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Application of the Autoregressive Integrated Moving Average (ARIMA) Model for Forecasting Indonesia's Non-Oil and Gas Export Values

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ABSTRACT: Forecasting non-oil and gas exports is essential for supporting economic planning and trade policy in Indonesia, as this sector represents the largest contributor to the country's export earnings. The dynamic nature of export values, influenced by changes in global demand, commodity prices, and macroeconomic conditions, necessitates an accurate forecasting approach. This study aims to develop an Autoregressive Integrated Moving Average (ARIMA) model for forecasting Indonesia's monthly non-oil and gas export values. Monthly export data from January 2012 to December 2024 were obtained from Statistics Indonesia (BPS). The dataset was divided into a training set (January 2012–August 2023) and a testing set (September 2023–December 2024). The modeling procedure included stationarity testing, parameter identification using the autocorrelation function (ACF) and partial autocorrelation function (PACF), parameter estimation, residual diagnostic checking, and model validation. Based on the Akaike Information Criterion

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(AIC), parameter significance, and diagnostic tests, the ARIMA (0,1,1) model was selected as the best forecasting model. The model produced a Mean Absolute Percentage Error (MAPE) of 7.0187% for the training data and 6.0948% for the testing data, indicating highly accurate forecasting performance. The relatively consistent MAPE values between the training and testing datasets demonstrate that the selected ARIMA model generalizes well to unseen data. Therefore, the ARIMA (0,1,1) model can be considered an effective statistical approach for short-term forecasting of Indonesia's non-oil and gas exports and may provide useful information for economic planning and export policy formulation.

Keywords: *ARIMA; time series forecasting; non-oil and gas exports; Indonesia; MAPE.*

1. INTRODUCTION

1.1 Background

Globalization has strengthened interdependence among countries, particularly in the economic sector through international trade activities. International trade provides opportunities for countries to expand market access, enhance product competitiveness, and stimulate national economic growth (Imannulloh & Rijal 2022). One of the most important indicators of international trade performance is exports. An increase in exports contributes to foreign exchange earnings, creates employment opportunities, expands production capacity, and supports the growth of a country's Gross Domestic Product (GDP) (Krugman et al. 2018).

Indonesia is endowed with abundant natural resources across various sectors, including agriculture, plantations, forestry, fisheries, mining, and manufacturing. These resources have positioned exports as one of the primary drivers of the national economy. Indonesian export commodities are broadly classified into two major categories: oil and gas exports and non-oil and gas exports. Since the late 1980s, Indonesia's export structure has undergone a substantial transformation due to the declining contribution of the oil and gas sector and the increasing role of non-oil and gas commodities. To date, non-oil and gas exports have become the largest contributor to Indonesia's total export value (Kurniawati & Islami 2022).

Despite their significant contribution, Indonesia's non-oil and gas export values exhibit considerable fluctuations over time. Variations in global demand, international commodity

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prices, exchange rates, geopolitical conditions, and international trade policies have caused export values to display unstable patterns. These fluctuations create uncertainty for both policymakers and business stakeholders in formulating trade, investment, and production strategies. Consequently, an appropriate forecasting method is required to effectively capture the historical behavior of export data and produce accurate predictions of future non-oil and gas export values.

Time series forecasting is one of the most widely applied statistical approaches for predicting future observations based on historical data patterns. Among the various forecasting techniques, the Autoregressive Integrated Moving Average (ARIMA) model, developed by George E. P. Box and Gwilym M. Jenkins, has become one of the most extensively used methods in time series analysis. The ARIMA model exploits the relationships between current observations, past observations, and previous random errors, enabling it to effectively capture the autocorrelation structure inherent in time series data (Box et al. 2016). Furthermore, ARIMA has been recognized as an effective approach for short-term forecasting, particularly when the underlying time series satisfies the stationarity assumption (Hyndman & Athanasopoulos 2021).

The ARIMA model has been successfully applied in numerous disciplines, including economics, finance, healthcare, energy, and international trade. According to Hyndman and Athanasopoulos (2021), ARIMA is considered one of the standard methods in time series analysis because of its strong theoretical foundation and robust forecasting performance across a wide range of economic datasets. Similarly, Jabnabillah et al. (2024) demonstrated that ARIMA provides reliable short-term forecasts for several fisheries commodities. Munarsih and Saluza (2020) further reported that ARIMA achieved lower forecasting errors than the exponential smoothing method in forecasting dengue hemorrhagic fever cases in Palembang City. These findings suggest that ARIMA is an appropriate and reliable approach for forecasting economic as well as other time series data.

One of the principal strengths of the ARIMA model lies in its ability to systematically model autocorrelation through the integration of autoregressive (AR), differencing (I), and moving average (MA) components. In addition, the Box–Jenkins modeling procedure—which involves model identification using the autocorrelation function (ACF) and partial autocorrelation function (PACF), parameter estimation, and residual diagnostic checking—

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facilitates the selection of a model that appropriately represents the characteristics of the observed data (Box et al. 2016). Consequently, ARIMA remains one of the most widely adopted statistical approaches in both academic research and practical economic forecasting.

Based on the foregoing discussion, this study aims to apply the ARIMA method to forecast Indonesia's non-oil and gas export values. The resulting forecasting model is expected to produce accurate short-term predictions that can serve as valuable information for policymakers and business stakeholders in formulating trade policies and economic planning strategies.

1.2 Objectives

The objective of this study is to apply the Autoregressive Integrated Moving Average (ARIMA) method to identify the most appropriate forecasting model for Indonesia's non-oil and gas export values and to generate forecasts for future export values over several upcoming periods.

1.3 Scope of the Study

This study is limited to univariate time series modeling using the Autoregressive Integrated Moving Average (ARIMA) method. The analysis utilizes historical monthly data on Indonesia's non-oil and gas export values without incorporating any exogenous explanatory variables. The analytical procedure consists of stationarity testing, model order identification using the autocorrelation function (ACF) and partial autocorrelation function (PACF), parameter estimation, residual diagnostic checking, model selection based on information criteria and forecasting error measures, and the generation of forecasts for Indonesia's non-oil and gas export values.

2. Data and Methods

2.1 Data

This study employed historical data on Indonesia's non-oil and gas export values obtained from the official One Data Portal of the Ministry of Trade of the Republic of Indonesia (https://satudata.kemendag.go.id). The dataset consists of monthly time series observations

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spanning January 2012 to December 2024, with export values expressed in millions of U.S. dollars (US$).

2.2 Analytical Procedure

The analytical procedure was carried out using the R programming language in RStudio and Python in Google Colab. The analysis consisted of the following steps:

1. Monthly non-oil and gas export data for Indonesia were downloaded from the Ministry of Trade database for each year and subsequently combined into a single continuous time series covering the period from January 2012 to December 2024.
2. An exploratory data analysis was conducted to examine the temporal pattern and characteristics of Indonesia's non-oil and gas export values.
3. The dataset was partitioned into training and testing datasets for model development and forecasting evaluation. The proportion of training and testing data was determined based on the characteristics observed during the exploratory analysis.
4. An Autoregressive Integrated Moving Average (ARIMA) model was developed to forecast Indonesia's non-oil and gas export values.

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used statistical methods for time series forecasting based on historical observations. As a univariate forecasting model, ARIMA has been extensively applied in economics, finance, climatology, and numerous other disciplines in which future observations depend primarily on historical patterns. The model was originally developed by George E. P. Box and Gwilym M. Jenkins and is therefore commonly referred to as the Box–Jenkins model. ARIMA combines the autoregressive (AR) and moving average (MA) components with a differencing procedure to transform the original series into a stationary process prior to model estimation (Shahraki 2019, cited in Hidayat & Mustawinar 2022).

The Box–Jenkins methodology encompasses several time series models, including the autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) models. The modeling procedure requires the time series to be stationary, exhibit a linear relationship, and have residuals

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that satisfy the white-noise assumption, namely independence, zero mean, constant variance, and normality, in order to produce reliable forecasts (Desi et al. 2022). Mathematically, an ARIMA model is denoted as ARIMA (p, d, q), where $p$represents the autoregressive order, $d$denotes the order of differencing, and $q$represents the moving average order (Cryer & Chan 2008). The general form of the ARIMA model is given by (Montgomery et al. 2015):

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)\varepsilon_t \qquad (30)$$

where

$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p,$

$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q.$

The notation is defined as follows:

- Y_t: observation at time t;
- ϕ_p: autoregressive coefficient of order p;
- θ_q: moving average coefficient of order q;
- ε_t: random error at time t;
- B: backshift operator;
- $(1-B)^d$: differencing operator, where $d$denotes the order of differencing.

The Box–Jenkins modeling procedure adopted in this study consists of the following stages.

a. Stationarity Assessment

Stationarity refers to the stability of the statistical properties of a time series, particularly its mean and variance, over time. A time series is considered strictly stationary if its statistical properties remain unchanged under time translation (Montgomery et al. 2015). Graphically, a stationary series fluctuates around a constant mean with approximately constant variance.

Stationarity should be examined with respect to both the mean and the variance.

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Stationarity in the Mean

Stationarity in the mean was assessed using time series plots, the autocorrelation function (ACF), and the Augmented Dickey–Fuller (ADF) unit root test. A slowly decaying ACF (i.e., *tails off slowly*) indicates that the series is non-stationary in the mean. According to Faulina et al. (2024), the alternative hypothesis of the ADF test states that the time series is stationary or does not contain a unit root.

