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RESEARCH PAPER

Comparison of the Portfolio Optimization Methods Based on Historical Return Approach and Predicted Return Using ARIMA Model

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Abstract

Risk assessment and the selection of an optimal portfolio selection are critical issues in financial research, investment firms, and among investors. Traditional optimization models like Mean-Variance, Value-at-Risk, Conditional Value-at-Risk, and Omega often rely on historical returns, which can be insufficient in optimizing return and reducing risk. Recently, researches have used predictive return models in the optimization process. This study uses ARIMA model to predict stock returns alongside a mean-variance optimization model (ARIMA_MV) using Iranian exchange market data from 1395 to 1401. First, stock returns have been predicted using ARIMA model and error criteria such as MSE, MAD, HR, HR+ and HR- are estimated. The results show that despite its simplicity, the ARIMA model has a relatively good performance in predicting the return of stock. Then, using the predicted return and the mean variance model, the optimal portfolio has been calculated in the sliding window process. The results show that portfolios calculated by ARIMA_MV model outperform the Tehran Exchange Index (TEDPIX), risk-adjusted criterion like Sharpe and Jensen's alpha ratios and mean_variance model with historical data (HMV). With the model developed in this project (ARIMA_MV), investment companies can offer shareholders higher returns and lower risks, potentially increasing company value in the capital market and boosting shareholder wealth.

Keywords:
ARIMA , Mean Variance, Portfolio Optimization, Historical Mean Variance.

Introduction

Investment choices and portfolio creation in capital markets are significant for economic development, requiring advanced methods to analyze complex time-series data for securities prices. The importance of risk management and portfolio optimization is amplified by crises such as the 2008 financial downturn. Traditional portfolio models have faced criticism for relying solely on historical mean asset returns, which don't accurately predict short-term trends, hence newer models like Mean Absolute Deviation and Mean Value-at-Risk have emerged to address these limitation [14,22].

This research proposes an approach that combines the ARIMA model with a Mean-Variance

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optimization method, helping investment companies for risk management and optimal portfolio selection. The goal is to continually monitor and optimize the portfolio of an Investment Company to rebalance portfolio.

The contribution of this article is described as followed. (1) the performance of the mean-variance portfolio has been compared based on both with return prediction and without return prediction. (2) With the current status of Iran's stock market being noticed in which there is no short selling possibilitty, this limitation has been applied to the model as one of the most important contributions of the research. (3) Also given the high amount of transaction cost in the Iran’s market exchange, models have both been evalutaded with and without the transaction cost for more reliable results.

The study is descriptive-correlational research, analyzing return modeling and stock portfolio optimization [3]. The data collection is documentary-library type, using information available in existing resources. The research aims to resolve an investment management issue, making it an applied study. In this article, we used 170 most liquid companies on the Tehran Stock Exchange data from 2016 to 2022. Data analysis includes statistical methods, hypothesis tests, and Python software.

Materials and Methods

Investing in the capital market is an attractive option for investors due to its decent returns compared to other markets, low initial capital requirements, liquidity, and ability to trade stocks anytime, anywhere. Despite the high-risk nature of this market and the possibility of long-term capital blocking, individuals can achieve profitable investments with sufficient knowledge and experience. Market risks arise from changes in price levels, economic laws, and other factors influencing supply and demand. Portfolio selection is one way to manage these risks, as diversifying stocks in a portfolio reduces overall risk due to varying impacts of different economic, political, and social conditions on companies. Thus, various methods have been explored to portfolio selection [21, 22, 4].

Harry Markowitz introduced the concept of portfolio selection in 1952. Sharp and Lintner proposed the Capital Asset Pricing Model (CAPM) in 1964 and 1965 respectively. This model predicts that the expected additional return of an asset relative to a risk-free asset should be a ratio of systematic risk measured by the covariance of asset returns with a portfolio consisting of all market assets. This theory was later expanded and developed through numerous studies, leading to newer versions of the initial CAPM [12, 14].

The classic intertemporal pricing model began with Harry Markowitz's (1952) portfolio selection problem, later modeled by Sharp (1964) and Lintner (1965), and further developed and expanded in numerous studies (such as Fama and French's) [3, 10]. Markowitz proposed that an investor selects an asset or portfolio that, compared to other assets or portfolios at a specific level of variance, yields the highest return or, at a specific level of return, has the lowest variance. Mathematically, we assume that the investor prefers a higher expected return over a lower one, and is risk-averse, where risk is represented by variance. Therefore, if this economic unit has access to two portfolios, A (comprising n assets) and B (comprising a different set of assets), portfolio A would be preferred over B according to the mean-variance criterion, if certain conditions are met.

$$\begin{aligned} & ER_A \geq ER_B \\ & and: \\ & \operatorname{var}(R_A) \leq \operatorname{var}(R_B) \end{aligned} \tag{1}$$

Mathematical programming models typically use nominal data for constraints or objective functions. However, in a financial market, data and parameters are uncertain, which must be considered when modeling stock portfolio selection. Several methods exist to deal with uncertainty, such as stochastic programming, fuzzy optimization, and robust optimization, each with their advantages and disadvantages. The study of portfolio optimization, considering all its aspects, is essential for investors in the securities exchange market [2, 30].

