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# EVALUATION OF EFFECTIVENESS OF ARIMA MODEL PREDICTIONS IN INVESTMENT PORTFOLIO FORMATION AND MANAGEMENT

**Iryna Brolinska[1], Grigorij Žilinskij[2]**

[1]*Vilnius Gediminas Technical University, Vilnius, Lithuania, irinabrolinska@gmail.com, ORCID: orcid.org/0009-0005-6288-3157*

[2]*Vilnius Gediminas Technical University, Vilnius, Lithuania, grigorij.zilinskij@vilniustech.lt, ORCID: orcid.org/0000-0002-8484-8695*

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**Abstract**

**Research purpose.** The increasing array of financial assets and investment opportunities nowadays is making investors consider new ways of investment portfolio formation and management. Many choose to take advantage of a wide variety of forecasting models in order to enhance investment portfolio performance results. However, each forecasting model has its application peculiarities, strengths, weaknesses and distinctive features. This paper offers a methodological basis and evaluation of the application of the ARIMA forecasting model in investment portfolio formation and management. The purpose of the research is to evaluate the effectiveness of ARIMA model predictions in investment portfolio creation and management.

**Design / Methodology / Approach.** The period of two years, from May 2023 to April 2025, was chosen as the interval for conducting this research. The dataset for this experiment comprised five years of monthly securities prices, therefore the ARIMA model application and reinvestment occurred on a monthly basis. For an accurate evaluation of the ARIMA model-based investment portfolio, it has been compared with an ordinary mean-variance investment portfolio which has been created and managed in the same way. Additionally, the accuracy of the forecasts and their influence on portfolio performance has been evaluated.

**Findings.** The findings of this study suggest that, given the monthly reinvestment and securities chosen, the implementation of the ARIMA model in investment portfolios is not recommended. This conclusion is based on the relatively low performance of the portfolio and the significant time and effort required to implement the ARIMA model, leading to its inefficiency.

**Originality / Value / Practical implications.** The practical implications of this study suggest that investors should consider alternative forecasting models, different trading frequencies, or other financial assets to achieve better results. If investors opt to implement the ARIMA model for investment portfolio formation and management, it is important to note that the forecasts have shown to be accurate for short-term predictions, particularly in securities with strong trends and low-price volatility.

**Keywords:** Investment portfolio; ARIMA model; forecasting; active management

**JEL codes:** G12; G17

## Introduction

An increasing interest in the topic of investment is drawing more and more attention from academics and practitioners alike. Some of the main reasons are that current financial markets offer improved opportunities, and investment accessibility has expanded even for those without formal financial education. Moreover, with technological innovations, such as artificial intelligence (AI), machine learning (ML), blockchain, etc., many new ways of investing are arising. Considering such an increasing trend, it becomes obvious just how important portfolio formation strategies are. Also, considering the rising competition, it is crucial to create and manage an investment portfolio in such a way, so that it

* Corresponding author. E-mail: *grigorij.zilinskij@vilniustech.lt*

would bear profits and minimize risks as much as possible. Depending on the investment objectives and methods chosen, investment portfolio formation and management can be a very time-consuming and complicated process. There are hundreds of models for portfolio creation, as well as hundreds of investment strategies and ways to manage the portfolio. Not only technical aspects of financial instruments are important, but also individual features of the investor and various macroeconomic trends (Bodie et al., 2020). With so many things to consider, modern investors are looking for new ways to improve some of the steps of investment portfolio formation and management and forecasting models are one such way. When used for the prediction of financial asset prices, they might reduce risks and maximize profits at the same time. However, no matter how effective the forecasting model is, it can't predict the future, and many models are struggling with highly volatile unpredictable data. Therefore, forecasting models are widely used to support portfolio managers, but it is not advised to solely rely on those predictions while making important investment decisions. Such a drawback is making many investors wonder whether forecasting models are worth using. Upon review of the existing scientific literature, it becomes evident that the ARIMA model is predominantly used for security price prediction and assessing its accuracy. However, there seems to be a lack of practical evidence of ARIMA model integration into the investment portfolio. Therefore, this work aims to find out just how effective the ARIMA model is in investment portfolio formation and management.

## Literature review

One of the most important trends in recent years is the increasing number of technological advances. As much as it is an opportunity, it is also a challenge, because those who fail to implement the latest technological innovations in their business, might lose a competitive advantage. Therefore, digital technology adaptation is not just an alternative but more of a necessity in an increasingly digitally connected era (Upe, 2023). One of the fields of digital technology adaptation is the development and improvement of various forecasting models.

As stated by Hassen et al., (2020), in general, forecasting models are divided into two categories: qualitative and quantitative. Qualitative forecasting models are usually subjective in nature and are mostly based on the opinions and judgments of experts. On the other hand, quantitative forecasting models make future predictions based on available data (Hassen et al., 2020). Examples of qualitative forecasting methods, also called judgemental methods, usually include various surveys and market research (Armstrong & Green, 2018; Cardoso & Duarte, 2006; Lee et al., 2008; Thoplan, 2014). However, all qualitative models lack precision and, therefore often don't produce accurate forecasts compared to quantitative models (Hassen et al., 2020). Quantitative models are then divided into 2 categories: time-series models and causal models. Causal models simply use causal variables for forecasting and are more accurate when large changes are expected (Allen & Fildes, 2001). A time series is defined as a sequence of observations taken sequentially in time (Box et al., 2016) and time-series forecasting is used across many fields of study, such as weather forecasting, earthquake prediction or astronomy (Ingsrisawang & Wongoutong, 2023). For example, financial time series analysis is concerned with the theory and practice of asset valuation over time (Box et al., 2016). Time series forecasting uses the model to predict future values based on previously observed values at present (Saha & Sinha, 2020). As mentioned by Brockwell & Davis (2016) there are continuous time series, where observations are recorded continuously over time and discrete time series if the set of observations is discrete. There are also deterministic time series, whose future values can be exactly determined by a mathematical function and non-deterministic time series, which have a certain random component which prevents us from describing their behaviour with analytical expression. Another important differentiation of time-series models is stationarity. Stationary series are processes for which some of their properties do not vary with time, while non-stationary processes include trends or seasonal effects (Brockwell & Davis, 2016)

As for the different examples of time-series forecasting models, classical widely used ones include such models as Autoregressive (AR), Moving Average (MA), Simple Exponential Smoothing (SES), and Autoregressive Integrated Moving Average (ARIMA) (Fatemi et al., 2023). However, recently deep learning-based forecasting models have also gained a lot of attention, especially the Long Short-Term Memory (LSTM) model (Fatemi et al., 2023). There are also hybrid methods, such as Gradient Boosting

Machines (GBMs) and Random Forests, which combine traditional statistical techniques with machine learning algorithms (Malik et al., 2023).

