 2. Bootstrap Trading Strategy Backtesting Results

6. P/L Distribution Analysis and Significance Test

To evaluate the profitability and risk characteristics of the bootstrapped trading strategy, we analyze the distribution of Profit/Loss (P/L) returns and assess whether the mean total return significantly differs from zero.

6.1. Overall P/L Distribution & Normal Distribution

We construct the empirical distribution of bootstrapped total returns and compare it against a normal distribution fitted to the same mean and standard deviation. The histogram and kernel density estimations (KDE) illustrate the differences in the return distributions.

- Bootstrapped Returns: Representing the distribution of simulated P/L outcomes from the trading strategy.
- Normal Distribution: A theoretical distribution centered at the mean of bootstrapped returns with the same standard deviation.

The bootstrapped return distribution demonstrates several key characteristics that distinguish it from a normal distribution, providing insights into both the potential profitability and risks of the strategy.

1. Significant Right Skewness: The bootstrapped return distribution exhibits asymmetry, with a longer right tail, indicating that the strategy is more likely to generate extreme positive returns rather than extreme losses. This suggests that the strategy may have the potential to capture large profit opportunities.
2. Higher Kurtosis: Compared to the normal distribution, the bootstrapped returns have a higher peak, indicating that most returns are concentrated around the mean. However, the distribution still features fat tails, implying that while returns tend to be stable, significant fluctuations can still occur.
3. Risk and Stability: Although the strategy shows a tendency towards positive returns, the prominent right tail suggests that substantial return fluctuations are still possible. Therefore, when applying this strategy, risk management should be incorporated to mitigate potential losses caused by extreme market volatility.

In summary, the bootstrapped return distribution exhibits significant right skewness, higher kurtosis, and pronounced tail behavior, suggesting a deviation from normality. The strategy shows a tendency towards positive returns with a concentration near the mean, yet the presence of heavy tails indicates that extreme returns—both gains and losses—are more likely than in a normal distribution. This deviation implies that the strategy may exploit market inefficiencies, but also necessitates careful risk management to mitigate potential losses due to market volatility.

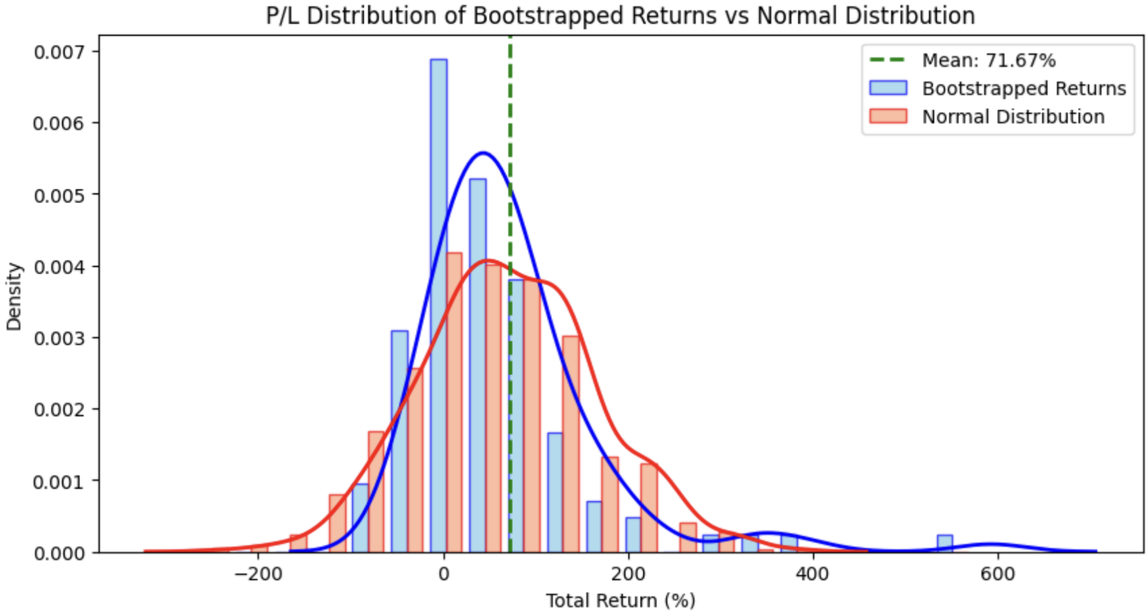

Fig. 4. P/L Distribution of Bootstrapped Returns vs Normal Distribution

6.2. Local P/L Distribution & Normal Distribution

To gain a deeper understanding of the bootstrapped return distribution, we analyze the local distributions. The local distribution, as illustrated in the dataset, primarily covers a return range from -100% to 140%, which represents the most frequently observed returns.

