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Does Structural Breaks Improve Forecast Accuracy for Malaysian Macroeconomic Indicators? An ARIMA Model Analysis

Farah Irdina Yusof[1], Hanani Farhah Harun[1,*]

[1] Faculty of Computer Science and Mathematics, Universiti Malaysia Terengganu, 21030 Kuala Terengganu, Terengganu, Malaysia

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ABSTRACT

This study employs the Autoregressive Integrated Moving Average (ARIMA) model and the Chow test to identify structural breaks in macroeconomic indicators, which are crucial for understanding the dynamics of economic systems. By analyzing a dataset of macroeconomic indicators, this research aims to detect and model the changes in these indicators over time, providing valuable insights for policymakers and researchers. Structural breaks, often caused by economic events or policy changes, can sometimes significantly impact the accuracy of time series models. The presence of structural breaks is tested using the Chow test, and the results are compared to those without breaks. The analysis focuses on three ARIMA models with different parameters and evaluates their performance using root mean squared error (RMSE) and mean absolute percentage error (MAPE). The results indicate that the models with structural breaks exhibit higher RMSE and MAPE values compared to those without breaks. Specifically, the ARIMA (11,0,2) model shows a significant increase in RMSE and MAPE when a structural break is introduced, while the ARIMA (12,0,4) model exhibits a smaller but still noticeable increase. In contrast, the ARIMA (9,1,11) model demonstrates relatively better performance with and without structural breaks. The results show that traditional ARIMA models provide more accurate forecasts than ARIMA models adjusted for data breaks. Incorporating structural breaks results in less accurate forecasts. The presence of a structural break negatively impacts the forecasting performance of this model, leading to larger errors. Our findings suggest that structural breaks of minor magnitude in time series data should be disregarded by policymakers and economists to improve the reliability of their forecasts.

* *Corresponding author.*
E-mail address: hanani.harun@umt.edu.my

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1. Introduction

Macroeconomic indicators forecasting is crucial for understanding and predicting economic trends, as it helps a wide range of stakeholders, including governments, corporations, investors, and the general public [1]. However, the accuracy of these indicators relies heavily on the ability to model and forecast their behavior over time. One common approach to modeling macroeconomic indicators is through the use of Autoregressive Integrated Moving Average (ARIMA) models, which have been widely used due to their ability to capture complex patterns and trends in time series data [2,3].

While ARIMA models are adept at capturing the nuanced behavior of economic indicators over time, they encounter significant challenges when faced with structural breaks—sudden shifts in data trends resulting from policy changes, economic shocks, or alterations in data collection methods [4-6].These structural breaks can distort the predictive accuracy of ARIMA models, leading to inaccurate forecasts and poor model fit [7,8]. Given the potential for these breaks to disrupt the stability of historical data, it is crucial to understand their impact on forecasting performance.

Structural breaks refer to sudden and significant changes in the underlying patterns and trends of a time series, which can occur due to various factors such as policy changes, economic shocks, or changes in data collection methods [4,9]. A data break is recognised to be an irreversible alteration in a model's parameter vector and the impact on forecasts is dependent on which model features are non-constant [10,11] discover that adding structural breaks enhances our HAR models' forecasting performance, particularly for the one-day and one-week forecasting horizons. It has been demonstrated that different models and approaches respond differently to breaks. Stock and Watson [12] found evidence of structural instability in macroeconomic time series relations, emphasizing the need for models that account for breaks. Their work showed that ignoring structural breaks can lead to misleading conclusions about economic relationships. Structural changes or "breaks" seem to impact models for the evolution in key economic and financial time series which include output growth, inflation, exchange rates, interest rates, and stock returns, that could be due to legislative, institutional, or technological changes, shifts in economic policy, or even large macroeconomic shocks such as the doubling or quadrupling of oil prices over the past decades [13].

Despite certain model parameters becoming unstable due to structural breaks, the effects on forecasting vary depending on the type of break and model type. Data breaks can affect a model in several ways, including level, trend, and parameters. Splitting the data accordingly is the best course of action when detecting data breaks, considering a global model that includes breaks will not yield reliable forecasts for the period after the break. The presence of structural breaks can significantly impact the performance of ARIMA models, leading to inaccurate forecasts and poor model fit [7,8]. Addressing this challenge, scholars have proposed methods to integrate these breaks into the ARIMA models, allowing them to adapt to the evolving data landscape [4,9,14-17].