The ARIMA forecasting model models trends, cycles, seasonality, and other determinants that affect the determined indicator (Lyulyov et al., 2024).  When working with time series it is very important to identify its stationarity, because a forecasting model must fit the data chosen. In general, financial asset price fluctuations are non-stationary processes as the prices are influenced by many factors and have various trends. According to Brockwell & Davis (2016) when coming upon a non-stationary time-series, there are two main approaches. The first approach is to attempt to fit an ARMA model by removing any trends, seasonality or significant residuals. Another approach is to create a new time series by a process called differentiation and fit an ARIMA (autoregressive integrated moving-average) model. ARIMA models can then additionally be extended to include the analysis of the seasonal component, these models are referred to as SARIMA (seasonal autoregressive integrated moving average models) (Brockwell & Davis, 2016).

Forecasting models often help investors make well-informed trading decisions by capturing short-term and long-term trends and predicting financial asset prices (Malik et al., 2023). Each time-series model has its advantages and disadvantages. For example, Liu et al., (2022) found out that the ARIMA model is effective in the short, but cannot predict long-term trends well, therefore should be combined with other models. According to several research, ARIMA model predictions are precise in the short term even while applying to different financial assets (Jiang, 2023; Mo, 2023; Shao, 2023; Tian, 2023). Besides time series models, Machine and Deep Learning prediction algorithms, which have been specifically designed to deal with large volume data, are used more and more often (Ndikum, 2020). The main advantage of such forecasting models is that they can automatically learn and adapt to intricate patterns while capturing both linear and nonlinear dependencies in the data, therefore benefiting from training data and constantly improving (Zhang et al., 2024) For example, LSTM and Random Forest (RF) model show much better results in long-term comparing to ARIMA model, and LSTM model can predict a higher degree of simulation of highly non-linear problems (Pan, 2023). Certain hybrid models have also shown much better results compared to the ARIMA model (Khadka et al., 2012; Yu et al., 2020). On the other hand, as mentioned by (Zhang et al., 2024), the higher the complexity of the model, and the higher the data volume used for its training – the higher the computational cost. Similar to active management, such costs of forecasting model application might not be worth the gains acquired thanks to it.

For this research, the ARIMA model has been chosen due to multiple indications of its effectiveness in predicting short-term stock prices according to the scientific literature. It is a commonly used traditional time series model that is relatively simple to apply compared to complex machine and deep learning models. However, there seems to be a lack of evidence of the effectiveness of ARIMA model predictions in investment portfolio formation and management. It is important to evaluate not only the forecasting accuracy of the model and rate of return for the asset but also the actual costs and benefits of implementing this forecasting model in investment portfolio formation and management. Moreover, each research result might differ significantly due to different securities taken into consideration, investment horizon, forecasting implementation methods and many other factors.

## Research methodology

The effectiveness of the ARIMA model in this research was evaluated by comparing two investment portfolios that were created using the same methodology and actively managed with monthly reinvestment. Both portfolios were constructed using the renowned Markowitz model with Sharpe ratio maximization. As a result, two portfolios were formed – an ordinary portfolio, used as a control group, and a portfolio with ARIMA model forecasts. Having downloaded the 5-years historical monthly prices dataset for both portfolios, the ARIMA model has been fitted following the detailed steps explained further in the methodology and each time prices have been forecasted for 1 month ahead. Due to the availability of historical data, those two processes have been performed simultaneously.

For this research 3 types of financial assets have been considered due to their notability and availability on demo trading platforms: stocks, cryptocurrencies, and ETFs. As for the security selection step, 10 securities from each of the three types of financial assets were chosen. Table 1 summarizing financial assets taken into consideration, is created by taking the top 10 stocks comprising S&P500 index, and the most popular and profitable cryptocurrencies and ETFs according to the demo trading platform – eToro.

**Table 1. Financial Assets taken into consideration during the investment portfolio formation step** (Source: created by authors)

| Stock | code | Cryptocurrency | code | ETFs | code |
|---|---|---|---|---|---|
| Microsoft Corporation | MSFT | Chainlink | LINK-USD | SPDR S&P 500 Trust ETF | SPY |
| Apple Inc | AAPL | Bitcoin Cash USD | BCH-USD | Vanguard 500 Index Fund | VOO |
| Alphabet Inc. | GOOGL | Optimism | OP-USD | iShares MSCI India ETF | INDA |
| Amazon.com, Inc. | AMZN | API3 | API3-USD | iShares 20+ Year Treasury Bond ETF | TLT |
| NVIDIA Corporation | NVDA | Render Token | RNDR-USD | Invesco QQQ Trust Series 1 | QQQ |
| Meta Platforms, Inc. | META | Bancor | BNT-USD | SPDR Gold Shares | GLD |
| Berkshire Hathaway Inc. | BRK-B | Ethereum | ETH-USD | Vanguard Total Stock Market Index Fund | VTI |
| Eli Lilly and Company | LLY | Build and Build | BNB-USD | Energy Select Sector SPDR Fund | XLE |
| Tesla, Inc. | TSLA | XRP | XRP-USD | ARK Innovation ETF | ARKK |
| Broadcom Inc. | AVGO | Lido DAO | LDO-USD | Global X Uranium ETF | URA |

