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Research Article

Utilization of Artificial Intelligence for Portfolio Optimization in Shallow Markets

Erdem Kilic[1*], Sıtkı Sönmezer[2]
[1]*Turkish-German University, Economics Department, Istanbul, Türkiye*
[2]*Istanbul Commerce University, Banking and Finance Department, Istanbul, Türkiye,* ssonmezer@ticaret.edu.tr
*Corresponding author: erdem.kilic@tau.edu.tr

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ABSTRACT

Introduction: Portfolio optimization remains a compelling research challenge despite advances in techniques and artificial intelligence. This complexity largely stems from the difficulty in accurately identifying and modeling dynamic market factors. Variables such as interest rates, inflation, economic growth, and foreign exchange rates fluctuate continuously, making portfolio construction and adjustment uncertain. As a result, portfolio strategies often rely on correction mechanisms that may be imprecise or insufficient under volatile and structurally complex market conditions.

Objectives: The objective of this study is to compare momentum-based algorithmic trading with buy-and-hold strategies in shallow markets, assessing AI’s ability to exploit inefficiencies and enhance portfolio performance.

Methods This study applies artificial intelligence optimization methods, including momentum strategies enhanced by Support Vector Machines (SVM), to construct actively managed portfolios. A sample of 10 equally weighted stocks is selected and rebalanced over a rolling 252-day window using adjusted closing prices retrieved from Yahoo Finance via STATA. The algorithm dynamically adjusts holdings based on market signals. The performance of the optimized algorithmic portfolios is compared against a traditional buy-and-hold strategy. Statistical significance of return differences is assessed using paired t-tests to evaluate the effectiveness of optimization in shallow and less efficient market conditions.

Results: The results show that the trading algorithm outperformed the buy-and-hold strategy in 18 out of 31 cases, while the buy-and-hold strategy outperformed in 13 cases. On average, the algorithm achieved higher returns in 51.85% of the observations. However, the difference in mean returns between the two strategies is not statistically significant at the 5% level, according to the paired sample t-test. This suggests that while the algorithm showed slightly better performance, the results do not provide strong statistical evidence of its superiority.

Conclusions: Portfolio optimization in shallow markets presents unique challenges due to limited liquidity and weaker market efficiency. While AI can exploit mispricing and enhance returns through active strategies, data flaws and structural constraints complicate its effectiveness. Competing algorithms, timing issues, and behavioral factors further intensify complexity in these less developed markets.

Keywords: Artificial Intelligence, Portfolio Optimization, Depth.

INTRODUCTION

Portfolio optimization is an interesting problem to research despite all the techniques available and IT developments such as artificial intelligence. The main reason may be the difficulty of determining market factors and their structure. Interest rate levels, inflation rates, growth rates or foreign exchange rates keep changing and require dubious correction mechanisms for the portfolios.

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OBJECTIVES

The objective of this study is to evaluate the performance of algorithmic trading strategies, specifically momentum-based approaches, in comparison to the traditional buy-and-hold strategy within the context of shallow markets. The research investigates whether artificial intelligence models can generate superior returns by effectively capturing inefficiencies and responding to market dynamics that are typical in environments with limited liquidity and weaker forms of market efficiency. In doing so, the study also analyzes the influence of market structure on the effectiveness of different portfolio types, including aggressive, defensive, and speculative portfolios. By examining the statistical significance of return differences over a defined holding period and rolling windows, the study contributes to the literature on portfolio theory and the role of AI in financial decision-making, particularly in less developed or structurally constrained markets.

METHODS

How a portfolio should be formed is a question that undermines portfolio managers' contribution most of the time. An active strategy may be adopted which requires trading based on the information received. The aim is to beat the market, which is rarely achieved. However, a buy and hold strategy may outperform professionals [12]. Once the strategy is selected, portfolio managers need to determine how they are going to conduct asset allocation and three of them are listed here below:

Mean-Variance Optimization Framework

It is very difficult to predict future returns accurately or even approximately. Covariance matrices are relatively easier to forecast compared to market returns of financial instruments [13]. However, mean-variance optimization is found to be very sensitive to the inputs of the model by intuition and for numerous studies in literature [15]; [10]. A portfolio with an equal return expectation shall seek to have the least variance [16]. However, once the distributions are polynomial and complex, mean-variance optimization weakens.

Fix-Mix Strategies

A fixed-mix strategy may be shown by a matrix α_{kj}, k, j ∈ {1, ..., K}, which can be found here below:[6]

$$\alpha kj > 0, \sum_{k=1}^{k} \alpha kj = 1 \tag{1}$$

In an important special case, α_{kj} does not depend on j:

$$\alpha_{kj} = \alpha_k \ [\alpha_k > 0, \alpha 1 + \ldots + \alpha K = 1]. \tag{2}$$

Relative shares in the portfolio are fixed in time. Keeping them at the fixed weight is far from easy [21].