If stationarity in the mean was not achieved, differencing was applied. The first-order differencing operator is defined as follows (Montgomery et al. 2015):

$$Z_t = (1 - B)Y_t = \nabla Y_t = Y_t - Y_{t-1},$$

where ∇denotes the differencing operator. More generally,

$$Z_t = (1 - B)^d Y_t = \nabla^d Y_t,$$

where $d$represents the differencing order required to achieve stationarity.

Stationarity in the Variance

Stationarity in the variance was evaluated using both the time series plot and the Box–Cox transformation plot. If the value of $\lambda = 1$falls within the 95% confidence interval of the Box–Cox plot, the variance is considered stable. Otherwise, a variance-stabilizing transformation should be applied.

When the assumption of homoscedasticity is violated, the Box–Cox transformation, a member of the power transformation family, can be employed to stabilize the variance (Box & Cox 1964). The Box–Cox transformation is defined as

$$Y^{(\lambda)} = \begin{cases} \dfrac{Y^\lambda - 1}{\lambda}, & \lambda \neq 0, \\ \ln(Y), & \lambda = 0. \end{cases}$$

where

- $Y$is the original observation;
- $Y^{(\lambda)}$is the transformed observation; and
- $\lambda$is the transformation parameter.

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The parameter $\lambda$is generally estimated using the maximum likelihood method, and the optimal value is selected by maximizing the profile log-likelihood. In practice, the estimated value is often rounded to a nearby convenient value, such as -2, -1, -0.5, 0, 0.5, 1, or 2, to facilitate interpretation and implementation. Accordingly, the appropriate box–cox transformation can be selected by choosing the value closest to the optimal λestimated from the profile likelihood, as summarized in Table 1.

Table 1. Box–Cox transformations (adapted from Box & Cox 1964; Cryer & Chan 2008)

λ	Transformation	**Transformation Name**
-2	$Y^{-2} = 1/Y^2$	Reciprocal square
-1	$Y^{-1} = 1/Y$	Reciprocal
$-0{,}5$	$Y^{-0{,}5} = 1/\sqrt{Y}$	Reciprocal square root
0	$\ln(Y)$	Natural logarithm
0,5	$\sqrt{Y}$	Square root
1	Y	No transformation
2	Y^2	Square transformation

b. Model Identification

The identification of candidate ARIMA models was performed by examining the autocorrelation function (ACF), partial autocorrelation function (PACF), and extended autocorrelation function (EACF) plots. The ACF and PACF plots generally exhibit two characteristic patterns, namely tails off (gradual decay) and cuts off (abrupt truncation). An MA (q) model is characterized by an ACF that cuts off after lag q, whereas an AR(p) model is characterized by a PACF that cuts off after lag p. When both the ACF and PACF display gradually decaying patterns, the underlying process may be represented by an ARMA (p, q) model. The general identification rules for AR, MA, and ARMA models are summarized in Table 2 (Cryer & Chan 2008).

Table 2. Identification of AR ($\boldsymbol{p}$), MA ($\boldsymbol{q}$), and ARMA ($\boldsymbol{p}, \boldsymbol{q}$) models (Cryer & Chan 2008)

Model	ACF	PACF
AR(p)	Tails off	Cuts off after lag p
MA(q)	Cuts off after lag q	Tails off
ARMA(p, q), $p > 0$, $q > 0$	Tails off	Tails off

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When an ARMA model is indicated, further identification was performed using the Extended Autocorrelation Function (EACF). The appropriate model order was determined by locating the characteristic zero-triangle pattern, in which the upper-left corner corresponds to the ARMA order.

c. Parameter Estimation

The parameters of the ARIMA model were estimated using the maximum likelihood estimation (MLE) method.

d. Model Diagnostic Checking

The adequacy of the fitted ARIMA model was evaluated by examining parameter significance and conducting residual diagnostic tests. A satisfactory ARIMA model should have statistically significant parameters and residuals that satisfy the assumptions of white noise and normality (Aswi & Sukarna 2006, cited in Muhammad et al. 2023). Accordingly, diagnostic checking included tests for residual independence, homoscedasticity, and normality.

Residual Independence

Residual independence (i.e., the absence of autocorrelation) was evaluated using the Ljung–Box test. The null hypothesis states that the residuals are independently distributed (white noise), whereas the alternative hypothesis states that residual autocorrelation exists. The null hypothesis is rejected when the Ljung–Box statistic exceeds the critical value $\chi^2_{\alpha,K-p-q}$ or when the p-value is less than the 5% significance level.

The Ljung–Box test statistic is given by (Wei 2006; Fadhilah et al. 2024):

$$Q = n(n+2)\sum_{k=1}^{K}\frac{\hat{r}_k^{\,2}}{n-k}, \qquad (33)$$

or equivalently,

$$Q = n(n+2)\left(\frac{\hat{r}_1^{\,2}}{n-1}+\frac{\hat{r}_2^{\,2}}{n-2}+\cdots+\frac{\hat{r}_K^{\,2}}{n-K}\right),$$

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where

- Q= Ljung–Box test statistic;
- n= number of observations;
- K= maximum lag considered in the test;
- k= lag order ($k = 1,2,\dots,K$);
- $\hat{r}_k$= residual autocorrelation coefficient at lag k.

Under the null hypothesis of independently distributed residuals, the test statistic approximately follows a chi-square distribution with

$\mathrm{df} = K - p - q,$

where $p$and $q$denote the autoregressive and moving average orders of the ARIMA model, respectively. The null hypothesis is rejected when

$Q > \chi^2_{\alpha,K-p-q},$

or equivalently, when the corresponding p-value is less than the significance level α.

Residual Homoscedasticity

Residual homoscedasticity was assessed using the Autoregressive Conditional Heteroskedasticity Lagrange Multiplier (ARCH–LM) test. The null hypothesis states that the residuals do not exhibit ARCH effects (homoscedasticity), whereas the alternative hypothesis states that ARCH effects are present.

The ARCH–LM test statistic is defined as (Ding 2007, cited in Nurhidayati et al. 2024):

$$LM = nR^2,$$

where

- $n$is the number of observations; and
- $R^2$is the coefficient of determination obtained from the auxiliary regression.

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The test statistic follows a chi-square distribution with degrees of freedom equal to the ARCH order (p). The null hypothesis is rejected when

$$LM > \chi^2_{\alpha,p},$$

or when the p-value is less than 0.05.

Residual Normality

Residual normality was first evaluated graphically using a quantile–quantile (Q–Q) plot. Residuals are considered approximately normally distributed when the plotted points closely follow the 45° reference line.

A formal assessment of normality was then conducted using the Kolmogorov–Smirnov (K–S) test, in which the null hypothesis states that the residuals follow a normal distribution.

The Kolmogorov–Smirnov test statistic is expressed as (Kolmogorov 1933, cited in Fadliani et al. 2021):

$$D_n = \sup \mid F_n(x) - F(x) \mid, \qquad (35)$$

where

- $D_n$is the Kolmogorov–Smirnov test statistic;
- $\sup$denotes the supremum (maximum absolute difference);
- $F_n(x)$is the empirical cumulative distribution function (ECDF) of the residuals; and
- $F(x)$is the theoretical cumulative distribution function of the normal distribution.

The null hypothesis is rejected when

$$D_n > D_{(n,\alpha)},$$

or when the corresponding p-value is less than 0.05.

e. Overfitting Procedure

An overfitting procedure was conducted by adding one additional AR or MA term to the tentative model in order to determine whether a more complex model provided a significantly better fit (Cryer & Chan 2008).

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f. Selection of the Best ARIMA Model

The optimal ARIMA model was selected based on the statistical significance of its parameters and the minimum Akaike Information Criterion (AIC) value. The AIC provides a balance between model goodness-of-fit and model complexity. According to Akaike (1974, cited in Montgomery et al. 2015), the AIC is calculated as

$$\text{AIC} = n\ln\left(\frac{\sum_{t=1}^{n} e_t{}^2}{n}\right) + 2k, \qquad (36)$$

where

- AIC= Akaike Information Criterion;
- e_t= residual at time t;
- $\sum_{t=1}^{n} e_t^2$= Sum of Squared Errors (SSE);
- n= number of observations; and
- k= number of estimated model parameters.

The model with the lowest AIC value was selected as the optimal forecasting model because it provides the best trade-off between model fit and complexity. If an overfitted model yielded a lower AIC than the initial tentative model, the model was re-evaluated through residual diagnostic tests—including independence, homoscedasticity, and normality—to ensure that all ARIMA assumptions were satisfied before the model was used for forecasting.

3. Results and Discussion

3.1 Data Exploration

Data exploration was conducted to understand the patterns and characteristics of the time series employed in this study. The analyzed data consist of Indonesia's non-oil and gas export values obtained from the official *Satu Data* portal of the Ministry of Trade of the Republic of Indonesia. The dataset comprises 156 monthly observations spanning from January 2012 to December 2024. All observations were complete, with no missing value;

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therefore, no imputation procedure was required. The exploratory analysis began by constructing a time series plot, where the *x*-axis represents the observation period and the *y*-axis represents Indonesia's non-oil and gas export values (in million US dollars).