Investment risk is a critical consideration for stock market investors, as they typically seek the highest returns at the lowest risk. The challenge lies in the portfolio formation—optimizing the proportion of various stocks in the portfolio to minimize risk. Variance was proposed as a risk index by Markowitz (1976), becoming a common risk criterion in portfolio selection. However, Markowitz (1959) later pointed out its flaws, namely, that variance treats both high and low returns equally, which doesn't reflect real-world investor behavior. Investors usually consider fluctuations in unfavorable returns as risk indicators. Studies have shown that asset returns do not have symmetric distribution [14, 3, 21]. Mandelbrot (1963) demonstrated that asset return distribution is fat-tailed. Researchers later found that asset returns exhibit negative skewness and clustering volatility, meaning high changes in asset returns tend to lead to high changes in the future and vice versa. They also exhibit leverage effects, where stock return changes negatively affect market volatility—market downswings increase market volatility. Recently, researchers have found that asset returns have asymmetric time-series dependence—the correlation of asset returns is significantly lower in booming markets than in downturns. In summary, multiple empirical findings about asset return distribution have been observed [11, 2].

Several researchers have explored different risk measurement models and their performance. Nystrom and Skoglund (2001) considered various properties in their research, including wide sequence, negative skewness, and clustering of oscillation. They used the ARMA/GARCH-EVT approach and demonstrated its effectiveness using data from the US dollar to the Swedish krona and S&P 500. Zhou and Galbreth (2002) applied a generalized Student's t-distribution to asset pricing models and found that this distribution outperformed the normal distribution, though it lacked stability. Hudson also used non-Gaussian distributions like Cauchy and Student's t, but did not conclusively demonstrate their superiority to traditional models. Huo and Kertchoval (2007) took skewness, asymmetric correlation, oscillation clustering, and half-sequence width into consideration. They used generalized hyperbolic distributions for risk estimation, with the T-Skewed distribution showing better performance. Zhou (2009), with Walsh, addressed the issue of fat tails in models using the skewed exponential power distribution (SEPD), demonstrating its stability. Finally, Thomas and Gap (2010) based their research on Pareto theory and found that, while the Pareto distribution might be suitable for modeling financial assets, it was not appropriate for financial data with wide sequences [21, 22, 3, 4, 7].

A variety of studies have explored the modeling of assets and estimating Value at Risk (VaR) using different approaches. Webb and Pedigree (2010) utilized Gaussian, Clayton, and T-copulas to estimate correlation, and used the GJR(p,q) model for modeling conditional volatility. Liu (2012) employed Generalized Hyperbolic Distributions for modeling asset returns and estimated conditional VaR using a CCC-GARCH filter. Lee and Lin (2014) examined the validity of asset pricing models, concluding that the variables μ and σ were not suitable for estimating asymmetric and exponential models. Lu (2016) used T-Skewed function for modeling asset return density and presented a model based on mean-VaR that performed better in financial crisis periods. Other studies by Lompidis and colleagues (2017), Karma and colleagues (2017), Lee and Yu (2016), and Tang and colleagues (2015) used GARCH-EVT-Copula approaches and various copulas to estimate VaR and optimize portfolios, demonstrating the effectiveness of these models [7, 16, 23, 24].

Portfolio optimization has consistently faced numerous problems concerning the prediction of expected returns and characteristics that assets actually have which are not considered in models. Therefore, researchers have usually used historical data in portfolio selection models. Recent articles [17,19] used several types of return predictions such as deep learning and combined it with portfolio selection models namely, mean_variance, VaR and etc. In this article ARIMA model has been used to predict stock return with combination of mean_variance method (ARIMA_MV). ARIMA model is a basic and great model to predict stock return and other articles have used this model in their researches [19].

Autoregressive Integrated Moving Average (ARIMA):

Autoregressive Integrated Moving Average (ARIMA), also known as Box-Jenkins models, is a classic statistical model often used for predicting security prices. It is a popular method for modeling time series data based on the philosophy of letting your data speak for itself. ARIMA models extend ARMA models to handle even non-stationary time series. The use of this method includes four steps: identification, estimation, diagnostic control, and prediction. This model, however, usually suffers from some significant limitations such as persistence. In the research, the ARIMA model was used as a benchmark for predicting stock prices and comparing it with other methods [1, 31].

$$\left(1-\sum_{i=1}^{p}\phi_{i}L^{i}\right)(1-L^{i})^{d}r_{t}=\delta+\left(1-\sum_{i=1}^{q}\theta_{i}L^{i}\right)\varepsilon_{t} \tag{2}$$

Methodology

This research focuses on companies trading in the Iranian capital market, with the required information usually disclosed by listed companies. The study uses the data of the 170 most liquid companies from 2016 to 2020 for training and structuring ARIMA model to stock return prediction, and data from 2021 to 2022 to test ARIMA_MV model. The research questions are the ability of models to portfolio selection, its performance in comparison to historical mean-variance method and risk adjusted models like Sharp and Jensen’s alpha and TEDPIX index. The research discusses a single portfolio optimization model, mean-variance. While historical information is typically used to estimate expected stock returns, it is suggested that using return prediction models could yield better results. The ARIMA model's parameters (p, d, q) were chosen based on a grid search over a range of values. The model with the lowest AIC (Akaike Information Criterion) was selected for stock return prediction. Additionally, cross-validation was used to ensure robustness in out-of-sample predictions. The study introduces some traditional optimization models before presenting the enhanced model incorporating return prediction [17, 30].

