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EXPLORING THE EFFECTIVENESS OF ARIMA MODELS IN PREDICTING INTEREST RATES IN SLOVAKIA

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Abstract:
Research background: Predicting movements in interest rates is of paramount importance to financial and economic planning. Accurate predictions allow policymakers, financial institutions, and businesses to make efficient investment decisions, risk management, and fiscal policy. Predicting movements in interest rates assists in providing useful information for the realignment of monetary policies and the optimization of capital allocation during times of uncertainty.
Purpose of the article: The aim of this paper is to fill a gap in the literature and examine the use of the ARIMA model to predict interest rates in Slovakia, a country subject to domestic as well as EU economic factors.
Methods: The ARIMA model is utilized within this study to forecast Slovak interest rates to test how accurate it can be in measuring Slovak interest rate intricate dynamics, which arise due to both EU and local monetary policy interventions. Traditional calibration metrics such as MAE, RMSE, and MAPE are used to gauge its precision in forecasting. The result provides information about the efficiency and limitations of using ARIMA as an instrument of economic forecasting in the Slovak context.
Findings & Value added: The ARIMA(2,1,1) model worked exceptionally well in interest rate prediction for Slovakia, explaining 99.1% of the variance with very low RMSE at 0.085 and MAPE at 1.864%. Significant coefficients, such as AR(1) 0.984 and MA(1) 0.692, indicate the success of the model in capturing the underlying time series dynamics. The Ljung-Box test also confirmed the existence of non-significant autocorrelation among the residuals, confirming the model's stability and reliability in economic forecasting. Practically, these findings are useful to policymakers, banks, and businesses in Slovakia, as accurate interest rate forecasts in guiding investment plans, credit risk, and fiscal policy. The findings underscore the need to utilize strong forecasting models like ARIMA to adjust policies in a setting dominated by both EU and domestic economics to enable economic choices to be guided by up-to-date information.

Keywords: interest rate prediction; monetary policy; economic dynamics; ARIMA model; Slovakia

JEL Classification: C22; E37; E43

1. Introduction

Interest rates are the most significant drivers of the economic climate, affecting everything from the borrowing patterns of individuals to the general dynamics of the financial markets. Primary drivers of changes in interest rates are inflationary expectations, economic growth, monetary policy, and risk premiums. Inflation, being the most proximate cause of interest rates, leads central banks to raise rates to offset inflationary pressures, while an episode of low inflation has the effect of leading to rate cuts to encourage economic growth. Economic growth and unemployment are also significant, as a surging economy can necessitate higher interest rates to prevent overheating, whereas, in an economic recession, central banks will seek to lower rates to encourage borrowing and investment. Central banks, such as the European central bank (ECB), heavily influence short- and long-term interest rates by their policy maneuvers. Monetary policy tools such as changes in interest rates or quantitative easing form the backbone of inflation management and economic stabilization (Duran and Gajewski, 2023; Frajtova Michalikova et al., 2024). The trajectory of interest rates in Slovakia, in particular, has been determined not only by the domestic economic setting but also by the broader European monetary policy setting, global financial crises, and even external shocks like the COVID-19 pandemic.

Earlier literature in interest rate modelling had seminal works such as Fauvel et al. (1999), who provided a survey of the empirical literature. Bidarkota (1998) derived a univariate unobserved components model for U.S. real interest rates, which stated that an error-correction model yielded better one-step-ahead forecast accuracy of the real rate, but unobserved components models generated lower variance of forecast values. These early models set the stage for the more advanced methods of interest rate prediction. Similarly, Butter and Jansen (2004) studied long-term German government bond yields with macroeconomic explanatory variables such as German 3-month Libor, US 10-year yields, and the German IFO business activity indicator. Although they were holistic in their approach, the models were limited by their inability to forecast macroeconomic trends, owing to issues such as data distortion during the quarterly calculation of the government balance. With advancements in interest rate modelling, researchers like Dua and Pandit (2002) focused on the Indian short- and long-term interest rate dynamics, formulating co-integrating relationships among real interest rates, money supply, and foreign interest rates. Their empirical findings confirmed the role of domestic and external variables in determining interest rates. In another research, Dua et al. (2004) forecasted models for 10-year Indian government security yields and determined that vector autoregressive (VAR) models performed better than vector error correction model (VECM) models, particularly due to the small sample size and continuous decline of interest rates during the sample period. These early studies helped refine variables and models used for interest rate forecasting, with an emphasis on foreign and domestic financial indicator interaction.

