Momentum Trading Strategies on the Russian Stock Market

Aleksey Osipenkov

1 Introduction

Modern financial markets offer a wide range of investment strategies, from passive index tracking to sophisticated quantitative approaches. Among these, momentum trading – the practice of buying assets with strong past performance and selling those with weak performance.

Momentum strategies typically exploit either:

- **Time-series momentum**: Following an asset's own price trajectory
- **Cross-sectional momentum**: Ranking assets by relative performance

This project aims to implement and evaluate momentum-based trading strategies in the Russian stock market. Specifically, we test:

1. A classical momentum strategy (*Buy Winners – Sell Losers*).
2. A technical indicator-based approach using the **Relative Strength Index (RSI)**.
3. Machine learning models, including **Random Forest** and **Support Vector Regression (SVR)**, trained on stock price time-series features.

The Russian market provides an interesting case study due to its emerging market characteristics, high volatility, and sector composition dominated by commodities and financials. Additionally, the chosen period (2022-2024) encompasses significant geopolitical and economic shocks, allowing us to assess the robustness of these strategies under extreme market conditions.

To evaluate the performance of these strategies, we compare them against:

- A **risk-free investment** benchmark using Russian zero-coupon bonds.
- A **buy-and-hold strategy**, which passively holds a diversified portfolio of Russian stocks.

Performance metrics include:

- The **Sharpe ratio** evaluates risk-adjusted performance by measuring excess returns per unit of volatility, calculated as:

$$\text{Sharpe}_{\text{daily}} = \frac{\bar{R}_p - \bar{R}_f}{\hat{\sigma}_p}, \quad \text{Sharpe}_{\text{annual}} = \text{Sharpe}_{\text{daily}} \times \sqrt{252}$$

where $\bar{R}_p$ is the sample mean of daily strategy returns, $\bar{R}_f$ the sample mean of daily risk-free rates, and $\hat{\sigma}_p$ the sample standard deviation of excess returns.

- The **t-statistic** tests $H_0 : R_P = 0$ against $H_a : R_p > 0$ for daily excess returns.
- Measures of **downside risk**, including Maximum Drawdown (MDD) and Maximum Drawdown Duration (MDDD).

All strategy implementations were developed from scratch, except for the built-in machine learning model training functions. The full code is available in the `Momentum.ipynb` file.

Our results suggest that, during the selected period, **RSI-based momentum trading and machine learning models achieved superior risk-adjusted returns**. The *Buy Winners – Sell Losers* strategy performed slightly worse but still outperformed the buy-and-hold approach and risk-free investments. These findings highlight the potential of momentum strategies in the Russian market.

2 Data Collection and Preprocessing

2.1 Data Sources

For this study, we utilize publicly available financial data from the Moscow Exchange (MOEX) via its open API. The dataset spans the period from April 1, 2022, to December 1, 2024. The list of stocks used for analysis consists of those included in the MOEX Index as of December 3, 2024, obtained from SberCIB Research.

Selecting stocks from a major index ensures:

- **High liquidity**: These stocks have sufficient trading volume, reducing slippage and improving execution reliability.
- **Efficient trading**: The ability to enter and exit positions with minimal market impact.

2.2 Data Cleaning and Adjustments

The initial dataset included 49 stock tickers; however, 12 of them had incomplete data due to API limitations. To avoid unnecessary complexity, we retained the remaining 37 tickers for analysis. This exclusion does not significantly impact our results, as:

- The liquidity and trading characteristics of the remaining 37 stocks remain representative of the broader index.
- Momentum strategies generally perform better with a diversified selection of stocks, and 37 assets provide a sufficiently large universe for robust performance evaluation.

Additionally, to accurately calculate historical returns, we adjust stock prices for corporate actions such as dividends and stock splits. Dividend and split data were obtained from Finrange and Investing.com, and stored in `dividends_splits.csv`.

2.3 Data Splitting for Backtesting

To ensure a rigorous evaluation of our trading strategies, we divide the dataset into in-sample and out-of-sample periods:

- **In-Sample** (80% of data) – Used for optimizing strategy parameters:
  - **Train** (60%) – Model training: *April 1, 2022 – November 27, 2023.*
  - **Validation** (20%) – Hyperparameter tuning: *November 28, 2023 – June 18, 2024.*
- **Out-of-Sample (Test)** (20%) – Used for final strategy evaluation and overfitting control: *June 19, 2024 – December 30, 2024.*

This approach ensures that strategy optimization is performed without exposure to the final test data, preserving the integrity of performance assessment.