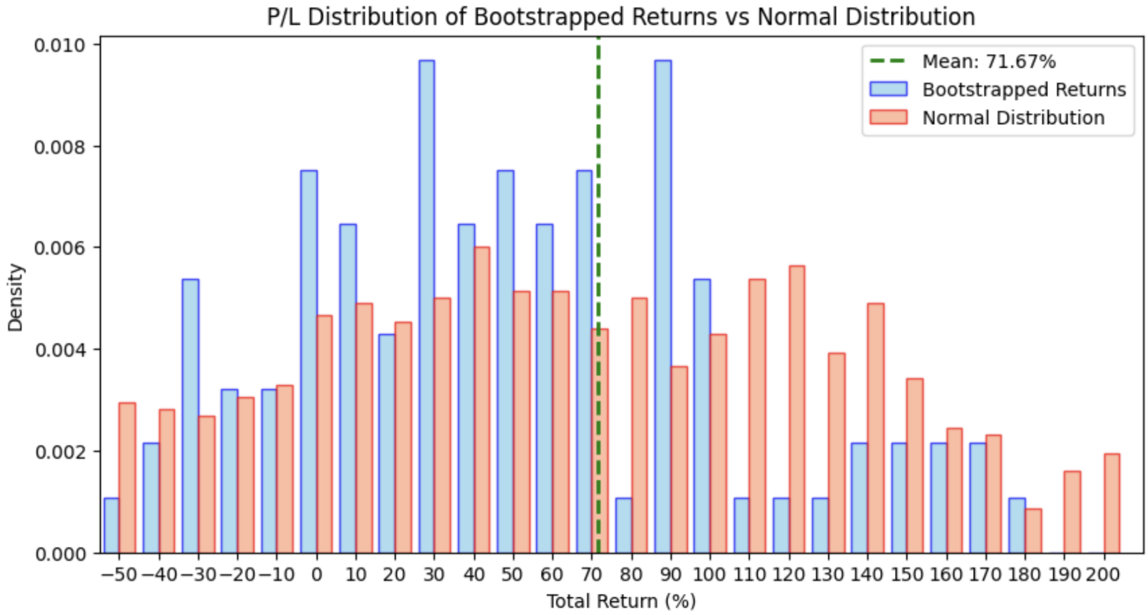

Fig. 5. P/L Distribution of Bootstrapped Returns vs Normal Distribution

Within the P/L range (-50% to 20%), the return distribution exhibits several notable characteristics. First, trading profits are primarily concentrated around 30%, 50%, and 90%, where the density is significantly higher than the expected values from a normal distribution. This suggests that the trading strategy tends to achieve higher frequency at these specific return levels rather than following a uniform distribution. Additionally, there is a certain degree of clustering around -10%, -20%, and -30%, indicating that the strategy may experience substantial drawdowns under certain conditions. However, overall, the concentration of positive returns is higher.

From the histogram, where blue bars represent the strategy's P/L distribution and red bars represent the normal distribution, it is evident that the blue bars at 30%, 50%, and 90% are significantly taller than their corresponding red bars. This indicates that the strategy has a higher likelihood of achieving returns at these specific levels, deviating from the assumption of a normally distributed return profile.
Moreover, LSE values are particularly high in the 30%-50% and above 90% return range, suggesting that the P/L distribution at these levels significantly deviates from a normal distribution.
Overall, this local P/L distribution further confirms the characteristics observed in the overall P/L distribution, namely the presence of right-skewness and high kurtosis.