Recently, the application of machine learning has transformed interest rate modeling with its adoption of alternative data sources and elaborate algorithms. Yasir et al. (2020) applied a deep learning model that incorporated sentiment information from sources like Twitter-based online forums to forecast interest rates. They observed the inclusion of sentiment significantly improving prediction power, especially amid turmoil like Hong Kong, pointing towards the application of machine learning to collate alternative data sources. This contrasts with traditional econometric models, where past financial data is relied upon completely. The superiority of machine learning techniques in interest rate prediction has also been indicated in earlier research. For instance, Tang (2023) examined the use of artificial neural networks (ANN) for financial market prediction and found that machine learning models performed particularly well with non-linear relationships as well as high-dimensional data. Similarly, Shen et al. (2021) and Makika et al. (2023) found that deep learning algorithms like long short-term memory (LSTM) networks could identify complex, non-linear patterns in finance data with better accuracy than traditional econometric models. While these advances in machine learning have brought encouraging outcomes, comparative analyses of different machine learning models are still needed, particularly for interest rate forecasting. In addition, computational cost, quality of data, and interpretability of models are still concerns. As shown in the work of Udoye et al. (2020), attempts at merging traditional econometric models with machine learning have sought to be transparent while increasing accuracy, but there are challenges in the full optimization of such hybrid approaches.

Several approaches have been developed to forecast interest rates, and among them, the autoregressive integrated moving average (ARIMA) model is one of the most widely employed. The ARIMA models are extremely popular since they can model and forecast time series data describing both long-term patterns and short-term relationships (Xie et al., 2022; Kolkova and Rozehnal, 2022). The model incorporates three principal components: (i) autoregression to represent the relationship between present and past observations (Rajab et al., 2022); (ii) integration, used for the reduction of non-stationary series to a stationary form through differencing (Kumar and Hariharan, 2022); and (iii) moving average to represent the relationship between an observation and past forecast errors (Tarmanini et al., 2023). The simplicity, interpretability, and effectiveness of ARIMA make it a strong candidate for time series forecasting, including interest rate forecasting. While ARIMA remains a favorite method, other time series modelling methods have also been used in interest rate forecasting. The generalized autoregressive conditional heteroscedasticity (GARCH) model is usually used for financial time series, particularly when volatility and heteroscedasticity must be modelled in the data (Ray et al., 2023). According to Cekin et al. (2024), GARCH models are excellent at modelling time-varying volatility, which is common in financial markets. Another approach that is commonly applied is the VAR model, which defines the relationship between multiple time series variables (Krishnan et al., 2024). The model is particularly useful when interest rates are influenced by a variety of macroeconomic variables, such as inflation, GDP, or exchange rates. In addition, machine learning techniques such as random forests, support vector machines, and deep learning algorithms have gained popularity recently due to their ability to recognize complex non-linear patterns in data. Yamacli and Yamacli (2023) concluded in their study that the ARIMA model is distinguished by the fact that it is extremely simple and interpretable, making it a favorite for economic forecasting. Different studies have managed to apply ARIMA models in forecasting interest rates across the globe, including in the United States (Gozgor, 2013), Europe (Guerrero et al., 2023; Hubik, 2024), and emerging economies (Alfaro et al., 2011). For instance, previous studies have established ARIMA's robustness in modelling interest rate behavior and its capacity to provide precise forecasts following domestic and foreign economic shocks. In Slovakia, the ARIMA model can uncover valuable information concerning how interest rates evolve in response to ECB policy, inflation trends, and other macroeconomic dynamics.

