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COMPARATIVE PERFORMANCE OF ARIMA, SARIMA AND GARCH MODELS IN MODELLING AND FORECASTING UNEMPLOYMENT AMONG ASEAN-5 COUNTRIES

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ABSTRACT

Unemployment, especially after the COVID-19 pandemic, is a critical issue for any country as it has economic and social ramifications. Consequently, forecasting unemployment becomes an essential task as it can guide government policy. Time series data are frequently influenced by outliers (unexpected events), and some outliers may exist with extreme observation to reduce the forecasting effectiveness of robust estimators. This study compared the performance of Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA) and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models in modelling and forecasting unemployment rates during the COVID-19 pandemic among the ASEAN-5 countries. These countries include Malaysia, Singapore, Thailand, the Philippines and Indonesia. The monthly unemployment data from January 2010 to December 2021 were applied for all cases, except Thailand, until December 2020. Each adequate model from both forecasting mechanisms underwent forecasting. Their performance was compared based on root mean squared error (RMSE), mean absolute error (MAE), Theil inequality coefficient and symmetric mean absolute percentage error (SMAPE). Static forecasting from the ARIMA and SARIMA models was found to perform better than the GARCH model in modelling and forecasting the unemployment rate among ASEAN-5 countries during the pandemic period.

Keywords: Unemployment, Forecasting, A/SARIMA and GARCH

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1. INTRODUCTION

Labour is one of the most important resources besides land and capital. As an essential quasi-input in production, labour issues, especially unemployment, will always be a focal point in the macroeconomy. People need work to survive, while work requires people to operate. Both depend on each other to achieve their objective. When people lose a job, they also lose their source of income. Many economic and social impacts arise from unemployment, such as poverty, reduced economic productivity, divorce and even suicides. In general, unemployment follows business cycle trends. When the business cycle goes downward, unemployment tends to increase. This situation results from the negative economic growth affecting business operations, thus reducing labour demand. Firms typically implement retrenchment as a survival technique during an economic crisis. In contrast, job opportunities are enhanced and associated with economic expansion. People attain jobs more easily, and this lessens unemployment. Consequently, a negative shock on the business cycle has a significantly positive impact on the job loss situation. The world has recently undergone a public health crisis, namely the Coronavirus disease (COVID-19) pandemic. The COVID-19 pandemic is not only a shock to the health system but also to the economy. During the COVID-19 pandemic, most governments implemented lockdown policies to reduce the transmission of the virus. For instance, Malaysia and Singapore started their lockdown policies on 18th March 2020 and 7th April 2020, respectively. Meanwhile, the lockdown policy implemented in Thailand and the Philippines started on 3rd April and 15th March, respectively. On 7th April 2020, Indonesia declared a regional lockdown policy in Jakarta. Consequently, the lockdown, which restricted the operation of economic activities, jeopardised the economy.

Table 1: The Lockdown and Reopening of the Border among ASEAN-5 Countries

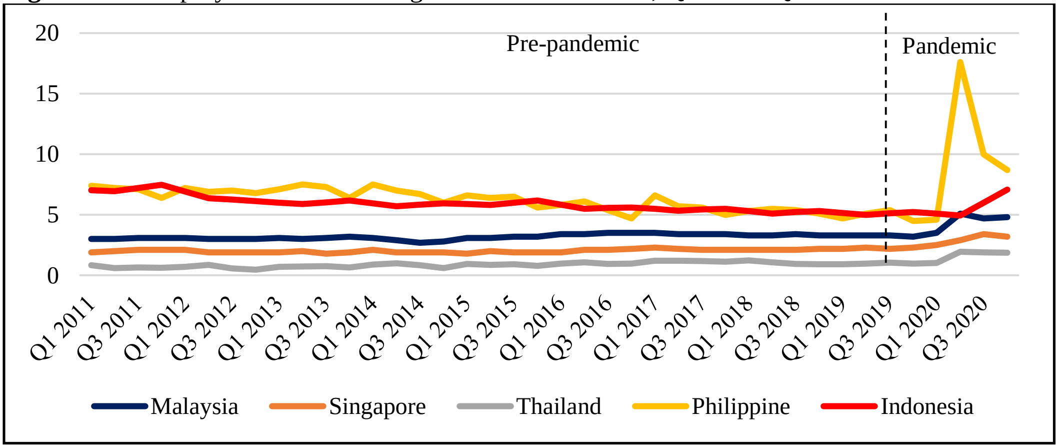
Country	Start lockdown	Days	Start reopening border
Malaysia	18th March 2020	2 years and 13 days	1st April 2022
Singapore	7th April 2020	1 year and 359 days	1st April 2022
Thailand	3rd April 2020	2 years and 28 days	1st May 2022
Philippines	15th March 2020	2 years and 17 days	1st April 2022
Indonesia (Jakarta)	7th April 2020	1 year and 281 days	12th January 2022

Sources: Sullivan (2022), Metro Manila to be placed (2020), Consulate General of the Republic of Indonesia (2021), Dechsupa et al. (2020), Tong (2022), Ministry of Foreign Affairs Malaysia (2022), 14-day movement control order (2020), Thailand drops post-arrival (2022), Singapore to see most workplaces (2020), Jakarta to impose partial lockdown (2020)

During the pandemic, ASEAN-5 countries faced a significant increase in unemployment. In Malaysia, the unemployment rate was beyond 4%, which was the total employment rate for the country. Besides, the unemployment rate of Singapore also increased and exceeded more than 3%. Meanwhile, it was over 1% and closer to a 2% unemployment rate in Thailand. Interestingly, unemployment in Malaysia, Singapore and Thailand was stable and under control during the pre-pandemic period. Nevertheless, it lost control and increased beyond the full employment line during the pandemic. The Philippines and Indonesia had an unemployment rate of more than 4%. Figure 1 reveals an unstable situation, which was an upward and downward trend, especially in the Philippines. During the pandemic, unemployment in the Philippines surged to 17.6% in the second quarter of 2020. It remained constant by more than 8%. Indonesia's unemployment rate demonstrated an upward trend beyond the 6% line after the second quarter of 2020.

From the previous discussion, the unemployment rate in ASEAN-5 countries was no longer at full employment nor stable due to the COVID-19 pandemic. The pandemic exacerbated unemployment as employers were forced to reduce the labour demand to sustain their businesses. Accordingly, job loss rose, leading to an imbalance between labour demand and supply. People lost faith in their government as it failed to solve unemployment, and the people's burden increased. Consequently, political stability is affected as people are unsatisfied with their government's performance (Dabros et al., 2015; Martin et al., 2022). A full employment rate is one of the targets for unemployment, enabling governments to convince their people regarding the credibility of their policies. Therefore, forecasting unemployment becomes a vital tool to ensure future policies concerning the disturbance of the labour market. When unemployment is forecasted to be high, the government needs to plan and implement appropriate policies to mitigate it.

Figure 1: Unemployment Rate Among ASEAN-5 Countries, Q1 2011–Q4 2020



Sources: Bank Indonesia (2022), Bank Negara Malaysia (2022), Bank of Thailand (2022), Ministry of Manpower Singapore (2022), Philippines Stastitics Authority (2022)

Regarding forecasting, the Box-Jenkins methods are always used, including Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA). Box-Jenkins involves stringent assumptions about residuals to determine the most desirable model (Mahipan et al., 2013). The ARIMA model is the most common model used for forecasting purposes. For instance, Malaysia (Ramli et al., 2018), Singapore (Lai et al., 2021), Thailand (Mahipan et al., 2013), the Philippines (Angco et al., 2021) and Indonesia (Mahmudah, 2017). The ARIMA model is conducive to forecasting because it is flexible for time series data in linear or non-linear forms (Mahipan et al., 2013). Moreover, it can handle many time series for forecasting, and the multivariate models' problem can be avoided via this model (Meyler et al., 1998). The model can be conveniently applied and manipulated, especially for a new forecaster. Conversely, SARIMA lacks the capability to estimate unemployment during the COVID-19 pandemic. During the pandemic, the unemployment rate exhibited a seasonal trend, which went upward and downward as it was impacted by the lockdown and confirmed cases. SARIMA is a modified version of the ARIMA model, with the additional set components of autoregressive average and moving average. This condition indicates the frequency of seasonality that can offset the additional lags for the model (Dritsaki, 2016; Davidescu et al., 2021). Besides the ARIMA and SARIMA models, another model is also popular in forecasting: the GARCH model. The GARCH model provides insights into the persistence and clustering of volatility, capturing important patterns in the data (Khan et al., 2023). It can improve the forecasting for the times series data with significant volatility and allow for more accurate risk assessments (Verma, 2021). Unemployment demonstrates a volatility clustering with an upward and downward trend (Katris, 2020). As a result, it suits the GARCH model for forecasting.

Additionally, Nkoane and Seeletse (2021) stated that robust estimators, such as ARIMA, can easily handle time series data affected by outliers, especially during the recent COVID-19 pandemic. Ab Aziz et al. (2023) also mentioned that outliers with extreme observation may influence the forecasting performance of the estimators. Therefore, this study responds to the call from Azimi and Shahidzada (2019), who claimed that a comparative analysis of the empirical findings regarding variance forecast and optimal estimation of time series variables with volatility using ARIMA and GARCH models remains largely unexplored. This study aims to compare the performance of ARIMA, SARIMA and GARCH models in modelling and forecasting unemployment rates during the COVID-19 pandemic among the ASEAN-5 countries. This paper is structured as follows: Section 2 touches on the empirical literature that used the ARIMA, SARIMA and GARCH models to forecast unemployment. Section 3 discusses the methodology adopted, while Section 4 presents the result of all models estimated by comparing the performance for the forecasting between these forecasting mechanisms. Lastly, the conclusion is discussed in Section 5.

