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PROFITABILITY OF CURRENT INVESTMENTS IN STOCK INDEXES

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Abstract. Investing in stock indexes has become an integral part of financial portfolios. Fearing the loss of savings value, households move their financial reserves into stocks, bonds and stock indexes; the latest concerns the subject of this article. The article focuses on determining the best method of forecasting the prices of stock indexes, S&P 500 and NASDAQ Composite, comparing the Simple moving average (SMA) technique with the Autoregressive integrated moving average (ARIMA) model based on free software RStudio. We formulated two plausible hypotheses: Which of these two methods - SMA or ARIMA - is more accurate for predicting the prices of selected stock indexes in the last thirty years? How will the price of the selected stock indexes develop according to the better of the suggested method through 2022? The ARIMA model indicated better results, proving great ability to forecast both indexes through 2022. The method determined the NASDAQ Composite stock index value to be 16,115.75 USD per stock through 31.12.2022, whereas S&P 500 index saw the value of 5,025.86 USD per stock through the same date. The follow-up research should deal with forecasting different stock indexes and comparing other conventional techniques for predicting time series. The subsequent study may also compare methods' forecasting accuracy between stock indexes and independent companies, whose stock volatility could favour different forecasting approaches.

Keywords: forecasting; the ARIMA model; moving averages; stock indexes; return on investmensts

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JEL Classifications: G22, G11, G17

Additional disciplines: mathematics

1. Introduction

Developed global economies have recently fostered a close interrelationship, jointly facing galloping inflation (Straková et al., 2021a). This nominal macro-economic variable made markets of multiple countries suffer from extreme price variations, e.g. caused by soaring or slumping commodity prices in global markets (Masood et al., 2019; Fernandes, 2020). The rise in inflation is more significant than in the years before the onset of the Covid-19 pandemic. Upon witnessing the price increase, households seriously reconsider their investment decisions (Abildgren and Kuchler, 2021). Fearing the loss of savings value, they move their financial reserves into stocks, bonds and stock indexes (Straková et al., 2020); the latest concerns the subject of this article. Choosing a good investment portfolio requires careful consideration of potential risks, involving keeping the balance between the stock and bond investments (Sinicakova et al. 2017; Gavurova et al. 2020). This harmony is changeable, depending on the situation in the market. Careful diversification of portfolios helps minimize the risk of substantial losses (Xiao and Tao, 2021; Bilan et al. 2017; Fedorko et al. 2018), making stock indexes an ideal investment. Forecasting the prices of stock indexes is an indispensable tool for reducing the risk and boosting the returns. Yet, it can be a high-stake venture due to multiple impactful hard-to-predict factors, which, for example, triggered the Great Recession in 2008 (Straková et al., 2021b; Gavurova et al. 2017, 2018). Today's world would have been much different if we had foreseen, mitigated, or even avoided this financial meltdown (Tang et al., 2015).

The article aims at forecasting the price movement of selected stock indexes. We formulated two plausible hypotheses:
1) Which of these two methods - Simple moving average (SMA) or Autoregressive integrated moving average (ARIMA) - is more accurate for predicting the prices of selected stock indexes in the last thirty years?
2) How will the price of the selected stock indexes develop according to the better of the suggested method through 2022?

2. Theoretical background

The return on stock indexes has recently been a widely discussed issue, drawing the attention of investors (Suler et al., 2020). From the very beginning of the existence of the stock market, various people have tried to predict its future development, or the future development of share prices. Nowadays, according to Machová et al., price forecasting in the stock markets is becoming (2020) an increasingly interesting topic. Fatal losses can occur in the event of a wrong estimate of the market's development tendency or in the event of a wrong decision. Kliěštik and Majerová (2015) also agree with this opinion, who state that the prediction of stock prices is a very important task for all people paying attention to the stock market. The authors further add that stock price forecasting is always a hot issue for shareholders, dealers and stock brokers. According to Etemadi et al (2015), managers, investors and financial analysts consider earnings per share as one of the most important financial indicators. Precisely for this reason, it is very useful to predict the stock price with high accuracy (Kučera and Andelík, 2021).

Koutroumanidis et al. (2011) state that the ability to predict stock price developments is a key task for investors in order to maximize their profits. Investors are able to make big profit using these quality tools with high accuracy. Stock price prediction is currently a very important financial topic and has huge potential for the market economy and investors in the future. Vochozka et al. (2020) state that the effort to forecast stock prices is becoming increasingly complex due to the increasing amount of historical data. The development of stock prices over time is very dynamic, complex and non-linear and can be predicted through many methods, one of which is the ARIMA model (Shi et al., 2012). For prediction, it is advisable to use the ARIMA model, because it uses and manages to calculate with time series data (Jiang and Subramanian, 2019). Using the ARIMA model on historical data to estimate returns and volatility of S&P BSE Essex and S&P BSE IT indexes in the Bombay Stock Exchange market showed a strong correlation between actual values and the estimates. The results indicate increasing returns, yet they gradually approach zero (Challa et al., 2020). The ARIMA method supplemented with the AdaBoost algorithm demonstrated the best results when determining the price movement of the Standard&Poor's 500 index (S&P 500).