This paper aims to present a significant gap in the current literature by trying to examine the application of the ARIMA model in interest rate forecasting in Slovakia. While the ARIMA model has been widely used across various economic settings, with fairly few specifically considering its ability to capture the complex dynamics of interest rate movements in the case of Slovakia, which is highly influenced by both domestic economic forces as well as monetary policy in the European Union. The primary purpose of this study is to evaluate the performance of ARIMA based on standard performance metrics, such as mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). Through the evaluation, the paper seeks to provide a complete judgment of the strengths and weaknesses of ARIMA for economic forecasting, particularly on Slovak interest rates. In doing so, this research will contribute to the current literature base in time series forecasting with a focus on the relevance of ARIMA in providing precise and meaningful forecasts of interest rate changes. Last, the findings will serve to be beneficial for policy-making, financial planning, and research in the area in the future, filling an intriguing gap in interest rate forecasting literature for Slovakia and comparable economies.

The following sections comprise the paper. The first section is a literature review, introducing the primary theoretical framework of the topic and emphasizing recent relevant studies in the area. The second section is a description of the methods used to fulfill the objectives of the paper, with particular reference to the application of the ARIMA model to forecast interest rates and also the criteria to be employed to assess the performance of the model. The third part presents the results of implementing the ARIMA model, including an accuracy analysis of the prediction and a comparison with other models. Finally, the paper summarizes the findings, constraints, and potential future study areas.

2. Methodology

The main aim of this paper is to analyze the application of the ARIMA model in time series forecasting, with a particular focus on predicting the evolution of interest rates in Slovakia. The study will critically analyze the performance of the ARIMA model based on conventional measures of forecasting performance. Furthermore, the paper examines the ability of the model to capture the underlying temporal structures of interest rate movements and provides insights into the reliability and accuracy of ARIMA-based forecasts in economic forecasting.

The data used for analysis here are monthly interest rates in Slovakia from January 2010 through December 2024. The data were gathered from the National Bank of Slovakia and are 180 observations in total, where each observation is the value of an interest rate for a given month. This one series of univariate information captures the historic volatility of interest rates for nearly 15 years, through all economic cycles, growth, recession, and external shocks such as the COVID-19 pandemic. The data set is a comprehensive base to analyze trends, patterns, and potential structural changes in the Slovak interest rate prediction.

The data were pre-processed prior to using it by dealing with any missing values and ensuring that the data were stationarized. Stationarity is essential in ARIMA models because the mean and variance of the series need to remain unchanged over time. If the series is not stationary, we make it stationary through differencing, which takes us to the next step (Adebiyi et al., 2014).

To appropriately apply the ARIMA model, the autoregressive, differencing, and moving average order should be ascertained from the observation of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the time series (Kumar and Vanajakshi, 2015). The autoregressive term (p) is the correlation between a point and several lagged points, as indicated by the PACF plot (Pang et al., 2020). Differencing (d) is employed to make the series stationary (Apley and Shi, 1999), and the Augmented Dickey-Fuller test is employed to identify the order of differencing (Kumar et al., 2022). The moving average component (q) captures the effect of an observation on the residual errors of a moving average model, and the ACF plot is employed to identify the optimal number of lagged forecast errors.

According to Alomari et al. (2023), after the values of p, d, and q were determined, the ARIMA model was then used to fit the historical interest rate data. The ARIMA model can be mathematically represented as:

$$(1-B)^d Y_t = \mu + \Phi(B)(1-B)^d Y_t = \mu + \Phi(B)Z(t) + \Theta(B)\epsilon_t \tag{1}$$

where $\Phi(B)$ represents the autoregressive operator of order p, that is

$$\Phi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p \tag{2}$$

$\Theta(B)$ represents the moving average operator of order q, that is

$$\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^p \tag{3}$$

$Z(t)$ is white noise process with zero mean and constant variance σ^2 and ϵ_t is the error term.

An ARIMA model necessitates that the time series be stationary, or have a constant mean and variance over time. The d in ARIMA refers to differencing, which is a process that is used to render the series stationary when it isn't. Differencing involves the computation of the difference between successive observations $(Y_t - Y_{t-1})$. If the series is still non-stationary after one round of differencing, it is possible to repeat this operation, as suggested by the d value in the ARIMA(p, d, q) model (Kumar et al., 2022). The ARIMA model can be stated in the alternative form:

$$Y_t = c + \varphi_1 Y_{t-1} + \cdots + \varphi_1 Y_{t-p} + \cdots + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{4}$$

where Y_t is the observation at time t, φ_j is the parameter of the autoregressive part of the model, θ_k is the parameter of the moving average part, and ε_t is the error term.