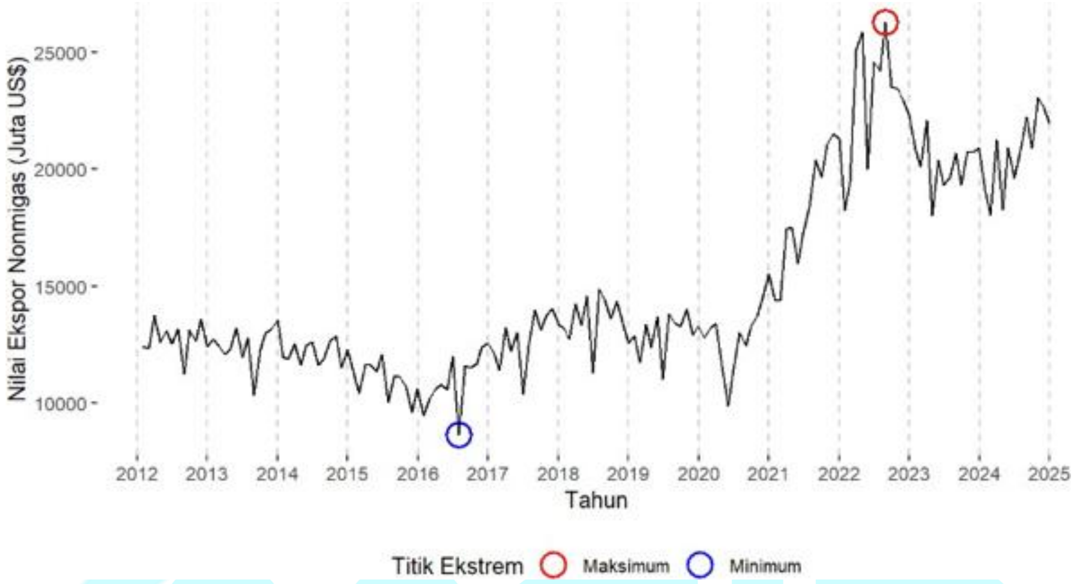

Figure 1. *Time series plot of Indonesia's non-oil and gas export values, January 2012–December 2024.*

Based on the time series plot presented in Figure 1, Indonesia's non-oil and gas exports exhibit considerable fluctuations while maintaining an overall upward trend. During 2012–2013, export values remained relatively stable at approximately US$12,600 million. The lowest value during this period occurred in August 2013, reaching US$10,363.19 million. Subsequently, exports declined gradually until reaching the minimum value of the entire observation period, namely US$8,650.86 million in July 2016. Thereafter, export values increased steadily and reached a local peak during the third quarter of 2018, particularly in July 2018, before gradually declining from September 2018 until early 2020. In mid-2020, exports experienced a sharp decline in May 2020, followed by a substantial upward trend. This recovery continued until exports reached the highest value of the study period, amounting to US$26,265.83 million in August 2022. Subsequently, export values declined during the first quarter of 2023 before stabilizing and exhibiting a moderate upward trend through December 2024.

Indonesia's non-oil and gas exports experienced a substantial decline in 2020, followed by a remarkable recovery in 2021. This decline was largely attributable to the COVID-19 pandemic, which triggered a global economic crisis and severely disrupted international

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trade due to the implementation of lockdown measures in many countries (Oraby, 2021, as cited in Prayoga et al., 2022). The pandemic reduced consumer purchasing power, created financial difficulties for businesses, increased unemployment, and slowed production and distribution activities. Nevertheless, many enterprises, particularly micro, small, and medium-sized enterprises (MSMEs), adapted by adopting digital marketing strategies and online sales platforms (Chaerani et al., 2020). The pandemic also caused contractions across all components of Indonesia's Gross Domestic Product (GDP), placing the national economy under considerable pressure. Entering 2021, the relaxation of public health restrictions, increased vaccination coverage, and economic stimulus programs facilitated the recovery of global industries, thereby increasing international demand for exports. In response, the Indonesian government implemented fiscal and monetary measures, including tax incentives and reductions in interest rates, to accelerate economic recovery and restore investor confidence (Rahmawati & Apriliasari, 2021; Gading et al., 2022).

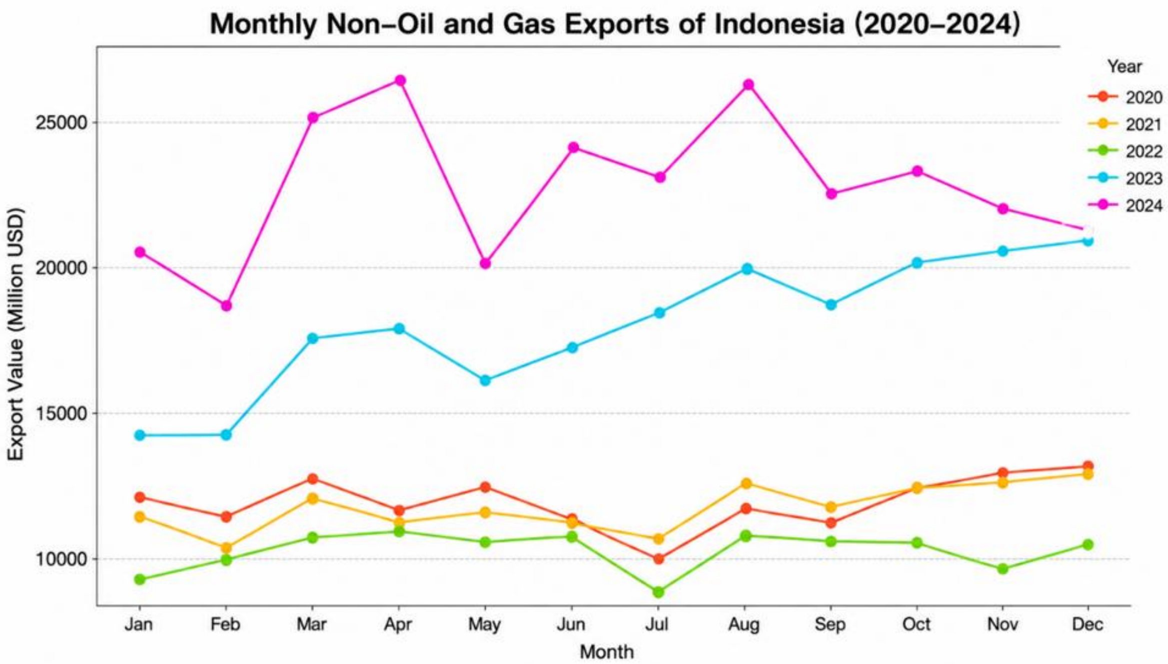

Figure 2. *Seasonal plot of Indonesia's non-oil and gas export values.*

The seasonal plot shown in Figure 2 indicates that fluctuations in Indonesia's non-oil and gas exports tend to recur during specific months in several years. For example, export values generally increase during March, July, and August. However, this seasonal pattern is not consistently observed across all years and appears to be influenced by external factors such as global economic conditions and fluctuations in international commodity prices.

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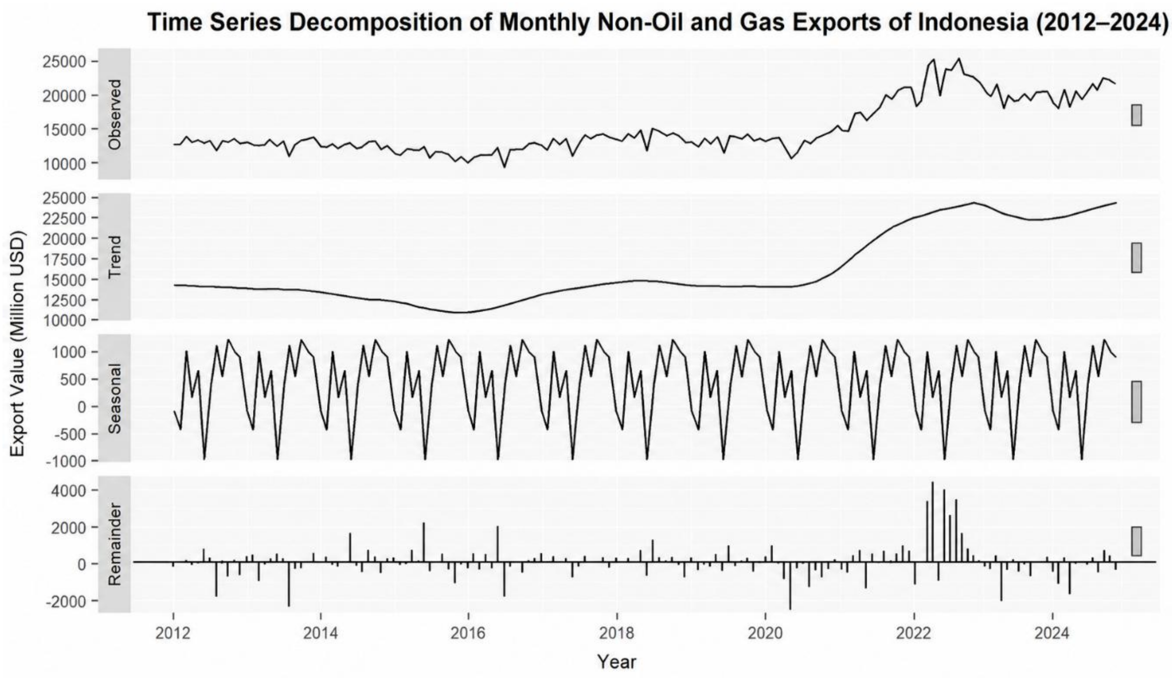

Figure 3. *STL decomposition of Indonesia's non-oil and gas export values.*

The STL (Seasonal and Trend decomposition using Loess) decomposition results presented in Figure 3 indicate that the trend strength of the series is 0.92, whereas the seasonal strength is only 0.12. These values were calculated using Equations (1) and (2). Trend strength (F_T) or seasonal strength (F_S) values approaching one indicate the presence of strong trend or seasonal components, whereas values approaching zero indicate weak components. In this study, the high trend strength suggests that most of the variability in the data is explained by the trend component, while the seasonal component contributes only marginally to the overall variation.