3 Benchmark Strategies

To evaluate the effectiveness of momentum strategies, we compare them against two benchmark strategies: the risk-free rate and the Buy-and-Hold approach. These benchmarks provide a baseline to assess the risk-adjusted returns of momentum-based trading.

3.1 Risk-Free Rate

The first benchmark is the risk-free rate, represented by Russian 3-month zero-coupon government bonds. This serves as the base rate for computing Sharpe ratios and assessing the excess returns of our strategies. We obtain these rates from the Moscow Exchange, stored in `risk_free_rates.csv`.

To convert annualized rates into daily rates using continuous compounding, we apply the formula:

$$r_{\text{daily}} = \frac{\ln(1 + r_{\text{annual}})}{252}$$

where 252 represents the average number of trading days in a year.

Additionally, we incorporate 30-year zero-coupon government bonds to compute the term spread (difference between long-term and short-term rates). The term spread is included as a potential predictor in our machine learning models, as it can signal economic cycles and shifts in market risk sentiment.

3.2 Buy-and-Hold Strategy

The second benchmark is the Buy-and-Hold strategy, which constructs an equally weighted portfolio of all selected stocks. The portfolio is purchased at the beginning of the period and held without rebalancing until the end.

- It provides a simple yet effective comparison against more complex strategies.
- It reflects overall market performance and trends during the given period.
- It is widely used by long-term investors as a passive investment approach.

The daily returns of the Buy-and-Hold portfolio are calculated as the percentage change in cumulative returns over time.

These benchmarks set a clear reference for evaluating the risk-adjusted returns of our proposed strategies.

4 Momentum Strategy: Buy Winners - Sell Losers

One of the most well-known momentum strategies is the Buy Winners - Sell Losers (Jegadeesh & Titman, Journal of Finance, 1993). We adapt this strategy to the Russian stock market, constructing a zero-cost portfolio that capitalizes on short-term price momentum.

4.1 Strategy Concept

The strategy operates in two stages:

1. **Selection (Assessing period, J)**: Over a lookback window of J days, we rank all available stocks based on their percentage price change.
    - The top-performing stocks (highest returns over J days) are included in a long portfolio.
    - The worst-performing stocks (lowest returns over J days) are included in a short portfolio.
2. **Holding period (K)**: The selected portfolios are held unchanged for K days before being closed.

This approach seeks to capture short-term momentum, exploiting the idea that past winners tend to continue rising, while past losers tend to keep declining.

4.2 Strategy Implementation

The momentum portfolio employs a zero-cost structure with equal-weighted long (top performers) and short (bottom performers) positions. Formation period J and holding period K (1-10 days) are optimized in-sample for short-term momentum effects.

Key features:

- **Static positions**: The portfolio is not rebalanced daily; it remains fixed for the entire holding period K.
- **Liquidity assumptions**: Ignores transaction costs/short constraints.
- **Market adaptation**: Parameters tuned for Russian stock liquidity.

4.3 Hyperparameter Optimization

To determine the optimal assessing and holding periods, we evaluate the daily Sharpe ratio and corresponding t-statistic for each pair (J, K). The heatmaps summarizing the results of the in-sample optimization process can be found in **Appendix 10.1**.

- **Best hyperparameters**: $J = 7$, $K = 8$
- **Highest Daily Sharpe Ratio**: 0.1444
- **t-statistic**: 3.41

These values indicate that the strategy exhibits statistically significant positive momentum effects for the given parameter choices.

5 Momentum Strategy: RSI-Based Trading

The Relative Strength Index (RSI) is a momentum oscillator that measures the speed and magnitude of recent price changes. It is commonly used to identify overbought and oversold conditions in financial markets. RSI values range from 0 to 100, with higher values indicating stronger upward momentum and lower values indicating stronger downward momentum.

5.1 Strategy Concept

This strategy leverages the principle that overbought stocks (high RSI) have strong momentum and are likely to continue rising, while oversold stocks (low RSI) tend to continue falling. Using this momentum-based assumption, we construct an equally weighted portfolio and execute trades based on RSI signals.

In financial markets, RSI levels of 70 and 30 are widely accepted as standard thresholds for overbought and oversold conditions. Since this strategy is applied across multiple stocks, using these classic levels ensures consistency and comparability across assets.