Pulungan et al., 2018 used the ARIMA model in the Indonesian stock market on daily data of the SRI-KEHATI index from 8th June 2009 to 17th July 2017, acquiring only unreliable non-stationary data. Upon extensive data processing, the authors transformed the seasonal differences into applicable stationary information, using the ARIMA model as the ideal method for data handling (3,1,1). The technique also proved practical for predicting stock prices in the Indonesian stock market (Pulungan et al., 2018). Gaspareniene et al. 2018 used the ARIMA method to forecast the price volatility of gold - an essential commodity in the financial sector, revealing that the technique is suitable only for short-term predictions (max. one year). Oil presents another primary asset, ensuring the smooth running of major economic ventures. To forecast the prices of this vital resource, the authors (Haque and Shaik, 2021) applied the ARIMA and GARCH models. Of all the categories, the ARIMA (4,1,4) and GARCH (1,1) showed the best accuracy, the former indicating higher accuracy in forecasting extreme and almost unpredictable situations, e.g. the Covid-19 pandemic.

Creating and forecasting the price movement in the stock market is a complicated issue. There have been many statistic models struggling to make almost impossible predictions (Tkacova et al. 2017; Gavurova et al. 2020; Kocisova et al. 2018). Islam and Nguyen, 2020 compared forecasts of a method of autoregressive integrated average, artificial neural network and stochastic process of Brownian motion with reality, revealing that the conventional statistic model and the stochastic technique yield more accurate results than artificial neural structures. Zakamulin and Giner 2020 contrasted a method of moments (MOM) and moving average (MA) to forecast time series, unveiling considerable similarities. Yet, MA made better forecasts regarding the future trends. The use of the MA method to predict stock prices within 50 days made investors receive higher returns (Almujamed, 2018). However, a survey from 1972 to 2015 proved a dramatic slump in the accuracy of moving averages (Strobel and Auer, 2018). Since financial trends are imperative in making sensible investment decisions, forecasting time series is subject to continuous improvement. Hybrid models also provide accurate forecasts, making better predictions than the ARIMA model or moving averages (Khashei and Hajirahimi, 2017). Kučera and Andelík (2021) say that although the ARIMA model and moving average method rank among less complex approaches to forecasting time series, they still find wide use in making accurate investment decisions. Using both techniques, investors significantly reduce the risk of loss, mainly in the event of ARIMA, which can handle unpredictable scenarios.

3. Data and Methodology

We used data from the S&P 500 and NASDAQ Composite Index for the calculation. The prediction of stock indexes through 2022 encompasses data from Yahoo Finance website from the last thirty years, from 31st March 1992 to 31st March 2022. The paper introduces the figures in American Dollars (USD), reflecting the closing prices of the indexes. We replaced the missing data with the information from the previous day, rounding the results to two decimal places (see Table 1 and Table 2).

Table 1. A basic data characteristic from NASDAQ Composite Index

Average price per stock	3578.63073 USD
Price median	2380.405 USD
Modus	2470.52 USD
Maximum stock price	16057.44 USD
Minimum stock price	547.84 USD
Max-min difference	15509.6 USD
Amount of data	10958

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Table 2. A basic data characteristic from S&P 500 Index

Average price per stock	1526.801 USD
Price median	1277.89 USD
Modus	1092.54 USD
Maximum stock price	4796.56 USD
Minimum stock price	394.5 USD
Max-min difference	4402.06 USD
Amount of data	10958

Source: Own

Figure 1 and 2 depict data used as input sources for the research.