After training the model, residuals are tested for patterns or a deviation from white noise, which might suggest model inadequacy. The Ljung-Box test and plots of the residuals were employed to validate that the model has picked up all the important autocorrelations in the data.

The final step is to use the estimated ARIMA model to forecast future interest rates in Slovakia. The predicted values are augmented by upper and lower control limits (UCL and LCL) to represent the prediction intervals for each forecast point (Christo et al., 2013). These intervals provide an interval where the true interest rate will be with some specified confidence level.

Evaluation metrics serve an important function in gauging the performance of statistical or machine-learning models through the comparison of observations with expected values. The choice of what metric to employ depends on the specific nature of the problem one is addressing since they perform distinct functions. Wang (2008) concluded that many evaluation metrics have historically been used in regression models.

Mean absolute error (MAE) is the simplest and most intuitive of regression metrics. It calculates the average of absolute differences between observed and predicted values, providing a straight-line measure of prediction error size (Kozuch et al., 2023). The formula for MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_i - F_i| \tag{5}$$

where Y_i is the observed value, F_i is the forecasted value, and n is the number of observations.

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Mean absolute percentage error (MAPE) is helpful if it is desirable to express the error as a fraction of the size of the observed value (Ray et al., 2023). It is particularly helpful if the data are on varying scales and is given by:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - F_i}{Y_i}\right| \tag{6}$$

Root mean squared error (RMSE) is, according to Noorunnahar et al. (2023), yet another well-liked metric that penalizes larger mistakes by squaring the differences between observed and predicted values. It is particularly valuable if large errors are unwanted. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - F_i)^2} \tag{7}$$

The coefficient of determination (R-squared) measures the proportion of the variance in the observed data explained by the model. It indicates how well the model fits the data, with high values being indicative of a good fit (Rezaiy and Shabri, 2024). R-squared is given by:

$$R - squared = 1 - \frac{\sum_{i=1}^{n}(Y_i - F_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{8}$$

where $\bar{Y}$ is the mean of the observed values.