5.2 Strategy Implementation

- **Long Position**: A stock is bought at the adjusted open price if its RSI from the previous day exceeds 70.
- **Short Position**: A stock is sold short at the adjusted open price if its RSI from the previous day is below 30.
- **Closing Long Position**: A long position is closed if either:
  - The stock's adjusted close price exceeds its purchase price.
  - The RSI signal indicates a short position (RSI falls below 30).
- **Closing Short Position**: A short position is closed if either:
  - The stock's adjusted close price drops below its entry price.
  - The RSI signal indicates a long position (RSI rises above 70).

5.3 In-Sample Results

To evaluate the effectiveness of the strategy, we analyze its in-sample performance:

- **In-sample Sharpe Ratio**: 0.1683
- **t-statistic**: 4.79

These results suggest a statistically significant momentum effect, confirming the validity of using RSI as a trading signal.

6 Feature Engineering for ML-Based Strategies

To develop robust machine learning models for stock price prediction, we first construct a set of meaningful features based on historical price movements, seasonal effects, and market indicators.

6.1 Autocorrelation Analysis

To determine relevant lag features, we analyze the autocorrelation of stock growth rather than raw prices, as stock prices exhibit trends that can obscure autocorrelation patterns. Figure 2 in **Appendix 10.2** illustrates the autocorrelation function (ACF) for AFKS and MGNT, where statistically significant lags are highlighted.

The assumption that stock prices follow a pure Brownian motion (implying no autocorrelation) does not hold perfectly in practice. Some lags demonstrate statistically significant dependencies, suggesting the presence of short-term predictability.

6.2 Selected Features

Based on the autocorrelation analysis and financial intuition, we incorporate the following features into our models:

- **Lagged Prices**: The past three adjusted close prices ($y_{t-1}, y_{t-2}, y_{t-3}$) serve as input features, capturing most recent actual prices.
- **Seasonality**: Since we analyze business-day data, we include a 5-day seasonal price component to capture weekly cyclical patterns.
- **Rolling Metrics**: To quantify short-term trends and volatility, we compute:
  - 5-day and 10-day rolling mean of adjusted close price.
  - 5-day rolling standard deviation of adjusted close price.
- **Macroeconomic Indicators**:
  - **Daily risk-free rate**: Reflects the opportunity cost of capital and overall market risk sentiment.
  - **Term spread (long-term rate - short-term rate)**: Serves as an indicator of future economic conditions.
- **Dividend Payments**: Shows dividends payout at any given date indicating, which may influence investor behavior and stock price adjustments.

6.3 Data Leakage Prevention

To ensure the integrity of our predictive models, we carefully shift features to avoid using information from the future. Lagged prices and rolling metrics are computed using only past data. Macroeconomic variables are aligned to reflect the information available at time t.

7 Machine Learning Models for Stock Price Prediction

To model stock price movements, we utilize two popular machine learning algorithms: **Random Forest** and **Support Vector Regression (SVR)**. Each stock ticker has its own independently trained model.

7.1 Model Descriptions

Random Forest (RF) is an ensemble learning method based on decision trees. It reduces overfitting by averaging predictions from multiple trees trained on random subsets of data. However, RF can still suffer from overfitting, especially in noisy financial data, as it tends to capture short-term fluctuations that may not generalize well.

Support Vector Regression (SVR) is a kernel-based method that seeks to find a function that best fits the data within a certain margin. SVR is more resistant to noise and works well with smaller datasets, but it can be computationally expensive and sensitive to hyperparameter tuning.

Both models are widely used in financial market predictions due to their ability to capture complex relationships in stock price movements.

7.2 Model Training and Hyperparameter Selection

For each stock ticker, we train a separate model using the following procedure:

1. **Training Phase**: The model is initially trained on the training dataset.
2. **Hyperparameter Optimization**: The best hyperparameters are selected by evaluating performance on a validation dataset.
3. **Final Model Training**: The final model is trained using both the training and validation data with the optimal hyperparameters.
4. **Testing Phase**: The trained model is used to make predictions on the test dataset.

7.3 Prediction Accuracy and Strategy Construction

While the models do not predict exact stock prices with high precision, they effectively capture price movements. Figure 3 in **Appendix 10.3** illustrates the predicted vs. actual prices for SBER. Notably, Random Forest tends to perform worse in estimating absolute prices, but both models successfully capture directional trends.

Given this property, we implement the following trading strategy:

- If $y_{\text{pred},t} < y_{\text{pred},t+1}$, we open a long position at time t.
- If $y_{\text{pred},t} > y_{\text{pred},t+1}$, we open a short position at time t.
- The position is always closed at time $t+1$.

This strategy is applied to each stock in the dataset, forming an **equally-weighted portfolio**.