6.3. Significance Test

6.3.1. t-test Results

To determine whether the trading strategy generates statistically significant returns, we first conducted a t-test on the total return distribution. The null hypothesis (H_0) assumes that the mean total return is zero, while the alternative hypothesis (H_1) states that the mean total return is significantly different from zero.

- Mean Total Return: 71.6742%
- T-statistic: 7.5752
- P-value: 0.0000

Since the p-value is far below 0.05, we reject the null hypothesis and conclude that the mean total return is significantly different from zero. This indicates that the strategy's returns are not driven by random fluctuations but exhibit statistically significant profitability, supporting the hypothesis that the strategy can generate consistent positive returns.

6.3.2. Wilcoxon Signed-Rank Test Results

Although the t-test assumes that returns follow a normal distribution, our P/L distribution analysis indicates that the return distribution may deviate from normality. Specifically, the distribution exhibits right skewness (longer right tail) and high kurtosis, suggesting the presence of extreme values. These characteristics may violate the assumptions of the t-test and affect its validity.
To address this issue, we further conducted the Wilcoxon Signed-Rank Test, a non-parametric test that does not rely on normality assumptions and is used to test whether the median is significantly different from zero.

- Wilcoxon Signed-Rank Test Statistic: 351.0000
- P-value: 0.0000

Since the p-value is far below 0.05, we again reject the null hypothesis and conclude that the median total return is significantly different from zero. This result further strengthens the statistical significance of the trading strategy and is robust to the assumption of normality.
In conclusion, combining the results of the t-test and the Wilcoxon Signed-Rank Test, we confirm that the profitability of the strategy is not a result of random fluctuations, and its statistical significance is validated under different testing methods. This suggests that the strategy is statistically reliable. However, the skewness and kurtosis of the return distribution indicate that special attention should be given to the risk of extreme return fluctuations in risk management.

7. Real-World Market Considerations

Although this study provides an idealized evaluation of the trading strategy's performance through backtesting, several real-world factors may affect the feasibility and final profitability of the strategy. These factors include, but are not limited to, strategy assumption biases and market impact. The following sections discuss these key real-world considerations in detail.

7.1. Strategy Assumption Bias

During backtesting, we assume that all buy and sell orders can be executed at the closing price, meaning the closing price serves as an unbiased estimate for both buying and selling. However, in real market conditions, this assumption does not hold. The use of closing prices for trading in backtests may introduce downward bias [5]. If the filter rule effectively detects trends, real-world execution using limit orders or intraday transactions may achieve better prices, thereby improving profitability. Consequently, the strategy's backtested performance may underestimate its potential returns in actual trading.

7.2. Market Impact

In real trading environments, market depth and liquidity are crucial for trade execution. If there are insufficient buy or sell orders in the market to meet trading demand, traders may be unable to execute transactions at their expected prices. This effect becomes even more pronounced for large transactions.
Additionally, the behavior of market participants can amplify market impact. For example, when large institutional investors execute substantial orders within a short period, their transactions may influence market prices, increasing purchase costs or decreasing selling prices. Moreover, market reactions to large orders may trigger cascading effects among other traders, further exacerbating price fluctuations.

8. P/L Improvement

Although the filter rule trading strategy has demonstrated a certain level of profitability and favorable risk-adjusted returns in backtesting, there is still significant room for optimization. To further enhance the Profit and Loss (P/L) performance, improvements can be made in several areas, including trade execution optimization, strategy parameter adjustments, market signal enhancement, risk management, trading mode upgrades (short selling and high-frequency trading), market selection, and asset diversification.

8.1. Dynamic Optimization of Strategy Parameters

The current strategy employs fixed breakout thresholds, which may not be optimal for all market conditions. Enhancing adaptability through dynamic optimization can improve strategy performance. Adjusting filter rules based on market volatility can help, where breakout thresholds increase in high-volatility markets to avoid noise trades and decrease in low-volatility markets to capture more trading opportunities. Machine learning techniques, such as genetic algorithms [4], can be utilized to dynamically fine-tune trading parameters. Furthermore, segmenting market phases by distinguishing between bullish and bearish market conditions, and refining strategies based on the COVID-19 impact and non-COVID periods from 2020 to 2025, can improve performance in different environments.