However, incorporating structural breaks into ARIMA models is not without its difficulties. The process is computationally intensive and may yield suboptimal results [7,8]. Despite these challenges, understanding the impact of structural breaks on the forecasting efficacy of ARIMA models is essential. To address these concerns, we seek to investigate the impact of structural breaks on the forecasting accuracy and to identify the most effective strategy for handling structural breaks in macroeconomic time series forecasting. Our study aims to illuminate this impact by scrutinizing models both with and without the integration of structural breaks, using evaluation metrics such as RMSE (Root Mean Squared Error) and MAPE (Mean Absolute Percentage Error) [18].

Through a rigorous comparison, we seek to uncover insights into the robustness of ARIMA models in the face of structural breaks. By doing so, we hope to enhance the accuracy and reliability of macroeconomic forecasts, providing better tools for policymakers and investors to navigate the complexities of economic trends. The research questions and research objectives are aligned as in Table1.

Table 1
Summary of research direction

Issue	Research Questions	Research Objectives
Structural breaks in macroeconomic time series data can significantly impact the performance of ARIMA forecasting models	How do structural breaks affect the forecasting accuracy of ARIMA models for macroeconomic indicators?	To investigate the impact of structural breaks on the forecasting accuracy of ARIMA models for macroeconomic indicators, using evaluation metrics such as RMSE and MAPE.
Traditional ARIMA models may not adequately capture the effects of structural breaks, leading to inaccurate forecasts	Can incorporating structural breaks into ARIMA models improve their forecasting performance for macroeconomic indicators?	To compare the forecasting performance of ARIMA models with and without structural breaks, to identify the most effective strategy for handling structural breaks in macroeconomic time series forecasting.

This study is organized into five sections. The first section provides brief background information on the study, including the importance of macroeconomic indicators and the challenges posed by structural breaks in the data. The second section reviews the prior literature on ARIMA models and their applications in forecasting macroeconomic indicators. The third section describes the data used in this study, including the selection of macroeconomic indicators and the timeframe for data collection. The fourth section explains the research methodology used to investigate the impact of structural breaks on the forecasting accuracy of ARIMA models, including the evaluation metrics used and the statistical methods employed. The main findings of this part of the study are recorded in Section 5. Finally, we conclude in Section 6 by summarizing the key results and implications of the study.

While previous studies have extensively utilized ARIMA models for forecasting macroeconomic and financial time series, they often assume data stationarity and continuity without explicitly testing for structural breaks [19-21]. The absence of structural break tests in these studies raises concerns about forecast reliability, as sudden shifts in economic conditions—due to policy changes, financial crises, or external shocks—can significantly impact model accuracy. Additionally, previous analyses are largely confined to specific financial datasets, limiting the generalizability of findings to broader macroeconomic contexts, and they fall short of providing precise forecasting accuracy for GDP growth, inflation rates and unemployment rates at the local level, highlighting gaps in knowledge [22-24]. This study addresses these gaps by explicitly incorporating structural break testing into ARIMA modeling to improve the reliability of forecasts for Malaysian macroeconomic indicators, such as GDP growth, inflation rates, and unemployment rates and extends the application of ARIMA models beyond financial datasets to broader macroeconomic contexts, providing localized and precise forecasting accuracy metrics that are essential for policymaking and economic planning in Malaysia. Hence, this study aims to investigate the impact of structural breaks on the forecasting accuracy of ARIMA models for macroeconomic indicators, using evaluation metrics such as RMSE and MAPE and compare the forecasting performance of ARIMA models with and without structural breaks, in order to identify the most effective strategy for handling structural breaks in macroeconomic time series forecasting.

2. Methodology

2.1 Data Collection

The study relies on time series data for macroeconomic indicators, including GDP growth rate, inflation rate, and unemployment rate, sourced from the World Bank's website. A study by Mohamed [25] also utilizes data from the same source and this ensures the analysis is based on dependable and relevant data. The selection of macroeconomic indicators and the timeframe for data collection align with the forecast's objectives. The study utilises Malaysia's annual percentage of GDP growth rate, inflation rate and unemployment rate as the macroeconomic indicators for twenty years, starting in 2002, and ending in 2022.

