eToro
Returns to Buying Winners and Selling Losers Implications for Stock Market Efficiency

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Abstract

This report explores the momentum strategy as outlined by Jegadeesh and Titman (1993) in their seminal work, "Returns to Buying Winners and Selling Losers." The strategy is replicated using U.S. stock market data from 2004 to 2024. Additionally, machine learning techniques are employed to enhance the performance of the traditional momentum strategy, offering insights into the potential improvements in predictive accuracy and return generation.

1 Replicating the Momentum Strategy

Using the relative strength strategy outlined in the paper under the "Trading Strategies" section, Applying this approach to U.S. market data spanning from 2004 to 2024. As shown in Fig 1, the strategy involves buying stocks that have shown strong past performance (winners) and selling those with weaker performance (losers). Specifically, ranking stocks based on their prior 12 months' returns (formation period) and hold these positions for the following 3 months.

1.1 Portfolio Construction Details

The initial 12 months (2004) serve as the formation period, and thus, portfolio transactions—both long and short—begin in January 2005, continuing until June 2024, which is 3 months before the end of the available data set.

The list of S&P 500 companies was sourced from Wikipedia, and each company's historical presence during this time frame was verified. As a result, 382 companies were included in this analysis.

The strategy employs a zero-cost portfolio by balancing the top decile of stocks (winners) against the bottom decile (losers) each month.

To calculate the *Sharpe Ratio*, the risk-free rate was derived from the CBOE 10-Year Treasury Note Yield Index.

To increase the power of our tests, the strategies we examine include portfolios with overlapping holding periods. Therefore, in any given month t, the strategies hold a series of portfolios that are selected in the current month as well as in the previous $K-1$ months, where K is the holding period. Specifically, a strategy that selects stocks on the basis of returns over the past J months and holds them for K months (we will refer to this as a J-month/K-month strategy) is constructed as follows: At the beginning of each month t the securities are ranked in ascending order on the basis of their returns in the past J months. Based on these rankings, ten decile portfolios are formed that equally weight the stocks contained in the top decile, the second decile, and so on. The top decile portfolio is called the "losers" decile and the bottom decile is called the "winners" decile. In each month t, the strategy buys the winner portfolio and sells the loser portfolio, holding this position for K months. In addition, the strategy closes out the position initiated in month $t-K$. Hence, under this trading strategy we revise the weights on $\frac{1}{K}$ of the securities in the entire portfolio in any given

Figure 1: The momentum strategy

1.2 Results

The portfolios, constructed with overlapping holding periods, exhibited an average return of -11.82% with a p-value of 35%. To explore the reasons for this poor performance, a time series of the portfolio performance was generated (see Fig. 2) which clearly indicates increasing volatility over time.
In order to investigate this further, an examination was made of a sub-period with a cut-off date of December 2017, chosen based on the findings in "Enhanced momentum strategies by Matthias X.Hanauer et al." [3], which covers data from 1930-2017. The sub-period examined is from 2004 to 2017.

Metric	**Value**
Annualized Return	-0.0564
Volatility	0.1864
Sharpe Ratio	-16.2057
Max Drawdown	-0.8200
VaR (1%)	-0.1283
VaR (5%)	-0.0868
Alpha	-0.7609

Table 1: Performance Metrics (2004-2024)

2004 - 2017 metrics results:
The momentum strategy results in losses over both periods. However, the

Metric	Value
Annualized Return	-0.0386
Volatility	0.2019
Sharpe Ratio	-14.8723
Max Drawdown	-0.7195
VaR (1%)	-0.1701
VaR (5%)	-0.0812
Alpha	-0.5474

Table 2: Performance Metrics (2004-2017)

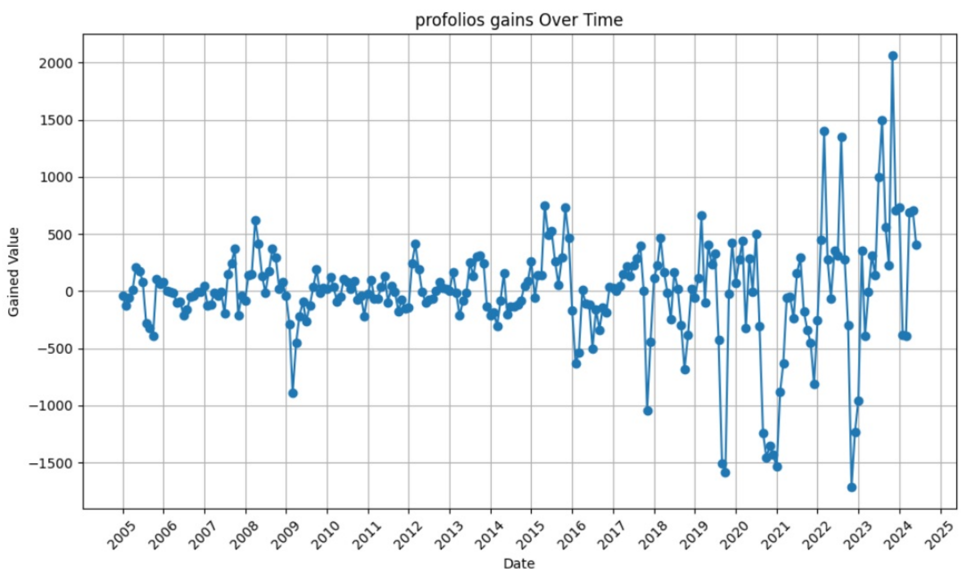

Figure 2: Portfolios gain over time

losses decrease when focusing on the shorter period from 2004 to 2017. As seen in Fig. 3, there is a relatively flat period between 2004 and 2008, following clear upward market trend begins in 2009. This indicates that the early years of the dataset may bias the overall results.

1.3 Code

- **"Momentum_Strategy"** - notebook for the momentum strategy.

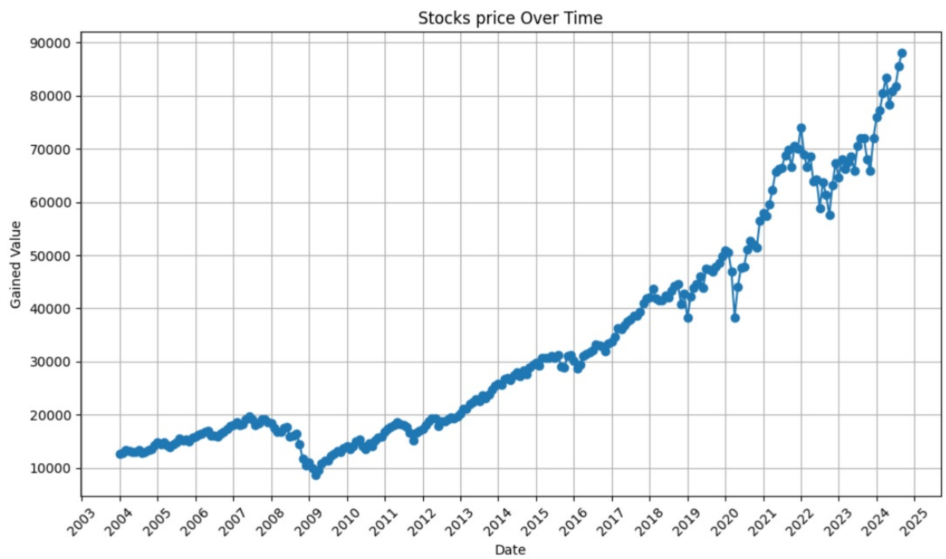

Figure 3: Stock prices over time

2 Enhanced Momentum Strategy

2.1 Assumption

In their study “Market Dynamics and Momentum Profits“ by Gloria Yuan Tian et al. [1] document that there are higher momentum returns when markets continue in the same state than when they transition to a different state. Furthermore, in “Enhanced Momentum Strategies“ by Pedro Barroso et al. [3] the authors compare three enhanced momentum strategies based on volatility scaling, which is grounded in the empirical observation that returns tend to be lower during periods of high volatility. Consequently, a strategy has been developed to predict increases in volatility prior to a trend transition.

Based on these findings, 4 variability features were extracted across 5 time periods, resulting in a total of 20 features.

The 4 variability features are as follows::

- **Open Price** - Monthly standard deviation normalized by its average.
- **Volume** - Monthly standard deviation normalized by its average.
- **Price Fluctuations** - The calculation for the difference between the closing and opening prices of each day.
- **Sharpe Ratio** - The Sharpe ratio.

The 5 time periods are: 1 year, first quarter, second quarter, third quarter, fourth quarter.

2.2 Enhanced momentum strategy

The enhanced momentum strategy builds upon the original momentum strategy by incorporating a decision-making process regarding whether to buy stocks in the top decile and a similar approach for short-selling stocks in the lower decile.