Risk Framework

Value at Risk is a model that has three different methods: the Analytical Method is easy to calculate but requires normal distribution; the historical method is also easy to apply but assumes history repeats itself and the Monte Carlo Simulation method requires random generators when there is lack of data. Value at risk applies to many assets, but a 5% VAR informs about the best among the worst scenarios, which could be misleading, and large portfolios may have hardship in utilizing VAR methodologies [11]. A Lower Partial Moment model may be an alternative due to lack of efficient algorithms for stochastic dominance [17]. The LPM model differentiates undesirable downside and desirable upside deviations and focuses on the left tail which is about risks associated with the investment. However, the model is affected by outliers.

Artificial intelligence in Portfolio Optimization

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Portfolio optimization can be achieved by intelligent approaches like neural network, reinforcement, Evolutionary, Quantum, Bayesian and Support Vector Models as well. Machine learning and deep learning approaches are integrated into robo-advisor frameworks for portfolio optimization [5].

Artificial Intelligence may provide weights of the assets in a portfolio as experts can. It is evident that investors favor human advice over algorithms, and they penalize ill-advice from algorithms heavily. Inaccurate recommendations by artificial intelligence may lead to losses and humans tend to discredit algorithms easier than humans [4].

Theoretical base and literature review

The Portfolio Theory of Markowitz underlines the trade-off between risk and return [8] and Expected Utility Theory assumes agents are risk averse, but their choices are rational. Prospect Theory claims agents have biases that deprive them of rational and psychological matters [19]. Credibility Theory, which deals with fuzzy phenomena, is followed by Uncertainty Theory and it is highly favored by researchers in the recent years [7].

Theoretically, future prices are key for any portfolio optimization framework. Random Forest, Extreme Gradient Boosting (XGBoost), Adaptive Boosting (AdaBoost), Support Vector Machine Regression (SVR), and k-Nearest Neighbors (KNN), and Artificial Neural Network (ANN) are adopted to forecast stock values for various Asian markets and mean value at risk model with Ada Boost prediction is found to outperform other methods [3].

Researchers form an algorithmic trading system with the support vector machine (SVM) factor model that shows robust performances over in-sample and out-of-sample trading periods for the ETF market in US [2]. The model has systematic risk factors, credit risk factors and market fear factors. "SVM is a supervised learning model which provides an optimal separating hyperplane that maximizes the distance from the plane to any point, in classifying data by finding supporting vectors that maximize the margin [20]. The author provides evidence that momentum patterns of ETF prices can be detected by the factor model.

Types of portfolios

Portfolios may suffer from transaction costs and some portfolios may aim to reduce these costs via techniques that penalize the portfolios by time or robust portfolio selection processes. Some portfolios aim to reduce the estimation error, and some try to incorporate the market information into their models [9].

Motivation behind the formation of portfolios is mostly based on investors' risk tolerance levels. Their need for funds, wealth, expectation and time horizon also plays a crucial role. Artificial Intelligence may cater for asset allocation process and the type of the portfolio. Yet, the type may change due to market dynamics and the timing of it shall be optimized. We introduce and discuss the effect of them being in a shallow market for each of the portfolios here below:

Aggressive Portfolio

As the name implies, these portfolios seek higher returns despite higher risks. These portfolios may have thinner tails as outliers will be larger due to lack of depth and breadth in smaller markets.

Defensive Portfolio

On the contrary, defensive portfolios are risk averse and operate at possible minimum risk levels and some portion of upside potential is forgone. Defensive Portfolios may suffer from higher inflation rates, which provides a cushion for investors. High inflation rates increase the likelihood that the market will increase so a defensive portfolio is likely to underperform.

Income Portfolio

Dividend-like receipts from investments are valued in these portfolios. Investors with high liquidity need favor these portfolios. Shallow markets may have few dividend- paying stocks and Artificial Intelligence may help to forecast times when firms will be unable to distribute profits and early warn investors to create their own dividends by selling the necessary portion of their shares.

Speculative Portfolio

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These portfolios are associated with IPOs with lottery-like structure. Losses from initial investment are highly possible but doubling it shall also be probable. Shares and particularly, IPOs increase by the ceiling price regime allowed by the exchange commission in majority of smaller markets. AI may help to forecast the steady ceiling amounts in a row by incorporating the factors into its model.

Hybrid Portfolio

Optimum return with optimum degree of risk is targeted. However, optimum levels are not stable, therefore, the portfolio may need to be rebalanced often in which case increasing transaction costs may decrease returns.

Strategies in Stock selection

• Buy and Hold Strategy

This strategy simply buys stocks into a portfolio and holds them until the holding period ends. This strategy assumes that even professionals' corrective action gains are less than the transaction costs incurred from these trades. Earlier research on the success of trading algorithms vs. Buy and Hold strategy was not promising [1]. After a decade-long development in the trading algorithms, researchers have provided evidence that buy-and- hold is outperformed [14]. By intuition, Transaction costs have decreased significantly with developments in digital finance, which may favor trading.