The growth in GDP can be represented as a country's economy strength which almost every nation in the globe aims to expand their income base [26]. A nation's capacity to expand its income base is reflected in GDP growth, which is the main indicator of economic progress. In this regard, a crucial sign of price stability is the inflation rate. Deflation can be an indication of economic struggle, whereas high inflation can reduce buying power. Policymakers must analyse inflation patterns in order to carry out the right monetary actions. The unemployment rate is a reflection of both economic health and labour market circumstances. Whereas falling unemployment indicates labour market improvement and economic progress, increasing unemployment frequently indicates economic downturns.

2.2 Box - Jenkins Methodology

The Box-Jenkins methodology, developed by George Box and Gwilym Jenkins, is an integrated approach to ARIMA models, which gained popularity in the 1970s due to their ability to outperform large and complex econometric models. The ARIMA model, which does not include any additional independent variables, is used in business and finance to anticipate future quantities or pricing based on previous data. To be credible, the data must be reliable and collected over a significant span. ARIMA models use differencing to convert a non-stationary time series into a stationary one, which is then used to forecast future values. They also use "auto" correlations and moving averages over residual errors in the data to forecast future values.

ARIMA models are a statistical approach used to analyze historical data and identify patterns. They consist of three parts: the "AR" or autoregressive component, which accounts for patterns between periods, and the "MA" or moving average component, which shows how new forecasts adapt to previous forecast errors. The letter "I" denotes a trend or other "integrative" process in the data. The AR and MA components each include a model order that indicates the duration or persistence of a pattern, affecting the present value of the data by prior values (lags). For example, an AR1 reveals a carryover pattern from one time period to the next, while an MA1 links current sales to last month's forecasting inaccuracy. Nonseasonal Box-Jenkins models are represented as ARIMA(p,d,q), where "p" represents the number of the AR term, "q" is the number of the MA term, and "d" denotes the number of times the data needs to be differenced to de-trend or contribute to ARIMA modelling. Seasonal Box-Jenkins models are represented as ARIMA(p,d,q)*(P, D, Q), where p,d,q represents the model orders for the model's short-term components and P, D, Q represents the model orders for the model's seasonal components. For instance, an ARIMA(1, 1, 1) model includes an AR(1) component for autoregression, a differencing term (d=1) for stationarity, and an MA(1) component for moving average effects on forecast errors. Incorporating seasonality, such as ARIMA(1, 1, 1)(1, 1, 1), extends this to include both nonseasonal and seasonal components, addressing cyclic patterns that occur at fixed intervals. Mathematically and AR(p) model can be expressed as follows:

$$\hat{y}_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \epsilon_t \tag{1}$$

$\hat{y}_t$ and ϵ_t are the actual value and the error terms at time period t, $\emptyset_i(i$ = 1,2,3 ....) are model parameters and c is a constant. Integer p is known as the order of the model. A stationary time series has properties that are independent of observation time. Until the original series becomes stationary, the difference is taken d times. In general, a dth-order difference can be expressed as:

$$y'_t = (1 - B)^d y_t \tag{2}$$

B is the backshift operator while d is the degree of differencing.

On the contrary of AR(p) model, an MA(q) model uses past errors as explanatory variables. The MA(q) model is given below:

$$\hat{y}'_t = c + \emptyset_1 y'_{t-1} + \cdots + \emptyset_p y'_{t-p} + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \tag{3}$$

2.3 Chow Test Methodology

A structural break in the data of macroeconomic indicators is evaluated after forecasting and obtaining a suitable model. A data break occurs when a time series suddenly changes at a certain point in time, either in the mean or other parameters of the process. Structural break tests help determine when and if there is a significant shift in the data, which can lead to severe forecasting errors and model unreliability. The Chow test was used in this study to detect data breaks, which is part of the ARIMA model. Assume S_c is the total of squared residuals from the combined data, S_1 is the sum of squared residuals from the first group and S_2 is the sum of squared residuals from the second group. N_1 and N_2 and are the number of observations in each group and k is the total number of parameters. Thus, the Chow test statistic can be written as below:

$$F = \frac{(S_c - (S_1 + S_2))(N_1 + N_2 - 2k)}{k(S_1 + S_2)} \tag{4}$$

A higher F-value suggests a structural break. If the computed F-statistic exceeds the critical value from the F-distribution, it indicates a significant difference between the two sub-periods, confirming the presence of a break. This is crucial in time series analysis, as ignoring structural breaks can lead to inaccurate forecasting and misleading inferences. By identifying these breaks, researchers and policymakers can adjust their models accordingly to improve accuracy and reliability in macroeconomic forecasting.