The decision-making process employs models that utilizes the aforementioned 20 features to determine whether to buy or sell a stock. Two separate models were trained: one for buying and another for selling.

The buying model was trained using two types of data, which indicated whether the price of a stock marked for buying would rise (indicating a buy) or fall (indicating not to buy). The labels were assigned accordingly: *w_stocks_higher*, *w_stocks_lower*. Similarly The selling model was trained using two types of data, if stock marked for selling would rise (indicating not to buy) or fall (indicating a buy): *l_stocks_higher*, *l_stocks_lower*.

2.3 Data visualization

To gain broader insights into the performance of this strategy, time series graphs were generated for each of the 20 features, both for stocks marked as buys and stocks marked as sells. The goal was to visually detect any trends or abnormalities. In Quarters 1 and 2, stocks marked as buys, whose prices increased, exhibited lower absolute Sharpe ratios, Fig.21 and Fig.12. Conversely, in Quarter 1, Fig.16, stocks marked as sells, whose prices decreased, showed higher absolute Sharpe ratios. Although these observations are limited, they provide some support for the initial assumption.

2.4 Model specifics

Each model was trained using grid search to optimize various hyper-parameters in 10 fold cross-validation across two different decision tree models: Random Forest and Gradient Boosting.

The train/test split for both models was 6383/2736, with the training set comprising the first 70% of the data and the test set comprising the remaining 30%. The data distribution for the buying model is illustrated in Fig. 10/Fig. 5 and for the sell model in Fig. 8/Fig. 9. The split is ∼60%/∼40% in favor of the stocks that their price went down

The best-fitted model for the stocks identified for purchase is the Random Forest, which demonstrates the following performance metrics on the buying test set can be seen in Table 3. While the best model for the stocks identified for sale is also the Random Forest, which exhibits the following performance metrics on the selling test set can be seen in Table 4.

The feature importance for the buying model is illustrated in Fig.7 and for the selling model is illustrated in Fig.6.

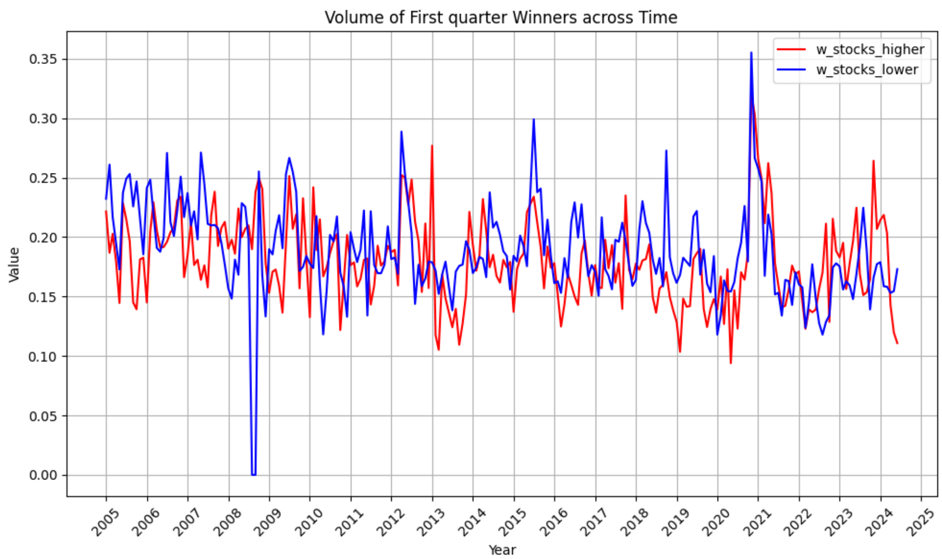

Figure 4: First quarter trading volume for stocks marked as winners

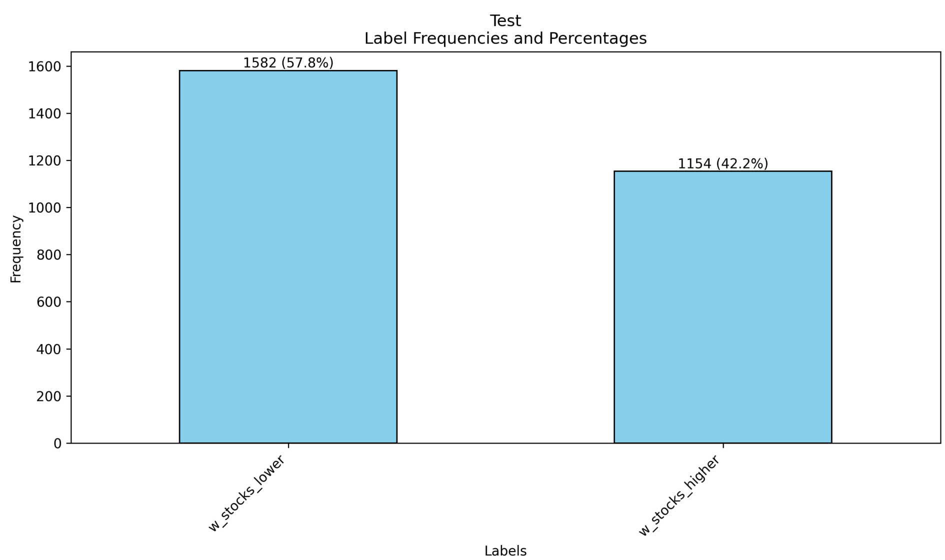

Figure 5: Test dataset for stocks marked as winners

2.5 Results

For simplicity, the risk-free rate was computed as the average of the historical risk-free rates over the collected period. The test dataset, spanning from August

Table 3: Buying Model Performance Metrics

Metric	**Value**
Precision	0.5533
Recall	0.5491
F1	0.5491

Table 4: Selling Model Performance Metrics

Metric	**Value**
Precision	0.5869
Recall	0.5548
F1	0.5548

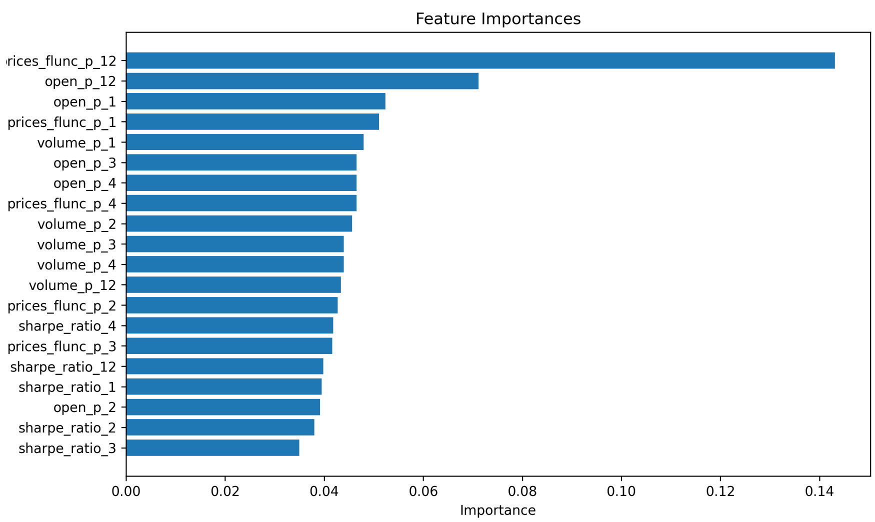

Figure 6: Selling model feature importance

2018 to June 2014, was applied to both strategies.

The results for the enhanced momentum strategy are presented in Table 5, while the results for the original momentum strategy are provided in Table 6.

2.6 Code

- **"feature_visualization"** - notebook for visualization.
- **"ML"** - notebook for the enhanced momentum strategy.