8 Results

8.1 Total Returns and Cumulative Performance

To assess the performance of each strategy, we calculate the cumulative returns, assuming an initial portfolio value of 1 RUB, with all profits reinvested. The cumulative return graph can be found in **Appendix 10.5**.

Among the strategies:

- **Buy Winners - Sell Losers** yields the highest overall return but exhibits significant fluctuations, with sharp rises and steep declines.
- **RSI Momentum** follows with more stable growth, though it also experiences some steep upward movements.
- **Support Vector Regression (SVR)** initially performs similarly to Random Forest but improves over time.
- **Random Forest (RF)** closely tracks the risk-free return, underperforming compared to other strategies.

All strategies outperform the benchmarks: **risk-free return** and **buy and hold**. Notably, the buy-and-hold strategy yields lower returns than the risk-free rate.

8.2 Maximum Drawdown (MDD) and Maximum Drawdown Duration (MDDD)

The table below summarizes the MDD and MDDD for each strategy:

Strategy	MDD (%)	MDDD (days)
Risk-Free Strategy	0.00	0
Buy and Hold	-27.86	130
Buy Winners - Sell Losers	-37.08	62
RSI Momentum	-5.46	32
Random Forest	-6.35	31
Support Vector Regression	-4.84	31

Table 1: Maximum Drawdown and Maximum Drawdown Duration for each strategy.

Key Observations:

- **Buy Winners - Sell Losers** has the highest drawdown (-37.08%), indicating significant volatility.
- **RSI Momentum** has a relatively low drawdown (-5.46%), demonstrating resilience.
- **Random Forest and SVR** have similar MDDs, with SVR slightly outperforming RF in drawdown recovery.
- **Buy and Hold** suffers from extended drawdowns, lasting 130 days.

8.3 Sharpe Ratio and Statistical Significance

The Sharpe ratio is a critical measure of risk-adjusted return. The table below presents daily and annualized Sharpe ratios, along with t-statistics for statistical significance.

Strategy	Daily Sharpe	Annualized Sharpe	t-Statistic
RSI Momentum	0.2594	4.1183	3.99
Buy Winners - Sell Losers	0.1390	2.2059	1.89
Support Vector Regression	0.1192	1.8926	2.03
Random Forest	0.0470	0.7465	1.25

Table 2: Sharpe Ratios and t-Statistics for each strategy.

Discussion:

- The **RSI Momentum** strategy exhibits an extremely high Sharpe ratio (4.1183 annualized). For comparison, its in-sample performance yielded a daily Sharpe of 0.1683 and a t-statistic of 4.79, translating to an annualized Sharpe of 2.6716. This suggests that the out-of-sample period might be too short, leading to an inflated Sharpe ratio.
- **Buy Winners - Sell Losers** has a reasonable Sharpe ratio (2.2059) but a lower t-statistic, indicating moderate statistical significance.
- **SVR** shows a solid improvement over RF, maintaining a Sharpe ratio of 1.8926.
- **Random Forest** underperforms with a low Sharpe ratio (0.7465), barely above the risk-free return.

9 Conclusion

Our analysis confirms the presence of momentum effects in the Russian stock market, which can be exploited through systematic trading strategies. Classical momentum-based strategies, such as **RSI Momentum** and **Buy Winners - Sell Losers**, provide strong foundations for leveraging these effects. However, their performance can potentially be enhanced by refining the selection of assets, adjusting holding periods, or incorporating additional risk-management mechanisms.

Machine learning models, despite using only simple and readily available time-series features, successfully outperformed the baseline benchmarks (risk-free rate and buy-and-hold strategy). However, they generally underperformed compared to classical momentum-based strategies. This suggests that while ML models capture market movements to some extent, they require further refinement to become competitive.

Future improvements for ML-based models may include:

- **Feature Engineering**: Incorporating additional predictors such as market microstructure variables, macroeconomic indicators, and alternative data sources (e.g., sentiment analysis).
- **Longer Training Horizons**: Expanding the training dataset to include more historical data can improve generalization and enhance predictive accuracy.

- **Hybrid Approaches**: Combining machine learning techniques with classical momentum models may provide a more robust predictive framework.
- **Regime-Switching Models**: Considering market regime changes to adjust strategy parameters dynamically.

Overall, this study demonstrates that momentum strategies remain a viable approach to trading in the Russian stock market. While classical methods currently outperform machine learning models, further research and refinements could lead to more sophisticated, adaptive, and profitable trading strategies.