Mean_Variance Model Using Historical Data (HMV):

In the variance-mean model at a certain level of return, the amount of risk (standard deviation) is minimized. The model used in this case is as follows:

$$\begin{aligned}
&Min \sum_{i,j=1}^{n} w_i w_j \sigma_{ij}\\
&\text{s.t.}\\
&\sum_{j=1}^{n} w_i\,\hat{r}_i > R\\
&\sum_{j=1}^{n} w_i = 1
\end{aligned} \tag{3}$$

where w_i is the ratio of asset i in the portfolio, n is the number of assets in the portfolio, σ_{ij} represents the covariance of assets i and j. The $\hat{r}_i$ is the estimated return of asset i using historical information. In mentioning other models, constraints including the sum of the weights equal to one, which is the same in all models, are not repeated for the sake of avoiding repetition, but these constraints are present by default in all models [3, 30].

Mean-Variance with Return Forecast (ARIMA_MV):

Markowitz, as the builder of modern portfolio theory, proposed the variance-mean model for optimization in which a mathematical modeling effort is made to form a portfolio with the highest return and least risk. Following the model presented by Yu et. al (2020), mean-variance modeling along with stock price prediction (MVF) is as follows. The MVF model is a multi-objective optimization model [17, 19].

$$\begin{aligned} & min \sum_{i,j=1}^{n} w_i w_j \sigma_{ij} - \sum_{i=1}^{n} w_i \hat{r}_i - \sum_{i=1}^{n} w_i \bar{\varepsilon}_i \\ & S.t. \\ & \sum_{i=1}^{n} w_i = 1 \\ & 0 \le w_i \le 1 \quad i = 1,2,\dots,n \end{aligned} \tag{4}$$

where w_i the weight of security i, n the number of securities, σ_{ij} the variance-covariance matrix, ($\hat{r}_i$) the return predicted by deep learning models, $\bar{\varepsilon}_i$ is the prediction error of the return of asset i compared to the actual value.

For portfolio optimization based on Eq. 4, it is necessary to predict stock return which ARIMA model have used in this article. We used training and test data to minimize errors like MSE, MAE, H_R, H_{R+}, and H_{R-}, For selecting the best structure of ARIMA model. Below we introduce the most important error criteria for return prediction [19, 13, 9].

$$\begin{aligned} & MSE = \frac{1}{N}\sum_{i=}^{N}(r_t - \hat{r}_t)^2 \\ & MAE = \frac{1}{N}\sum_{i=}^{N}|r_t - \hat{r}_t| \\ & H_R = \frac{Count_{t=1}^{n}(r_t\hat{r}_t > 0)}{Count_{t=1}^{n}(r_t\hat{r}_t \neq 0)} \\ & H_{R+} = \frac{Count_{t=1}^{n}(r_t > 0 \; and \; \hat{r}_t > 0)}{Count_{t=1}^{n}(\hat{r}_t > 0)} \\ & H_{R-} = \frac{Count_{t=1}^{n}(r_t < 0 \; and \; \hat{r}_t < 0)}{Count_{t=1}^{n}(\hat{r}_t < 0)} \end{aligned} \tag{5}$$

where r_t and $\hat{r}_t$ represent actual return and predictive return at time t respectively.

After selecting portfolio using ARIMA_MV by Eq. 5 and historical prediction mean_variance (HMV) by Eq. 4, it is necessary to compare performance of those models in the optimal portfolio selection with each other, TEDPIX and with risk adjusted return like Sharpe and Jensen's alpha ratio. The performance of the ARIMA_MV model was evaluated using out-of-sample testing and compared to the HMV model. The models were assessed based on their Sharpe ratios, Jensen’s alpha, and TEDPIX index performance. Cross-validation was applied to ensure that the results were not overfitted to the training data, and metrics like MSE, MAE, and HR were used to measure prediction accuracy [18].

Results

Data description are shown in table 1.

Table 1. Summary of statistical characteristics

Description	Amount
No. of stocks	170
Number of trading days of all stocks	272,209
Average return	%0.22
Std. Dev. Of return	%4.78
First quantile of return	-%1.18
Second quantile of return	%0.00
Third quantile of return	%1.46

Several structures of the ARIMA model have been examined to minimize the error criteria presented in Eq. 5. Calculations show that the best model for this purpose is ARIMA (5,0,1). Error criteria is shown in Table 2.

Table 2. Performance of the return prediction model (ARIMA (5,0,1))

ARIMA(5,0,1)	MSE	MAE	HR	HR^+	HR^-
Mean	0.001119	0.026600	53.6%	58.2%	43.7%
Std. Dev.	0.000171	0.002345	0.00536	0.00906	0.03544

As mentioned in Eq. 5, HR denotes total hit rate, $HR+$ means accuracy of positive prediction and $HR-$ is accuracy of negative prediction. Note that this paper sets MAE and MSE as the key metrics since they play important roles in building portfolio with return prediction. The results show that ARIMA (5,0,1) correctly identified the trend of stock in more than 53.6% predictions (HR). A notable point is the relatively suitable performance of the ARIMA model in the HR performance index, but it had a disappointing performance in the HR- index. It seems that this has happened because the capital market was mostly positive between 1395 and 1400, and the ARIMA model mostly predicts the stock as positive. This factor causes the HR ratio to increase simply due to the high number of positive trends or returns. In comparison with Ma (2021), the result of ARIMA model is quite promising [19, 1].