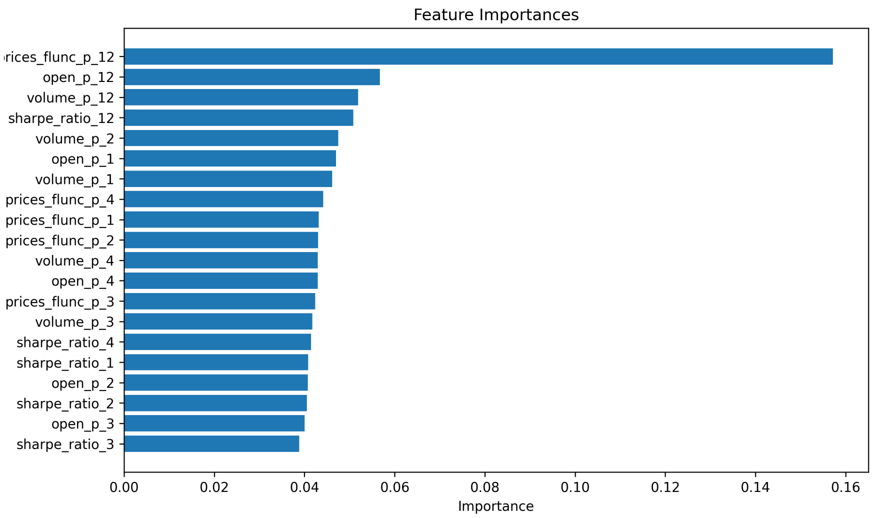

Figure 7: Buying model feature importance

Metric	**Value**
Annualized Return	-0.1544
Volatility	0.2355
Sharpe Ratio	-13.2393
Max Drawdown	-0.7116
VaR 1%	-0.1764
VaR 5%	-0.1444
Alpha	-1.9588

Table 5: Performance Metrics of Enhanced Momentum Strategy

Metric	**Value**
Annualized Return	-0.1129
Volatility	0.1609
Sharpe Ratio	-19.1239
Max Drawdown	-0.6028
VaR 1%	-0.1051
VaR 5%	-0.0955
Alpha	-1.4653

Table 6: Metrics of Original Momentum Strategy

3 Conclusions and Discussion

- **Overall Results** Both the enhanced and original momentum strategies produced poor results across all tests. Given that several studies, such as [2] and [3], have demonstrated that volatility-scaling can enhance the performance of momentum strategies, and considering the high p-values associated with my findings, it is likely that there may be an issue with the code or that the data used in this analysis is either unreliable or unsuitable for replicating the original results.

- **Data Considerations** Several factors may explain the observed discrepancies:

  - **Price Adjustment** The momentum strategy used the open price, with gains calculated including dividends. However, an adjusted closing price might be more appropriate, especially when accounting for stock splits, which could impact returns.

  - **Black Swan Events** The dataset used for this analysis encompasses a higher frequency and severity of black swan events compared to the original study. These include the *Dot-Com Bubble (2000–2002)*, *Global Financial Crisis (2008)*, *Flash Crash (2010)*, *COVID-19 Pandemic (2020)*, and *Russian Invasion of Ukraine (2022)*. In contrast, the original period examined only a few major disruptions, such as the *1973 Oil Crisis* and *Black Monday (1987)*.

  - **Survivorship Bias** The dataset only includes companies that have survived until 2024, potentially skewing results by excluding firms that were delisted or failed, which are often classified as "losers" in momentum strategies. This bias may distort performance metrics.

  - **Market Efficiency** Over time, as momentum strategies have become more widely adopted, markets may have become more efficient in pricing momentum-driven opportunities. This heightened efficiency, combined with the rapid dissemination of information, could reduce the potential for abnormal returns.

- **Enhanced Momentum Strategy**

  - **Sharpe Ratio** Interestingly, in the feature importance analysis, the Sharpe ratio highest ranking among the models is only fourth in significance, which is unexpected given initial assumptions about its influence.

  - **Model Performance** Despite incorporating more sophisticated features such as volatility scaling and decision-making across 20 variables, the enhanced model still underperformed. This suggests that the selected features may not have been effective in identifying optimal stocks. This is further evidenced by the fact that only one feature demonstrated exceptionally high importance, while the others exhibited low, uniform significance.

– **Model Features** The model currently measures only the magnitude of variables, which may not be sufficient. Converting these scalar values into vector-based metrics, such as capturing the trend direction by comparing data against moving averages rather than overall averages, could yield better results.

Further research is needed, particularly to replicate the original study's results using the same dataset. Extending the analysis to data up to 2024 for validation could provide additional insights. However, replicating the original results falls outside the scope of the current assignment.

References

[1] Ebenezer Asem and Gloria Tian. "Market Dynamics and Momentum Profits". In: *Journal of Financial and Quantitative Analysis* 45 (Dec. 2010), pp. 1549–1562. DOI: `10.2139/ssrn.1009318`.

[2] Pedro Barroso and Pedro Santa-Clara. "Momentum has its moments". In: *Journal of Financial Economics* 116.1 (2015), pp. 111–120. ISSN: 0304-405X.

[3] Matthias X. Hanauer and Steffen Windmüller. "Enhanced momentum strategies". In: *Journal of Banking Finance* 148 (2023), p. 106712. ISSN: 0378-4266. DOI: `https://doi.org/10.1016/j.jbankfin.2022.106712`. URL: `https://www.sciencedirect.com/science/article/pii/S0378426622002928`.