Figure 1. Price movement of the S&P 500 Index from 31.3.1992 to 31.3 2022

Source: Authors' elaboration reflecting processed data from Yahoo Finance

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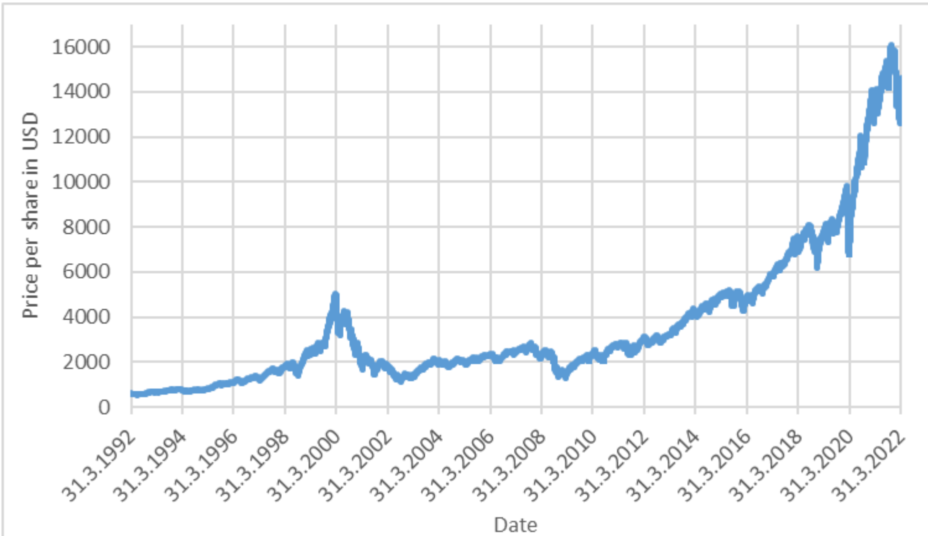

Figure 2. Price movement of NASDAQ Composite Index from 31.3.1992 to 31.3 2022
Source: Authors' elaboration reflecting processed data from Yahoo Finance

In the first part, we used the SMA method to forecast stock index prices, deliberately disregarding the trend and seasonality of the data. Firstly, the calculation of the future values involved known data, followed by previously predicted figures. Individual categories of the SMA comprised 50, 100 and 300 days. The research tested the data regarding their abilities to forecast stock indexes, verifying this capacity on the already known data from 31st March to 31st March 2021 to preserve similarities of the predicted periods. A close comparison of the resulting forecast with reality allowed selecting the most accurate category to predict prices through 2022.

The ARIMA model is the second chosen method, involving RStudio statistic software for selecting the most relevant model parameters. The used commands were as follows:

- Class(File_name)
- File_name_time=ts(File_name$Price,start=min(File_name$Date),end=max(File_name$Date)
- Class(File_name_time)
- Library(Forecast)
- Library(tseries)
- Plot(File_name_time)
- Acf(File_name_time)
- Pacf(File_name_time)
- Adf.test(File_name_time)
- File_name_MODEL=auto.arima(File_name_time, ic='aic',trace=true)

R program tested and chose the best ARIMA parameters. Upon uploading the criteria to Microsoft Excel, XLSTAT software predicted year 2022, setting the confidence interval to 95%.

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4. Results

The blue curve of Figures 3 and 4 illustrates the actual stock index value from 1.4.2021 through 31.12.2021, contrasting with the red line values provided by a 50-day SMA. The green line depicts a forecast made by a 100-day SMA, and the purple trend tracks the estimated price using a 300-day SMA. The figures suggest that the 100-day SMA draws nearest to the actual value in the NASDAQ Composite, whereas the 50-day SMA is the closest to the real value of the S&P 500 index.

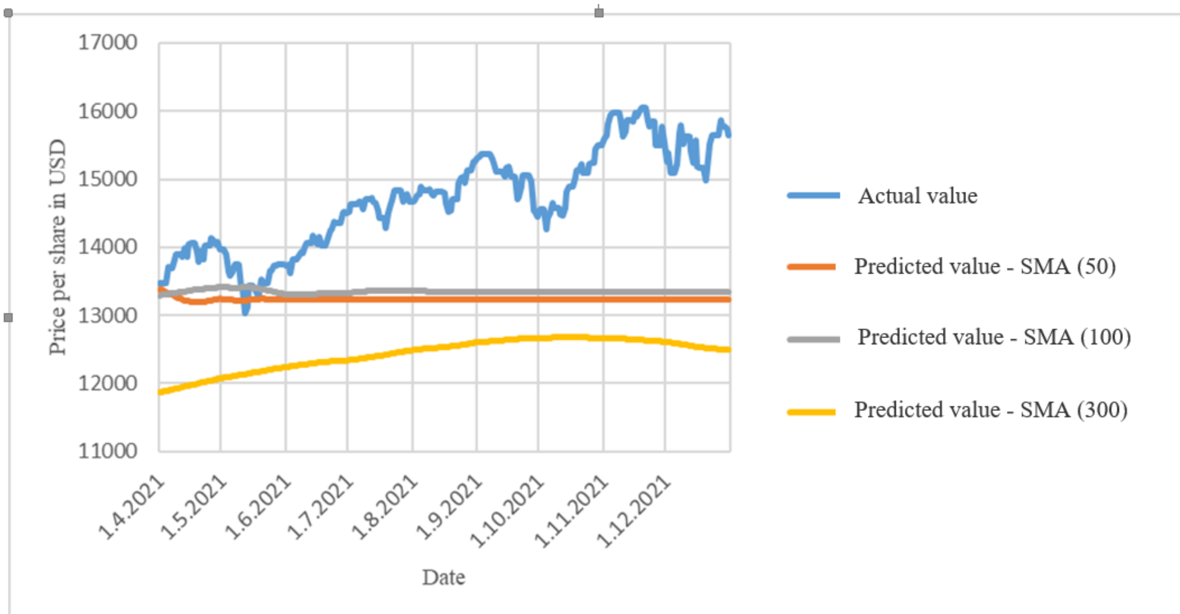

Figure 3. Comparing individual forecasts with real values of the NASDAQ Composite
Source: Own