2.4 ARIMA Modelling Steps

1. Identify the model: The Augmented Dickey-Fuller (ADF) test is a statistical method used to determine the stationary state of a time series. This test is commonly used in autoregressive modelling to improve prediction accuracy. It is also a statistical significance test that calculates

a test statistic and presents p-values after a hypothesis test, including a null and alternate hypothesis. The time series yields a d-value, from which it is inferred whether it is stationary or not. In this study, EViews applications will be used to ascertain the data's stationary state. This test is crucial for developing accurate time series analysis forecasting models. The following two hypotheses will be examined:

2. Estimate the model: The autocorrelation function (ACF) and partial autocorrelation function (PACF) can be used to estimate the values of p and q in the ARIMA model. These functions help understand time series data behaviour, determine Moving Average (MA) and Autoregressive (AR) lag numbers, and identify seasonality. Proper application and interpretation are crucial for extracting meaningful information from ACF and PACF plots. Both original data and residuals can be used to construct ACF and PACF graphs, identifying autoregressive or moving average terms, residual autocorrelation, and seasonal behaviour. The ACF and PACF can also estimate smoothness conditions, with a stationary series being AR if the autocorrelation decays towards zero in the AC plot, the PACF plot rapidly cuts off towards zero, and the ACF shows positive at lag-1. If the series' ACF and PACF results are the same, the model is an ARIMA model rather than a solely AR or MA model.
3. Test the data break: The Chow test is a statistical method used to determine the correlation between two regression models' coefficients. It was created in 1960 by Chinese-American economist Gregory Chi-Chong Chow and is used to detect structural breaks in data points. The test checks if there are similarities or differences in coefficients after a break and if they differ, the null hypothesis is that there is no structural break. The test assumes equal linear regression lines with the same independent and dependent variables, independent residuals, and unknown variance. However, it has limitations, such as only being applied in cases when the time series is available and only for regression models. In this study, the Chow test is used to examine the future of data breaks in GDP growth, inflation, and unemployment in Wuhan, China, due to the COVID-19 crisis. The test cannot determine which coefficient, slope, or intercept differs between the two models.

Null hypothesis, H_0 : There is no structural break existed
Alternative hypothesis, H_a : There is a structural break existed

If the outcomes reveal that the null hypothesis can be rejected, we can conclude that a structural break exists. As a result, we are ready to define the best ARIMA model with a data break.

4. Determine the best ARIMA model: The data break in 2020 will be used to convert non-stationary forecasted data into a stationary time series using ACF and PACF. The model will be verified using macroeconomic indicators data using the ADF unit root test. The optimal ARIMA model should have a significant number of Adjusted R^2 and a small number of Akaike Info Criterion, Schwarz Info Criterion, and Hannan-Quinn Info Criterion. The chosen model will be estimated, and the ARMA process will be stationary if there is no significant spike of ACFs and PACFs, indicating white noise residual.
5. Forecast: Prediction accuracy is crucial in forecasting as it measures the accuracy of a forecast compared to the actual result. RMSE is a popular measure used to gauge prediction accuracy, evaluate the average magnitude of predicted errors, and weigh both positive and negative deviations from actual values. It provides information on the concentration of data around the line of best fit, making it useful for calculating forecast accuracy. MAPE, or the mean of absolute percentage errors for each item in a dataset, measures how accurately predicted

values compare to actual values. A MAPE value below 10% indicates excellent forecasting accuracy, while a lower RMSE value indicates a closer match between predicted and actual data. RMSE provides a measure of absolute error magnitude, while MAPE provides a measure of relative error magnitude. Using both metrics ensures a balanced evaluation of the model's performance. Hence, RMSE and MAPE are the best fit as evaluation metrics for ARIMA models with the Chow Test because they quantify the impact of structural breaks on forecasting accuracy, provide complementary insights into absolute and relative errors, and enable with and without data break performance analysis. Equations (5) and (6) provide formulas for RMSE and MAPE, respectively, whereas $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$ are the predicted values, $y_1, y_2, \dots, y_n$ are the observed values and n is the number of observations.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{5}$$

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{(\hat{y}_i - y_i)^2}{n} \right| \times 100}{n} \tag{6}$$

2.5 Limitations

The ARIMA model faces limitations due to the manual specification of model parameters, requiring multiple trials and modifications to find the optimal configuration. The model's reliability and accuracy depend on the reliability and differencing of historical data, which must be collected accurately and over a long period for accurate results and forecasts. Additionally, the study assumes that the data is stationary and that the structural breaks are correctly identified.