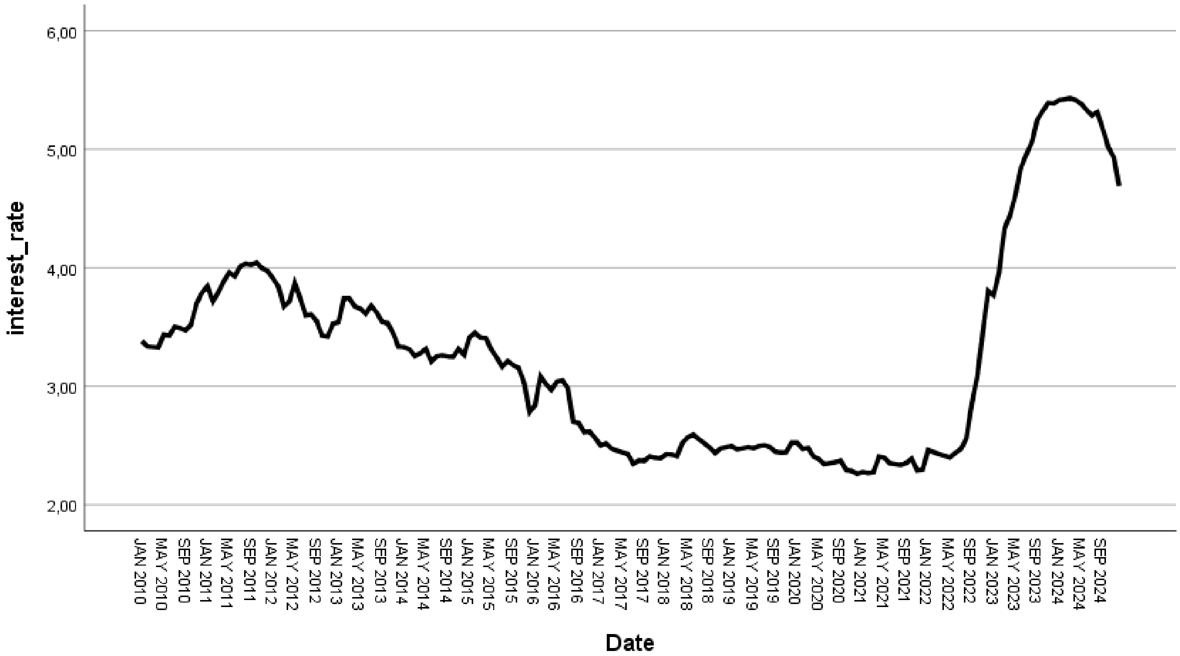
3. Results and Discussion

Figure 1 presents how the interest rate evolved in Slovakia between January 2010 and December 2024 and represents various economic developments. Between 2010 and 2013, interest rates gradually increased due to economic recovery from the global financial crisis, with the peak coming in late 2011. Between 2014 and 2015, the rates declined steadily due to the accommodative monetary policy of the ECB in response to low inflation and sluggish economic growth. Between 2016 and 2019, interest rates remained low due to the ECB's continuous efforts to stimulate the economy. The onset of the COVID-19 pandemic in 2020 led to subsequent rate reductions to soften the economic downturn. The record-low rate was felt during December 2020. In 2021 and 2022, as the economy started to rebound, rates began to climb because of inflationary pressures driven by supply chain shocks and elevated energy prices. By 2023 and 2024, interest rates surged again because of chronic inflation, reaching 4.69% as of December 2024. This pattern highlights the impact of foreign and domestic factors on the interest rates in Slovakia in the past decade.

High autocorrelation was observed in the ACF and PACF plots of the time series with a high value of 0.987 at lag 1, showing that the data is non-stationary. The PACF indicated that an order of 1 autoregression was suitable. Based on these observations, first-order differencing of the data was done to eliminate trends and to make it stationary for further model fitting.

After differencing the time series, the ACF showed severe autocorrelation at the first few lags, with the highest value being 0.408 at lag 1, indicating a moderate autocorrelation. Autocorrelation decreased smoothly at subsequent lags, i.e., correlation decreased. The PACF showed that partial correlations were small at lags higher than 1, where values at lag 2 and

Figure 1: Interest rate fluctuations in Slovakia (2010–2024)



Source: National Bank of Slovakia (n.d.)

beyond were close to zero. Based on the results, the optimal model was selected as ARIMA(2,1,1).