Visually, the trend component exhibits gradual and persistent changes that represent the long-term movement of Indonesia's non-oil and gas exports. In contrast, the seasonal component displays recurring annual fluctuations of relatively small magnitude. The gray boxes located on the right side of each panel indicate the numerical scale of the corresponding component. It should be noted that the small gray box in the trend panel is equivalent in scale to the larger box in the seasonal panel. Consequently, seemingly minor changes in the trend panel may correspond to substantial changes in the original data. Therefore, the size of these boxes should not be interpreted as representing the relative contribution of each component to the data variance; rather, they merely indicate the numerical scale used for visualization.

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These findings suggest that forecasting models that do not explicitly incorporate seasonal components remain appropriate for this dataset. Such an approach is consistent with the underlying data structure, which is predominantly driven by the trend component, and aligns with the principle of parsimony by favoring a simpler model that adequately captures the underlying dynamics. A parsimonious model not only simplifies the modeling process but also enhances computational efficiency and facilitates clearer interpretation of forecasting results.

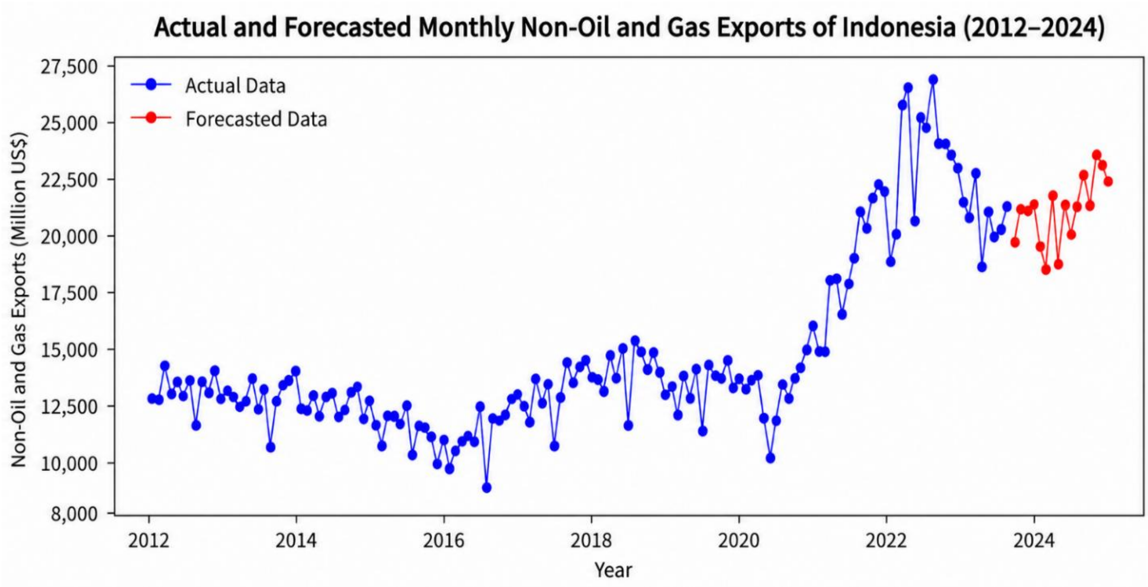

Figure 4. *Training and testing data partition for Indonesia's non-oil and gas export values.*

The dataset was subsequently divided into training and testing subsets using a 90:10 ratio. Data partitions of 70:30, 80:20, and 90:10 are commonly adopted in time series forecasting, depending on the characteristics of the data and the objectives of the modeling process. In this study, the 90:10 partition was selected to preserve the continuity of the temporal pattern within the training data.

Using alternative partitions, such as 80:20 or 70:30, would place the splitting point within a period when the upward trend was still evolving, potentially disrupting the continuity of the historical pattern required for effective model training. Accordingly, the data were divided at August 2023, resulting in a training set consisting of 140 monthly observations from January 2012 to August 2023 and a testing set comprising 16 monthly observations from September 2023 to December 2024. The training testing partition is illustrated in Figure 4.

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3.2 ARIMA Model

ARIMA modeling begins with an assessment of data stationarity. If the series is non-stationary in the mean, differencing is required, whereas non-stationarity in the variance can be addressed using the Box–Cox transformation. An initial exploratory assessment of stationarity can be performed by visually examining the time series plot. Based on the exploratory analysis presented previously, the data exhibit both an upward trend and considerable fluctuations, indicating that the series is non-stationary in both the mean and the variance. This is evidenced by observations that do not fluctuate consistently around a constant mean over time and by non-uniform variability throughout the series. These findings were further confirmed through the autocorrelation function (ACF) plot and the Augmented Dickey–Fuller (ADF) test for stationarity in the mean, as well as the Box–Cox plot for assessing stationarity in the variance.

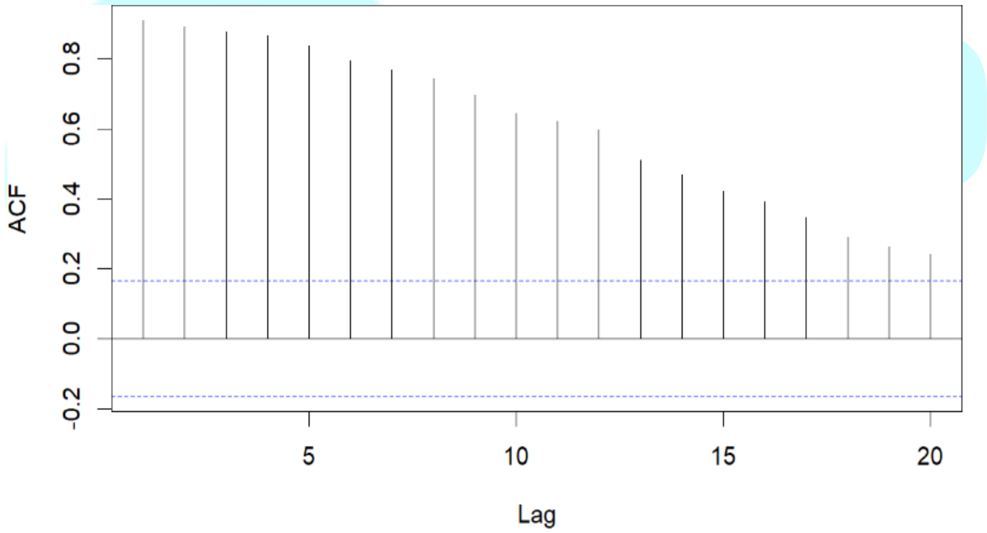

Figure 5. *ACF plot of Indonesia's non-oil and gas export values.*

As shown in Figure 5, the ACF exhibits a slow decaying (tails-off) pattern, indicating that the series is non-stationary in the mean. In addition to the graphical assessment, a formal stationarity test was conducted using the ADF test. The null hypothesis of the ADF test states that the series is non-stationary in the mean (i.e., contains a unit root), whereas the alternative hypothesis states that the series is stationary (i.e., does not contain a unit root). The ADF test produced a *p*-value of 0.6262, which exceeds the 5% significance level. Therefore, the null hypothesis cannot be rejected, indicating that Indonesia's non-oil and gas export series is non-stationary in the mean.