4 Appendix

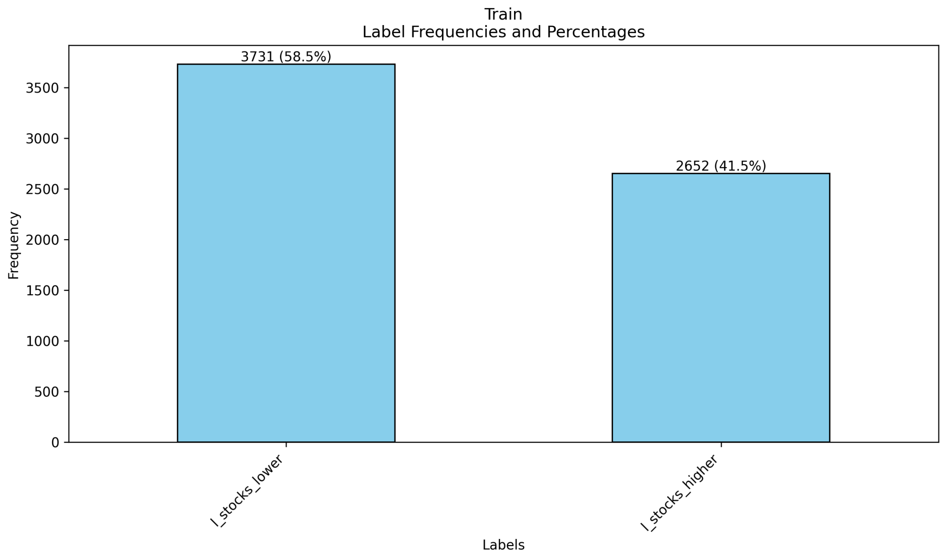

Figure 8: Train dataset for stocks marked as losers

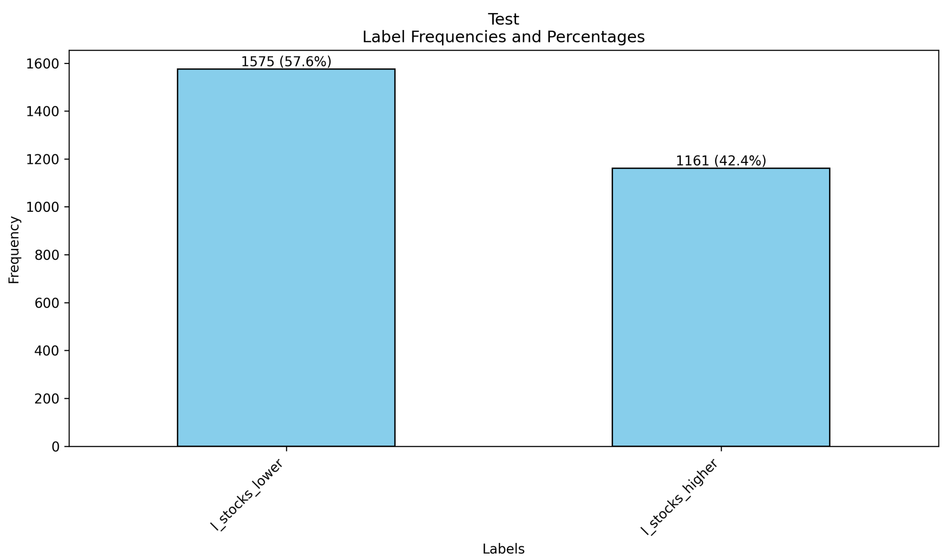

Figure 9: Test dataset for stocks marked as losers

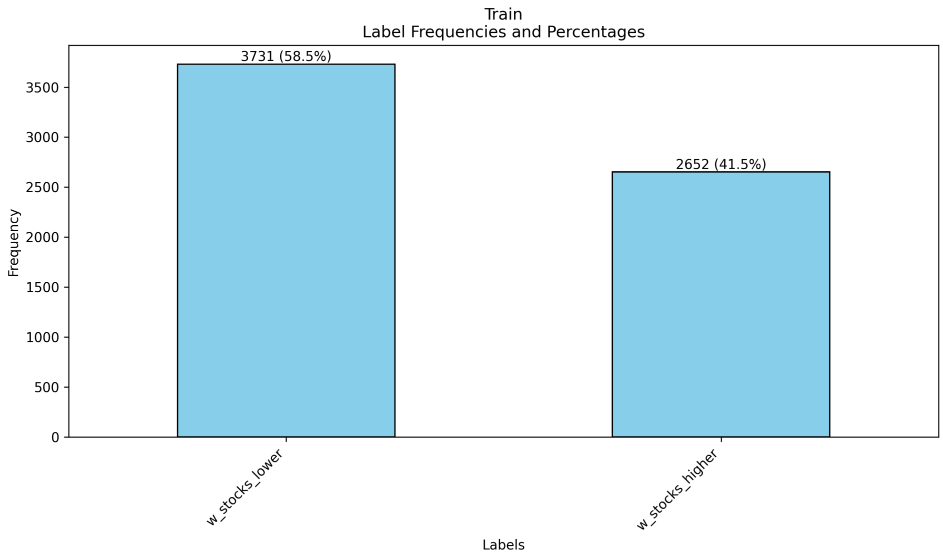

Figure 10: Train dataset for stocks marked as winners

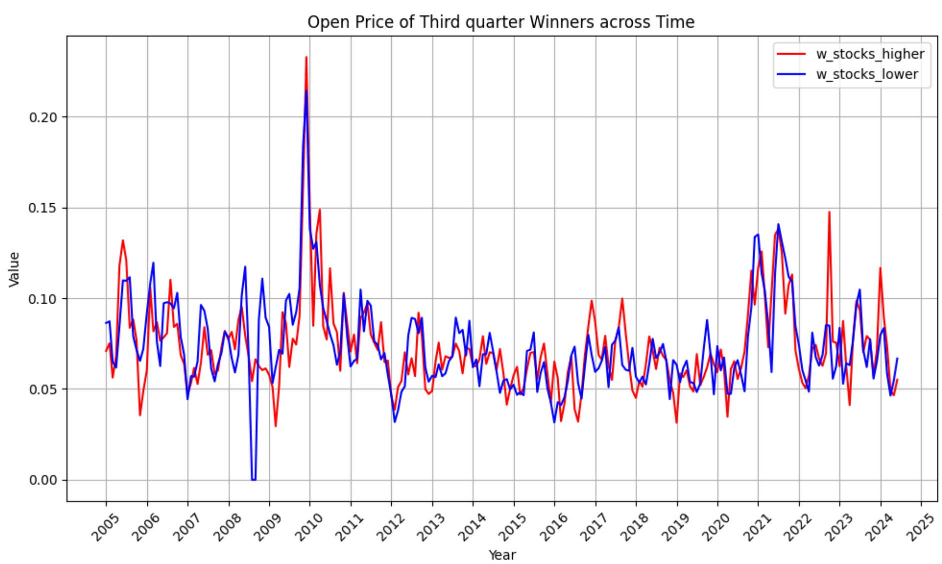

Figure 11: Third quarter open prices for stocks marked as winners

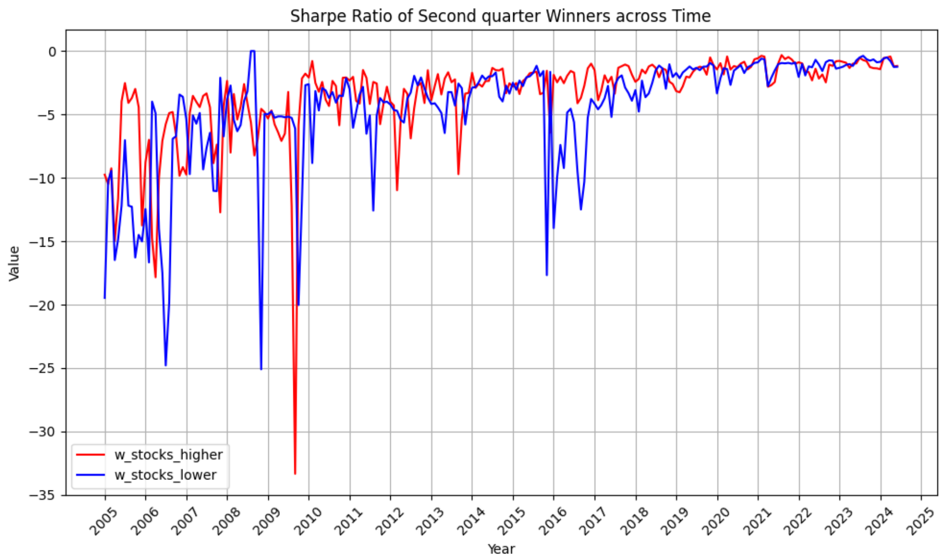

Figure 12: Second quarter Sharpe ratio for stocks marked as winners

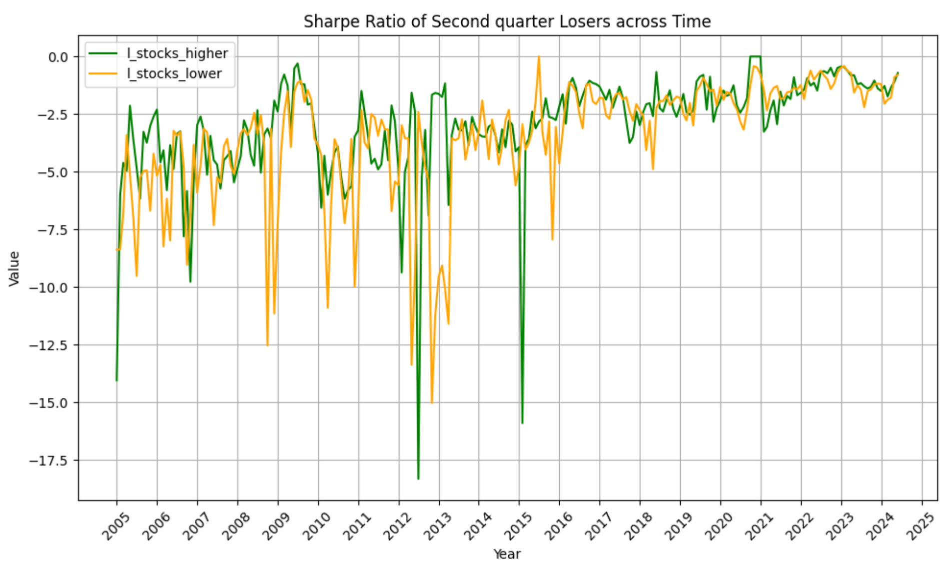