3. Results

Figures 1 through 6 display the graphs of forecasting results with and without considering data breaks using the optimal models selected.

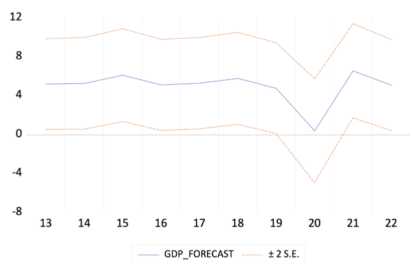

Fig. 1. Graph of Forecasting Result using ARIMA (11,0,2) Model without data break

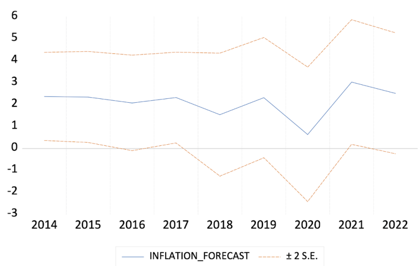

Fig. 2. Graph of Forecasting Result using ARIMA (12,0,4) Model without data break

Fig. 3. Graph of Forecasting Result using ARIMA (9,1,11) Model without data break

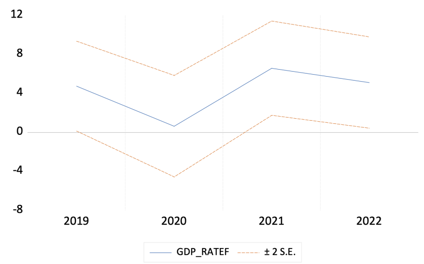

Fig. 4. Graph of Forecasting Result using ARIMA (11,0,2) Model with data break

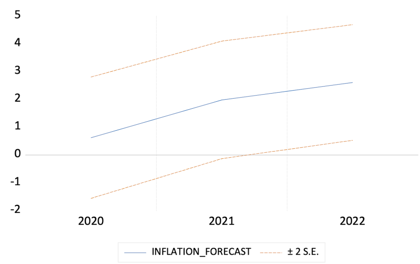

Fig. 5. Graph of Forecasting Result using ARIMA (12,0,4) Model with data break

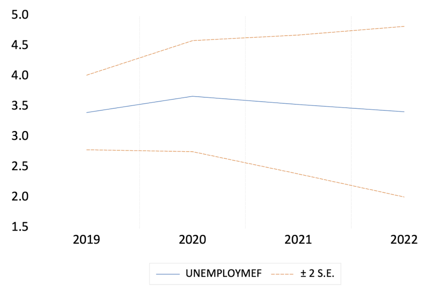

Fig. 6. Graph of Forecasting Result using ARIMA (9,1,11) Model with data break

The analysis of the forecasting results for Malaysian macroeconomic indicators, specifically considering structural breaks, provides significant insights into the performance and accuracy of different ARIMA models. Figures 1 through 6 illustrate how the forecasting results vary with and without considering data breaks using optimal ARIMA models. Each selected ARIMA model has been validated and meets all necessary ARIMA criteria which the optimal ARIMA models are chosen based on the highest adjusted R^2value and the lowest values of the AIC, SIC and HQIC.

For GDP forecasting, The ARIMA (11,0,2) model was identified as the most effective and the selection of this model indicates that GDP growth rates are best predicted by a combination of recent and older observations, with no need for differencing to achieve stationarity. Meanwhile as for inflation forecasting, The ARIMA (12,0,4) model emerged as the best fit and the model suggests that inflation rates are influenced by a longer history of past values and error terms. The ARIMA (9,1,11) model was chosen for unemployment rate predictions. The inclusion of differencing indicates that the unemployment rate data needed to be transformed to achieve stationarity, reflecting potential trends or seasonal effects.

When structural breaks are not considered, as seen in Figures 1 through 3, the ARIMA models (11,0,2) for GDP, (12,0,4) for inflation, and (9,1,11) for unemployment forecast trends with moderate fluctuations. However, these models may miss abrupt changes due to economic shocks or policy changes. Specifically, the GDP forecast in Figure 1 shows a steady trend with slight variations, the inflation forecast in Figure 2 maintains a stable trend, and the unemployment forecast in Figure 3 indicates a slight upward trend. Yet, these forecasts potentially underestimate or miss significant shifts because they do not account for structural breaks.