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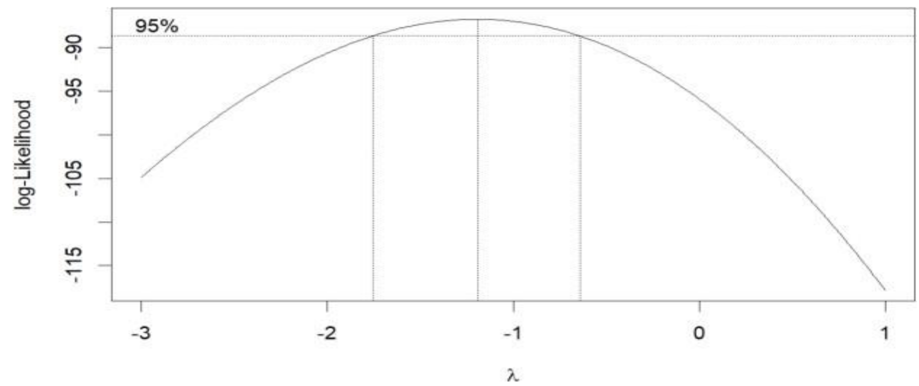
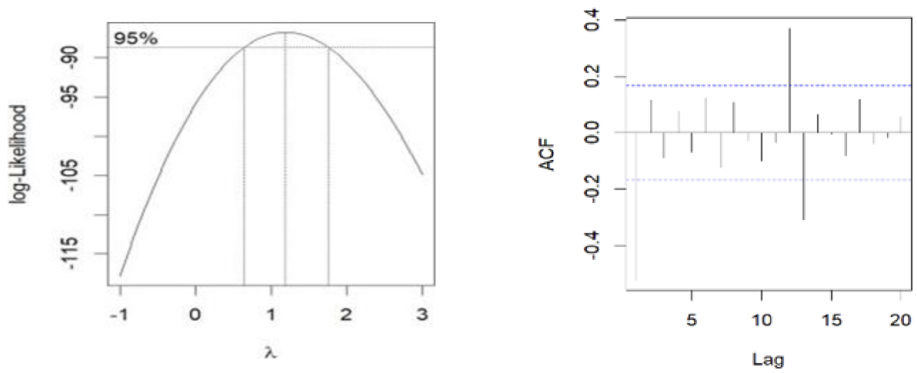


Figure 6. *Box–Cox plot of Indonesia's non-oil and gas export values.*

The data were also found to be non-stationary in the variance, as indicated by the Box–Cox plot shown in Figure 6. The optimal Box–Cox transformation parameter was estimated as $\lambda=-1.19$, with a 95% confidence interval ranging from -1.75 to -0.65. Since this interval does not include the value of one, the variance of the series cannot be considered stable, indicating that the data are also non-stationary in the variance.

To address these issues, a Box–Cox transformation with $\lambda=-1$, corresponding to the reciprocal transformation (1/Y), was applied to stabilize the variance. In addition, first-order differencing was performed to achieve stationarity in the mean. The results of these procedures are presented in Figure 7, demonstrating that the transformed series satisfies the stationarity assumption. This conclusion is supported by the fact that the 95% Box–Cox confidence interval includes the value of one after transformation, while the ADF test yields a p-value of less than 0.01, which is below the 5% significance level. Consequently, the null hypothesis is rejected, confirming that the transformed series is stationary in both the mean and the variance. Furthermore, the ACF plot no longer exhibits the characteristic slowly decaying pattern, consistent with the ADF test results.



(A) (B)

Figure 7. (a) Box–Cox plot and (b) ACF plot after Box–Cox transformation and first-order differencing.

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The transformed and difference series is presented in Figure 8. The observations fluctuate around a relatively constant meaning with approximately homogeneous variance, and no discernible trend is apparent, indicating that the stationarity assumption has been successfully achieved.

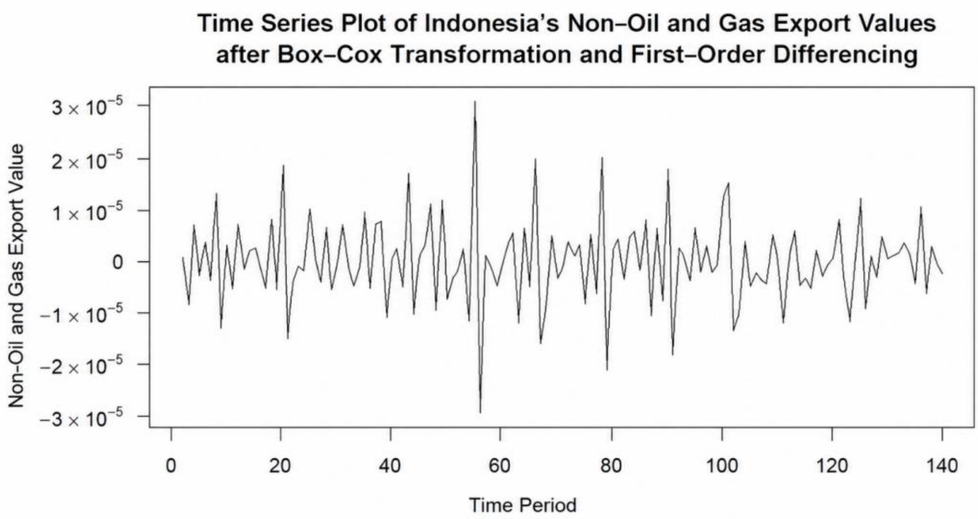

Figure 8. Time series plot of Indonesia's non-oil and gas export values from January 2012 to August 2023 after Box–Cox transformation and first-order differencing.

Once stationarity had been established, tentative ARIMA models were identified by examining the ACF and partial autocorrelation function (PACF) plots. As illustrated in Figure 9(a), the ACF exhibits a cut-off at lag 1, suggesting a moving average order of q=1, thereby indicating the candidate model ARIMA (0,1,1). Meanwhile, the PACF shown in Figure 9(b) cuts off at lag 3, suggesting an autoregressive order of p=3, which corresponds to the candidate model ARIMA (3,1,0).

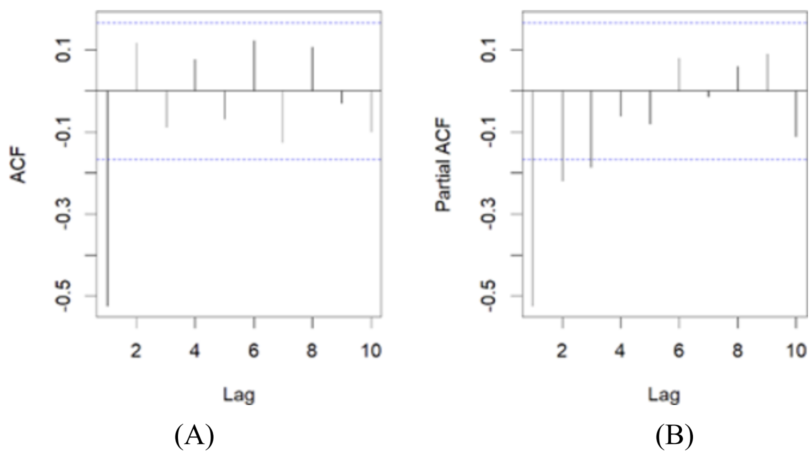

Figure 9. (a) ACF plot and (b) PACF plot of Indonesia's non-oil and gas export values.

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Tentative ARIMA models were also identified using the Extended Autocorrelation Function (EACF), as presented in Figure 10. The EACF facilitates the identification of appropriate combinations of autoregressive and moving average orders. Based on the EACF results, four candidate models were identified: ARIMA (0,1,1), ARIMA (0,1,2), ARIMA (1,1,2), and ARIMA (2,1,2).

```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10
0 x o o o o o o o o o o
1 x x o o o o o o o o o
2 x x o o o o o o o o o
3 x x o o o o o o o o o
4 x x x x x o o o o o o
5 x x x x o o o o o o o
6 o x o x o o o o o o o
```

Figure 10. EACF plot of Indonesia's non-oil and gas export values.

The parameter estimates for the tentative ARIMA models are summarized in Table 3. The optimal model was selected based on two criteria: (1) all estimated parameters must be statistically significant, and (2) the model must have the lowest Akaike Information Criterion (AIC) among the candidate models. According to these criteria, ARIMA (0,1,1) was identified as the most appropriate model because all of its parameters were statistically significant and it achieved the smallest AIC value.

Table 3. Parameter estimates for the tentative ARIMA models

Model	Parameter	Coefficient	*p*-value	AIC
ARIMA (0,1,1)	MA (1)	0.6115	0.0000*	-2907.76
ARIMA (0,1,2)	MA (1)	0.6865	0.0000*	-2907.58
	MA (2)	-0.1069	0.1749	
ARIMA (1,1,2)	AR (1)	-0.8924	0.0000*	-2906.66
	MA (1)	-0.2426	0.0752	
	MA (2)	0.4799	0.0000*	
ARIMA (2,1,2)	AR (1)	-0.9692	0.0000*	-2904.87
	AR (2)	-0.0632	0.6491	
	MA (1)	-0.2982	0.0834	
	MA (2)	0.4619	0.0000*	
ARIMA (3,1,0)	AR (1)	-0.6707	0.0000*	-2905.77
	AR (2)	-0.3288	0.0007*	
	AR (3)	-0.1791	0.0308*	

Significant at the 5% significance level.

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Following parameter estimation, the ARIMA (0,1,1) model was identified as the best tentative model. Subsequently, diagnostic tests were performed to evaluate whether the model residuals were randomly distributed, exhibited constant variance, and followed a normal distribution. An initial exploratory assessment of residual normality was conducted using the quantile–quantile (Q–Q) plot presented in Figure 11. The plot indicates that the residual points deviate from the 45° reference line, suggesting a violation of the normality assumption for the residuals of the ARIMA (0,1,1) model.

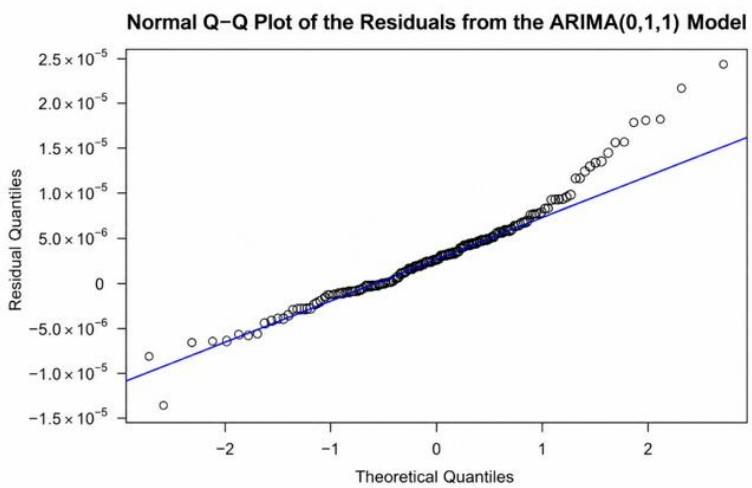

Figure 11. Normal Q–Q plot of the residuals from the ARIMA(0,1,1) model.