Figure 13: Second quarter Sharpe ratio for stocks marked as losers

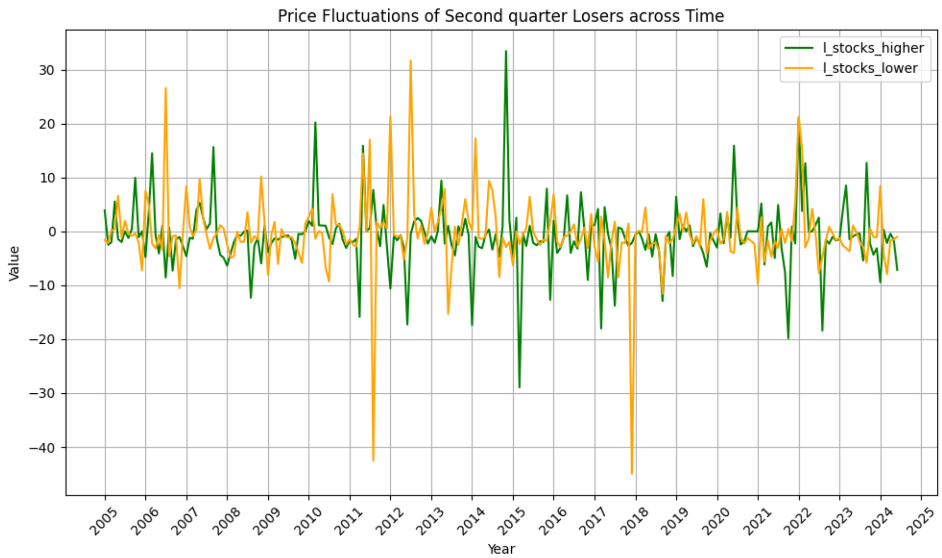

Figure 14: Second quarter price fluctuations for stocks marked as losers

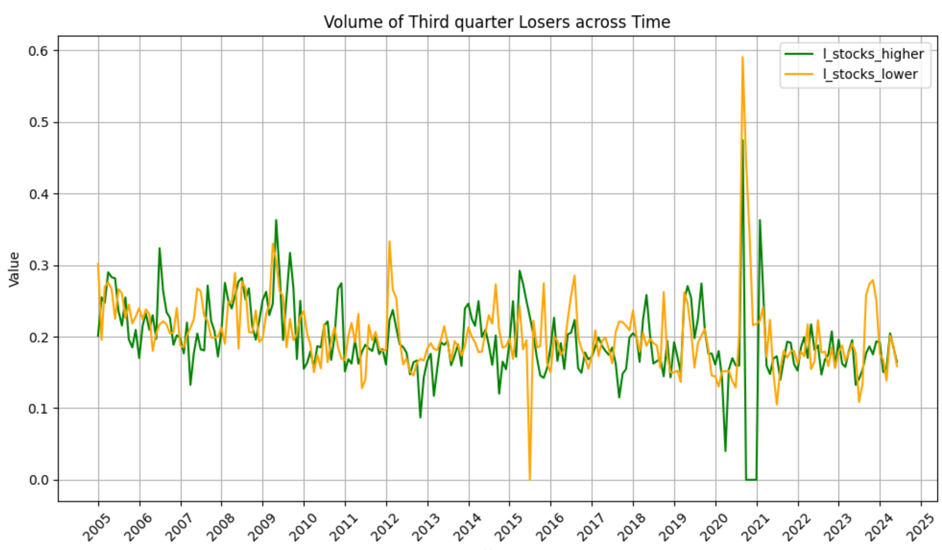

Figure 15: Third quarter trading volume for stocks marked as losers

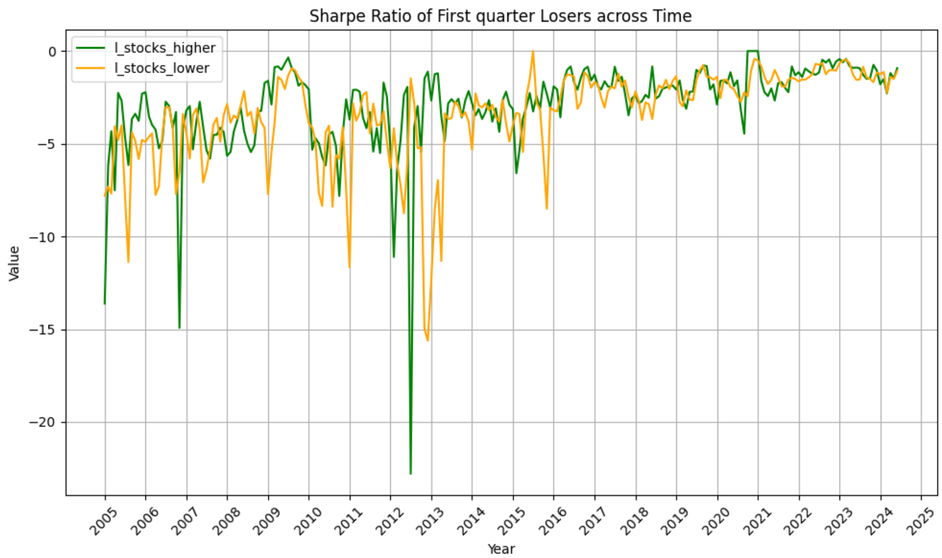

Figure 16: First quarter Sharpe ratio for stocks marked as losers

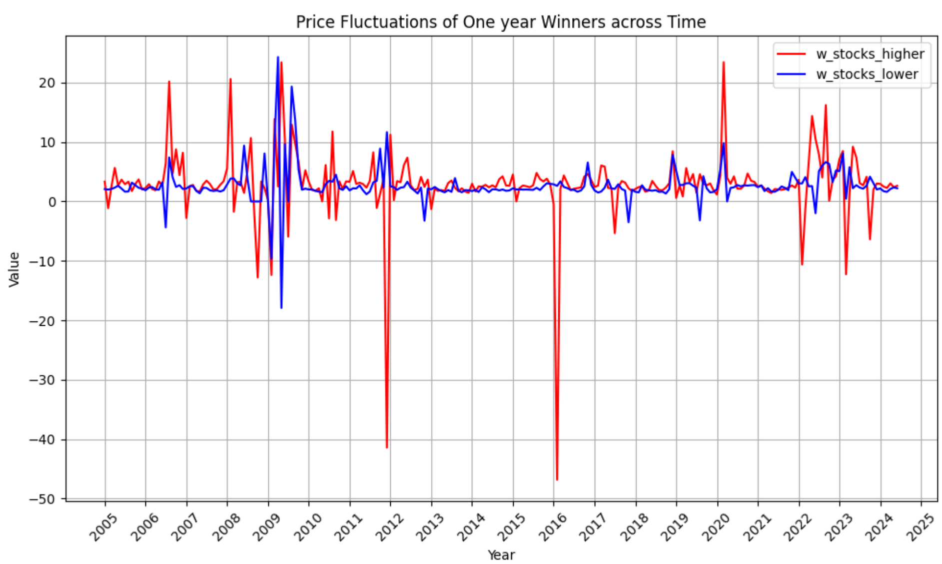

Figure 17: One year price fluctuations for stocks marked as winners

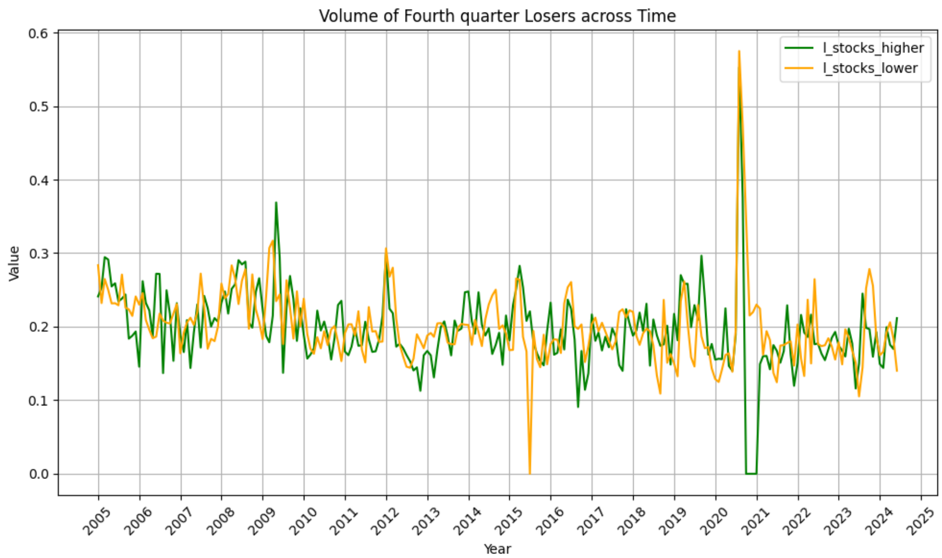

Figure 18: Fourth quarter trading volume for stocks marked as losers