Going further, only 10 financial assets with the most statistically significant trends have been chosen from Table 1. It has been done to reduce the amount of assets considered in the portfolio formation as the fitting process of the forecasting model and portfolio optimization takes a significant amount of time and effort. This step is also important since ARIMA model forecasts are more accurate when the data shows a certain trend or seasonality, or, in other words, more predictable based on historical values. The dataset has been analysed using RStudios, an integrated development environment for R, a programming language for statistical computations. Four main trendlines have been taken into consideration while conducting this research: (1) linear, (2) logarithmic, (3) polynomial and (4) exponential. The polynomial trend has been evaluated for the second, third and fourth degree. The significance of the regression coefficients has also been accounted for.

$$y = ax + b \tag{1}$$

$$y = a + b \cdot \log(x) \tag{2}$$

$$y = a_n x^n + a_{n-1} x^{n-1} + \ldots + a_2 x^2 + a_1 x + a_0 \tag{3}$$

$$y = a \cdot e^{(b \cdot x)} \tag{4}$$

where:

$y$ – dependent variable;

$x$ – independent variable;

$a$ and $b$ – coefficients of the function;

$n$ – degree of the polynomial (for polynomial trend);

e – mathematical constant, base of the natural logarithm.

After applying each trend to the time series, the statistical significance of each of them has been measured. This step has been performed with hypothesis testing where the null hypothesis indicates that there is no trend, while the alternative hypothesis indicates that a trend exists. In this study, the null hypothesis is tested at a 95% ($\alpha = 0.05$) confidence level. After ensuring that the trend is statistically significant the top 10 assets which had the highest Adjusted R-squared metric from all 4 trends in consideration have been chosen.

$$R^2 = \frac{SSreg}{SYY} = 1 - \frac{RSS}{SYY} \tag{5}$$

where:

$SSreg$ - regression sums of squares;
$RSS$ – residual sum of squares;
$SYY$ – total sum of squares ($RSS$ + $SSreg$)

$$Adjusted\ R^2 = 1 - \left(\frac{(1 - R^2) - (n-1)}{n-k-1}\right) \tag{6}$$

Moving on to the forecasting stage, the notation of the ARMA model is determined by the autoregression order, AR (p) and moving average order, MA (q).

$$Y_t = c + b_1 Y_{t-1} + b_2 Y_{t-2} + \cdots + b_p Y_{t-p} e_t - w_1 e_{t-1} - w_2 e_{t-2} - \cdots - w_q e_{t-q} + e_t \tag{7}$$

where:

$Y_t$ – dependent variable;
$c$ – constant

Following the fitting process described by Kenmei et al., (2008), below mentioned steps were done:

1. Checking the stationarity of the time series and applying differentiation (when applicable) until the process becomes non-stationary.
2. Analysing ACF and PACF functions to decide on AR and MA orders.
3. Applying the ARIMA model to time series and accessing the main summary statistics of the model applied.
4. Residuals diagnosis and ensuring independence of errors.

For checking the time series stationarity Augmented Dickey Fuller (ADF) test was used. During the measuring of model fit, particular attention has been paid to the Akaike Information Criterion (AIC), the significance of plotted AR and MA functions, Mean Absolute Percentage Error (MAPE) and independence or residuals mapped on the scatter plot. In instances where a fitted model exhibits a relatively high AIC and low MAPE but lacks statistically significant regression coefficients, an alternative model fit has been selected. In cases of uncertainty due to similar indicator values, the decision hierarchy prioritizes the significance of regression coefficients, followed by AIC, MAPE, and the examination of residuals scatterplot. Model re-fitting for each security and forecasting of prices have been applied each month together with reinvestment as a part of active portfolio management.

As it has been mentioned earlier, the Markowitz model has been used for portfolio formation. In Markowitz's model risk is measured by the standard deviation or variance, while the expected return is measured by the average return (Bodie et al., 2020). Equations for average rate of return (8) expected rate of return (9), variance of rate of return (10), portfolio rate of return (11), expected portfolio rate of return (12)(12) and portfolio variance (13) are presented below (Bodie et al., 2020). It must be noted that the expected return for the first portfolio (ordinary portfolio) has been evaluated as the average monthly rate of return of 5 years, see (Eq. 8), while the expected return for the ARIMA portfolio has been calculated using the expected rate of return as shown in (Eq. 9).

$$r_{avg} = \frac{1}{n}\sum_{s=1}^{n} r \tag{8}$$

where:

$n$ – number of rate of returns;
$r$ – security rate of return.

$$E(r) = \frac{x_{t+1} - x_t}{x_t} \tag{9}$$

where:

$x_t$ – price of financial asset at t time (current price);
$x_{t+1}$ – price of financial asset at t+1 time (forecasted).

$$\sigma^2 = \frac{\sum(r - \mu)^2}{n} \tag{10}$$

where:

$r$ – rate of return;
μ – mean of rate of return;
$n$ – number of rate of returns.

$$r_p = \sum_{i=1}^{n} w_i r_i \tag{11}$$

where:

$r_i$ – rate of return of financial asset in portfolio;
$w_i$ – weights of each financial asset in portfolio.

$$E(r_p) = \sum_{i=1}^{n} w_i E(r_i) \tag{12}$$

where:

$E(r_i)$ – expected rate of return of financial asset in the portfolio;
$w_i$ – weights of each financial asset in the portfolio.

$$\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \, Cov(r_i, r_j) \tag{13}$$

where:

$r$ – rate of return of each financial asset in the portfolio;
$w$ – weights of each financial asset in the portfolio;
$Cov$ – covariance of rate of returns between each financial asset.