8.2. Incorporating Short Selling

The current strategy only considers long trades, which may underperform during market downturns. Introducing short selling can provide additional profit opportunities. Developing a long-short strategy enables taking long positions when the price breaks the upper threshold and short positions when it drops below the lower threshold, allowing performance in diverse market environments. Implementing short selling can improve profitability in bear markets or volatile conditions and stabilize overall P/L performance.

8.3. Shifting Towards High-Frequency Trading (HFT)

The current strategy operates on daily data, limiting trading frequency. Transitioning to High-Frequency Trading may improve capital efficiency, though it introduces execution risks. Utilizing shorter time-frame data, such as minute- or second-level data, can capture brief price movements and increase trading opportunities. Enhancing real-time trading signals by using order flow data and market depth information improves decision-making accuracy. Since HFT strategies depend on ultra-low transaction costs, reducing trading costs through careful exchange selection, commission reduction, and execution efficiency improvements is necessary. HFT can optimize capital utilization but requires a robust infrastructure, including low-latency data, optimized trading APIs, and efficient order execution systems, while carefully managing trading costs.

8.4. Incorporating the Hurst Exponent for Market Selection

Lento's research [2] suggests a correlation between the Hurst exponent and the profitability of technical analysis strategies. The Hurst exponent measures long-term market dependence. When the Hurst exponent is below 0.5, the market exhibits mean-reverting behavior, making trend-following strategies ineffective. When it is approximately

0.5, the market behaves as a random walk, reducing the effectiveness of technical analysis. When it is greater than 0.5, the market exhibits trend-reinforcing behavior, making trend-following strategies more likely to be profitable. Improvements can be made by adjusting strategies based on the Hurst exponent. When the Hurst exponent is greater than 0.5, trend-following strategies such as filter rules and moving average breakouts can be applied. Conversely, when the Hurst exponent is below 0.5, mean-reversion strategies such as Bollinger Bands and RSI-based contrarian trading may be more effective. Additionally, market screening can be improved by calculating the Hurst exponent before entering trades and applying the filter rule strategy only when the Hurst exponent is above 0.5 to enhance success rates. Incorporating the Hurst exponent enables the strategy to adapt to varying market environments and select optimal trading conditions, thereby improving overall profitability.
In addition, Lento's research [2] also points out that in developing countries, the Hurst index is generally higher, which means that these markets are more trend-oriented and better suited to trend-following strategies. Therefore, we can test the strategy in the stock markets of developing countries to assess its applicability and potential profitability.

8.5. Multi-Asset Trading for Risk Diversification

Relying on a single market or asset class may increase exposure to specific risks. Expanding the strategy to multiple assets can reduce risk and enhance P/L stability. Trading across multiple asset classes, such as forex, commodities, and cryptocurrencies, allows for better portfolio diversification. Leveraging inter-asset correlations, such as safe-haven assets like gold or bonds during equity market downturns, enables dynamic capital allocation. By diversifying asset classes, the strategy reduces dependence on a single market, mitigates systemic risks, and enhances capital efficiency.

9. Conclusion

This research provides an empirical evaluation of a filter rule trading strategy applied to Microsoft (MSFT) stock, assessing its performance through historical data and bootstrapped simulations. The strategy demonstrates consistent profitability, albeit with lower total returns compared to a buy-and-hold approach. However, its superior Sharpe ratio indicates a more favorable risk-adjusted return profile, suggesting that it offers an attractive alternative for risk-conscious investors.
Bootstrapped analyses confirm the robustness of the strategy, revealing that returns exhibit right skewness and high kurtosis, implying that certain market inefficiencies may be exploitable. Additionally, statistical tests validate that the strategy's returns are significantly different from zero, reinforcing its effectiveness as a structured trading approach.
Despite these positive findings, the strategy has notable limitations, particularly its reliance on fixed parameter settings. Future research should focus on dynamic optimization techniques. Additionally, exploring its applicability across multiple asset classes and varying market conditions could further refine its utility.
In conclusion, while the filter rule trading strategy presents a structured approach to capitalizing on short-term trends, its effectiveness remains conditional on market conditions and risk tolerance. By incorporating adaptive elements and broadening its scope to diverse trading environments, its potential as a viable trading tool could be further optimized.