2. LITERATURE REVIEW

Scholars usually adopt the ARIMA model or Box-Jenkins method in forecasting certain variables. As unemployment is an important variable in the economy, it is used for forecasting the period before and during the COVID-19 pandemic. Prior to the COVID-19 pandemic, yearly unemployment was applied for forecasting (Ayik & Erkal, 2021; Mahmudah, 2017; Nguyen et al., 2021). Mahmudah (2017) used the yearly unemployment data in Indonesia by utilising the ARIMA model. He found that ARIMA (0, 2, 1) was the most suitable model in the case of Indonesia. Meanwhile, Ayik and Erkal (2021) and Nguyen et al. (2021) denoted that ARIMA (2,1,1) and ARIMA (1,0,1) were the most adequate ARIMA models for Turkey and Vietnam, respectively. Moreover, it was determined that ARIMA (2,1,0) was suitable for forecasting the quarterly unemployment in the Philippines by utilising the quarterly data from 2005 to 2019 (Angco et al., 2021). Davidescu et al. (2021) also conducted this quarterly forecasting method in Romania by applying data from the first quarter of 2000 to the fourth quarter of 2018. Besides yearly and quarterly data, unemployment was also forecasted monthly. Lip et al. (2021) manipulated the monthly data from January 2012 until December 2018 to forecast unemployment in Malaysia. They discovered that ARIMA (2,1,3) suited the model and stated that the forecasted unemployment portrayed low fluctuation from January 2019 until December 2019. Their model conflicted with Ramli et al.’s (2018) case, which stated that ARIMA (2,1,2) was the most suitable model in Malaysia. Nonetheless, Ramli et al. (2018) used the yearly unemployment data for Malaysia’s case.

During the COVID-19 pandemic, the popularity of ARIMA in forecasting was still high. Ismail et al. (2022) applied the monthly unemployment from January 2010 until July 2021 to forecast this variable from January 2021 to July 2021, the COVID-19 pandemic period. From the ARIMA result, they found that ARIMA (2,1,2) was the most appropriate model after filtering by the Akaike information criterion (AIC) and Schwarz criterion (SC). This result differed from Lip et al.'s (2021) study, although the same form of time series data was adopted. Lai et al. (2021) predicted five advanced and five developing countries in Asia regarding unemployment, whereby Malaysia, Singapore and Indonesia were included in their study. Interestingly, their results revealed that ARIMA (2,1,2) was suited for Singapore, ARIMA (3,1,2) was suited for Malaysia, and Indonesia was suited to ARIMA (3,1,2). Meanwhile, Tufaner and Sözen (2021) argued that ARIMA (3, 1, 2) was the best unemployment model in Turkey between January 2014 and November 2020. The quarterly unemployment data from 2010 to 2020 fitted the ARIMA (1,1,1) model in South Africa (Nkoane & Seeletse, 2021).

Apart from the ARIMA, the modified version of the ARIMA model, namely SARIMA, was also applied in previous studies. Generally, the SARIMA model best fits data with seasonal trends. Dritsaki (2016) emphasised that SARIMA $(0,2,1)(1,2,1)_{12}$ best fitted the unemployment model from April 1998 until September 2015 in Greece. She noticed that static forecasting had better performance and ability than dynamic forecasting, according to the root mean squared error (RMSE), mean absolute error (MAE) and Theil index. The SARIMA model was also adopted by Dritsakis and Klazoglou (2018) to predict unemployment in the United States. By employing the unemployment data from January 1955 to July 2017, they emphasised that SARIMA $(1,1,2)(1,1,1)_{12}$ – GARCH (1,1) was the best model. In other European countries, Sójka (2017) and Stoklasova (2012) studied the forecasting of unemployment by adopting monthly unemployment. Stoklasova (2012) found that SARIMA $(1,1,0)(1,1,0)_{12}$ was well suited to estimating the forecasted unemployment in the Czech Republic. For the case of ASEAN-5 countries, SARIMA was also conducted in the Philippines and Thailand. Urrutia et al. (2017) finalised that SARIMA $(6,1,5)(0,1,1)_{4}$ was best for the Philippines, where a range of data between the first quarter of 1988 and the fourth quarter of 2014 was used. Meanwhile, SARIMA $(1,1,0)_{12}$ was proven by Mahipan et al. (2013) as an adequate model for forecasting unemployment in Thailand.

During the COVID-19 pandemic, the SARIMA model's capacity to forecast unemployment continued in some countries. Most studies concentrated on the progress of unemployment during the COVID-19 pandemic. Cuestas et al. (2021), Waffa and Wahiba (2022) and Davidescu et al. (2021) mentioned that SARIMA $(1,1,1)(1,1,1)_{4}$, SARIMA $(5,1,3)(1,0,0)_{12}$ and SARIMA $(0,1,6)(1,0,1)_{12}$ were the ideal SARIMA models in forecasting unemployment in Spain, Algeria and Romania, respectively. Besides, Cuestas et al. (2021) denoted that the impact of COVID-19 on the forecasted unemployment was long-lasting and persistent, enhancing unemployment at a higher rate in Spain. Waffa and Wahiba (2022) also found a steady and substantial growth of the forecasted unemployment rate in Algeria between January 2021 and December 2021.

Another forecasting tool is the GARCH model. The GARCH model is normally used for a model with high volatility. It is used to forecast economic indicators, such as gross domestic product (GDP) growth (Dritsaki & Dritsaki, 2021), inflation (Uwilingiyimana et al., 2016) and exchange rate (Zhou et al., 2020). Importantly, it also includes unemployment (Azimi & Shahidzada, 2019). Habibullah et al. (2022) forecasted the loss of employment in Malaysia using the GARCH family models, namely GARCH-M, EGARCH-M and PGARCH-M models. Most of the studies utilised the combination of the ARIMA and GARCH models or a comparison between ARIMA and GARCH in forecasting unemployment. Katris (2020) employed the FARIMA models with GARCH to predict the monthly unemployment rate from M1 2000 to M12 2014 among 22 Mediterranean countries. Muğaloğlu & Kiliç (2021) claimed that the SARIMA-GARCH model offered a better unemployment prediction between 1995 and 2019 among G-7 countries. Meanwhile, several studies compared the forecasting machines between ARIMA and GARCH. Azimi and Shahidzada (2019) explained that the GARCH model forecasted better than ARIMA, as GARCH demonstrated a lower standard error and provided closer values with the actual data. Miswan et al. (2014) and Ab Aziz et al. (2023) also emphasised that the GARCH model had a better performance in forecasting than the ARIMA model. Nonetheless, it has been shown that the ARIMA model is better than GARCH in forecasting according to performance (Haque & Shaik, 2021; Nuryatin, 2020).

Consequently, this study used the ARIMA, SARIMA and GARCH models to forecast unemployment during the COVID-19 pandemic among ASEAN-5 countries, i.e., Malaysia, Singapore, Thailand, the Philippines and Indonesia. The forecasting performance between both forecasting mechanisms was compared to identify the adequate mechanism in terms of forecast unemployment among ASEAN-5 countries.

3. RESEARCH METHODOLOGY

3.1. ARIMA model

In the ARIMA model, AR indicates autoregressive, I is integrated, and MA is the moving average (Box & Jenkins, 1976). In the AR(p) and MA(q) models, p and q in the bracket represent the number of the models' lagged dependent variables. The AR(p) model has the following equation:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + ... + \emptyset_p Y_{t-p} + u_t \tag{1}$$

Meanwhile, the MA(q) model has the following equation:

$$Yt = u_t + \theta_1 u_{t-1} + \emptyset_2 u_{t-2} + \ldots + \emptyset_q u_{t-1-q} \tag{2}$$

After that, the ARMA (p,q) model is generated from the combination of the two processes shown below:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + ... + \emptyset_p Y_{t-p} + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \ldots + \theta_q u_{t-1-q} \tag{3}$$

Where:

Y_t = Unemployment
u = Error or residuals
$\emptyset$ = Polynomial function of unemployment
θ = Polynomial function of error

3.2. SARIMA model

$$\Delta_S^d y_t = (1 - L^S)^{\mathrm{D}} y_t \tag{4}$$

Where:

Δ_S^d = Δ order difference
L^S = The lag operator, which demonstrated periodic seasonal behaviour.

Afterwards, the seasonal ARMA (p,q) model for every s is rewritten into:

$$\emptyset(L^S) y_t = \theta(L^S) u_t \tag{5}$$

Where:

u_t = White noise
θ = Seasonal lag parameter, u_{t-12}

Following the ARMA (p,q) model, Equation (5) is considered in the form of Equation (6).

$$\mathrm{A(L)} u_t = \Theta(L) \varepsilon_t \tag{6}$$

Where:

A(L) = Polynomial for p;
$\Theta(L)\varepsilon_t$ = Polynomial for q.

The seasonal ARMA model $(p,q)(p,q)_s$ formed as a result of the replacement of Equation (7) substitutes Equation (6).

$$\mathrm{A(L)}\emptyset(L^S) y_t = \theta(L)\Theta(L)\varepsilon_t \tag{7}$$

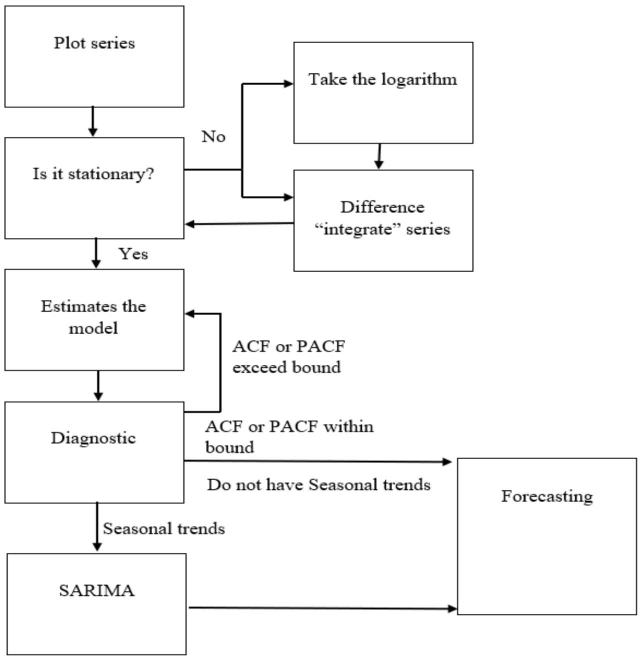
Lastly, Equation (8) will be modified to suit ARIMA $(p,d,q)(P,D,Q)_s$, in which the p,d,q in front stand for ARIMA while the P,D,Q at the back represent the additional seasonal components.

$$\mathrm{A(L)}\emptyset(L^S)(1 - L)^d (1 - L^S)^D y_t = \theta(L)\Theta(L)\varepsilon_t \tag{8}$$

3.3. Box-Jenkins Procedure

The Box-Jenkins procedure is divided into three stages: identification, estimation and diagnostics. In the identification process, the first step is to check the stationary of the model. The stationary test of this paper was done through the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests to identify whether the model has either a “unit root” problem or no “unit root” problem. Otherwise, spurious regression may exist in the model. If the P-value from the test is less than 5%, the “unit root” problem does not exist in the model, the null hypothesis is rejected and the model is stationary over time. If the P-value exceeds 5%, this indicates the existence of the “unit root” problem in the model. The null hypothesis failure is rejected, and the model is not stationary over time. Therefore, the first differences should be taken to the model, and then the unit root test is repeated to determine its stationarity.