10 Appendix

10.1 Buy Winners - Sell Losers: In-Sample Optimization Results

10.2 Autocorrelation Analysis for AFKS and MGNT

10.3 Prediction Accuracy for SBER

10.4 Feature Importance for RF and SVR

10.5 Cumulative Returns

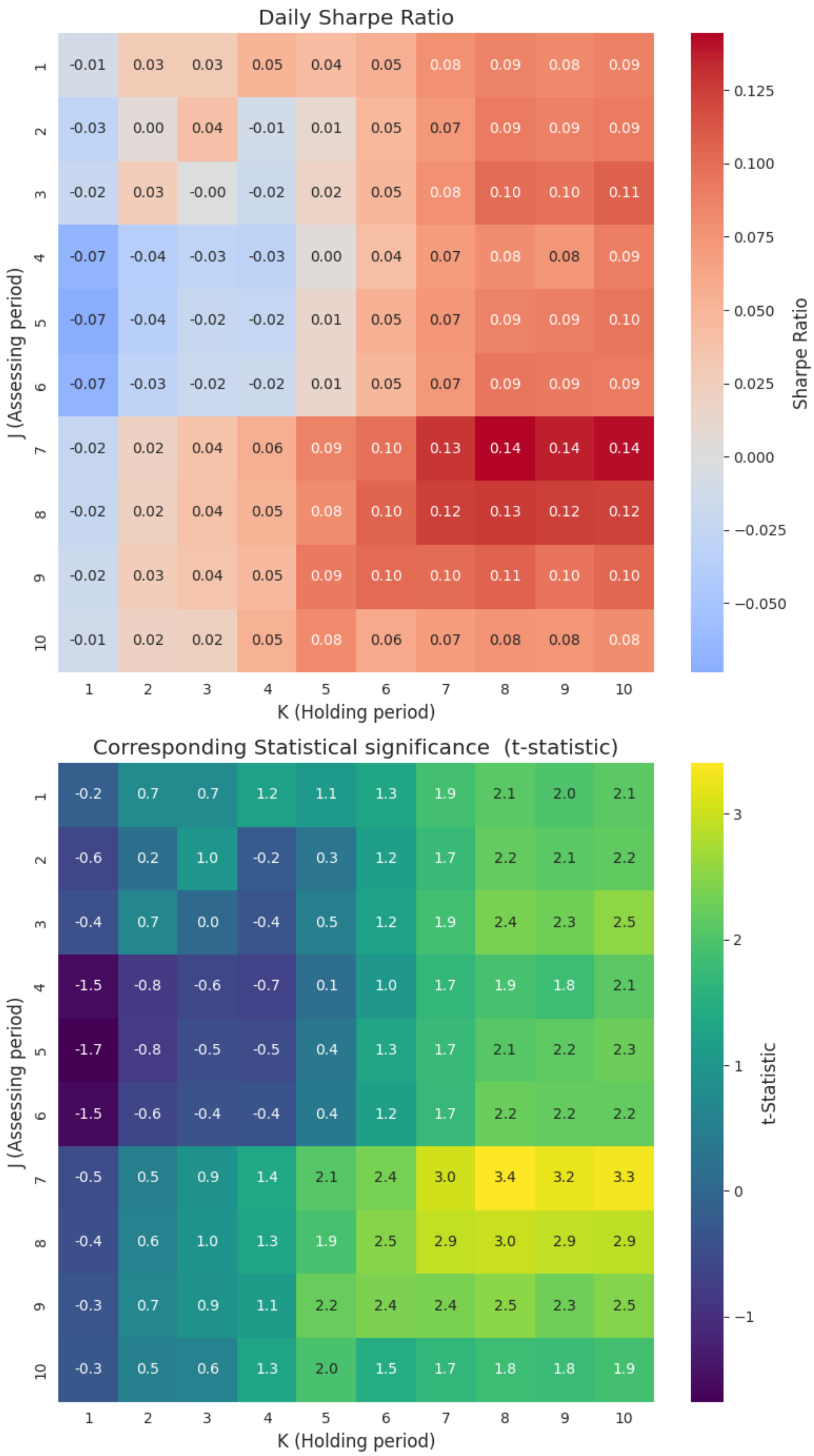

Figure 1: In-sample optimization results: Sharpe ratio (left) and t-statistic (right) for different values of J and K.