To get closer to reality, ARIMA_MV and HMV models have been used in two scenarios: (1) without transaction cost and (2) with transaction cost.

Portfolio Optimization without Transaction Cost

Based on Eq. 4 and Eq. 5, portfolio selection is made in rebalancing date. The performance of these models in maximizing return and minimizing risk is estimated. In this research, it is assumed that stocks are just bought and sold on portfolio rebalancing days. For simplicity, leverage and short selling are ignored. Transaction costs are also assumed to be zero in this section. For testing the efficiency of return forecasting models and optimization methods, data have been used from March 2021 to October 2022. A rolling window method with a 20-day interval has been considered for this purpose. The algorithm for selecting optimal stock in every rebalancing day is shown in Algorithm1[17].

Algorithm1: The Algorithm of the calculations for rebalancing date:

For t=1 to t=T do:
    Prepare data up to t=1
    Minimize $w^T \sum w + w^T \hat{R} - w^T \in$
    Calculate the weight of stocks
    Calculate portfolio return and risk (beta)
End For.

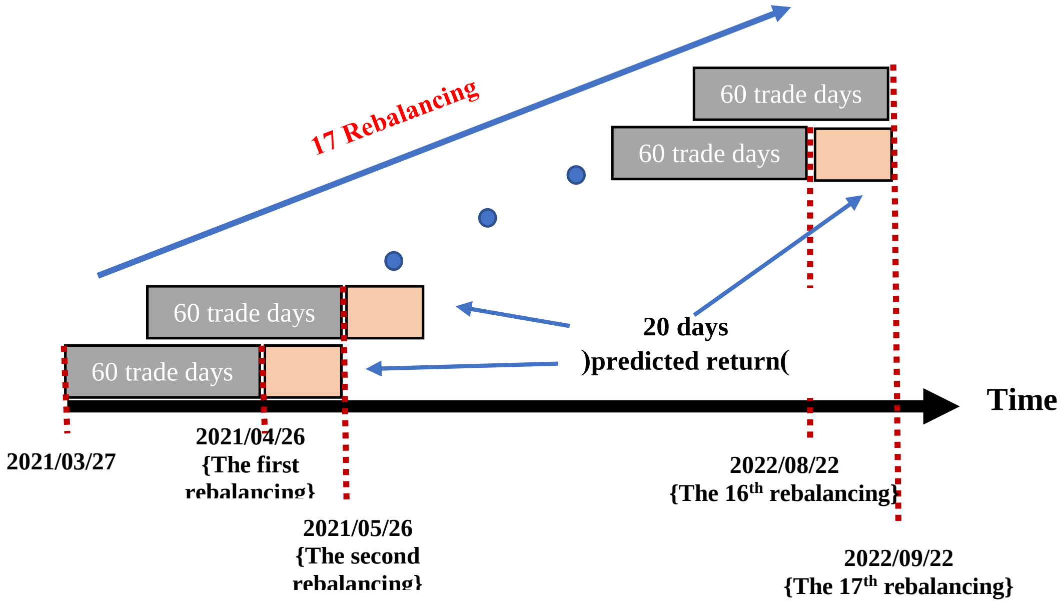

Figure 1. Rebalancing Algorithm system

As is clear from Fig. 1, the first portfolio rebalancing date is 2021/04/26. On this date, the 60-day return of stocks is given as input to predict the return of stocks for 20 days. Then, by solving the optimization model Eq. 4, the optimal weights of each stock are determined. In the next step, the actual portfolio return along with beta and the number of selected stocks for the next 20-day period are calculated. This process is carried out every 20 trading days, and consequently, the final portfolio value and risk-adjusted return measures, including the Sharpe ratio and Jensen's alpha, are reported as output. According to the available data, the last portfolio rebalancing day is 2022/09/22. For better comparison, the return of TEDPIX, Equality weights and historical portfolio optimization (HMV) are used as performance evaluation indicators. Table 3 presents the output ARIMA_MV model and other criteria. For ease of display, some of the portfolio rebalancing dates have been omitted. It is assumed that the initial amount of the portfolio is 1,000,000 units.

Table 3. The output of the yield predictor model along with the optimization methods

Models	Indicators	2021/04/26	2021/05/26	2021/08/02	2022/08/22	2022/09/22
Equality Weights	Value of Portfolio	1,000,000	907,744	1,086,918	979,783	980,121
	Beta	1.00	0.93	0.93	0.93	0.93
	No. of Stocks	0	170	170	170	170
ARIMA_MV	Value of Portfolio	1,000,000	993,818	1,065,795	3,153,103	3,531,800
	Beta	1.00	0.53	0.67	0.17	0.04
	No. of Stocks	0	14	7	8	8
HMV	Value of Portfolio	1,000,000	986,018	1,003,617	1,894,240	1,919,632
	Beta	1.00	0.86	0.89	0.88	0.88
	No. of Stocks	0	11	9	9	8
TEDPIX	Value of Portfolio	1,000,000	934,652	1,144,099	1,200,149	1,141,800

As it is clear from table 3, by using the ARIMA_MV model, an efficiency of about 253% has been achieved. In the same period, the return of the portfolio based on the HMV model was about 92%, the return of the TEDPIX was about 14% and the return of the equality weights was about -2%. The number of selected stocks based on ARIMA_MV models and the HMV are almost similar, but the portfolio risk (indicated by beta) estimated by ARIMA_MV is lower on average than the HMV model. This case shows that the risk-adjusted measures of ARIMA_MV is better than HMV.