Figure 2: Box-Jenkins Procedure



Source: Author's construct

After the model is stationary, the process proceeds to determine the p and q orders of the ARIMA model through the correlogram. Significant spikes from the ACF for AR or PACF for MA are detected. After the number of lags for the combination of the ARMA (p,q) model is determined, several models are estimated to determine the most adequate model. The Akaike information criterion (AIC), Schwarz Bayesian criterion (SC) and Hannan-Quinn criterion (HQ) are used to compare the estimated result. The best model is selected according to the requirement, with the smallest AIC, SC and HQ. Then, the model undergoes diagnostic checking again to ensure that all the spikes are within the bounds of the stationarity for the AR and MA coefficients. If the model exists with seasonal trends or characteristics, the model proceeds with SARIMA. The procedure is similar to the Box-Jenkins process by adding the seasonal P and Q lags (s = 12, s=24). Nevertheless, if the seasonal component for the model is not significant, the adequate model adopts the ARIMA model only, which is the non-seasonal model.

3.4. Generalised Auto-Regressive Conditional Heteroscedasticity (GARCH)

The GARCH model is renowned for addressing heteroscedasticity, where the variance is not constant over time. This model has gained popularity in the forecasting field. These domains often exhibit data with significant variability and high volatility throughout different periods. The GARCH model will be transformed for p = 0 for the model to be reduced to ARCH (q). The value of the variance scaling parameter, h_t, now depends on its past values and the shocks' past values. Lagged squared residual terms capture the past values of the shocks, whereas lagged h_t terms capture the past values of the model. As a result, the GARCH model is written as GARCH (p,q) and can be indicated as the equation below:

$$h_t = \gamma_0 + \delta_1 h_{t-i} + \gamma_1 u_{t-i}^2 \tag{9}$$

3.5. Forecasting

After the three stages of the Box-Jenkins procedure, the adequate model for ARIMA or SARIMA is identified. Meanwhile, the appropriate model of GARCH is recognised. Next, the models from both methods are utilised and compared for forecasting. Dynamic and static forecasting are generated, and their performance is compared by evaluating the criteria. These criteria are based on the mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE) and Theil inequality index.

$$\text{MSE} = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{Y}t - Yt\right)^2 \tag{10}$$

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{Y}t - Yt)^2} \tag{11}$$

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\hat{Y}t - Yt}{Yt}\right| \tag{12}$$

$$\text{Theil inequality index, U} = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{Y}t - Yt)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{Y}t)^2 + \frac{1}{T}\sum_{t=1}^{T}(Yt)^2}} \tag{13}$$

Where:

$\hat{Y}t$ = Actual output

Yt = Observed output

T = Number of time-varying observation

4. RESULTS AND DISCUSSION

4.1. Data

The monthly data on the unemployment rate is adopted and applied in this study. As the targeted countries were Malaysia, Singapore, Thailand, the Philippines and Indonesia, the unemployment data from the five countries were required. The unemployment data from January 2011 to December 2021 were obtained for Malaysia, Singapore, the Philippines and Indonesia. The sources were Bank Negara Malaysia (BNM), the Ministry of Manpower of Singapore, the Philippines Statistics Authority (PSA) and Bank Indonesia. Meanwhile, for Thailand's case, the monthly unemployment data from January 2011 to December 2020 were applied because the authority had not generated the data for 2021. The data were gained from the Bank of Thailand (BOT).

4.2. ARIMA or SARIMA Model

4.2.1. Identification

According to the Box-Jenkins procedure, the identification stage first underwent the unit root test to determine whether the variable was clear from the "unit root" problem or stationary. The Augmented Dickey-Fuller test was conducted for this objective. This result was supported by using the Phillips-Perron test.

Table 2: Results of the Augmented Dickey-Fuller Test

Variable	Level		First Difference	
	Intercept	Trend and intercept	Intercept	Trend and intercept
Unemployment of Malaysia (UEM)	-1.6781	-3.0885	-12.3207***	-12.2663***
Unemployment of Singapore (UES)	-2.3162	-3.1293	-4.2098***	-4.2028***
Unemployment of Thailand (UET)	-1.8548	-5.0755***	-10.3252***	-10.3194***
Unemployment of the Philippines (UEP)	-4.2182***	-4.2515***	-8.5286***	-8.4994***
Unemployment of Indonesia (UEI)	-3.1937**	-2.7916	-2.8601*	-3.2341*

Notes: (***), (**) and (*) denote the significance level at 1%, 5% and 10%, respectively.

Table 3: Results of the Phillips-Perron Test

Variable	Level		First Difference	
	Intercept	Trend and intercept	Intercept	Trend and intercept
Unemployment of Malaysia (UEM)	-1.5692	-3.1008	-12.7999***	-12.7626***
Unemployment of Singapore (UES)	-1.7068	-2.1809	-4.3003***	-4.2948***
Unemployment of Thailand (UET)	-2.8041*	-5.2866***	-14.6827***	-14.7937***

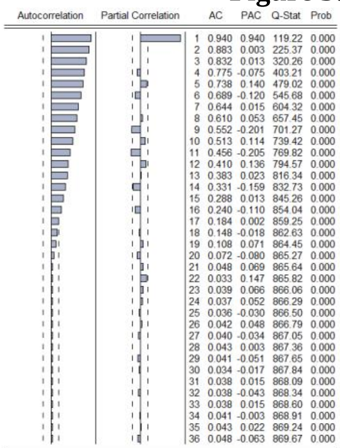
Unemployment of the Philippines (UEP)	-2.9164**	-2.9319	-8.6643***	-8.6143***
Unemployment of Indonesia (UEI)	-2.0756	-1.6347	-4.6573***	-4.7019***

Notes: (***), (**) and (*) denote the significance level at 1%, 5% and 10%, respectively.

From Table 2, the Augmented Dickey-Fuller result demonstrated that the unemployment data in the level form existed with a “unit root” problem for Malaysia and Singapore either in the intercept or trend and intercept form. Meanwhile, a “unit root” problem occurred when unemployment was in the intercept form in Thailand and the trend and intercept form in Indonesia. Nonetheless, the result revealed that no “unit root” problem existed in the level of unemployment in the Philippines case. When unemployment was the first difference, all the unemployment data among the ASEAN-5 countries were stationary in both forms. The result from the Phillips-Perron test was also in line with the result of the Augmented Dickey-Fuller test, except for Indonesia’s case. The Phillips-Perron test stated that the level of unemployment data was not stationary for intercept and trend and intercept forms. Therefore, it was suggested that the unemployment data of Indonesia should be the first difference. Nevertheless, this stationary result was verified again by using the Correlogram.

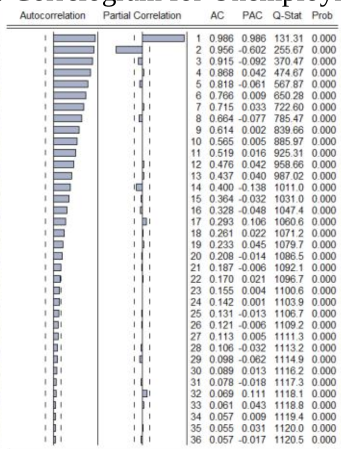
The procedure was continued with the correlogram. Figure 3 demonstrates the correlogram of the unemployment rate level, while Figure 4 reveals the correlogram of the first difference in the unemployment rate. From Figure 2, the autocorrelation (ACF) for Malaysia, Singapore, Thailand, the Philippines and Indonesia cases was observed that they did not diminish or experience a slow downturn. The result indicated that the series for those cases were non-stationary. It demonstrated that the model was non-stationary. Consequently, the first difference was replaced with the level form of the data to prevent spurious regression in the models of Malaysia, Singapore, Thailand, the Philippines and Indonesia cases. When taking the first difference, it was observed that the autocorrelation exhibited a quick fall, indicating that the data were stationary for each case. Therefore, the ARIMA (p, d, q) value was d = 1 for the Malaysia, Singapore, Thailand, the Philippines and Indonesia cases.

Figure 3: Correlogram for Unemployment Levels



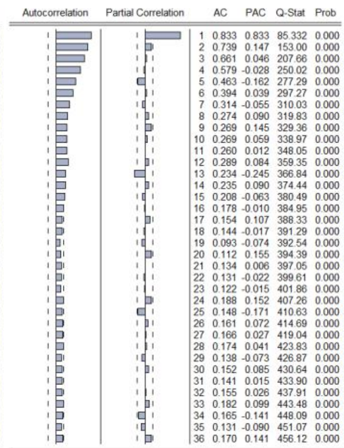
	AC	PAC	Q-Stat	Prob
1	0.940	0.940	119.22	0.000
2	0.883	0.003	225.37	0.000
3	0.832	0.013	320.26	0.000
4	0.775	-0.075	403.21	0.000
5	0.738	0.140	479.02	0.000
6	0.689	-0.120	545.68	0.000
7	0.644	0.015	604.32	0.000
8	0.610	0.053	657.45	0.000
9	0.552	-0.201	701.27	0.000
10	0.513	0.114	739.42	0.000
11	0.456	-0.205	769.82	0.000
12	0.410	0.136	794.57	0.000
13	0.383	0.023	816.34	0.000
14	0.331	-0.159	832.73	0.000
15	0.288	0.013	845.26	0.000
16	0.240	-0.110	854.04	0.000
17	0.184	0.002	859.25	0.000
18	0.148	-0.018	862.63	0.000
19	0.108	0.071	864.45	0.000
20	0.072	-0.080	865.27	0.000
21	0.048	0.069	865.64	0.000
22	0.033	0.147	865.82	0.000
23	0.039	0.066	866.06	0.000
24	0.037	0.052	866.29	0.000
25	0.036	-0.030	866.50	0.000
26	0.042	0.048	866.79	0.000
27	0.040	-0.034	867.05	0.000
28	0.043	0.003	867.36	0.000
29	0.041	-0.051	867.65	0.000
30	0.034	-0.017	867.84	0.000
31	0.038	0.015	868.09	0.000
32	0.038	-0.043	868.34	0.000
33	0.038	0.015	868.60	0.000
34	0.041	-0.003	868.91	0.000
35	0.043	0.022	869.24	0.000
36	0.048	-0.063	869.67	0.000