After the calculation of the portfolio rate of return and variance, a Sharpe-ratio maximization model has been applied. As mentioned by Kalebos and Rudianto (2022), it works by comparing the portfolio risk premium with the portfolio risk, represented by standard deviation (σ). The benefit of this model is that it can compare financial assets with various degrees of risk exposure. The formula for the Sharpe ratio is provided in (Eq. 14) below:

$$S_p = \frac{r_p - r_f}{\sigma_p} \tag{14}$$

where:

$r_p$ – portfolio rate of return;
$r_f$ – risk-free rate of return;
$\sigma_p$ – portfolio standard deviation.

The optimization process has been performed by using the Excel Solver tool. The risk-free rate is taken as a 10-year Treasury Rate. Since the data has been analysed on a monthly basis the annual risk-free rate has been divided by 12.

## Research results

In this paragraph the results of the research are presented in the same order as the methodology part describes – security selection and asset allocation (i.e. trend application), evaluation of forecasts accuracy and investment portfolio performance results. Table 2 shows securities with the most statistically significant trends, listing the codes of financial assets, as well as the trend type and the adjusted R-square values.

**Table 2. Top 10 securities with the most statistically significant trends** (Source: created by authors)

| Financial asset | Adjusted R-squared | Trend type |
|---|---|---|
| LLY | 0.9833 | polynomial, 4th degree |
| AVGO | 0.9606 | polynomial, 4th degree |
| NVDA | 0.9329 | polynomial, 4th degree |
| XLE | 0.9247 | polynomial, 3rd degree |
| BRK-B | 0.912 | polynomial, 4th degree |
| MSFT | 0.9021 | polynomial, 4th degree |
| AAPL | 0.9008 | polynomial, 2nd degree |
| VOO | 0.8947 | polynomial, 4th degree |
| GLD | 0.8855 | polynomial, 4th degree |
| TLT | 0.8845 | polynomial, 3rd degree |

The best-fit trend type for most of the securities has shown to be polynomials of various degrees. It is likely due to the fact that financial securities prices are affected by market fluctuations and often experience ups and downturns. The financial assets with the most statistically significant trends turned out to be 4 ETFs and 6 stocks. Cryptocurrencies are highly volatile and unpredictable in nature; therefore, their price fluctuations cannot be easily predicted even by the algorithms.

Moving on to forecasting results, (

Table 3) presents a comparative analysis of monthly forecasted prices, denoted as (f), with actual prices over a two-year duration. The forecasted values are distinctly marked in grey for an easier comparison.

**Table 3. Comparison of monthly forecasted prices and actual prices for the securities analysed** (Source: created by authors)