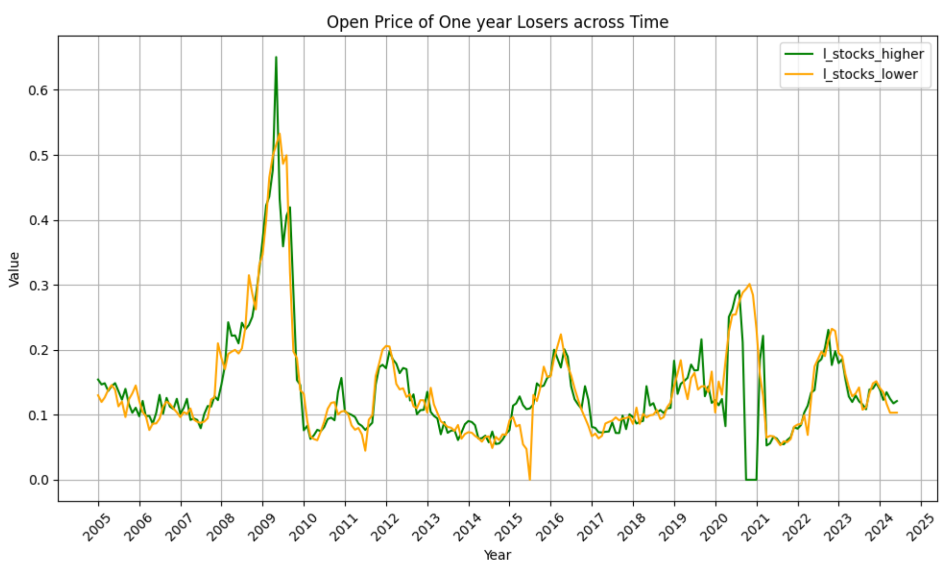

Figure 19: One year open prices for stocks marked as losers

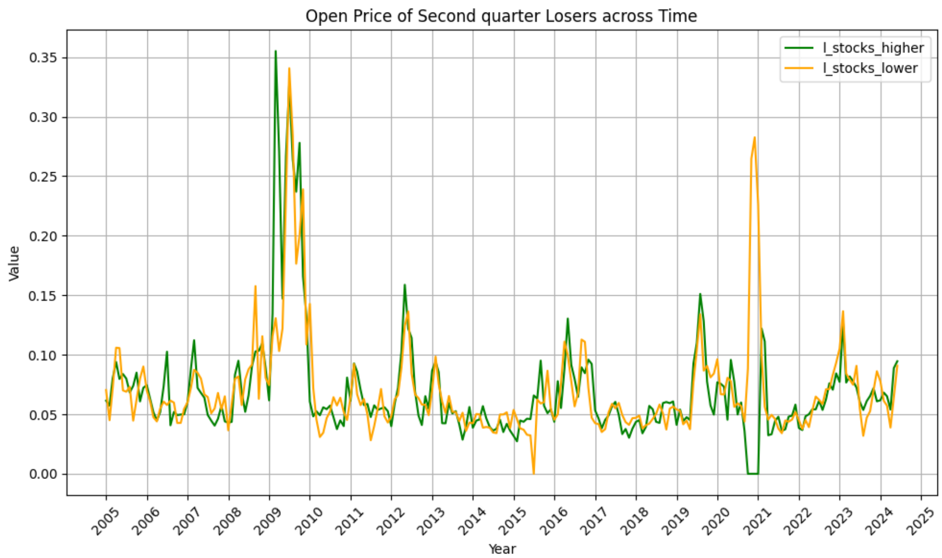

Figure 20: Second quarter open prices for stocks marked as losers

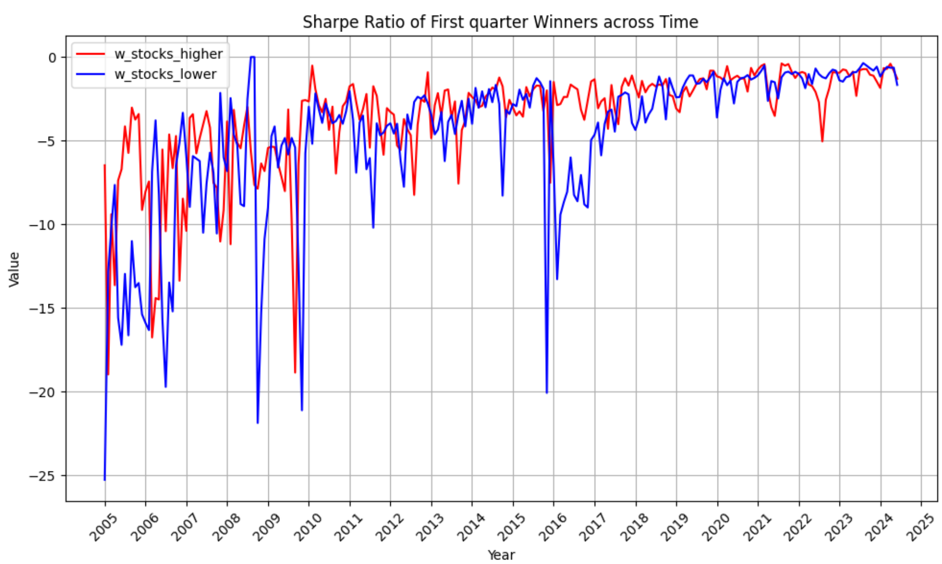

Figure 21: First quarter Sharpe ratio for stocks marked as winners

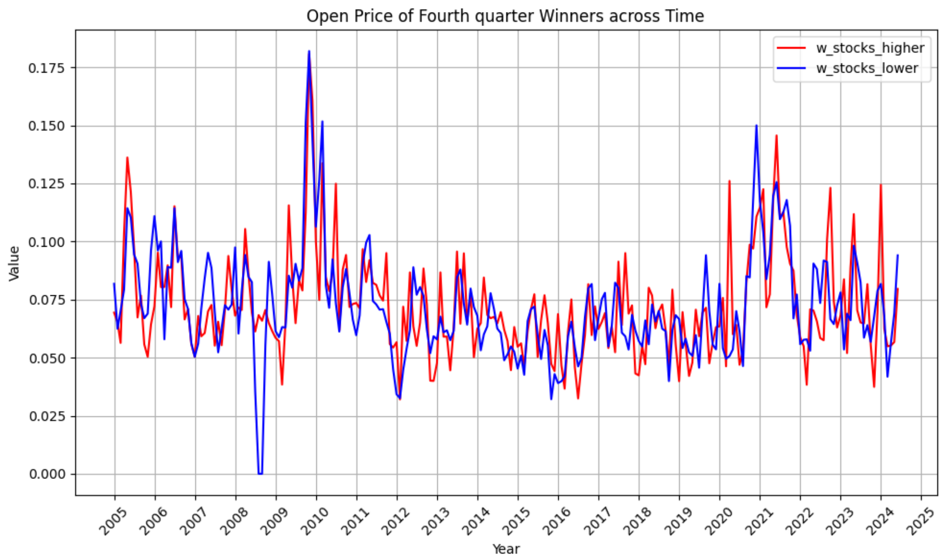

Figure 22: Fourth quarter open prices for stocks marked as winners

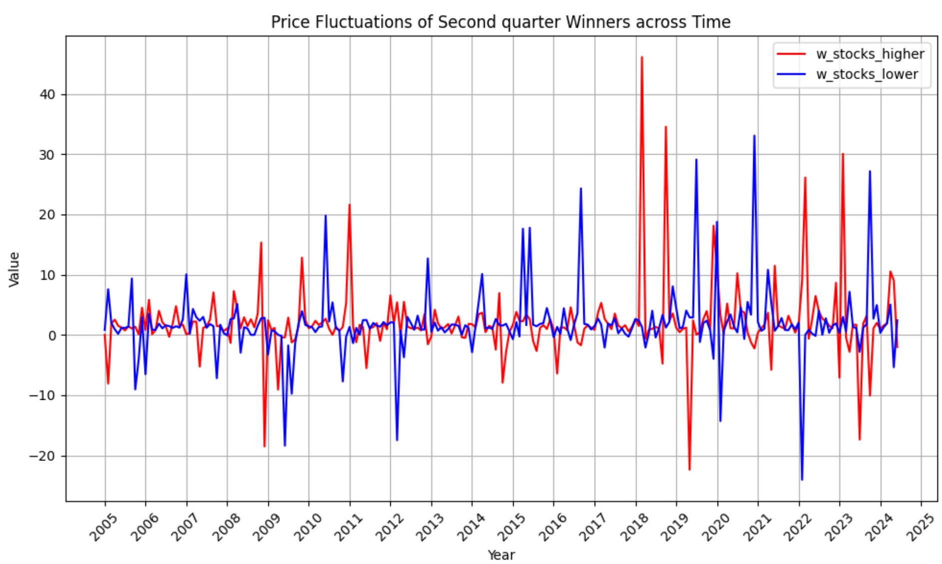

Figure 23: Second quarter price fluctuations for stocks marked as winners

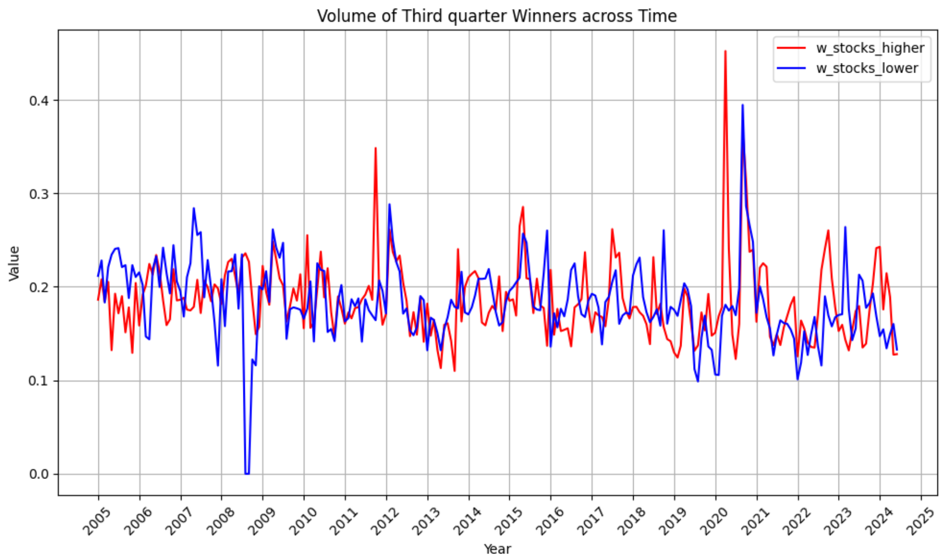