This observation was further confirmed through a formal Kolmogorov–Smirnov (K–S) test. The null hypothesis states that the residuals follow a normal distribution, whereas the alternative hypothesis states that they do not. The K–S test yielded a p-value of $< 2.2 \times 10^{-16}$, which is well below the 5% significance level. Therefore, the null hypothesis was rejected, indicating that the model residuals are not normally distributed. Although the normality assumption was violated, Bowerman et al. (2017), as cited in Yuliyanti and Arliani (2022), argued that for sufficiently large sample sizes, statistical inference remains valid because the sampling distribution is approximately normal regardless of the residual distribution.

The homoscedasticity assumption was subsequently examined using the ARCH–LM test. The null hypothesis states that no heteroscedasticity is present, whereas the alternative hypothesis indicates the presence of heteroscedasticity. For the ARIMA(0,1,1) model, all p-values across the examined lags exceeded the 5% significance level. Consequently, the null hypothesis could not be rejected, indicating that the residual variance is homogeneous.

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Residual independence was assessed using the Ljung–Box test, whose null hypothesis states that the residuals are independently distributed and free from autocorrelation. At lag 1, the Ljung–Box test produced a p-value of 0.3044, exceeding the 5% significance level, indicating that the null hypothesis could not be rejected and that the residuals were independent. However, from lag 12 onward, significant autocorrelation was detected, implying that the assumption of residual independence was only partially satisfied.

To identify the most appropriate forecasting model, an overfitting procedure was performed on the selected tentative ARIMA model. Overfitting was conducted by increasing the autoregressive (AR) and moving average (MA) orders by one. Since the selected ARIMA (0,1,1) model generated two possible overfitted models, namely ARIMA (1,1,1) and ARIMA (0,1,2), and ARIMA (0,1,2) had already been evaluated during the tentative model selection stage, only ARIMA (1,1,1) required additional parameter estimation.

The overfitting results are presented in Table 4 and indicate that the ARIMA (1,1,1) model contains statistically insignificant parameters. Consequently, ARIMA (0,1,1) remained the preferred model because all of its parameters were statistically significant and it produced the lowest Akaike Information Criterion (AIC). The final ARIMA (0,1,1) model for Indonesia's non-oil and gas export values can be expressed as follows:

$$(1 - B)Z_t = (1 - \theta_1 B)\varepsilon_t \qquad (47)$$

$$Z_t - BZ_t = \varepsilon_t - \theta_1 B\varepsilon_t \qquad (48)$$

$$Z_t - Z_{t-1} = \varepsilon_t - 0.6115\varepsilon_{t-1} \qquad (49)$$

$$Z_t = Z_{t-1} + \varepsilon_t - 0.6115\varepsilon_{t-1},$$

where

$$Z_t = \frac{1}{Y_t}, Z_{t-1} = \frac{1}{Y_{t-1}}. \qquad (50)$$

Table 4. Comparison of overfitted ARIMA models.

Model	Parameter	Coefficient	*p*-value	AIC
ARIMA(1,1,1)	AR(1)	-0,1740	0,1676	-2907,61
	MA(1)	0,5112	0,0000*	

Significant at the 5% significance level.

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The ARIMA (0,1,1) model was selected to represent Indonesia's non-oil and gas export series because it successfully captured most of the short-term dynamics in the data. Nevertheless, the model was not entirely adequate, as residual autocorrelation remained, suggesting that certain underlying patterns were not fully explained. This observation indicated the possible presence of seasonal behavior that could not be captured by the non-seasonal ARIMA model. Therefore, an alternative modeling approach incorporating seasonal components was subsequently investigated using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model extends ARIMA by explicitly incorporating seasonal autoregressive and moving average components. A SARIMA model is denoted as ARIMA $(p, d, q)(P, D, Q)_s$, where (p, d, q)represent the non-seasonal autoregressive (AR), differencing, and moving average (MA) orders, respectively, whereas (P, D, Q)denote the corresponding seasonal orders. The parameter $s$represents the seasonal period. The general SARIMA model can be expressed as follows (Montgomery et al., 2015):

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D Y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t. \qquad (51)$$

where

- $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$,
- $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$,
- $\Phi_P(B^s) = (1 - \Phi_1 B^s - \cdots - \Phi_P B^{Ps})$,
- $\Theta_Q(B^s) = (1 - \Theta_1 B^s - \cdots - \Theta_Q B^{Qs})$,
- Y_t is the observation at time t,
- Bdenotes the backshift operator,
- s is the seasonal period,
- $(1-B)^d$is the non-seasonal differencing operator,
- $(1-B^s)^D$is the seasonal differencing operator, and
- $\varepsilon_t$is the random error term.

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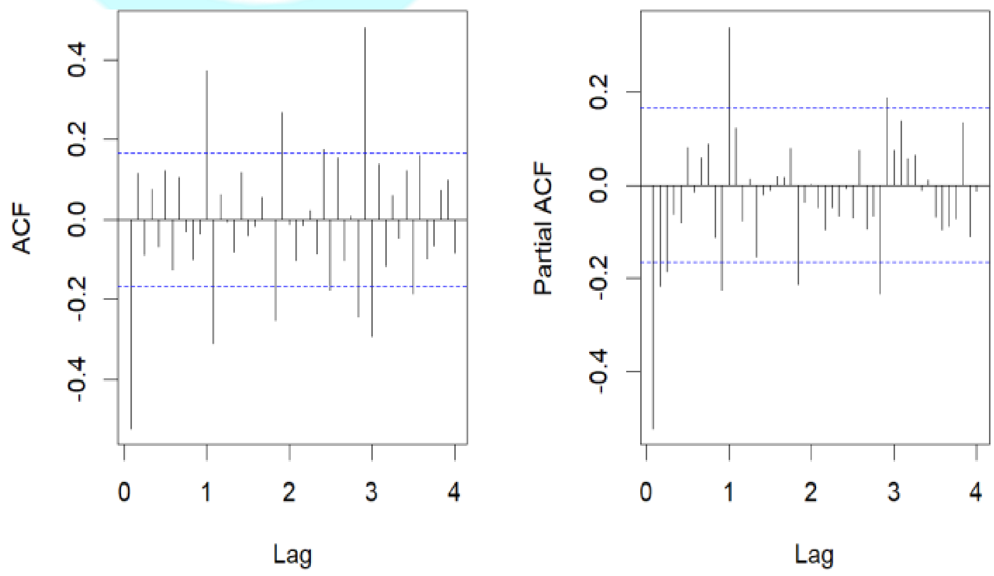
SARIMA modeling also begins by ensuring stationarity of the time series. Since the data set consists of monthly observations, the seasonal period was specified as $s = 12$, corresponding to an annual cycle. Variance stationarity was achieved using the Box–Cox transformation with $\lambda = -1$, while first-order non-seasonal differencing was applied to achieve stationarity in the mean. Because no evidence of seasonal non-stationarity was observed, seasonal differencing was unnecessary and the seasonal differencing order was set to $D = 0$. Consequently, the preprocessing procedure for the SARIMA model was essentially identical to that employed for the ARIMA model.

The SARIMA model orders were identified using the ACF and PACF plots together with the auto. Arima procedure. The non-seasonal orders $p$and q were determined from the overall lag structure in the ACF and PACF plots, whereas the seasonal orders $P$and Qwere identified from the seasonal lags (12, 24, 36, and so forth).

As illustrated in Figure 12, the PACF exhibits a cut-off at lag 3, indicating a non-seasonal autoregressive order of $p = 3$, whereas the ACF cuts off at lag 1, indicating a moving average order of $q = 1$. Since first-order non-seasonal differencing had already been applied, the corresponding non-seasonal candidate models were ARIMA (3,1,0) and ARIMA (0,1,1).



(A) (B)

Figure 12. (a) ACF plot and (b) PACF plot for SARIMA model identification.

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For the seasonal component with $s = 12$, the PACF cuts off at the first seasonal lag (lag 12), indicating a seasonal autoregressive order of $P = 1$. Meanwhile, the ACF cuts off at the third seasonal lag (lag 36), indicating a seasonal moving average order of $Q = 3$. Since seasonal differencing was unnecessary ($D = 0$), the seasonal candidate models were ARIMA$(1,0,0)_{12}$ and ARIMA$(0,0,3)_{12}$. Parameter estimates for the tentative SARIMA models are presented in Table 5.

Table 5. Parameter estimates of the tentative SARIMA models.