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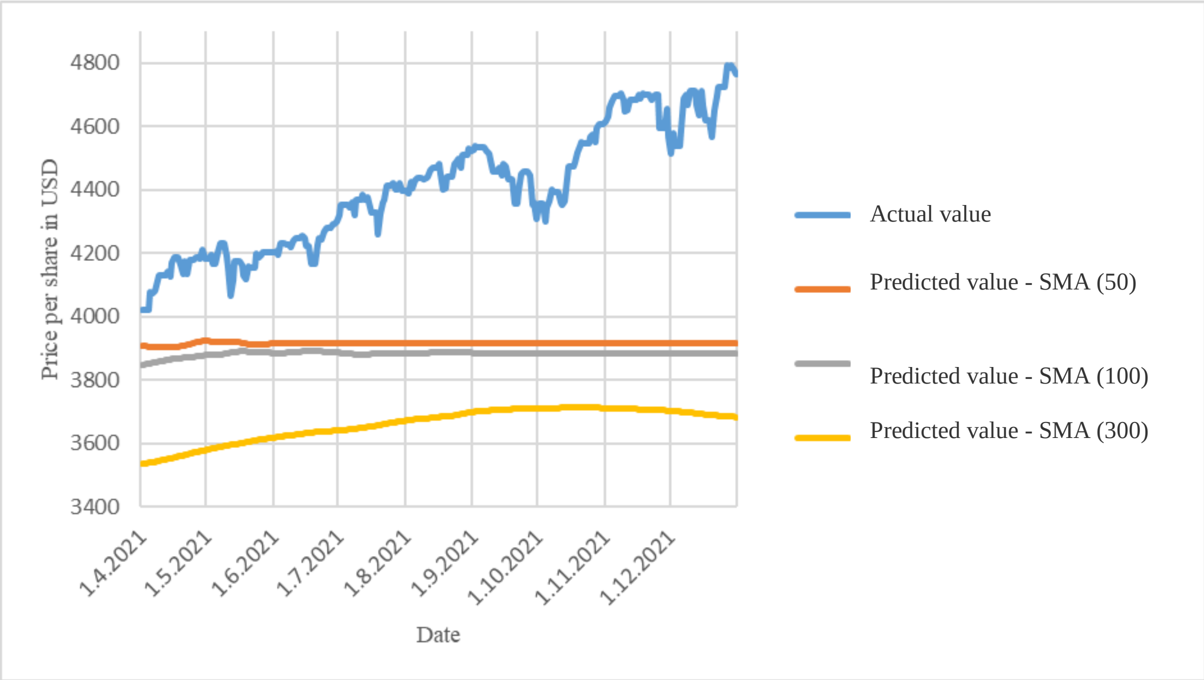

Figure 4. Comparing individual forecasts with real values of S&P 500
Source: Own

Tables 3 and 4 suggest other essential data for comparing the accuracy of separate forecasts. Each prediction contrasts with the average actual stock value for a defined period. The first indicator compares the average price of one predicted stock and the average real price per stock. The second indicator involves the mean absolute error (MAE), while the third indicator refers to the mean absolute percentage error (MAPE). The figures acquired from the experiment comply with the data suggested in Figures 3 and 4. The NASDAQ Composite index saw the average price per stock at 13,231.43$ using a 100-day SMA, which is the closest to the average actual value of 14,697.95 USD. The MAE amounts to 1,356.00 USD, and the MAPE equals 9%, indicating the lowest value of all the forecasts. The S&P 500 index was the closest to the average actual price per stock using a 50-day SMA amounting to 3,914.79 USD, while the real price was 4,403.14 USD. The average MAE in this prediction was 488.36 USD, whereas the MAPE equalled 10.92 %. The 300-day SMA made the worst prediction, varying by about 6% from the most accurate forecast in both cases.