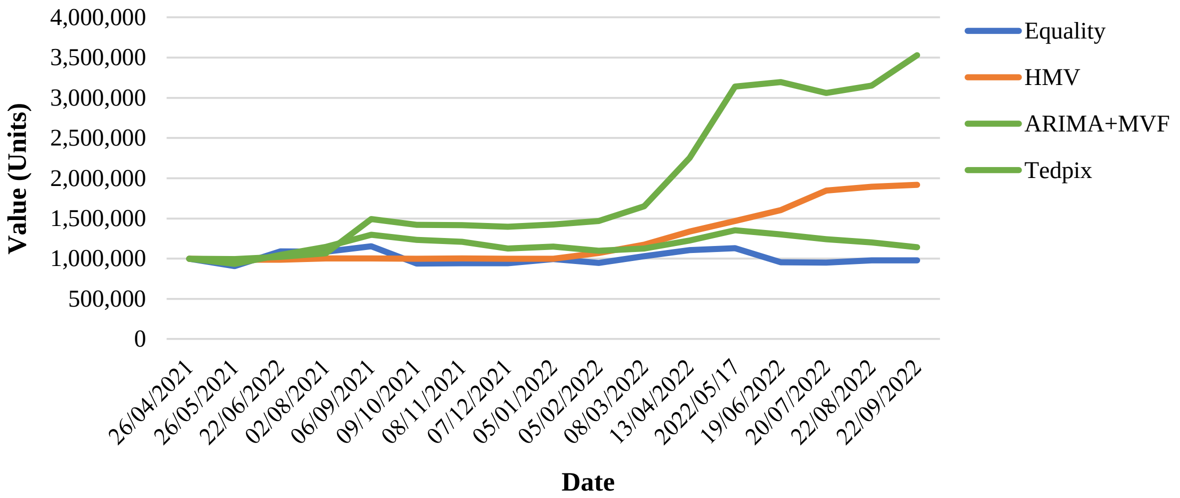

Figure 2. Portfolio value without transaction cost

In table 4, we briefly present the performance of different models and methods in a comparative manner. It should be noted that the results presented in table 4 are the average of all rebalancing periods.

Table 4. Comparing the performance of different models

ARIMA_MV					
Model	**Mean Return**	**std return**	**std/mean**	**No. of Stock**	**Mean beta**
Equality Weight	0.29%	9.33%	31.9	170	0.93
TEDPIX	1.07%	7.26%	6.8	-	1.00
HMV	4.30%	5.58%	1.3	9.0	0.85
ARIMA_MV	9.12%	15.32%	1.7	10.1	0.47

As indicated in table 4, the performance ARIMA_MV model have outperformed HMV, respectively. It's noteworthy that although return is an important parameter, its high fluctuations can reduce the model's reliability. Therefore, the standard deviation and the coefficient of variation (ratio of standard deviation to mean) are also important. The lower the model's coefficient of variation, the more suitable the chosen model is. Results show that the ARIMA_MV does not select many stocks for diversification, seemingly capping portfolio diversification at 10 stocks. On average, the ARIMA_MV selects about 11 stocks per rebalancing period. The average beta of the ARIMA_MV is relatively low, implying that this model achieves high returns while accepting low risks. Table 5 shows the risk-adjusted performance of the models, using the Sharpe ratio and Jensen's alpha.

Table 5. Sharpe ratio

Sharpe ratio			
Model	**Mean**	**std**	**std/mean**
Equality	-0.01	0.10	10.9
Tedpix	0.00	0.07	-
HMV	0.04	0.07	1.7
ARIMA_MV	0.69	2.00	2.9

Table 6. Jensen's Alpha

Jensen's alpha			
Model	**Mean**	**std**	**std/mean**
Equality	-0.78%	7.20%	9.2
Tedpix	0.00%	0.00%	-
HMV	3.19%	8.00%	2.5
ARIMA_MV	7.62%	13.15%	1.7

As it is clear in tables 5 and 6, ARIMA_MV have been able to create more excess return. The excess return (Jensen's alpha) of the models in the test period is as follows.