References

1. Anatoly B. Schmidt. *Modern Equity Investing Strategies*. World Scientific Publishing Co Pte Ltd, October 2021.
2. Camillo Lento. *Long-term Dependencies and the Profitability of Technical Analysis*. Faculty of Business Administration, Lakehead University, Thunder Bay, Ontario, Canada.
3. Haotian Cai and Anatoly B. Schmidt. *What's So Special about the Time Series Momentum?*. August 22, 2019.
4. Mehmet Ozcalici and Mete Bumin. *Optimizing filter rule parameters with genetic algorithm and stock selection with artificial neural networks for an improved trading: The case of Borsa Istanbul*. Expert Systems with Applications, Vol. 208, 2022, p. 118120. DOI: https://doi.org/10.1016/j.eswa.2022.118120.
5. Richard J. Sweeney. *Some New Filter Rule Tests: Methods and Results*. The Journal of Financial and Quantitative Analysis, Vol. 23, No. 3 (Sep., 1988), pp. 285-300. Published by Cambridge University Press on behalf of the University of Washington School of Business Administration. Stable URL: https://www.jstor.org/stable/2331068.

10. Appendix

Bootstrap Result

Sample	# of round-trip trades	Total return, %	Sharpe Ratio	B & H return, %
Historical	18	51.32	1.839	174.36
B1	16	42.66	1.78	119.04
B2	21	91.62	1.76	424.8
B3	16	592.77	2.87	1629.45
B4	16	226.05	2.29	557.04
B5	17	51.59	2.23	190.41
B6	17	69.16	2	269.4
B7	18	39.13	2.33	243.1
B8	19	8.11	1.54	87.73
B9	15	52.04	2.21	25.23
B10	18	148.01	2.46	513.2
B11	17	73.72	1.82	183.65
B12	17	175.41	2.5	642.88
B13	17	33.41	1.56	192.26
B14	20	31.91	1.43	217.98
B15	15	162.62	2.54	426.87
B16	19	-16.85	1.65	57.62
B17	18	99.81	2.28	263.36
B18	17	67.92	1.99	70.24
B19	14	159.92	2.75	238.3
B20	18	-39.17	0.46	-19.15
B21	15	72.44	1.77	90.49
B22	14	94.17	2.34	64.36
B23	16	179.7	2.57	314.98
B24	16	21.26	1.44	37.62
B25	19	-1.25	1.36	97.51
B26	15	391.92	3.67	821.54
B27	16	41.04	1.55	44.61
B28	22	-19.49	1.25	96.76
B29	16	10.4	1.54	77.93
B30	22	-28.74	1.17	29.53
B31	18	33.4	1.69	140.25
B32	19	2.79	1.53	142.12
B33	15	107.41	2.19	178.75
B34	19	68.32	2.17	326.74
B35	17	108.04	2.06	196.98
B36	19	95.6	2.05	353.43
B37	18	71.65	2.11	249.15
B38	20	-20.06	1.31	69.7
B39	15	115.39	2.65	73.34
B40	14	340.89	2.28	625.45
B41	19	53.36	2.09	223.46
B42	18	71.14	1.58	252.65
B43	18	95.54	2.07	219.95