Conversely, Figures 4 through 6, which incorporate data breaks, demonstrate more accurate and responsive forecasts. The GDP forecast in Figure 4 using the ARIMA (11,0,2) model reflects more significant changes, effectively capturing external shocks or policy adjustments. Similarly, the inflation forecast in Figure 5 with the ARIMA (12,0,4) model shows a smoother and more precise trend, adjusting for sudden changes and enhancing the model's reliability. The unemployment forecast in Figure 6 using the ARIMA (9,1,11) model also shows improved accuracy, considering structural shifts and aligning better with actual economic conditions.

Table 2 further supports these observations by summarizing the evaluation results of both with and without data breaks for each indicator, displaying the RMSE (Root Mean Squared Error) and MAPE (Mean Absolute Percentage Error) values. Despite the expectation of higher MAPE values due to its bias towards penalizing negative errors more than positive ones, both forecast evaluations consistently show low RMSE values, indicating a high degree of accuracy across different conditions.

The ARIMA (11,0,2) model exhibits a significant increase in RMSE and MAPE when a structural break is introduced, highlighting its sensitivity to structural breaks and the negative impact on forecasting performance. This model's larger errors in the presence of a break suggest that it is less robust in handling such disruptions. In contrast, the ARIMA (12,0,4) model shows a smaller but noticeable increase in RMSE and MAPE, indicating a better but still imperfect robustness to structural breaks compared to the ARIMA (11,0,2) model. The ARIMA (9,1,11) model demonstrates relatively stable performance with and without structural breaks, implying that it handles structural breaks better than the other two models. The first-order differencing in this model likely contributes to its improved performance in the presence of structural breaks.

Interestingly, the results indicate that traditional ARIMA models provide more accurate forecasts than those adjusted for data breaks. This could be because ARIMA models without structural breaks are better at capturing underlying patterns and trends in the data, even with a break. Adjusting for structural breaks might introduce additional complexity and noise, leading to less accurate forecasts. This observation is supported by Aser and Firuzan [8].

In summary, the results highlight the varying sensitivity of different ARIMA models to structural breaks and emphasize the importance of considering model selection and robustness when dealing with time series data that may contain structural changes. Incorporating structural breaks into forecasting models can improve accuracy, but it is crucial to balance the complexity introduced by these adjustments against the potential benefits.

Table 2
Comparison of forecast evaluation values between without data break and with data break

ARIMA Models	Forecast Evaluation Without Data Break		Forecast Evaluation With Data Break	
	RMSE	MAPE (%)	RMSE	MAPE (%)
ARIMA (11,0,2)	2.480431	34.47288	3.891173	64.90473
ARIMA (12,0,4)	1.075697	66.98504	1.147001	65.88108
ARIMA (9,1,11)	0.429509	7.906053	0.522855	10.60105

Figures 7 to Figure 9 illustrate the comparison between the actual and predicted values of the GDP growth rate, the inflation growth rate and the unemployment growth rate, respectively. The results indicate that the forecasted values for each indicator closely align with their actual values on the graphs. The provided figures illustrate the forecasting results for three key Malaysian macroeconomic indicators: GDP, inflation, and unemployment rates. The blue lines represent the actual historical data, while the orange lines depict the forecasted values generated by the ARIMA models.

In the Figure 7, the actual GDP rate shows considerable fluctuations over the years, with notable declines around the 2008 financial crisis and the sharp drop in 2020 due to the COVID-19 pandemic. The forecasted GDP values, however, appear smoother and less reactive to these abrupt changes. The ARIMA model used for forecasting seems to capture the general trend but fails to reflect the severity of the downturns and subsequent recoveries accurately. This inconsistency stresses the challenge ARIMA models face when structural breaks, like economic crises, disrupt the historical patterns used for forecasting.