• Momentum Strategies

Momentum strategies pursue stocks that are in high demand. They believe it is possible to time the market. Momentum strategies follow the trend or mean-reverting cycles. The effects of algorithmic trading with regards to momentum are addressed by i.e. [22].

• Value Strategies

Value strategies are pursued when investors believe they can assess the stock is undervalued. It is best to wait till the stock price reaches its intrinsic value. [18] claims he can select winner stocks via financial statement analysis techniques.

This study aims to compare the results of Buy-and-hold strategy in terms of trading algorithms for our sample.

Data and Methodology

Our holding period is between 02/01/2023 - 23/02/2024 and there are 286 trading days. Originally, the algorithm picks 10 stocks and takes corrective actions when needed. Adjusted closing prices are retrieved from Yahoo Finance via STATA. The first 30 days' portfolios are tested for comparison with the algorithm returns vs the buy and hold strategy as a rolling window for 252 working days.

The portfolio value is originally 1000 and there are always 10 stocks in the portfolio. We have given equal weight to every stock and calculated the amount of shares we could buy on the first date. We hold the basket for 252 days and calculate the portfolio value respectively. We seek statistical significance between buy-and-hold returns and trading algorithm returns via our model. Our model is shown here below:

H_0: There is no difference between the portfolio returns of the Buy-and-hold strategy and the momentum strategy in the trading algorithm basket.

RESULTS

In Table 1, the results from the trading algorithm in comparison to the buy and hold strategy are presented. It can be observed that the trading algorithm outperforms 18 times and buy-and-hold strategy outperforms 13 times form a total of 31 cases. On average, algorithmic trade outperforms the buy and hold strategy in 51.85% of the selected cases.

Table 1: Algorithm Results

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Day	Algo	B&H	Result
1	0.3727	0.374582	B&HWINS
2	0.3438	0.332869	Algowins
3	0.3283	0.066742	Algowins
4	0.3516	0.043995	Algowins
5	0.4607	0.064956	Algowins
6	0.3847	0.374673	Algowins
7	0.447	0.265929	Algowins
8	0.5147	0.457006	Algowins
9	0.5689	0.301701	Algowins
10	0.4984	0.362041	Algowins
11	0.4932	0.368232	Algowins
12	0.4493	0.452504	B&HWINS
13	0.4406	0.437622	Algowins
14	0.4604	0.541781	B&HWINS
15	0.4381	0.593537	B&HWINS
16	0.4124	0.365507	Algowins
17	0.3879	0.43736	B&HWINS
18	0.4262	0.382744	Algowins
19	0.4402	0.741961	B&HWINS
20	0.4713	0.676083	B&HWINS
21	0.5067	0.60839	B&HWINS
22	0.5668	0.32379	Algowins
23	0.621	0.302194	Algowins
24	0.7438	0.576445	Algowins
25	0.7188	0.867761	B&HWINS
26	0.6369	1.01662	B&HWINS
27	0.6728	0.858058	B&HWINS
28	0.8847	0.694018	Algowins
29	0.7195	0.872257	B&HWINS
30	0.6576	0.965075	B&HWINS
31	0.6545	0.33427	Algowins
Average	0.5185	0.485829	
T-test *(P-value)*	0.533		

The T-test of different means suggest that the computed difference in results is not significant at 5% significance level.

DISCUSSION

Market optimization is a heavily studied challenge, and many researchers have put effort into optimizing portfolios from various aspects. IT Innovations and artificial intelligence may approach the challenge from different aspects but for sure AI has to take a different approach for shallow markets as the structure is different and market efficiency is weaker than the weak-form of efficient markets.

AI may exploit better the mispricing for shallow markets and may have higher returns by pursuing an active strategy. When that is the case, the number of trading algorithms guided by artificial intelligence and experts will compete to exploit the mispricing first. In an ideal world, assets will be priced at their intrinsic values as all the algorithms will be fed with the same accurate and complete data.

In markets where data is flawed, AI will compete to get rid of the make-up in financial statements or mitigate the errors in the data set, which requires assumptions and guesses.

Less developed markets will be harder games for AI, also from the liquidity perspective. Purchasing a stock in bulk may require moving prices higher in shallow markets. AI has to time both the entry and exit of a trade, which may be a case for game theory in the coming future. When the depth is lower, the early investors that take a short position will find bids in the market. The rest of the investors or algorithms must sell at lower prices. Investors' psychology is an important factor in shallow markets, but AI is free of such biases.

AI has to take all inefficiencies of shallow markets into consideration, and it will. However, the move of many other AI-led algorithms is hard to assess and will remain a challenge at least in shallow markets for a while.

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