B44	19	14.51	1.33	169.39
B45	19	-8.23	1.44	68.89
B46	21	6.34	1.35	141
B47	21	13.82	1.41	242.15
B48	19	67.48	1.93	338.13
B49	19	44.37	1.69	192.67
B50	22	-23.18	1.18	167.28
B51	19	-14.12	1.08	-21.8
B52	21	2.84	1.86	159.76
B53	23	5.74	1.95	210.93
B54	20	21.09	1.54	219.76
B55	18	105.79	2.76	222.16
B56	20	-28.98	0.76	38.67
B57	18	18.35	1.52	126.13
B58	17	151.08	2.84	291.47
B59	15	30	1.96	15.06
B60	16	55.33	1.82	148.2
B61	18	51.07	1.74	182.22
B62	24	-51.55	0.79	27.67
B63	16	67.84	2.15	150.12
B64	17	40.8	2.01	-15.34
B65	20	22.72	1.62	59.46
B66	22	-2.37	1.07	160.23
B67	16	188.53	2.49	267.75
B68	15	165.03	2.86	137.69
B69	14	139.9	1.7	501.29
B70	19	90.75	1.94	415.57
B71	20	3.89	1.6	115.79
B72	23	-40.45	0.94	92.67
B73	16	75.62	2.09	205.83
B74	17	128.38	2.44	258.1
B75	17	95.25	2.1	344.16
B76	17	109.18	2.38	239.25
B77	16	79.6	1.76	198.4
B78	17	47.35	1.79	122.53
B79	18	71.85	1.9	395.61
B80	21	36.56	1.97	423.4
B81	18	109.88	1.89	322.01
B82	17	68.82	1.83	259.7
B83	21	98.5	2.32	475.85
B84	16	224.02	2.4	489.22
B85	17	91.46	2	325.89
B86	19	29.53	1.43	211.62
B87	20	44.38	2.13	180.13
B88	18	32.8	1.5	142.66
B89	20	3.86	1.7	99.15

B90	19	16.16	1.54	221.27
B91	16	39.43	1.7	62.91
B92	23	-25.2	0.94	133.11
B93	18	12.34	1.83	88.24
B94	15	148.4	2.13	300.92
B95	18	80.86	1.52	335.27
B96	17	339.34	2.95	863.92
B97	17	34.03	2.42	-21.97
B98	18	50.42	2.26	154.46
B99	21	-39.87	0.59	71.92
B100	20	37.44	1.7	161.16
Average	18.03	71.5354	1.8743	229.504

Sample	B & H Sharpe Ratio	Winning trades, %	Max drawdown, %	Calmar Ratio
Historical	0.751	50	22.77	0.379
B1	0.6	31.25	28.27	0.26
B2	1.16	42.86	38.85	0.36
B3	2.03	62.5	18.37	2.57
B4	1.25	50	28.71	0.93
B5	0.77	41.18	34.77	0.25
B6	0.95	29.41	31.65	0.35
B7	0.9	44.44	38.16	0.18
B8	0.5	52.63	42.28	0.04
B9	0.24	53.33	28.7	0.3
B10	1.25	50	23.03	0.87
B11	0.75	35.29	21.94	0.53
B12	1.35	52.94	26.93	0.83
B13	0.8	47.06	28.47	0.21
B14	0.85	50	25.45	0.22
B15	1.21	73.33	23.18	0.92
B16	0.38	31.58	49.17	-0.07
B17	0.98	38.89	26.27	0.57
B18	0.45	52.94	26.14	0.42
B19	0.94	78.57	16.18	1.3
B20	-0.06	27.78	50.41	-0.19
B21	0.53	33.33	24.56	0.47
B22	0.42	64.29	25.51	0.56
B23	1.02	43.75	33.76	0.68
B24	0.3	37.5	25.21	0.16
B25	0.55	36.84	47.68	-0.01
B26	1.49	66.67	21.75	1.73
B27	0.33	50	21.99	0.32
B28	0.53	31.82	56.23	-0.08
B29	0.47	31.25	36.1	0.06
B30	0.26	31.82	50.6	-0.13
B31	0.67	38.89	32.67	0.18
B32	0.67	42.11	32.85	0.02
B33	0.76	26.67	34.13	0.46
B34	1	42.11	26.32	0.42
B35	0.8	35.29	25.58	0.62
B36	1.09	47.37	33.19	0.43
B37	0.96	38.89	37	0.31
B38	0.44	30	32.49	-0.13
B39	0.45	46.67	22.87	0.73
B40	1.42	78.57	15.61	2.21
B41	0.88	42.11	53.91	0.17
B42	0.93	55.56	21.13	0.54
B43	0.85	61.11	20.85	0.69