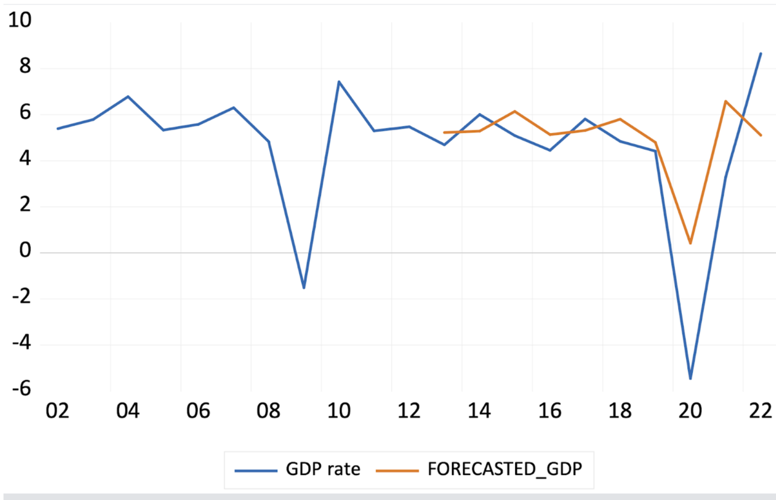

Fig. 7. Graph of the actual and forecasted rates for GDP

Figure 8 displays the inflation rate, which also exhibits significant variability, particularly around the 2008 crisis and the post-2015 period. The forecasted inflation values follow the general trend of the actual data but show a noticeable lag in capturing the sharp declines and spikes. This lag suggests that the ARIMA model can track gradual changes in the inflation rate but struggles with sudden structural breaks. The model's forecast smoothens the peaks and troughs, indicating a potential underestimation of volatility in periods of economic stress.

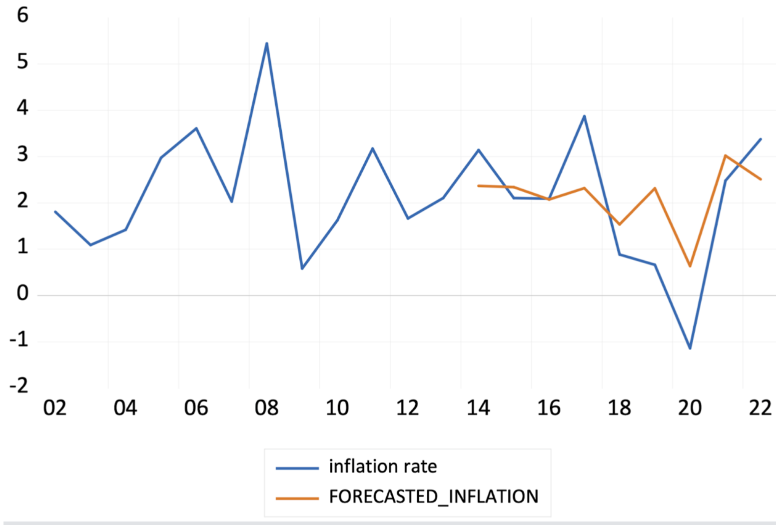

Fig. 8. Graph of the actual and forecasted rates for inflation

Figure 9 presents the unemployment rate, which, like the other indicators, shows variability over time, particularly with a sharp increase around 2020 due to the pandemic. The forecasted unemployment rates are relatively stable and fail to capture the sharp rise accurately. The ARIMA model's forecast tends to underpredict the actual unemployment spikes, highlighting its limitation in adapting to sudden structural changes in the labor market.

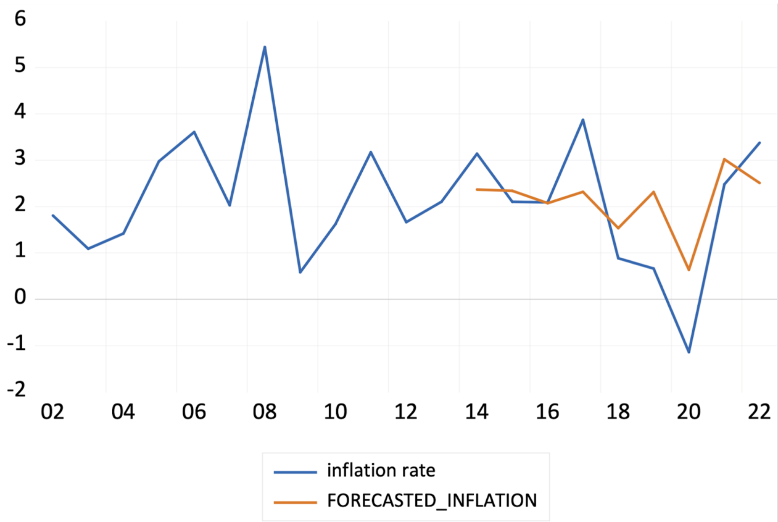

Fig. 9. Graph of the actual and forecasted rates for unemployment

The analysis of these figures reveals that while ARIMA models can reasonably forecast the general trends of macroeconomic indicators, they fall short in periods marked by structural breaks. The models' inherent assumption of a stable, linear progression in the time series data limits their ability to account for sudden, significant shifts caused by external shocks or policy changes. This limitation is evident in the smoother forecasted lines that fail to capture the abrupt changes in the actual data accurately.