| | LLY | AAPL | XLE | AVGO | TLT | BRK-B | MSFT | NVDA | GLD | VOO |
|---|---|---|---|---|---|---|---|---|---|---|
| June 2023 (f) | 419.79 | 179.99 | 74.65 | 80.44 | 94.66 | 329.59 | 343.30 | 42.04 | 186.03 | 381.54 |
| June 2023 | 462.34 | 192.05 | 75.98 | 84.03 | 95.19 | 341.00 | 335.33 | 42.27 | 178.27 | 395.89 |
| July 2023 (f) | 458.25 | 196.91 | 75.88 | 93.43 | 94.86 | 348.36 | 364.18 | 47.02 | 176.13 | 402.93 |
| July 2023 | 448.11 | 194.50 | 82.61 | 87.52 | 92.76 | 351.96 | 330.78 | 46.70 | 182.35 | 410.52 |
| August 2023 (f) | 431.28 | 192.55 | 81.48 | 94.11 | 92.45 | 350.37 | 343.58 | 53.36 | 182.83 | 421.98 |
| August 2023 | 546.35 | 186.01 | 83.97 | 89.88 | 89.84 | 360.20 | 322.74 | 49.33 | 180.02 | 403.83 |
| September 2023 (f) | 549.19 | 189.15 | 85.35 | 95.14 | 87.89 | 373.63 | 325.86 | 53.24 | 179.84 | 419.36 |
| September 2023 | 530.66 | 169.74 | 85.36 | 80.89 | 82.68 | 350.30 | 311.57 | 43.48 | 171.45 | 383.21 |
| October 2023 (f) | 551.22 | 178.77 | 86.60 | 81.43 | 77.60 | 354.45 | 320.74 | 43.18 | 168.78 | 384.23 |
| October 2023 | 547.26 | 169.31 | 81.04 | 82.39 | 78.15 | 341.33 | 333.64 | 40.76 | 184.09 | 376.32 |
| November 2023 (f) | 556.60 | 174.03 | 82.09 | 78.97 | 73.19 | 344.11 | 334.05 | 42.02 | 183.14 | 364.44 |
| November 2023 | 583.92 | 188.32 | 80.46 | 90.65 | 85.88 | 360.00 | 373.90 | 46.75 | 188.75 | 410.83 |
| December 2023 (f) | 598.92 | 189.26 | 81.67 | 89.85 | 85.83 | 360.30 | 380.90 | 48.40 | 192.23 | 405.44 |
| December 2023 | 576.96 | 191.13 | 79.75 | 109.31 | 93.07 | 356.66 | 371.82 | 49.50 | 191.17 | 427.88 |
| January 2024 (f) | 595.27 | 193.12 | 79.14 | 120.12 | 97.95 | 358.18 | 378.67 | 49.41 | 197.95 | 439.83 |
| January 2024 | 639.01 | 183.06 | 80.11 | 116.08 | 91.56 | 383.74 | 393.12 | 61.50 | 188.45 | 436.55 |
| February 2024 (f) | 661.82 | 192.89 | 81.79 | 128.47 | 91.82 | 384.94 | 391.13 | 68.64 | 189.51 | 459.37 |
| February 2024 | 745.98 | 179.44 | 82.73 | 127.93 | 89.21 | 409.40 | 409.00 | 79.08 | 189.31 | 459.28 |
| March 2024 (f) | 803.28 | 184.06 | 83.15 | 138.86 | 88.78 | 425.48 | 425.05 | 91.49 | 188.83 | 474.93 |
| March 2024 | 771.36 | 170.45 | 90.67 | 130.38 | 89.91 | 420.52 | 416.77 | 90.32 | 205.72 | 472.82 |
| April 2024 (f) | 802.73 | 163.27 | 91.00 | 138.15 | 89.27 | 443.52 | 418.38 | 98.12 | 210.24 | 486.27 |
| April 2024 | 774.47 | 169.31 | 90.54 | 128.46 | 84.10 | 396.73 | 385.67 | 86.37 | 211.87 | 455.33 |
| May 2024 (f) | 812.57 | 172.18 | 93.99 | 133.05 | 83.08 | 402.51 | 385.52 | 87.15 | 213.11 | 461.95 |
| May 2024 | 813.38 | 191.10 | 90.23 | 131.25 | 86.51 | 414.40 | 411.23 | 109.60 | 215.30 | 478.21 |
| June 2024 (f) | 835.13 | 207.11 | 90.87 | 142.43 | 86.95 | 414.07 | 417.26 | 119.35 | 216.26 | 479.19 |
| June 2024 | 899.23 | 209.64 | 88.25 | 158.61 | 88.09 | 406.80 | 443.55 | 123.50 | 215.01 | 493.52 |
| July 2024 (f) | 952.78 | 207.61 | 84.79 | 166.35 | 87.53 | 411.37 | 458.47 | 134.19 | 216.46 | 525.64 |
| July 2024 | 798.80 | 221.05 | 90.97 | 159.24 | 91.31 | 438.50 | 415.17 | 116.99 | 226.55 | 501.01 |
| August 2024 (f) | 850.68 | 212.77 | 92.56 | 171.68 | 91.01 | 438.50 | 422.31 | 122.42 | 227.95 | 514.32 |
| August 2024 | 953.49 | 227.93 | 89.08 | 161.36 | 93.22 | 475.92 | 413.97 | 119.34 | 231.29 | 513.00 |
| September 2024 (f) | 955.32 | 224.32 | 89.56 | 168.90 | 93.13 | 480.67 | 419.52 | 124.60 | 232.56 | 506.54 |
| September 2024 | 881.15 | 232.18 | 85.69 | 170.96 | 95.09 | 460.26 | 427.80 | 121.41 | 243.06 | 522.54 |
| October 2024 (f) | 944.75 | 238.19 | 89.40 | 173.19 | 95.16 | 467.64 | 449.47 | 118.22 | 246.16 | 531.16 |
| October 2024 | 825.25 | 225.12 | 87.17 | 168.81 | 89.91 | 450.92 | 403.99 | 132.74 | 253.51 | 519.20 |
| November 2024 (f) | 872.14 | 222.71 | 87.83 | 175.56 | 91.06 | 456.07 | 408.66 | 139.44 | 258.93 | 524.43 |
| November 2024 | 791.05 | 236.50 | 94.00 | 161.16 | 91.68 | 483.02 | 421.00 | 138.23 | 245.59 | 549.78 |
| December 2024 (f) | 821.65 | 241.90 | 93.53 | 164.39 | 92.36 | 485.33 | 424.64 | 142.00 | 249.35 | 555.25 |
| December 2024 | 769.10 | 249.82 | 84.29 | 230.52 | 85.49 | 453.28 | 419.89 | 134.27 | 242.13 | 535.24 |
| January 2025 (f) | 762.26 | 251.59 | 86.34 | 239.95 | 84.44 | 459.27 | 424.81 | 137.74 | 243.58 | 548.65 |
| January 2025 | 808.03 | 235.43 | 86.96 | 220.60 | 86.54 | 468.67 | 413.47 | 120.06 | 258.56 | 551.42 |
| February 2025 (f) | 817.36 | 234.31 | 88.44 | 227.49 | 85.10 | 472.46 | 417.88 | 118.90 | 261.78 | 559.36 |
| February 2025 | 917.17 | 241.26 | 90.30 | 198.83 | 91.15 | 513.83 | 395.47 | 124.91 | 263.27 | 544.44 |
| March 2025 (f) | 915.57 | 248.41 | 83.10 | 230.03 | 92.03 | 509.45 | 397.65 | 126.66 | 266.64 | 555.78 |
| March 2025 | 824.22 | 221.84 | 92.73 | 166.92 | 90.09 | 532.58 | 374.70 | 108.37 | 288.14 | 512.13 |
| April 2025 (f) | 858.35 | 221.43 | 93.22 | 193.81 | 88.35 | 89.03 | 379.56 | 99.73 | 292.67 | 526.61 |
| April 2025 | 897.11 | 212.22 | 80.50 | 192.47 | 88.82 | 533.25 | 394.54 | 108.92 | 303.77 | 509.74 |
| May 2025 (f) | 843.41 | 224.43 | 94.13 | 169.41 | 88.17 | 539.29 | 378.55 | 101.34 | 294.11 | 518.30 |
| May 2025 | 722.57 | 199.95 | 82.26 | 241.97 | 86.15 | 506.18 | 458.68 | 139.19 | 305.61 | 542.32 |

However, since the range of prices for each security varies greatly, (Fig. 1-3) present graphs of forecasted and actual rates of return throughout the period of 2 years and their monthly fluctuations. Each graph depicts 2 securities and for each one forecasted (f) and actual (a) rate of return are presented.

For a more convenient visualization forecasted prices are represented by the dotted lines. Forecasted rate of return implies expected rate of return calculated for the ARIMA portfolio and used in the optimization model. While actual rate of return uses the adjusted prices at the moment when all positions have been closed.