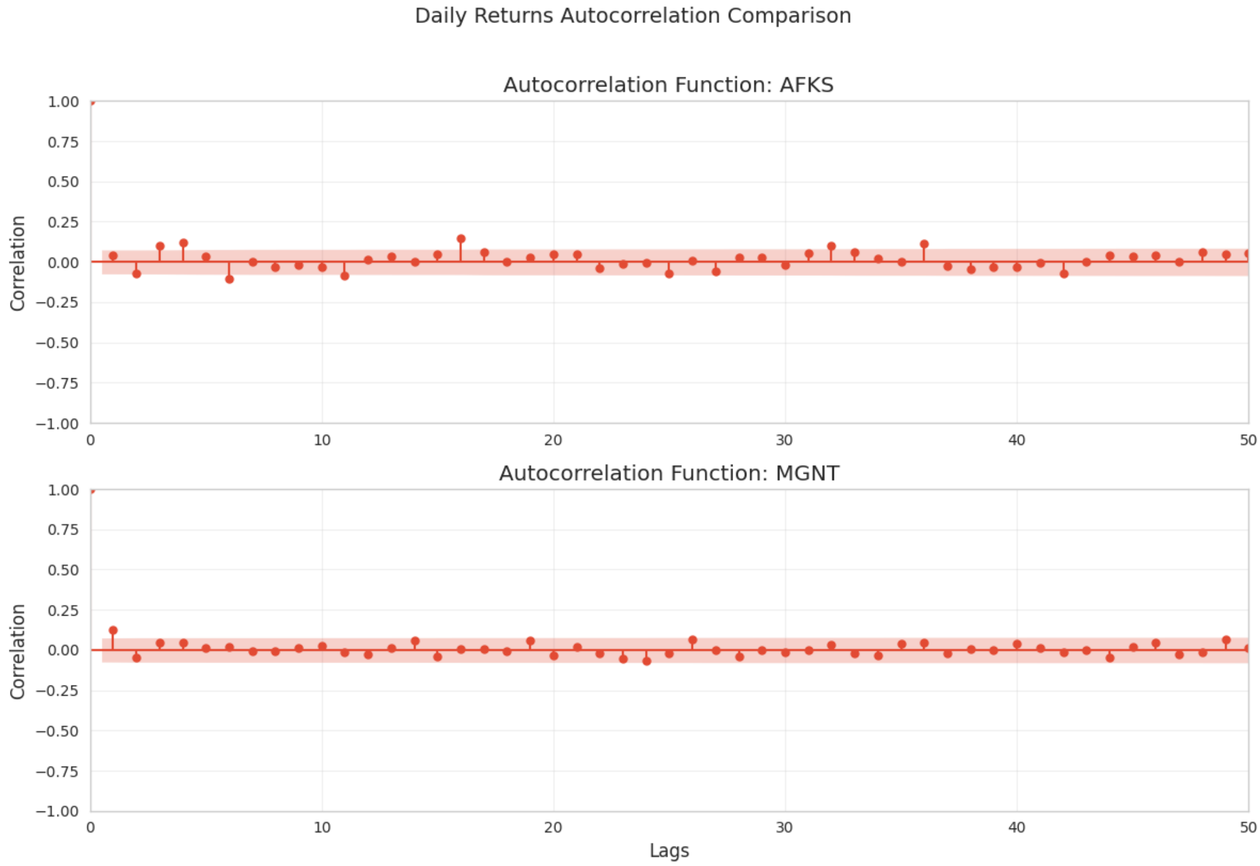

Figure 2: Autocorrelation function (ACF) for AFKS and MGNT stock returns. Shaded regions indicate statistically significant lags.