Model	Parameter	Coefficient	p-value	AIC
ARIMA(0,1,1)(0,0,1)12	MA(1)	0,5968	0,0000*	-2925,18
	SMA(1)	-0,3587	0,0000*	
ARIMA(0,1,1)(0,0,3)12	MA(1)	0,5652	0,0000*	-2925,07
	SMA(1)	-0,4160	0,0000*	
	SMA(2)	-0,0648	0,4871	
	SMA(3)	0,1429	0,1123	
ARIMA(3,1,0)(1,0,0)12	AR(1)	-0,6591	0,0000*	-2924,24
	AR(2)	-0,2649	0,0078*	
	AR(3)	-0,1322	0,1181	
	SAR(1)	0,3693	0,0000*	
ARIMA(3,1,1)(1,0,1)12	AR(1)	-0,4898	0,3666	-2921,44
	AR(2)	-0,1739	0,6249	
	AR(3)	-0,1179	0,3981	
	MA(1)	0,1725	0,7526	
	SAR(1)	0,1831	0,3463	
	SMA(1)	-0,2162	0,2515	
ARIMA(1,1,1)(0,0,1)12	AR(1)	-0,2172	0,0963	-2925,81
	MA(1)	0,4629	0,0000*	
	SMA(1)	-0,3650	0,0000*	
ARIMA(3,1,0)(0,0,1)12	AR(1)	-0,6691	0,0000*	-2924,42
	AR(2)	-0,3025	0,0020*	
	AR(3)	-0,1650	0,0483*	
	SMA(1)	-0,3688	0,0000*	

Significant at the 5% significance level.

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Following parameter estimation, two SARIMA models satisfied the model selection criteria: ARIMA (0,1,1)$(0,0,1)_{12}$ and ARIMA (3,1,0)$(0,0,1)_{12}$. These models were subsequently evaluated through diagnostic tests to assess residual normality, homoscedasticity, and independence. The results are summarized in Tables 6 and 7.

Table 6. Diagnostic Test Results for the ARIMA (0,1,1)$\mathbf{(0, 0, 1)_{12}}$ Model

Assumption	**Formal Test**	***p*-value**	**Result**
Normality	Kolmogorov–Smirnov Test	$< 2.2 \times 10^{-16}$	Violated
Homoscedasticity	ARCH-LM Test	Several lags < α	Violated
Residual Independence	Ljung–Box Test	0.266	Satisfied*

** Satisfied partially.*

According to Table 6, the Kolmogorov–Smirnov test indicates that the residuals are not normally distributed, as evidenced by the extremely small *p*-value. Likewise, the ARCH–LM test detected heteroscedasticity because several lags produced *p*-values below the 5% significance level. The Ljung–Box test indicates that residual independence was only partially satisfied, with significant autocorrelation observed between lags 35 and 109 before disappearing at subsequent lags.

Table 7. Diagnostic test results for ARIMA (3,1,0) $(0,0,1)_{12}$.

Assumption	**Formal Test**	**p-value**	**Result**
Normality	Kolmogorov–Smirnov Test	$< 2.2 \times 10^{-16}$	Violated
Homoscedasticity	ARCH-LM Test	All lags > α	Satisfied
Residual Independence	Ljung–Box Test	0.8827	Satisfied*

** Partially satisfied*

As shown in Table 7, the Kolmogorov–Smirnov test again indicates non-normal residuals. However, unlike the previous model, the ARCH–LM test confirms homoscedasticity, as all lag-specific *p*-values exceed the 5% significance level. The Ljung–Box test also indicates partial residual independence, with autocorrelation detected only between lags 35 and 102.

Among the seasonal models considered, ARIMA (3,1,0)$0,0,1)_{12}$ exhibited superior diagnostic performance compared with ARIMA (0,1,1) $(0,0,1)_{12}$, which violated both the

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homoscedasticity and residual independence assumptions. Nevertheless, when compared with the simpler non-seasonal ARIMA (0,1,1) model, both models still exhibited residual autocorrelation. This finding suggests that external factors not included in the current univariate framework may influence Indonesia's non-oil and gas export values. Because the scope of this study is limited to univariate time series modeling, exogenous variables were intentionally excluded. Therefore, considering both model parsimony and computational efficiency, the ARIMA (0,1,1) model was ultimately selected as the final forecasting model for Indonesia's non-oil and gas export values.

3.3. Model Validation

Model validation was conducted to evaluate the forecasting performance of the ARIMA (0,1,1) model in predicting Indonesia's non-oil export values. The evaluation was performed using both visual and analytical approaches. Visually, the forecasted values were compared with the observed values using time series plots. The closer the forecasted values were to the observed data pattern, the better the model's ability to capture the underlying dynamics of the series. Analytically, forecast performance was assessed using the Mean Absolute Percentage Error (MAPE), which measures the magnitude of forecasting errors. A lower MAPE value indicates higher forecasting accuracy.

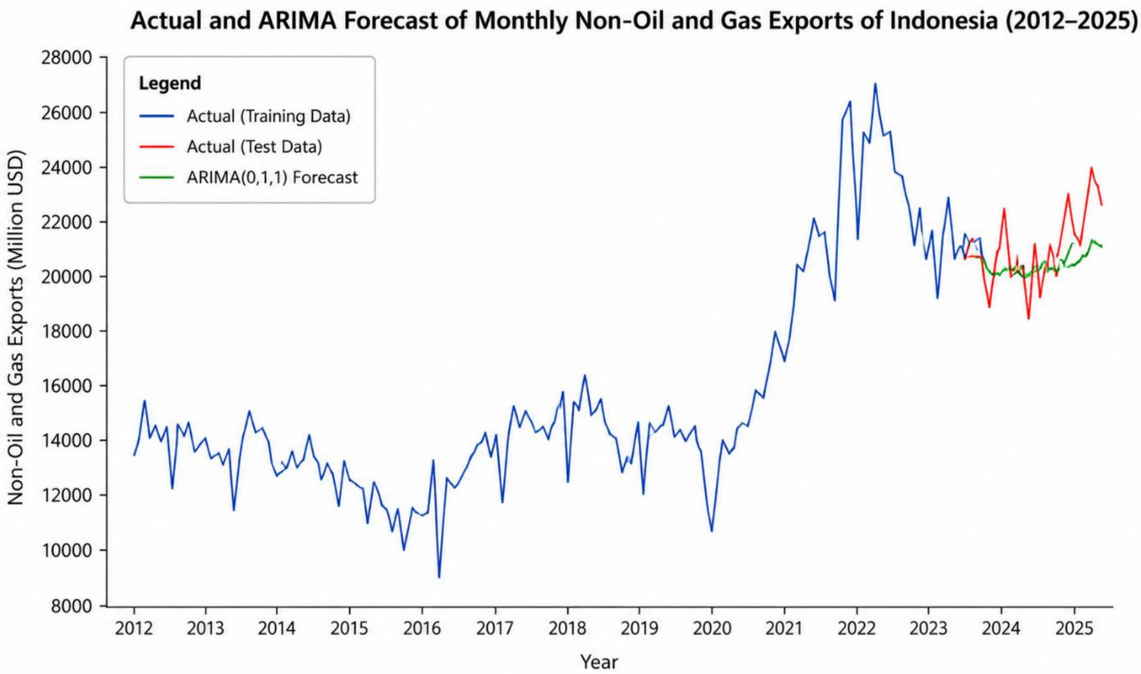

Figure 13. Actual and ARIMA forecast of monthly non-oil and Gas Export of Indonesia (2012-2015)

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Figure 13 presents the forecasting results of the ARIMA (0,1,1) model for the training data. The figure shows that the model closely follows the observed pattern of Indonesia's non-oil export values. The fluctuations in export values from January 2012 to August 2023 are generally well represented, although slight deviations are observed during periods of abrupt changes. Overall, the model successfully captures the underlying trend and historical movement of the data, indicating that it is suitable for forecasting purposes.

The analytical evaluation showed that the ARIMA (0,1,1) model achieved a MAPE of 7.0187% for the training data. According to the forecasting accuracy criteria proposed by Lewis (1982), a MAPE value below 10% indicates highly accurate forecasting. This result suggests that the ARIMA (0,1,1) model provides estimates that closely approximate the observed values during the training period.

The model was subsequently validated using 16 observations from the testing dataset, covering the period from September 2023 to December 2024, to evaluate its forecasting performance on unseen data. Validation was performed using a one-step-ahead forecasting approach, in which the model generated a forecast for one period ahead, after which the corresponding observed value was incorporated into the model before forecasting the next period. This approach was selected because it closely reflects real-world forecasting scenarios, where new observations become available sequentially over time. The comparison between the forecasted and observed values for the testing data is presented in Figure 13.

Figure 13 illustrates the forecasting performance of the ARIMA (0,1,1) model on the testing dataset. Visually, the forecasts continue to follow the overall pattern of the observed data, although the model does not fully capture several sudden fluctuations in export values. Nevertheless, the forecasts remain generally consistent with the actual observations, demonstrating that the model possesses good generalization capability when applied to out-of-sample data.

The evaluation of the testing data yielded a MAPE of 6.0948%, which is also below the 10% threshold for highly accurate forecasting. This finding indicates that the ARIMA (0,1,1) model maintains excellent forecasting performance when applied to new data. Moreover, the testing MAPE is comparable to the training MAPE (7.0187%), suggesting

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that the model does not exhibit overfitting and is able to preserve its predictive performance on previously unseen observations.

Overall, the evaluation results obtained from both the training and testing datasets demonstrate that the ARIMA (0,1,1) model provides consistent forecasting performance for Indonesia's non-oil export values. The MAPE values of 7.0187% for the training data and 6.0948% for the testing data indicate that the model achieves a high level of forecasting accuracy. Therefore, the ARIMA (0,1,1) model can be considered an appropriate and reliable model for short-term forecasting of Indonesia's non-oil export values.