Table 3. Comparing predicted values with real values of the NASDAQ Composite index

	Real value	SMA(50)	SMA(100)	SMA(300)
Average price per stock (USD)	14,697.95	13,231.43	13,348.59	12,430.28
Average MAE (USD)	X	1,468.58	1,356.00	2,267.67
Average MAPE	X	9.77 %	9.00 %	15.28 %

Source: Own

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Table 4. Comparing predicted values with real values of the S&P 500 index

	Real value	SMA(50)	SMA(100)	SMA(300)
Average price per stock (USD)	4,403.14	3,914.79	3,882.61	3,659.95
Average MAE (USD)	X	488.36	520.53	743.19
Average MAPE	X	10.92 %	11.66 %	16.76 %

Source: Own

Based on the findings, we chose the 100-day SMA for the NASDAQ Composite index and the 50-day SMA for the S&P 500. Figures 5 and 6 depict the predicted values of the discussed stock indexes through the end of the year. To make the charts less complex, we included figures as of 1.1.2002. The stock price of the NASDAQ Composite index should reach 13,846.26 USD, whereas the value S&P 500 index should hit 4,408.48 USD per stock.

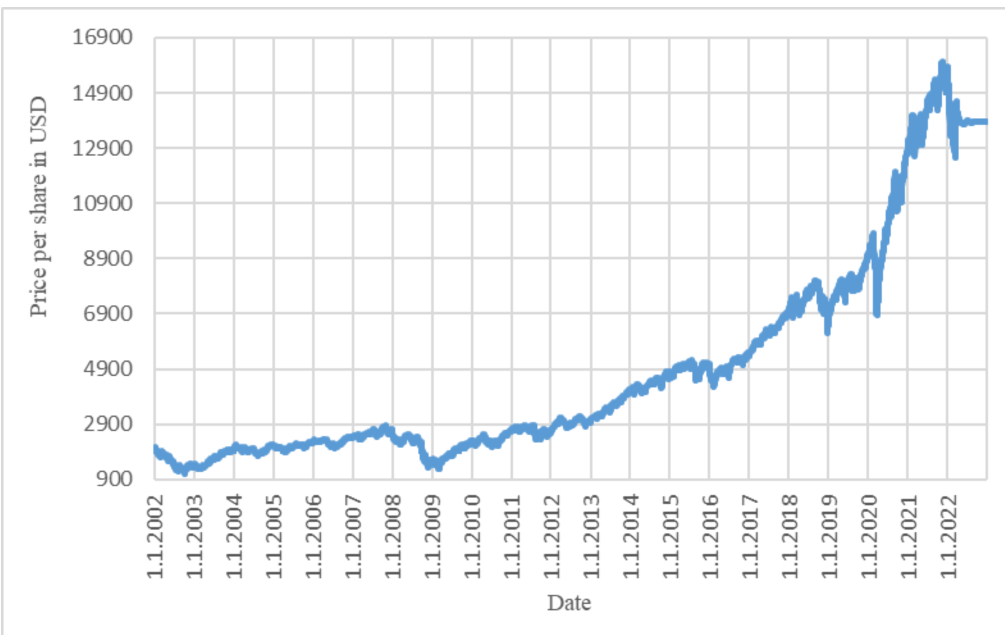

Figure 5. The predicted price movement of the NASDAQ Composite index as of 1.1.2002 through 31.12.2022
Source: Own

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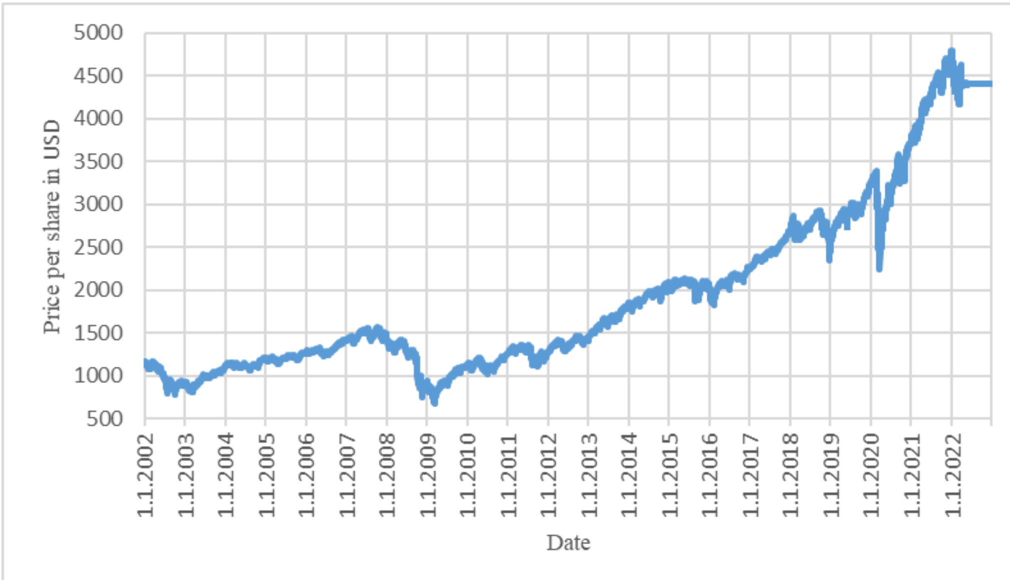