Malaysia



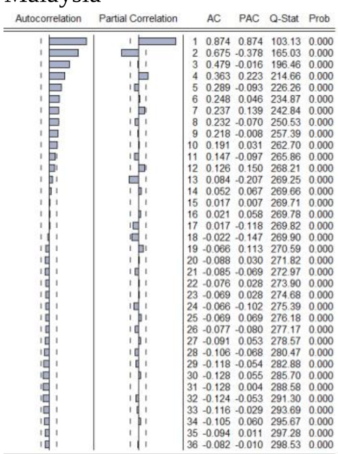
	AC	PAC	Q-Stat	Prob
1	0.986	0.986	131.31	0.000
2	0.956	-0.602	255.67	0.000
3	0.915	-0.092	370.47	0.000
4	0.868	0.042	474.67	0.000
5	0.818	-0.061	567.87	0.000
6	0.766	0.009	650.28	0.000
7	0.715	0.033	722.60	0.000
8	0.664	-0.077	785.47	0.000
9	0.614	0.002	839.66	0.000
10	0.565	0.005	885.97	0.000
11	0.519	0.016	925.31	0.000
12	0.476	0.042	958.66	0.000
13	0.437	0.040	987.02	0.000
14	0.400	-0.138	1011.0	0.000
15	0.364	-0.032	1031.0	0.000
16	0.328	-0.048	1047.4	0.000
17	0.293	0.106	1060.6	0.000
18	0.261	0.022	1071.2	0.000
19	0.233	0.045	1079.7	0.000
20	0.208	-0.014	1086.5	0.000
21	0.187	-0.006	1092.1	0.000
22	0.170	0.021	1096.7	0.000
23	0.155	0.004	1100.6	0.000
24	0.142	0.001	1103.9	0.000
25	0.131	-0.013	1106.7	0.000
26	0.121	-0.006	1109.2	0.000
27	0.113	0.005	1111.3	0.000
28	0.106	-0.032	1113.2	0.000
29	0.098	-0.062	1114.9	0.000
30	0.089	0.013	1116.2	0.000
31	0.078	-0.018	1117.3	0.000
32	0.069	0.111	1118.1	0.000
33	0.061	0.043	1118.8	0.000
34	0.057	0.009	1119.4	0.000
35	0.055	0.031	1120.0	0.000
36	0.057	-0.017	1120.5	0.000

Singapore



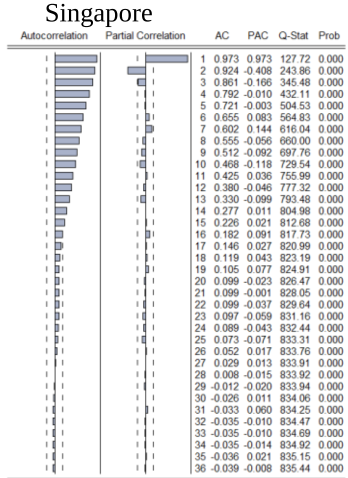
	AC	PAC	Q-Stat	Prob
1	0.833	0.833	85.332	0.000
2	0.739	0.147	153.00	0.000
3	0.661	0.046	207.66	0.000
4	0.579	-0.028	250.02	0.000
5	0.463	-0.162	277.29	0.000
6	0.394	0.039	297.27	0.000
7	0.314	-0.055	310.03	0.000
8	0.274	0.090	319.83	0.000
9	0.269	0.145	329.36	0.000
10	0.269	0.059	338.97	0.000
11	0.260	0.012	348.05	0.000
12	0.289	0.084	359.35	0.000
13	0.234	-0.245	366.84	0.000
14	0.235	0.090	374.44	0.000
15	0.208	-0.063	380.49	0.000
16	0.178	-0.010	384.95	0.000
17	0.154	0.107	388.33	0.000
18	0.144	-0.017	391.29	0.000
19	0.093	-0.074	392.54	0.000
20	0.112	0.155	394.39	0.000
21	0.134	0.006	397.05	0.000
22	0.131	-0.022	399.61	0.000
23	0.122	-0.015	401.86	0.000
24	0.188	0.152	407.26	0.000
25	0.148	-0.171	410.63	0.000
26	0.161	0.072	414.69	0.000
27	0.166	0.027	419.04	0.000
28	0.174	0.041	423.83	0.000
29	0.138	-0.073	426.87	0.000
30	0.152	0.085	430.64	0.000
31	0.141	0.015	433.90	0.000
32	0.155	0.026	437.91	0.000
33	0.182	0.099	443.48	0.000
34	0.165	-0.141	448.09	0.000
35	0.131	-0.090	451.07	0.000
36	0.170	0.141	456.12	0.000

Thailand



	AC	PAC	Q-Stat	Prob
1	0.874	0.874	103.13	0.000
2	0.675	-0.378	165.03	0.000
3	0.479	-0.016	196.46	0.000
4	0.363	0.223	214.66	0.000
5	0.289	-0.093	226.26	0.000
6	0.248	0.046	234.87	0.000
7	0.237	0.139	242.84	0.000
8	0.232	-0.070	250.53	0.000
9	0.218	-0.008	257.39	0.000
10	0.191	0.031	262.70	0.000
11	0.147	-0.097	265.86	0.000
12	0.126	0.150	268.21	0.000
13	0.084	-0.207	269.25	0.000
14	0.052	0.067	269.66	0.000
15	0.017	0.007	269.71	0.000
16	0.021	0.058	269.78	0.000
17	0.017	-0.118	269.82	0.000
18	-0.022	-0.147	269.90	0.000
19	-0.066	0.113	270.59	0.000
20	-0.088	0.030	271.82	0.000
21	-0.085	-0.069	272.97	0.000
22	-0.076	0.028	273.90	0.000
23	-0.069	0.028	274.68	0.000
24	-0.066	-0.102	275.39	0.000
25	-0.069	0.069	276.18	0.000
26	-0.077	-0.080	277.17	0.000
27	-0.091	0.053	278.57	0.000
28	-0.106	-0.068	280.47	0.000
29	-0.118	-0.054	282.88	0.000
30	-0.128	0.055	285.70	0.000
31	-0.128	0.004	288.58	0.000
32	-0.124	-0.053	291.30	0.000
33	-0.116	-0.029	293.69	0.000
34	-0.105	0.060	295.67	0.000
35	-0.094	0.011	297.28	0.000
36	-0.082	-0.010	298.53	0.000

Philippines



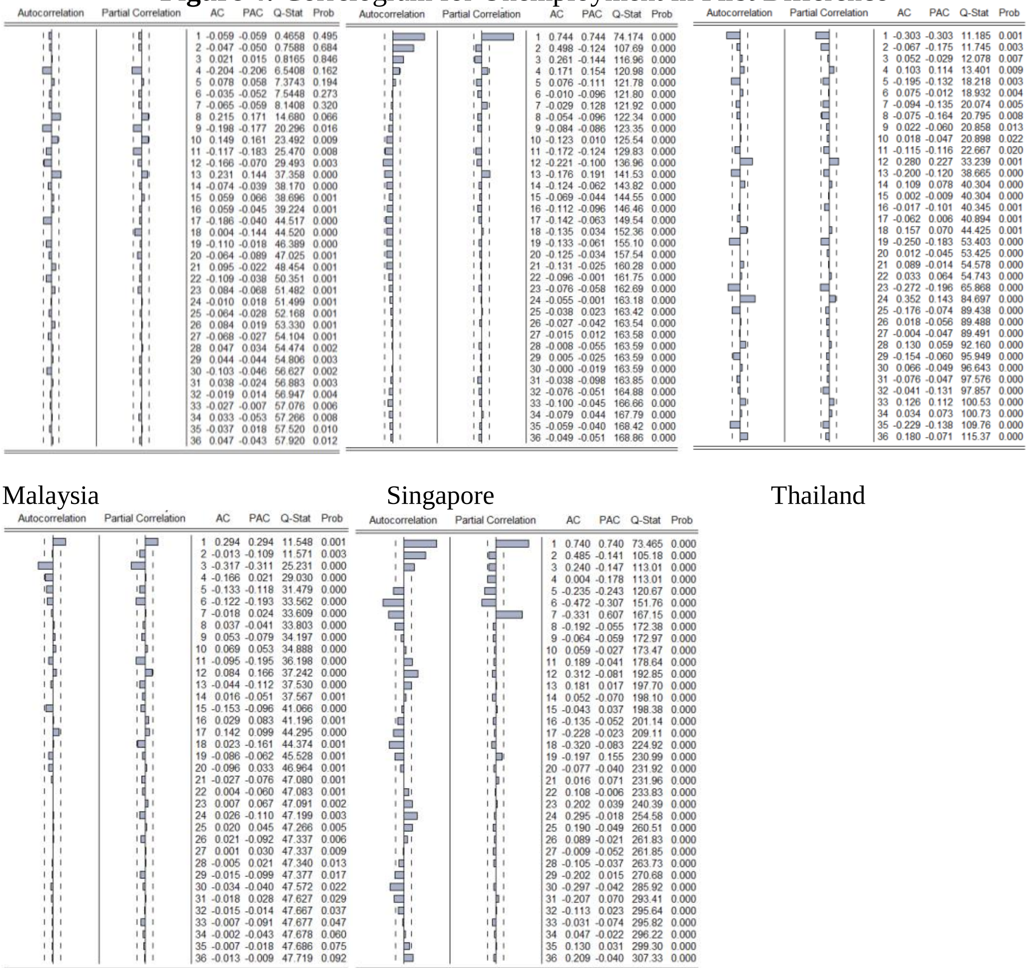
	AC	PAC	Q-Stat	Prob
1	0.973	0.973	127.72	0.000
2	0.924	-0.408	243.86	0.000
3	0.861	-0.166	345.48	0.000
4	0.792	-0.010	432.11	0.000
5	0.721	-0.003	504.53	0.000
6	0.655	0.083	564.83	0.000
7	0.602	0.144	616.04	0.000
8	0.555	-0.056	660.00	0.000
9	0.512	-0.092	697.76	0.000
10	0.468	-0.118	729.54	0.000
11	0.425	0.036	755.99	0.000
12	0.380	-0.046	777.32	0.000
13	0.330	-0.099	793.48	0.000
14	0.277	0.011	804.98	0.000
15	0.226	0.021	812.68	0.000
16	0.182	0.091	817.73	0.000
17	0.146	0.027	820.99	0.000
18	0.119	0.043	823.19	0.000
19	0.105	0.077	824.91	0.000
20	0.099	-0.023	826.47	0.000
21	0.099	-0.001	828.05	0.000
22	0.099	-0.037	829.64	0.000
23	0.097	-0.059	831.16	0.000
24	0.089	-0.043	832.44	0.000
25	0.073	-0.071	833.31	0.000
26	0.052	0.017	833.76	0.000
27	0.029	0.013	833.91	0.000
28	0.008	-0.015	833.92	0.000
29	-0.012	-0.020	833.94	0.000
30	-0.026	0.011	834.06	0.000
31	-0.033	0.060	834.25	0.000
32	-0.035	-0.010	834.47	0.000
33	-0.035	-0.010	834.69	0.000
34	-0.035	-0.014	834.92	0.000
35	-0.036	0.021	835.15	0.000
36	-0.039	-0.008	835.44	0.000