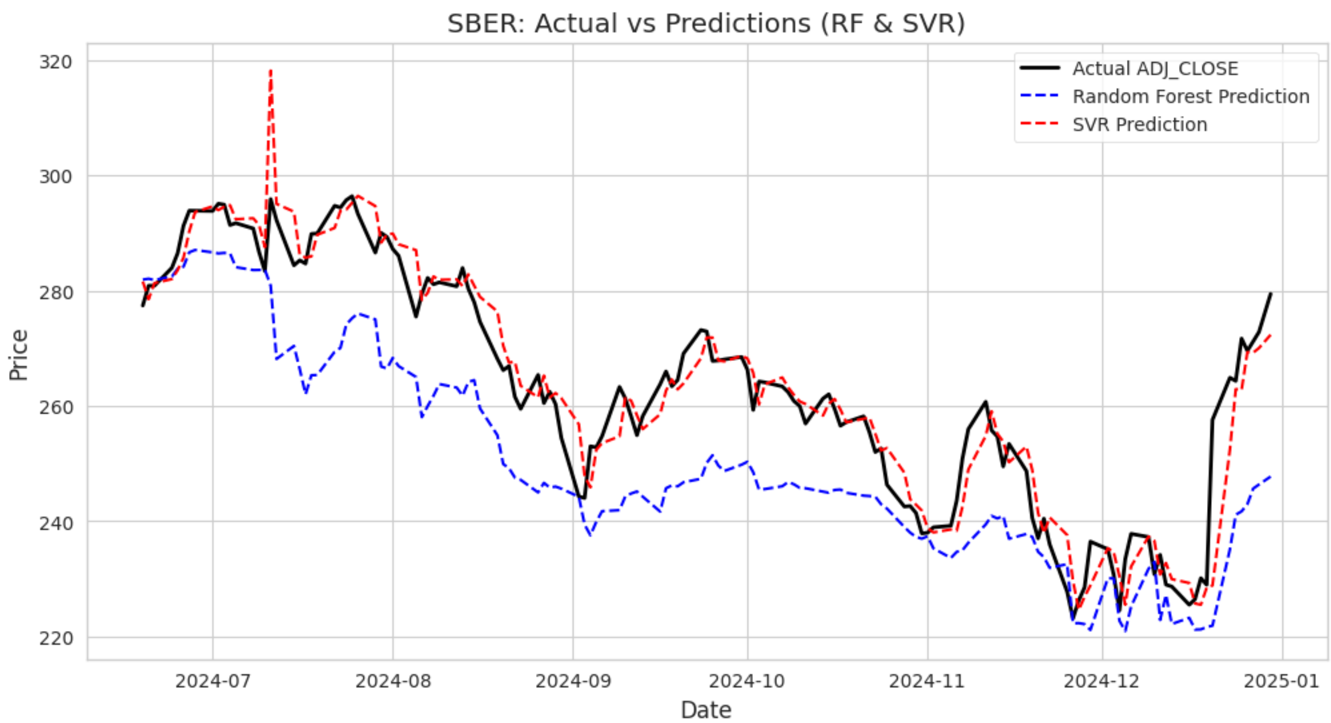

Figure 3: Predicted vs. actual stock prices for SBER. Random Forest struggles to capture exact price values but both models effectively predict price direction.