B44	0.74	36.84	45.73	0.06
B45	0.44	36.84	30.74	-0.06
B46	0.67	38.1	35.4	0.03
B47	0.93	42.86	40.93	0.06
B48	1.05	57.89	26.43	0.41
B49	0.79	42.11	26.45	0.29
B50	0.74	45.45	42.05	-0.12
B51	-0.07	26.32	34.08	-0.09
B52	0.69	38.1	29.03	0.02
B53	0.81	47.83	27.61	0.04
B54	0.81	45	29.38	0.13
B55	0.85	50	29.73	0.52
B56	0.3	30	42.68	-0.16
B57	0.62	61.11	29.08	0.12
B58	1.01	52.94	20.06	1.01
B59	0.18	33.33	39.86	0.14
B60	0.69	50	37.43	0.25
B61	0.76	55.56	18.97	0.45
B62	0.25	20.83	60.39	-0.22
B63	0.68	62.5	29.94	0.36
B64	0	47.06	37.62	0.19
B65	0.4	45	24.35	0.17
B66	0.7	36.36	34.58	-0.01
B67	0.94	75	24.59	0.96
B68	0.64	53.33	20.11	1.07
B69	1.32	57.14	34.39	0.56
B70	1.24	36.84	28.91	0.48
B71	0.59	40	24.59	0.03
B72	0.51	34.78	55.8	-0.18
B73	0.79	43.75	28.11	0.42
B74	0.9	52.94	24.05	0.75
B75	1.11	58.82	20.66	0.69
B76	0.92	52.94	20.73	0.77
B77	0.82	50	32.03	0.39
B78	0.58	35.29	26.21	0.31
B79	1.14	44.44	30.04	0.38
B80	1.15	47.62	42.42	0.15
B81	1.05	50	18.58	0.86
B82	0.93	29.41	36.04	0.31
B83	1.3	52.38	31.18	0.47
B84	1.27	68.75	18.57	1.43
B85	1.05	35.29	32.88	0.42
B86	0.86	42.11	32.03	0.17
B87	0.75	40	36.16	0.21
B88	0.66	50	30.24	0.19
B89	0.54	35	47.88	0.02

B90	0.82	47.37	32.25	0.09
B91	0.41	43.75	25.01	0.27
B92	0.64	30.43	46.95	-0.12
B93	0.51	38.89	35.99	0.07
B94	0.99	46.67	31.23	0.64
B95	1.11	50	23.86	0.53
B96	1.56	58.82	23.35	1.48
B97	-0.05	52.94	31.54	0.19
B98	0.72	38.89	38.37	0.22
B99	0.44	19.05	58.83	-0.16
B100	0.72	50	32.27	0.2
Average	0.7709	45.2327	31.8729	0.3912

P/L Distribution of Bootstrapped Returns vs Normal Distribution

P/L, %	Count	Density	N(F1,G1)	LSE
-50	1	0.01075269	0.00183822	7.95E-05
-40	2	0.02150538	0.00209686	0.00037669
-30	5	0.05376344	0.00236506	0.00264179
-20	3	0.03225807	0.00263763	0.00087737
-10	3	0.03225807	0.00290862	0.00086139
0	7	0.07526882	0.00317146	0.00519803
10	6	0.06451613	0.00341925	0.00373283
20	4	0.04301075	0.00364504	0.00154966
30	9	0.09677419	0.00384215	0.00863637
40	6	0.06451613	0.00400447	0.00366166
50	7	0.07526882	0.00412682	0.00506118
60	6	0.06451613	0.0042052	0.00363741
70	7	0.07526882	0.00423699	0.00504552
80	1	0.01075269	0.00422112	4.27E-05
90	9	0.09677419	0.00415812	0.00857774
100	5	0.05376344	0.00405012	0.00247142
110	1	0.01075269	0.00390065	4.70E-05
120	1	0.01075269	0.00371455	4.95E-05
130	1	0.01075269	0.00349764	5.26E-05
140	2	0.02150538	0.00325645	0.00033302
150	2	0.02150538	0.00299787	0.00034253
160	2	0.02150538	0.00272886	0.00035256
170	2	0.02150538	0.00245612	0.00036287
180	1	0.01075269	0.00218584	7.34E-05
190	0	0	0.00192347	3.70E-06
200	0	0	0.00167361	2.80E-06