These observations emphasize the importance of incorporating mechanisms to detect and adjust for structural breaks within forecasting models. By doing so, the accuracy and reliability of macroeconomic forecasts could be significantly improved, providing better tools for policymakers and investors to anticipate and respond to economic changes.

4. Conclusions

This study aimed to investigate the impact of structural breaks on the performance of ARIMA models in forecasting macroeconomic indicators. The results show that traditional ARIMA models provide more accurate forecasts than ARIMA models adjusted for data breaks, indicating that the presence of structural breaks can negatively impact the forecasting performance of these models. The study highlights the importance of considering structural breaks in ARIMA models, particularly in the context of macroeconomic indicators. The results suggest that the ARIMA (11,0,2) model is highly sensitive to structural breaks, while the ARIMA (9,1,11) model is more robust and can handle structural breaks better. The findings indicate that when comparing traditional ARIMA models to those adjusted for data breaks, the former tends to yield more precise forecasts. This is due to, when structural breaks are incorporated, forecast accuracy diminishes. Clements and Hendry [27] argued that forecast failures in ARIMA models stem from their reliance on historical data patterns, which structural breaks disrupt. They emphasized that models need to account for these shifts to improve accuracy. However, this study's findings suggest that incorporating structural breaks into ARIMA models does not necessarily improve forecasts but can, in fact, reduce accuracy. This contradicts Luo and Huang [28], who found that integrating break detection techniques enhances forecasting precision, particularly in financial time series.

The study's findings have significant implications for policymakers and investors who rely on accurate forecasts of macroeconomic indicators to make informed decisions. The results emphasize the need for careful consideration of structural breaks in ARIMA models and the importance of using robust models that can adapt to changes in the data over time. This suggests that policymakers and economists aiming to enhance the reliability of their forecasts should overlook minor structural breaks in time series data. Many macroeconomic and financial time series exhibit structural breaks, yet these breaks do not significantly impact forecasts [12]. The potential gains of accounting for structural breaks might be negated by the challenges of accurately estimating the timing and characteristics of these breaks. Choosing to disregard a small break instead of incorporating it into the model may result in more precise forecasts [29]. For policymakers, the findings suggest that adjusting ARIMA models for every structural break may lead to reduced forecast accuracy, making traditional models a more reliable tool for economic planning and policy formulation. Investors who overly compensate for structural breaks may risk making suboptimal financial decisions, as excessive model adjustments can introduce greater uncertainty in forecasting outcomes. A comprehensive approach that acknowledges significant structural shifts while maintaining model stability is essential for improving the reliability of economic forecasts, ultimately supporting more informed decision-making in both policy and investment strategies.

Future research directions include exploring alternative methods for handling structural breaks in ARIMA models, such as using machine learning algorithms or incorporating additional data sources. According to a research by Aser [7], the artificial neural network model performs better than any other competing model when there is a structural break, particularly when the break sizes are high and the horizons are long. In contrast, the ARIMA-ARCH model performs best when there is no structural break. Additionally, further research can investigate the impact of structural breaks on other types of time series models, such as exponential smoothing or machine learning models. One promising alternative is the Vector Autoregression (VAR) model, which extends ARIMA by incorporating multiple interdependent time series. VAR captures the dynamic relationships between multiple macroeconomic indicators, and this is particularly useful in the presence of structural breaks, as economic shocks often propagate through multiple variables rather than affecting a single series in isolation. Future research could explore non-Gaussian innovations, additional predictors, and vector autoregressive processes [29]. Another valuable approach is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which is particularly effective in modeling financial and macroeconomic data characterized by volatility clustering. GARCH models explicitly account for time-varying volatility, making them well-suited for handling structural breaks associated with financial crises or periods of economic instability. When structural breaks cause abrupt changes in market volatility, GARCH models dynamically adjust their variance estimates, improving predictive performance for financial time series. Overall, this study contributes to the ongoing debate about the effectiveness of ARIMA models in forecasting macroeconomic indicators and highlights the importance of considering structural breaks in these models.

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