Figure 6. The predicted price movement of the S&P 500 index as of 1.1.2002 through 31.12.2022
Source: Own

To test the accuracy of the ARIMA model (5,1,0) based on the results from the RStudio statistic program, we chose the period from 1.4.2021 to 31.1.2021. The blue curve of Figures 7 and 8 illustrates the actual value of one stock of the selected index contrasted with the red central line; the green line represents the lower prediction boundary, whereas the purple curve tracks the outer limit of the estimate. The figures suggest that the purple line is the closest to the actual index value.

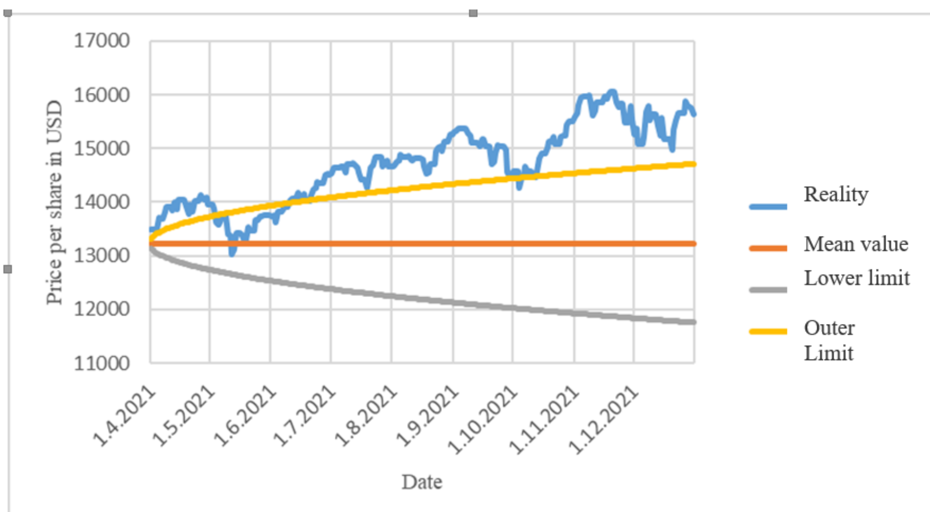

Figure 7. Comparing the forecasts of the ARIMA model with the actual value of the stock index NASDAQ Composite
Source: Own

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2022 Volume 10 Number 1 (September)
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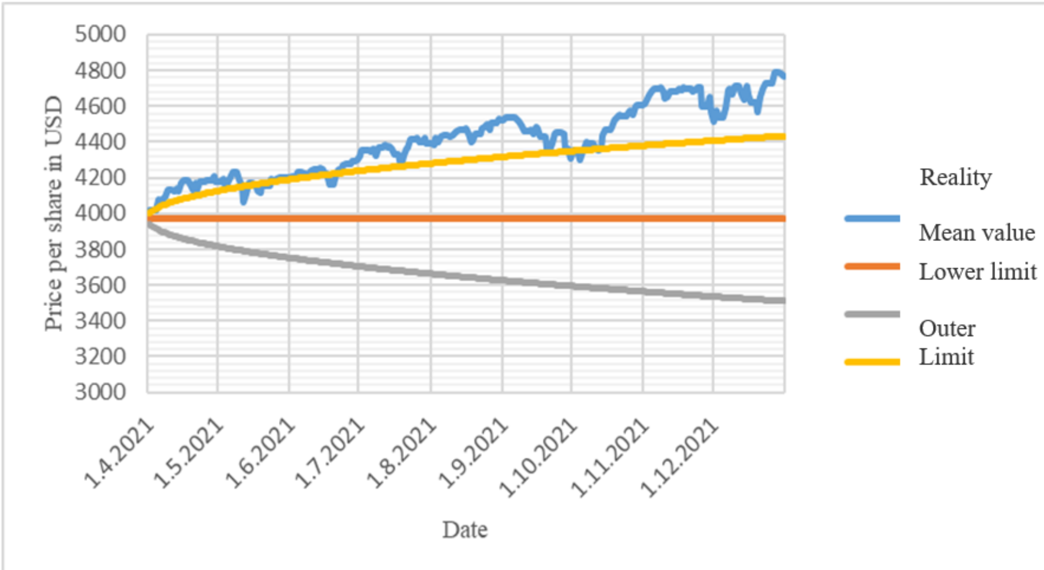

Figure 8. Comparing the forecasts of the ARIMA model with the actual value of the stock index S&P 500
Source: Own

Tables 5 and 6 propose essential parameters to determine the accuracy of the forecasts. The figures comply with Figures 7 and 8. A close comparison of the limits shows a similar MAPE average in both indexes.