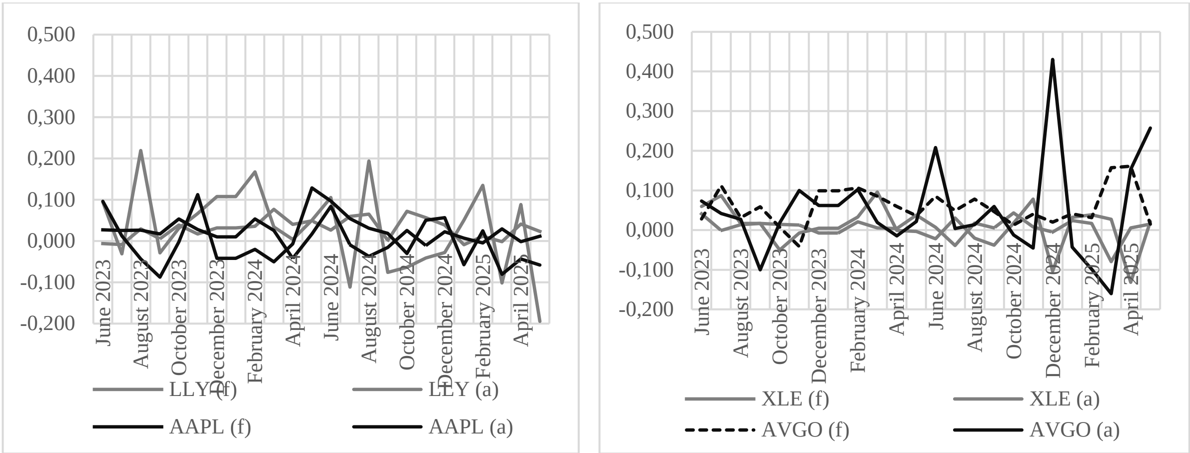


**Fig. 1. Comparison of forecasted and actual rates of return for securities LLY, AAPL, XLE and AVGO**
(Source: created by authors)

As can be observed from Figure 1, LLY and AAPL stocks exhibit certain fluctuations over the period. However, it is clearly visible that the volatility of the forecasted rates of return is smaller than the actual rates of return, which indicates a sudden change in the market price for the presented stocks. On the other hand, the right graph with XLE and AVGO securities shows similar volatility of forecasted rates of return. Moreover, forecasts seem to be quite close to the actual rates or return, however, there are still quite visible gaps between the lines which might indicate the low accuracy of the forecasts. For instance, the AVGO actual rate of return has experienced a drastic increase in December 2024 with a decrease up until March 2025. The forecasted rates of return have followed a similar pattern, starting to increase in February and decreasing in May 2025, but with a slight delay of approximately two months.

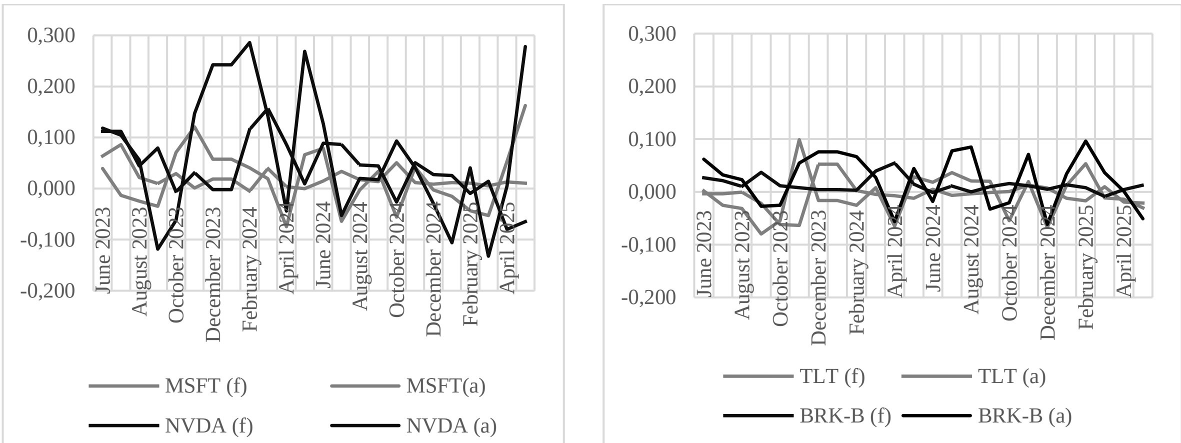


**Fig. 2. Comparison of forecasted and actual rates of return for securities MSFT, NVDA, TLT and BRK-B**
(Source: created by authors)

Figure 2 shows approximately the same findings as the previous two graphs in Figure 1 – forecasted rates of return having slightly lower volatility than actual ones. A certain delay in the accuracy of the forecasted rates of return is visible once again. For example, actual rates of return for NVDA have shown a clear increasing trend starting in October 2023, however, an increase in the forecasted rates of return has begun only from January 2024, which indicates an approximately 3-month delay. As for the TLT and BRK-B, it seems that those securities rates of return are not very volatile in nature, therefore forecasted values represent the actual ones more accurately. Another delay in the upturn of the forecasted rates of return is visible on the right graph. There was an upturn trend in actual rates of return for TLT starting September 2023, the forecasted ones have followed this increase in November 2023. As expected from the model based on historical prices, the predictions are not accurate in case of any sudden price shifts in financial markets. Moreover, even though the forecasted rates of return seem to be quite accurate for those two securities, they still don't follow the same pattern and are slow to respond to market price changes.