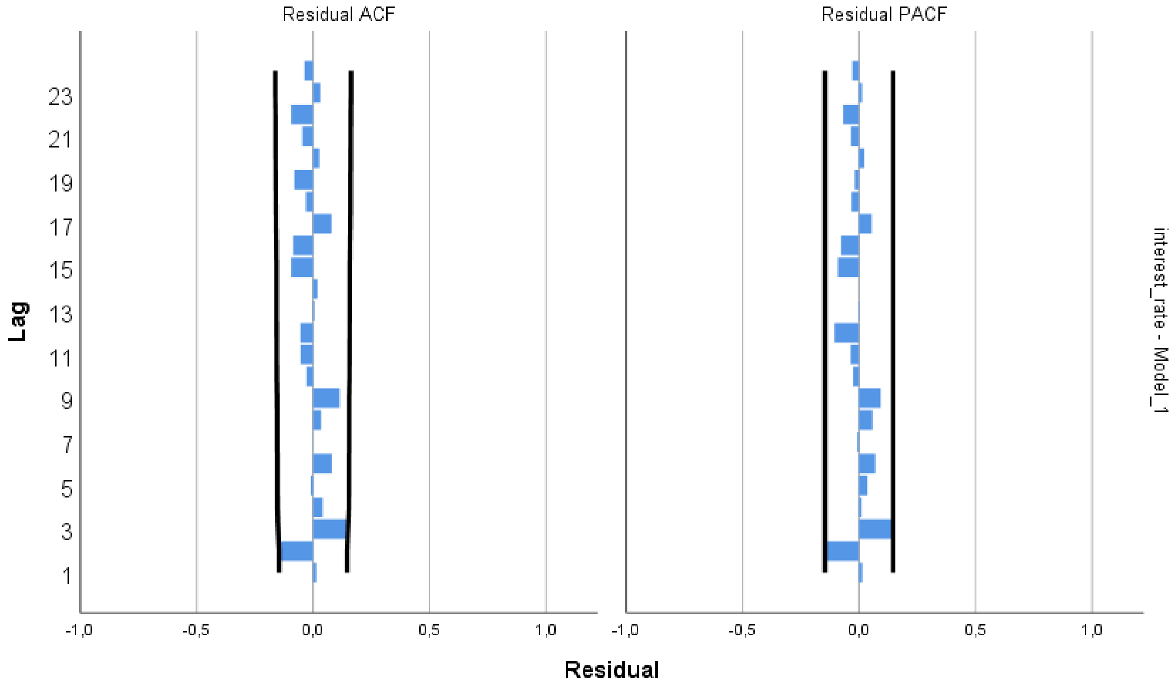
ARIMA(2,1,1) fits the data very well with 99.1% variance explained. RMSE is minimal at 0.085, and predictions are, therefore, correct. MAPE is 1.864%, showing minimal average deviation from actual values. A normalized BIC of -4.815 shows a balance between model fit and simplicity. The high value of the large AR(1) coefficient value of 0.984 and MA(1) coefficient of 0.692 indicates the model's largest autoregressive and moving average characteristics. The Ljung-Box test confirms any noteworthy autocorrelation among the residuals, indicating that the model accounts for the time series behaviour properly.

The residual ACF and PACF (Figure 2) show that the ARIMA(2,1,1) model has successfully captured the patterns in the time series. Most of the autocorrelations and partial autocorrelations are close to zero, and none of them is outside the standard error range. While there are minor fluctuations at some of the lags (e.g., lags 1 and 3), they do not suggest any autocorrelation, which means the residuals are about white noise, and the model interpolates the data well, leaving no significant residual temporal structure.

The prediction of the interest rate, as forecasted by the ARIMA(2,1,1) model, is a gradual reduction in the forthcoming year. Beginning at 4.59% in January 2025, the interest rate will continue to drop steadily to 4.00% in December 2025. The UCL fluctuates between 4.75% in January and 5.20% in December, and the LCL reduces from 4.42% in January to 2.79% in December. These forecasted values, along with the confidence intervals, provide the anticipated trend and the associated uncertainty over the forecast horizon, as given in Table 1 and Figure 3.

Within the Slovak situation, the predicted decrease in interest rates is additionally consistent with broader economic trends, such as European Central Bank policy and inflation stabilization. Slovakia, along with other Eurozone nations, has experienced increasing and decreasing interest rates over the past several years, largely influenced by the ECB's monetary policy interventions aimed at controlling inflation and improving economic growth. The forecasted decline illustrates the potential for monetary policy relaxation, which can lead to more accommodative

Figure 2: Residual ACF and PACF of the ARIMA Model



Source: own elaboration

borrowing conditions for Slovak consumers and businesses. The uncertainty reflected in the confidence intervals, however, indicates the volatility of economic conditions, with an emphasis on the need for continued monitoring of exogenous variables that will influence future interest rates.