Table 5. A tabular comparison of a forecast of ARIMA model with the actual value of the NASDAQ Composite stock index

	Actual value	Central limit	Lower limit	Outer limit
Average price per stock (USD)	14,697.95	13,233.3	12,245.12	14,221.47
MAE average (USD)	X	1,4466.91	2,452.83	550.72
MAPE average	X	9.73 %	16.38 %	3.66 %

Source: Own

Table 6. A tabular comparison of a forecast of ARIMA model with the actual value of the S&P 500 stock index

	Actual value	Central limit	Lower limit	Outer limit
Average price per stock (USD)	4,403.14	3,971.43	3,662.52	4,280.34
MAE average (USD)	X	431.72	740.63	126.93
MAPE average	X	9.63 %	16.56 %	2.8 %

Source: Own

We applied the ARIMA model (5,1,0) to the up-to-date information of the S&P 500 index and NASDAQ Composite, forecasting a time series through 31.12.2022 depicted in Figures 9 and 10.

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The NASDAQ Composite index hit the mean value per stock at 14,439.44 USD, the lower limit of 13,348.19 USD and the outer boundary of 15,560.69 USD in the predicted period. The 31st December 2022 saw the highest foreseen price per stock at 16,115.71 USD, with a trough of 12,763.14 USD. The S&P 500 index hit the forecast mean value of 4,535.05 USD, the lower limit of 4,206.75 USD and the outer value of 4,863.36 USD. The index hit the lowest estimated stock price at 4,044.24 USD and the highest at 5,025.86 USD on 31.12.2022.

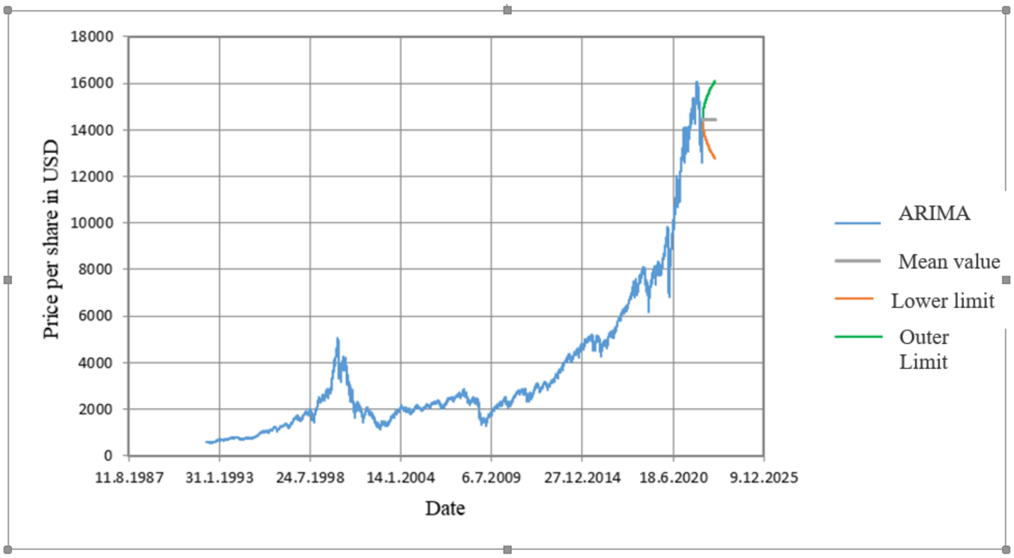

Figure 9. Graphical depiction of the movement of the NASDAQ Composite index by the ARIMA model
Source: Own