Figure 24: Third quarter trading volume for stocks marked as winners

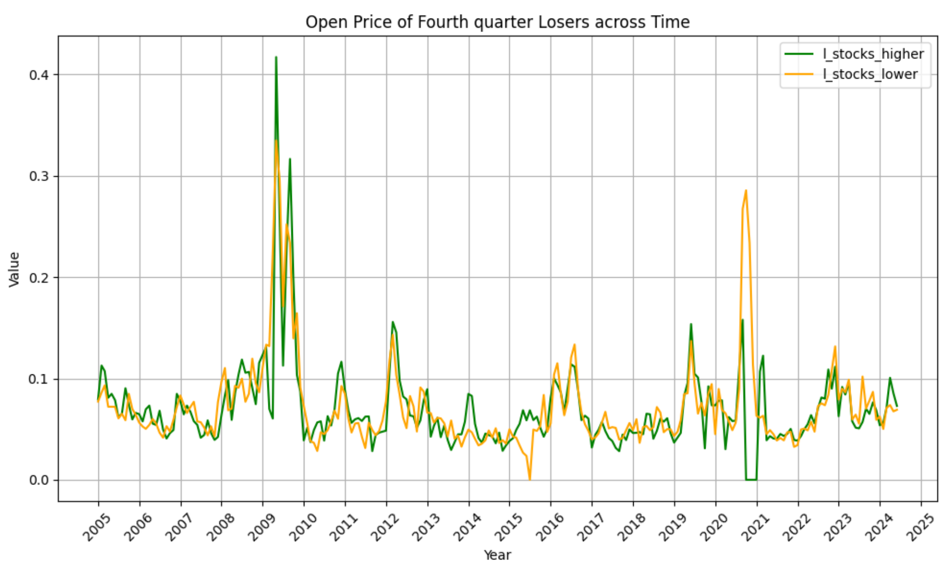

Figure 25: Fourth quarter open prices for stocks marked as losers

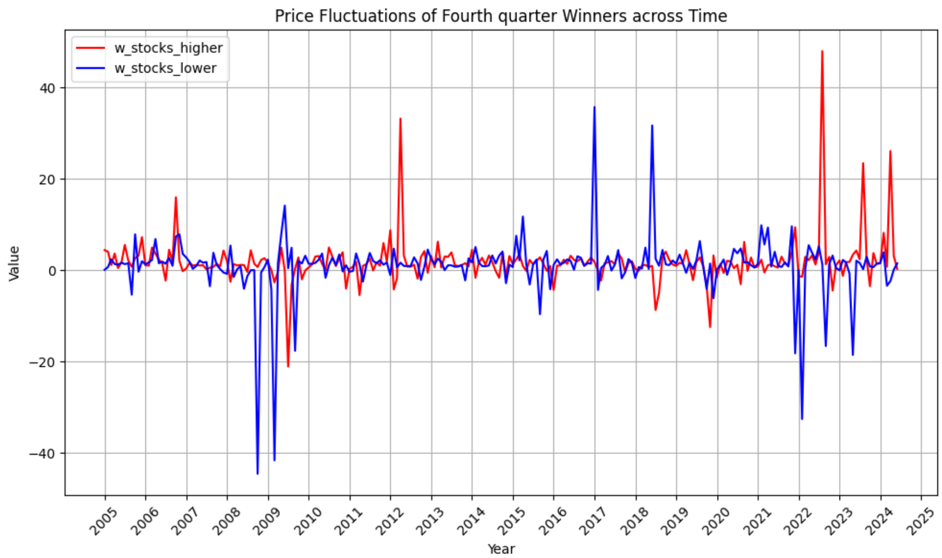

Figure 26: Fourth quarter price fluctuations for stocks marked as winners

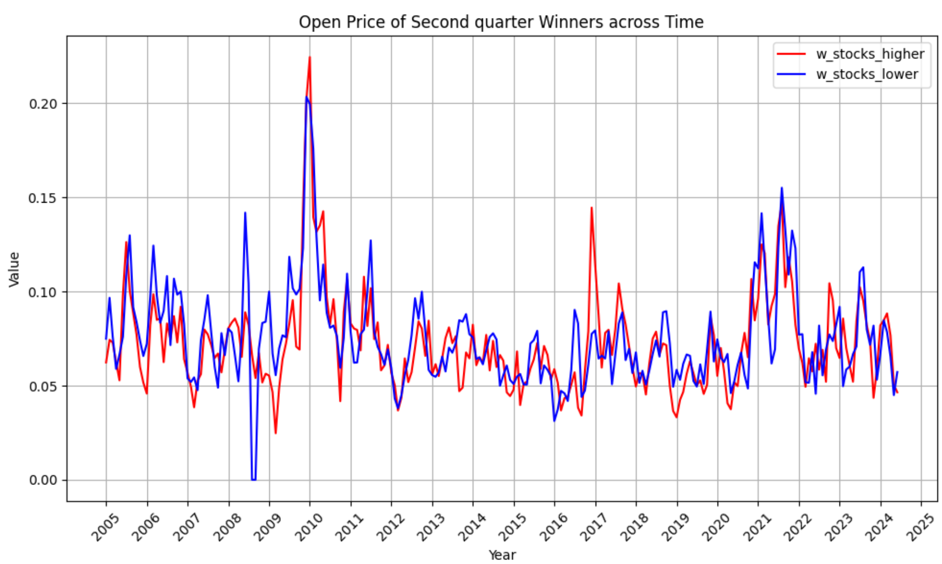

Figure 27: Second quarter open prices for stocks marked as winners

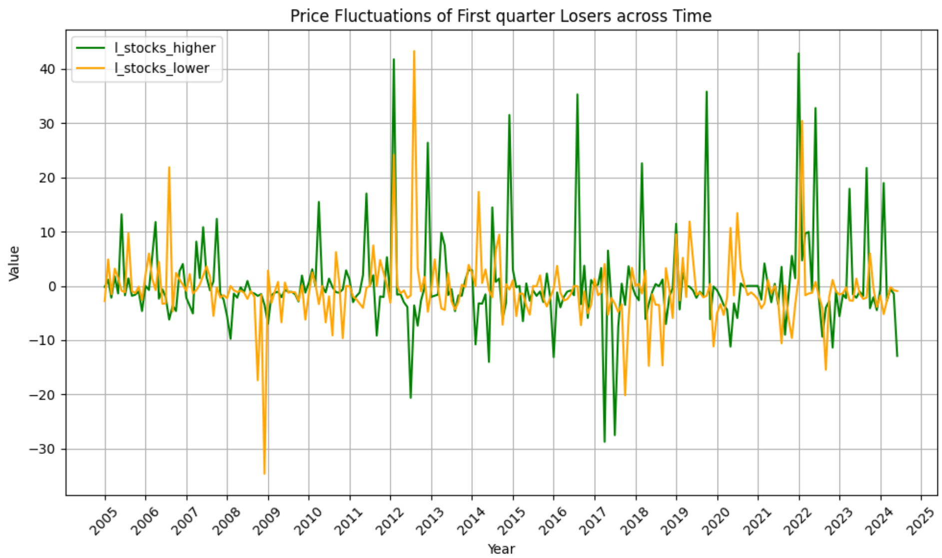

Figure 28: First quarter price fluctuations for stocks marked as losers

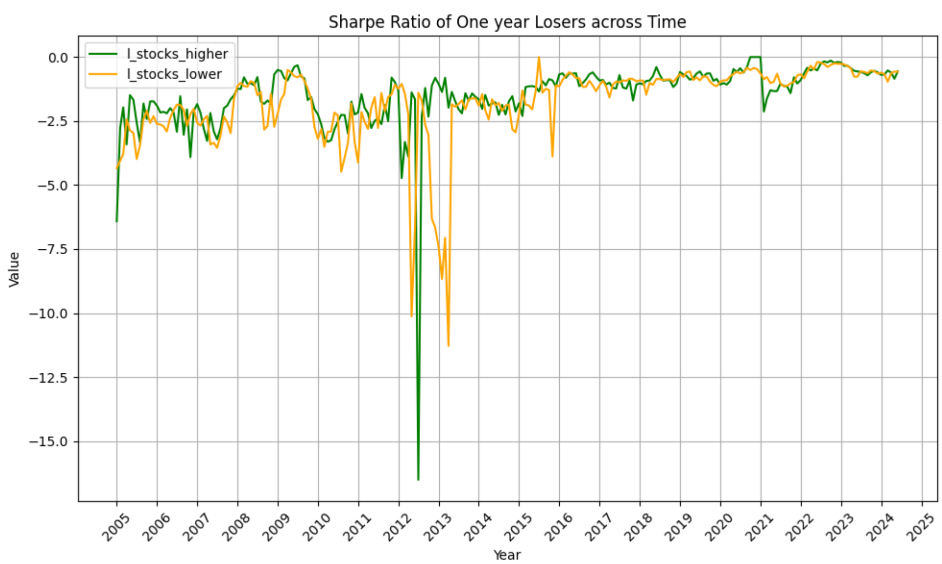