Table 1: Forecast of interest rates with UCL and LCL for 2025

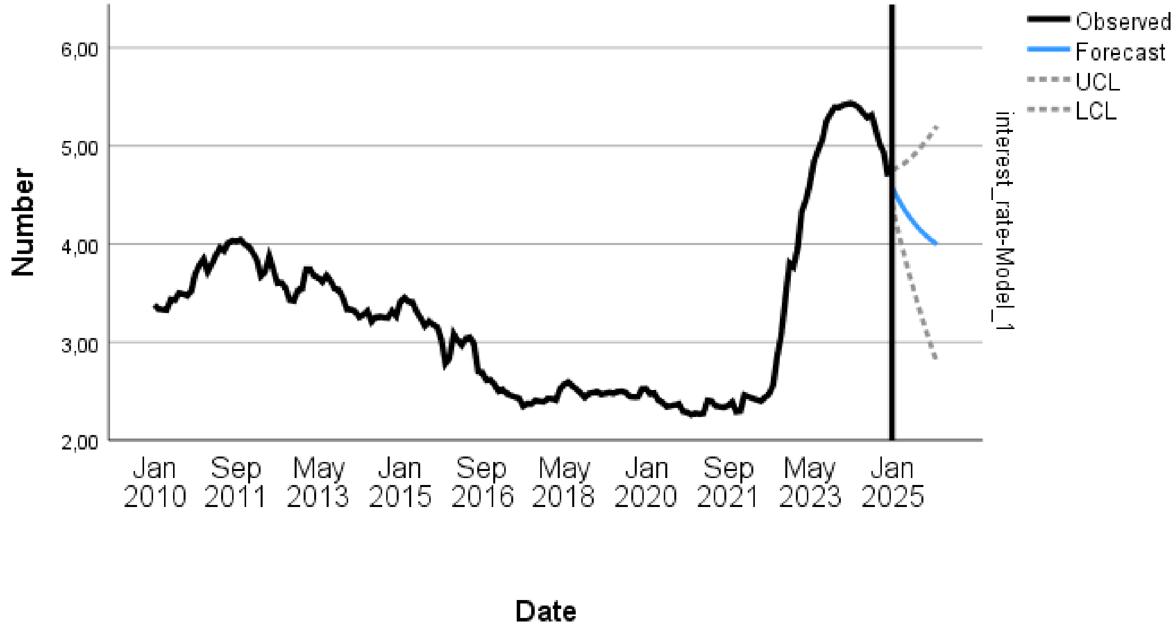
	Jan 2025	**Feb 2025**	**Mar 2025**	**Apr 2025**	**May 2025**	**Jun 2025**
Forecast	4.59	4.50	4.42	4.35	4.29	4.23
UCL	4.75	4.77	4.80	4.82	4.86	4.89
LCL	4.42	4.23	4.05	3.88	3.73	3.58
	Jul 2025	**Aug 2025**	**Sep 2025**	**Oct 2025**	**Nov 2025**	**Dec 2025**
Forecast	4.18	4.14	4.10	4.06	4.03	4.00
UCL	4.94	4.98	5.03	5.09	5.14	5.20
LCL	3.43	3.29	3.16	3.03	2.91	2.79

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

Source: own elaboration

Xiao and Pang (2017) used a structural vector autoregression model to analyse the influence of expected and unexpected monetary policy shocks on Chinese real estate prices. They found that unexpected interest rate changes had a more immediate and significant effect, while expected shocks were less as they had been priced into market expectations. Canpolat (2022) used the log-normal variable ARIMA model to predict the weighted average funding cost of Turkey's Central Bank and concluded that the nonlinear model performed better than conventional ARIMA in terms of prediction accuracy, particularly in times of economic change. Hua et al. (2020) compared the Nelson-Siegel model and a neural network model in predicting the RMB exchange rate and concluded the latter to be more effective, performing better with greater predictive accuracy through lower MAPE and RMSE values. Mallick and Mishra (2019) used a principal analysis component ARIMA hybrid model in interest rate prediction in India

Figure 3: ARIMA model forecast with observed data, UCL, and LCL



Source: own elaboration

and obtained improved prediction accuracy through macroeconomic trend capture. Liang et al. (2022) combined ARIMA and convolutional neural network models to predict the RMB exchange rate, achieving significant prediction improvements with MAPE values less than 2%, showing the value of combining deep learning with traditional models. Ahmed et al. (2017) used the ARIMA model to forecast KIBOR in Pakistan, achieving high precision with a MAPE of 1.92%.