Indonesia

Source: Result from Eview-10

Figure 4 shows that the correlogram for the first difference series in the cases of Singapore, Thailand, the Philippines and Indonesia had seasonal properties. This situation was because the autocorrelation at lags 1 and 12 was greater than the bounds of the correlogram in Singapore. Besides, the cases in Thailand, the Philippines and Indonesia were more than the bounds for the autocorrelation's lags 1, 12 and 24. Nevertheless, the first difference indicated no seasonal pattern in Malaysia's case. As a result, Malaysia's unemployment was forecasted using the ARIMA model, while the SARIMA model was applied to Singapore, Thailand, the Philippines and Indonesia.

Figure 4: Correlogram for Unemployment in First Difference



Malaysia Singapore Thailand

Philippines Indonesia

Source: Result from Eview-10

4.2.2. Estimation

The procedure was continued to identify the corresponding ARIMA (p,q) through the correlogram. The estimation process is displayed in Table 4.

Table 4: Estimation of the ARIMA Model

Malaysia				
ARIMA model	**(4,1,4)**	(4,1,9)	(9,1,4)	(9,1,9)
AIC	-0.4713	-0.4632	-0.4523	-0.4350
SC	-0.3835	-0.3754	-0.3645	-0.3472

HQ	-0.4356	-0.4275	-0.4166	-0.3993
		Singapore		
ARIMA model	(1,1,1)	**(1,1,3)**	(3,1,1)	(3,1,3)
AIC	-3.8258	-3.9111	-3.5127	-3.0785
SC	-3.7380	-3.8233	-3.4249	-2.9907
HQ	-3.7901	-3.8754	-3.4771	-3.0429
		Thailand		
ARIMA model	(1,1,1)	(1,1,2)	**(2,1,1)**	(2,1,2)
AIC	-0.6503	-0.6509	-0.6518	-0.5173
SC	-0.5569	-0.5575	-0.5583	-0.4239
HQ	-0.6124	-0.6130	-0.6138	-0.4794
		Philippines		
ARIMA model	(1,1,1)	**(1,1,3)**	(3,1,1)	(3,1,3)
AIC	2.5061	2.3299	2.4029	2.4223
SC	2.5939	2.4377	2.4907	2.5101
HQ	2.5418	2.3856	2.4386	2.4580
		Indonesia		
ARIMA model	(1,1,1)	**(1,1,6)**	(6,1,1)	(6,1,6)
AIC	-2.4321	-3.0307	-2.5620	-2.0605
SC	-2.3443	-2.9429	-2.4742	-1.9727
HQ	-2.3964	-2.9950	-2.5263	-2.0249

Source: Result from Eview-10

Figure 5: ARIMA (4,1,4) for Malaysia

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007222	0.016301	0.443018	0.6585
AR(4)	-0.773457	0.189565	-4.080174	0.0001
MA(4)	0.575194	0.260021	2.212106	0.0287
SIGMASQ	0.034238	0.001961	17.46130	0.0000

Source: Result from Eview-10

From the estimation result, the ARIMA model, which had the lowest AIC, SC, and HQ, was considered the most adequate. By comparing the criterion, ARIMA (4,1,4) in Malaysia, ARIMA (1,1,3) in Singapore, ARIMA (2,1,1) in Thailand, ARIMA (1,1,3) in the Philippines and ARIMA (1,1,6) in Indonesia were the most suitable ARIMA models for each case respectively. Consequently, the ARIMA model chosen for Malaysia's case was resumed for the diagnostic stage. In contrast, the selected ARIMA model for the Singapore, Thailand, Philippines and Indonesia cases was modified into SARIMA.

4.2.3. Seasonal Autoregressive Model (SARIMA)

As mentioned, Singapore, Thailand, the Philippines and Indonesia's unemployment variables had seasonal trends. Therefore, these cases were eligible for the SARIMA model. The estimation of the SARIMA is shown in Table 5.

Table 5: Estimation of the SARIMA Model

			Singapore		
ARIMA model	(1,1,3)(1,1,1)$_{12}$	(1,1,3)(1,1,0)$_{12}$	**(1,1,3)(0,1,1)$_{12}$**	(1,1,3)(2,1,0)$_{12}$	(1,1,3)(2,1,1)$_{12}$
AIC	-3.9511	-3.9232	-3.9275	-3.8972	--3.9185
SC	-3.8194	-3.8135	-3.8177	-3.7875	-3.7868
HQ	-3.8976	-3.8786	-3.8829	-3.8527	-3.8650
			Thailand		
ARIMA model	(2,1,1) (1,1,1)$_{12}$	(2,1,1) (1,1,0)$_{12}$	(2,1,1) (0,1,1)$_{12}$	(2,1,1) (2,1,0)$_{12}$	**(2,1,1) (2,1,1)$_{12}$**
AIC	-0.8100	-0.7420	-0.6965	-0.7683	-0.8121
SC	-0.6698	-0.6252	-0.5797	-0.6515	-0.6720
HQ	-0.7531	-0.6946	-0.6491	-0.7209	-0.7552
			Philippines		
ARIMA model	(1,1,3)(1,1,1)$_{12}$	**(1,1,3)(1,1,0)$_{12}$**	(1,1,3)(0,1,1)$_{12}$	(1,1,3)(2,1,0)$_{12}$	(1,1,3)(2,1,1)$_{12}$
AIC	2.3690	2.3539	2.3541	2.3646	2.3689
SC	2.5007	3.4636	2.4639	2.4744	2.5005
HQ	2.4225	2.3984	2.3987	2.4092	2.4223
			Indonesia		
ARIMA model	(1,1,6) (1,1,1)$_{12}$	(1,1,6) (1,1,0)$_{12}$	(1,1,6) (0,1,1)$_{12}$	(1,1,6) (2,1,0)$_{12}$	**(1,1,6) (2,1,1)$_{12}$**
AIC	-3.3234	-3.2120	-3.1381	-3.3111	-3.3455
SC	-3.1917	-3.1023	-3.0283	-3.2014	-3.2138
HQ	-3.2699	-3.1674	-3.0935	-3.2665	-3.2920

Source: Result from Eview-10

For the Singapore case, SARIMA (1,1,3)(1,1,1)$_{12}$ had the lowest value for AIC, SC and HQ. Nevertheless, this model's SMA(12) component was insignificant. As a result, SARIMA (1,1,3)(0,1,1)$_{12}$ was the most suitable for Singapore's case.

Figure 6: SARIMA (1,1,3)(1,1,1)$_{12}$ and (1,1,3)(0,1,1)$_{12}$ for Singapore

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002731	0.006859	0.398183	0.6912
AR(1)	0.860726	0.062664	13.73564	0.0000
SAR(12)	0.698173	0.203120	3.437240	0.0008
MA(3)	-0.481668	0.065910	-7.307968	0.0000
SMA(12)	-1.000000	833.6974	-0.001199	0.9990
SIGMASQ	0.000921	0.383811	0.002400	0.9981

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002345	0.010862	0.215912	0.8294
AR(1)	0.860054	0.057038	15.07873	0.0000
MA(3)	-0.472548	0.063034	-7.496704	0.0000
SMA(12)	-0.194571	0.062488	-3.113744	0.0023
SIGMASQ	0.001053	8.29E-05	12.70352	0.0000

Source: Result from Eview-10

Figure 7: SARIMA (2,1,1)(2,1,1)$_{12}$ for Thailand

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.010403	0.018248	0.570093	0.5697
AR(2)	-0.152271	0.088845	-1.713905	0.0893
SAR(24)	0.465079	0.120156	3.870626	0.0002
MA(1)	-0.272341	0.084257	-3.232251	0.0016
SMA(12)	0.322853	0.105380	3.063702	0.0027
SIGMASQ	0.022320	0.002928	7.623086	0.0000

Source: Result from Eview-10

Figure 8: SARIMA (1,1,3)(1,1,0)$_{12}$ for the Philippines

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000548	0.100647	-0.005448	0.9957
AR(1)	0.302392	0.033900	8.920158	0.0000
SAR(12)	0.115155	0.068351	1.684777	0.0945
MA(3)	-0.435891	0.046812	-9.311523	0.0000
SIGMASQ	0.567356	0.032658	17.37247	0.0000

Source: Result from Eview-10

Figure 9: SARIMA (1,1,6)(2,1,1)$_{12}$ for Indonesia

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.005330	0.033965	-0.156925	0.8756
AR(1)	0.916445	0.066071	13.87067	0.0000
SAR(24)	0.682331	0.076662	8.900495	0.0000
MA(6)	-0.897182	0.050572	-17.74053	0.0000
SMA(12)	0.253940	0.069380	3.660151	0.0004
SIGMASQ	0.001666	0.000118	14.09141	0.0000

Source: Result from Eview-10

Meanwhile, SARIMA (2,1,1)(2,1,1)$_{12}$, SARIMA (1,1,3)(1,1,0)$_{12}$ and SARIMA (1,1,6) (2,1,1)$_{12}$ were the most suitable models for Thailand, the Philippines and Indonesia, respectively. These models were selected based on the lowest criterion among AIC, SC and HQ.