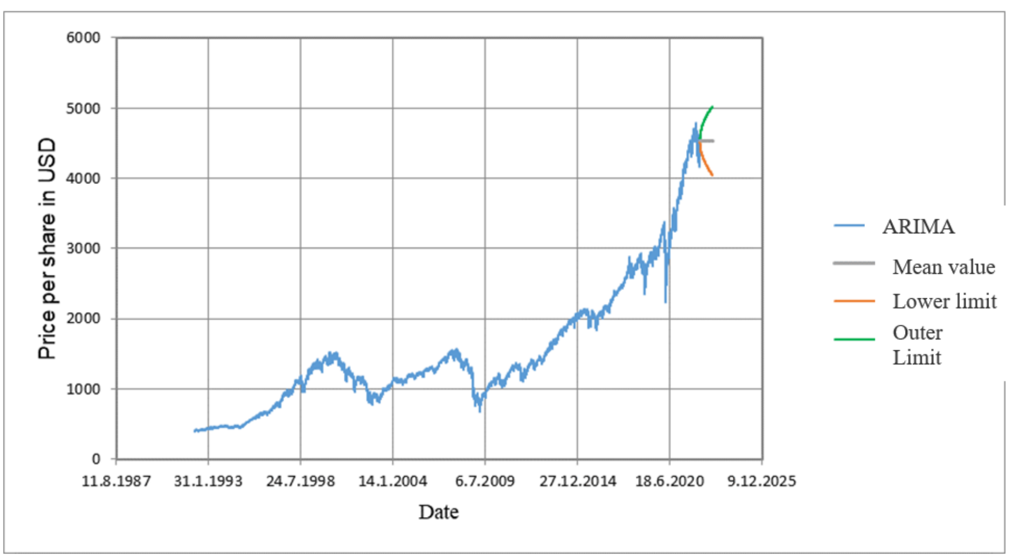

Figure 10. Graphical depiction of the movement of the S&P 500 index by the ARIMA model
Source: Own

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2022 Volume 10 Number 1 (September)
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5. Discussion

The research revealed that the 100-day SME best reflects the NASDAQ Composite index, whereas the 50-day SME closely corresponds to S&P 500. The indexes showed different SMAs as the most accurate technique because the NASDAQ Composite had suffered an unexpected, short-term decline upsetting the resulting predicted price per stock. The 100-day SMA did better in forecasting the constantly upward trend of the index, smoothing the downturn by the previous values. The S&P 500 index did not witness any striking variations, retaining its steadily increasing trend. That is why this index best correlates with the 50-day moving average. The testing forecasts further proved that moving averages are not a wise choice for a long-term prediction of the price movement of stock indexes. Both experimental scenarios showed the MAPE at around 10%, indicating an unacceptably high percentage. The short-term SMA cannot readily respond to the index volatility, and the long-term SMA displays strong bias given the past low index prices. Despite their inaccuracies, the methods may help investors roughly estimate the future market trend. Almujamed (2018) stated that investors' incomes dramatically increased using a 50-day SMA.

Upon verifying the accuracy of the ARIMA model (5,1,0), the highest forecast estimate proved the most realistic, indicating a constant upward trend in both stock indexes. The average MAPE ranged around 3%. Pulungan et al. (2018) arrived at similar results, using ARIMA (3,1,1) for predicting SRI-KEHATI stock index prices.

Thanks to these findings, we found the answer to the first hypothesis: 1) Which of these two methods - Simple moving average (SMA) or Autoregressive integrated moving average (ARIMA) - is more accurate for predicting the prices of selected stock indexes in the last thirty years? The results indicate that the ARIMA model (5,1,0) greatly outplays the SMA in both index scenarios. Gaspareniene et al. (2018) arrived at the same conclusions, revealing that the ARIMA model is instrumental in short-term forecasts for up to one year. A close comparison between the most accurate test prediction of the NASDAQ Composite index using the ARIMA model and the SMA revealed that the latter method was worse than the ARIMA model by 6.11% in making the most accurate forecast at the average MAPE. The S&P 500 index indicated an even sharper difference of 8.12%, favouring the ARIMA model.

The second hypothesis relates to the first one: 2) How will the price of the selected stock indexes develop according to the better of the suggested method through 2022? Both approaches (the ARIMA model and SMA) have foreseen a further steady rise in the stock indexes. To satisfactorily answer the hypothesis, we chose the ARIMA model (5,1,0) and its highest limit as the most accurate method. The technique estimates the value of the NASDAQ Composite index to be 16,115.71 USD per stock to 31.12.2022, expecting the S&P 500 index to hit 5,025.86 USD per stock. Jiang and Subramanian (2018) share the same opinion, proving the ARIMA model's great utility in forecasting time series.

Conclusions

The article sought to estimate stock index prices through 2022. We fulfilled this objective by suggesting the most accurate method. Although forecasts are never fully authentic (stock markets are unpredictable), they provide at least a rough estimate of the price movement. Using the MAPE technique, we compared the testing predictions based on the SMA and ARIMA models (5,1,0), obtaining better results from the ARIMA model. The method suggests that the S&P 500 index price should soar to 5,025.86 USD per stock, and the NASDAQ Composite index should hit 16,115.71 USD per stock through 2022. Yet, the ARIMA model does not apply to other stock indexes with the same accuracy, which constitutes a pitfall of our analysis. Further research would have to involve a different ARIMA model to estimate the movement of other stock indexes. Follow-up studies should focus on forecasting various stock indexes and comparing different methods not included in our research to predict time series. The scientists may also compare the accuracies of the forecasting methods between stock indexes and corporate stocks, which are more volatile and require different forecasting approaches.

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