Abounoori and Tazehabadi (2009) used a hybrid model that combined autoregressive distributed lag (ARDL), ARIMA, and ANN to predict stock prices from macro variables and illustrated combined approach greatly improved the forecasting accuracy. Paik and Ko (2024) applied ARIMA, seasonal autoregressive integrated moving average (SARIMA), and GARCH models in the analysis of Credit Guarantee Funds in Korea, and SARIMA was superior to ARIMA, particularly in the seasonal periods with MAPE below 3%. Zasadnyi et al. (2024) used ARIMA, LSTM, and decision trees with business intelligence software to forecast financial metrics and concluded that the best predictions were provided by LSTM models with MAPE from 1.5% to 2.3%. Antwi et al. (2022) used a hybrid decomposition approach with wavelet transform, ARIMA, and machine learning models to forecast commodity futures and had a MAPE of 1.76% and RMSE of 0.092. Mgammal et al. (2023) integrated ARIMA with difference-in-difference in estimating the impact of value-added tax increases to illustrate short-run economic distortions, and patterns of recovery were accurately identified by employing ARIMA. Alshawarbeh et al. (2023) employed a hybrid model (ARIMA-ANN) in forecasting high-frequency financial time-series data and obtaining superior MAPE (1.57%) and greater accuracy prediction. Li and Zhou (2024) developed an LSTM-based model to forecast interest rates and stock prices, beating ARIMA with lower MAPE (1.23%) and RMSE, pointing out the robustness of LSTM to learn non-linear patterns.

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4. Conclusions

Compared to other models, such as GARCH, VAR, and machine learning models, ARIMA has inherent strengths derived from its simplicity, interpretability, and capacity to capture linear interactions. While models like GARCH perform extremely well in capturing volatility and non-linearities, and machine learning models are efficient in handling complex data structures, ARIMA remains one of the best options for economic forecasting due to transparency, computational simplicity, and ease of implementation. The excellent performance of the ARIMA (2,1,1) model in this study, illustrated by an outstanding RMSE of 0.085, MAPE of 1.86%, and R^2 value of 0.991, only serves to further increase its utility and applicability to forecasting interest rates in the Slovak context, particularly for short-run forecasting.

Nonetheless, the vulnerability of ARIMA must not be underestimated. Although its performance is robust, ARIMA is a linear model in nature, and, therefore, it can fall short of capturing nonlinear dynamics and structural breaks that abound in financial time series. For instance, sudden market shocks or behavioral shifts, usually brought about by external forces, may not be well reflected by ARIMA's reliance on past information and stationarity conditions. In addition, the model's focus on historic values and its differencing procedure, although essential for stationarity attainment, potentially mask long-term patterns and undermine its reaction to sudden regime changes.

These limitations show the potential for improvement in forecast models. ARIMA-based hybrid models or nonlinear approaches combined with machine learning algorithms can make the model more flexible to adjust to such complexities. These techniques can address the rigidity of ARIMA through the incorporation of adaptability and flexibility to support evolving patterns. Notably, exogenous variables in the model, such as inflation, GDP growth, and monetary policy interventions, through methods like ARIMAX, could improve the accuracy of forecasting and explanation capability of the model. The incorporation would enable the model to have a wider framework in forecasting, where it can explain the macroeconomic impacts on interest rate changes better.

The significance of this study is for Slovakia's economic policymakers and financial planners. The trend of falling interest rates, if realized, could, in the best-case scenario, create an encouraging environment to borrow and invest and hence accelerate economic growth and catalyse post-pandemic rebound. However, the uncertainty depicted in the confidence intervals necessitates conservative interpretation given the prevailing risks emanating from geopolitical instability, inflationary forces, and changing monetary policy in the EU. Because of such uncertainties, the ARIMA model offers a valuable but limited forecasting tool, and its findings have to be augmented by other models to engage in a sounder analysis.

This study contributes to the broader literature on economic forecasting by providing empirical support for the effectiveness of ARIMA in forecasting interest rates, particularly in the case of an emerging EU economy like Slovakia. It also hints at the need for a richer appreciation of the dynamics of interest rates involving both linear and non-linear aspects. Such research in the future can therefore focus on examining models that can detect and respond to structural breaks or regime shifts, which often occur under situations of economic transition. Extending the forecast horizon and accounting for a more broad-based set of economic indicators will be critical if an improved overall picture of what causes interest rates is to be obtained.

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Conflicts of Interest: The authors declare no conflict of interest.

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