4.2.4. Diagnostic

The last stage after the estimation process was diagnostic checking. The residuals test for the autocorrelation with conditional heteroscedasticity was conducted for Malaysia's ARIMA model and the SARIMA model of Singapore, Thailand, the Philippines and Indonesia. The result revealed that the P-value for autocorrelation and partial autocorrelation coefficients were more than 0.05, indicating that all lags were insignificant. As a result, the residuals were not autocorrelated, thus allowing the model to be used for forecasting.

Figure 10: Diagnostic Residuals' Autocorrelation Test

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.009	-0.009	0.0111	
		2	-0.079	-0.079	0.8436	
		3	-0.012	-0.013	0.8627	0.353
		4	0.051	0.045	1.2208	0.543
		5	-0.003	-0.004	1.2221	0.748
		6	-0.015	-0.008	1.2554	0.869
		7	-0.088	-0.089	2.3527	0.799
		8	0.046	0.041	2.6586	0.850
		9	-0.134	-0.150	5.2391	0.631
		10	0.147	0.158	8.3390	0.401
		11	-0.129	-0.156	10.758	0.293
		12	-0.047	-0.019	11.080	0.351
		13	0.166	0.166	15.167	0.175
		14	-0.036	-0.088	15.365	0.222
		15	0.023	0.090	15.444	0.280
		16	-0.043	-0.094	15.718	0.331
		17	-0.118	-0.092	17.857	0.270
		18	-0.060	-0.124	18.405	0.301
		19	-0.082	-0.060	19.460	0.303
		20	-0.021	-0.064	19.532	0.360
		21	0.020	0.020	19.595	0.419
		22	-0.057	-0.000	20.112	0.451
		23	0.065	-0.026	20.803	0.471
		24	-0.034	0.033	20.991	0.521
		25	-0.006	-0.063	20.997	0.581
		26	0.030	0.001	21.151	0.630
		27	-0.042	-0.055	21.441	0.668
		28	0.059	0.029	22.035	0.687
		29	0.003	-0.017	22.036	0.736
		30	-0.068	-0.044	22.824	0.742
		31	0.006	0.007	22.830	0.784
		32	-0.013	-0.004	22.861	0.821
		33	-0.002	-0.012	22.862	0.854
		34	-0.017	-0.060	22.912	0.881
		35	-0.008	0.002	22.923	0.905
		36	0.049	-0.041	23.363	0.915

Malaysia

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.026	0.026	0.0928	
		2	0.024	0.023	0.1677	
		3	0.092	0.091	1.3208	
		4	0.026	0.021	1.4109	0.235
		5	0.004	-0.001	1.4134	0.493
		6	-0.163	-0.174	5.1071	0.164
		7	0.024	0.028	5.1892	0.268
		8	-0.009	-0.003	5.1996	0.392
		9	-0.101	-0.072	6.6692	0.353
		10	0.008	0.017	6.6796	0.463
		11	-0.024	-0.020	6.7624	0.562
		12	-0.001	-0.012	6.7625	0.662
		13	-0.030	-0.019	6.8989	0.735
		14	-0.021	-0.018	6.9620	0.802
		15	0.105	0.085	8.6189	0.735
		16	-0.059	-0.052	9.1461	0.762
		17	-0.027	-0.033	9.2537	0.814
		18	-0.054	-0.078	9.7048	0.838
		19	-0.040	-0.037	9.9546	0.869
		20	-0.019	-0.016	10.012	0.903
		21	-0.145	-0.105	13.323	0.772
		22	0.006	-0.003	13.329	0.821
		23	-0.037	-0.038	13.545	0.853
		24	-0.061	-0.046	14.153	0.863
		25	0.006	-0.007	14.159	0.896
		26	-0.026	-0.027	14.274	0.919
		27	0.029	-0.008	14.419	0.937
		28	-0.020	-0.018	14.486	0.953
		29	0.023	0.008	14.574	0.965
		30	0.044	-0.007	14.904	0.971
		31	-0.001	0.006	14.904	0.979
		32	-0.009	-0.037	14.917	0.986
		33	-0.102	-0.117	16.760	0.975
		34	-0.006	-0.020	16.767	0.982
		35	0.002	-0.004	16.767	0.988
		36	-0.048	-0.016	17.196	0.989

Singapore

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.015	0.015	0.0289	
		2	0.006	0.006	0.0335	
		3	0.029	0.029	0.1368	
		4	0.045	0.044	0.3926	
		5	-0.096	-0.098	1.5479	0.213
		6	-0.039	-0.038	1.7454	0.418
		7	-0.001	-0.001	1.7455	0.627
		8	-0.099	-0.096	3.0088	0.556
		9	-0.023	-0.009	3.0777	0.688
		10	-0.041	-0.046	3.2986	0.771
		11	0.146	0.149	6.1537	0.522
		12	-0.031	-0.028	6.2793	0.616
		13	-0.053	-0.071	6.6674	0.672
		14	0.101	0.094	8.0553	0.623
		15	-0.003	-0.030	8.0562	0.708
		16	-0.074	-0.057	8.8311	0.717
		17	-0.015	-0.010	8.8622	0.783
		18	0.030	0.003	8.9945	0.831
		19	-0.194	-0.157	14.402	0.495
		20	0.009	0.024	14.414	0.568
		21	0.001	-0.005	14.414	0.638
		22	0.075	0.072	15.254	0.644
		23	-0.074	-0.065	16.066	0.653
		24	-0.095	-0.122	17.427	0.625
		25	-0.047	-0.090	17.768	0.664
		26	-0.030	-0.033	17.909	0.711
		27	-0.021	-0.002	17.982	0.758
		28	0.072	0.077	18.793	0.763
		29	-0.055	-0.111	19.274	0.784
		30	-0.125	-0.079	21.806	0.699
		31	0.021	-0.010	21.880	0.743
		32	0.015	-0.039	21.917	0.785
		33	0.080	0.110	22.990	0.777
		34	0.044	0.042	23.317	0.802
		35	-0.121	-0.176	25.836	0.729
		36	-0.005	-0.021	25.839	0.771

Thailand

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.022	0.022	0.0653	
		2	-0.067	-0.067	0.6640	
		3	0.018	0.021	0.7079	
		4	-0.031	-0.037	0.8437	0.358
		5	-0.109	-0.106	2.4942	0.287
		6	-0.073	-0.075	3.2417	0.356
		7	0.036	0.026	3.4274	0.489
		8	-0.058	-0.068	3.9049	0.563
		9	0.051	0.054	4.2722	0.640
		10	0.067	0.040	4.9133	0.671
		11	-0.177	-0.190	9.4656	0.305
		12	0.009	0.021	9.4764	0.395
		13	-0.080	-0.119	10.421	0.404
		14	0.081	0.103	11.405	0.410
		15	-0.179	-0.207	16.227	0.181
		16	-0.012	-0.014	16.250	0.236
		17	0.169	0.119	20.610	0.112
		18	-0.048	-0.070	20.972	0.138
		19	-0.086	-0.107	22.119	0.139
		20	-0.053	-0.075	22.566	0.164
		21	0.016	-0.009	22.607	0.206
		22	0.019	0.030	22.665	0.252
		23	0.014	-0.005	22.696	0.304
		24	0.010	-0.073	22.713	0.359
		25	0.003	0.069	22.714	0.418
		26	0.028	-0.104	22.844	0.470
		27	-0.024	-0.008	22.938	0.523
		28	-0.005	0.004	22.943	0.581
		29	0.006	0.016	22.950	0.636
		30	-0.036	-0.069	23.172	0.676
		31	-0.005	-0.083	23.176	0.724
		32	0.002	0.040	23.177	0.768
		33	-0.020	-0.030	23.246	0.805
		34	0.002	-0.056	23.246	0.840
		35	0.015	-0.032	23.285	0.869
		36	-0.015	0.014	23.326	0.894

The Philippines

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.030	0.030	0.1185	
		2	0.019	0.018	0.1676	
		3	-0.102	-0.103	1.5843	
		4	0.018	0.025	1.6312	
		5	0.015	0.018	1.6615	0.197
		6	0.091	0.080	2.8223	0.244
		7	0.029	0.028	2.9407	0.401
		8	0.008	0.006	2.9497	0.566
		9	-0.056	-0.042	3.3900	0.640
		10	-0.034	-0.031	3.5606	0.736
		11	0.049	0.051	3.9028	0.791
		12	0.028	0.010	4.0208	0.855
		13	-0.004	-0.017	4.0235	0.910
		14	0.017	0.028	4.0687	0.944
		15	-0.038	-0.030	4.2854	0.961
		16	-0.048	-0.045	4.6366	0.969
		17	0.047	0.051	4.9729	0.976
		18	-0.121	-0.141	7.2479	0.925
		19	-0.000	-0.005	7.2479	0.950
		20	-0.010	0.009	7.2643	0.968
		21	-0.034	-0.054	7.4477	0.977
		22	-0.013	0.003	7.4730	0.985
		23	0.006	0.007	7.4796	0.991
		24	-0.006	0.002	7.4863	0.995
		25	-0.023	-0.024	7.5711	0.997
		26	0.027	0.041	7.6949	0.998
		27	-0.038	-0.038	7.9330	0.998
		28	-0.006	-0.021	7.9387	0.999
		29	0.008	0.034	7.9492	1.000
		30	-0.010	-0.018	7.9681	1.000
		31	-0.039	-0.052	8.2322	1.000
		32	0.044	0.069	8.5739	1.000
		33	-0.050	-0.059	9.0169	1.000
		34	0.015	-0.009	9.0574	1.000
		35	-0.012	0.025	9.0845	1.000
		36	0.010	-0.026	9.1016	1.000

Indonesia

Source: Result from Eview-10

4.3. Generalised Auto-Regressive Conditional Heteroscedasticity (GARCH)

Before adopting the GARCH model, it is required to check the volatility of the data. Ab Aziz et al. (2023) suggested that the methods of kurtosis and skewness can be applied, in which the kurtosis value is larger than three while the skewness is either to the left or right.