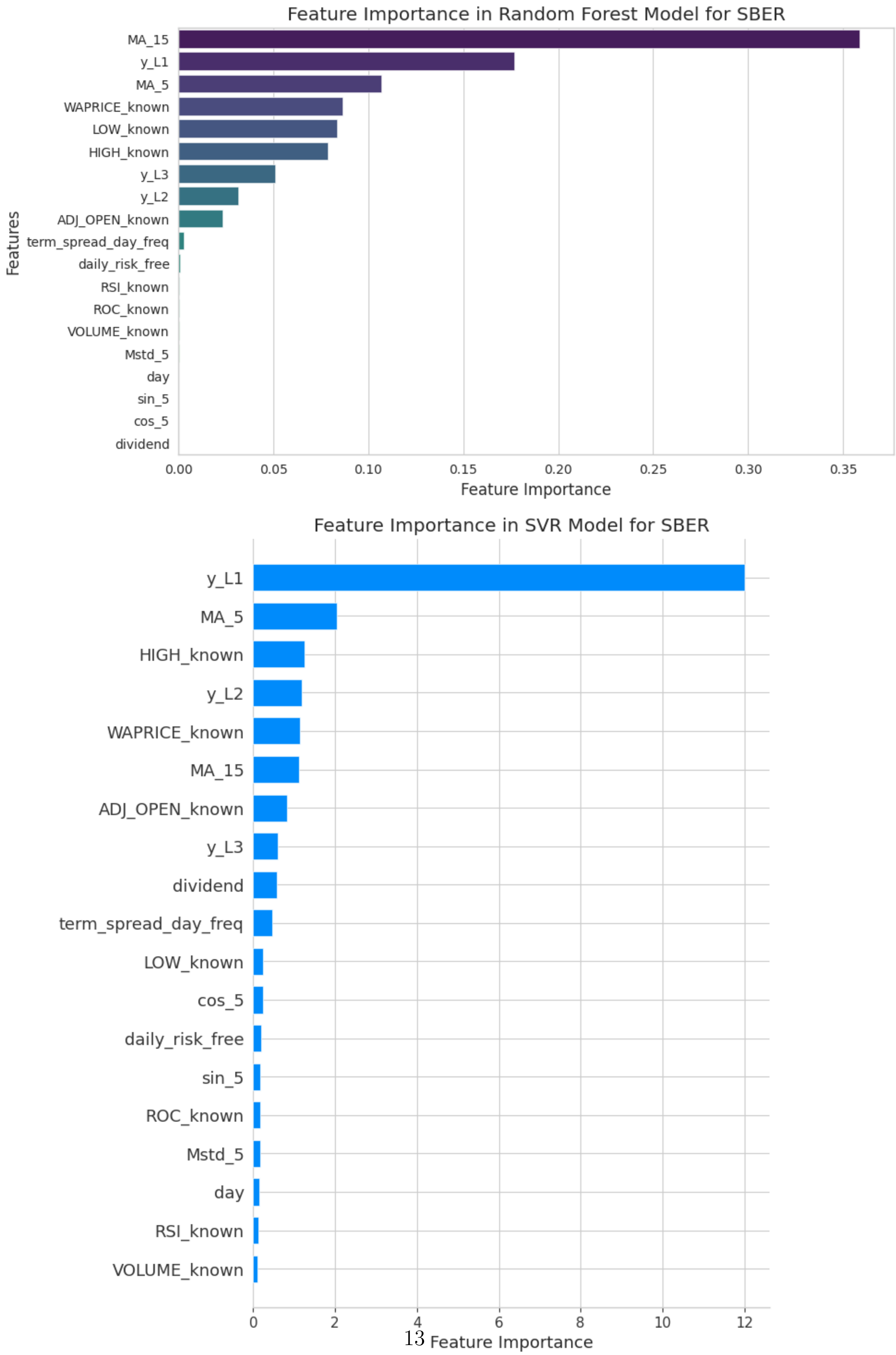

Figure 4: Feature importance analysis for Random Forest and SVR models.

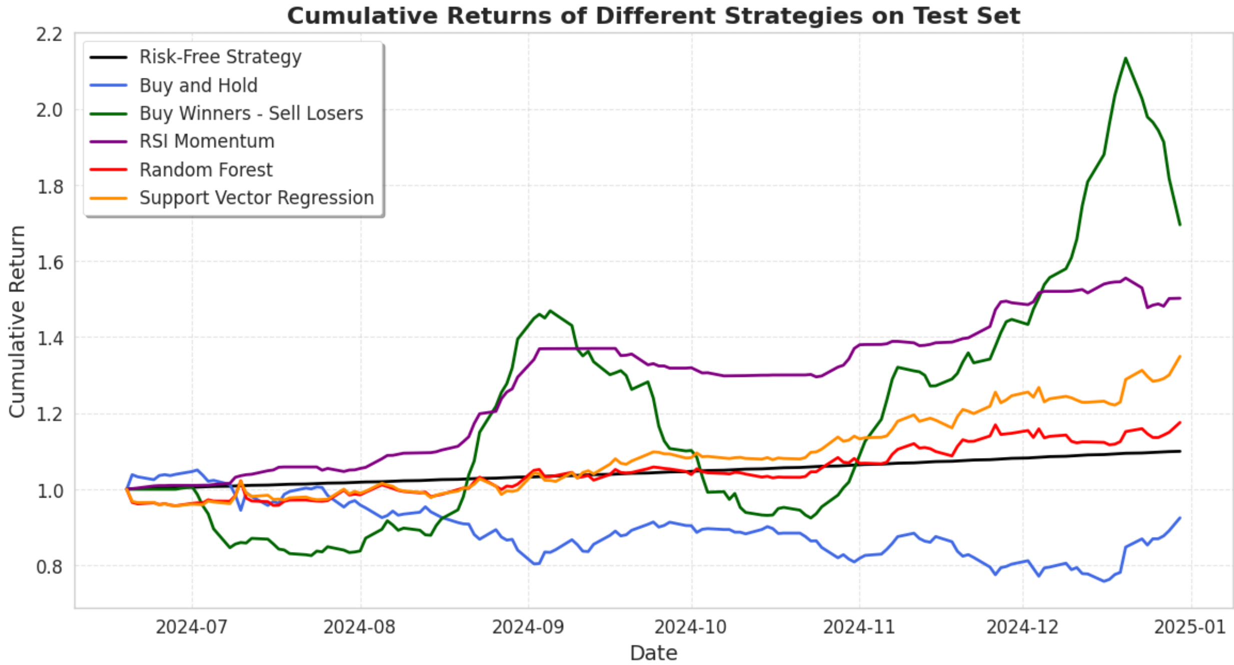

Figure 5: Cumulative returns for all strategies. RSI Momentum and Buy Winners - Sell Losers achieve the highest returns, while Random Forest struggles to outperform the risk-free rate.