Table 8. Mean Absolute Percentage Error (MAPE) of the ARIMA (0,1,1) Model

Dataset	MAPE (%)	Category
Training data	7.0187	Highly accurate
Testing data	6.0948	Highly accurate

4. Conclusion

This study successfully applied the ARIMA method to forecast Indonesia's monthly non-oil and gas export values. Based on the Box–Jenkins modeling procedure, ARIMA (0,1,1) was identified as the most appropriate model after satisfying the requirements of stationarity, parameter significance, and residual diagnostic tests.

The forecast performance evaluation showed that the ARIMA (0,1,1) model achieved a MAPE of 7.0187% for the training dataset and 6.0948% for the testing dataset. Both values are below 10%, indicating that the model provides highly accurate forecasts. Furthermore, the similarity between the training and testing errors suggests that the model is stable and does not exhibit substantial overfitting.

Overall, the ARIMA (0,1,1) model effectively captures the temporal pattern of Indonesia's non-oil and gas export values and provides reliable short-term forecasts. The forecasting results can support policymakers and stakeholders in planning export strategies, evaluating trade performance, and anticipating future fluctuations in export values. Future research may improve forecasting accuracy by incorporating external explanatory variables through ARIMAX or SARIMAX models, or by comparing ARIMA with more advanced machine learning and deep learning approaches.

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References

1. Box GEP, Jenkins GM, Reinsel GC, Ljung GM. 2016. *Time Series Analysis: Forecasting and Control*. 5th ed. Hoboken (US): John Wiley & Sons.

2. Box GEP, Cox DR. 1964. *An Analysis of Transformations*. Journal of the Royal Statistical Society: Series B (Methodological). 26(2):211–252.

3. Cryer JD, Chan KS. 2008. Time series analysis with applications in r. New York (USA): Springer Science+Business Media.

4. Chaerani D, Talytha MN, Perdana T, Rusyaman E, Gusriani N. 2020. Mapping Micro, Small, and Medium Enterprises (MSMEs) During the COVID-19 Pandemic Using Social Media Analysis to Enhance Income. *Dharmakarya: Journal of Science and Technology Applications for the Community*. (Pemetaan usaha mikro kecil menengah (UMKM) pada masa pandemi Covid-19 menggunakan analisis media sosial dalam upaya peningkatan pendapatan. Dharmakarya: Jurnal Aplikasi Ipteks untuk Masyarakat). 9(4):275–282. doi:10.24198/dharmakarya.v9i4.30941.

5. Desi D, Rizki SW, Yundari Y. 2022. Combined model time series regression ARIMA on stocks prices. Tensor: Pure and Applied Mathematics Journal. 3(2):65–72. doi: 10.30598/tensorvol3iss2pp65-72.

6. Fadhilah DN, Parmikanti K, Ruchjana BN. 2024. Forecasting Stock Returns in the Banking Subsector Using the ARIMA–GARCH Model. (Peramalan return saham subsektor perbankan menggunakan model ARIMA-GARCH). J Fourier. 13(1):1–19. doi:10.14421/fourier.2024.131.1-19.

7. Fadliani I, Purnamasari I, Wasono W. 2021. Forecasting Inflation Using the SARIMA Method and Identifying Outlier Types: A Case Study of Indonesia's Inflation Data from 2008 to 2014. *Journal of Statistics, Muhammadiyah University of Semarang* (Peramalan dengan metode SARIMA pada data inflasi dan identifikasi tipe outlier (studi kasus: data inflasi Indonesia tahun 2008-2014). J Stat Univ Muhammadiyah Semarang). 9(2):109–116. doi:10.26714/jsunimus.9.2.2021.109-116.

 DOI: ***10.5281/zenodo.22093010***

8. Faulina, Fitri F, Amalita N, Salma A. 2024. Vector error correction model to analyze the impact of exchange rates and money supply on inflation in Indonesia. UNP Journal of Statistics and Data Science. 2(3):295–303. doi:10.24036/ujsds/vol2-iss3/188.

9. Gading MM, Steven S, Maulana A. 2022. Analysis of Bank Indonesia's Monetary Policy in Responding to the COVID-19 Pandemic. (Analisis kebijakan moneter Bank Indonesia dalam menangani pandemi Covid-19). Accounting Student Research Journal. 1(1):102–116. doi:10.62108/asrj.v1i1.4839.

10. Hidayat R, Mustawinar BH. 2022. Forecasting the Number of International Tourists Using the ARIMA Model. *Infinity: Journal of Mathematics and Its Applications*. (Peramalan jumlah wisatawan asing dengan model ARIMA. Infinity: Jurnal Matematika dan Aplikasinya). 2(2):104–115. doi:10.30605/27458326-100.

11. Hyndman RJ, Athanasopoulos G. 2021. *Forecasting: Principles and Practice*. 3rd ed. Melbourne (AU): OTexts.

12. Imannulloh ER, Rijal NK. 2022. Indonesia's Efforts to Promote the Prioritization of Developing Countries' Economies through the G20: A Hyper-Globalist Perspective. *Indonesian Perspective*. (Upaya Indonesia dalam mendorong prioritisasi perekonomian negara berkembang melalui G20: Perspektif hyper-globalist. Indonesian Perspective). 7(1):79–101. doi:10.14710/ip.v7i1.48596.

13. Jabnabillah F, Munir Z, Permatasari RD, Anggraeni AS, Safitriyana S. 2024. Forecasting Exports of Three Major Fishery Commodities Using the ARIMA Time Series Method**.** *Lebesgue Journal*. (Peramalan ekspor tiga komoditas utama sektor perikanan menggunakan metode time series: ARIMA. Jurnal Lebesgue). 5(2):681–696. doi:10.46306/lb.v5i2.593.

14. Krugman PR, Obstfeld M, Melitz MJ. 2018. *International Economics: Theory and Policy*. 11th ed. Pearson.

15. Kurniawati DL, Islami FS. 2022. Analysis of the Effects of Foreign Direct Investment (FDI), Domestic Investment (DI), and Oil and Gas and Non-Oil and Gas Exports on Indonesia's Economic Growth. (Analisis pengaruh PMA, PMDN

 DOI: ***10.5281/zenodo.22093010***

dan ekspor migas-nonmigas terhadap pertumbuhan ekonomi Indonesia). Transekonomika. 2(1):13–28. doi:10.55047/transekonomika.v2i1.98.

16. Montgomery DC, Jennings CL, Kulahci M. 2015. Introduction to time series analysis and forecasting. Ed ke-2. New Hoboken (NJ): John Wiley & Sons.

17. Munarsih E, Saluza I. 2020. Comparison of exponential smoothing method and autoregressive integrated moving average (ARIMA) method in predicting dengue fever cases in the city of Palembang. J Phys: conference series. 1521(3):1–7. doi:10.1088/1742-6596/1521/3/032100.

18. Muhammad FS, Ruliana R, Sitti SMM. 2023. Comparison of the ARIMA and Single Exponential Smoothing Methods for Forecasting Indonesia's Cocoa Export Value. *VARIANSI: Journal of Statistics and Its Applications in Teaching and Research*. (Perbandingan metode ARIMA dan single exponential smoothing dalam peramalan nilai ekspor kakao Indonesia. VARIANSI: Journal of Statistics and Its application on Teaching and Research). 5(3):163–176. doi:10.35580/variansiunm193

19. Nurhidayati, Rohaeti E, Sumarsa A. 2024. Comparison of the Asymmetric Power ARCH and Threshold GARCH Models for Forecasting the Pound Sterling Exchange Rate Against the Indonesian Rupiah. *MATHunesa: Journal of Mathematics.*(Perbandingan model asymmetric power arch dengan threshold GARCH dalam peramalan kurs poundsterling terhadap kurs rupiah. MATHunesa: Jurnal Ilmiah Matematika). 12(1):11–20. doi: 10.26740/mathunesa.v12n1.p11-20.

20. Prayoga ER, Ryansyah M, Jannah N. 2022. The Impact of COVID-19 on Economic Growth in Indonesia's Export and Import Sectors. *El-Mal: Journal of Islamic Economics and Business Studies.* (Dampak Covid-19 terhadap pertumbuhan ekonomi pada sektor ekspor dan impor Indonesia. El-Mal: Jurnal Kajian Ekonomi & Bisnis Islam). 3(3):457–465. doi: 10.47467/elmal.v3i3.924.

21. Rahmawati E, Apriliasari V. 2021. Government-Borne Final Income Tax Incentives During the COVID-19 Pandemic for Micro, Small, and Medium Enterprises (MSMEs) with Specified Gross Annual Turnover**.** *Journal of State Finance and*

 DOI: ***10.5281/zenodo.22093010***

Taxation. (Insentif pph final ditanggung pemerintah selama pandemi Covid-19 bagi UMKM yang memiliki peredaran bruto tertentu. Jurnal Pajak dan Keuangan Negara (PKN)). 3(1):81–97. doi: 10.31092/jpkn.v3i1.1273.

22. Wei. 2006. *Time Series Analysis: Univariate and Multivariate Methods*. 2nd ed. Boston: Pearson Addison Wesley

 DOI: ***10.5281/zenodo.22093010***