Table 6: Skewness, Kurtosis and Normality Tests

Country	Skewness	Kurtosis	Jarque-Bera	Probability
Malaysia	1.3023	10.7448	364.4266	0.0000
Singapore	0.6912	4.1884	18.1401	0.0001
Thailand	1.3331	5.8417	75.9215	0.0000
The Philippines	2.2545	19.2745	1556.668	0.0000

Indonesia	1.5322	7.1824	146.7334	0.0000

Source: Result from Eview-10

From Table 6, each country portrayed a rightward skewness, and the values of kurtosis were more than three. Both indicators revealed that the volatility of the model allowed the application of the GARCH model. Nevertheless, the volatility should be ensured in the heteroscedastic state (Yunita, 2016). The white test demonstrated that the model fulfilled the heteroscedastic with all the P-values smaller than 0.05.

Table 7: White Test

Country	Obs*R-squared	Prob. Chi-square
Malaysia	131	0.0000
Singapore	131	0.0000
Thailand	119	0.0000
The Philippines	131	0.0000
Indonesia	131	0.0000

Source: Result from Eview-10

As the models were volatile, stationary and heteroscedastic, they were eligible for the GARCH model. Several models were estimated for each country, and the most appropriate model depended on the smallest AIC and SC values. From the outcome of the estimation for the GARCH model, the most appropriate model for Malaysia was GARCH (1,0), Singapore was GARCH (3,0), Thailand was GARCH (1,3), the Philippines was GARCH (2,2) and Indonesia was GARCH (3,3).

Table 8: GARCH Model

Model (p,q)	p=1	p=2	p=3	q=1	q=2	q=3	AIC	SC
				Malaysia				
GARCH (1,0)	**0.8232***						**-0.9377**	**-0.8495**
GARCH (2,0)	0.7636*	0.1207					-0.9350	-0.8247
GARCH (3,0)	0.7735*	0.1586	-0.0316				-0.9191	-0.7868
GARCH (1,1)	0.7616*			0.1301			-0.9353	-0.8351
GARCH (1,2)	0.5720*			0.2564	-0.1593		-0.9075	-0.7752
GARCH (1,3)	0.7470*			0.1495	-0.0143	-0.0079	-0.9043	-0.7499
GARCH (2,1)	0.7723*	-0.0199		0.1523			-0.9190	-0.7867
GARCH (2,2)	0.7334*	-0.4432		0.7624	-0.1066		-0.9064	-0.7520
GARCH (2,3)	0.5023*	0.2462		-0.2780	0.0517	-0.0904	-0.8942	-0.7177
GARCH (3,1)	0.7378*	-0.2996	-0.0933	0.5947			-0.9065	-0.7521
GARCH (3,2)	0.7393*	-0.3755	-0.0352	0.6736	-0.0610		-0.8909	-0.7145

GARCH (3,3)	0.6042*	0.1898	0.0438	0.0274	-0.1565	-0.0161	-0.8808	-0.6822
Singapore								
GARCH (1,0)	-0.0251						-3.8313	-3.7430
GARCH (2,0)	0.2524	0.5334**					-3.9048	-3.7945
GARCH (3,0)	**-0.0307***	**-0.0261***	**0.4928***				**-4.4038**	**-4.2714**
GARCH (1,1)	0.2279			0.6025*			-3.9357	-3.8254
GARCH (1,2)	0.3099			0.9905*	-0.4483*		-4.0849	-3.9526
GARCH (1,3)	0.2968*			0.506**	0.1445	-0.27	-4.0062	-3.8518
GARCH (2,1)	-0.0658*	0.6242*		0.3792*			-4.0277	-3.8954
GARCH (2,2)	-0.0637**	0.5574*		0.6418*	-0.2732*		-4.1380	-3.9836
GARCH (2,3)	-0.0433	0.307**		0.5916	-0.2071	-0.0728	-4.0624	-3.8860
GARCH (3,2)	-0.0437*	-0.0255*	0.6552*	0.1750	-0.0366		-4.3420	-4.1655
GARCH (3,3)	-0.0413	-0.0136	0.5555*	0.1847	-0.0457	-0.0810	-4.2294	-4.0309
Thailand								
GARCH (1,0)	0.0502						-0.6324	-0.5385
GARCH (2,0)	0.0014	0.3479**					-0.6619	-0.5445
GARCH (3,0)	-0.0068	0.3626*	0.0574				-0.6452	-0.5043
GARCH (1,1)	0.1122			0.7694*			-0.6370	-0.5196
GARCH (1,2)	0.0954			0.9916	-0.1950		-0.6207	-0.4798
GARCH (1,3)	**0.1612****			**1.1737***	**-1.1613***	**0.5853***	**-0.6849**	**-0.5205**
GARCH (2,1)	-0.0017	0.3525**			0.0668		-0.6456	-0.5047
GARCH (2,2)	-0.0106	0.3689**		0.1297	-0.2686		-0.6747	-0.5103
GARCH (2,3)	-0.0186	0.3480**		0.1509	-0.3262	0.3514	-0.6736	-0.4857
GARCH (3,1)	0.0065	0.3402**	-0.1872	0.5509			-0.6254	-0.4610
GARCH (3,2)	-0.0075	0.3609**	-0.0964	0.3718	-0.3022		-0.6464	-0.4585
GARCH (3,3)	0.0103	0.3064**	-0.0754	0.3708	-0.3943	0.2724	-0.6485	-0.4372
The Philippines								

GARCH (1,0)	6.2306*						1.1090	1.1972
GARCH (2,0)	6.2281*	-0.0036					1.1237	1.2340
GARCH (1,1)	6.2302*			-0.0006			1.1242	1.2345
GARCH (1,2)	3.1042*			-0.2595*	0.0887*		1.3723	1.5047
GARCH (1,3)	1.6655*			-0.4456*	0.0302	0.1492*	1.2687	1.4231
GARCH (2,2)	**1.5251**	**-0.2598**		**0.0463**	**0.4299***		**0.9589**	**1.1133**
GARCH (3,1)	1.4105*	-1.0142*	0.8961*	0.5018*			0.9745	1.1289
GARCH (3,2)	1.6801*	-1.0102	0.2910	0.0882	0.0851		1.4844	1.6608
GARCH (3,3)	0.2762	0.4695	0.0274	0.3014	-0.0634	-0.0845	1.7642	1.9627
				Indonesia				
GARCH (1,0)	0.4293***						-2.5043	-2.4161
GARCH (2,0)	0.0665	0.4209					-2.5075	-2.3973
GARCH (3,0)	0.0681	0.4677	-0.0177				-2.4934	-2.3610
GARCH (1,1)	0.1277			0.6046			-2.4966	-2.3863
GARCH (1,2)	0.0644			1.5560*	-0.7433*		-2.5725	-2.4402
GARCH (1,3)	0.0590			1.1972	-0.0911	-0.3392	-2.5518	-2.3974
GARCH (2,1)	0.0578	0.0673		0.6031			-2.4836	-2.3513
GARCH (2,2)	0.0803	0.0938		-0.2989	0.706**		-2.6921	-2.5377
GARCH (2,3)	-0.0157	0.0555*	0.4006*	-0.5396*	0.8852*		-2.7174	-2.5410
GARCH (3,1)	0.0653	0.4845	-0.2962	0.5369			-2.4794	-2.3250
GARCH (3,2)	0.0051	-0.0064	0.0947	1.4706**	-0.7915		-2.6364	-2.4599
GARCH (3,3)	**-0.0193****	**-0.0066**	**0.2575**	**0.0250**	**-0.0385**	**0.4071**	**-2.7465**	**-2.5479**

Notes: (*), (**) and (***) denote the significance level at 1%, 5% and 10%, respectively.
Source: Result from Eview-10

4.4. Forecasting

After completing the Box-Jenkins and the GARCH model procedures, the models most suitable for every case were ready for forecasting. Both dynamic and static methods of forecasting were compared with the performance.

Table 9: Type of Forecasting According to Performance

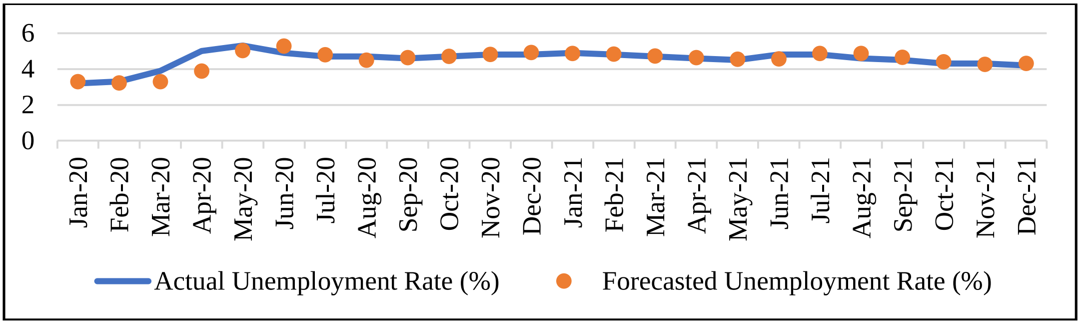
Method	Type of forecasting	Root Mean Squared Error	Mean Absolute Error	Theil Inequality Coefficient	Symmetric MAPE
Malaysia					
ARIMA (4,1,4)	Dynamic	0.1885	0.1156	0.8947	189.7260
	Static	**0.1829**	**0.1128**	**0.7341**	**162.2057**
GARCH (1,0)	Dynamic	0.1900	0.1175	0.9286	188.7749
	Static	0.1934	0.1196	0.8142	175.9895
Singapore					
SARIMA $(1,1,3)(0,1,1)_{12}$	Dynamic	0.0523	0.0373	0.9335	190.5053
	Static	**0.0326**	**0.0195**	**0.3515**	112.0736
GARCH (3,0)	Dynamic	0.0532	0.0391	0.8700	177.0393
	Static	0.0349	0.0197	0.3699	**109.5522**
Thailand					
SARIMA $(2,1,1)(2,1,1)_{12}$	Dynamic	0.1631	0.1317	0.7104	152.7781
	Static	**0.1483**	**0.1135**	**0.5367**	**118.1269**
GARCH (1,3)	Dynamic	0.2807	0.1471	0.9338	184.9316
	Static	0.1713	0.1327	0.6895	132.3059
The Philippines					
SARIMA $(1,1,3)(1,1,0)_{12}$	Dynamic	0.9048	0.4139	0.9843	189.5218
	Static	**0.7922**	0.3938	**0.5956**	**135.9636**
GARCH (2,2)	Dynamic	0.8642	0.3937	0.9886	188.0251
	Static	0.8318	**0.3646**	0.6843	137.9364
Indonesia					
SARIMA $(1,1,6)(2,1,1)_{12}$	Dynamic	0.0956	0.0513	0.6455	97.3473
	Static	**0.0418**	**0.0207**	**0.2088**	**39.7484**