Figure 29: One year Sharpe ratio for stocks marked as losers

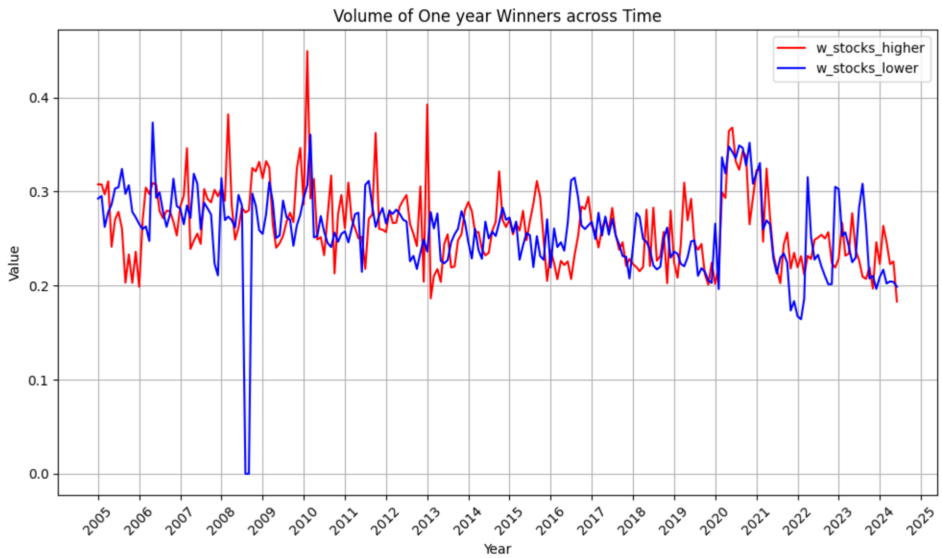

Figure 30: One year trading volume for stocks marked as winners

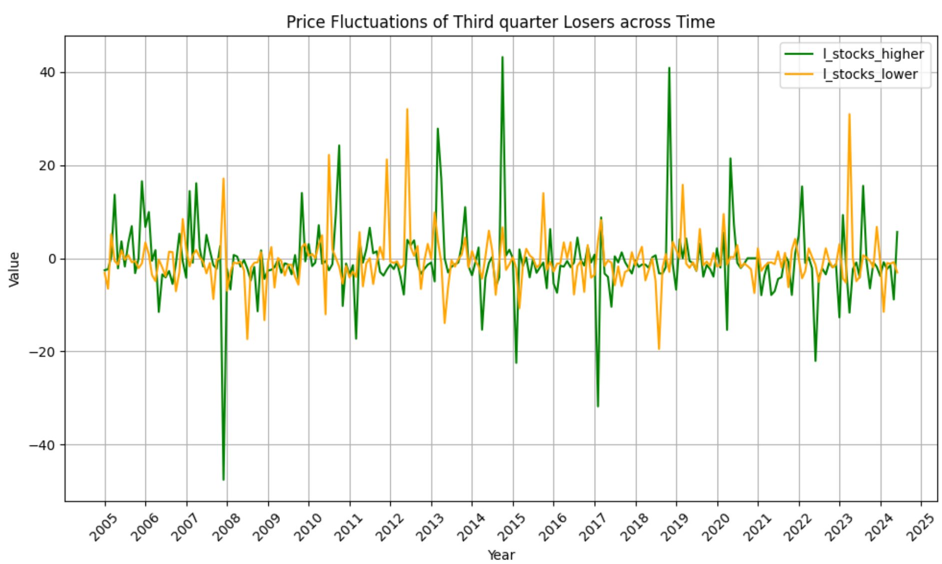

Figure 31: Third quarter price fluctuations for stocks marked as losers

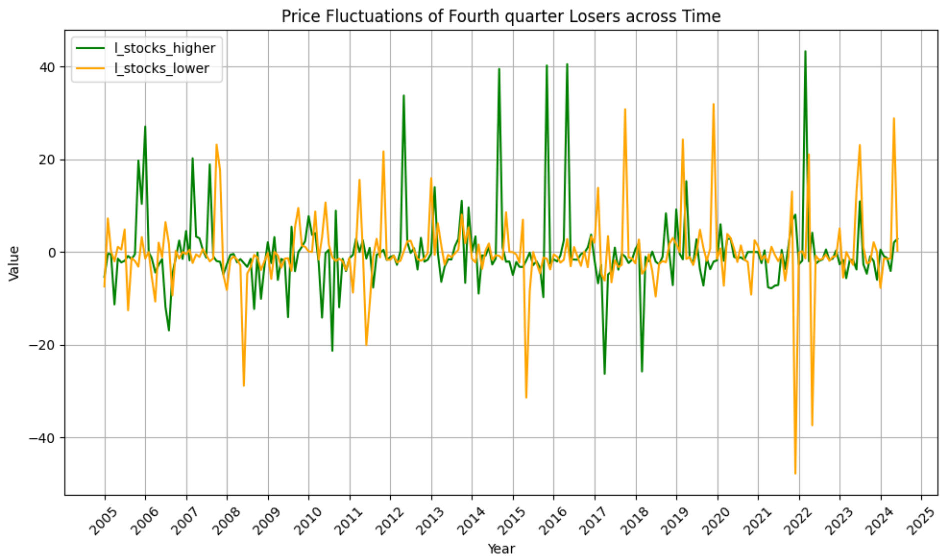

Figure 32: Fourth quarter price fluctuations for stocks marked as losers

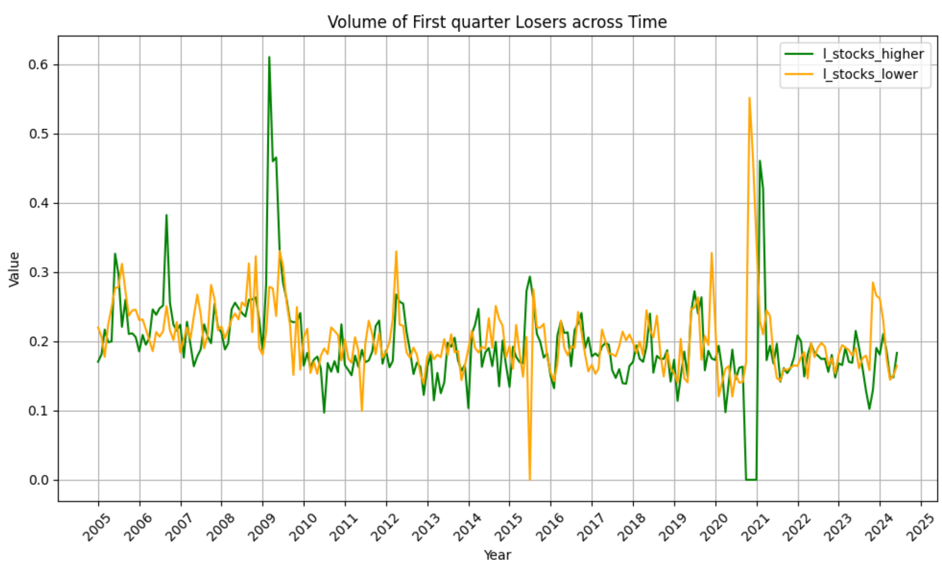

Figure 33: First quarter trading volume for stocks marked as losers

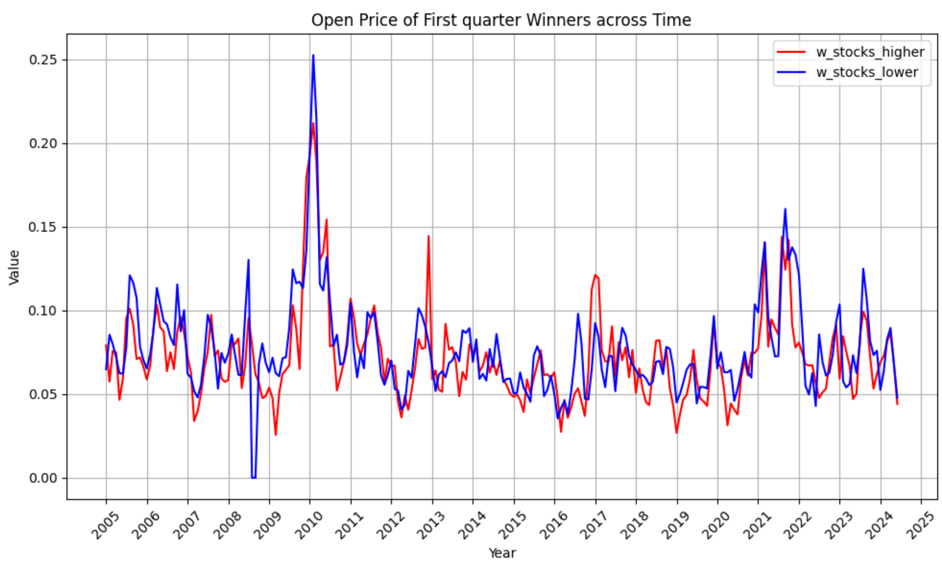

Figure 34: First quarter open prices for stocks marked as winners