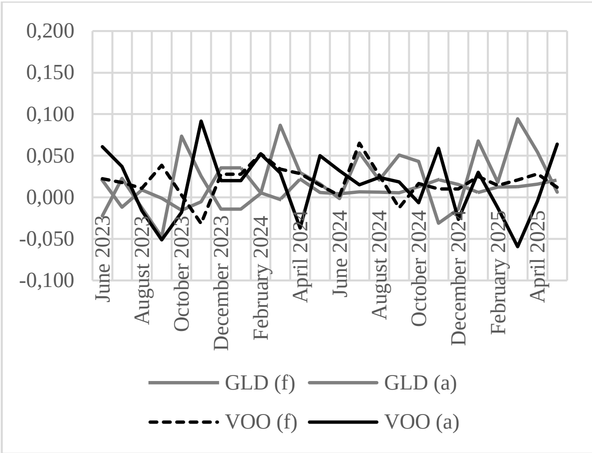


**Fig. 3. Comparison of forecasted and actual rates of return for securities GLD and VOO** (Source: created by authors)

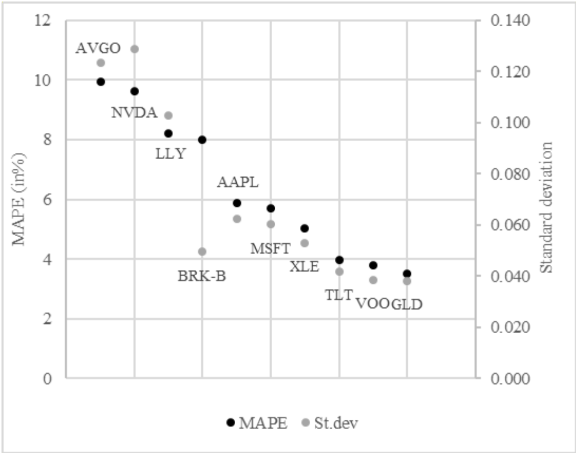


**Fig. 4. MAPE of the forecasted prices and standard deviation of actual rates of return** (Source: created by authors)

Finally, (Fig. 3) confirms some of the findings of the previous graphs. The VOO security has experienced a decrease in rates of return from June till September 2023 followed by a sudden increase up until November 2023. Meanwhile, the forecasted rates of return for VOO have seen a decrease from September to November 2023 with a slight increase till December 2023. This once again points to the one to two-month delay in the forecasted rates of return compared to the actual ones. Another interesting observation is that when both securities' actual rates of return started to experience sudden up-and-down trends around October 2024 and going forward, the forecasted rates of return volatility decreased significantly as both lines have almost merged into a single straight line. It seems that when the market prices change suddenly without any clear trend to follow, ARIMA model forecasts take a more conservative approach and this decreases the accuracy of the forecasts, therefore also decreasing the forecasted rates of return.

As has been previously mentioned and stressed, the volatility of the forecasted rates of return is lower than the actual ones, and Appendix A provides actual estimates for the confirmation of such assumptions. The data has shown that the standard deviation is indeed lower for the forecasted rates of return. There are no cases where the forecasted rates of return are more volatile than the actual ones. To evaluate the precision of ARIMA model forecasts, the Mean Absolute Percentage Error (MAPE) was calculated and shown in Appendix B. The data has shown that securities with higher standard deviations correspond to higher MAPE values, which are also conveniently visualized on the scatterplot (Fig. 4).

The main purpose of this work was to evaluate the effectiveness of ARIMA model predictions by creating and managing an investment portfolio. Regardless of the accuracy of the forecasts, the main effectiveness criteria for the investment portfolio performance are portfolio risk and return. **Error! Reference source not found.**4 presents a comparison of monthly rates of return and a Share-ratio for both portfolios throughout the investment period. Moreover, the average monthly rate of return and standard deviation as a measure of portfolio risk are presented in the table below. It must be noted that the portfolio without forecasts is referred to as an "ordinary portfolio", while the portfolio with ARIMA model forecasts is referred to as an "ARIMA portfolio".

**Table 4. Comparison of rate of return, risk and Sharpe ratio of portfolios** (Source: created by authors)

| ACTUAL, AFTER INVESTMENT | | | | |
|---|---|---|---|---|
| | **Portfolio return** | | **Sharpe-ratio** | |
| | **ARIMA** | **Ordinary** | **ARIMA** | **Ordinary** |
| **MAY 2023** | 0.026 | 0.070 | 0.456 | 1.233 |
| **JUNE 2023** | 0.006 | 0.008 | 0.039 | 0.096 |
| **JULY 2023** | 0.041 | 0.101 | 0.352 | 1.846 |
| **AUGUST 2023** | -0.064 | -0.055 | -1.080 | -1.077 |
| **SEPTEMBER 2023** | 0.012 | 0.014 | 0.131 | 0.173 |
| **OCTOBER 2023** | 0.099 | 0.079 | 1.359 | 1.241 |
| **NOVEMBER 2023** | 0.010 | 0.013 | 0.151 | 0.132 |
| **DECEMBER 2023** | 0.009 | 0.116 | 0.140 | 1.677 |
| **JANUARY 2024** | 0.100 | 0.166 | 1.283 | 2.420 |
| **FEBRUARY 2024** | 0.072 | 0.070 | 0.851 | 1.014 |
| **MARCH 2024** | 0.002 | -0.005 | -0.040 | -0.131 |
| **APRIL 2024** | 0.033 | 0.102 | 0.471 | 1.607 |
| **MAY 2024** | 0.154 | 0.091 | 2.043 | 1.306 |
| **JUNE 2024** | -0.011 | -0.065 | -0.293 | -1.023 |
| **JULY 2024** | 0.089 | 0.096 | 1.198 | 1.408 |
| **AUGUST 2024** | 0.059 | -0.019 | 0.642 | -0.363 |
| **SEPTEMBER 2024** | -0.034 | 0.009 | -0.725 | 0.097 |
| **OCTOBER 2024** | -0.032 | -0.012 | -0.830 | -0.288 |
| **NOVEMBER 2024** | -0.013 | -0.027 | -0.391 | -0.526 |
| **DECEMBER 2024** | 0.010 | -0.001 | 0.105 | -0.079 |
| **JANUARY 2025** | -0.008 | 0.037 | -0.278 | 0.631 |
| **FEBRUARY 2025** | -0.141 | -0.043 | -1.575 | -0.954 |
| **MARCH 2025** | 0.108 | 0.044 | 1.603 | 0.852 |
| **APRIL 2025** | -0.014 | 0.026 | -0.543 | 0.549 |
| **MEAN** | **0.021** | **0.034** | **0.211** | **0.493** |
| **ST.DEV.** | **0.063** | **0.060** | | |

As it can be seen the overall performance of the portfolio with ARIMA model predictions is worse than the ordinary one. The rate of return of the ordinary portfolio is higher not only on the average basis (3.4% vs 2.1%), but on the monthly basis as well. There were a couple of months when the ARIMA portfolio outperformed the ordinary one, however, in those instances the rates of return were not much higher regardless. Another interesting observation is that the rates of return for the ARIMA portfolio follow the same up and downward trends as the ordinary portfolio. This is particularly unique given that the weights of each security have been quite different for each of the portfolios. Overall, the ordinary portfolio has shown to be more diversified for each period analysed. This can be attributed to the fact that the optimization model for the ordinary portfolio has used the average rate of return for the period of 5 years, while the ARIMA portfolio has used the expected rate of return which was highly affected by price forecasts.