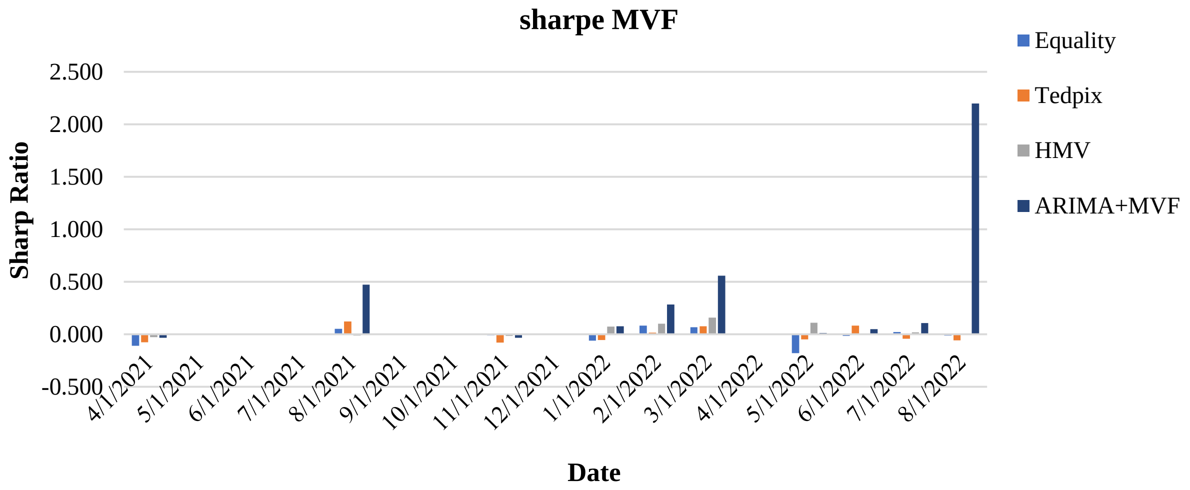

Figure 3. Sharp Ratio

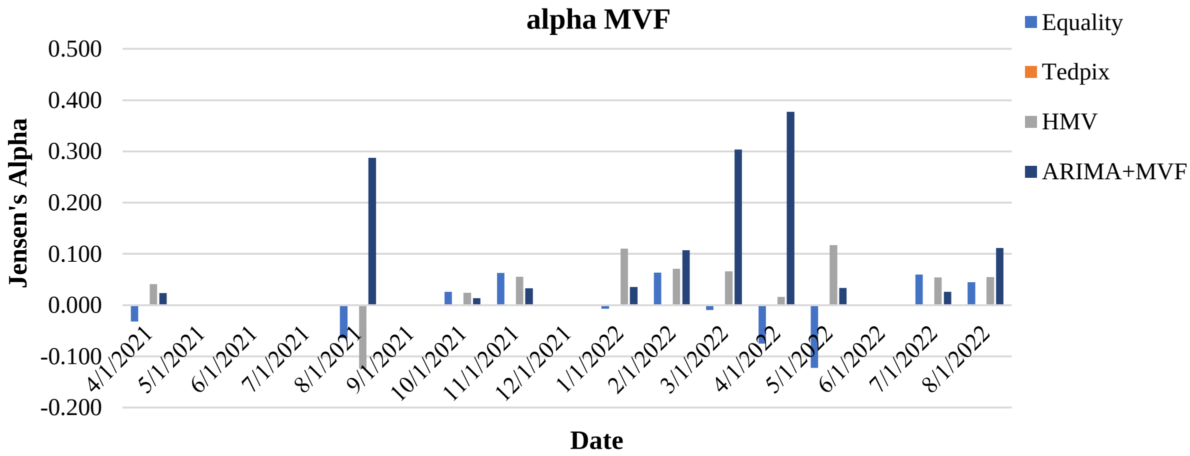

Figure 4. Jensen's alpha

Portfolio Optimization with Transaction Cost

The calculations are done exactly the same as before, with the difference that the transaction fees are subtracted from the value of the portfolio. According to the latest Iranian capital market fees, the purchase fee is equal to 0.3712% and the sales transaction fee (including tax) is equal to 0.88%. Also, to be conservative, it has been assumed that none of the transactions will hit the price ceiling [15].

Table 7. Investigating the performance of optimization models with the transaction cost

Models	Indicators	2021/04/26	2021/05/26	2021/08/02	2022/08/22	2022/09/22
Equality Weights	**Value of Portfolio**	1,000,000	907,744	1,086,918	979,783	980,121
	Beta	1.00	0.93	0.93	0.93	0.93
	No. of Stocks	0	170	170	170	170
ARIMA_MV	**Value of Portfolio**	1,000,000	990,129	1,041,462	2,767,308	3,085,138
	Beta	1.00	0.53	0.67	0.17	0.04
	No. of Stocks	0	14	7	8	8
HMV	**Value of Portfolio**	1,000,000	981,808	997,956	1,854,403	1,878,024
	Beta	1.00	0.86	0.89	0.88	0.88
	No. of Stocks	0	11	9	9	8
TEDPIX	**Value of Portfolio**	1,000,000	934,652	1,144,099	1,200,149	1,141,800

According to the results of table 7, considering trading fees has only affected a percentage of the portfolio's return. The return of the ARIMA_MV is estimated to be about 208%. This value is considered an acceptable return compared to the HMV return (87%), TEDPIX return (14%) and the equality weights (-2%). In the following, the results of the daily value of the portfolio and the performance criteria of the optimization methods are displayed.