GARCH (3,3)	Dynamic	0.1058	0.0756	0.9100	159.5516
	Static	0.0722	0.0312	0.3611	47.9911

Source: Result from Eview-10

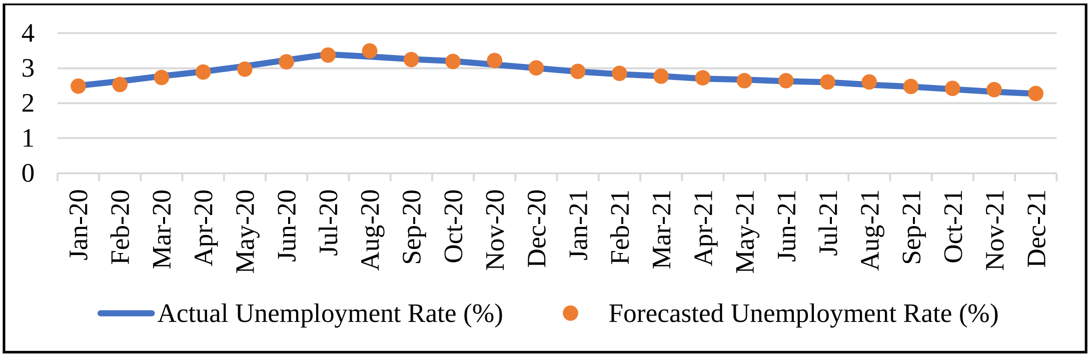
From Table 9, the static models exhibited lower values for RMSE, MAE, Theil inequality coefficient, and symmetric MAPE compared to the dynamic forecasting method. Consequently, this study used static forecasting for each country case. Based on the forecasting performances, both the ARIMA and SARIMA models outperformed the GARCH model. Therefore, the ARIMA and SARIMA models were more suitable for forecasting unemployment among ASEAN-5 countries when compared to the GARCH model. Using ARIMA or SARIMA, the forecasted unemployment rates were compared with the actual unemployment rate. The comparison focused on the COVID-19 pandemic period, from January 2020 to December 2021 for Malaysia, Singapore, the Philippines and Indonesia, and from January 2020 to December 2020 for Thailand. The results are displayed in Figures 11 to 15.

Figure 11: The Actual and Forecasted Unemployment Rates in Malaysia, January 2020–December 2021



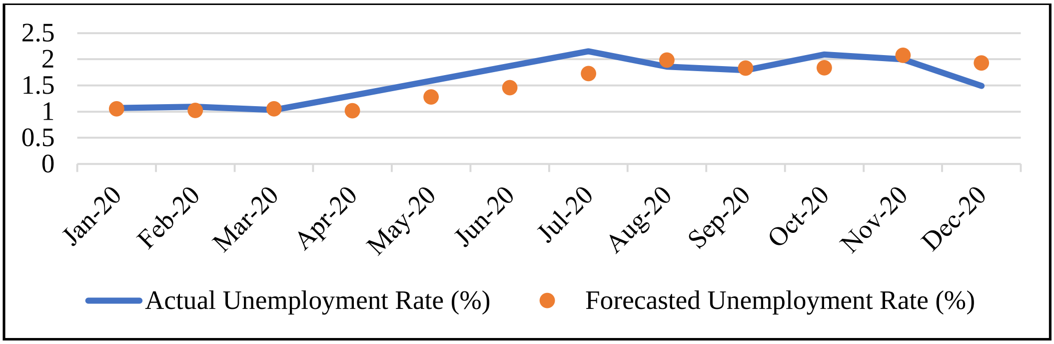
Source: Result from Eview-10

Figure 12: The Actual and Forecasted Unemployment Rates in Singapore, January 2020–December 2021



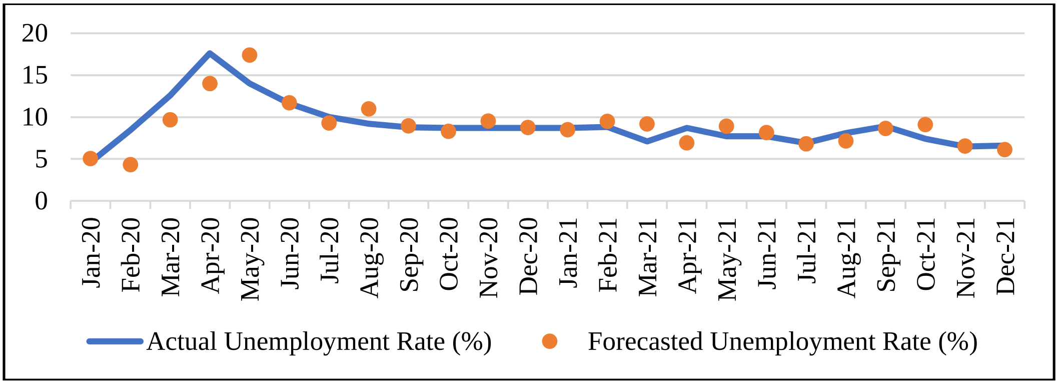
Source: Result from Eview-10

Figure 13: The Actual and Forecasted Unemployment Rates in Thailand, January 2020–December 2020



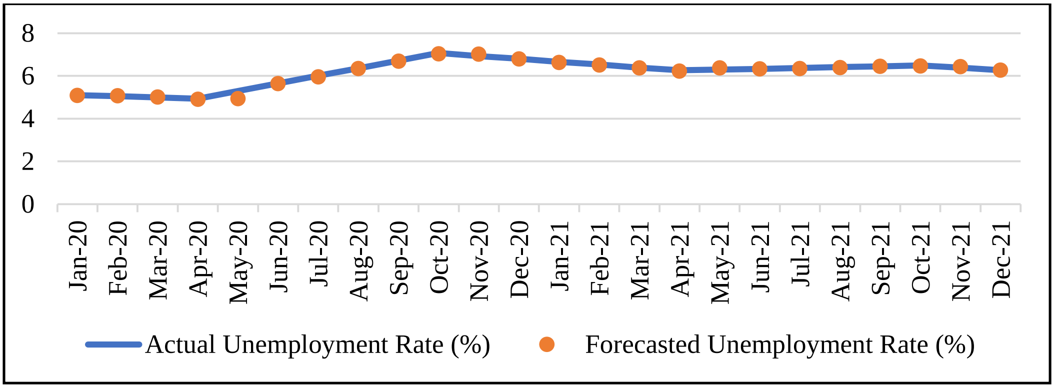
Source: Result from Eview-10

Figure 14: The Actual and Forecasted Unemployment Rates in the Philippines, January 2020–December 2021



Source: Result from Eview-10

Figure 15: The Actual and Forecasted Unemployment Rates in Indonesia, January 2020–December 2021



Source: Result from Eview-10

Based on the findings, the forecasted unemployment rate was the same as the actual unemployment rate for Malaysia, Singapore and Indonesia. Therefore, the ARIMA model was suitable for forecasting unemployment in Malaysia. This result was in line with the studies by Ismail et al. (2022) and Lip et al. (2021). Meanwhile, the SARIMA model adequately forecasted unemployment in Singapore and Indonesia. For these two countries, the forecasted results added new knowledge to the existing literature review, whereby the SARIMA model can compute with suitable forecasted results. The forecasted results in Thailand and the Philippines deviated from the actual data; however, the trends still followed the same pattern as the actual result. Therefore, the SARIMA model was suitable for forecasting unemployment in Thailand and the Philippines and tallied with the studies conducted by Mahipan et al. (2013) and Urrutia et al. (2017).

5. CONCLUSION

In conclusion, this study aimed to compare the performance of ARIMA, SARIMA, and GARCH models in modelling and forecasting unemployment rates during the COVID-19 pandemic among the ASEAN-5 countries: Malaysia, Singapore, Thailand, the Philippines and Indonesia. An adequate model is vital to obtain a better forecast result. Each country's ARIMA and SARIMA models were selected based on the lowest value in the Akaike information criterion, Schwarz Bayesian criterion and Hannan-Quinn criterion. From the results, Malaysia's case could not proceed with SARIMA because there was no seasonal pattern in the unemployment variable. Therefore, the most fitted model for Malaysia was ARIMA (4,1,4). Meanwhile, Singapore, Thailand, the Philippines and Indonesia were most suited with SARIMA $(1,1,3)(0,1,1)_{12}$, SARIMA $(2,1,1)$ $(2,1,1)_{12}$, SARIMA $(1,1,3)(1,1,0)_{12}$ and SARIMA $(1,1,6)$ $(2,1,1)_{12}$, respectively. The adequate GARCH model was selected according to the lowest AIC and SC values. The most appropriate model for Malaysia was GARCH (1,0), Singapore was GARCH (3,0), Thailand was GARCH (1,3), the Philippines was GARCH (2,2) and Indonesia was GARCH (3,3).

Based on the root mean squared error, mean absolute error, Theil inequality coefficient and symmetric MAPE, the ARIMA and SARIMA models showed a better result when compared with the GARCH model among theASEAN-5 countries to forecast unemployment. Consequently, this condition was the same as that of Haque and Shaik (2021) and Nuryatin (2020). This study's result was also aligned with Ismail et al. (2022) and Waffa and Wahiba (2022), in which the ARIMA and SARIMA models are the best fit to forecast unemployment, even during the COVID-19 pandemic period. Therefore, forecasting is paramount to planning future policies to overcome economic disturbance. The COVID-19 pandemic has deteriorated ASEAN economies, especially in terms of unemployment. The forecasted unemployment rate can guide government agencies in implementing related policies to recover from unemployment. Future studies can utilise different types of time series data, for example, yearly and quarterly data, to further the forecasting capacity. Moreover, other forecasting techniques, including Simple Exponential Smoothing (SES), Holt's model and Artificial Neutral Network (ANN), are recommended to be adopted and compared with the ARIMA and SARIMA models.

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