As has been mentioned, besides the rate of return, risk is another important evaluation of portfolio performance. In this research, risk has been represented by the standard deviation. The standard deviation for the ARIMA portfolio (0.063) is slightly higher than the standard deviation of the ordinary portfolio (0.060). Therefore, a lower rate of return cannot be attributed to the lower risk of the portfolio.

The Sharpe ratio is another measure of portfolio performance used in this work as a mean of portfolio results evaluation. As shown in (Table 4) the average monthly Sharpe-ratio for the ARIMA portfolio (0.211) is much lower than for the ordinary one (0.493). Evidently, the performance of the ordinary portfolio surpasses that of the ARIMA portfolio.

Finally, it should be noted that even though the performance of the ARIMA portfolio is not significantly worse compared with the ordinary one, another important factor that should be accounted for is time. This work aims to evaluate not only the results of the investment portfolio but more importantly - the effectiveness of the implementation of the ARIMA model in investment portfolio formation and management. The forecasting process and active investment portfolio management are complicated and time-consuming. Therefore, the efforts should be compensated for by a better portfolio performance. Moreover, as such processes are not automated this leaves a higher probability of human error which might lead to inaccurate or erroneous calculations.

The effectiveness of the ARIMA model in this research was evaluated by comparing two investment portfolios that were created using the Markowitz model with Sharpe-ratio maximization and actively managed with monthly reinvestment. Frequently in scientific research, the accuracy of forecasting models' predictions overlooks the efforts and time required by investors to construct such models and implement them in investment portfolios. Even though certain forecasting models such as Machine and Deep Learning prediction algorithms (Ndikum, 2020) or hybrid models, such as Gradient Boosting Machines (GBMs) and Random Forests (Khadka et al., 2012; Malik et al., 2023; Yu et al., 2020) are said to be more effective, as mentioned by Zhang et al., (2024), higher complexity of such models leads to higher computational costs. Not only the costs are to be considered, but also the access to software and vast knowledge needed to apply some of those innovative models. The works of other authors have demonstrated that ARIMA models provide accurate short-term predictions (Jiang, 2023; Mo, 2023; Shao, 2023; Tian, 2023). However, for investors aiming to minimize portfolio management costs (both computational and time-related) ARIMA forecasts have shown to be insufficiently accurate to enhance portfolio performance. Given the high volatility of financial asset prices in markets and the ever-changing economic trends, it becomes evident that the ARIMA model, although traditional and straightforward, lacks some essential features necessary for efficient investment portfolio formation and management. One of the main reasons for such is not only the relatively low accuracy of the predictions itself, but rather a need for regular reinvestment in order to update the model with latest data available and enhance predictions accuracy. And, as summarized by Leković, (2022) frequent active portfolio management gives the possibility of achieving above-average returns, but it comes with higher investment risks and managing costs.

## Conclusions

To summarize, the ARIMA portfolio has shown a lower average rate of return (0.021 vs 0.034) and a slightly higher risk (0.063 vs 0.060), represented by the standard deviation compared to the ordinary portfolio. On the other hand, a much lower Sharpe-ratio for the ARIMA portfolio (0.211) clearly shows that the ordinary portfolio (0.493) has outperformed the ARIMA one. However, there is no clear evidence that such portfolio performance can fully be attributed to the ARIMA model since the accuracy of the forecasts is quite low. There have been a couple of months during the two-year period when the ARIMA portfolio has outperformed the ordinary one. Nevertheless, the average monthly rate of return for the ARIMA portfolio is still evidently lower. Additionally, the poor performance of the ARIMA portfolio does not justify the efforts of the forecasting model implementation and regular active portfolio management. Therefore, investors are not advised to implement the ARIMA model for forecasting monthly securities. If the investors do choose to implement the ARIMA model for investment portfolio formation and management, it should be taken into account that the forecasts are the most accurate for the short-term predictions, in securities with strong trends and low-price volatility. Further research should be conducted to test the effectiveness of ARIMA model implementation in investment portfolio formation and management taking into consideration different financial assets, investment horizon and reinvestment frequency.

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## Appendices

**Appendix A. Standard deviation of forecasted and actual rates of return** (Source: created by authors)

| | forecasted | actual |
|---|---|---|
| **LLY** | 0.025 | 0.103 |
| **AAPL** | 0.028 | 0.063 |
| **XLE** | 0.025 | 0.053 |
| **AVGO** | 0.048 | 0.048 |
| **TLT** | 0.026 | 0.042 |
| **BRK-B** | 0.014 | 0.050 |
| **MSFT** | 0.021 | 0.060 |
| **NVDA** | 0.058 | 0.129 |
| **GLD** | 0.013 | 0.038 |
| **VOO** | 0.019 | 0.039 |
| **Average** | 0,028 | 0,062 |

**Appendix B. MAPE of the forecasted prices and standard deviation of actual rates of return** (Source: created by authors)

| | MAPE | ST.DEV |
|---|---|---|
| **AVGO** | 9.944 | 0.124 |
| **NVDA** | 9.636 | 0.129 |
| **LLY** | 8.207 | 0.103 |
| **BRK-B** | 8.016 | 0.050 |
| **AAPL** | 5.896 | 0.063 |
| **MSFT** | 5.695 | 0.060 |
| **XLE** | 5.046 | 0.053 |
| **TLT** | 3.962 | 0.042 |
| **VOO** | 3.781 | 0.039 |
| **GLD** | 3.523 | 0.038 |