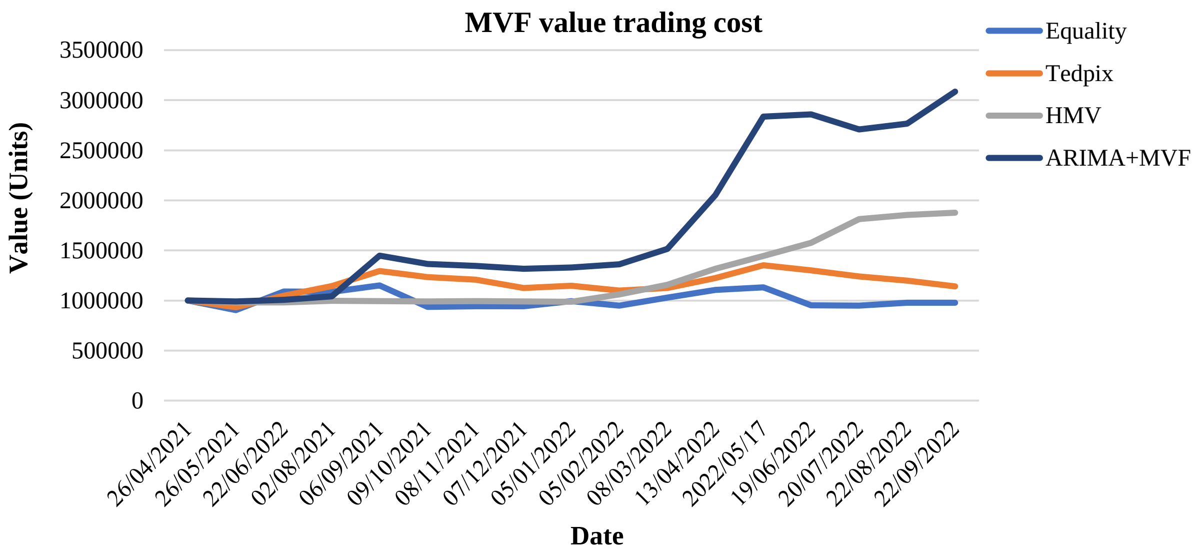

Figure 5. Portfolio value with transaction cost

Conclusion

In traditional investment literature, various methods are used for portfolio optimization, such as Mean-Variance, VaR, CVaR, Omega and etc. In those models, stock returns are usually estimated based on historical data, which can reduce the efficiency of that models in portfolio optimization. In recent studies, researchers have changed the optimization models and have used the predicted stock returns in portfolio optimization models instead of historical returns [17, 19]. Then, they have analyzed the performance of each prediction return model in portfolio optimization [3, 21].

In this research, we analyzed whether the performance of portfolio optimization based on predicted return along with mean variance model (ARIMA_MV) is superior to portfolio optimization based on the historical estimation of returns (HMV) in case of using the return forecast based on the ARIMA (5,0,1) model. For this purpose, the data of the Iranian capital market between 2016 and 2022 have been used.

First, stock returns are predicted based on the ARIMA model and error criteria such as MSE, MAD, HR, HR+ and HR- are estimated. The MSE error criterion was equal to 0.1% and the HR error criterion was equal to 53.6%. The results show that despite its simplicity, the ARIMA model has a relatively good performance in predicting the stock returns compared to the forecasting models presented in the article by Ma et al. Then, using the predicted return and the mean variance model, the optimal portfolio has been calculated by sliding windows. In the other words, from the beginning of 1400 to the end of Aban 1401, the optimal portfolio has been calculated based on ARIMA_MV and after every 20-day rebalancing day, portfolio revising has been done. Then, the return and risk (estimated by beta) of the portfolio have been calculated. The results show that the returns and adjusted returns of the portfolio created by ARIMA is more attractive than other index (Equality weighted, TEPDIX, HMV).

In the sliding windows period (2021 to 2022), the results show that the ARIMA model achieved a mean portfolio return of 253%, significantly outperforming the HMV model's return of 92% and the TEDPIX return of 14%. Additionally, ARIMA_MV's beta of 0.47 compared to HMV's beta of 0.85 indicates a superior risk-adjusted return performance.

Finally, in order to obtain more realistic results, we also considered the transaction costs in the model. In this case, the performance of the ARIMA_MV was more promising compared to the HMV model and other indices. Although the ARIMA_MV model demonstrated promising results, there are limitations in using ARIMA for stock return predictions, particularly in capturing complex, nonlinear relationships in financial data. Future studies could explore more advanced predictive models, such as artificial intelligence and deep learning techniques, to further enhance portfolio optimization and risk-adjusted returns. [27, 28, 19, 6]

References

[1] Adebiyi AA, Adewumi AO, Ayo CK. Comparison of ARIMA and artificial neural networks models for stock price prediction. Journal of Applied Mathematics. 2014;2014(1):614342. doi:10.1155/2014/614342

[2] Ghasemi A, Zahediasl S. Normality tests for statistical analysis: a guide for non-statisticians. International journal of endocrinology and metabolism. 2012;10(2):486. doi: 10.5812/ijem.3505.

[3] Esmaeili B, Souri A, Mirlohi SM. Higher moments portfolio Optimization with unequal weights based on Generalized Capital Asset pricing model with independent and identically asymmetric Power Distribution. Advances in Mathematical Finance and Applications. 2021 Apr 1;6(2):263-83. DOI: https://doi.org/10.22034/amfa.2020.1909590.1484

[4] Rom BM, Ferguson KW. Post-modern portfolio theory comes of age. Journal of investing. 1994 Aug 31;3(3):11-7. Doi: 10.3905/joi.2.4.27

[5] Weng B, Lu L, Wang X, Megahed FM, Martinez W. Predicting short-term stock prices using ensemble methods and online data sources. Expert Systems with Applications. 2018 Dec 1; 112:258-73. doi: 10.1016/j.eswa.2018.06.016

[6] Huang CF. A hybrid stock selection model using genetic algorithms and support vector regression. Applied soft computing. 2012 Feb 1;12(2):807-18. doi:10.1016/j.asoc.2011.10.009

[7] Kharoubi-Rakotomalala C, Maurer F. Copulas in finance ten years later. Journal of Applied Business Research. 2013 Sep 1;29(5):1555. doi:10.19030/jabr.v29i5.8036

[8] Lu CJ, Lee TS, Chiu CC. Financial time series forecasting using independent component analysis and support vector regression. Decision support systems. 2009 May 1;47(2):115-25. doi: 10.1016/j.dss.2009.02.001

[9] Lin CM, Huang JJ, Gen M, Tzeng GH. Recurrent neural network for dynamic portfolio selection. Applied Mathematics and Computation. 2006 Apr 15;175(2):1139-46. doi:10.1016/j.amc.2005.08.031

[10] Gandhmal DP, Kumar K. Systematic analysis and review of stock market prediction techniques. Computer Science Review. 2019 Nov 1;34:100190. doi:10.1016/j.cosrev.2019.08.001

[11] Jondeau E. Asymmetry in tail dependence in equity portfolios. Computational Statistics & Data Analysis. 2016 Aug 1;100:351-68. Doi: 10.1016/j.csda.2015.02.014

[12] Lakzaie F, Bahiraie A. Visualized Portfolio Optimization of stock market: Case of TSE. Advances in Mathematical Finance and Applications. 2024 Feb;2(2):707.

[13] Hamedinia H, Raei R, Bajalan S, Rouhani S. Analysis of Stock Market Manipulation using Generative Adversarial Nets and Denoising Auto-Encode Models. Advances in Mathematical Finance and Applications. 2022 Jan 1;7(1):133-51.DOI: https://doi.org/10.22034/amfa.2021.1933112.1608

[14] HM M. Portfolio selection: efficient diversification of investments.

[15] Yu JR, Chiou WJ, Lee WY, Lin SJ. Portfolio models with return forecasting and transaction costs. International Review of Economics & Finance. 2020 Mar 1;66:118-30.doi:10.1016/j.iref.2019.11.002.

[16] Viebig J, Poddig T. Modeling extreme returns and asymmetric dependence structures of hedge fund strategies using extreme value theory and copula theory. Journal of Risk. 2011;13(2):23. Doi: 10.21314/JOR.2010.220

[17] Yu JR, Chiou WJ, Lee WY, Lin SJ. Portfolio models with return forecasting and transaction costs. International Review of Economics & Finance. 2020 Mar 1; 66:118-30. doi: https://doi.org/10.1016/j.iref.2019.11.002.

[18] Wang JZ, Wang JJ, Zhang ZG, Guo SP. Forecasting stock indices with back propagation neural network. Expert Systems with Applications. 2011 Oct 1;38(11):14346-55. doi:10.1016/j.eswa.2011.04.222

[19] Ma Y, Han R, Wang W. Portfolio optimization with return prediction using deep learning and machine learning. Expert Systems with Applications. 2021 Mar 1; 165:113973. Doi: 10.1016/j.eswa.2020.113973

[20] Kapsos M, Christofides N, Rustem B. Worst-case robust Omega ratio. European Journal of Operational Research. 2014 Apr 16;234(2): 499-507.DOI: 10.1016/j.ejor.2013.04.025

[21] Zanjirdar M. Overview of portfolio optimization models. Advances in mathematical finance and

applications. 2020 Oct 1;5(4): 419-35.DOI: https://doi.org/10.22034/amfa.2020.674941
[22] Ustun O, Kasimbeyli R. Combined forecasts in portfolio optimization: a generalized approach. Computers & Operations Research. 2012 Apr 1;39(4): 805-19.doi:10.1016/j.cor.2010.09.008
[23] Taleblou R, Davoudi MM. Estimation of Optimal Investment Portfolio Using Value at Risk (VaR) and Expected Shortfall (ES) Models: GARCH-EVT-Copula Approach. Economics Research. 2018 Dec 22;18(71):91-125. (in persian)
[24] Fallahpour S, Ahmadi E. Estimating value at risk of portfolio of oil and gold by Copula-GARCH method. Financial Research Journal. 2014 Sep 23;16(2):309-26. (in persian)
[25] Lee SI, Yoo SJ. Threshold-based portfolio: the role of the threshold and its applications. The Journal of Supercomputing. 2020 Oct;76(10): 8040-57.doi:10.48550/arXiv.1709.09822
[26] Deng S, Min X. Applied optimization in global efficient portfolio construction using earning forecasts. The Journal of Investing. 2013 Nov 30;22(4):104-14. DOI:10.3905/joi.2013.22.4.104
[27] Ta VD, Liu CM, Tadesse DA. Portfolio optimization-based stock prediction using long-short term memory network in quantitative trading. Applied Sciences. 2020 Jan 7;10(2):437. Doi:10.3390/app10020437
[28] Wang W, Li W, Zhang N, Liu K. Portfolio formation with preselection using deep learning from long-term financial data. Expert Systems with Applications. 2020 Apr 1; 143:113042. doi: 10.1016/j.eswa.2019.113042
[29] Hong Y, Tu J, Zhou G. Asymmetries in stock returns: Statistical tests and economic evaluation. The Review of Financial Studies. 2007 Sep 1;20(5):1547-81. DOI:10.1093/rfs/hhl037
[30] Zhang Y, Li X, Guo S. Portfolio selection problems with Markowitz's mean–variance framework: a review of literature. Fuzzy Optimization and Decision Making. 2018 Jun; 17:125-58. DOI: 10.1007/s10700-017-9266-z
[31] Eghtesad A, Mohammadi Ů. Portfolio optimization with return prediction using LSTM, Random forest, and ARIMA. Financial Management Perspective. 2023 Dec 22;13(43):9-28. https://doi.org/10.48308/jfmp.2024.104191